UNIVERSITY OF SOUTHAMPTON

A MODEL OF E-LEARNING UPTAKE AND CONTINUANCE IN HIGHER EDUCATIONAL INSTITUTIONS

by

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ABSTRACT

FACULTY OF PHYSICAL SCIENCES AND ENGINEERING
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To predict and explain E-learning usage in higher educational institutes (HEIs) better, this research conceptualized E-learning usage as two steps, E-learning uptake and continuance. The aim was to build a model of effective uptake and continuance of E-learning in HEIs, or 'EUCH'.

The EUCH model was constructed by applying five grounded theories: Unified Theory of Acceptance and Use of Technology (UTAUT); Keller's ARCS model; Theory of Reasoned Action (TRA); Cognitive Dissonance Theory (CDT); and Adaptation Level Theory (ALT). The preliminary study was conducted with experts and end users (students) to confirm the factors of E-learning uptake and continuance. With confirmation through triangulation from at least two source of data (literature, expert and end user review), all the proposed factors were indeed confirmed. A longitudinal study was conducted in a Thai university to: (a) assess the model's performance for E-learning uptake and continued use; (b) validate the relationships between the proposed EUCH model variables; and (c) investigate the consequence of E-learning usage on students' learning performance. The results of the longitudinal study suggested that: (a) the EUCH model does as well in predicting the uptake and continued use of E-learning as the existing comparative models (TAM, UTAUT and ECM), the improvement however was found in its explanation; (b) students' initial expectations influence their uptake of E-learning and the changes in their expectation during usage time period have an influence on their continued use; (c) no influence was found from E-learning usage on students' learning performance.

Even though the effect of E-learning usage to a student's learning performance are not confirmed by the empirical results of this study, it could be argued that E-learning usage is an *initial* condition for realizing the benefits of E-learning on

students and HEI: if there is no use, there will be no benefit. Although its predictive power and precision of equation prediction on E-learning uptake and continuance was not found to be an improvement on comparative models on purely statistical grounds, the EUCH model, which bridges the existing gap between findings on uptake and continuance of E-learning, provides an improved understanding of the processes of E-learning usage and the prediction of E-learning usage at any given time within a single model.

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DECLARATION OF AUTHORSHIP

I, **Nakarin Pinpathomrat,**

declare that this thesis and the work presented in it are my own and have been generated by me as the result of my own original research.

A MODEL OF E-LEARNING UPTAKE AND CONTINUANCE IN HIGHER EDUCATIONAL INSTITUTIONS

I confirm the following:

- This work was done wholly or mainly while in candidature for a research degree at this University.
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- Where I have consulted the published work of others, this is always clearly attributed.
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- Either none of this work has been published before submission, or parts of this work have been published as:

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Signed:

Date:

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Definitions and Abbreviations

ECM	Expectation Confirmation Model of IS Continuance
EDT	Expectation Disconfirmation Theory
EE	Effort Expectancy
EEC	Effort Expectancy Confirmation
EUCH	E-learning Uptake and Continuance in Higher Educational Institutions
FCE	Facilitating Condition Expectancy
FCEC	Facilitating Condition Expectancy Confirmation
LCE	Learning Consistency Expectancy
LCEC	Learning Consistency Expectancy Confirmation
PE	Performance Expectancy
PEC	Performance Expectancy Confirmation
SEE	Social Encouragement Expectancy
SEEC	Social Encouragement Expectancy Confirmation
TAM	Technology Acceptance Model
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology

Chapter 1 Introduction

1.1 Overview of Research

E-learning is a learning system that uses web and internet technology to facilitate teaching and learning (Ngai et al., 2007). It is an enhanced method that allows students to undertake personalized learning in a flexible manner in terms of time and place, and may also reduce the operational costs of on-campus teaching (Lee et al., 2009; Sánchez and Hueros, 2010). Based on the anticipated benefits of E-learning for students and universities themselves, many higher education institutions (HEIs) around the world have made substantial investments in this technology, and E-learning is now thought to be the fundamental tool to gain a competitive edge (Adwan et al., 2013).

The benefits of E-learning to students and HEIs will not be realized if students fail to use this technology (Mathieson, 1991; Lee et al., 2005; Chen, 2011). Since usage is a necessary condition for deriving benefit from E-learning technology (Taylor and Todd, 1995; Pituch and Lee, 2006) and the use of E-learning by students is not guaranteed (Chiu et al., 2005; Chen, 2011), HEIs that plan to invest or continue investing in E-learning need to be able to predict whether a prospective group of students will use it (Davis et al., 1989). If low-level use is found, HEIs need an understanding of why students fail to take up or resist continuing to use E-learning, so they can create an effective strategy for increasing usage (Szajna and Scamell, 1993; Parker, 1999).

Models have been developed for predicting and explaining the use of E-learning in HEIs. Most researchers ground their E-learning usage models on acceptance of technology models (such as the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology) (Šumak et al., 2011a). These view E-learning usage as an extension of acceptance behaviour: if individual students accept E-learning technology, they will both take it up and continue using it. These studies therefore encounter difficulty in explaining why those students who do start to use the technology opt out later (the '*acceptance discontinuance anomaly*') (Bhattacherjee, 2001). Some researchers have realized the limited application of E-learning usage models in continued use behaviour (Chiu et al., 2005; Lee, 2010). Since deriving the benefits of E-learning depends not only on initial uptake but continuance, they have developed E-learning continuance models. However, there are no existing models that bridge the gap between acceptance (uptake of E-learning) and continuance to explain better the use of E-learning technology in the process.

Furthermore, based on the review of literature on both acceptance and continuance of E-learning, existing models account for approximately only 40 per cent of the variance in the level of E-learning usage for a given time period. This is a relatively low percentage, for practical purposes, and there are probably other relevant factors that have been overlooked. Researchers view E-learning as a kind of technology, and in this view students fail to take up and continue using E-learning because they are not motivated to use this technology (Chen, 2011; Šumak et al., 2011a). E-learning has two aspects to its definition: 'E' (referring to technology) and 'learning' (referring to teaching and learning activities). Focusing only on technological motivation seems insufficient to explain the use of E-learning over a given time period. The effect of learning motivation on E-learning uptake and continued use is a research area waiting for investigation.

The validation of E-learning models of uptake and usage might be another weakness in the field. Studies in the area of E-learning usage usually measure behavioural intention to use E-learning to validate models, rather than actual use (Šumak et al., 2011a). Since there is empirical evidence that intention may not always accurately predict behaviour (Davis et al., 1989; Chuttur, 2009), and the goal of E-learning usage research is to ultimately improve the prediction and explanation of usage behaviours (not just usage intention), the validation of models with the actual usage is required (Bhattacherjee et al., 2008).

While prior research has concentrated on identifying determinants of E-learning usage (both uptake and continuance), the consequences of E-learning usage have received very little attention (McGill and Klobas, 2009; Islam, 2013). Understanding the consequences of E-learning system use is important for evaluating and developing the system in order to encourage individual users to enhance their learning performance. E-learning usage, the main dependent variable in prior research, should now become a predictor of a dependent variable, the consequence of E-learning usage.

1.2 Research Objective

To predict and explain E-learning usage in higher educational institutes (HEIs) better, this research conceptualized E-learning usage as two steps, E-learning uptake and continuance (Davis et al., 1989; Bhattacherjee, 2001), and the aim was to construct and validate the model of effective uptake and continuance of E-learning in HEIs, or ‘EUCH’. The research was divided into two phases. Model construction was the first phase in which three research questions were asked and answered:

> RQ1: What are the factors likely to affect the uptake of E-learning among HEI students?
>
> RQ2: What are the factors likely to affect the continued use of E-learning among HEI students?
>
> RQ3: What is an appropriate model of uptake and continued use of E-learning?

Model validation was the second phase, in which four research questions were asked and answered:

> RQ4: How well does the EUCH model predict and explain the uptake of E-learning?
>
> RQ5: How well does the EUCH model predict and explain the continued use of E-learning?
>
> RQ6: What are the relationships between the EUCH model variables?
>
> RQ7: Is there a relationship between E-learning usage and student’s learning performance?

1.3 Generalisation of Research

The EUCH model was grounded in five theories (UTAUT, ARCS, TRA, CDT, and ALT) which were developed in western countries. There was therefore an assumption in this research that *EUCH is general and could be applicable in western cultural context.* Cultural dimensions were examined by Hofstede (1993) who conducted research with 117,000 IBM employees from 40 different countries. He analysed culture into four dimensions (individualism vs. collectivism, masculinity vs. femininity, low vs. high power distance, and low vs. high uncertainty avoidance) and suggested that western and eastern cultures may have different patterns: western (individualism, masculinity, low power distance, and low uncertainty avoidance), eastern (collectivism, femininity, high power distance, and high uncertainty avoidance). There are different technology usage patterns depending on cultural context and the application of western theories of technology usage may not be fully effective in eastern cultural context (Watson et al. 1994; Straub et al. 1997). The issue was now '*could the EUCH apply in the context of eastern culture?'*

A review of the literature suggested that the factors affecting E-learning uptake and continuance between different countries (different cultural context) may be the same (Linjub et al. 2003; Teo et al. 2008; Zhao and Tan, 2010; Gaitan et al. 2011). However, it is the strength of the relationship of each factor with E-learning usage that may be different. This infers that cultural factors may have moderate effects on the relationships between expectation and E-learning usage. Based on this analysis, it was concluded that the EUCH model would find application in both western and eastern cultural contexts, while it may be expected that the detailed relationship between the EUCH factors could vary.

With the practical reason that the researcher could get a large sample size which would reduce the error of estimation in statistical analyses, Thai HEIs was selected as representative of eastern cultural context for validating the proposed model.

In future work, the EUCH 2 model will take cultural factor to account as moderator in order to improve the 'predictive power of the model'. Hofstede's four cultural dimensions (power distance, uncertainty avoidance, individualism and masculinity) would be applied.

1.4 Thesis Structure

To make the EUCH model viable, the research: (1) reviewed the basic background of the subject (Chapter 2); (2) reviewed the literature on E-learning uptake and continuance to identify the factors likely to affect the uptake and continued use of E-learning (Chapter 3); (3) conducted a preliminary study to confirm the E-learning uptake and continued use factors found from the literature (Chapter 4); (4) integrated the confirmed factors into the EUCH model (see Chapter 5); (5) carried out a longitudinal study to assess the model's performance, and validate the relationships of the proposed model variables, and between E-learning usage and student's learning performance (see Chapter 6); (6) analysed longitudinal study data and interpret research findings (see Chapter 7); (7) discussed possible reasons for obtaining the findings (see Chapter 8); and (8) provided the conclusion of the research and gave the direction for future work (see Chapter 9).

Chapter 2 E-learning in Higher Education Institutions

The purpose of this chapter is to provide the background to the research. The chapter begins with how people learn (section 2.1, learning), followed by how education facilitates learning (section 2.2, education). Section 2.3 explains what E-learning is and how it facilitates education. Section 2.4 gives details about the investment of E-learning in HEIs and the benefit of E-learning for students and HEIs. Section 2.5 clarifies the relationship between students' E-learning usage and the productivity pay-off from E-learning investment. Section 2.6 explores how modelling could encourage HEIs to devise an effective strategy for increasing usage. A summary of the chapter is provided in section 2.7.

2.1 Learning

There are three influential schools of thought in the literature on learning: behaviourism, cognitivism and constructivism. Each school of thought is summarized in the following sections.

2.1.1 Behaviourism

Behaviourism became the dominant school of thought during the first half of the twentieth century (Schunk, 2012). Behaviourism was developed by four influential psychologists: I. P. Pavlov (classical conditioning theory), J. B. Watson (applying Pavlov's theory to human emotional reactions), E. L. Thorndike (associationism theory) and B.F. Skinner (operant conditioning theory). This school of thought explained learning in terms of a change in overt behaviour as a result of external environmental events. Viewing behaviour this way allows learning to be observable and measurable, and inner thought processes in learning are not investigated (the organism is viewed as 'a black box') (Ally, 2004; Boghossian, 2006; Schunk, 2012).

Four behaviourism learning theories were derived from 'conditioning theory'; that is, a change in an organism's strength of response is the consequence of presenting a reinforcing stimulus (reward or punishment) in a certain temporal relation to that response (Skinner, 1937). What is more, based on Thorndike's associationism theory, in order to learn (change behaviour), repetition of the same conditioning is required by the learner to form an association between the two external events of stimulus (environmental stimulus set up) and response (learner's behaviour), and reinforcement (consequence of behaviour) (Schunk, 2012).

Learning within behaviourism theory is a process for changing natural (unlearned) behaviour into desired (learned) behaviour, in which the external conditional events (environmental stimulus set up and reinforcement) and their repetition are required to facilitate a change towards the desired behaviour.

2.1.2 Cognitivism

Between the late 1950s and the 1970s, behaviourism was replaced by cognitivism as the mainstream school of thought in learning (Mayer, 1996). The latter lays little emphasis on the effects of external conditions (stimuli and response) on learning (Schunk, 2012). It focuses on the internal mental processes that intervene between receiving a stimulus and producing a response: the metaphorical 'black box' of the mind was opened up to be understood (Dabbagh, 2005). In this school of thought, learning is viewed as an acquisition process of mental representations (pieces of information) in the learner's mind; it is not only about how information is received, organized and stored in the mind, but how the stored information is retrieved (recalled) and translated into behaviour (Lachman et al., 1979; Ertmer and Newby, 1993; Mayer, 1996). To put it more simply, learning is a process of information absorption, and learning is demonstrated when the learner can recall stored information from their mind to be used.

2.1.3 Constructivism

Between the 1980s and the 1990s, constructivism became the prevalent school of thought (Mayer, 1996). Both cognitivism and constructivism have their roots in cognitive science (Rovai, 2004), however a fundamental difference is their differing view on reality: constructivism views reality subjectively, where knowledge and truth exist inside the mind of the learner and have to be constructed by the learner through their previous experience (Duffy and Jonassen, 1991; Mayer, 1996; Johnson, 2009). This leads it to lay more emphasis on the mental process of knowledge construction than on information absorption expressed by cognitivism: how new experience is selected and integrated with existing knowledge inside the learner's mind (Cooper, 1993; Ertmer and Newby, 1993; Powell and Kalina, 2009).

Constructivism can be divided into two main types: cognitive constructivism (Piaget) and social constructivism (Vygotsky). Cognitive constructivism sees individuals interacting directly with the environment and obtaining new experience (Bodner, 1986). New experience fits in with pre-existing stored knowledge (assimilation), or pre-existing knowledge is realigned to fit with the new experience (accommodation) (Piaget, 1964; Bodner, 1986). New knowledge consists of new experience and previous knowledge (Schunk, 2012). To complement cognitive constructivism, social constructivism notes that learners interact socially with their environment, and cognitive development can be improved by using culture transmission tools (language, symbols) through interpersonal interaction: guidance from other individuals can accelerate the process of cognitive development (Vygotsky, 1978a, 1978b).

To sum up, in this school of thought learning can be described as the process of knowledge construction in which learners interact with physical and social environments. Their new experience is assimilated or accommodated to yield new knowledge.

2.2 Education

From the previous section, learning can be defined in various ways depending on the school of thought. By synthesizing the three dominant learning theories, it may be concluded that learning is a result of external and internal processes that lead to a change in a learner's capability (Gagné, 1985). The purpose of an educational system is to facilitate intentional learning: supporting the learner to achieve intended learning outcomes that would take much longer than incidental learning or without instruction (Gagne et al., 2005). A learner processes information and constructs knowledge. What we do in an educational system is to provide a learning environment to facilitate the learner's learning process. Essential components within an educational environment to support learning are identified in the model of the learning transaction (see Figure 2-1).

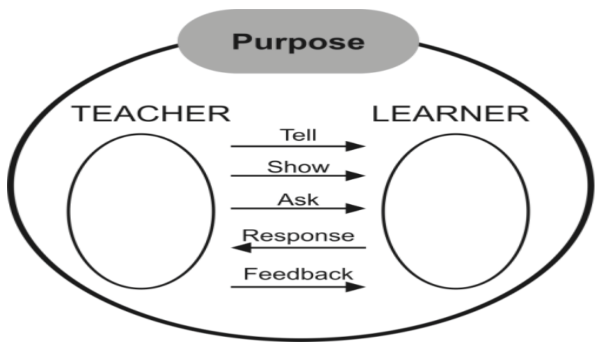


Figure 2-1: Model of learning transaction (Gilbert et al., 2005)

The three essential components are: purpose, two roles (teacher and learner), and activities between them. The activity can be divided into two main types depending on the agent who undertake these activities: teaching activity (tell, show, ask and feedback) and learning activity (response to what teacher asked) (see Table 2-1).

Table 2-1: How learning is promoted by learning transaction

Learning transaction	**Description**	**How it support learning process**
Tell	Information transmission activity: lecture, providing diagram and giving alternative explanations etc.	Based on cognitivism, learning is an internal process for receiving meaningful information to be stored in the long-term memory. We cannot help learners to process information; what we do is to give them information.
Show		
Ask	Ask learner to do some activities for: ▪ recalling information ▪ using or apply what they learn ▪ creating something new	Based on behaviourism and constructivism, learning can be promoted by providing learning activity. Learners interact with the activity and have an experience from the consequence of their response.
Response	Reply to what teacher ask to do	
Feedback	The information given by the teacher following the learner's response.	

The table shows how teaching and learning activities are related to the way people learn. The learning process can be facilitated by arranging a learning environment involving teaching and learning activities. As the purpose of an educational system is to support a learner to achieve intended learning outcomes, each learning and teaching activity needs to be guided and aligned with the purpose of education (Gagne et al., 2005; Biggs and Tang, 2011).

2.3 E-learning

Even though E-learning technology has been widely used in education, a definition of E-learning has not been clearly agreed (Lee et al., 2009). It may be necessary in future to provide E-learning definitions each time the term is used in literature in order to enable comparisons between studies. For the purpose of this study, E-learning is viewed as a web-based learning system, because such a system is widely used in HEIs. According to the definition of the IEEE Learning Technology Standards Committee, a web-based learning system is: '*a learning technology system that uses web-browsers as the primary means of interaction with learners, and the internet or an intranet as the primary means of communication among its subsystems and with other systems*' (as cited in Ngai et al., 2007, p.252). Web and internet technology work as a platform to facilitate teaching (tell, show, ask and feedback) and learning activity (response) to promote learning.

2.4 Investment in E-learning by HEIs and its Benefits and Drawbacks

With the expectation of achieving new levels of institutional and instructional productivity, many HEIs around the world have made substantial investment in E-learning (Alexander, 2001; Adwan et al., 2013). The number of research publications and websites of national bodies related to learning and teaching in HEIs may be an indicator of the popularity of E-learning in HEIs (Ellis et al., 2009).

The benefits and drawbacks of E-learning for students are summarized in Table 2-2. Since E-learning allows students to undertake personalized learning with unlimited access to learning resources, E-learning is expected to enhance their learning performance. The use of E-learning is also expected to reduce the instructional cost of:

(a) delivery of learning materials; (b) the use of physical infrastructures in universities such as lecture rooms; and (c) the need to hire more lecturers (Cantoni et al., 2004). With the expectation that the integration of E-learning into teaching and learning process can enhance students' academic performance and also reduce instructional costs in on-campus teaching, even though the costs of both initial implement and maintenance is high, E-learning is now a fundamental tool for HEIs in gaining a competitive edge.

Table 2-2: Benefits and drawbacks of E-learning for HEI students

E-learning benefits to students	E-learning drawbacks to students
Flexibility of time and place: a learner can learn when and where they want **Self-paced learning:** a learner can direct his/her own learning process (e.g. how fast and how much to learn) **Personalized learning:** a learner can tailor learning content and activity to meet learning style, individual interest and previous knowledge, leading to faster learning **Accessibility and repeatability:** a learner has: ▪ Many diverse learning resources ▪ Opportunity to review course materials many times ▪ Opportunity for more up-to-date information **A risk-free simulation environment:** a learner can make mistakes while learning without being exposed to risk or ridicule **Cost saving:** a learner can save money due to lower travelling and accommodation costs.	**Less social interaction and loss of personal contact:** E-learning reduces personal face-to-face contact between teachers and learners and among learners themselves.

Source: Cantoni et al. (2004); Song et al. (2004); Hubble and Richards (2006); Laurillard (2006); Tan (2013)

2.5 E-learning Usage and Pay-off of E-learning Investment

The models of Information Systems Success (DeLone and McLean, 1992) and Task-Technology Fit (Goodhue and Thompson, 1995) state that technology usage is a necessary condition for ensuring IT pay-off: if technology is compatible with the tasks, use of the system could lead to an impact on individual user performance that itself affects the organization productivity and pay-off from IT investment. In the IT literature, there is evidence that more use of technology has a greater impact on individual users' performance and organizational productivity (Jurison, 1996; Igbaria and Margaret, 1997; Gelderman, 1998; Devaraj and Kohli, 2003).

In the E-learning research area, however, there has been very little research into the impact of E-learning usage on a student's performance and university productivity (Oye et al.; 2012, Islam, 2013). Among those that have investigated the impact of E-learning usage on student academic performance (academic score), usually there are contradictory results: some studies have found that greater use of E-learning has a positive impact on students' academic score (Palmer et al.; 2008; Rodgers, 2008; Madar and Ibrahim, 2011), while others have found no effect (Arbaugh, 2000; Davies and Graff, 2005). The impact of E-learning usage on university productivity has not been reviewed through the literature, because it is difficult to assess the productivity pay-off of E-learning technology in a real world situation since a large portion of the costs and benefits is intangible (Gelderman, 1998). Even though there are contradictory and inconclusive reports about the consequence of E-learning usage on students' academic performance and the university's productivity pay-off, a study of E-learning usage is still necessary. This is because usage is a first and vital condition for realizing the benefits of E-learning for students and HEIs: if there is no use, there will be no benefit to either (Davis, 1989; Mathieson, 1991; Taylor and Todd, 1995).

2.6 The Model of E-learning Usage

If E-learning is not used, there is benefit for neither students nor university (Pituch and Lee, 2006). The use of E-learning by students is not guaranteed; they are sometime unwilling to use the technology, even if it affords them benefits (Nickerson, 1981; Chen, 2011); and those who do start to use it sometimes opt out later (Bhattacherjee, 2001; Chiu et al., 2005). It is necessary for HEIs to predict and understand E-learning usage in order to devise effective strategies for increasing usage (Šumak et al., 2011a). A model could help HEIs to understand E-learning usage behaviour by identifying the set of underlying factors and their quantitative relationships (Edwards and Bagozzi, 2000; Shmueli, 2010). A model could be used to predict what is likely to happen (Aris, 1994; Bender, 2000).

E-learning usage is student behaviour in employing the technology until competing course or graduation (Goodhue and Thompson, 1995). Conceptually, E-learning usage may be divided into two steps: uptake (initial usage) and continuance (usage until completing the expected course) (Bhattacherjee, 2001). Since E-learning uptake and continuance are somewhat different research areas, there are two limitations to existing models: (a) little distinction between the process of E-learning uptake and continued use; (b) existing models may not be able to predict usage separately, as either uptake or continuance, or both (Lee, 2010).

2.7 Summary of Chapter 2

E-learning is the use of web and internet technology to facilitate teaching and learning. Many HEIs around the world have made substantial investment in E-learning with the expectation of enhanced institutional and instructional productivity. E-learning usage is a necessary initial condition for realizing the benefits of E-learning for students and HEIs. However, the use of E-learning by students is not guaranteed. The aim of this research is to construct a model of uptake and continuance of E-learning to support HEIs to devise effective strategies for increasing usage.

Chapter 3 E-learning Uptake and Continuance

The research began with the examination of existing theories and related research to answer the first two research questions in a model construction phase:

> RQ1: What are factors likely to affect the uptake of E-learning among students in HEIs?
>
> RQ2: What are factors likely to affect the continuance of E-learning among students in HEIs?

The factors of E-learning uptake and continued use found in the literature are explained in this chapter. The first section identifies factors affecting E-learning uptake, while the second identifies those affecting continued use of E-learning. A summary of the chapter is provided at the end.

3.1 Factors Likely to Affect the Uptake of E-learning among HEI Students

To answer research question RQ1, a systematic review was conducted of the existing literature. A search of different databases (ScienceDirect, IEEExplore, ACM, etc) and publicly available search engines (Google) using keywords (E-learning, HEIs, uptake and acceptance, etc.) provided 42 related studies. A review of each study is provided in Appendix 3-A. The factors affecting the uptake of E-learning were investigated from 2002 onwards in the research area of E-learning technology acceptance in HEIs. By far the most papers on this topic have been published in the journal *Computer & Education* (see Table 3-1).

Table 3-1: Distribution of E-learning uptake in HEI research papers

Where published	Count of papers (total = 42)
Computers & Education	25
Educational Technology & Society	2
Information & Management	2
Computers in Human Behaviour	1
Human-Computer Studies	1
Information Systems in Developing Countries	1
Issues in Information Systems	1
Online Information Review	1
Peer-reviewed conference papers	8

No definition of E-learning uptake was given by any researchers in the field. Following the review of the literature, it can be assumed that the term ‘E-learning uptake’ mentioned by this group of researchers meant a student’s behaviour in accepting and starting to employ the E-learning technology available at their university (Davis, 1989). Most researchers in this area viewed E-learning as a kind of technology, and this rationale led the majority to believe that the reason why an individual student does not take up E-learning is because they do not accept this technology (Šumak et al., 2011a). Consequently, most researchers grounded their research in acceptance of technology models to explain and predict the uptake of E-learning (see Figure 3-1).

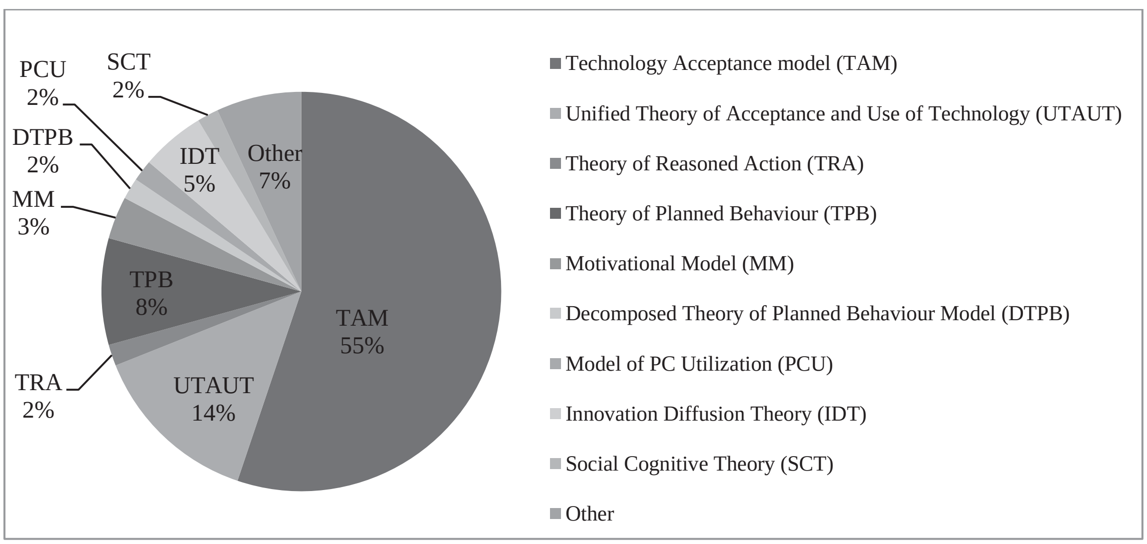


Figure 3-1: Theories grounded in E-learning uptake in HEIs research

It can be seen from Figure 3-1 that, of the authors of 42 published research papers, more than half grounded their research on the Technology Acceptance Model (TAM) to explain and predict the uptake of E-learning in HEIs.

3.1.1 Technology Acceptance Model (TAM)

The TAM model was constructed by Davis (1980), based on the Theory of Reasoned Action (TRA), to explain and predict the acceptance and uptake of new information technology. TRA asserts that individuals' behaviour is driven by their intention (motivation) to perform that behaviour. It is a function comprising a person's attitude (personal expectations) towards a target behaviour and subjective norm (social expectations) (Fishbein and Ajzen, 1974): see Figure 3-2.

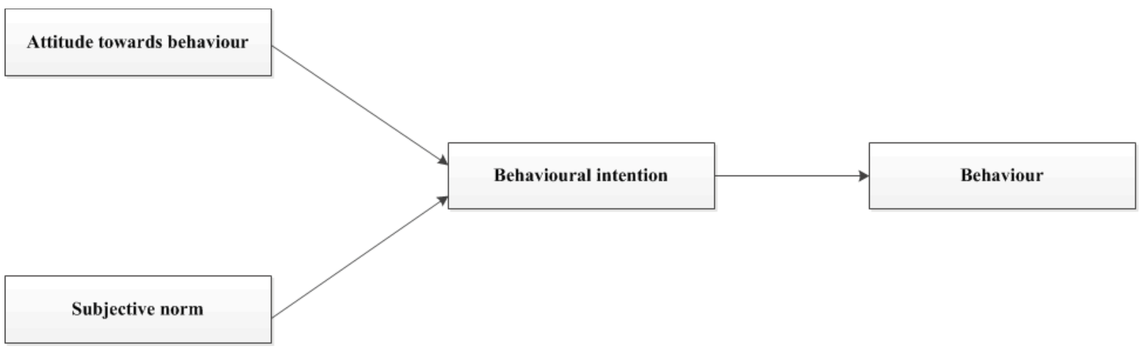


Figure 3-2: Theory of Reasoned Action (Fishbein and Ajzen, 1975)

In the TRA model, '*behavioural intention'* (BI) is used to measure the level of motivation, defined as an individual's subjective probability that he/she will perform that target behaviour (Ajzen, 1991). '*Attitude towards behaviour'* is a function of prior beliefs about the consequences of performing the target behaviour and the evaluation of those consequences. '*Subjective norm'* is the individual's perception that most people who are important to them will approve or disapprove of the intended behaviour (Fishbein and Ajzen, 1975).

Applying TRA in an information technology context, TAM posits that there are two particular beliefs that impact on a user's attitude towards system adoption: perceived usefulness and perceived ease of use (Davis et al., 1989). '*Perceived usefulness'* (PU) refers to the degree to which an individual believes that the use of a new system enhances their job performance (Davis, 1989). '*Perceived ease of use*'

(PEU) is defined as the degree to which an individual believes that the use of that system does not require an increase in effort: see Figure 3-3.

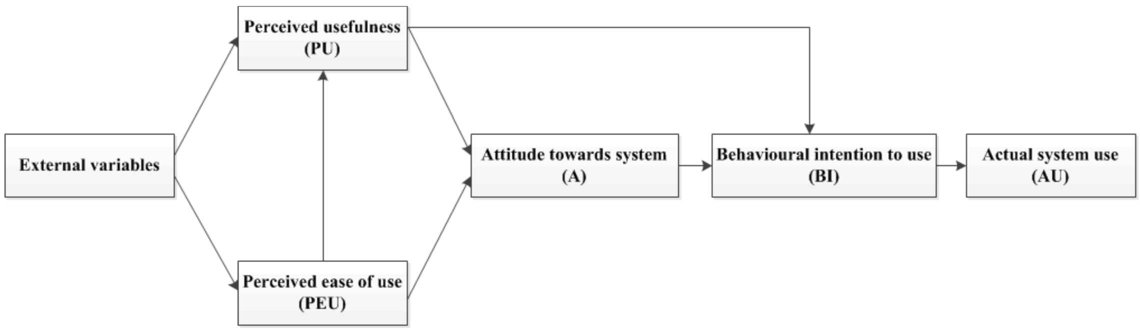


Figure 3-3: Technology Acceptance Model (Davis et al., 1989)

TRA and TAM share the same rationale, that the uptake of a new system is a result of BI. However, TAM differs from TRA in its belief that BI is a function of perceived usefulness and a user's attitude towards the system. The influence of perceived usefulness on BI comes from the assumption that, within organizations, if an individual believes that the adoption of a new system can improve their job performance in a way that will lead them to achieving incentives (e.g. increased pay and promotion), the system will be adopted, regardless of the individual's positive or negative attitudes towards the system. As Davis's research did not find any influence by the subjective norm towards user intentions, TRA's subjective norm was not included in TAM to explain the adoption of technology (Venkatesh and Davis, 2000).

3.1.2 TAM model in E-learning uptake in HEIs research area

There are three main reasons why TAM has become the accepted norm to explain and predict students' uptake of E-learning. TAM is tailored to the IT context. It is considered as a reliable model based on empirical evidence, with considerable support in explaining and predicting user's uptake of various technologies (Lee et al., 2005; Raaij and Schepers, 2008). It is also both parsimonious and the simplest model, yet powerful: TAM accounts for 40 per cent of the variance in user intention towards the adoption of new IT by using only two key factors (PU and PEU) (Yi and Hwang, 2003; Šumak et al., 2011a). Moreover, the practical utility of the model lies in the fact that PU and PEU are factors over which the system designer and developer have come degree of control (Mathieson et al., 2001; Taylor and Todd, 2001). In the E-learning uptake research area, researchers have so far validated the impact of two TAM factors on

E-learning uptake or extended TAM models in four ways: (1) the relationship between TAM factors (Lee et al., 2003; Ndubisi, 2004); (2) prior TAM factors (Saadé and Bahli, 2005; Lee, 2006); (3) moderate effect of culture (Zhao and Tan, 2010); (4) other relevant factors (Chen, 2011; Lai et al., 2012) (see Appendix 3-A).

By using TAM, researchers have confirmed that E-learning uptake is directly influenced by a student's intention, itself a function of PU and PEU (Yi and Hwang, 2003; Saadé and Bahli, 2005; Pituch and Lee, 2006). However, the consensus among researchers is that the use of only two TAM factors may not be sufficient to explain the issue of E-learning uptake. Other possible factors should be combined with the two key influences (Lee, 2008; Liu et al., 2009; McGill and Klobas, 2009). For instance, students may take up E-learning without a prior positive attitude towards the system if their significant persons (e.g. parents, teachers and friends) recommend and encourage them to adopt it (Abbad, 2011). Thus, social factors seem to influence the uptake of E-learning, as indicated by TRA and literature on the subject (McGill and Klobas, 2009; Park and Choi, 2009). Another limitation is TAM's assumption of volitional information technology usage; should students decide to adopt E-learning, the decision has no barriers (Mathieson et al., 2001). Students may not adopt E-learning, even when they have a positive attitude towards a system and it has been recommended by their significant persons, if they simply lack access to the IT resource (Jong and Wang; 2009; Abbad, 2011). The Theory of Planned Behaviour (TPB) can explain this, because the TPB is an extension of TRA. It incorporates perceived behavioural control factors for explaining and predicting an individual's intention; if two individuals have equal levels of intention towards a behaviour, the individual who can access the required resources is more likely to perform the behaviour (Ajzen, 1991).

TAM highlights the importance of a user's attitude (personal factors) towards the system, but its lack of emphasis on social and resource factors is criticized as a weakness (Bourgonjon et al., 2010). All of these factors are modelled in the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). Furthermore, the UTAUT model was constructed by empirically comparing and integrating eight prominent theories from human behaviour and IT acceptance: the theory of reasoned action (TRA); the technology acceptance model (TAM); the motivational model (MM); the theory of planned behaviour (TPB); the decomposed theory of planned behaviour model (DTPB); the model of PC utilization (PCU); the innovation diffusion theory (IDT); and the social cognitive theory (SCT). All of these eight theories have been applied to date by researchers in the field of E-learning uptake (see Figure 3-1). Because of this, it could be said that UATUT presents a more comprehensive and conclusive understanding of E-learning uptake than any other individual model. It seems most appropriate to adopt UTAUT as the grounded theory for this research.

3.1.3 Unified Theory of Acceptance and Use of Technology (UTAUT)

Comparing TAM and UTAUT in the E-learning adoption area, the UTAUT model is a novelty that has not been widely adopted by researchers as their theoretical model (Šumak et al., 2011a): only 14 per cent of researchers use it (see Figure 3-1). Venkatesh and colleagues constructed the UTAUT model in 2003. In an empirical comparison of the 32 beliefs from the eight models mentioned above, they asserted that there are four factors that directly affect an individual's acceptance and uptake of new information technology: (1) *'performance expectancy'* (PE); (2) *'effort expectancy'* (EE); (3) *'social influence'* (SI) and (4) *'facilitating conditions'* (FC) (Venkatesh et al., 2003).

PE is similar to TAM's 'perceived usefulness', and EE is similar to the 'perceived ease of use' in TAM. SI, termed *'social encouragement expectancy'* (SEE) in this study, is defined as the degree to which an individual believes that their significant persons will approve and encourage the use of new information technology. The degree to which individual users believe that an existing infrastructure can support the use of a new technology is the definition of FC, called *'facilitating condition expectancy'* (FCE) in this study (Venkatesh, 2011): see Figure 3-4.

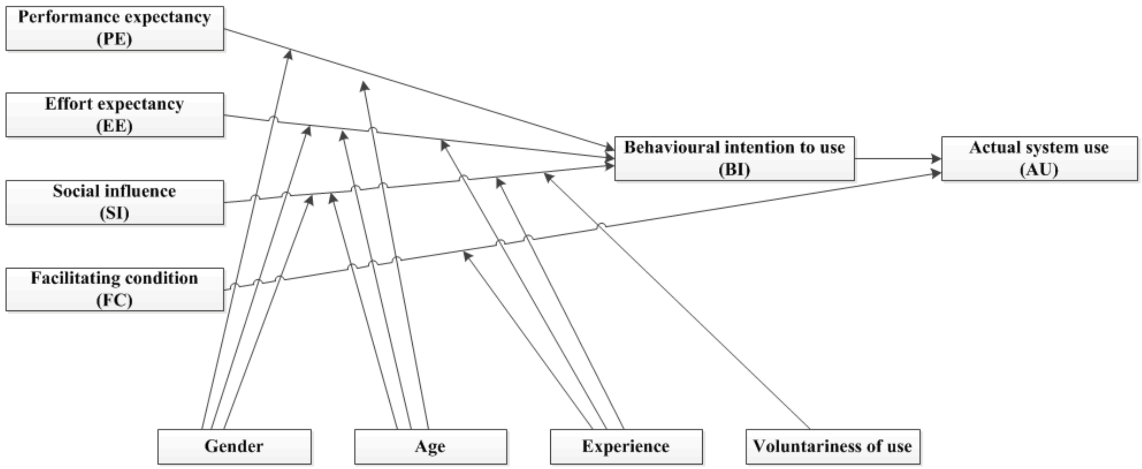


Figure 3-4: Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003)

PE, EE and SI influence the intention towards uptake of a system, while FC is a direct antecedent of the uptake. Interestingly, the model also indicates that the influence of these factors on intention towards use and actual use can be moderated by individuals' background, such as gender, age, experience and how voluntary is their use.

3.1.4 The application of UTAUT in this research

Similar to UTAUT, BI was adopted in this study to capture students' motivational level in order to predict their E-learning uptake: they would take up the system if they had high levels of intention. TRA and researchers in this field supported this idea; their findings confirmed that the uptake of E-learning is a function of student intention (Yi and Hwang, 2003; Lee, 2006; Šumak et al., 2010). While the UTAUT model asserts that facilitating conditions directly impacts on uptake, other theories (e.g. TPB and DTPB) and research in E-learning uptake (Shih, 2008; Šumak et al., 2010) describe facilitating conditions as having an indirect impact on uptake through student intention.

In total, there are four key factors that influence a student's intention to take up E-learning, and these are PE, EE, SEE and FCE. The moderating effect of an individual's background (gender, age, how voluntary is their use, and experience with IT) upon the influence of the UTAUT factors on a student's intention was not a focus of this study. This research was undertaken in a higher education context; students may have the same range of age and experience with IT (Tan, 2013), thus age and experience variables were not included in the proposed model. Furthermore, within the same university or study course, the degree to which use was voluntary may not be different. Therefore, no variable measuring voluntariness of use was included. Even though the moderating effect of gender upon the influence of the UTAUT factors on a student's intention to take up E-learning remains uninvestigated to date in the area of E-learning in HEIs and this could have been a new contribution, the gender variable was not integrated into the model in this research. A model is a simplified view of a complex domain (Aris, 1994), and so to begin with, this research focused on the major variables. The moderating effect of gender will be investigated in the future work.

The factors in the UTAUT model seemed sufficient to explain the uptake of E-learning. However, when critically evaluated, they could only explain problems from a technical point of view, with emphasis solely on 'technological motivation'. E-learning has two aspects to its definition, 'E' (referring to technology) and 'learning' (referring to teaching and learning activities); the latter has been overlooked by almost all researchers in the field, therefore no existing model can fully explain or predict uptake of E-learning (Chen, 2011). This study aimed to fill the gap left by other researchers by adding 'learning motivation' to the model, as explained in more detail in the next section.

3.1.5 Learning motivation factors on the uptake of E-learning

The expectancy–value theory asserts that an individual's decision to execute an activity is a function of their motivation, which is a product of the consequent value of the activity and the individual's proficiency in the activity (Atkinson, 1957; Wigfield, 1994; Schunk, 2012). Teaching and learning activities are constructed to support students to achieve the Intended Learning Outcome (ILO) (Gilbert and Gale, 2008); in value terms, this ILO is a by-product of teaching and learning activities. E-learning is simply teaching and learning facilitated by technology. Should learners not perceive the ILO's value (intrinsically or extrinsically) and feel it inadequate to the learning task, their level of learning motivation will be low. Such low motivation may lead them to forego teaching and learning activities, ultimately neglecting E-learning (Chen, 2011).

Chen's (2011) research focused on technology and learning motivation for the uptake of E-learning, and it confirmed that the two motivations significantly influence students' intention towards their uptake of E-learning. This verified that this study was heading in the right direction, focusing on both aspects of motivation to increase system uptake. However, Chen's coverage of learning motivation was weak; it only covered the compatibility of the system and the learning style. Other, hitherto unmentioned factors needed to be revealed to understand the decision to take up E-learning.

In order to find other possible learning motivation factors, the ARCS model (see below) was adopted in this research. This was for two main reasons. First, the model simplified complicated human motivation theories in a learning and educational context (Keller, 1999, 2008). Second, the ARCS model has been widely validated and confirmed to make instructional material motivationally more appealing (Winiecki et al., 1999).

3.1.6 Keller's ARCS model

The ARCS model asserts that four major factors influence students' learning motivation: *'attention'* (A); *'relevance'* (R); *'confidence'* (C); and *'satisfaction'* (S) (Keller, 1987). *'Attention'* refers to how learners' attention is gained by arousing their curiosity: learning motivation is a by-product of their realization of a perceived gap in their current knowledge (Keller, 2008). *'Relevance'* was integrated into Keller's model on the basis that learning motivation will occur once the ILO is perceived to be valuable and meaningfully relevant to a learner's personal goals (Keller, 1999). The learner's goals can be divided into: (a) extrinsic to ILO: the student may want to learn merely to pass a course that aligns him or her with a desired future opportunity; (b) intrinsic to ILO: the goal may be to satisfy a learner's personal interest in the subject (Keller and Suzuki, 2004). Furthermore, the '*relevance'* factor in Keller's model refers to matching teaching strategies to the student's learning style (Keller, 2008). *'Confidence'* is the third factor required for learning motivation. This factor is derived from the concept that individual learners are motivated to learn when they have enough previous knowledge about what is to be learned, which will lead them to believe that what is to be learned can be mastered (Keller, 1987). Finally, *'satisfaction'* was incorporated into the model on the basis that levels of learning motivation will be sustained when the learner experiences the desired outcome (Keller, 1999).

3.1.7 The application of Keller's ARCS model in this research

There are two ARCS factors that will be not investigated in this research. According to Keller (2000, 2008), attention can be promoted by arousing the learner's curiosity in what is being taught at the beginning of a lesson, such as introducing a fact that seems to contradict the learner's past experience, or using interesting graphics, animation, or any kind of event that introduces incongruity. From that concept, attention may occur when student starts and takes part in E-learning learning activity. E-learning uptake research however mainly deals with how to motivate a learner to start using E-learning. Since attention manifests after the uptake of E-learning, this factor was not directly included as a factor affecting the uptake of E-learning in the EUCH model. Satisfaction in the ARCS model deals with appropriately reinforcing learner's accomplishment based on their extrinsic and intrinsic motivation, which will anchor the learner's positive feeling about their accomplishments (Keller, 1999). Conceptually, satisfaction may occur during or at the end of lesson in E-learning. At the initial stage (t_0), before a student takes up E-learning, satisfaction with the provided course in E-learning has not yet been manifested. Satisfaction or learning reinforcement factor therefore was not directly included as factor affecting the uptake of E-learning. The EUCH model uses the student's expectancy as a predictive variable. It is considered that such expectancy would be a function of the student's motivation and past experience. This would indirectly include motivational factors arising from attention, curiosity and satisfaction from that past experience.

From the start we wished to ensure that learning motivation affects the uptake of E-learning. Therefore, in this research, the remaining two ARCS factors (relevance and confidence) were combined into a single factor to be termed the *'learning consistency expectancy'* (LCE) factor. This led LCE to be defined as the degree to which an individual student expects that E-learning's instructional environment (including content, teaching and learning activities) is relevant to their goals, learning styles and their past experience about what is being studied.

To summarize, by integrating grounded theories (UTAUT and ARCS models), influential factors for the uptake of E-learning and the relationship between them were identified, as shown in Figure 3-5.

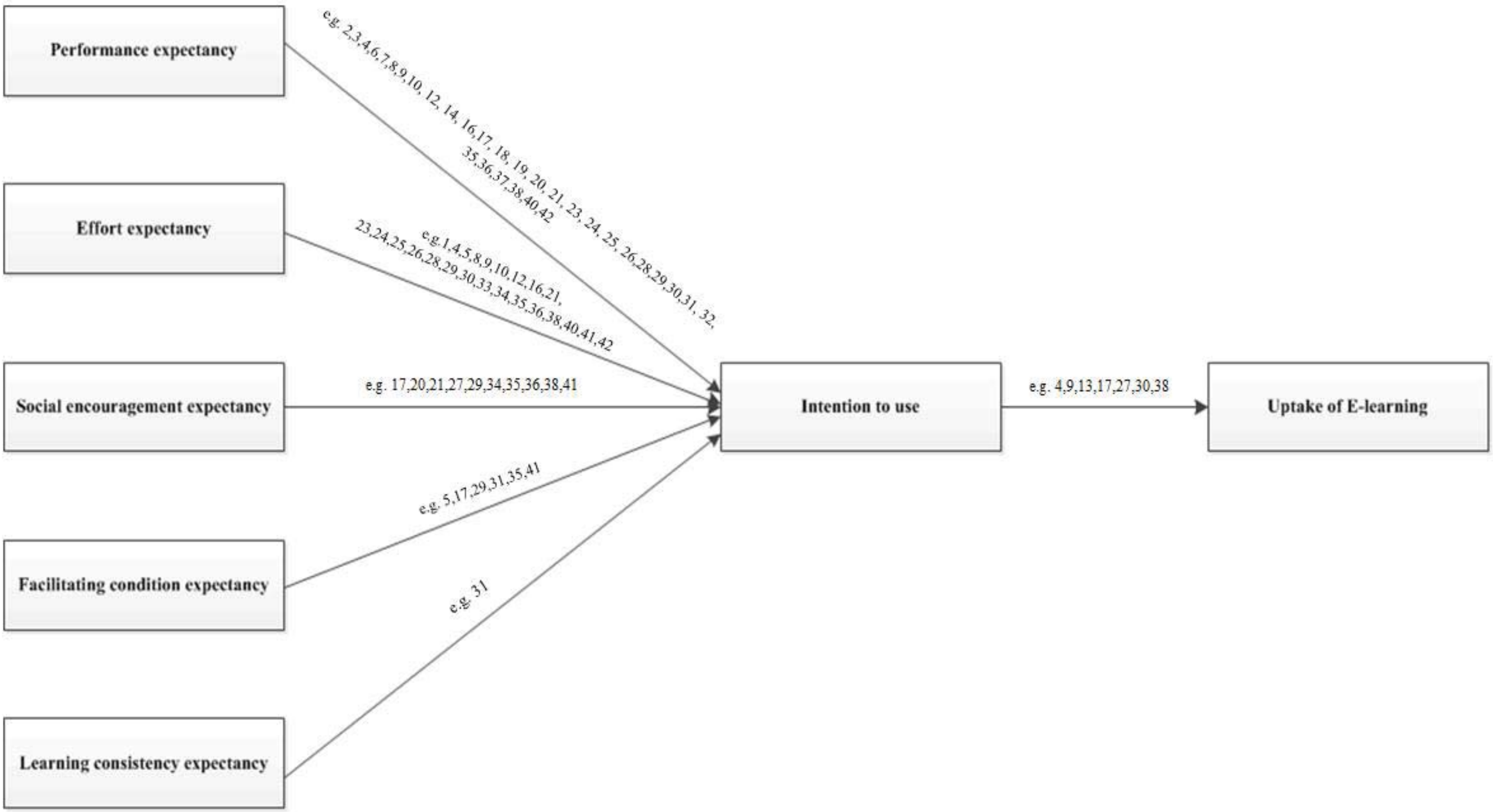


Figure 3-5: Factors affecting the uptake of E-learning and supportive research

The arrow represents the influence (causal path) of one factor on another, and the numbers on each arrow represent supportive research, as listed and noted in Appendix 3-A. Intention to use, which promotes the actual uptake of E-learning, is influenced by five initial expectations: performance expectancy; effort expectancy; social encouragement expectancy; facilitating condition expectancy; and learning consistency expectancy. To make them more relevant to the E-learning context, the definitions of each factor are defined and provided in Table 3-2.

Table 3-2: Definition of each E-learning uptake factor

Factor	Definition
Uptake of E-learning	A student's behaviour of accepting and starting employ the E-learning technology available at their university.
Intention to use (uptake)	An individual student's subjective probability that he/she will take up E-learning and the strength of effort (level of use) he/she will devote to using E-learning.
Performance expectancy	The degree to to which an individual student expects that using an E-learning will be useful in his/her education and enhance his/her learning performance.
Effort expectancy	The degree to which an individual student expects that the use of E-learning system does not require an increase in effort.
Social encouragement expectancy	The degree to which an individual student expects that his/her significant persons will encourage the use of an E-learning system.
Facilitating condition expectancy	The degree to which an individual student expects that there are IT resource to support the use of E-learning.
Learning consistency expectancy	The degree to which an individual expects that the instructional environment in E-learning – including the ILO, content, teaching and learning activities – is relevant to the learner's goals, learning styles and past experiences.

3.2 Factors Likely to Affect the Continuance of E-learning among HEI Students

While uptake of E-learning is the important initial step towards realizing the benefits of E-learning, exploiting the full potential benefits of E-learning depends on its continued use or 'continuance' (Chiu et al., 2005; Lee, 2010). For this reason, research question RQ2, '*What are the factors likely to affect the continuance of E-learning among students in HEIs?'* needs to be answered. A search using the keywords E-learning, HEIs, continuance and continued use in different publication databases and available search engines provided 19 related studies. A review of each study is provided in

Appendix 3-B. The factors affecting the continued use of E-learning have been investigated by researchers since 2005 under 'E-learning technology continuance in HEIs', in order to complement the incomplete explanations of E-learning uptake (acceptance) for why students do not continue to use E-learning after accepting it initially. By far the most papers are published by the journal *Computer & Education* (see Table 3-3).

Table 3-3: Distribution of research papers on topic of E-learning continuance in HEIs

Where published	**Count of papers (total = 19)**
Computers & Education	14
Electronic Business Management	1
Human-Computer Studies	1
Information & Management	1
Peer reviewed conference papers	2

The term 'E-learning continuance' used by this group of researchers probably indicates a student's continuance behaviour when using the E-learning technology available at their university, following the student's initial use. There are two schools of thought among these researchers (Islam, 2013). The first group views continued use of E-learning as an extension of students' uptake and uses the same variables (expectations) to explain and predict E-learning continuance, namely research grounded in TAM (Cho et al., 2009; Islam, 2013) and UTAUT (Chiu and Wang, 2008). The other group uses specific continuance models as the main theoretical lens: the Expectation Disconfirmation Theory (EDT) (Tao et al., 2009; Almahamid and Rub, 2011) and the Expectation Confirmation Model of IS Continuance (ECM) (Sun et al., 2011; Terzis et al., 2013) (see Figure 3-6).

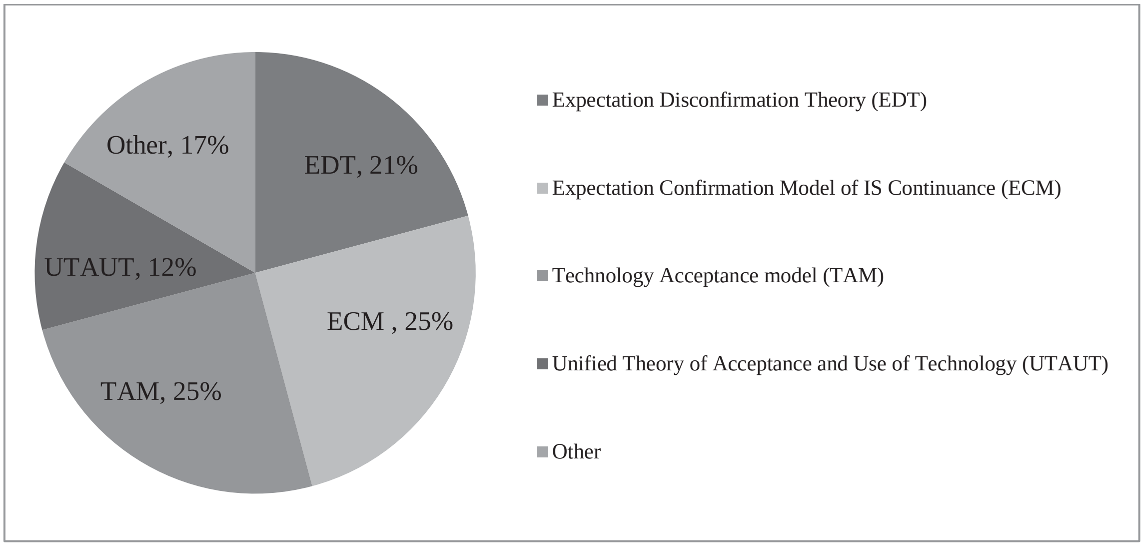


Figure 3-6: Theories grounded in E-learning continuance in HEIs research

TAM and UTAUT models were explained in the E-learning uptake, in sections 3.1.1 and 3.1.3, respectively. Both TAM and UTAUT are grounded in the theory of reasoned action and users' expectations as a predictor of technology usage. The following section describes Expectation Confirmation Model of IS Continuance (ECM) and Expectation Disconfirmation Theory (EDT).

3.2.1 Expectation Confirmation Model of IS Continuance and Expectation Disconfirmation Theory

ECM was developed by Bhattacherjee (2001) to explain the impact of existing users' cognitive belief on their intention to continue to use information technology. The model was adapted from TAM and EDT. EDT was constructed by Oliver (1980) to explain customer behavioural intention towards product repurchase or service continuance. It proposes that consumer intention to repurchase is influenced primarily by the level of consumer satisfaction from prior use of that product. In turn, satisfaction is a function of two constructs: initial expectation and expectancy confirmation (the difference between the perceived actual performance and the prior expectation): see Figure 3-7.

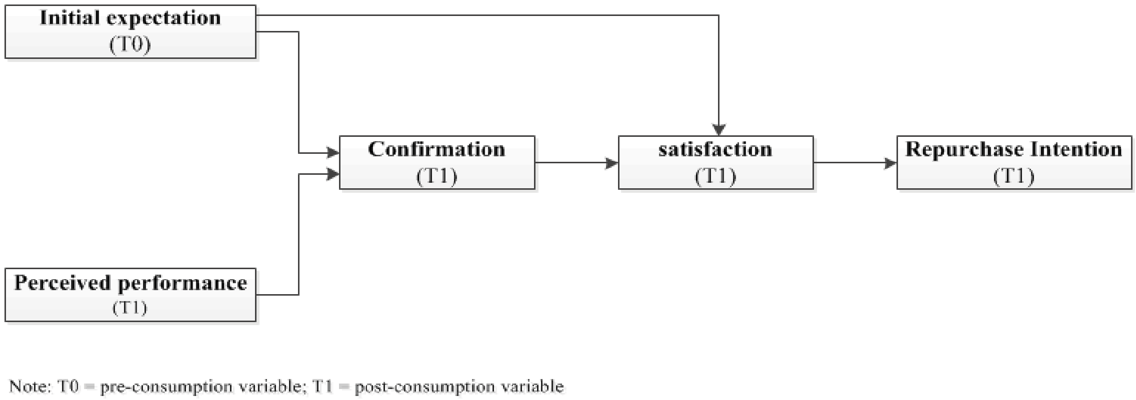


Figure 3-7: Expectation Disconfirmation Theory (Oliver, 1980)

By applying TAM and EDT, the ECM model suggested that individual users' IT continuance intention is determined by satisfaction with prior use of that technology and perceived usefulness of further use (Bhattacherjee, 2001). Both satisfaction and perceived usefulness are driven by confirmation of expectation from prior IS. Additionally, perceived usefulness is proposed to impact satisfaction perception (see Figure 3-8).

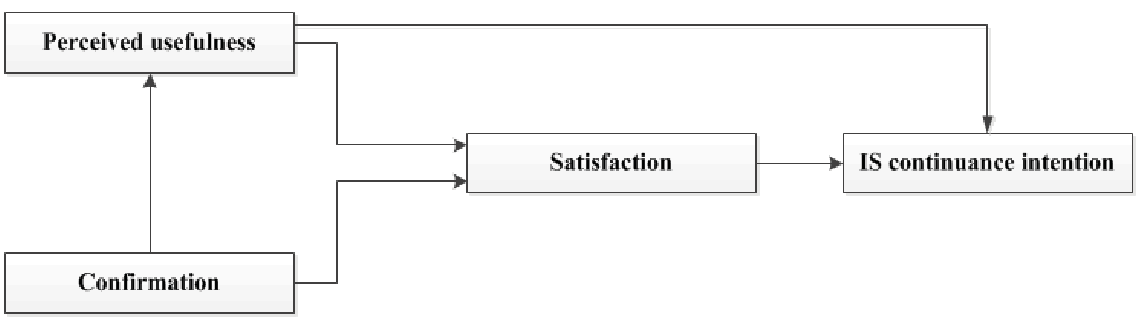


Figure 3-8: Expectation Confirmation Model of IS continuance (Bhattacherjee, 2001)

3.2.2 *Satisfaction and expectations*

There are two schools of thought on the continued use of E-learning, as mentioned earlier. The first school, based on TAM and UTAUT, views E-learning continuance as a function of a student's expectations, while the second, based on EDT and ECM, views E-learning continuance as a function of a student's satisfaction.

The satisfaction function from the EDT can be reinterpreted in the light of the theory of reasoned action (TRA) on the components of attitude (see Figure 3-9).

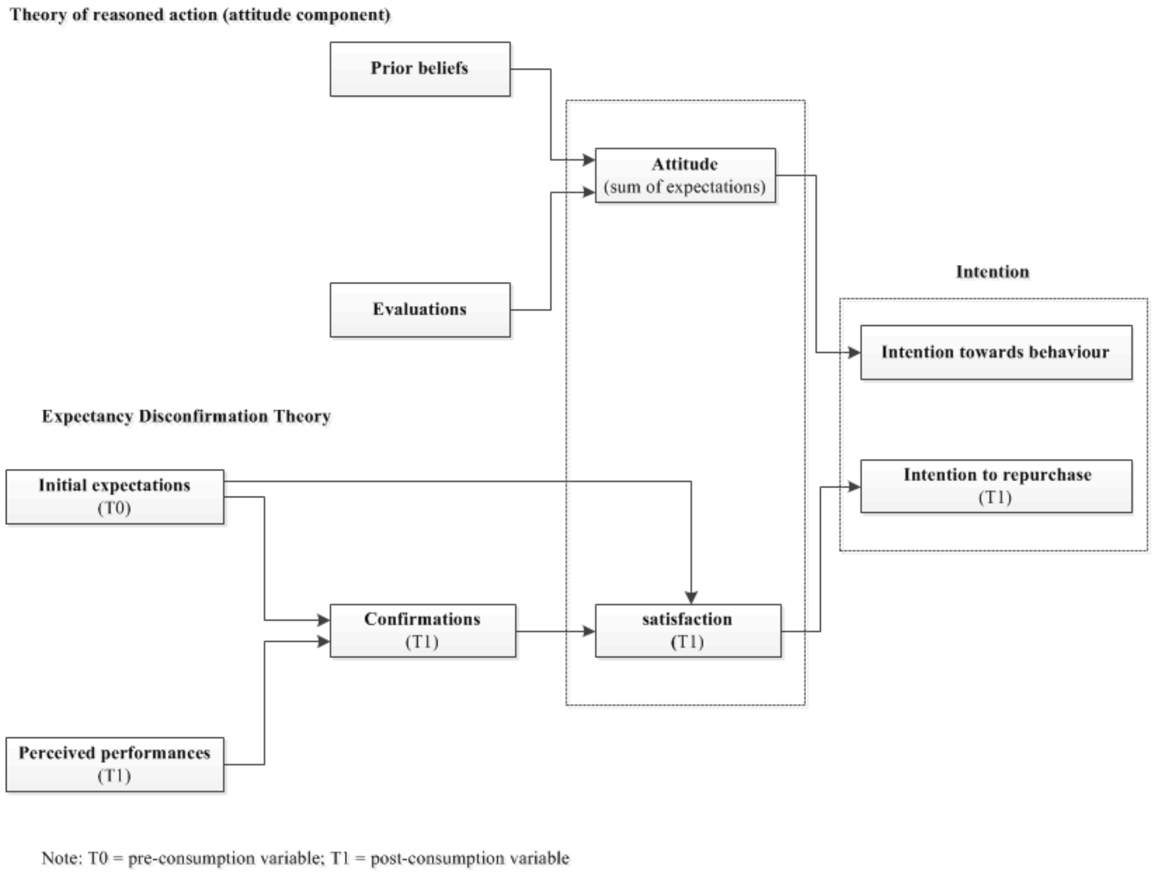


Figure 3-9: Expectation Disconfirmation theory and attitude component in theory of reasoned action

Figure 3-9 indicates that the sum of expectations (attitude) in TRA is equivalent to satisfaction in EDT, and these affect an individual's intention behaviour (Oliver, 1980). In TRA, attitude was taken as the sum of individual's expectations towards the target behaviour, determined by prior beliefs about consequences of performing the behaviour (initial expectations, in EDT) multiplied by the evaluation of those consequences (confirmations, in EDT) (Fishbein and Ajzen, 1975). Oliver (1981) defined satisfaction as the pleasurable feeling that results from an individual's high initial expectations being at least confirmed, after using a product. If we use the condition of satisfaction (high initial expectations and high expectancy confirmations) as an input to TRA's attitude equation, then a student's sum of new expectations towards the continued use will be high or they will have positive attitude towards the continued use. This is an important reason why many researchers believe that satisfaction is a crucial factor, which affect the continued use of E-learning. Since satisfaction or a positive attitude occur when student's high level of new expectations, after using E-learning, the expectations construct was selected in this research as a predictor of continued use of E-learning.

3.2.3 Expectations and continued use of E-learning

A relationship between expectation and the continued use was found in research concerning information technology (Davis et al., 1989; Taylor and Todd, 1995; Szajna, 1996; Karahanna et al., 1999; Venkatesh and Morris, 2000; Bhattacherjee et al., 2008) and E-learning (Chiu and Wang, 2008; Cho et al., 2009; Lin, 2011; Sun et al., 2011; Islam, 2013). In the technology continuance literature, there was empirical evidence that users' expectations changed over time as they experienced the system after taking it up (Szajna and Scamell, 1993; Venkatesh and Morris, 2000; Bhattacherjee and Premkumar, 2004). This change in expectations might have a corresponding impact on users' continuance behaviour: people opted out from the system because their expectations changed from high before uptake, to low after using the system.

3.2.4 Factors affecting the change in student's expectations after using the system

The above studies provided preliminary evidence regarding temporal changes in expectations that corresponded to continued use. To enhance continued use of E-learning, the question was now '*Why and how expectations do change or are modified over time?'*

Taylor and Todd (1995) compared the strength of the relationship between TAM variables on usage of technology between experienced and novice users, and found that the strength of the relationship was significantly different in experienced and novice users. This study then suggested that users' experience with the system might be a moderator of the change from one level of expectation to another.

To complement Taylor and Todd's (1995) research finding, Bhattacherjee and Premkumar (2004) investigated the *emergent* factors behind the temporal change in users' expectations by applying EDT and TAM. They discovered that the new expectation (perceived usefulness) was a function of prior expectation and disconfirmation (the difference between perceived actual performance and prior expectation), suggesting that users' expectation of IS instrumentality can be adjusted by the extent of disconfirmation. Bhattacherjee and Premkumar (2004) grounded their research in EDT (Oliver 1980), an extension of cognitive dissonance theory (Festinger, 1962) and adaptation level theory (Helson, 1948). These two theories provide theoretical support for Bhattacherjee and Premkumar's (2004) research findings.

Cognitive dissonance theory (CDT)

Festinger (1962) formulated Cognitive Dissonance Theory (CDT) to explain why discrepancies (dissonance) between a person’s cognition and reality change that person's subsequent cognition and behaviour. Under the assumption that individuals have a need to maintain some level of consistency between their cognition and reality (consonance), there will be a psychological state of dissonance when cognitive structures (expectation) and reality are inconsistent with each another. There are two kinds of dissonance (disconfirmation): negative disconfirmation, when actual performance is less than expected performance; and positive disconfirmation, when actual performance exceeds expected performance. Dissonance produces discomfort and, correspondingly, an individual will attempt to reduce it in three possible ways: (a) change their beliefs (expectation); (b) acquire new information that causes the dissonance to be reduced; or (c) forget the importance of those in a dissonant relationship.

It should be mentioned that CDT provides theoretical support for the relationship between disconfirmation and new expectations. In the research area of E-learning continuance, there is evidence of this relationship in students (Roca et al., 2006; Ho, 2010; Lee, 2010; Lin and Wang, 2012; Alraimi et al., 2015). In E-learning usage, students may experience cognitive dissonance during the period of technology usage if their initial expectations (that earlier led to acceptance and uptake) are disconfirmed by the actual performance of the system. Rational students may remedy this dissonance by distorting or modifying their expectations so they are more consistent with reality.

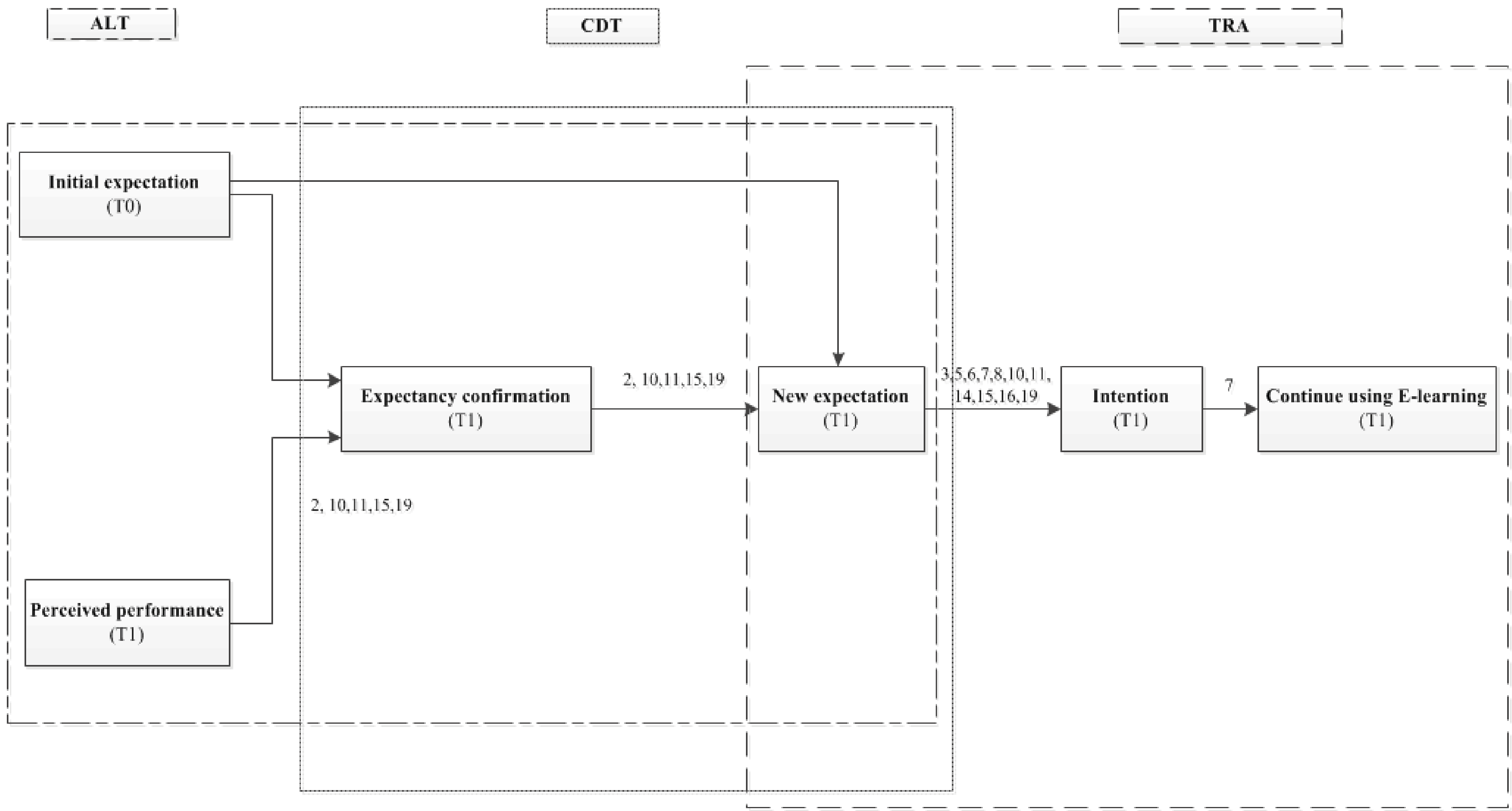
Adaptation level theory (ALT)

Adaptation level theory (ALT) was formulated by Helson (1948). It asserted that one perceives stimuli only in relation to an adapted standard organism, and that the judgment of new perceived stimuli is influenced by the prior determined stimulus level with object (the adaptation level) and the discrepancy perceived between the new stimulus and this level. This discrepancy then revises the level of adaptation used in further stimuli evaluations.

According to ALT, individual students’ initial expectations serve as their level of adaptation, by which they make a cognitive comparison between the adaptation level (initial expectation) and perceived actual performance to determine disconfirmation of E-learning. The disconfirmation then adjusts the initial expectation to the new expectation with more consistency with reality. The new (modified) expectation suggests subsequent judgment of behaviour and revises the adaptation level used in future continued use evaluation.

3.2.5 The application of CDT and ALT in this research

By using the theory of reasoned of action (TRA), cognitive dissonance theory (CDT) and adaptation level theory (ALT), the continued use of E-learning may be explained in the following steps. First, students form *initial expectations of E-learning*. Initial expectations perform two functions: they serve to provide the motivation (intention) to take up E-learning, accordingly to TRA, and they serve as an adaptation level for subsequent continued use decision, accordingly to ALT. If individual students have a high level of initial expectation, they take up E-learning. Following a period of initial usage, they form a perception about actual E-learning performance, or *perceived performance of the system*. Third, they assess the perceived performance against their initial expectation to determine an *expectancy confirmation*. According to CDT, the level of confirmation of each expectation then adjusts each of their initial expectations. The (adjusted) *new expectation towards E-learning* replaces initial expectations in the students' cognitive memory as the basis for guiding subsequent decision of continued use of E-learning. If students have a high level of new expectations, they will have high intentions, and consequently will continue to use E-learning (see Figure 3-10).



Note: T0 = pre-E-learning usage variable; T1 = post-E-learning usage variable
The references (number) relevant to the relationship are noted and listed in Appendix 3-B

Figure 3-10: Factors affecting the continued use of E-learning and supportive research

The arrow represents the influence of one factor on another, and the numbers on each arrow represent supportive research in the E-learning continuance area, as listed and noted in Appendix 3-B. The figure shows that there was no existing research to link the E-learning uptake at time t_0 construct (initial expectation) to the E-learning continuance construct at time t_1: neither was there supportive research on the line of the relationship between initial expectations and expectancy confirmation, initial expectations and new expectations. The definitions of each continuance factor are provided and defined in Table 3-4.

Table 3-4: Definition of each E-learning continuance factor

Factor	Definition
Initial expectation	An individual student's initial expectation about the consequences of using E-learning before taking up E-learning
Perceived performance	An individual student's perception of the actual consequences of using E-learning
Expectancy confirmation	The discrepancy between the perceived actual consequences and the prior expectation about that consequence
New expectation	An individual student's expectation about the consequences of using E-learning before continue using E-learning
Intention towards continued use	An individual student's subjective probability that he/she will continue using E-learning and the strength of effort (level of use) they will put on using E-learning
Continued use	A student's behaviour of continuance in using E-learning technology available in their university after initial use

3.3 Summary of Chapter 3

The main purpose of this chapter was to describe the factors found in the review of literature that influence a student's uptake and continuance of E-learning. A preliminary study (explained in the next chapter) was conducted to confirm the effect of these factors, before using them to construct a model of effective uptake and continuance of E-learning in HEIs (EUCH).

Chapter 4 Preliminary Study

The preliminary study was conducted after the review of literature to confirm the uptake and continuance of E-learning factors found in the literature in order to answer fully the first two research questions in the model construction phase. These are:

> RQ1: What factors likely to affect the uptake of E-learning among students in HEIs?
>
> RQ2: What factors likely to affect the continuance of E-learning among students in HEIs?

The confirmed factors from the preliminary study were then integrated to construct the EUCH model, as expressed in Research Question RQ3 (explained in the next chapter). The first section of this chapter provides an overview of the uptake and continuance of E-learning factors found in the review of the literature. The second describes the research methodology used in the preliminary study. The third provides and discusses the results in terms of uptake factors, while the fourth section provides and discusses them in terms of continued use factors. A summary of the findings from the preliminary study is given in the fifth section.

4.1 Overview

Following the review of literature, five initial expectation factors were found to affect a student's uptake of E-learning: *performance expectancy (PE)*; *effort expectancy (EE)*; *social encouragement expectancy (SEE)*; *facilitating condition expectancy (FCE)*; and *learning consistency expectancy (LCE)*. During the usage period, students perceive the actual performance of the system and estimate their confirmation by comparing their level of perceived performance with level of each initial expectation (considered as a reference level). The level of confirmation of each expectation then adjusts each of their initial expectations. New (adjusted) expectations replace initial expectations in student cognitive memory as the basis for guiding their subsequent decisions on continued use of E-learning. For that reason, the factors affecting continued use are the expectancy confirmation of each initial expectation: *performance expectancy confirmation (PEC)*; *effort expectancy confirmation (EEC)*; *social encouragement expectancy confirmation (SEEC); facilitating condition expectancy confirmation (FCEC)*; and *learning consistency expectancy confirmation (LCEC)*. The preliminary study was conducted to confirm the five uptake factors (PE, EE, SEE, FCE and LCE) and five continued use factors (PEC, EEC, SEEC, FCEC and LCEC).

4.2 Preliminary Study Methodology

Triangulation was used to confirm the factors of E-learning uptake and continuance. This is a 'cross-examination technique' that facilitates the validation of research findings through cross-verification between several sources of data or methods (Denzin, 1978; Jick, 1979; Olsen, 2004). By using triangulation, a researcher can overcome the weakness of any single method and any bias inherent in each source of data (Cohen and Manion, 2000; O'Donoghue and Punch, 2003; Altrichter et al., 2008). The triangulation in this research included: (1) a review of related theories and literature; (2) expert validation; and (3) end-user (student) validation. A review of literature was first undertaken, as described in Chapter 3. The aim of the preliminary study was to gather data from a group of experts and students.

The technique used in the preliminary study for collecting and analysing the data from a group of experts and students was that of 'mixed methods'. This is the combination of qualitative and quantitative research methodologies in a single study, either at the same time (in parallel) or one after the other (sequentially) (Johnson and Onwuegbuzie, 2004). Due to differences in the underlying paradigms, the characteristics of qualitative and quantitative methodology are dissimilar (see Table 4-1).

Table 4-1: Summary of key differences between qualitative and quantitative methodology

	Qualitative methodology	Quantitative methodology
Data	Textual data	Numerical data
Population	Small number of participants	Large number of participants
Data collection	Interview and observation	Survey
Data analysis	Analysis is interpretative	Analysis is statistical
Advantages	1. Achieves depth of information on the research topic 2. Explores possible issues in the research context 3. Chances to discover unanticipated findings on research topic	1. Generalization to a population 2. Minimize the researcher's biases in research findings
Disadvantages	1. The findings are not generalized to the population 2. Researcher's bias on research findings.	1. Failure to find unanticipated findings on the research topic.

Source: Bryman (1984); Hancock (2002); Taylor (2005); Hennink et al. (2011); Berg and Lune (2012); Hammersley (2013)

Qualitative and quantitative methodologies complement each other well; the drawbacks of each are overcome by the other. Considering the benefits and drawbacks of each, qualitative methodology was selected for collecting data from the group of experts in this preliminary study. Its use to elicit the experts' experiences on the phenomenon facilitated the researcher in discovering possible factors of E-learning uptake and continued use, as the findings may have confirmed the proposed factors and suggested others factors not mentioned in the literature. Using qualitative methodology with the experts may also have helped the researcher to understand better how these factors affected the uptake and continued use of E-learning. However, due to its ability to make a generalization from a sample to a population, quantitative methodology was adopted for collecting the data from the group of students in order to confirm the proposed factors from this perspective.

In this study, qualitative and quantitative research methodologies were conducted at the same time, in parallel. At the end of the preliminary study, the findings from the three different sources (the literature review, the experts and the students) were compared in order to decide whether or not the factor was to be included in the EUCH model. If there was confirmation of the factor from at least two sources of data triangulation, the factor was included.

4.2.1 Qualitative methodology with experts

Interviews formed the qualitative data collection technique for collecting data from the expert group. There are two main types of interview: the individual interview and the group interview (or focus group) (Krueger and Casey, 2009). The key characteristic distinguishing a focus group is its use of interactive discussion between participants to produce data and insights into issues that would not arise from asking each participant a series of questions (Stewart and Shamdasani, 1990; Ackroyd and Hughes, 1993; Kitzinger, 1994; Hennink et al., 2011). Some researchers have claimed that individual interviews provide a wider range of information than a focus group with the same number of participants (Fern, 1982; Morgan, 1996; Kaplowitz and Hoehn, 2001; Berg and Lune, 2012), because participants in individual interviews are more confident in expressing their views on a subject than they would be in a focus group. The individual interview is free from issues such as the presence of dominant group members, peer pressure and group dynamics that may steer a participant's responses. However, another group of researchers has asserted that the dynamics of group interaction can generate a variety of new information, because one individual's idea may spark off another's, suggesting dimensions and nuances for each comment that no single participant may have thought of (Gibbs, 1997; Rabiee, 2004; Flick, 2009; Saunders et al., 2009).

The strength of the focus group over individual interviews is that the information from a focus group seems to have a greater degree of validity (Rubin and Rubin, 1995). In an individual interview, a participant may suggest information that is extreme or not socially shared without other members' evaluation of that information. In contrast, as participants can ask questions and comment on each other's points of view in a focus group, social interaction facilitates the researcher in determining which information is valid. Another limitation of the individual interview is exploration of the degree of consensus among participants on a given topic (Bryman, 1984). The degree of consensus among participants was important to this preliminary study. It indicates how the experts agree on each factor. In one-to-one interviews, a researcher would need to undertake comparisons of interview data to determine similarities and differences in order to find a consensus (Kaplowitz and Hoehn, 2001). However, the technique is insufficient to determine the level of consensus, as a researcher would never know if a participant agrees or disagrees with other participants on an issue that he or she did not propose. In a focus group, participants have a chance to hear all the views from each member's perspective and give their view on that information (Gibbs, 1997). The researcher can easily observe each participant's agreement and disagreement with each factor (Kaplowitz and Hoehn, 2001). However, it is important to note that consensus between participants in a focus group on any single factor may be influenced by a dominant participant or peer pressure, which in turn may steer an individual perspective; this is called 'group thinking' (Hennink et al., 2011).

Focus groups were used in the preliminary study instead of individual interviews to provide valid information and an agreed set of factors.

Selection of experts

Two categories of experts were selected as participants in the focus group. The first comprised leadership of the university with responsibility for initiatives concerning strategies to support E-learning in the university, such as the Vice-president on Online Education and the Director of E-learning Projects. The second comprised university lecturers who had conducted E-learning courses over the past five years. The benefit of their positions to the research was that they fully understood at a top and practical level the problem of students either not taking up or discontinuing E-learning. From these experts' experience of the problems, they could suggest possible factors affecting the uptake and continued use of E-learning at a university. The experts were chosen only from universities in the central part of Thailand. According to Brown (1999) and Lindlof (1995), the proper number of participants for focus group is six to twelve people. Thus, ten experts (five lecturers and five administrators) were contacted by email or telephone to arrange participation in the focus group. Eight experts accepted the invitation to join the focus group: four lecturers and four leadership staff (see Table 4-2).

Table 4-2: Participants in the focus group

Participant	Position	Institution
A	Senior Lecturer	Kasetsart University
B	Senior Lecturer	Sukhothai Thammairat Open University
C	Senior Lecturer	King Mongkut's Institute of Technology Ladkrabang
D	Senior Lecturer	Rajamangala University of Technology Thanyaburi
E	Director of E-learning project	King Mongkut's Institute of Technology North Bangkok
F	Director of E-learning project	Thai Cyber University
G	Thai educational expert	Ministry of Thai Education
H	Vice-President for Distance Education	Bangkokthonburi University

Qualitative data collection process

The focus group was conducted on from 1–4pm at Rajamangala University of Technology, Thanyaburi on 18 January 2013. Before the focus group started, the research background and purpose of the focus group was explained. Then a consent form was given to experts to sign to indicate their agreement to participate in the study. The focus group was divided into two sections, as follows:

E-learning: uptake section (1–2.20pm): the experts were asked to discuss the following topics:

- What are the factors likely to affect the uptake of E-learning among students in HEIs?
- How do these factors affect a student's uptake of E-learning?

E-learning: continuance section (2.40–4pm): experts were asked to discuss the following topics:

- What are the factors likely to affect the continued use of E-learning among students in HEIs?
- How do these factors affect a student's continued use of E-learning?

The Thai language was used in discussion. As suggested by Polgar and Thomas (1995) and Israel and Galindo-Gonzalez (2008), a video recorder was used to help the researcher to focus on the session and was useful in gathering both verbal and non-verbal data, recording the focus group environment and what participants said. At the end of the focus group, the researcher thanked participants for coming and gave them a souvenir as an expression of appreciation.

Qualitative analysis procedure

The qualitative data from the focus group were analysed using thematic analysis, a technique that identifies and reports the themes within collected data (Braun and Clarke, 2006; Guest, 2012). Themes represent patterns within the data set that capture something important to describe the phenomenon of specific research questions (Daly et al., 1997). The key concept of this method is to organize and outline a corpus in detail (Braun and Clarke, 2006). As the purpose of this preliminary study was mainly to confirm the proposed factors affecting E-learning uptake and its continued use, a theory-driven thematic analysis was chosen to analyse the data. This form of analysis is limited to preconceived frames; a researcher can easily see participants' opinions on each factor (Boyatzis, 1988). Consequently, the results of this analytic method can confirm the factors and provide in-depth reasons on how these factors affect E-learning uptake and its continued use (Braun and Clarke, 2006).

Data preparation

NVivo 10 software was used to facilitate the qualitative data analysis. After the raw data were collected from the focus group, a data preparation process was conducted (see Figure 4-1).

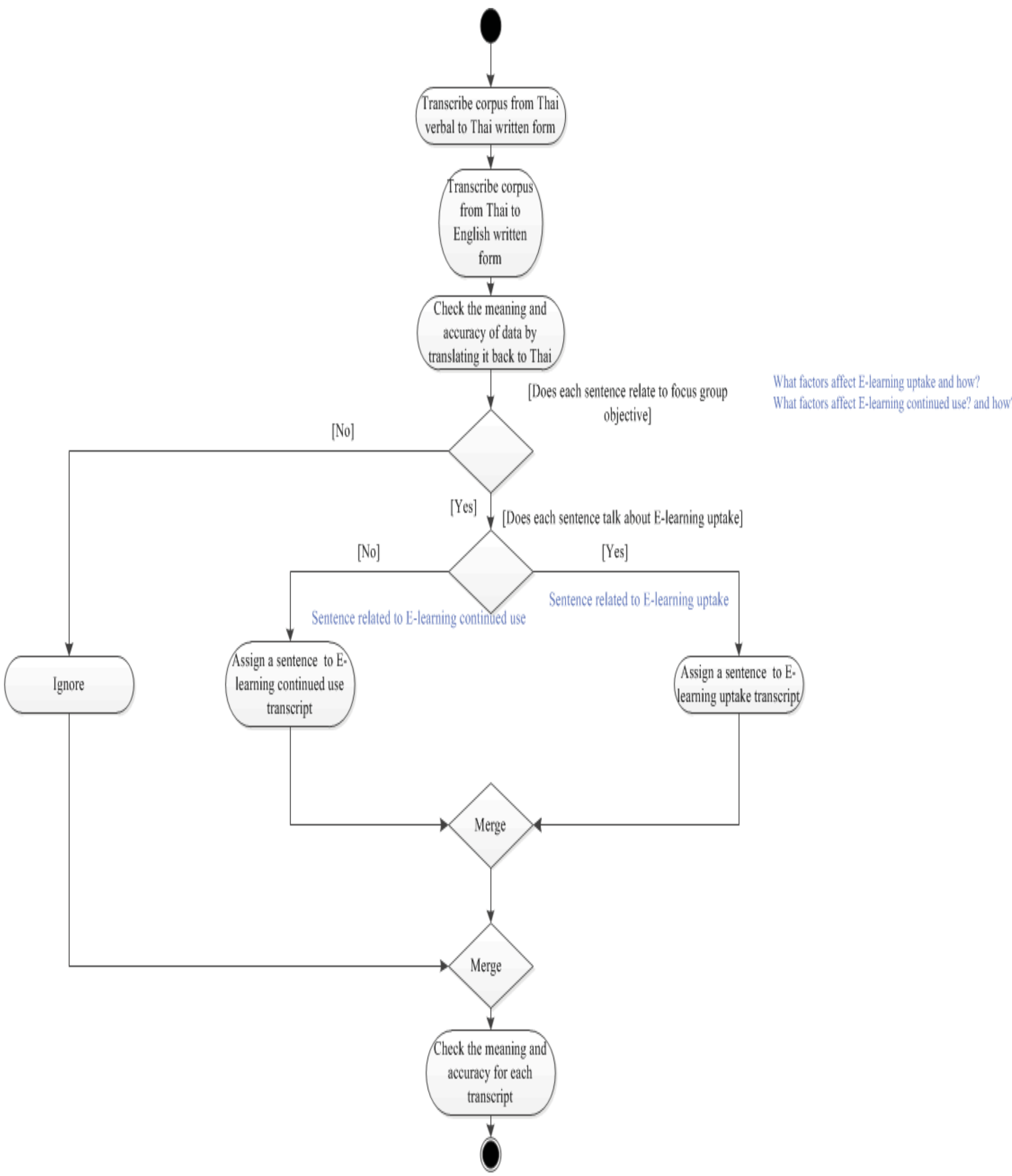


Figure 4-1: Activity diagram explaining qualitative data preparation process

As can be seen from Figure 4-1, the recorded data were first transcribed into Thai, then the transcript checked against the original video for accuracy. The Thai transcripts were subsequently translated into English, then, for easier analysis, sentences unrelated to the research questions or beyond their scope were discarded. As there were two research questions to be answered, sentences relating to E-learning uptake were separated from those relating to continued use of E-learning, and collated into different transcriptions. The NVivo program was then used and two nodes were set, based on the research questions: one for factors affecting E-learning uptake, and one for factors affecting E-learning continuance.

Analysis process

To confirm the proposed factors, codes were set in each node, according to the proposed factors (see Figure 4-2).

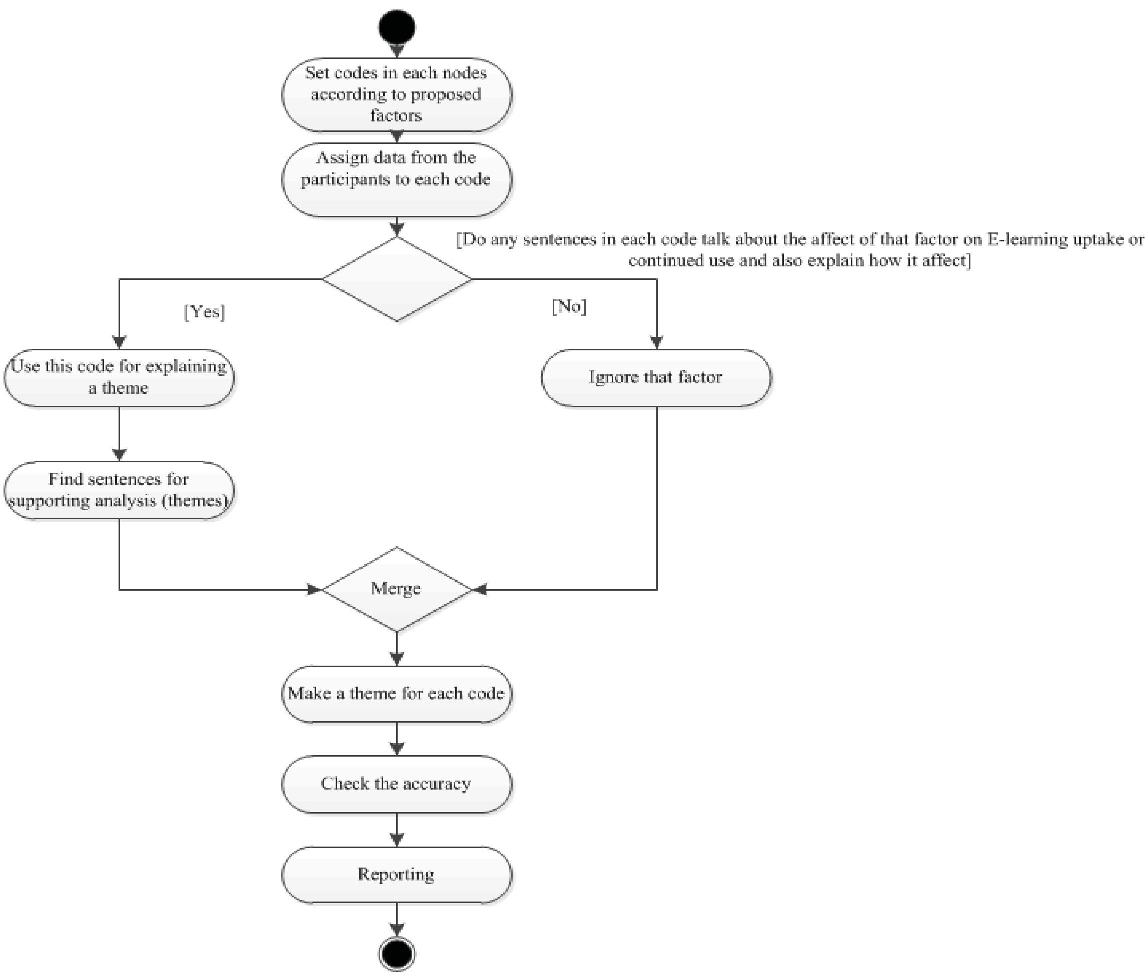


Figure 4-2: Activity diagram explaining qualitative data analysis process

However, to avoid failing to identify other possible factors relating to the uptake of E-learning and its continued use, an additional finding code was included in both nodes to capture these data (see Table 4-3). Next, data from the transcripts were assigned to the related code then the data in each code were read and checked for accuracy again. After that, the data in each code were read to establish how many experts proposed any particular factor and how it affected the phenomenon. Finally, the findings were checked for accuracy again and a report produced. Each factor proposed by at least half the experts (4) was to be confirmed from their perspective.

Table 4-3: Node and code setting in NVivo program

	Factors affecting E-learning uptake	**Factors affecting continued use of E-learning**
Codes	Performance expectancy	Performance expectancy confirmation
	Effort expectancy	Effort expectancy confirmation
	Social encouragement expectancy	Social encouragement expectancy confirmation
	Facilitating condition expectancy	Facilitating condition expectancy confirmation
	Learning consistency expectancy	Learning consistency expectancy confirmation
	Additional finding	Additional finding

4.2.2 Quantitative methodology with students

A questionnaire was used to collect the data from a group of students. There are two main types of questionnaire: self-administered and interview-administered. (Saunders et al., 2009). The self-administered questionnaire is completed by respondents themselves (Bourque and Fielder, 2002), whereas an interview-administered questionnaire contains structured questions that are asked and recorded by the researcher (Brace, 2008). Although the use of an interview-administered questionnaire allows misunderstood questions to be clarified, interaction between the researcher and a respondent may result in low accuracy in the data; participants may respond with what they perceive the researcher desires to hear, or they consider acceptable, rather than what they actually believe (Leung, 2001; Bowling, 2005; Chang and Krosnick, 2010). Furthermore, an interview-administered questionnaire requires more time and greater financial resources than a self-administered questionnaire (Saunders et al., 2009). Therefore, a self-administered questionnaire was adopted as the tool for collecting data from students in this preliminary study. There are three main types of self-administered questionnaire: a delivery and collection questionnaire; an internet-mediated questionnaire; and a postal questionnaire (Czaja and Blair, 2005) (see Table 4-4).

Table 4-4: Advantages and disadvantages of three main types of self-administered questionnaire

	Delivery and collection questionnaire	Internet-mediated questionnaire	Postal questionnaire
How data is collected	Questionnaire is delivered by hand to each respondent and collected later.	Questionnaire is administered electronically using internet; it can be delivered by email or accessed via a web page.	Questionnaire is posted to respondents who return them by post after completion.
Time taken to complete collection	Short	Long	Very long
Cost	High	Low	Medium
Advantages	1. Obtaining representative sample of the population: the researcher can see who completes a questionnaire; therefore unrelated people do not have the chance to fill in the questionnaire. 2. Respondents can ask if they do not understand questions: small errors (such as uncompleted questionnaires) can be avoided by ticking the answer.	1. Convenience: respondents can answer questions on their own schedule at their own pace. 2. Respondents have time to consider questions or can leave the questionnaire while they go away to check information. 3. Anonymity: makes it easier for respondents to give an honest response. 4. Automation: respondents' input data is automatically stored in electronic files ready for analysis.	1. Convenience: respondents can answer questions on their own schedule at their own pace. 2. Respondents have time to consider questions or can leave the questionnaire while they go away to check information. 3. Anonymity: makes it easier for respondents to give an honest response.
Disadvantages	1. Pressure by friends and researchers leads respondents to give information that they may not actually believe.	1. Respondents cannot ask if they do not understand: they will probably not complete the questionnaire or will make errors. 2. Lack of complete lists of private email addresses. 3. Difficult to control who fills in the questionnaire. 4. Takes time to learn how to do an online survey.	1. Respondents cannot ask if they do not understand: they will probably not complete the questionnaire or will make errors. 2. It is not easy to find students' up-to-date postal address. 3. Respondents have to return the questionnaire by post.

Source: May (1993); Bourque and Fielder (2002); Vaus (2004); Bowling (2005); Czaja and Blair (2005); Brace (2008); and Saunders et al. (2009)

In this preliminary study for collecting the data from Thai HEI students, the delivery and collection questionnaire was adopted. This is a technique whereby each questionnaire is delivered and collected by hand. By using it, the researcher could be sure that the questionnaires were from a group of HEI students. Since the researcher was physically present and to give respondents the questionnaire and collect it, he could clarify any misunderstandings of questions, so this technique reduced potential errors such as uncompleted questionnaires (Brace, 2008). The anonymity and the time to consider the questions were important factors if respondents were to provide honest and accurate data (May, 1993; Vaus, 2004).

Questionnaire design

There are two main types of question that can be used in a questionnaire: open-ended questions and closed questions (Bryman, 2008). An open-ended question gives respondents a greater freedom to formulate their own answers, while a closed or forced-choice question has a set of fixed alternative answers provided and respondents have to choose an appropriate answer (Vaus, 2004). The advantages and disadvantages of these question types are compared in Table 4-5.

Table 4-5: Advantages and disadvantages of question types in a questionnaire

Question type	Advantage	Disadvantage
Open-ended question	1. Allows exploration of the range of possible factors affecting the uptake and continued use of E-learning (not limited to the literature). 2. Bias is reduced because the response is not limited to certain options.	1. Time consuming for a researcher to administer and analyse data compared with closed questions. 2. Requires greater effort and time from respondents in answering questionnaires. 3. Comparison and statistical analysis becomes more difficult.
Closed question	1. More convenient for a respondent to fill in a questionnaire. 2. The availability of options may help to clarify the meaning of a question or the misunderstanding of a question. 3. Easy to code and analyse the data. 4. Allows the comparison of options among respondents. 5. More suitable for use as a statistical tool to confirm the proposed factors and make a generalization of the finding to a population.	1. May fail to discover the key factors on the issue that are not mentioned in the literature. 2. Misleading conclusions may be drawn when respondents' desired answer is not one of the options, because they are unable to express fully their personal opinion.
Source: May (1993); Coombes (2001); Leung (2001); Vaus (2004); Brace (2008); and Bryman (2008)		

Closed questions were used in the quantitative study of the preliminary study. These generate numerical data, in which it is easier to observe respondents' opinions on each proposed factor than in the textured data received from open-ended questions (Coombes, 2001). Furthermore, numerical data are more suitable for analysis by statistical tools for statistical confirmation of the factors (Leung, 2001). Moreover, the use of closed questions seems to save time and is easier both for the respondent to answer and the researcher to administer and analyse (Bryman, 2008).

A Likert scale was used for responses to the closed questions in the questionnaire. This is an ordinal response scale that measures respondents' opinion on statements where they are asked to indicate a degree of agreement or disagreement in a multiple-choice format (Vaus, 2004). As the Likert scale does not force the participant to take a stand on a concrete 'yes' or 'no' answer, it encourages an easier answer (Lehmann and Hulbert, 1972; Brace, 2008). Furthermore, as the Likert scale provides interval data, means score for each representative question can be calculated to provide an overall attitudinal score for each proposed factor, and it is also applicable for the one sample *t*-test that constituted the major statistical analysis in this preliminary investigation (Taylor, 2005; Saunders et al., 2009). A five-point Likert scale that started from 'No, not at all' (level 1) to 'Yes, absolutely' (level 5) was provided for respondents to indicate their level of agreement with each statement.

To cross-check the data, three groups of students were selected as respondents to confirm the proposed uptake factors: (1) those who had never used an E-learning system before; (2) those who had opted out of E-learning; and (3) those who had continued to use E-learning. The uptake factor would be confirmed if at least two groups of students agreed with it. Students who had opted out and those who were continuing to use E-learning systems were selected as respondents to confirm the factors proposed for continuing use. The proposed continuing use factor would be confirmed if at least one group of students agreed with it.

The questionnaire comprised three sections (see Appendix 4-A). Section A was a general information section used to check that the respondent was a representative sample of the population (Thai HEI students) and to classify which group of respondents they fell into. Section B was designed for students who had never used E-learning before. It included questions about the factors affecting the uptake of E-learning. In this section, respondents were asked to indicate on a Likert scale their level of agreement with statements about the impact of proposed factors on their decision to take up E-learning. Section C was designed for students who had either opted out or continued to use E-learning. The aim of this section was to measure students' opinions about the effect of the proposed E-learning uptake and continuance factors on their decision to take up and continue using E-learning. Similar to Section B, a Likert scale was used in this section. In total there were 17 questions in the questionnaire. To make it easier and more understandable for the respondents, the questionnaire was translated into Thai.

Data analysis tools

In order to confirm factors affecting the uptake or continued use of E-learning by students in each group, a one sample *t*-test was used to determine whether the mean rating for a representative question of each proposed factor was significantly different from a rating of 3. The reason why the mean value of each proposed factor was compared with this rating was because this value indicated ‘Neither agree nor disagree’ on the five-point Likert scale adopted in this study. This one sample *t*-test used a 95 per cent confidence level; α (alpha) was set at 0.05. The null hypothesis and alternative hypothesis were set as follows:

H_0: The mean rating on a representative question is equal to a rating of 3 ($m_1 = 3$)

H_1: The mean rating on a representative question is not equal to a rating of 3 ($m_1 \neq 3$)

If the null hypothesis was rejected ($p < 0.05$) and the mean rating of the question was significantly higher than 3, it could be concluded that this factor influenced students to take up or to continue to use E-learning, for that group of students.

Sample size and sampling method

Statistical analysis tools help a researcher to determine whether the null hypothesis should be accepted or rejected (Bryman, 2008). However, this process has two kinds of error: Type I and Type II errors (Czaja and Blair, 2005). Type I error occurs when the null hypothesis is rejected incorrectly (Accept H_1 when H_0 is true). Type II errors occur when the null hypothesis is accepted incorrectly (Accept H_0 when H_1 is true)

Statistical power analysis helps a researcher to know how many respondents are required in order to detect the effect (the difference in the mean value) with an acceptable percentage of Type I or Type II errors (Jones et al., 2003). As statistical power analysis is not easy to undertake by hand (Faul et al., 2007), the G*power 3.1.5 program was used to facilitate the researcher in calculating the sample size for this preliminary study. By using *a priori* power analysis, there are four variables involved in determining a sample size: (1) type of statistical technique; (2) effect size; (3) significance level (α); and (4) statistical power (Cohen, 1992).

The one sample *t*-test was the statistical technique adopted by this preliminary quantitative study. The effect size was chosen to be 0.75. This study fell between confirmation and exploration: the technological motivation factors were widely validated and confirmed by the previous studies, and it was intended to confirm them, yet, while there was little research investigating the impact of learning motivation impact on E-learning usage, it was necessary to explore its impact. Because of this, the compromise alpha (Type I error) value between 0.1 (exploration research) and 0.01 (confirmation research) was set at 0.05. To reduce the risk of failure to detecting the real effect (Type II error) and the cost of conducting the survey was not much high, power was set maximally at 0.99. To detect the effect size of 0.75 with 99 per cent power, G*power suggested that at least 35 participants were required. As a consequence, the total number of respondents in this quantitative study was 105 students: (1) 35 who had never use E-learning; (2) 35 who had opted out of E-learning; and (3) 35 who continued to use E-learning.

In this study, the sampling frame was a complete list of all the undergraduate students who were currently studying at Rajamangala University of Technology Thanyaburi (RMUTT). E-learning has been implemented at RMUTT as a complementary tool for supporting traditional lectures since 2006. As students at this university could decide on their uptake of E-learning and continued use at university, this group would be able to confirm whether or not the proposed factors affected their decision to take up and continue using E-learning.

A simple random sampling technique was adopted to select the individual students to participate in this study. By using this technique, all students had an equal opportunity to be included in the study, therefore the findings could be generalized from the sample to the population (Mitchell and Jolley, 2007). In the data collection process, we did not know who the students were, as the respondents were selected randomly at the university (RMUTT) by a ‘delivery and collection’ method until we received 35 completed questionnaires from each group type.

4.2.3 Ethical approval

The preliminary study, including qualitative methodology with experts and quantitative methodology with students, was approved by the Ethical Committee of Electronic and Computer Science at the University of Southampton. This indicates that the study met the required ethical standards. Ethical approval was granted under reference number 4726.

4.3 Confirmation of E-learning Uptake Factors

There were five initial expectation factors likely to affect a student's uptake of E-learning, including *performance expectancy* (PE), *effort expectancy* (EE), *social encouragement expectancy* (SEE), *facilitating condition expectancy* (FCE) and *learning consistency expectancy* (LCE). This section examines each of these five factors by using data triangulation (the literature review, results from the preliminary study with the experts and results from students) to answer fully the first research question (RQ1, above).

4.3.1 Performance expectancy factor

The *'performance expectancy'* factor is the degree to to which an individual student expects that using an E-learning will be useful for his/her education and enhance his/her learning performance. Based on this definition, the results from the focus group showed that five (B, D, F, G and H) of the eight experts proposed that '*performance expectancy'* has an impact on the uptake of E-learning. They mentioned that students will take up E-learning if the system supports them in achieving their expected ILO faster than other possible ways of learning. The following examples demonstrate this issue:

Expert B: *The poor performance of E-learning systems leads students to not take up this technology.*

Expert D: *For a student to take up E-learning, the system has to support the student to achieve their intended learning outcome faster than other possible ways of learning. One of my students said that he never thought about using E-learning because he believes that his learning performance cannot be improved by use of this technology.*

Expert H: *E-learning in Thailand is not attractive to students because they believe that the use of the system cannot help them learn better.*

The impact of the '*performance expectancy'* factor on the uptake of E-learning was confirmed by all three groups of students. There was a statistically significant difference in mean ratings for the question about the impact of '*performance expectancy'* on E-learning uptake and the rating of 3, as follows: (1) students who had never used E-learning before, the mean rating (3.8), $t(34) = 6.6$, $p < 0.01$; (2) students who opted out of E-learning, the mean rating (3.6), $t(34) = 4.1$, $p < 0.01$; (3) students who continued using E-learning, the mean rating (4.3), $t(34) = 14.8$, $p < 0.01$.

The findings from the preliminary study on this factor are not only in line with the TAM and the UTAUT models, but with the extensive research undertaken in the research area of E-learning uptake (Selim, 2003; Lee, 2006; Theng et al., 2008) (see Appendix 3-A). With confirmation from all three sources of data to serve as triangulation, it can be concluded that '*performance expectancy'* is a factor likely to affect a student's uptake of E-learning. Therefore, this factor was included in the proposed model as a variable within the '*initial expectation of E-learning'* construct.

4.3.2 Effort expectancy factor

The *'effort expectancy'* factor is defined as the degree to which an individual student expects that the use of E-learning does not require an increase in effort. Under this definition, only three (D, F and G) of the eight experts proposed that the *'effort expectancy'* factor affects the uptake of E-learning. These three experts suggested that a student would take up E-learning if they had enough IT skills, or the system was designed to be easy for students to use. The following comments support this finding:

Expert F: *A student's IT skill is one possible factor affecting their uptake of E-learning.*

Expert D: *A student's IT skill also affects their decision to take up E-learning. Many students believe that the use of E-learning is quite difficult for them because of their low IT skills.*

Expert G: *In order to increase the uptake of E-learning, we need to consider the technology itself. The system should be designed to be easy for students to use.*

All three groups of students in the preliminary study confirmed that their decision to take up E-learning was influenced by its *'effort expectancy'*: a one sample *t*-test revealed a statistically significantly difference between the rating of 3 and the mean rating of the question about the impact of this factor on E-learning uptake in all three groups: (1) students who had never used E-learning before, the mean rating (3.9), $t(34) = 6.0$, $p < 0.01$; (2) students who opted out of E-learning, the mean rating (3.8), $t(34) = 5.7$, $p < 0.01$; (3) students who continued using E-learning, the mean rating (4.4), $t(34) = 11.9$, $p < 0.01$.

Only three of the eight experts mentioned the impact of '*effort expectancy'* on the uptake of E-learning. A possible explanation for why the majority of experts did not mention the impact of this factor might be due to their confidence in students' IT skills (Lee et al., 2005; Park, 2009). According to Thai government policy on ICT in education, many Thai students from high school onwards have had the chance to use technology to support their education (Becker and Maunsaiyat, 2002; Rueangprathum et al., 2008). This may lead most experts to believe that, from their high school days, students have gained sufficient IT skill to use E-learning. However, recent research on E-learning adoption in Thai HEIs (Bhrommalee, 2012; Premchaiswadi et al., 2012) and a group of students in this preliminary study has suggested that a system's ease of use is still a crucial factor in the uptake of E-learning. With confirmation from two of the three groups to triangulate the data, it was decided to include '*effort expectancy'* as a variable affecting the uptake of E-learning in the EUCH model.

4.3.3 Social encouragement expectancy factor

The *'social encouragement expectancy'* factor is defined as the degree to which an individual student expects that his/her significant persons will encourage the use of an E-learning system. Based on the mentioned definition, the result from the focus group showed that seven (B, C, D, E, F, G and H) of the eight experts proposed an impact by *'social encouragement expectancy'* on E-learning uptake. The group of experts suggested that there are three social agents that influence a student's decision to take up E-learning, including parents, teachers and friends.

Expert E proposed the effect of parental encouragement on the uptake of E-learning. He gave his opinion that parents can encourage students to take up E-learning by providing the necessary IT resources (such as a computer and internet). This is his comment:

> *Parents are a significant social agent for increasing the uptake of E-learning. Many Thai students know that E-learning can improve their learning performance, but their family has not encouraged them to use it. Their parents did not provide a computer and internet for them.*

Six experts (B, C, D, E, F and G) mentioned that a teacher may be a social agent who influences a student's decision on the uptake of E-learning. To take up E-learning, a student needs online teachers to be available to encourage them when they have a problem about what is being learned, and actively to take part in the student's learning process. The following examples demonstrate this issue:

Expert B: *A teacher's active encouragement is a significant factor. Thai students want their online teacher to be with them to encourage their learning process and answer their questions in real time, similar to a face-to-face traditional classroom.*

Expert F: *The factor which influences Thai students' decisions to take up E-learning is the 'teacher's encouragement'. To illustrate the point, Thai students believe that their teachers are knowledgeable about that subject and can support them to achieve their intended learning outcome. It is not surprising that our students will only ask their teacher a question when they have questions on that subject; therefore, in order to increase the uptake of E-learning, an online teacher should do the same as a face-to-face teacher: they should be available to answer a student's questions when the student needs it.*

Expert G: *In order to tackle the low E-learning uptake problem, a teacher's role is crucial; teachers need to stimulate their students and help them whenever they find a problem with what is being learned.*

Two experts (C and E) proposed that a student's friends have an impact on the decision to take up E-learning. Students will take up the system if they observe their friends' success and have their encouragement. Expert C gave her opinion on this issue:

> *The social factor is also important. Many of my students take up E-learning because their friends encourage them to use it, or they found that their friends who used the system before have a higher learning performance.*

The impact of the *'social encouragement expectancy'* factor was also confirmed by the group of students, the mean rating on a question about the impact of encouragement from their important persons on the uptake of E-learning was statistically significantly different from a rating of 3: (1) students who had never used E-learning before, the mean rating (3.8), $t(34) = 5.3$, $p < 0.01$; (2) students who opted out of E-learning, the mean rating (3.5), $t(34) = 3.1$, $p < 0.01$; (3) students who continued using E-learning, the mean rating (3.9), $t(34) = 5.7$, $p < 0.01$.

Consistent with the findings from the preliminary study, the UTAUT and research papers confirmed the impact of this factor on the uptake of E-learning (McGill and Klobas, 2009; Park, 2009) (see Appendix 3-A). As there was convergence between the findings from all data triangulation on this factor, it can be concluded that *'social encouragement expectancy'* is a factor likely to affect a student's uptake of E-learning. This factor was therefore included in the proposed EUCH model as a variable within the '*initial expectation of E-learning'* construct.

4.3.4 Facilitating condition expectancy factor

The *'facilitating condition expectancy'* factor is defined as the degree to which an individual student expects that there are IT resource to support the use of E-learning. Six experts (A, B, D, F, G and H) mentioned the effect of the *'facilitating condition expectancy'* factor on the uptake of E-learning. They mentioned that, as E-learning is the way to learn with an IT device, the availability of an IT device (such as a computer/internet) and IT staff are necessary and affect students' decision to take up E-learning. The following comments support the findings:

Expert H: *IT infrastructure is also important. In order to use E-learning, a receiver (such as computer or tablet) and networking (internet signal) need to be provided for the users.*

Expert B: *We need to accept that there is a problem of inequality between students with IT resources. This is because the price of IT equipment in Thailand is quite high. This problem may result in the poor level of E-learning uptake; many of my students want to use E-learning but they cannot, because they do not have a necessary IT resources to use the system, such as a computer and internet.*

Expert A: *IT staffs are important. One of my students said he used to use E-learning one time and never thought to use it again, because IT staff were not available to help him when he had a problem with the system: he needed to wait for IT staff for one week. Would you use it?*

Consistent with the results from the experts, the confirmation of the *'facilitating condition expectancy'* factor was also found in a group of students: (1) students who had never used E-learning before, the mean rating (4.0), $t(34) = 6.5$, $p < 0.01$; (2) students who opted out of E-learning, the mean rating (3.5), $t(34) = 3.1$, $p < 0.01$; (3) students who continued using E-learning, the mean rating (4.4), $t(34) = 12.9$, $df = 34$, $p < 0.01$.

The findings of the preliminary study are consistent with TPB and UTAUT models, and existing research (Ndubisi, 2004; Shih, 2008; Bhrommalee, 2012) (see Appendix 3-A). With convergence between the three sources of information, it was concluded that *'facilitating condition expectancy'* was a factor likely to affect the uptake of E-learning in HEIs and was included as one of variables within the '*initial expectation of E-learning'* construct.

4.3.5 Learning consistency expectancy factor

The *'learning consistency expectancy'* factor in this research is defined as the degree to which an individual student expects that an instructional environment in E-learning (which includes the content, teaching and learning activities) is relevant to their goals, learning styles and past experience. Six experts (A, C, E, F, G and H) suggested that the consistency between a student's learning goal and the intended learning outcome of an E-learning course affects the decision to take up E-learning. In order to increase the uptake, the expert recommended that we establish what students want to learn and provide them with a course corresponding to their learning goal.

The following comments support this finding:

Expert A: *In order to increase the uptake of E-learning, we first need to focus on the student. We need to know what they want to learn. If we provide content that is responsive to what they want, their motivation to learn will be there and they will actually use the system.*

Expert C: *What is more, in order to be taken up, the content in an E-learning system needs to be useful for them in their education or future work. It is quite the same concept as cooking food: if we cook what they like, they will eat this meal.*

Expert E: *Low E-learning uptake has been tackled for a long period of time and it seems to be a little better. For me, one factor that causes Thai students to take up E-learning more than before is the content readiness: there are more online contents, and each of these is more responsive to what students want to learn than before.*

Expert G: *As E-learning is a learning environment, we first have to know what they want to learn in order to provide relevant content for them. From my experience, Thai higher education students prefer E-learning content that will be useful to them for achieving a high grade or can be applied in the future for their career.*

Expert H: *Learning cannot occur if the learner did not perceive the value of the learning outcome. As we cannot ask them to learn, what we can do in order to increase E-learning uptake is to provide courses that are responsive to what they want.*

Five of the eight experts (A, B, C, F and H) recommended that consistency between a student's learning style and the learning activity in E-learning affects the uptake of this technology. The following comments support the finding:

Expert C: *In order to be taken up, the way we teach online also needs to be consistent with their learning style.*

Expert H: *As we cannot ask them to learn, what we can do in order to increase E-learning uptake is to provide a learning activity that is responsive to the way they learn.*

Expert A: *We need to focus on the way they learn. As mentioned by others, Thai culture affects the national characteristic of Thais to be interdependent. Thai students expect that E-learning will provide them a space for discussing with friends in order to support each other to achieve the course goals.*

Expert B: *Furthermore, our culture affects the way students learn. They are social learners; they love to learn in groups with their friends to support each other to get their intended learning outcome. Therefore, they will take up E-learning if the system also provides them with functionality to contact their friends throughout the online learning process.*

Similar to the finding from the group of experts, the confirmation of this factor was found in the group of students. The mean rating on a question about the impact of this factor on the uptake of E-learning was statistically significantly different from the rating of 3 in all three groups: (1) students who had never used E-learning before, the mean rating (3.9), $t = 7.8$, $df = 34$, $p < 0.01$; (2) students who opted out of E-learning, the mean rating (3.7), $t = 5.2$, $df = 34$, $p < 0.01$; (3) students who continued using E-learning, the mean rating (4.2), $t = 15.2$, $df = 34$, $p < 0.01$.

The expectancy-value theory (Atkinson, 1957; Wigfield, 1994), Keller's ACRS model and the work of Chen (2011) supported this finding. With confirmation of the factor from the data triangulation, this *'learning consistency expectancy'* was a factor likely to affect the uptake of E-learning factor and was therefore included in the EUCH model as a predictor of E-learning uptake.

4.3.6 Additional findings (Culture)

There were two experts (A and B) who mentioned the effect of culture on the uptake of E-learning. However, this factor does not affect uptake directly; it affects the E-learning uptake through the learner's learning style. The experts mentioned that a Thai learner's learning style is influenced by the interdependent national characteristic of Thais. This shapes Thai students to be social learners: group learning is their preferred way of learning. The following comments support the finding:

Expert A: *Thai culture affects the national characteristic of Thais to be interdependent. Thai students expect that E-learning will provide them a space for discussing with friends in order to support each other to achieve the course goals.*

Expert B: *Our culture affects the way students learn. They are social learners; they love to learn in groups with their friends to support each other to get their intended learning outcome. Therefore, they will take up E-learning if the system also provides them with functionality to contact their friends throughout the online learning process.*

These comments from the experts suggest future work on the application of the model in the countries with different cultures.

4.4 Confirmation of E-learning Continued Use Factors

Five factors found in the literature seem to affect a student's continuance of E-learning; *performance expectancy confirmation (PEC)*; *effort expectancy confirmation (EEC)*; *social encouragement expectancy confirmation (SEEC); facilitating condition expectancy confirmation (FCEC);* and *learning consistency expectancy confirmation (LCEC)*. This section discusses the results from experts and students on the impact of each on the continuing use of E-learning, to answer the second question (RQ2).

4.4.1 Performance expectancy confirmation factor

'Performance expectancy confirmation' is defined as the degree to which an individual student confirms that an E-learning system has a higher ability to support them to achieve their intended learning outcome than they previously expected. Based on this definition, the results from the focus group were that three experts (F, G and H) mentioned the influence of a '*performance expectancy confirmation'* factor on E-learning's continued use. The experts suggested that a student's motivation to continue using E-learning is affected by the student's attitude towards the system after using it. A student will have a positive attitude towards an E-learning system if he/she confirms that its use supports them to learn better, or achieve the intended learning outcome faster, than other possible ways of learning. The following comments address this issue:

Expert F: *The system itself is also important. The system needs to help students to learn better. If the system can do this, their attitude towards the system will be positive, which will cause them to continue with E-learning.*

Expert G: *Students will have a positive attitude towards the system when they perceive that the system can support them to achieve their intended learning outcome faster than other possible ways of learning.*

Expert H: *If students perceive that the system can support them to learn faster and better, students will have a positive attitude towards the system and this will cause them to continue with E-learning.*

The students agreed that the *'performance expectancy confirmation'* factor affected their decision to continue using E-learning: (1) students who opted out of E-learning, the mean rating (3.7), $t(34) = 4.7$, $p < 0.01$; (2) students who continued using E-learning, the mean rating (4.2), $t(34) = 11.2$, $df = 34$, $p < 0.01$.

Cognitive Dissonance theory (Festinger, 1962), the expectancy confirmation model of IS continuance (Bhattacherjee et al., 2008) and six studies on the continued use of E-learning suggest that there is a relationship between '*performance expectancy confirmation'* and a student's decision to continue using E-learning (Chiu et al., 2005; Roca et al., 2006) (see Appendix 3-B). With confirmation from two groups as data triangulation, it was concluded that '*performance expectancy confirmation'* was a factor likely to affect the continued use of E-learning and therefore it was included as a variable in expectancy confirmation constructs.

4.4.2 Effort expectancy confirmation factor

The *'effort expectancy confirmation'* factor is defined as the degree to which an individual student confirms that the use of an E-learning system was easier than he/she expected. Based on this definition, four experts (B, D, E and H) proposed that the *'effort expectancy confirmation'* factor affected the continued use of E-learning. The experts mentioned that students would be frustrated by the system if they perceived that the use of the system is complicated, which may impede their learning progress. Frustrated feelings will lead them to opt out of the system. The following comments support the finding:

Expert B: *The system itself is also important. The system need to be easy for students to use. If we can do this, their attitude about the system will be positive, which will cause them to continue to learn by E-learning.*

Expert D: *As we know, E-learning in our country has quite a poor user interface design, many students perceived the use of this technology as quite complicated. This factor can affect the continued use of E-learning because it will make students frustrated and annoyed with the system, which will lead them to opt out from the system.*

Expert H: *Furthermore, the lack of ease of use can also impede their learning progress, which will result in opting out from the system. You can imagine that we would not continue to use any technology, even if it is helpful, for doing our tasks if we found that it is complicated to use.*

Consistent with the results from the experts, there was confirmation of this factor by students. A one sample *t*-test detected a statistically significantly difference in the mean rating on the question about the impact of the '*effort expectancy confirmation'* factor on the continued use of E-learning from a rating of 3: (1) students who opted out of E-learning, the mean rating (3.8), $t(34) = 5.7$, $p < 0.01$; (2) students who continued using E-learning, the mean rating (4.2), $t(34) = 11.2$, $p < 0.01$.

The findings from the preliminary study on this factor seemed consistent with three studies in the field that '*effort expectancy confirmation'* had an impact on a student's intention to continue using E-learning (Chiu et al., 2007; Liaw, 2008; Almahamid and Rub, 2011). With this data triangulation, it was concluded that the factor was likely to affect the continued use of E-learning and therefore the '*effort expectancy confirmation'* factor is included in the model.

4.4.3 Social encouragement expectancy confirmation factor

The *'social encouragement expectancy confirmation'* factor is defined as the degree to which an individual student confirms that encouragement from their significant persons on the use of E-learning was better than expected. The results from the focus group showed that no expert mentioned the impact of this factor on continued use of E-learning, contrary to the results from the group of students who confirmed the factor. The mean rating on a question of the impact of the '*social encouragement expectancy confirmation'* factor on a student's decision to take up E-learning was statistically significantly different from a rating 3: (1) students who opted out of E-learning, the mean rating (3.7), $t(34) = 4.5$, $p < 0.01$; (2) students who continued using E-learning, the mean rating (4.1), $t(34) = 9.8$, $p < 0.01$. Thai students are social learners and rely heavily on their lecturers (Adamson, 2003; Carter, 2006). If they perceived that their teachers and friends were not available to encourage them when they had a problem with what was being learned using E-learning, they may have opted out of the system and gone back to relying on traditional lectures, where their lecturers and friends were available to support them (Pagram and Pagram, 2006). Although there was no confirmation from the experts on this factor, it was included in the model due to confirmation from both the group of students and the literature review.

4.4.4 Facilitating condition expectancy confirmation factor

The *'facilitating condition expectancy confirmation'* factor is the degree to which an individual student confirms that there are IT resources (IT devices and staff) to support their use of E-learning. Based on this definition, five experts (A, B, D, G and H) suggested that a '*facilitating condition expectancy confirmation'* factor would result in continued use of E-learning. Experts said the unavailability of IT equipment or poor support from staff would lead a student to opt out of E-learning, and as they would be wasting their time with poor support they would not perceive the main benefit of E-learning, that is, to support learners to learn faster. The following comments give examples on this issue:

Expert G: *Most important of all is sufficient IT equipment accessibility, as it can obstruct a student's motivation to use and continue to use it even if they found the system is useful for them.*

Expert H: *However, their motivation to continue using E-learning may decrease if we do not continue supporting them with the necessary IT resources.*

Expert A: *Another thing that we need to be concerned with is 'IT service'. Poor or slow IT service from staff may make students opt out from the system. As they need to waste their time waiting for the service, they cannot perceive the benefit of E-learning that supports learner to learn faster. If they have a negative attitude towards the system, they will not continue to use it.*

Expert B: *To begin with, universities should make more investment in their E-learning projects by providing more computers and internet access. It really irritates many students when they have to wait for a computer in a computer room.*

Similar to the expert group, confirmation of the factor was also found among students: (1) students who opted out of E-learning, the mean rating (4.1), $t(34) = 8.6$, $p < 0.01$; (2) students who continued using E-learning, the mean rating (4.1), $t(34) = 10.5$, $p < 0.01$. The consistency between the experts' and the students' information supported using this factor in the model.

4.4.5 Learning consistency expectancy confirmation factor

The *'learning consistency expectancy confirmation'* is defined as the degree to which an individual student confirms that the instructional environment in E-learning is relevant to his/her goals, learning style and existing skills. Based on this definition, four experts (A, B, C and E) mentioned the impact of this factor.

Experts A and E proposed that the relevance between the content and learners' goal affects their continued use of E-learning; students continue using E-learning if they perceive that the online content is relevant to their education and can help them to achieve good results. The following comments support the finding:

Expert A: *The learning environment needs to be responsive to what they want to learn; the content supports them to achieve good grades.*

Expert E: *For me, the most significant factor affecting the continued use of E-learning is the usefulness of the online content. If students perceive that the content is useful for them and the system can support them to get a good GPA, they will have the motivation to continue using E-learning.*

Experts B and C mentioned that students would continue to use E-learning if they perceived that the online learning activity is responsive to the way they learn (their learning style). When students take part in their preferred learning activity, they will be happy with the system and this results in continued use of E-learning. The following comments demonstrate this issue:

Expert B: *As I mentioned in the first section, a Thai student is a social learner. We need to provide them with online chat. I think it can make them feel happier with the system, and their friends can also give them moral support whenever they are inclined to opt out from the system. It can sustain them to continue using E-learning.*

Expert C: *The system needs to be designed to be compatible with the way they learn. By doing this, our learners will feel comfortable with the E-learning system and will continue to use it.*

Consistent with experts, the students confirmed that consistency between the E-learning learning environment and their learning expectations affected their decision to continue to use E-learning; the group of students who opted out of the system showed a significantly different mean rating (3.9) from 3 (t = 9.6, df = 34, $p < 0.001$) and the group of students who continued using the system showed a significantly different mean rating (4.2) from 3 (t = 14.6, df = 34, $p < 0.001$), With this consistency from the groups of experts and end users, *'learning consistency expectancy confirmation'* was found to be a factor likely to affect continued use of E-learning and was included as a variable in the expectancy confirmation construct.

4.5 Summary of Chapter 4

The preliminary study was conducted with a group of experts and a group of students for confirmation of the factors affecting E-learning uptake and continuance identified in the literature, in order to answer fully the first two research questions (RQ1 and RQ2).

To begin with the E-learning uptake factor (RQ1), from the triangulated data it was concluded that there were five factors likely to affect the uptake of E-learning: *performance expectancy (PE); effort expectancy (EE); social encouragement expectancy (SEE: facilitating condition expectancy (FCE); and learning consistency expectancy (LCE)* (see Table 4-6). These factors were included in the ECUH's *'initial* *expectation of E-learning'* construct for explaining and predicting the uptake of E-learning.

Table 4-6: Summary of data triangulation on the factors affecting the uptake of E-learning

Factor	Literature review	Expert validation	Student validation	Confirmation
PE	TAM, UTAUT	✓ (5/8)	✓ (3/3)	✓ (3/3)
EE	TAM, UTAUT	× (3-8)	✓ (3/3)	✓ (2/3)
SEE	UTAUT	✓ (7/8)	✓ (3/3)	✓ (3/3)
FCE	UTAUT	✓ (6/8)	✓ (3/3)	✓ (3/3)
LCE	Keller's ARCS & Expectancy-value theory	✓ (8/8)	✓ (3/3)	✓ (3/3)

With confirmation by two or three sources of data, it was concluded that there were five factors that affect continued use of E-learning: *performance expectancy confirmation (PEC); effort expectancy confirmation (EEC); social encouragement expectancy confirmation (SEEC); facilitating condition expectancy confirmation (FCEC); and learning consistency expectancy confirmation (LCEC)* (see Table 4-7). Consequently, these factors were included in the EUCH's *'expectancy confirmation'* construct for explaining and predicting the continued use of E-learning.

Table 4-7: Summary of data triangulation on the factors affecting continued use of E-learning

Factor	Literature review	Expert validation	Student validation	Confirmation
PEC	TRA, ALT, CDT, ECM	× (3/8)	✓ (2/2)	✓ (2/3)
EEC	TRA, ALT, CDT	✓ (4/8)	✓ (2/2)	✓ (3/3)
SEEC	TRA, ALT, CDT	× (0/8)	✓ (2/2)	✓ (2/3)
FCEC	TRA, ALT, CDT	✓ (5/8)	✓ (2/2)	✓ (3/3)
LCEC	TRA, ALT, CDT	✓ (4/8)	✓ (2/2)	✓ (3/3)

Chapter 5 A Model of E-learning Uptake and Continuance in HEIs (EUCH)

The factors of E-learning uptake and continuance confirmed by data triangulation were next integrated to construct the model of E-learning uptake and continuance in HEIs (EUCH) expressed in Research Question RQ3. This chapter starts with the explanation of the proposed EUCH model, followed by an explanation of how learning theories relate to the EUCH, and a description of the application of the EUCH model in HEIs. A summary is provided at the end of the chapter.

5.1 EUCH model

The EUCH model was constructed to explain and predict the use of E-learning in HEIs in two parts: the first is a sub-model of E-learning uptake, termed the *EU sub-model*, explaining and predicting E-learning usage in the first time period, t_0 to t_1 (E-learning uptake); the second is a sub-model of E-learning continuance, termed the *EC sub-model*, explaining and predicting E-learning usage in the second time period, t_1 to t_2 (E-learning continuance).

In Figure 5-1 the model is represented as a set of processes. The boxes with solid borders represent the psychological stages and processes of the model prediction. Small boxes with dashed borders show the variables in each prediction process.

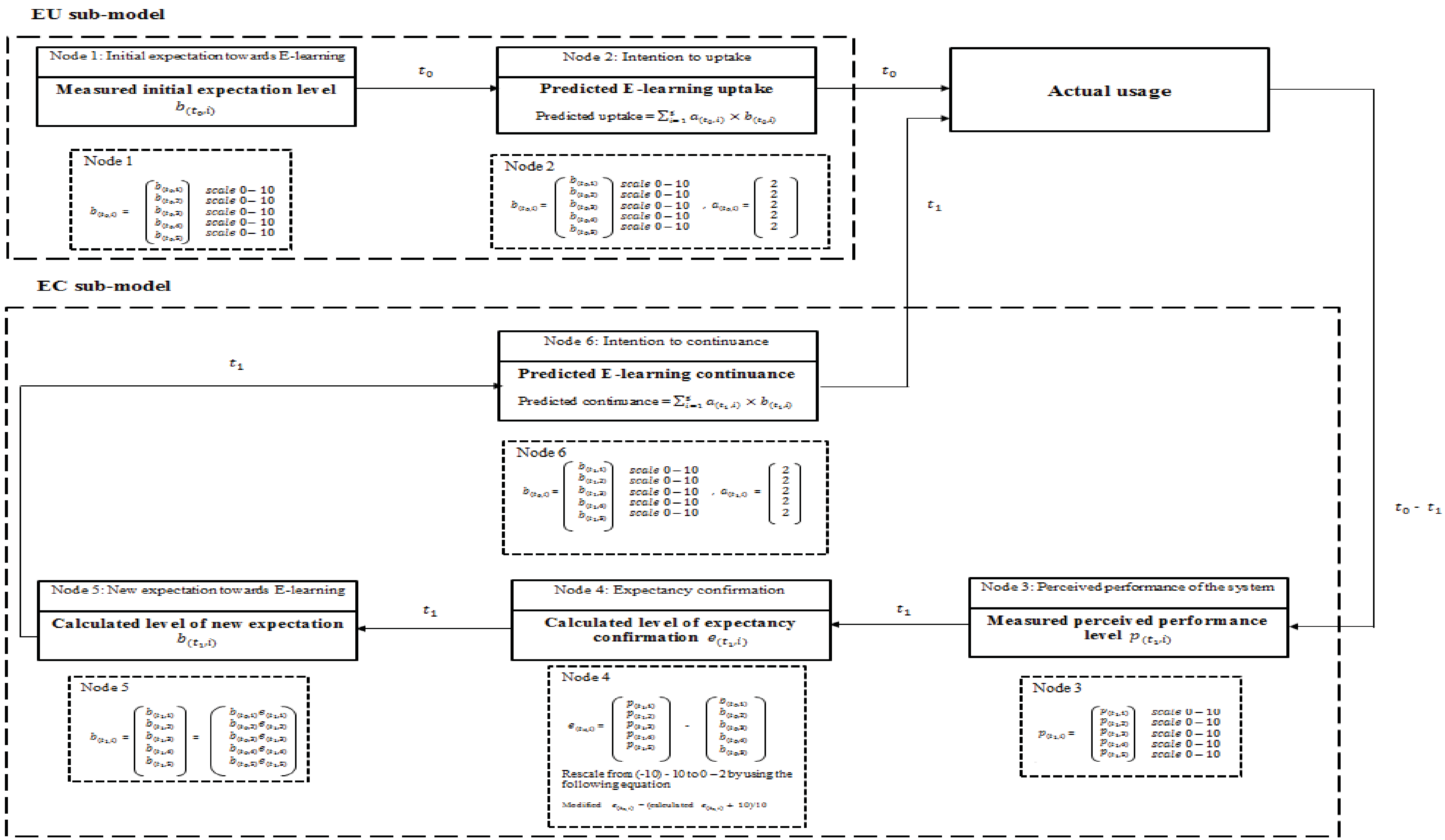


Figure 5-1: Model of E-learning Uptake and Continuance of E-learning in HEIs

The key processes of the model are the prediction of E-learning uptake at Node 2 and of continuance at Node 6. Following the Theory of Reasoned Action, the EUCH model predicts E-learning usage in each time period as a function of student expectations. There are five expectations in the model: *performance expectancy* ($b_{t_n,1}$); *effort expectancy* ($b_{t_n,2}$); *social encouragement expectancy* ($b_{t_n,3}$); *facilitating condition expectancy* ($b_{t_n,4}$); and *learning consistency expectancy* ($b_{t_n,5}$). The model predicts E-learning usage on a scale of 0 to 100: each expectation is measured in the range of 0 to 10, and the weight of each variable is set at 2.

Model prediction of E-learning uptake at t_0 = $2 \times (\mathrm{b}_{\mathrm{t}_0,1} + \mathrm{b}_{\mathrm{t}_0,2} + \mathrm{b}_{\mathrm{t}_0,3} + \mathrm{b}_{\mathrm{t}_0,4} + \mathrm{b}_{\mathrm{t}_0,5})$ Eq. 5-1

Model prediction of continued use of E-learning at t_1 = $2 \times (\mathrm{b}_{\mathrm{t}_1,1} + \mathrm{b}_{\mathrm{t}_1,2} + \mathrm{b}_{\mathrm{t}_1,3} + \mathrm{b}_{\mathrm{t}_1,4} + \mathrm{b}_{\mathrm{t}_1,5})$ Eq. 5-2

The weight of each expectation is set equally: this is because there is no prior research reporting that one expectation has a significantly greater contribution to E-learning use than another. The detail of each prediction process (node) is explained in the following.

Node 1: before a student takes up E-learning, an initial expectation is created. From the UTAUT and ARCS model, a student has five initial expectations towards E-learning*: 'performance expectancy at* t_0*'* ($b_{t_0,1}$); *'effort expectancy at* t_0*'* ($b_{t_0,2}$); *'social encouragement expectancy at* t_0*'* ($b_{t_0,3}$); *'facilitating condition expectancy at* t_0*'* ($b_{t_0,4}$); *and 'learning consistency expectancy at* t_0*'* ($b_{t_0,5}$). The *'initial expectation towards E-learning'* construct ($b_{t_0,i}$) is added to the model to capture levels of each initial expectation expressed as:

Initial expectation towards E-learning ($b_{t_0,i}$) = $$\begin{pmatrix} b_{t_0,1} \\ b_{t_0,2} \\ b_{t_0,3} \\ b_{t_0,4} \\ b_{t_0,5} \end{pmatrix}$$ Eq.5-3

Node 2: Students' intention (motivation) towards the uptake of E-learning is formed according to their level of five initial expectations towards the system (Ajzen and Fishbein, 1973). To predict the uptake of E-learning (E-learning usage during first time period t_0 to t_1), the measured initial expectations ($b_{t_0,i}$) from Node 1 are input into Equation 5-1.

Node 3: during the usage time period, t_0 to t_1, perceptions of the actual system performance will be formed (Helson, 1948, 1964). The perception of the system performance is measured from each student at time t_1 and is used to calculate the new level of their expectations towards the system ($b_{t_1,i}$) for the next prediction. Adaptation level theory suggests that the initial expectation is formed for creating a reference level that a student then uses to make a comparison with perceived system performance, in order to determine his/her level of confirmation. Thus, in the *'perceived performance of the system'* construct ($p_{t_1,i}$), there are five variables based on each expectation, expressed as:

$$\text{Perceived performance of the system } (p_{t_1,i}) = \begin{pmatrix} p_{t_1,1} \\ p_{t_1,2} \\ p_{t_1,3} \\ p_{t_1,4} \\ p_{t_1,5} \end{pmatrix} = \begin{pmatrix} \text{perceived performance of } b_{t_0,1} \\ \text{perceived performance of } b_{t_0,2} \\ \text{perceived performance of } b_{t_0,3} \\ \text{perceived performance of } b_{t_0,4} \\ \text{perceived performance of } b_{t_0,5} \end{pmatrix} \quad \text{Eq. 5-4}$$

To be able to compare with the level of initial expectations, the scale of 0-10 is also used for measuring *'perceived performance of the system'*.

Node 4: according to Cognitive Dissonance Theory (Festinger, 1962), students evaluate their perceived actual performances with their initial expectations to determine expectancy confirmations. With this concept, the *EC sub-model* then compares the *'perceived performance of the system'* ($p_{t_1,i}$) with the '*initial expectation of E-learning'* ($b_{t_0,i}$) to determine their level of *'expectancy confirmation'* construct ($e_{t_1,i}$), expressed as follows:

$$\text{Expectancy confirmation} = (e_{t_1,i}) = \begin{pmatrix} e_{t_1,1} \\ e_{t_1,2} \\ e_{t_1,3} \\ e_{t_1,4} \\ e_{t_1,5} \end{pmatrix} = \begin{pmatrix} p_{t_1,1} \\ p_{t_1,2} \\ p_{t_1,3} \\ p_{t_1,4} \\ p_{t_1,5} \end{pmatrix} - \begin{pmatrix} b_{t_0,1} \\ b_{t_0,2} \\ b_{t_0,3} \\ b_{t_0,4} \\ b_{t_0,5} \end{pmatrix} \quad \text{Eq. 5-5}$$

By using Equation 5-5 to calculate the level of *expectancy confirmation*($e_{t_1,i}$), the possible range of values for the variable in this construct is -10 (0–10) to 10 (10–0). To make the range of calculated new expectation lie between 0–10 (the same as the initial expectation), the model then rescales the value of each *expectancy confirmation* ($e_{t_1,i}$) from (-10–10) to (0–2) by using the following equation:

$$\text{Modified } (e_{t_1,i}) = (\text{calculated}(e_{t_1,i}) + 10)/10 \quad \text{Eq. 5-6}$$

Node 5, dissonance (expectancy confirmation) produces discomfort and, correspondingly, students modify each of their expectations to be consistent with reality or the level of confirmation. The EUCH model therefore uses *expectancy confirmation'* ($e_{t_1,i}$) to adjust '*initial expectation of E-learning'* ($b_{t_0,i}$) and the level of new expectation is calculated using the TRA equation of expectation, captured by '*new expectation towards E-learning'* construct $b_{(t_1,i)}$ using the following equation:

$$\text{New expectation towards E-learning } (b_{t_1,i}) = \begin{pmatrix} b_{t_1,1} \\ b_{t_1,2} \\ b_{t_1,3} \\ b_{t_1,4} \\ b_{t_1,5} \end{pmatrix} = \begin{pmatrix} b_{t_0,1} \times e_{t_1,1} \\ b_{t_0,2} \times e_{t_1,2} \\ b_{t_0,3} \times e_{t_1,3} \\ b_{t_0,4} \times e_{t_1,4} \\ b_{t_0,5} \times e_{t_1,5} \end{pmatrix} \qquad \text{Eq.5-7}$$

Finally, at Node 6, the calculated value of $b_{(t_1,i)}$ is used as an input to Equation 5-2 for predicting the E-learning usage for second time period (continued use).

5.2 Relation between Learning Theories and EUCH model

Behaviourism considers psychology as a science (Schunk, 2010). Explanation and prediction are two important tasks of a scientific theory: behaviourist school of thought deals with the prediction and explanation of behaviour (Kuipers et al. 2007). The EUCH model is consistent with behaviourism because the EUCH model was constructed to predict and explain E-learning usage, which is a kind of behaviour.

Cognitivism, which focuses on information absorption (Lachman et al., 1979), also plays a significant role in the EUCH model, especially for E-learning uptake. Before taking up E-learning, since a student does not have any chance to interact with an E-learning system, their expectation is formed through absorption of second-hand information from others' opinions or information disseminated through media.

Both behaviourism and constructivism focus on interaction with the environment and the results of such interaction (Skinner, 1937; Piaget, 1964). EUCH model is certainly consistent with these two schools of thought. The EUCH suggests that, during E-learning usage time period (interaction with environment), students form a perception about actual system performance (experience with the system) which then adjusts their previous expectations and their E-learning usage behaviour (the result of such interaction).

5.3 Example of the EUCH Model Prediction

It may be helpful to give an example of the EUCH model prediction for a student in an HEI. Let us called him Nakarin. Nakarin's level of expectation towards E-learning ($b_{t_0,i}$) is measured by the questionnaire at the beginning of the first time period. Let us assume that his expectation is as follows:

$$b_{t_0,i} = \begin{pmatrix} performance\ expectancy \\ effort\ expectancy \\ social\ encouragement\ expectancy \\ facilitaing\ condition\ expectancy \\ learning\ consistence\ expectancy \end{pmatrix} = \begin{pmatrix} b_{t_0,1} \\ b_{t_0,2} \\ b_{t_0,3} \\ b_{t_0,4} \\ b_{t_0,5} \end{pmatrix} = \begin{pmatrix} 8 \\ 8 \\ 4 \\ 3 \\ 9 \end{pmatrix} \qquad \text{Eq. 5-8}$$

To predict the level of E-learning usage during the first time month (uptake), the five measured initial expectations are input into Equation 5-1. The model's prediction of Nakarin's E-learning uptake is:

Model prediction for t_0 to t_1 = $(2 \times b_{t_0,1}) + (2 \times b_{t_0,2}) + (2 \times b_{t_0,3}) + (2 \times b_{t_0,4}) + (2 \times b_{t_0,5})$

$= (2 \times 8) + (2 \times 8) + (2 \times 4) + (2 \times 3) + (2 \times 9)$

$= 64$

From the collected initial expectations (Equation 5-8), Nakarin has a low level of initial expectation regarding the social encouragement ($b_{t_0,3}$) and facilitating conditions ($b_{t_0,4}$). This indicates that his important persons do not encourage his E-learning usage much and he does not have good enough IT resources to use the system. Combined with the collected initial expectations from its other students, the university now knows the area of focus and can devise an effective strategy for stimulating E-learning uptake.

At the end of the first time period, time t_1, the HEI staff check on the E-learning tracking system whether Nakarin has used E-learning. If he did not take up E-learning, the expectation questionnaire is selected to measure his initial expectations again to find out which aspect of his initial expectations was low. Combined with the collected initial expectations from other students who do not take up E-learning, the university now knows the most effective strategy for increasing uptake, or the new area of focus to stimulate the level of E-learning uptake.

If Nakarin took up E-learning, HEI staff now measure the level of performance he perceives in the system ($p_{t_1,i}$). Let us assume that Nakarin's perception of the performance of the system is as follows:

$$p_{t_1,i} = \begin{pmatrix} p_{t_1,1} \\ p_{t_1,2} \\ p_{t_1,3} \\ p_{t_1,4} \\ p_{t_1,5} \end{pmatrix} = \begin{pmatrix} \text{perceived performance of } b_{t_0,1} \\ \text{perceived performance of } b_{t_0,2} \\ \text{perceived performance of } b_{t_0,3} \\ \text{perceived performance of } b_{t_0,4} \\ \text{perceived performance of } b_{t_0,5} \end{pmatrix} = \begin{pmatrix} 8 \\ 10 \\ 6 \\ 6 \\ 4 \end{pmatrix} \qquad \text{Eq.5-9}$$

Then, the model compares the level of his initial expectation ($b_{t_0,i}$) measured at time at t_0, and the level of his perceived performance of the system ($p_{t_1,i}$) measured at time at t_1 to find the level of his expectancy confirmation $e_{(t_1,i)}$

$$(e_{t_1,i}) = \begin{pmatrix} e_{t_1,1} \\ e_{t_1,2} \\ e_{t_1,3} \\ e_{t_1,4} \\ e_{t_1,5} \end{pmatrix} = \text{(Eq. 5-9) – (Eq. 5-8)} = \begin{pmatrix} p_{t_1,1} \\ p_{t_1,2} \\ p_{t_1,3} \\ p_{t_1,4} \\ p_{t_1,5} \end{pmatrix} - \begin{pmatrix} b_{t_n,1} \\ b_{t_n,2} \\ b_{t_n,3} \\ b_{t_n,4} \\ b_{t_n,5} \end{pmatrix}$$

$$= \begin{pmatrix} 8-8 \\ 10-8 \\ 6-4 \\ 6-3 \\ 4-9 \end{pmatrix} = \begin{pmatrix} 0 \\ +2 \\ +2 \\ +3 \\ -5 \end{pmatrix}$$

After that, Nakarin's calculated expectancy confirmation level ($e_{t_1,i}$) is rescaled using Equation 5-6:

Modified $e_{(t_n,i)}$ = (calculated $e_{(t_n,i)} + 10)/10$

$$= \begin{pmatrix} (0+10)/10 \\ (+2+10)/10 \\ (+2+10)/10 \\ (+3+10)/10 \\ (-5+10)/10 \end{pmatrix} = \begin{pmatrix} 1 \\ 1.2 \\ 1.2 \\ 1.3 \\ 0.5 \end{pmatrix} \qquad \text{Eq.5-10}$$

Next, the model will calculate Nakarin's level of new expectation at t_1 using Equation 5-7:

$$\text{New expectation towards E-learning } (b_{t_1,i}) = \begin{pmatrix} b_{t_1,1} \\ b_{t_1,2} \\ b_{t_1,3} \\ b_{t_1,4} \\ b_{t_1,5} \end{pmatrix} = \begin{pmatrix} b_{t_0,1} \times e_{t_1,1} \\ b_{t_0,2} \times e_{t_1,2} \\ b_{t_0,3} \times e_{t_1,3} \\ b_{t_0,4} \times e_{t_1,4} \\ b_{t_0,5} \times e_{t_1,5} \end{pmatrix}$$

$$= \begin{pmatrix} 8 \times 1.0 \\ 8 \times 1.2 \\ 4 \times 1.2 \\ 3 \times 1.3 \\ 9 \times 0.5 \end{pmatrix} = \begin{pmatrix} 8 \\ 9.6 \\ 4.8 \\ 3.9 \\ 4.5 \end{pmatrix}$$

The model then predicts Nakarin's E-learning usage level for the second time period (continued use), using the calculated value of $b_{(t_{1,i})}$ as an input of Equation 5-2:

Model prediction for t_1 to t_2 = $(2 \times b_{t_{1},1}) + (2 \times b_{t_{1},2}) + (2 \times b_{t_{1},3}) + (2 \times b_{t_{1},4}) + (2 \times b_{t_{1},5})$

$= (2 \times 8) + (2 \times 9.6) + (2 \times 4.8) + (2 \times 3.9) + (2 \times 4.5)$

$= 61.6$

From Equation 5-10, Nakarin's low confirmation score on learning consistency (0.5) indicates that he perceives that the E-learning system in the university is not consistent with his learning goal, past experience and learning style. Combined with confirmation from other students at the university, that is, if other students also have a low confirmation of learning consistency (less than 1), the university now knows the area of focus is the E-learning system's content and learning activity in E-learning.

5.4 Summary of Chapter 5

At the end of the model construction phase, the EUCH model was constructed to predict and explain E-learning uptake and its continuance after confirmation of the factors from the group of experts and end users (students) in the preliminary study. The next phase comprised model validation and is described in the next chapter.

Chapter 6 EUCH Model Validation Methodology

The aim of the model validation phase was to: assess the performance of a sub-model of E-learning uptake, *EU sub-model* (RQ4); assess the performance of a sub-model of E-learning continuance, *EC sub-model* (RQ5); validate the relationships between the proposed EUCH variables (RQ6); and investigate the influence of E-learning usage on an individual student's learning performance (RQ7).

This chapter explains the research methodology of the model validation, while the next will describe the statistical analysis techniques used to analyse the data and also report the results of the model validation. Chapter 6 starts with an overview of the research questions for the model validation phase, their sub-research questions and the methods for answering them. The second section of the chapter describes the research methodology used in model validation. The third section gives details on question design and the pilot study of the question items. The fourth section explains the design of sample size and participants in the study, while the fifth presents the ethical approval of the study. A summary of the chapter is provided at the end.

6.1 Overview of Research Questions in the Model Validation Phase

The model validation phase was conducted to answer four research questions, RQ4, RQ5, RQ6 and RQ7. There were 13 sub-research questions to be answered. Each research question and sub-research question, and the method for answering the sub-research questions, are shown in Table 6-1.

Table 6-1: Research questions, sub-research questions and methods for answering

Experimental objective	Research question	Method for answering sub-research question
RQ4: To assess the performance of *EU sub-model*	RQ4a: How well does the *EU sub-model equation* predict the uptake of E-learning?	The *EU sub-model equation*'s prediction of E-learning uptake calculated at the beginning of the first usage time period was regressed against the actual uptake of E-learning (E-learning usage during the first time period) measured at the end of first usage time period for representing the degree of consistency (predictive performance).
	RQ4b: Is the *EU sub-model equation's* predictive performance of E-learning uptake higher than the two general technology usage models (TAM and UTAUT)?	The *EU sub-model equation's* predictive performance was compared to the prediction of the two general technology usage models (TAM and UTAUT) within the same context.
	RQ4c: How well do the *EU sub-model variables* predict the uptake of E-learning?	The *EU sub-model*'s predictive power (expressed by a goodness-of-fit measure) was calculated by regressing the five initial expectation variables measured at the beginning of first usage time period with the actual uptake of E-learning measured at the end of first usage time period.
	RQ4d: Is the *EU sub-model*'s predictive power of E-learning uptake higher than the two general technology use models (TAM and UTAUT)?	The *EU sub-model*'s predictive power was compared to the TAM and UTAUT model within the same context.
RQ5: To assess the performance of *EC sub-model*	RQ5a: How well does the *EC sub-model equation* predict the continued use of E-learning?	The *EC sub-model equation's* prediction of continued use of E-learning calculated at the beginning of the second usage time period, was regressed against the actual continuance of E-learning (E-learning usage during second time period) measured at the end of second usage time period.
	RQ5b: Is the *EC sub-model equation*'s performance of continued use of E-learning higher than the two general technology use models (TAM and UTAUT) and one general technology continuance model (ECM)?	The *EC sub-model equation*'s performance of continued use of E-learning was compared to the prediction of the three models (TAM, UTAUT and ECM) within the same context.
	RQ5c: How well do the *EC sub-model variables* predict the continuance of E-learning?	The *EC sub-model*'s predictive power was calculated by regressing the *EC sub-model* variables (calculated new expectations) with the actual continued use of E-learning.
	RQ5d: Is the *EC sub-model*'s predictive power of E-learning continuance higher than the three comparative models?	The *EC sub-model*'s predictive power of E-learning continuance was compared to the power of the three models (TAM, UTAUT and ECM) within the same context.

Experimental objective	Research question	Method for answering sub-research question
RQ6: To validate the relationships between the proposed EUCH model variables	RQ6a: Do the five initial expectations influence the uptake of E-learning?	Initial expectations were measured at the beginning of the first usage time period, while the actual uptake of E-learning (level of E-learning usage during the first time period) was measured at the end. A canonical correlation analysis shows the influence of each initial expectation on E-learning uptake.
	RQ6b: Do the level of five expectations change over the time as students use E-learning?	At the end of first usage time period, the levels of five expectations were measured again. The levels of new expectations were then compared pair-wise with the levels of initial expectations to check the difference in mean value and the consistency between them.
	If the change in expectation was found: RQ6c: What are the factors influencing the change of each expectation?	The stepwise regression analysis was conducted using change of each expectation as the dependent variable and uses 23 variables as independent variables: 4 other initial expectations; 5 perceived performances; 5 expectancy confirmation; 4 other new expectations; and 4 changes of other expectation.
	RQ6d: Do the changes in the level of five expectations affect change in the level of E-learning usage?	At the end of second usage time period, the level of E-learning usage during the second time period was measured. Then, the change in level of E-learning usage between the first and second time period was calculated. The changes in the level of the five expectations were regressed against the change in level of E-learning usage using canonical correlation analysis.
RQ7: To investigate the influence of E-learning usage on an individual student's learning performance	RQ7: Does E-learning usage level influence student's learning performance?	At the beginning of first E-learning usage time period, student's midterm score was measured for representing score before using E-learning. Two month later, at the end of second usage time period, the level of E-learning usage over two time usage periods and student's final score (representing learning performance after using the system) was measured. The level of E-learning usage during two months and midterm score were regressed against the student's final score.

6.2 Research Methodology for the Model Validation Phase

Positivism is a philosophy of science, which seeks the verification of proposed theories using empirical evidence: empirical research is conducted to decide the validity of proposed theories (Saunders et al. 2009). There are two types of empirical research: qualitative and quantitative. Qualitative research is guided by an interpretative paradigm: textual data is collected and analysed by an interpretative process (Bryman, 1984). This type of research may not be appropriate for assessing the validity of the proposed model and investigating the relationships between variables. Quantitative research was selected as appropriate the model validation phase. There are two research methodologies under this type of research: (a) experimental, (b) observational (Taylor, 2005). Each quantitative methodology's approach, advantages, and disadvantages are shown in Table 6-2.

Table 6-2: Approach, advantages, and disadvantages of quantitative methodologies

Approaches	Advantages	Disadvantages
Observational (field study)		
Field study involves collecting data outside of an experimental setting. This type of research methodology often done in natural settings or where the variables naturally occur. A questionnaire is used often for measuring the level of each required constructs from a group of sample in a real world situation. The statistical technique will then be used for analysing collected data.	1. Observation can be conducted with a large number of participants which may reduce error in the estimation in statistical technique. 2. Higher realism. 3. Some degree of control of variables via statistical technique. 4. Comparing to a laboratory experiment in which we would need to construct an artificial setting, an observation requires lower use of resources and time.	1. Weak control of variables in natural settings
Experimental (Laboratory)		
The researcher applies treatments to units (participants) and then proceeds to observe the effect of the treatments on the units. In E-learning uptake study, to give an example, The researcher manipulates each group of students into different level of expectation (eg. low, medium, high and control group of no expectation). The research will then measure the amount of E-learning uptake and compare between four groups. After that, the statistical technique will be used for analysing collected data.	1. Manipulate variables provides stronger claims of causation. 2. Tighter control of variables	1. Lower realism: since treatment is assigned to the objects 2. The researcher may not be able to manipulate variables either due to ethical or practical reasons

Source: Harrison and List (2004); Levitt and List (2007); and Chang et al. (2009)

Observation allows the conduct of the research with a larger number of students than experiment, thus reducing error of estimates in the statistics. Observation gives more realistic data. Even though the degree of control over the irrelevant variables is higher in an experiment compared to observation, statistical techniques (eg. multiple regression analysis) can remove the effect of other variables and better identify the effect of variables of interest (such as beta weight or part correlation coefficient). Characteristically, observation can only yield weak claims of causation. Manipulated variables under strict controlled conditions in laboratories may provide stronger claims of causation. However, since the participants of this research are students, it is considered unethical to manipulate people. Furthermore, for practical reasons, it is not easy to manipulate individuals' expectation. With these reasons and the limited budget for conducting research, observation is the type of methodology used in the model validation phase.

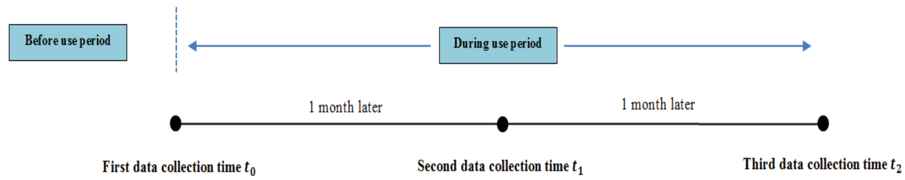
Upon the review of the literature, research in E-learning usage usually measures behavioural intention to use E-learning rather than actual use. There are two main reasons for this: (a) limitations of time and resources for conducting research, (b) researchers' belief in the ability of intention to predict future behaviour (Šumak et al., 2011a). However, there is empirical evidence that intention may not always accurately predict behaviour, or may do so in an inconsistent manner: the time period between the measurement of intention and actual usage could be full of uncertainties and other factors that may affect students' decision to adopt or change their usage behaviour (Ajzen & Fishbein, 1980; Davis et al., 1989; Chuttur, 2009). For that reason, and with the goal of the E-learning usage model to predict and explain usage behaviours (not just usage intention), the EUCH model was assessed using usage behaviours and a longitudinal field study was selected as a research methodology in the model validation phase.

A longitudinal field study was conducted over a period of two months with three points of measurement: t_0, t_1 and t_2. Time t_0 represented the pre-usage point of time, while time $t_1$and t_2 represented post-usage after one and two months, respectively. There were three main reasons for setting each usage time period at one month (t_0 - t_1, t_1 - t_2): (a) there was empirical evidence that a one-month time period is enough to detect a change of expectations, which was one of research question needing to be answered (Venkatesh and Morris, 2000; Bhattacherjee and Premkumar, 2004); (b) one of the research questions was to investigate the effect of the changes in expectations on the change in level of E-learning usage, so the ranges of the first and second time period were designed to be equal; (c) the period of two months was the time between the midterm and the final exam, so it allowed an examination of the effect of E-learning usage on student learning performance by comparing their midterm and final score.

The data from the first usage time period (t_0 to t_1) allowed the following: the assessment of the *EU sub-model*'s predictive performance and explanatory power on the uptake of E-learning (RQ4a, RQ4b, RQ4c and RQ4d); the examination of the influence of initial expectations on the uptake of E-learning (RQ6a); and the investigation of the change in expectations (RQ6b) and emergent factors (RQ6c). The data from the second time period (t_1 to t_2) allowed: the investigation of the influence of the change in expectations on the change of E-learning usage (RQ6d); and the assessment of the *EC sub-model*'s predictive performance and explanatory power on the continued use of E-learning (RQ5a, RQ5b, RQ5c and RQ5d). The data of E-learning usage in the period t_0 - t_2 allowed the examination of the influence of E-learning usage on a student's learning performance between the midterm and final exams (RQ7).

To control the potential effect of university variables (e.g. type of E-learning system and infrastructural constraints) on individual student use of E-learning, the participants in this experiment were students at a single Thai university, Rajamangala University of Technology Thanyaburi, or RMUTT (Mathieson, 1991; Bhattacherjee, 2001). Furthermore, to control the effect that average time spent on E-learning in the different subjects might be different, the study examined only students' E-learning uptake and continued use in the subject of General Statistics. To ensure fair comparison of performance between the EUCH model and comparative existing models such as TAM, UTAUT and ECM, this was assessed by using the data from the same samples, and the same measurement was used to measure common factors for the three models (Cooper and Richardson, 1986). Accordingly, we could expect that any observed difference in performance between models would be due to the models themselves, rather than differences in the contexts and measurements used.

The research methodology for each point in the longitudinal data collection is shown in Figure 6-1:



Measure	initial expectations at t_0 midterm score on General Statistics subject	new expectations at t_1 perceived performances at t_1 E-learning actual uptake (E-learning usage during t_0-t_1)	E-learning actual continued use (E-learning usage during t_1-t_2) final score on General Statistics subject
Calculated	EU sub-model prediction of E-learning uptake TAM model prediction of E-learning uptake UTAUT model prediction of E-learning uptake	difference between initial expectations at t_0 and new expectations at t_1 expectancy confirmations at t_1 EC sub-model calculated expectations at t_1 EC sub-model prediction of E-learning continued use ECM prediction of E-learning continued use TAM model prediction of E-learning continued use UTAUT model prediction of E-learning continued use	

Figure 6-1: Longitudinal data collection schedule

At time t_0

The aim of this phase was to: (a) measure each participant's initial expectations; (b) calculate the three models' prediction of E-learning uptake for each participant in general statistics; and (c) measure participants' midterm score in General Statistics.

Step 1: Measure level of initial expectations (expectations at t_0)

The Thai questionnaire was used to measure the level of five initial expectations at time t_0: performance expectancy at t_0 (PE_{t_0}); effort expectancy at t_0 (EE_{t_0}); social encouragement expectancy at t_0 (SEE_{t_0}); facilitating condition expectancy at t_0 (FCE_{t_0}); learning consistency expectancy at t_0 (LCE_{t_0}) (see Appendix 6-A). Each item was measured on an 11-point Likert scale ranging from 0 ('Not at all') to 10 ('Very much'). As each variable was measured by multiple question items (3 or 4 items), a mean aggregated score was calculated to indicate the level of each initial expectation variable for individual participants. The aggregated score of each expectation ranged from 0 to 10.

Step 2: Predict the uptake of E-learning for each participant using the three models

The three models of interest (TAM, UTAUT and *EU sub-model*) predicted E-learning uptake for each participant using the following equations:

TAM prediction at $t_0 = 5\times PE_{t_0} + 5\times EE_{t_0}$ Eq. 6-1

UTAUT prediction at $t_0 = 2.5\times PE_{t_0} + 2.5\times EE_{t_0} + 2.5\times SEE_{t_0} + 2.5\times FCE_{t_0}$ Eq. 6-2

EU sub-model prediction at $t_0 = 2\times PE_{t_0} + 2\times EE_{t_0} + 2\times SEE_{t_0} + 2\times FCE_{t_0} + 2\times LCE_{t_0}$ Eq. 6-3

The three models have a different number of predictors: (a) TAM uses two predictors, including PE_{t_0} and EE_{t_0}; (b) UTAUT uses four predictors, including PE_{t_0}, EE_{t_0}, SEE_{t_0} and FCE_{t_0}; (c) EU sub-model uses five predictors, including PE_{t_0}, EE_{t_0}, SEE_{t_0}, FCE_{t_0} and LCE_{t_0}. To allow the same scale for prediction among the models, ranging from 0 to 100, the number of predictors in each model was weighted appropriately.

Step 3: Measure student's midterm score in General Statistics

Each participant's midterm score in General Statistics was collected, ranging from 0 to 30.

At time t_1

The second data collection was conducted one month after the first. At this point, the participants were divided into two groups: those who had used E-learning during t_0 and t_1, and those who had not. For the first group of students (had used E-learning), the aim was to measure or calculate: (a) the actual uptake of E-learning subjective and objective; (b) perceived performances; (c) new expectations; (d) the change of expectations; (e) expectancy confirmations; (f) calculated expectations; and (g) the model prediction of E-learning continuance. For the second group of students (had not used E-learning), their subjective and objective E-learning usage t_0 and t_1 were measured.

Step 1: Measure the actual uptake of E-learning subjective, perceived performances and new expectations

The Thai questionnaire, consisting of three sections (see Appendix 6-B), was used: the first subjectively measured the actual uptake of E-learning; the second measured the perceived performances; and the third measured the new expectations. The students who had used E-learning during the first usage time period were asked to answer all three sections, while students who had not used it were asked to answer just the first.

Section 1: The actual uptake of E-learning subjective

Both groups of participants were asked to fill in this section. There were two subjective measures of E-learning actual usage in this research: subjective time spent learning with E-learning during t_0 and t_1 (*subjective time spent during* t_0 *and* t_1); and subjective percentage of E-learning usage in education during t_0 and t_1 (*subjective percentage during* t_0 *and* t_1). To measure subjectively the actual uptake of E-learning, the first section of the questionnaire asked participants to estimate how many times per week and for how long did they work on each learning activity outside the General Statistics class. There were 15 learning activities in total, consisting of five learning activities in E-learning and 10 learning activities not in E-learning. The sum of estimated time spent on each E-learning activity was calculated to indicate the level of *subjective time spent during* t_0 *and* t_1 for each participant. To calculate the *subjective percentage during* t_0 *and* t_1 for each participant, the total time spent on E-learning was divided by total time spent on their learning beyond the classroom, including both activities on E-learning and outside the system.

Section 2: Perceived performances

The second section of the questionnaire was used to measure the level of perceived performance variables of students who had used E-learning during the first usage time period (t_0 and t_1). The five perceived performance variables were: perceived performance of the system at t_1 (PPS_{t_1}); perceived ease of use at t_1 (PEU_{t_1}); perceived social encouragement at t_1 (PSE_{t_1}); perceived facilitating condition at t_1 (PFC_{t_1}); and perceived learning consistency at t_1 (PLC_{t_1}). To be able to compare the level of each initial expectation (expectations at t_0) to determine the level of expectation confirmation of each, an 11-point rating scale starting from 0 ('Not at all') to 10 ('Very much') was used to measure perceived performance variables. The mean aggregated score was then calculated to indicate the level of each perceived performance variable.

Section 3: New expectations (expectations at t_1)

This section was designed for students who had used E-learning. The set of items to measure new expectations at t_1 (PE_{t_1}, EE_{t_1}, SEE_{t_1}, FCE_{t_1} and LCE_{t_1}) in the third section of the questionnaire was the same as that used to measure initial expectations at

t_0. The mean aggregated score was calculated to indicate the level of each expectation at t_1.

Step 2: Measure the actual uptake of E-learning objective

To avoid problems associated with subjective measurement (such as inaccurate estimation and hypothesis guessing), an objective measure (system tracking tool) was also applied to measure the level of E-learning usage of three aspects: objective time spent on E-learning during t_0 and t_1 (*objective time spent during* t_0 *and* t_1); objective total number of times logging onto E-learning during t_0 and t_1 (*objective logging on during* t_0 *and* t_1); and objective total number of activities involving E-learning during t_0 and t_1 (*objective activities on during* t_0 *and* t_1).

Step 3: Calculate the change of each expectation

The change of expectation is the discrepancy between the new expectations measured at time t_1 and initial expectations measured at time t_0. There were five variables within this construct:

$$\text{Change of expectation} = \begin{pmatrix} \text{change of performance expectancy} \\ \text{change of effort expectancy} \\ \text{change of social encouragement expectancy} \\ \text{change of facilitaing condition expectancy} \\ \text{chnage of learning consistency expectancy} \end{pmatrix} = \begin{pmatrix} PE_{diff} \\ EE_{diff} \\ SEE_{diff} \\ FCE_{diff} \\ LCE_{diff} \end{pmatrix}$$

$$= \begin{pmatrix} PE_{t_1} & PE_{t_0} \\ EE_{t_1} & EE_{t_0} \\ SEE_{t_1} - & SEE_{t_0} \\ FCE_{t_1} & FCE_{t_0} \\ LCE_{t_1} & LCE_{t_0} \end{pmatrix} \qquad \text{Eq. 6-4}$$

Since the expectations ranged from 0 to 10, the possible value of the change of each expectation variable ranges from -10 (0-10) to 10 (10-0).

Step 4: Calculated expectancy confirmations

Expectancy confirmation is the discrepancy between an individual student's perceived performance of E-learning system and his/her initial expectation level (Festinger, 1962). There are five variables within the expectancy confirmation construct:

$$\text{Expectancy confirmation} = \begin{pmatrix} \text{performance expectancy confirmation} \\ \text{effort expectancy confirmation} \\ \text{social encouragement expectancy confirmation} \\ \text{facilitaing condition expectancy confirmation} \\ \text{learning consistency exepctancy confirmation} \end{pmatrix} = \begin{pmatrix} PEC_{t_1} \\ EEC_{t_1} \\ SEEC_{t_1} \\ FCEC_{t_1} \\ LCEC_{t_1} \end{pmatrix}$$

$$= \begin{pmatrix} PPS_{t_1} & & PE_{t_0} \\ PEU_{t_1} & & EE_{t_0} \\ PSE_{t_1} & - & SEE_{t_0} \\ PFC_{t_1} & & FCE_{t_0} \\ PLC_{t_1} & & LCE_{t_0} \end{pmatrix} \quad \text{Eq. 6-5}$$

Each expectancy confirmation variable was assessed as the difference between the mean aggregated score of perceived performance measured at time t_1 and the mean aggregated score of initial expectation measured at time t_0. The possible range of expectancy confirmation variables is -10 (0-10) to 10 (10–0). To make the range of adjusted expectations (calculated new expectations at t_1) lie between 0–10, the expectancy confirmation of each expectation was rescaled from (-10–10) to (0–2) by using the following equation:

$$\text{Modified expectancy confirmation} = \begin{pmatrix} mPEC_{t_1} \\ mEEC_{t_1} \\ mSEEC_{t_1} \\ mFCEC_{t_1} \\ mLCEC_{t_1} \end{pmatrix} = \begin{pmatrix} (PEC_{t_1} + 10)/10 \\ (EEC_{t_1} + 10)/10 \\ (SEEC_{t_1} + 10)/10 \\ (FCEC_{t_1} + 10)/10 \\ (LCEC_{t_1} + 10)/10 \end{pmatrix} \quad \text{Eq.6-6}$$

Step 5: Calculate new expectations at t_1

The new expectations were calculated by applying TRA equation of expectation:

$$\text{Calculated expectations} = \begin{pmatrix} cPE_{t_1} \\ cEE_{t_1} \\ cSEE_{t_1} \\ cFCE_{t_1} \\ cLCE_{t_1} \end{pmatrix} = \begin{pmatrix} mPEC_{t_1} \times PE_{t_0} \\ mEEC_{t_1} \times EE_{t_0} \\ mSEEC_{t_1} \times SEE_{t_0} \\ mFCEC_{t_1} \times FCE_{t_0} \\ mLCEC_{t_1} \times LCE_{t_0} \end{pmatrix} \quad \text{Eq.6-7}$$

Step 6: Predict the continued use of E-learning for each participant using the four models

There are two types of model for predicting continued use of E-learning. The first kind predicts continued use by measuring expectations directly at the predicted point of time, for instance TAM and UTAUT. The equation for each model's prediction is as follows:

TAM prediction at $t_1 = 5\times PE_{t_1} + 5\times EE_{t_1}$ Eq. 6-8

UTAUT prediction at $t_1 = 2.5\times PE_{t_1} + 2.5\times EE_{t_1} + 2.5\times SEE_{t_1} + 2.5\times FCE_{t_1}$ Eq. 6-9

The second type of model measures the expectancy confirmations at the predicted point of time to adjust the expectations measured at the previous point of time, and use the adjusted expectation to predict the continued use of E-learning, for instance the ECM and EC sub-models:

ECM prediction at t_1 = $10 \times cPE_{t_1}$ Eq. 6-10

EC sub-model prediction at t_1 = $2 \times (cPE_{t_1} + cEE_{t_1} + cSEE_{t_1} + cFCE_{t_1} + cLCE_{t_1})$ Eq. 6-11

The weights of each model's variables were adjusted to make all four models' prediction of E-learning continuance range from 0 to 100.

At time t_2

The aim of this phase was to measure and calculate: (a) the actual continued use of E-learning subjective and objective; (b) participants' final score in General Statistics; and (c) the change in E-learning usage between the first and the second time period. Only participants who took up E-learning during the first time period joined this phase of data collection.

Step 1: Measure the actual continued use of E-learning subjective

In this phase, the questionnaire was used in which the set of items for measuring the actual continued use of E-learning subjective at time t_2 was the same of that used to measure the actual uptake of E-learning subjective at time t_1 (see Appendix 6-C). After that, the subjective time spent learning with E-learning during t_1 and t_2 (*subjective time spent during* t_1 *and* t_2), and subjective percentage of E-learning usage in education during t_1 and t_2 (*subjective percentage during* t_1 *and* t_2) were calculated for each participant.

Step 2: Measure the actual continued use of E-learning objective

Tracking data on E-learning use during the periods t_1 and t_2 were collected for three aspects: objective time spent on E-learning during t_1 and t_2 (*objective time spent during* t_1 *and* t_2), objective total number of times logging onto E-learning during t_1 and t_2 (*objective logging on during* t_1 *and* t_2) and (3) objective total number of activities involving E-learning during t_1 and t_2 (*objective activities on during* t_0 *and* t_1).

Step 3: Calculate the change in level of E-learning usage

The change in level of E-learning usage between the first and second time period was calculated using the following equation:

$$\text{Change in level of usage} = \begin{pmatrix} \text{subjective time spent}_{\text{diff}} \\ \text{subjective percetage}_{\text{diff}} \\ \text{objective time spent}_{\text{diff}} \\ \text{objective logging on}_{\text{diff}} \\ \text{objective activities}_{\text{diff}} \end{pmatrix}$$

$$= \begin{pmatrix} \text{subjective time spent}_{t_{1-2}} & & \text{subjective time spent}_{t_{0-1}} \\ \text{subjective percetage}_{t_{1-2}} & & \text{subjective percetage}_{t_{0-1}} \\ \text{objective time spent}_{t_{1-2}} & - & \text{objective time spent}_{t_{0-1}} \\ \text{objective logging on}_{t_{1-2}} & & \text{objective logging on}_{t_{0-1}} \\ \text{objective activities}_{t_{1-2}} & & \text{objective activities}_{t_{0-1}} \end{pmatrix} \quad \text{Eq. 6-12}$$

Step 4: Measure student's final score in General Statistics

The final step of the experiment was to collect each participant's final score in General Statistics. The data ranged from 0 to 40.

6.3 Question Item Design and Pilot Study

From section 6.2 (research methodology design), there were three sets of question items used in the model validation phase: (1) the items measuring expectations; (2) the items measuring perceived performances; and (3) the items measuring subjective E-learning usage. The design and validation of the items is explained in the following section.

Question item design

There were five expectation variables in this study: performance expectancy (PE); effort expectancy (EE); social encouragement expectancy (SEE); facilitating condition expectancy (FCE); learning consistency expectancy (LCE). Each expectation was measured by three or four items (see Table 6-3).

The reasons for using multi-item measures instead of a single item for each expectation variable was because multiples would give more reliable measures and less random measurement error, and could more fully measure each expectation variable with several aspects in its definition (Gliem and Gliem, 2003). The questionnaire was developed primarily by adapting previously validated items to fit study's purpose. However, for learning consistency expectancy we were not able to locate previously validated items to match; the items were constructed based on the definition of variables.

Table 6-3: Definition of five expectation variables, the source of items, and question items

	Definition	Adapted from	Items
PE	The degree to to which an individual student expects that using an E-learning will be useful in his/her education and enhance his/her learning performance.	Davis et al. (1989)	1. How much do you expect that E-learning will be useful for your education? 2. How much do you expect that E-learning will allow you to learn more quickly? 3. How much do you expect that E-learning will improve your grade?
EE	The degree to which an individual student expects that the use of E-learning system does not require an increase in effort.	Davis et al. (1989)	1. How much do you expect that learning to operate E-learning system will be easy? 2. How much do you expect that you will become skilful at using E-learning? 3. How much do you expect that E-learning will be easy to use?
SEE	The degree to which an individual student expects that his/her significant persons will encourage the use of an E-learning system.	Venkatesh et al. (2003)	1. How much do you expect that your parents will encourage the use of E-learning? 2. How much do you expect that the director of your university will encourage the use of E-learning? 3. How much do you expect that your lecturers will encourage the use of E-learning? 4. How much do you expect that your friends will encourage the use of E-learning?
FCE	The degree to which an individual student expects that there are IT resource to support the use of E-learning.	Venkatesh et al. (2003)	1. How much do you expect that you will have necessary IT resources (e.g. a computer and internet) to use E-learning? 2. How much do you expect that the university will provide you with the necessary IT resources to use E-learning? 3. How much do you expect that IT staffs will assist you with the use of E-learning system when you need help?
LCE	The degree to which an individual student believes that the instructional environment in E-learning – which includes the ILO, content, teaching and learning activities – is relevant with the learner's goals, learning styles and past experiences.	New scale developed	1. How much do you expect that E-learning will provide the content that is relevant to you? 2. How much do you expect that E-learning will provide teaching and learning activities that suit the way you learn? 3. How much do you expect that E-learning will provide the content that is appropriate for your present competencies (not too easy or not too hard)?

According to Adaptation Level Theory, initial expectation is used to create a reference level that the customer uses to make a comparison with their perceived performance to determine their level of confirmation. There are five variables of perceived performance: perceived performance of the system (PPS); perceived ease of use (PEU); perceived social encouragement (PSE); perceived facilitating condition (PFC); and perceived learning consistency (PLC). Question items for measuring each were derived from the expectation question by subtitling 'think' for 'expect' and using the past tense in place of the future (see Table 6-4). To be able to compare them against the level of each expectation variable, an 11-point rating scale starting from 0 ('Not at all') to 10 ('Very much') was used to measure perceived performance variables.

Table 6-4: Question items of five perceived performance variables

	Items
PPS	1. How much do you think that E-learning was useful for your education? 2. How much do you think that E-learning allowed you to learn more quickly? 3. How much do you think that E-learning improved your score?
PEU	1. How much do you think that learning to operate E-learning system was easy? 2. How much do you think that you became skilful at using E-learning? 3. How much do you think that E-learning was easy to use?
PSE	1. How much do you think that your parents encouraged the use of E-learning? 2. How much do you think that the director of your university encouraged the use of E-learning? 3. How much do you think that your lecturers encouraged the use of E-learning? 4. How much do you think that your friends encouraged the use of E-learning?
PFC	1. How much do you think that you have necessary IT resources (e.g. a computer and internet) to use E-learning? 2. How much did the university provide you with the necessary IT resources to use E-learning? 3. How much did the IT staff assist you with the use of E-learning system when you needed help?
PLC	1. How much do you think that E-learning provided the content that is relevant to you? 2. How much do you think that E-learning provided teaching and learning activities that suit the way you learn? 3. How much do you think that E-learning provided the content that is appropriate for your present competencies (not too easy or not too hard)?

There were 15 items (activities) to measure subjective time spent learning with E-learning and percentage of E-learning usage in education (see Table 6-5). The possible learning activities outside classroom were identified in a discussion with the General Statistics lecturer in RMUTT.

Table 6-5: Question items measuring subjective time spent on study in General Statistics outside class

Learning activity	Items
E-learning	1. Reading course related documents from E-learning 2. Watching the course video from E-learning 3. Doing course exercise from E-learning 4. Discussing with lectures using E-learning 5. Discussing with friend using E-learning
Not in E-learning	6. Reviewing lecture notes 7. Reading course related documents from other sources 8. Watching the course video from other sources 9. Doing course exercise from other sources 10. Discussing with lecture face-to-face 11. Discussing with lecture using social media (such as Facebook, Line) 12. Discussing with friends face-to-face 13. Discussing with friends using social media (such as Facebook, Line) 14. Personal tutors 15. Other (please specify)

All three sets of question items were translated into Thai by the researcher to make them easier for participants to answer.

Pilot study

A pilot study was conducted to evaluate and develop the Thai question items:

1. Consistency of the translation between English and Thai

Since the items were translated from English into Thai, the Thai question items were first tested by five experts in E-learning in Thai HE with good English skills (a degree from an English speaking country or international programme) in order to ensure that they could be understood by participants while preserving the meaning of the original version. In this step, the experts were asked to rate each item on the degree to which the item was consistent with the English version by assigning a rating of -1, 0 or +1:

+1 the item is consistent with the English version
0 undecided about whether the item is consistent with the English version
-1 the item is not consistent with the English version.

If the experts assigned a rating of -1 or 0 to an item, they were requested to give a comment to improve the item. The items were duly amended. The results of the test of language consistency in the pilot study are shown in Appendix 6-D. The experts suggested improvements in: (a) 9 of 16 expectation questions; (b) 9 of 16 perceived performance questions; and (c) 5 of 15 subjective E-learning actual usage questions.

2. Content validity

After improving the consistency of the translation, the second step of the pilot study was to evaluate the content validity of the items. Lawshe's (1975) content validity method was applied. A second group of five experts on E-learning in Thai HEIs was asked to assess how well each Thai item measured the variable that it intended to measure. The experts evaluated each item by assigning a rating of -1, 0 or +1:

+1 the item is a measure of the intended variable
0 undecided about whether the item is a measure of the intended variable
1 the item is not a measure of the intended variable.

If an expert assigned a rating of –1 or 0 to an item, they were requested to suggest a way to improve the content validity of that item. Lawshe's (1975) equation was again used to determine the degree of content validity that existed for each question:

$$\mathrm{CVR} = (n_e - \mathrm{N}/2)/(\mathrm{N}/2) \qquad \text{Eq. 6-13}$$

where CVR is content validity ratio; n_e is the number of experts rating the item +1; N is total number of the experts.

Equation 6-13 yields values that range from +1 to -1. According to Lawshe (1975), if more than half the experts mentioned that an item is a measure of an intended variable, the item had at least some content validity. For this reason, if the CVR score for an item was positive, it was used in the model validation phase to measure its intended variable.

The results suggested that all the questions could be used, because all had positive CVR scores (see Appendix 6E). However, two experts (3 and 5) suggested that the word ‘skilful’ in Item 5 of the expectation and perceived performance questionnaire be clarified in order to measure EE and perceived EE better. Experts 1, 3 and 4 made the additional comment that the questions should be specific and consistent with respect to the target system (RMUTT online classroom), subject (General Statistics) and time (one month). To give an example, items should be changed from *‘How much do you expect that E-learning will be useful for your education’* to *‘Using the RMUTT online classroom for General Statistics next month, how much do you expect that the system will be useful for your study in General Statistics*. In Thai, the question was ‘*ระดับความคาดหวังของท่านว่า ระบบ E-learning จะมีประโยชน์ต่อการศึกษาของท่านนั้นอยู่ในระดับใด’*. It was modified to ‘*ในการใช้งานระบบ RMUTT online classroom ของวิชาสถิติทั่วไปในครั้งต่อไป (1เดือนข้างหน้า) ระดับความคาดหวังของท่านว่า ระบบ RMUTT online classroom จะมีประโยชน์ต่อการศึกษาของท่านในวิชาสถิติทั่วไป นั้นอยู่ในระดับใด’*.

3. Reliability of items

After improving the content validity of questions, following the experts’ recommendations, the three sets of questions were combined into a single questionnaire, Section 1 measuring perceived performances, Section 2 expectations, and Section 3 subjective actual use of E-learning. Since perceived performance questions were designed for respondents who had used E-learning, the third step was conducted with 30 students who had used the RMUTT online classroom in General Statistics. The questionnaires were distributed and collected directly. No respondents expressed any concerns about any items, and all completed the questionnaire within 10 minutes. The objective was first to establish the reliability of the perceived performance and expectation question items, assessing how far the set of question items measuring the intended variable yielded consistent results (Santos, 1999). Reliability can be established by demonstrating interval consistency. Cronbach's (1951) technique was used to determine the internal consistency of the set of items.The results indicated that Cronbach's α values for the sets of items in the section measuring perceived performance ranged from .72 to .87 (see Table 6-6), while values for the sets of items on expectations ranged from .83 to.92 (see Table 6-7).

Table 6-6: Cronbach's alpha value of each set of items measuring perceived performances

Factor	Number of items	Items	Cronbach's alpha
PPS	3	▪ After using RMUTT online classroom in general statistics last month, how much do you think that the system was useful for your study in General Statistics? ▪ After using RMUTT online classroom in general statistics last month, how much do you think that the system allowed you to learn General Statistics more quickly? ▪ After using RMUTT online classroom in general statistics last month, how much do you think that system improved your scores in general statistics?	.87
PEU	3	▪ After using RMUTT online classroom in general statistics last month, how much do you think that learning to operate the system was easy? ▪ After using RMUTT online classroom in general statistics last month, how much do you think you became skilful at using the system (capable of asking the system to do what you want it to do)? ▪ After using RMUTT online classroom in general statistics last month, how much do you think that the system was easy to use?	.77
PSE	4	▪ After using RMUTT online classroom in general statistics last month, how much did your parents encourage the use of the system? ▪ After using RMUTT online classroom in general statistics last month, how much did the director of your university encourage the use of the system? ▪ After using RMUTT online classroom in general statistics last month, how much did your lecturers encourage the use of the system? ▪ After using RMUTT online classroom in general statistics last month, how much did your friends will encourage the use of the system?	.80
PFC	3	▪ After using RMUTT online classroom in general statistics last month, how much do you think that you have necessary IT resources (e.g. a computer and internet) to use the system? ▪ After using RMUTT online classroom in general statistics last month, how much did the university provide you with the necessary IT resources to use the system? ▪ After using RMUTT online classroom in general statistics last month, how much did the IT staffs assist you with the use of the system when you needed help?	.72
PLC	3	▪ After using RMUTT online classroom in general statistics last month, how much do you think that E-learning provided the content that is relevant to you? ▪ After using RMUTT online classroom in general statistics last month, how much do you think that E-learning provided teaching and learning activities that suit the way you learn? ▪ After using RMUTT online classroom in general statistics last month, how much do you think that E-learning provided the content that is appropriate for your present competencies (not too easy or too hard)?	.77

Table 6-7: Cronbach's alpha value of each set of items measuring expectations

Factor	Number of items	Items	Cronbach's alpha
PE	3	▪ Before using RMUTT online classroom in general statistics next month, how far do you expect that the system will be useful your study in General Statistics? ▪ Before using RMUTT online classroom in general statistics next month, how far do you expect that the system will allow you to learn General Statistics more quickly? ▪ Before using RMUTT online classroom in general statistics next month, how far do you expect that the system will improve your score in general statistics?	.92
EE	3	▪ Before using RMUTT online classroom in general statistics next month, how far do you expect that learning to operate the system will be easy? ▪ Before using RMUTT online classroom in general statistics next month, how far do you expect that you will become skilful at using the system (capable of asking the system to do what you want it to do)? ▪ Before using RMUTT online classroom in general statistics next month, how far do you expect that the system will be easy to use?	.88
SEE	4	▪ Before using RMUTT online classroom in general statistics next month, how much do you expect that your parents will encourage the use of the system? ▪ Before using RMUTT online classroom in general statistics next month, how much do you expect that the director of your university will encourage the use of the system? ▪ Before using RMUTT online classroom in general statistics next month, how much do you expect that your lecturers will encourage the use of the system? ▪ Before using RMUTT online classroom in general statistics next month, how much do you expect that your friends will encourage the use of the system?	.83
FCE	3	▪ Before using RMUTT online classroom in general statistics next month how far do you expect that you will have necessary IT resources (e.g. a computer and internet) to use the system? ▪ Before using RMUTT online classroom in general statistics next month, how far do you expect that the university will provide you with the necessary IT resources to use the system? ▪ Before using RMUTT online classroom in general statistics next month, how far do you expect that IT staff will assist you with the use of the system when you need help?	.89
LCE	3	▪ Before using RMUTT online classroom in general statistics next month, how far do you expect that the system will provide the content that is relevant to you? ▪ Before using RMUTT online classroom in general statistics next month, how far do you expect that the system will provide teaching and learning activities that suit the way you learn? ▪ Before using RMUTT online classroom in general statistics next month, how far do you expect that the system will provide the content that is appropriate for your present competencies (not too easy or not too hard)?	.89

All values were above 0.7, exceeding the threshold value recommended by Nunnally (1978). Therefore, the questionnaire for measuring perceived performances and expectations was considered a reliable measurement instrument.

In the pilot study, the questions measuring subjective E-learning usage (E-learning usage and percentage of E-learning usage in education) evaluated the General Statistics learning activities in which students actually took part beyond the classroom. The participants were asked to fill out the time they spent on each learning activity. While it was intended that any learning activity not actually undertaken by participants would be discarded from the final version of the questionnaire, the results showed that all the activities were undertaken (see Table 6-8). All questions were used in the model validation phase.

Table 6-8: Number of participants who filled in the number of time spent on each learning activity

Q	Items	Number of respondents undertaking the activity	Conclusion
1.	Reviewing lecture notes of General Statistics	29/30	Keep
2.	Reading General Statistics documents from RMUTT online classroom	26/30	Keep
3.	Reading documents related to General Statistics from other sources *(please specify)*	12/30	Keep
4.	Watching the General Statistics video from RMUTT online classroom	11/30	Keep
5.	Watching the video related General Statistics from other sources *(please specify)*	7/30	Keep
6.	Doing General Statistics exercise from RMUTT online classroom	14/30	Keep
7.	Doing General Statistics exercise from other sources *(please specify)*	10/30	Keep
8.	Discussing with friends face-to-face about General Statistics	22/30	Keep
9.	Discussing with friends using about General Statistics using RMUTT online classroom	7/30	Keep
10.	Discussing with friends about General Statistics using social media (Facebook, Line) or other communication tools *(please specify)*	20/30	Keep
11.	Discussing with lecturers face-to-face about General Statistics	8/30	Keep
12.	Discussing with lecturers about General Statistics using RMUTT online classroom	4/30	Keep
13.	Discussing with lecturers about General Statistics using social media (Facebook, Line) and online communication tool *(please specify)*	2/30	Keep
14.	Personal tutor for General Statistics	1/30	Keep

6.4 Sample Size Design and Participants

The G*power 3.1.5 program was used to calculate the optimum sample size for each data analysis to yield the desired Type I and Type II error rates (see Appendix 6-F). The largest sample size was derived from analysis of the relationship between change in five expectations between time t_0 and t_1 ($\mathrm{PE_{diff}}$, $\mathrm{EE_{diff}}$, $\mathrm{SEE_{diff}}$, $\mathrm{FCE_{diff}}$ and $\mathrm{LCE_{diff}}$) and the change of five E-learning actual usages between the first (t_0 to t_1) and the second (t_1 to t_2) defined period of time (the change of subjective time spent, the change of subjective percentage, the change of objective time spent, the change of objective logging on, and the change of objective activity). G*power suggested that at least 57 participants were required for this analysis. Assuming that an estimated 50 per cent of participants would not use E-learning during the first month, the required number of participants for this longitude study was approximately 114 (57*2) students.

In the model validation phase, the participants were students taking General Statistics at RMUTT. All were second-year students. E-learning was not new to them: they may have had second-hand information or actual experience with E-learning in the university. This group of students came from three faculties: Engineering, General Science and Business. The findings may be generalized to students across the whole university.

In total, there were 170 students on the course. At time t_0, 138 participants had joined the experiment. At time t_1, 36 participants had left, since they did not re-join the class for the second data collection. Among the participants who joined the experiment at time t_1 were 77 participants who had used E-learning and 25 participants who had not used E-learning during the first time period, t_0 to t_1. At time t_2, data were collected only from those 77 participants who had used E-learning during the first time period (see Figure 6-2).

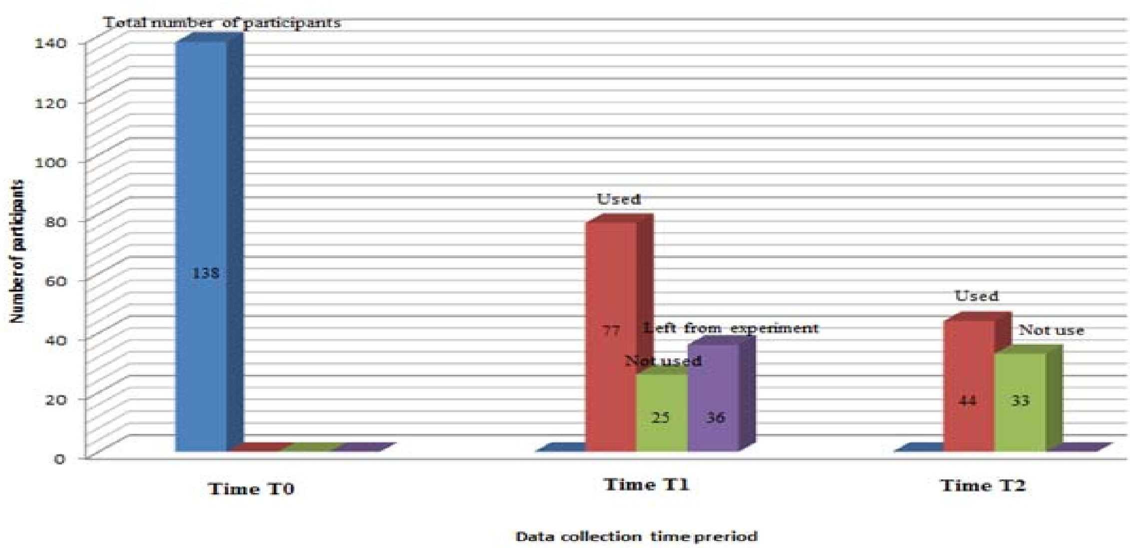


Figure 6-2: Participants in each point of longitudinal data collection

The data from those 77 participants who had taken up E-learning during the first time period were used for investigating: uptake, continuance and consequence of usage on learning performance research questions (RQ4, RQ5, RQ6 and RQ7). Data from participants who did not take up E-learning (25 students) were combined with data from those who did to investigate the EU sub-model performance (RQ4), and the effect of five initial expectations on E-learning uptake (RQ6a).

6.5 Ethical Approval

The model validation phase, including pilot study and longitudinal study, was approved by the Ethical Committee of Electronic and Computer Science at the University of Southampton, in that the study met the required ethical standards. Ethical approval was granted under reference number 8330.

6.6 Summary of Chapter 6

The model validation phase was conducted to: (a) assess the EUCH model performance; (b) validate the relationships between the proposed EUCH model variables; and (c) investigate the influence of E-learning usage on a student's learning performance. This chapter described the research methodology used in the validation phase. The next chapter will describe the statistical analysis techniques used to analyse the data and reported the results.

Chapter 7 EUCH Model Validation Data Analysis and Results

This chapter describes the statistical analysis techniques used to analyse the data and reports on the results of the model validation phase to answer the four research questions, RQ4, RQ5, RQ6 and RQ7. The chapter begins with an assessment of EU sub-model performance (RQ4). The second section reports on the results of an assessment of EC sub-model performance (RQ5). The third reports on the results of validations of relationships between EUCH model variables (RQ6), while the fourth provides the results of the relationship between E-learning usage and a student's learning performance (RQ7). The fifth section gives a summary of the chapter.

7.1 Assessment of EU sub-model Performance (RQ4)

For Research Question RQ4, on assessing the performance of the EU sub-model, four sub-research questions needed to be answered:

7.1.1 The EU sub-model equation's performance of E-learning uptake (RQ4a)

An equation is usually assessed in two aspects: accuracy and precision. The equation is considered *valid* if it is both accurate and precise. The accuracy of an equation is the degree of closeness of the predicted value to the actual value in reality (Kuipers et al. 2007). The accuracy of the equation predicting E-learning uptake and continued use was not assessed in this research. This is because the EUCH equation's prediction of E-learning usage and the five measurements of actual E-learning usage are on different scales. Actual level of use data could be used to calibrate the model prediction to be the same scale as five measurements of actual E-learning usage. This would be future work.

In such future work, we would use the data on equation prediction and each measurement of E-learning usage in both time periods (t_0 - t_1, and t_1 - t_2) to recalibrate the equation prediction to be a same scale of each measurement, as following steps:

1. Simple linear regression analysis was applied use EUCH equation prediction as independent variable and each measurement of actual E-learning usage as dependent variable. Because of this, five regression models are required.
2. Each multiple regression model provided mathematical equation for rescaling of the equation prediction to the same scale of each measurement.

However, the average level of E-learning usage within the same subject between different universities or countries may not be the same. The calibration of the model prediction would be specific to each context.

The focus in this research was thus on the precision, which is the degree of consistency with actual E-learning usage. A multiple regression analysis was conducted between *the EU sub-model equation's prediction of E-learning uptake at time* t_0 and the five measurements of actual E-learning uptake at time t_1 (*subjective percentage of E-learning usage in education during* t_0 *and* t_1; *subjective time spent learning with E-learning during* t_0 *and* t_1; *objective time spent on E-learning during* t_0 *and* t_1; *objective total number of times logging onto E-learning during* t_0 *and* t_1; and *objective total number of activities involving E-learning during* t_0 *and* t_1). The degree of precision was given by the multiple correlation coefficient, *R*.

Cohen's (1992) effect size was applied for assessing the EU sub-model equation performance (precision degree) of E-learning uptake. The scale was set as follows:

R = 0.1 represented *low* predictive performance

R= 0.3 represented *moderate* predictive performance

R = 0.5 represented *high* predictive performance

Multiple regression analysis between the EU sub-model equation's prediction of E-learning uptake at t_0 ***and the five measurements of actual E-learning uptake at*** t_1

The statistical conditions and assumptions for the analysis were found not to be violated (see Appendix 7-A). The linear combination of the five measurements of actual E-learning uptake at t_1 was significantly related to *the EU sub-model equation's* *prediction of E-learning uptake at* t_0: $F(5, 95) = 6.1$, $p < .001$ (see Table 7-1). The multiple correlation coefficient was .49, indicating that approximately 24 per cent of the variance of *the EU sub-model's prediction of E-learning uptake at* t_0 was accounted for by the linear combination of the five measurements of actual E-learning uptake at t_1. According to Cohen (1992), the EU sub-model equation had moderate predictive performance of E-learning uptake ($R = .49$). Of the five measurements of actual E-learning uptake at t_1, only *subjective percentage of E-learning usage in education during* t_0 *and* t_1 contributed significantly to *the EU sub-model's prediction of E-learning uptake at* t_0: $\beta = .38$, $t(100) = 3.3$, $p = .001$.

Table 7-1: Multiple regression analysis result between the EU sub-model equation's prediction of E-learning uptake at t_0 and the five measurements of actual E-learning uptake at t_1

Independent variables	**Non-standardized coefficients**		**Standardized coefficients**	**t**	**Sig.**
	B	SE	β		
Constant	53.9	5.3		10.1	<.001
Percentage (subjective) during t_0 and t_1	.26	.08	.38	3.3	.001
Time spent (subjective) during t_0 and t_1	.76	2.6	.03	.30	.77
Time spent (objective) during t_0 and t_1	4.5	2.9	.27	1.5	.13
Number of times logging on (objective) during t_0 and t_1	2.3	7.3	.05	.32	.75
Number of activities (objective) during t_0 and t_1	-6.1	5.4	-.20	-1.1	.26
a. Dependent variable: EU sub- model equation's prediction of E-learning uptake at t_0					
$R = .49$; $R^2 = .24$; $F(5, 95) = 6.1$; p-value < .001					

7.1.2 *The EU sub-model equation's performance of E-learning uptake compared with TAM and UTAUT equations (RQ4b)*

The second sub-research question (RQ4b) is, *Is the EU sub-model equation's predictive performance of E-learning uptake greater than the two general technology use models (TAM and UTAUT)?* To answer it, the TAM and UTAUT equations' performance of E-learning uptake were calculated by (a) multiple regression analysis using the TAM equation's prediction of E-learning uptake at t_0 and the five measurements of actual E-learning uptake at t_1; and (b) multiple regression analysis using the UTAUT equation's prediction of E-learning uptake at t_0 and the five measurements of actual E-learning uptake at time t_1. The performance of the EU sub-model equation was then compared with the performance shown by the TAM and UTAUT equations using Fisher's Z-transform technique. The procedure was as follows:

First, the multiple correlation coefficient (R) from each regression model was transformed using the Fisher (1921) equation:

$$Z_r = \frac{1}{2} \ln \frac{1+R}{1-R} \qquad \text{Eq. 7-1}$$

Then, a z-score of the difference between the two multiple correlation coefficients was computed:

$$z_{difference} = \frac{Z_{R1} - Z_{R2}}{\sqrt{\frac{1}{N_1-3} + \frac{1}{N_2-3}}} \qquad \text{Eq. 7-2}$$

where

Z_{R1} is the z-score of the multiple correlation coefficient from the first regression model

Z_{R2} is the z-score of the multiple correlation coefficient from the second regression model

N_1 and N_2 is the sample size of the first and second regression model, respectively.

Finally, a *p*-value for the computed $z_{difference}$ was obtained using the table of standard normal distribution. As this analysis involved multiple comparisons, Bonferroni's correction was applied in order to reduce Type I error. The significance level for this analysis was set at .025 (.05/2). The results of these analyses are as follows:

Multiple regression analysis between the TAM model equation's prediction of E-learning uptake at t_0 and the five measurements of actual E-learning uptake at t_1

The statistical conditions and assumptions were checked and found not to be violated (see Appendix 7-B). The linear combination of the five measurements of actual E-learning uptake at t_1 was significantly related to *the TAM model equation's prediction of E-learning uptake at* t_0: $F(5, 95) = 5.8$, $p < .001$ (see Table 7-2). The multiple correlation coefficient was .48, indicating that approximately 23 per cent of the variance of *the TAM model equation's prediction of E-learning uptake at* t_0 was accounted for by the linear combination of the five measurements of actual E-learning uptake at t_1. Among the five measurements of actual E-learning uptake at t_1, only the *subjective percentage of E-learning usage in education during* t_0 *and* t_1 made a significant contribution to *the TAM model equation's prediction of E-learning uptake at* t_0: $\beta = .32$, $t(100) = 2.8$, $p = .007$.

Table 7-2: Multiple regression analysis result between the TAM model equation's prediction of E-learning uptake at t_0 and the five measurements of actual E-learning uptake at t_1

Independent variables	Non-standardized coefficients		Standardized coefficients	t	Sig.
	B	SE	β		
Constant	50.9	5.8		8.8	< .001
Percentage (subjective) during t_0 and t_1	.23	.09	.32	2.8	.007
Time spent (subjective) during t_0 and t_1	1.1	2.8	.04	.41	.69
Time spent (objective) during t_0 and t_1	5.0	3.1	.29	1.6	.11
Number of times logging on (objective) during t_0 and t_1	-6.5	7.9	-.13	-.82	.41
Number of activities (objective) during t_0 and t_1	.12	5.9	.004	.02	.98
a. Dependent variable: TAM model equation's prediction of E-learning uptake at t_0					
R = .48; R^2 = .23; F(5, 95) = 5.8; p-value < .001					

According to Cohen (1992), the TAM equation had moderate performance of E-learning uptake (R = .48).

Multiple regression analysis between the UTAUT model equation's prediction of E-learning uptake at t_0 and the five measurement of actual E-learning uptake at t_1

The statistical conditions and assumptions required for this analysis were checked and found not to be violated (see Appendix 7-C). The linear combination of the five measurements of actual E-learning uptake at $t_1$was significantly related to *the UTAUT model equation's prediction of E-learning uptake a* t_0: F(5, 95) = 5.3, p < .001 (see Table 7-3). The multiple correlation coefficient was .47, indicating that approximately 22 per cent of the variance in the linear combination of the five measurements of actual E-learning uptake at t_1 was accounted for by *the UTAUT model equation's prediction of E-learning uptake at* t_0. According to Cohen (1992), the UTAUT equation had moderate predictive performance for uptake of E-learning (R = .47). Of the five measurements of actual E-learning uptake at t_1, only *subjective percentage of E-learning usage in education during* t_0 *and* t_1 contributed significantly to *the UTAUT model's prediction of E-learning uptake at* t_0: β = .35, t(100) = 3.1, p = .003.

Table 7-3: Multiple regression analysis result between the UTAUT model equation's prediction of E-learning uptake at t_0 and the five measurements of actual E-learning uptake at t_1

Independent variables	**Non-standardized coefficients**		**Standardized coefficients**	**t**	**Sig.**
	B	SE	β		
Constant	55.5	5.5		10.4	< .001
Percentage (subjective) during t_0 and t_1	.24	.08	.35	3.1	.003
Time spent (subjective) during t_0 and t_1	.12	2.6	.01	.04	.96
Time spent (objective) during t_0 and t_1	4.4	2.9	.27	1.5	.14
Number of times logging on (objective) during t_0 and t_1	.49	7.4	.01	.06	.95
Number of activities (objective) during t_0 and t_1	-4.5	5.4	-.15	-.83	.41
a. Dependent variable: UTAUT model equation's prediction of E-learning uptake at t_0					
R = .47; R^2 = .22; $F(5, 95)$ = 5.3; p-value < .001					

Comparisons of the multiple correlation coefficients of the relationship between the model equation prediction of E-learning uptake at t_0 and the five measurements of actual E-learning uptake at t_1 between EU sub-model and TAM, UTAUT

The multiple correlation coefficient between the model equation prediction of E-learning uptake at t_0 and the linear combination of the five measurements of actual E-learning uptake at t_1 (precision) between the EU sub-model and the two comparative models (TAM and UTAUT) was not statistically significantly different: *EU sub-model* and *TAM* (R difference = .01, p = .93); *EU sub-model* and *UTAUT* (R difference = .02, p = .81) (Table 7-4). These results suggested that *EU sub-model equation* predicted the uptake of E-learning as well as *TAM* and *UTAUT*.

Table 7-4: z-score comparing EU sub-model euqation's performance of E-learning uptake with TAM and UTAUT

Model 1	**Model 2**	**R1**	**R2**	$\mathbf{Z_{R1}}$	$\mathbf{Z_{R2}}$	**P-value**	**Conclusion (P < .025)**
EU sub-model	TAM	.49	.48	.54	.53	.93	Not sig. different
EU sub-model	UTUAT	.49	.47	.54	.51	.81	Not sig. different

7.1.3 The EU sub-model variables' predictive power and explanatory power of E-learning uptake (RQ4c)

Prediction is considered the basis of a scientific approach (Simon, 2002). Prediction uses existing data to forecast future values of an outcome variable under specific conditions and time intervals (Shmueli, 2010). In this research, *predictive power* is the overall ability of model predictors (variables) to fit with the observed outcome data, expressed by a goodness-of-fit measure, such as the square of regression coefficient R^2 (Prairie, 1996). Cohen's (1992) effect size was applied for assessing the EUCH model predictive power degree. The scale was set as follows:

R = 0.1 or R^2 = .01 represented *low* predictive performance

R= 0.3 or R^2 = .09 represented *moderate* predictive performance

R = 0.5 or R^2 = .25 represented *high* predictive performance

Explanation is considered to be the highest aim of a scientific approach (Simon, 2002). Explanatory models have greater strategic value than prediction models since they give information about the individual predictors and their relationships with the outcome variable (Sutton, 1998). In this research, *explanatory power* is the ability of the model to individually identify the unique contribution of the predictors to the outcome variables. Beta weight and *p*-value of each predictor variable are used to provide model explanatory power: if a predictor variable contributes statistically significantly, it infers that those variables have some unique contribution (explanation) that is not accounted by other variables within the same model.

Causation is a form of explanation which is stronger than an explanation based only on the relationship between variables (Wright, 1921). A causal explanation is based upon a change in one or more variables causing consequential changes in the outcome variable (Lewis, 1921). There are usually experimental grounds for claiming that a certain factor is a direct cause of variation in another. This research however used observation and this makes no claims about causal relationships: the EUCH is a model of relationships not causation.

To investigate the predictive and explanatory power of EU sub-model variables (five initial expectations) on E-learning uptake (RQ4c) and the influence of each EU sub-model initial expectation on E-learning uptake (RQ6a), canonical correlation analysis was applied using the five EU sub-model initial expectation variables measured at time t_0 (*performance expectancy at* t_0, *effort expectancy at* t_0, *social encouragement expectancy at* t_0, *facilitating condition expectancy at* t_0, and *learning consistency expectancy at* t_0) as independent variables, while the five measurements of actual E-learning uptake measured at time t_1 (*subjective percentage of E-learning usage in education during time* t_0 *to* t_1; *subjective time spent learning with E-learning during time* t_0 *to* t_1; *objective time spent on E-learning during time* t_0 *to* t_1; *objective total number of times logging onto E-*

learning during time t_0 to t_1; and *objective total number of activities involving E-learning during time t_0 to t_1*) were used as dependent variables. The concept and procedure works of canonical correlation analysis are explained in Appendix 7-D. Canonical correlation analysis requires a number of conditions and assumptions that were not violated in this analysis (see Appendix 7-E)

In canonical correlation analysis, Wilks' λ value represents the percentage of variance in the combination of dependent variables that is not accounted for by the group of independent variables (Meyers et al., 2006). To represent the EU sub-model's predictive power of E-learning uptake, R^2, Wilks' λ value was then subtracted from constant 1. To assess the predictive power using Cohen's effect size (section 7.1.1), R^2 was taken as the square root to represent *R*. To investigate the influence of each EU sub-model initial expectation on the uptake of E-learning, as expressed in research question RQ6a, the sum square of part-correlation for each initial expectation variable across two canonical functions (h^2) was applied.

Canonical correlation analysis of the relationship between the five EU sub-model initial expectation variables at t_0 and the five measurement of actual E-learning uptake at t_1

The relationship between the set of the five EU sub-model initial expectations at t_0 and the five measurements of actual E-learning uptake at t_1 was statistically significant, Wilks' λ criterion = .49, $F(25, 339.5) = 2.9$, $p < .001$. Accordingly, there was at least one significant relationship between the five EU sub-model initial expectations at t_0 and the five measurements of actual E-learning uptake at t_1. Because Wilks' λ represents the variance in the combination of dependent variables unexplained by the set of independent variables, 51 per cent (1- λ) of variance in actual E-learning uptake was accounted for by EU sub-model initial expectation variables.

The canonical correlation analysis yielded five functions with squared canonical correlations (${R_c}^2$) of .32, .22, .06, .03 and .001, respectively, for each successive function (see Table 7-5).

Table 7-5: Canonical correlation analysis of the relationship between the five EU sub-model initial expectation variables at t_0 and the five measurements of actual E-learning uptake at t_1

Function	Eigenvalue	%	Cumulative %	Canonical correlation	Squared correlation
1	.47	55.5	55.5	.56	.32
2	.28	32.8	88.3	.47	.22
3	.07	7.9	96.3	.25	.06
4	.03	3.6	99.9	.17	.03
5	.001	.13	100	.03	.001

Dimension reduction analysis was used to determine which functions should be interpreted. Functions 1 to 5 and Functions 2 to 5 were statistically significant, $F(25, 339.6) = 2.9$, $p < .001$, and $F(16, 281.7) = 2.1$, $p = .01$, respectively (see Table 7-6), however the cumulative effects of Functions 3 to 5, Functions 4 to 5 and Function 5 in isolation were not statistically significant. Because of this, the first two functions were considered noteworthy in the context of this study (32% and 22% of shared variance, respectively). Functions 3, 4 and 5 were not interpreted, as they only explained 6 per cent, 3 per cent and 1 per cent of the remaining variance in the variable sets after the extraction of the prior functions.

Table 7-6: Dimension reduction analysis for canonical functions of the relationship between the five EU sub-model initial expectation variables at t_0 and the five measurements of E-learning actual uptake at t_1

Roots	Wilks' λ	F	Hypothesis DF	Error DF	Significance of F
1 to 5	.49	2.9	25	339.6	< .001
2 to 5	.71	2.1	16	281.7	.01
3 to 5	.91	1.0	9	226.5	.43
4 to 5	.97	.74	4	188.0	.57
5 to 5	.99	.10	1	95.0	.75

The initial canonical weight (*beta*), canonical loading (r_s), part-correlation between variable and its variate (r_p), square of part-correlation (${r_p}^2$) and sum square of part-correlation for each variable across the two selected functions (h^2) are shown in Table 7-7.

Table 7-7: Initial canonical solution for canonical Function 1 & 2 of the relationship between the five EU sub–model initial expectation variables at t_0 and the five measurements of actual E–learning uptake at t_1

	Variable	Function 1					Function 2					h^2(%)	Summary
		β	r_s	r_p	r_p^2	*Summary*	β	r_s	r_p	r_p^2	*Summary*		
Dependent variable	Percentage (subjective) during t_0 and t_1	–.70	−.83	−.55†	.30	Contributed	–.06	−.40	–.05	.003	No	.30	Relevant
	Time spent (subjective) during t_0 and t_1	–.18	−.50	–.16	.03	No	–.23	−.37	–.21	.05	No	.07	No
	Time spent (objective) during t_0 and t_1	–.79	−.63	−.40†	.16	Contributed	.62	−.46	.31†	.10	Suppressor contributed	.26	Relevant
	Number of times logging on (objective) during t_0 and t_1	–.24	−.37	−.14	.02	No	.62	−.38	.35†	.12	Suppressor contributed	.14	No
	Number of activities (objective) during t_0 and t_1	.97	−.26	.48†	.23	Suppressor contributed	–1.7	−.81	−.85†	.73	Contributed	.96	Relevant
Independent variable	Performance expectancy at time t_0	.17	−.55	.10	.01	No	–1.1	−.67	−.64†	.41	Contributed	.42	Important
	Effort expectancy at time t_0	–.55	−.80	−.36†	.13	Contributed	.40	−.21	.26	.07	No	.20	Important
	Social encouragement expectancy at time t_0	.42	−.56	.23	.05	No	–.31	−.37	–.17	.03	No	.08	No
	Facilitating condition expectancy at time t_0	–.12	−.71	–.07	.01	No	1.0	.19	.62†	.38	Contributed	.39	Important
	Learning consistency expectancy at time t_0	–.88	−.92	−.45†	.20	Contributed	–.33	−.20	–.17	.03	No	.23	Important

β = Standardized coefficient between variable and with its variate
r_s = Zero order correlation between variable and with its variate
r_p = Part-correlation († greater than $|.30|$)
r_p^2 = Squared part-correlation between variable and with its variate
h^2 = sum squared part-correlation across the two CCA functions (greater than .20 or 20% is underlined)

In canonical Function 1, as can be seen from Table 7–7, with the high part-correlation (r_p > .30) and the difference in the sign between canonical loading (r_s) and beta, the variable *objective total number of activities involving E-learning during* t_0 *and* t_1 was suspected to be a suppressor (Friedman and Wall., 2005). It is not easy to interpret the effect of a suppressor variable on contributing variables within the Function 1-dependent variate (*subjective percentage of E-learning usage in education during* t_0 *and* t_1, *objective time spent on E-learning during* t_0 *and* t_1) if these contributing variables are all have negative beta and canonical loading. To make it easier, the variable *objective total number of activities involving E-learning during* t_0 *and* t_1 was inverted: this process consisted of subtracting the variable from a constant, being the maximum of the variable. The resulting inverted variable can be said to measure objectively the total number of non-E-learning activities during t_0 and t_1. A canonical analysis was then carried out using the inverted variable (see Table 7-8).

The results showed that the magnitude of *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 canonical loading (r_s) and beta were the same as before the inversion, while the sign was changed. With such a change in the sign of beta and loading of the suppressor variable (*objective total number of activities involving E-learning during* t_0 *and* t_1), the magnitude of the beta and canonical loading for every other variable within Function 1 was the same, while the sign of these variables were all changed. Accordingly, the beta and loading for *subjective percentage of E-learning usage in education during* t_0 *and* t_1, *objective time spent on E-learning during* t_0 *and* t_1 became positive: it was now easier to interpret the effect of suppressor variable on these two contributing dependent variables. The *objective total number of activities involving E-learning during* t_0 *and* t_1 was not a suppressor variable in Function 2, so the change in the sign of this variable did not affect other variables' sign and magnitude in this function. Even though there were two suspected suppressors in the Function 2-dependent variate (*subjective time spent learning with E-learning during* t_0 *and* t_1, *objective total number of times logging onto E-learning during* t_0 *and* t_1), these two variables were not inverted. This is because the effect of these two suspected suppressor variables on the contributing variable (*inverted objective total number of activities involving E-learning during* t_0 *and* t_1) can be straightforwardly interpreted after inversion of the *objective total number of activities involving E-learning during* t_0 *and* t_1.

Table 7-8: Final canonical solution for canonical Function 1 & 2 of the relationship between the five EU sub-model initial expectation variables at t_0 and the five measurements of actual E-learning uptake at t_1

	Variable	Function 1					Function 2					Overall	
		β	r_s	r_p	r_p^2	*Summary*	β	r_s	r_p	r_p^2	*Summary*	$h^2(\%)$	Summary
Dependent variable	Percentage (subjective) during t_0 and t_1	0.70	.83	0.55†	0.30	Contributed	-0.06	−.40	-0.05	0.003	No	<u>0.30</u>	Relevant
	Time spent (subjective) during t_0 and t_1	0.18	.50	0.17	0.03	No	-0.23	−.37	-0.21	0.05	No	0.07	No
	Time spent (objective) during t_0 and t_1	0.79	.63	0.40†	0.16	Contributed	0.62	−.45	0.31†	0.10	Suppressor contributed	<u>0.26</u>	Relevant
	Number of times logging on (objective) during t_0 and t_1	0.24	.37	0.14	0.02	No	0.62	−.38	0.35†	0.12	Suppressor contributed	0.14	No
	Inverted number of activities (objective) during t_0 and t_1	0.97	−.26	0.48†	0.23	Suppressor contributed	1.7	.81	0.85†	0.73	Contributed	<u>0.96</u>	Relevant
Independent variable	Performance expectancy at time t_0	-0.17	.55	-0.10	0.01	No	-1.1	−.67	−0.64†	0.41	Contributed	<u>0.42</u>	Important
	Effort expectancy at time t_0	0.55	.80	0.36†	0.13	Contributed	0.40	−.21	0.26	0.07	No	<u>0.20</u>	Important
	Social encouragement expectancy at time t_0	-0.42	.56	-0.23	0.05	No	-0.31	−.37	-0.17	0.03	No	0.08	No
	Facilitating condition expectancy at time t_0	0.12	.71	0.07	0.01	No	1.0	.19	0.62†	0.38	Contributed	<u>0.39</u>	Important
	Learning consistency expectancy at time t_0	0.88	.92	0.45†	0.20	Contributed	-0.33	−.20	-0.17	0.03	No	<u>0.23</u>	Important

beta = Standardized coefficient between variable and with its variate
r_s = Zero order correlation between variable and with its variate
r_p = Part-correlation († greater than $|.30|$)
r_p^2 = Squared part-correlation between variable and with its variate
h^2 = sum squared part-correlation across the two CCA functions (greater than .20 or 20% is underlined)

The inversion of *objective total number of activities involving E-learning during* t_0 *and* t_1 did not affect the result of the multivariate test (Wilks' λ), the canonical correlation and the dimension reduction analysis. In the following, the result of the canonical analysis after inversion is discussed.

Dependent variate Function 1

Three dependent variables contributed to the Function 1-dependent variate, where $|r_p| > .3$: (a) *subjective percentage of E-learning usage in education during* t_0 *and* t_1 (r_p = .55); (b) *objective time spent on E-learning during* t_0 *and* t_1 (r_p = .40); and (c) *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 (r_p = .48). A sizable increase in the beta weight from the zero order correlation of *objective time spent on E-learning during* t_0 *and* t_1 (from r_s = .63 to beta = .79) and *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 (from r_s = -.26 to beta = .97) indicated the occurrence of suppression in the Function 1-dependent variate (Tzelgov and Henik, 1991). The suspected suppressor variable was the *inverted objective total number of activities involving E-learning during* t_0 *and* $t_{1,}$ because of the difference in the sign between its zero order correlation (negative) and beta (positive) (Thompson and Levine, 1997). To investigate whether the *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 is a suppressor variable, multiple regression analysis was carried out: (i) the Function 1-dependent variate regressed with all dependent variables apart from the *inverted objective total number of activities involving E-learning during* t_0 *and* t_1, and (ii) the Function 1-dependent variate regressed with all dependent variables, including the *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 (Paulhus et al., 2004) (see Table 7-9).

Table 7-9: Multiple regression analysis result between Function 1-dependent variate and dependent variables before and after adding inverted objective total number of activities involving E-learning during t_0 and t_1

Variable	**(i) Before adding beta**	**(ii) After adding beta**	**Change in beta**
Percentage (subjective) during t_0 and t_1	.64	.70	.06
Time spent (subjective) during t_0 and t_1	.19	.18	-.01
Time spent (objective) during t_0 and t_1	.32	.79	.47
Number of times logging on (objective) during t_0 and t_1	-.17	.24	.41
Inverted number of activities (objective) during t_0 and t_1	-	.97	-
	R^2 = .77	R^2= 1	$R^2{}_{chnage}$ = .23

Even though the variable of *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 had the smallest value of zero order correlation with its variate (r_s = -.26), when it was added to the equation of ii: (a) it was found to be a contributing variable (*beta* = .97); (b) it removed or suppressed criterion-irrelevant variance from *objective time spent on E-learning during* t_0 *and* t_1(increased the beta weight from *beta* = .32 to *beta* = .79); and (c) the variance of Function 1-dependent variate accounted for by a set of dependent variables increased by 23 per cent. The result confirmed that the *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 is a suppressor variable for the *objective time spent on E-learning during* t_0 *and* t_1.

Following the appearance of a suppressor, further examination divided the *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 into low (less than mean) and high (equal to or greater than mean). Multiple regression analysis was then conducted, regressing Function 1-dependent variate with *subjective percentage of E-learning usage in education during* t_0 *and* t_1 and *objective time spent on E-learning during* t_0 *and* t_1 (the two contributing variables for the Function 1-dependent variate) in the low and high *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 group of participants (Thompson and Levine, 1997) (see Table 7-10).

Table 7-10: Multiple regression analysis result between Funtion1-dependent variate and two contributing dependent variables in low and high inverted objective total number of activities involving E-learning during t_0 and $t_1$group of participants

Variable	Low inverted number of activities group		High inverted number of activities group		Change in beta
	beta	Sig.	beta	Sig.	
Percentage (subjective) during t_0 and t_1	.80	< .001	.63	< .001	-.17
Time spent (objective) during t_0 and t_1	.10	.19	.53	< .001	.43
	R^2 = .76		R^2= .89		$R^2{}_{chnage}$ = .23

The results indicated that *subjective percentage of E-learning usage in education during* t_0 *and* t_1 was a relevant outcome of contributing initial expectation variables of CCA Function 1 in both high and low *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 group, because the beta weight of this variable was significant in both groups (lower group, *beta* = .80, *p* < .001, higher group *beta* = .63, *p* < .001). The R-square in high *inverted objective total number of activities involving E-learning during* t_0 *and* $t_1$group (.89) was higher than the lower group (.76). The increase in R-square is because *objective time spent on E-learning during* t_0 *and* t_1's beta weight increased from *beta* = .10, *p* = .19 to *beta* = .53, *p* < .001. This implied that *objective time spent on E-learning system during* t_0 *and* t_1 was not a relevant outcome of the contributing initial expectation variables of CCA Function 1 in the high number of activities group (low inverse), whereas it was a relevant outcome when students had a low number of activities(high inverse).

Independent variate Function 1

There were two independent variables contributing to the Function 1-independent variate: *learning consistency expectancy at* t_0 (r_p = .45) and *effort expectancy at* t_0 (r_p = .36). The canonical loading (r_s) for the two contributing independent variables had the same sign: these two variables were positively related to one another.

Summary of CCA Function 1

For Function 1, it can be concluded that: (a) there was a positive relationship between the dependent and independent variates, since the canonical correlation between the dependent and the independent variates (R_c = .56) in Function 1 was positive; (b) the *learning consistency expectancy at* t_0 and *effort expectancy at* t_0 contributed to the Function 1-independent variate; while (c) the *subjective percentage of E-learning usage* *in education during* t_0 *and* t_1, *objective time spent on E-learning during* t_0 *and* t_1, and *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 contributed to the Function 1-dependent variate; (d) the *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 was a suppressor variable for the *objective time spent on E-learning during* t_0 *and* t_1 (see Figure 7-1).

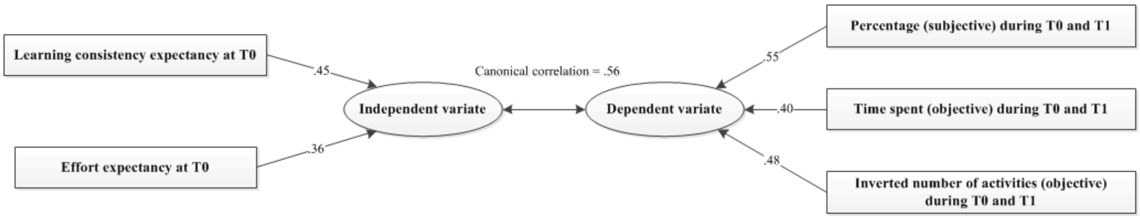


Figure 7-1: Summary of canonical correlation analysis Function 1 of the relationship between the five EU sub-model initial expectation variables at t_0 and the five measurements of actual E-learning uptake at t_1

Dependent variate Function 2

There were three dependent variables contributing to the Function 2-dependent variate: (a) *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 (r_p = .85); (b) *objective total number of times logging onto E-learning during* t_0 *and* t_1 (r_p = .35); and (c) *objective time spent on E-learning during* t_0 *and* t_1 (r_p =.31). A sizable increase in the beta weight from zero order correlation with the different sign indicated that there were two suppressor variables in the Function 2-dependent variate: the *objective total number of times logging onto E-learning during* t_0 *and* $t_{1,}$ and the *objective time spent on E-learning during* t_0 *and* t_1 (Maassen and Bakker, 2001).

To investigate whether the *objective total number of times logging onto E-learning during* t_0 *and* t_1 is a suppressor variable, two multiple regression models were required: the Function 2-dependent variate regressed with all dependent variables apart from *objective total number of times logging onto E-learning during* t_0 *and* t_1, and the Function 2-dependent variate regressed with all dependent variables including the *objective total number of times logging onto E-learning during* t_0 *and* t_1 (see Table 7-11).

Table 7-11: Multiple regression analysis result between Funtion 2-dependent variate and dependent variables before and after adding objective total number of times logging onto E-learning during t_0 and t_1

Variable	(i) Before adding	(ii) After adding	Sizable change in beta
	beta	beta	
Percentage (subjective) during t_0 and t_1	-.13	-.06	.07
Time spent (subjective) during t_0 and t_1	-.21	-.23	-.02
Time spent (objective) during t_0 and t_1	.83	.62	-.21
Number of times logging on (objective) during t_0 and t_1	-	.62	-
Inverted number of activities (objective) during t_0 and t_1	1.4	1.7	.30
	R^2 = .88	R^2= 1	R^2_{change} = .12

When the *objective total number of times logging onto E-learning during* t_0 *and* $t_1$was added to the equation of ii: (a) this variable was a contributing variable (*beta* = .62), even though its zero order correlation was small; (b) it increased the *inverted objective total number of activities involving E-learning during* t_0 *and* t_1's beta from *beta* = 1.4 to *beta* = 1.7; and (c) it improved the prediction (boosted to 12% of R-square). Thus, the *objective total number of times logging onto E-learning during* t_0 *and* t_1 was a suppressor variable for the *inverted objective total number of activities involving E-learning during* t_0 *and* t_1.

To investigate whether the *objective time spent on E-learning during* t_0 *and* t_1 is a suppressor variable, multiple regression analysis was carried out: (i) the Function 2-dependent variate regressed with all dependent variables apart from the *objective time spent on E-learning during* t_0 *and* t_1; (ii) the Function 2-dependent variate regressed with all dependent variables including the *objective time spent on E-learning during* t_0 *and* t_1 (see Table 7-12).

Table 7-12: Multiple regression analysis result between Function 2-dependent variate and dependent variables before and after adding objective time spent on E-learning during t_0 and t_1

Variable	(i) Before adding	(ii) After adding	Sizable change in beta
	beta	beta	
Percentage (subjective) during t_0 and t_1	.07	-.06	-.11
Time spent (subjective) during t_0 and t_1	-.21	-.23	-.02
Time spent (objective) during t_0 and t_1	-	.62	-
Number of times logging on (objective) during t_0 and t_1	.78	.62	-.16
Inverted number of activities (objective) during t_0 and t_1	1.4	1.7	.30
	R^2 = .90	R^2= 1	R^2_{chnage} =.10

Since the beta for the *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 was increased (from 1.4 to 1.7) and R-square increased to approximately ten per cent when the *objective time spent on E-learning during* t_0 *and* t_1 was included in equation, this variable was found to be another suppressor for the *inverted objective total number of activities involving E-learning during* t_0 *and* t_1.

The appearance of two suppressors for the *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 led us to examine further what was taking place by: (a) regressing the Function 2-dependent variate with the *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 in both the high (equal to or greater than mean) and low (less than mean) *objective total numbers of times logging onto E-learning during* t_0 *and* t_1 groups; (b) regressing the Function 2-dependent variate with the *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 in both the high (equal to or greater than mean) and the low (less than mean) *objective time spent on E-learning during* t_0 *and* t_1 groups.

The result showed the beta of *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 was significantly high in both the higher (*beta* = .93, $p < .001$) and the lower group of *objective total number of times logging onto E-learning during* t_0 *and* t_1 (*beta* = .83, $p < .001$), but that the better prediction (a higher R-square) was found in the higher group (R-square = .87) (see Table 7-13).

Table 7-13: Multiple regression analysis result between Function 2-dependent variate and inverted objective total number of activities involving E-learning during t_0 and t_1 in the low and high objective total number of times logging onto E-learning during t_0 and t_1 groups of participants

Variable	Low number of times logging on group		High number of times logging on group		Sizable change in beta
	beta	Sig.	beta	Sig.	
Inverted number of activities (objective) during t_0 and t_1	.83	< .001	.93	< .001	.10
	R^2 = .69		R^2= .87		R^2_{chnage} = .18

This result implied that the *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 was relevant to the contributing initial expectations within the CCA Function 2 in both the high and low *objective total numbers of times logging onto E-learning during* t_0 *and* t_1 groups. However, this measurement was more relevant when a student had a high *objective total number of times logging onto E-learning during* t_0 *and* t_1.

The beta of the *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 was significantly high in both the higher (*beta* = .90, *p* < .001) and lower *objective time spent on E-learning during* t_0 *and* t_1 groups (*beta* = .71, *p* < .001), but the better prediction was found in the higher group (R-square was higher 31%) (see Table 7-14).

Table 7-14: Multiple regression analysis result between the Function 2-dependent variate and inverted objective total number of activities involving E-learning during t_0 and t_1 in the low and high objective time spent on E-learning during t_0 and t_1 groups of participants

Variable	**Low objective time spent group**		**High objective time spent group**		**Sizeable change in beta**
	beta	**Sig.**	**beta**	**Sig.**	
Inverted number of activities (objective) during t_0 and t_1	.71	< .001	.90	< .001	.19
	R^2 = .50		R^2= .81		R^2_{chnage} = .31

These findings indicated that the *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 was an important outcome of the contributing initial expectations within Function 2 in both the high and low *objective time spent on E-learning during* t_0 *and* t_1 groups, but this measurement was a more relevant outcome when students had a high level of *objective time spent on E-learning during* t_0 *and* t_1.

Independent variate Function 2

There were two independent variables contributing to the Function 2-independent variate: the *performance expectancy at* t_0 (r_p = -.64) and the *facilitating condition expectancy at* t_0 (r_p = .62). The canonical loading (r_s) for these two had a different sign: this means they were negatively related.

Summary of CCA Function 2

It can be concluded that: (a) there was a positive relationship between the dependent and the independent variates in Function 2, since the canonical correlation between the dependent and the independent variates (.47) in Function 2 was positive; (b) *performance expectancy at* t_0 and *facilitating condition expectancy at* t_0 contributed to the Function 2-independent variate; while (c) *inverted objective total number of activities involving E-learning during* t_0 *and* t_1, *objective total number of times logging* *onto E-learning during t_0 and t_1*and *objective time spent on E-learning during t_0 and t_1*contributed to the Function 2-dependent variate; and (d) the *objective total number of times logging onto E-learning during t_0 and t_1* and the *objective time spent on E-learning during t_0 and t_1* were suppressor variables for the *inverted objective total number of activities involving E-learning during t_0 and t_1* (see Figure 7-2).

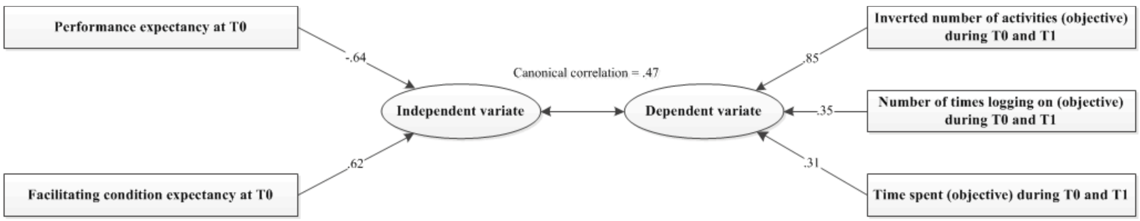


Figure 7-2: Summary of canonical correlation analysis Function 2 of the relationship between the five EU sub-model initial expectation variables at t_0 and the five measurements of actual E-learning uptake at t_1

Summary of CCA of the relationship between the five EU sub-model initial expectation variables at t_0 and the five measurements of E-learning actual uptake at t_1

Based on Cohen's work (1992), the EU sub-model variables demonstrated great predictive power for E-learning uptake (R^2 = .51, R = .71). Among the five measurements of actual E-learning uptake, the *subjective time spent learning with E-learning during t_0 and t_1*did not contribute to any canonical functions. Thus, *subjective time spent learning with E-learning during t_0 and t_1* was an irrelevant outcome for the set of contributing EU sub-model initial expectations. Even though the *objective total number of times logging onto E-learning during t_0 and t_1* acted as a suppressor in canonical Function 2, with a very small contribution to Function 1 ($r_p{}^2$ = .02), this outcome was not relevant to the set of contributing initial expectations. There were three actual E-learning uptake measurements relating to a set of contributing initial expectations: (a) the *inverted objective total number of activities involving E-learning during t_0 and t_1* (h^2 = .96); (b) the *subjective percentage of E-learning usage in education during t_0 and t_1* (h^2 = .30); and (c) the *objective time spent on the E-learning during t_0 and t_1* (h^2 = .26). In the independent variable set, *social encouragement expectancy at t_0* was the only predictor that did not contribute to any function. Accordingly, it was not an important influence on the uptake of E-learning. The results from canonical correlation analysis suggested that four (*performance expectancy at t_0*, *effort expectancy at t_0*, *facilitating condition expectancy at t_0*, and *learning consistency expectancy at t_0*) of the five initial expectation variables influenced the uptake of E-learning (h^2 > .20). The independent variables of *learning consistency expectancy at* t_0 and *effort expectancy at* t_0 acted somewhat independently of *performance expectancy at* t_0 and *facilitating condition expectancy at* $t_{0,}$ because of the independence of each canonical function. The dependent variables of *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 and *objective time spent on E-learning system during* t_0 *and* t_1 were common to both functions, while the *subjective percentage of E-learning usage in education during* t_0 *and* t_1 related more to *learning consistency expectancy at* t_0 and *effort expectancy at* t_0 (see Figure 7-3).

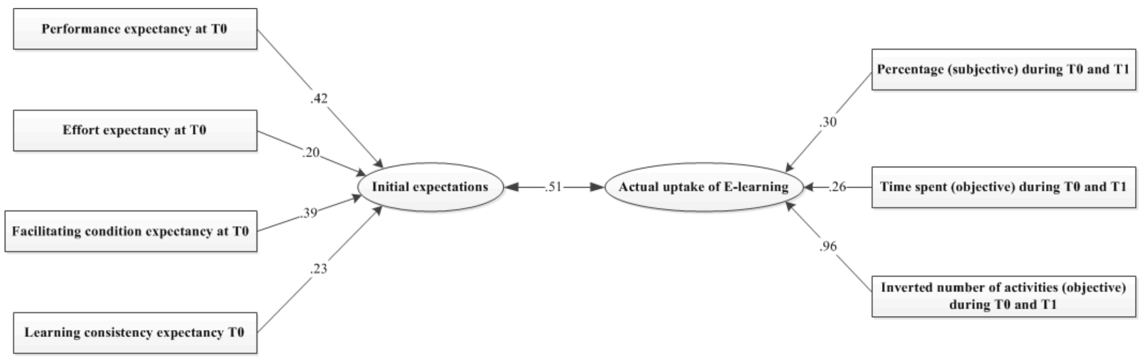


Figure 7-3: Summary of canonical correlation analysis of the relationship between the five EU sub-model initial expectation variables at t_0 and the five measurements of actual E-learning uptake at t_1

7.1.4 The EU sub-model variables' predictive power and explanatory power of E-learning uptake compared with TAM and UTAUT (RQ4d)

To compare the EU sub-model's predictive power on E-learning uptake with TAM and UTAUT, as expressed in RQ4d, the TAM and UTAUT models' predictive power on E-learning uptake were calculated by: (a) canonical correlation analysis using the two TAM model variables measured at time t_0 (PE_{t_0} and EE_{t_0}) as predictors of the five measurements of actual E-learning uptake measured at time t_1; and (b) canonical correlation analysis using the four UTAUT model variables measured at time t_0 (PE_{t_0}, EE_{t_0}, SEE_{t_0} and FCE_{t_0}) as predictors of the five measurements of actual E-learning uptake measured at time t_1. Canonical correlation analysis provided Wilks' λ value. To enable a statistical comparison of predictive power among the three models, Wilks' λ value of each model was transformed into R^2 value by subtracting it from the constant 1. All the three models' predictive power (R^2) was transformed into R by taking the square root. Fisher's (1921) Z-transform technique was then applied to compare correlation coefficients between the three models. Bonferroni's correction was applied in order to reduce Type I error and the significance level for this analysis was set at .025 (.05/2).

Canonical correlation analysis of the relationship between the two TAM model variables at t_0 and the five measurements of actual E-learning uptake at t_1

The required statistical conditions and assumptions for this analysis were checked and found not to be violated (see Appendix 7-F). The relationship between the set of TAM model variables at time t_0 (PE_{t_0} and EE_{t_0}) and the set of five measurements of actual E-learning uptake at time t_1 was statistically significant, as Wilks' λ criterion =.68, $F(10, 188) = 4.1$, $p < .001$. Accordingly, there was at least one significant relationship between the TAM model variables at t_0 and actual E-learning uptake measurements at t_1. Because Wilks' λ represents variance in the combination of five measurements of actual E-learning uptake unexplained by the set of TAM variables, 32 per cent (1- λ, R^2) of variance in actual E-learning uptake was accounted for by TAM model variables. According to Cohen (1992), since the multiple correlation coefficient between the set of TAM model variables and the set of actual E-learning uptake measurements was higher than .5 (R = .57), it could be concluded that the TAM model variables had strong predictive power on the uptake of E-learning. The analysis of the relationship between the two TAM model variables at t_0 and the five measurements of E-learning actual uptake at t_1 is explained in Appendix 7-G.

Canonical correlation analysis of the relationship between the four UTAUT model variables at t_0 and the five measurements of actual E-learning uptake at t_1

The required statistical conditions and assumptions for this analysis were checked and found not to be violated (see Appendix 7-H). The relationship between the set of UTAUT model variables (PE_{t_0}, EE_{t_0}, SEE_{t_0} and FCE_{t_0}) and the five measurements of actual E-learning uptake was statistically significant, as Wilks' λ criterion = .55, $F(20, 306.1) = 3.0$, $p < .001$. Accordingly, there was at least one significant relationship between the UTAUT model variables and the measurements of actual E-learning uptake. Wilks' λ represents the variance in the combination of dependent variables unexplained by the set of independent variables: 45 per cent (1- λ) of variance in E-learning actual uptake was accounted for by the UTAUT model variables. Based on the work of Cohen (1992), the UTAUT model variables had great predictive power for

E-learning: the multiple correlation coefficient between the set of UTAUT model variables and the set of actual E-learning measurements was higher than 0.5 (R = .67). The analysis of the relationship between the four UTAUT model variables and the five measurements of E-learning actual uptake is explained in Appendix 7-I.

Comparisons of the square of multiple correlation coefficient of the relationship between model variables at t_0 and the five measurements of E-learning actual uptake at t_1 between EU sub-model and TAM, UTAUT

The predictive power of the model variables on E-learning uptake (R^2) between the EU sub-model and the two comparative models (TAM and UTAUT) was not statistically significantly different: *EU sub-model* and *TAM* (${R^2}_{difference}$= .19, p = .07); *EU sub-model* and *UTAUT* (${R^2}_{difference}$= .06, p = .53) (see Table 7-15).

Table 7-15: Z-score comparing EU sub-model's predictive power of E-learning uptake with TAM and UTAUT

		Model 1		**Model 2**				
Model 1	**Model 2**	**λ**	R^2	**λ**	R^2	${R^2}_{difference}$	**P-value (two-tail)**	**Conclusion (alpha = .05/2)**
EU sub-model	TAM	.49	.51	.68	.32	.19	0.07	No sig. diff
EU sub-model	UTAUT	.49	.51	.55	.45	.06	0.53	No sig. diff

These results suggested that the EU sub-model variables' predictive power on E-learning uptake was not different from TAM and UTAUT: the EU sub-model explained the uptake of E-learning as well as TAM and UTAUT.

7.2 Assessment of EC sub-model Performance (RQ5)

There were four sub-research questions to be answered for Research Question RQ5, on assessing the EC sub-model performance:

7.2.1 *The EC sub-model equation's performance of continued use of E-learning (RQ5a)*

A multiple regression analysis was conducted between *the EC sub-model equation's prediction of continued use of E-learning at* t_1 and the five measurements of actual continued use of E-learning at t_2 (*subjective percentage of E-learning usage in* *education during* t_1 *and* t_2, *subjective time spent learning with E-learning during* t_1 *and* t_2, *objective time spent on E-learning during* t_1 *and* t_2, *objective total number of times logging onto E-learning during* t_1 *and* t_2, and *objective total number of activities involving E-learning during* t_1 *and* t_2). The model equation's performance was given by the multiple correlation coefficient, *R*. Cohen's effect size was applied as a scale for assessing the EU sub-model's predictive performance.

The required statistical conditions and assumptions for this analysis were checked and the result of the VIF test suggested that the multicollinearity assumption was violated: the VIF for the variable of *objective time spent on E-learning during* t_1 *and* t_2 was higher than 10. Multicollinearity among independent variables does not affect accuracy in the estimation of multiple correlation coefficient (R) between the dependent variable and the set of independent variables, used as an indicator of the predictive performance of the model; what it affects is the individual *p*-value for each independent variable (measurements of actual continued use of E-learning). It cannot be significant, even if the variable is a significant variable. Multicollinearity increases the standard error of coefficients for independent variables. Because of increased standard errors, the coefficients for some independent variables may not be detected as significant even if, without multicollinearity, they would be a significant variable (Farrar and Glauber, 1967). Consequently, the relevant measurements of model prediction may not be found.

The easiest way to deal with the problem of multicollinearity is to drop one or more independent variables from the regression equation (Graham, 2003). VIF value provides information about sources of multicollinearity, but they do not tell us which variables should be dropped from the regression model (Cohen and Manion, 2000). It is better to state that there is a risk to delete significant contributing variables, if a researcher deletes them exclusively on the basis of VIF value. Therefore, to avoid this risk, a correlation analysis between the five measurements of continued use of E-learning was conducted to find the possible cause of multicollinearity in *objective time spent on E-learning system during* t_1 *and* t_2 (see Appendix 7-J). The result of the correlation matrix between the five measurements of actual continued use of E-learning suggested that there are three measurements that might be the cause of multicollinearity in *objective time spent on E-learning during* t_1 *and* t_2: (a) *objective time spent on E-learning during* t_1 *and* t_2 itself; (b) *objective total number of times logging onto*

E-learning during t_1 *and* t_2, $r_{with\ time\ spent\ objective}$ = .89; and (c) *objective total number of activities involving E-learning during* t_1 *and* t_2 $r_{with\ time\ spent\ objective}$ = .93. Next, a backward stepwise regression was applied using the five measurements of actual continued use of E-learning at t_2 as a predictor of the EC sub-model's prediction of continued use of E-learning at t_1 to find the least useful variable: the smallest part-correlation between the independent and the dependent variable (Field, 2013) (see Appendix 7-K). The result from the backward stepwise regression between the EC sub-model prediction of continued use of E-learning at t_1 and the five measurements of actual continued use of E-learning at t_2 showed that: (a) the *objective total number of activities involving E-learning during* t_1 *and* t_2 was the first excluded variable; (b) after removing this variable from the regression model, the VIF value for the rest variables was lower than 10; (c) there was very little change in multiple correlation coefficients of the model and beta level for each measurement of continued use of E-learning. Therefore, the EC sub-model predictive performance of continued use of E-learning was represented by the multiple correlation coefficient between the model prediction of continued use of E-learning at t_1 and the four measurements of actual continued use of E-learning at t_2. These were: *the subjective percentage of E-learning usage in education during* t_1 *and* t_2; *the subjective time spent learning with E-learning during* t_1 *and* t_2*; the objective time spent on E-learning during* t_1 *and* t_2*; and the objective total number of times logging onto E-learning during* t_1 *and* t_2. After removing the *objective total number of activities involving E-learning during* t_1 *and* t_2, the required assumptions were tested (see Appendix 7-L) and were not violated.

Multiple regression analysis between the EC sub-model equation's prediction of continued use of E-learning at t_1 ***and the four measurement of actual continued use of E-learning at*** t_2

The linear combination of the four measurements of actual continued use of E-learning at t_2 was significantly related to *the EC sub-model's prediction of continued use of E-learning at* t_1: $F(4, 71) = 6.1$, $p < .001$ (see Table 7-16). The multiple correlation coefficient was .51, indicating that approximately 26 per cent of the variance of *the EC sub-model's prediction of continued use of E-learning at* t_1 was accounted for by the linear combination of the four measurements of actual continued use of E-learning at t_2. Based on the work of Cohen (1992), the EC sub-model equation showed a highly predictive performance regarding the continued use of E-learning: the multiple correlation coefficient was higher than 0.5 (.51). Among the four measurement of actual continued use of E-learning at t_2, there was no single significant contributing predictor.

Table 7-16: Multiple regression analysis result between EC sub-model equation 's prediction of continued use of E-learning at t_1 and the four measurements of actual continued use of E-learning at t_2

Independent variables	**Non-standardized coefficients**		**Standardized coefficients**	**t**	**Sig.**
	B	**SE**	**β**		
Constant	48.9	6.4		7.6	< .001
Percentage (subjective) during t_1 and t_2	.12	.09	.21	1.3	.20
Time spent (subjective) during t_1 and t_2	4.7	3.5	.20	1.4	.18
Time spent (objective) during t_1 and t_2	3.7	2.2	.42	1.7	.09
Number of times logging on (objective) during t_1 and t_2	-11.6	8.1	-.33	-1.4	.15
a. Dependent variable: EC sub- model equation's prediction of continued use of E-learning at t_1					
R = .51; R^2 = .26; F(4, 71) = 6.1; p-value < .001					

7.2.2 *The EC sub-model equation's performance of continued use of E-learning compared with TAM, UTAUT and ECM (RQ5b)*

The second sub-research question (RQ5b) was: *Is the EC sub-model equation's predictive performance of continued use of E-learning greater than the three comparative models (TAM, UTAUT and ECM)*. To answer this question, the TAM, UTAUT and ECM models' predictive performances of continued use of E-learning were calculated. Since there was a problem of multicollinearity in a set of actual continued use of E-learning measurements, a backward stepwise regression between each model prediction at t_1 and the five measurements of continued use of E-learning at t_2 was conducted to find which measurements should be removed. The results showed that the *objective total number of activities involving E-learning during* t_1 *and* t_2 was the first excluded in all the three regression models. Therefore, the degree of predictive performance for the three comparative models (TAM, UTAUT and ECM) was represented by the multiple correlation coefficient between each model prediction of continued use of E-learning at t_1 and the four measurements of actual continued use of E-learning at t_2: these were *subjective percentage of E-learning usage in education during* t_1 *and* t_2; *subjective time spent learning with E-learning during* t_1 *and* t_2;

objective time spent on E-learning system during t_1 and t_2; and *objective total number of times logging onto E-learning during t_1 and t_2*.

The EC sub-model's predictive performance of continued use of E-learning was then compared with the performance showed by the TAM, UTAUT and ECM models using Fisher's Z-transform technique. As this analysis involved multiple comparisons, Bonferroni's correction was applied in order to reduce Type I error. The significance level for this analysis was set at .016 (.05/3). The results of these analyses are as follows:

Multiple regression analysis between the TAM model equation's prediction of continued use of E-learning at t_1 and the four measurements of actual continued use of E-learning at t_2

The required statistical conditions and assumptions for this analysis were checked and found not to be violated (see Appendix 7-M). The linear combination of the four measurements of actual continued use of E-learning at t_2 was significantly related to *the TAM model equation's prediction of continued use of E-learning at t_1*: $F(4, 71) = 2.9$, p =.03(see Table 7-17). The multiple correlation coefficient was .37, indicating that approximately 14 per cent of the variance of *the TAM model equation's prediction of continued use of E-learning at t_1* was accounted for by the linear combination of the four measurements of actual continued use of E-learning at t_2. According to the work of Cohen (1992), the TAM equation showed moderate performance on the continued use of E-learning (R = .37). Among the four measurements of actual continued use of E-learning at t_2, there was no individual significant contributing predictor.

Table 7-17: Multiple regression analysis result between the TAM model equation's prediction of continued use of E-learning at $t_1$and the four measurements of actual continued use of E-learning at t_2

Independent variables	**Non-standardized coefficients**		**Standardized coefficients**	**t**	**Sig.**
	B	SE	β		
Constant	55.3	7.9		7.0	<.001
Percentage (subjective) during t_1 and t_2	.16	.11	.25	1.4	.17
Time spent (subjective) during t_1 and t_2	2.2	4.3	.08	.52	.61
Time spent (objective) during t_1 and t_2	2.7	2.7	.27	1.0	.32
Number of times logging on (objective) during t_1 and t_2	-10.1	10.0	-.25	-1.0	.31
a. Dependent variable: TAM model equation's prediction of continued use of E-learning at t_1					
R = .37; R^2 = .14; $F(4, 71)$ = 2.9; p-value = .03					

Multiple regression analysis between the UTAUT model equation's prediction of continued use of E-learning at t_1 and the four measurement of actual continued use of E-learning at t_2

The required statistical conditions and assumptions for this analysis were checked and found not to be violated (see Appendix 7-N). The linear combination of the four measurements of actual continued use of E-learning at t_2 was significantly related to *the UTAUT model equation's prediction of continued use of E-learning at* t_1: $F(4, 71) = 4.0$, $p = .005$ (see Table 7-18). The multiple correlation coefficient was .44, indicating that approximately 19 per cent of the variance of *the UTAUT model equation's prediction of continued use of E-learning at* t_1 was accounted for by the linear combination of the four measurements of actual continued use of E-learning at t_2. According to the work of Cohen (1992), the UTAUT model showed moderate performance in the prediction of continued use of E-learning ($R = .44$). Among the four measurement of actual continued use of E-learning at t_2, there was no single significant contributing predictor.

Table 7-18: Multiple regression analysis result between UTAUT model equation's prediction of continued use of E-learning at $t_1$and the four measurements of actual continued use of E-learning at t_2

Independent variables	**Non-standardized coefficients**		**Standardized coefficients**	**t**	**Sig.**
	B	**SE**	**β**		
Constant	50.0	7.7		6.5	< .001
Percentage (subjective) during t_1 and t_2	.14	.11	.23	1.3	.19
Time spent (subjective) during t_1 and t_2	5.3	4.2	.20	1.3	.21
Time spent (objective) during t_1 and t_2	2.4	2.6	.24	.91	.37
Number of times logging on (objective) during t_1 and t_2	-10.0	9.7	-.25	-1.0	.31
a. Dependent variable: UTAUT model's prediction of continued use of E-learning at t_1					
$R = .44$; $R^2 = .19$; $F(4, 71) = 4.0$; p-value = .005					

Multiple regression analysis between the ECM model equation's prediction of continued use of E-learning at t_1 and the four measurements of continued use of E-learning at t_2

The required statistical conditions and assumptions for this analysis were checked and found not to be violated (see Appendix 7-O). The linear combination of the four measurements of actual continued use of E-learning at t_2 was significantly related to *the ECM model equation's prediction of continued use of E-learning at* t_1: $F(4, 71) = 7.9$,

p < .001 (see Table 7-19). The multiple correlation coefficient was .55, indicating that approximately 31 per cent of the variance of *the ECM model equation's prediction of continued use of E-learning at* t_1 was accounted for by the linear combination of the four measurements of actual continued use of E-learning at t_2. Among the four measurements of actual continued use of E-learning at t_2, only the *objective time spent on E-learning during* t_1 *and* t_2 made a significant contribution to *the ECM model's prediction of continued use of E-learning at* t_1: β = .59, $t(75)$ = 2.4, p = .02. With a multiple correlation coefficient higher than .50, it can be concluded that the ECM had good predictive performance on the continued use of E-learning.

Table 7-19: Multiple regression analysis result between the ECM model equation's prediction of continued use of E-learning at t_1 and the four measurements of actual continued use of E-learning at t_2

Independent variables	**Non-standardized coefficients**		**Standardized coefficients**	**t**	**Sig.**
	B	SE	β		
Constant	49.3	7.0		7.0	< .001
Percentage (subjective) during t_1 and t_2	.10	.10	.16	.99	.32
Time spent (subjective) during t_1 and t_2	3.7	3.8	.14	.96	.34
Time spent (objective) during t_1 and t_2	5.8	2.4	.59	2.4	.02
Number of times logging on (objective) during t_1 and t_2	-11.8	8.8	-.29	-1.3	.19
a. Dependent variable: ECM model equation's prediction of continued use of E-learning at t_1					
R = .55; R^2 = .31; $F(4, 71)$ = 7.9; p-value < .001					

Comparisons of the multiple correlation coefficients of the relationship between model equation prediction of continued use of E-learning at t_1 and the four measurements of actual continued use of E-learning at t_2 between EC sub-model and TAM, UTAUT, ECM

The multiple correlation coefficient between the model equation prediction of continued use of E-learning at t_1 and the actual continued use of E-learning at t_2 was not significantly different from that of the EC sub-model with the three comparative models: *EC sub-model* and *ECM* (R difference = .04, p = .69); *EC sub-model* and *UTAUT* (R difference = .07, p = .62); EC sub-model and TAM (R difference = .14, p = .31) (see Table 7-20). These results suggested that the *EC sub-model* did as well in predicting the continued use of E-learning as ECM, TAM and UTAUT.

Table 7-20: z-score comparing EC sub-model's predictive performance of continued use of E-learning with TAM, UTAUT and ECM

Pair 1	Pair 2	R1	R2	Z_{R1}	Z_{R2}	P-value	Conclusion (P < .017)
EC sub-model	**ECM**	.51	.55	.62	.56	.69	Not sig. different
	UTAUT	.51	.44	.56	.48	.62	Not sig. different
	TAM	.51	.37	.56	.39	.31	Not sig. different

7.2.3 The EC sub-model variables' predictive power and explanatory power of continued use of E-learning (RQ5c)

To investigate the predictive power and explanatory power of the EC sub-model variables, canonical correlation analysis was undertaken between the EC sub-model variables at t_1 (*calculated performance expectancy at* t_1; *calculated effort expectancy at* t_1; *calculated social encouragement expectancy at* t_1; *calculated facilitating condition expectancy at* t_1; and *calculated learning consistency expectancy at* t_1) and the five measurements of actual continued use of E-learning at t_2. Since a problem of multicollinearity was found in the set of actual continued use of E-learning measurements, one of the measurements needed to be cut from the analysis. To find which measurement should be cut, the canonical correlation analysis was first conducted using the EC sub-model variables and all five measurements of continued use of E-learning. Then, of the three suspected causes of multicollinearity (*objective time spent on E-learning during* t_1 *and* t_2; *objective total number of times logging onto E-learning during* t_1 *and* t_2; *objective total number of activities involving E-learning during* t_1 *and* t_2), the one with the smallest part-correlation with its variate was decided upon. The result suggested that the measurement *objective total number of activities involving E-learning during* t_1 *and* t_2 should be the one to be dropped. After removing the suggested measurement from the analysis, the required assumptions for canonical correlation analysis were checked and all were found not to be violated (see Appendix 7-P).

Canonical correlation analysis of the relationship between the five EC sub-model variables at t_1 ***and the four measurements of actual continued use of E-learning at*** t_2

The independent variables were the five calculated expectations at time t_1 from the EC sub-model: (a) *calculated performance expectancy at* t_1; (b) *calculated effort expectancy at* t_1; (c) *calculated social encouragement expectancy at* t_1; (d) *calculated* *facilitating condition expectancy at* t_1; and (e) *calculated learning consistency expectancy at* t_1. The dependent variables were the four measurements of actual continued use of E-learning at t_2: (a) *subjective time spent learning with E-learning during* t_1 *and* t_2*;* (b) *subjective percentage of E-learning usage in education during* t_1 *and* t_2*;* (c) *objective time spent on E-learning during* t_1 *and* t_2*;* and (d) *objective total number of times logging onto E-learning during* t_1 *and* t_2.

The relationship between the set of dependent and independent variables was statistically significant, as Wilks' λ criterion = .57, *F*(20, 223.2) = 2.1, *p* = .006. Accordingly, there was at least one significant relationship between the EC sub-model variables at t_1 and the measurements of actual continued use of E-learning at t_2. Because Wilks' λ represents the variance in the combination of dependent variables unexplained by the set of independent variables, 43 per cent (1- λ) of variance in actual continued use of E-learning was accounted for by the EC sub-model variables. According to the work of Cohen (1992), since the multiple correlation coefficient between the set of EC sub-model variables and the set of continued use of E-learning measurements was higher than .5 (*R* = .66), it may be concluded that the EC sub-model variables had good predictive power for the continued use of E-learning.

The canonical correlation analysis yielded four functions with squared canonical correlations (R_c^2) of .32, .12, .04 and .01 respectively for each successive function (see Table 7-21).

Table 7-21: Canonical correlation analysis of the relationship between the five EC sub-model variables at $t_1$and the four measurements of actual continued use of E-learning at t_2

Function	Eigenvalue	%	Cumulative %	Canonical Correlation	Squared Correlation
1	.47	71.1	71.1	.56	.32
2	.14	20.8	91.8	.35	.12
3	.05	6.8	98.1	.21	.04
4	.01	1.4	100.0	.10	.01

Dimension reduction analysis was used to determine which functions should be interpreted (see Table 7-22). Functions 1 to 4 were statistically significant, *F*(20, 223.2) = 2.1, *p* = .006. The cumulative effects of Functions 2 to 4, Functions 3 to 4, and Function 4 in isolation were not statistically significant. Accordingly, the first function was considered noteworthy in the context of this study (32% of shared variance).

Functions 2, 3 and 4 were not chosen for interpretation, as they only explained 12 per cent, 4 per cent and 1 per cent of the variance in the variable sets remaining after the extraction of the prior functions.

Table 7-22: Dimension reduction analysis for canonical functions of the relationship between the five EC sub-model variables at t_1 and the four measurements of actual continued use of E-learning at t_2

Roots	Wilks' λ	F	Hypothesis DF	Error DF	Significance of F
1 to 4	.57	2.1	20.0	223.2	.006
2 to 4	.84	1.1	12.0	180.2	.40
3 to 4	.95	.61	6.0	138.0	.72
4 to 4	.99	.32	2.0	70.0	.73

The canonical weight (*beta*), canonical loading (r_s), part-correlation between variable and its variate (r_p), square of part-correlation ($r_p{}^2$) for each variable within the Function 1 are shown in Table 7-23.

Table 7-23: Canonical solution of the relationship between the five EC sub-model variables at t_1 and the four measurements of actual continued use of E-learning at t_2

	Variable	Function 1				
		Coef	r_s	r_p	$r_p{}^2$ *(%)*	*Summary*
Dependent variable	Percentage (subjective) during t_1 and t_2	-.27	−.83	-.16	.03	No
	Time spent (subjective) during t_1 and t_2	-.26	−.72	-.18	.03	No
	Time spent (objective) during t_1 and t_2	-1.1	−.86	−.44†	.19	Relevant
	Number of times logging on (objective) during t_1 and t_2	.53	−.63	.24	.06	No
Independent variable	Calculated performance expectancy at t_1	-.94	−.98	−.58†	.34	Important
	Calculated effort expectancy at t_1	.05	−.63	.04	$1.6*10^{-3}$	No
	Calculated social encouragement expectancy at t_1	.04	−. 65	.03	$9*10^{-4}$	No
	Calculated facilitating condition expectancy at t_1	.23	−.63	.14	.02	No
	Calculated learning consistency expectancy at t_1	-.36	−.80	-.17	.03	No

Coef = Standardized coefficient (beta) between variable and with variate;
r_s = Zero order correlation
r_p = Part-correlation († greater than $|.30|$)
$r_p{}^2$ = Squared part-correlation between variable and with its variate

There was a positive relationship between the dependent and the independent variates in the Function 1 since the canonical correlation between the dependent and the independent variates (R_c = .56) 1 was positive. *Calculated performance expectancy at* t_1 (r_p = -.58) was a contributed independent variable, while *objective time spent on E-learning during* t_1 *and* t_2 (r_p = -.44) was a contributed dependent variable (see Figure 7-4).

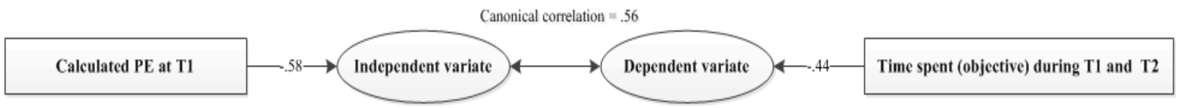


Figure 7-4: Summary of canonical correlation analysis of the relationship between the five EC sub-model variables at $t_1$and the four measurements of actual continued use of E-learning at t_2

7.2.4 The EC sub-model variables'' predictive power and explanatory of E-learning continue use compared with TAM, UTAUT, and ECM (RQ5d)

To compare the EC sub-model's predictive power on continued use of E-learning with the three models (TAM, UTAUT and ECM), as expressed in RQ5d, these three models' predictive power on continued use of E-learning were calculated. Since the problem of multicollinearity was found in the set of actual continued use of E-learning measurements, canonical correlation analysis was first conducted using model variables and all five measurements for all the three models to find the least relevant outcome behind the multicollinearity. The result suggested that the measurement of *objective total number of activities involving E-learning during* t_1 *and* t_2 should be cut from the analysis of the ECM, while the measurement *objective total number of times logging onto E-learning during* t_1 *and* t_2 should be cut from the analysis of the TAM and UTAUT models. Fisher's (1921) Z-transform technique was then used for comparing the EC sub-model's predictive power on continued use of E-learning with the three comparative models. Bonferroni's correction was applied in order to reduce Type I error and the significance level for this analysis was set at .016 (.05/3).

Canonical correlation analysis of the relationship between the two TAM model variables at $\boldsymbol{t_1}$ ***and the four measurement of actual continued use of E-learning at*** $\boldsymbol{t_2}$

The independent variables were the two measured TAM expectations at time t_1: *measured performance expectancy at* t_1 and *measured effort expectancy at* t_1. The dependent variables were the four measurements of actual continued use of E-learning at time t_2: (a) *subjective percentage of E-learning usage in education during* t_1 *and* t_2; (b) *subjective time spent learning with E-learning during* t_1 *and* t_2; (c) *objective time spent on E-learning during* t_1 *and* t_2; and (d) *objective total number of activities involving E-learning during* t_1 *and* t_2. The required statistical conditions and assumptions for this analysis were checked and found not to be violated (see Appendix 7-Q).

The relationship between the set of dependent and independent variables was statistically significant, Wilks' λ criterion = .77, *F*(8, 140.0) = 2.5, *p* = .014. Accordingly, there was at least one significant relationship between the TAM model variables at t_1 and the measurements of actual continued use of E-learning at t_2. Because Wilks' λ represents the variance in the combination of dependent variables unexplained by the set of independent variables, 23 per cent (1- λ) of variance in actual continued use of E-learning was accounted for by the TAM model variables. According to the work of Cohen (1992), since the multiple correlation coefficient between the set of TAM model variables and the set of actual continued use of E-learning measurements was higher than .5 (*R* = .57), it could be concluded that the TAM model had great predcitve power on continued use of E-learning. The analysis of the relationship between the two TAM model variables at t_1 and the four measurements of actual continued use of E-learning at t_2 is explained in Appendix 7-R.

Canonical correlation analysis of the relationship between the four UTAUT model variables at t_1 ***and the four measurement of actual continued use of E-learning at*** t_2

The independent variables were the four measured expectations from UTAUT model at t_1: *measured performance expectancy at* t_1; *measured effort expectancy at* t_1; *measured social encouragement expectancy at* t_1; *and measured facilitating condition expectancy at* t_1. The dependent variables were the four measurements of actual continued use of E-learning *at* t_2: *subjective time spent learning with E-learning during* t_1 *and* t_2; *subjective percentage of E-learning usage in education during* t_1 *and* t_2; *objective time spent on E-learning during* t_1 *and* t_2; and *objective total number of activities involving E-learning during* t_1 *and* t_2. The required statistical conditions and assumptions for this analysis were checked and found not to be violated (see Appendix 7-S).

The relationship between the set of dependent and independent variables was statistically significant, as Wilks' λ criterion = .65, $F(16, 208.4) = 2.0$, $p = .014$. Accordingly, there was at least one significant relationship between the UTAUT model variables at t_1 and the measurements of actual continued use of E-learning at t_2. Because Wilks' λ represents the variance in the combination of dependent variables unexplained by the set of independent variables, 35 per cent (1- λ) of variance in the actual continued use of E-learning was accounted for by the UTAUT model variables. Since the multiple correlation coefficient between the set of UTAUT model variables and the set of continued use of E-learning measurements was higher than .5 ($R = .59$), it could be concluded that UTAUT model variables had great predictive power on the continued use of E-learning. The analysis of the relationship between UTAUT model variables at t_1 and the five measurements of E-learning actual continued use t_2 is explained in Appendix 7-T.

Multiple regression analysis between the ECM model variable at t_1 and the four measurement of E-learning actual continued use at t_2

Since ECM has a single model variable, the *calculated performance expectancy at* t_1, multiple regression analysis was conducted using the four measurements of actual continued use of E-learning at t_2 (*subjective percentage of E-learning usage in education during* t_1 *and* t_2; *subjective time spent learning with E-learning during* t_1 *and* t_2; *objective time spent on E-learning during* t_1 *and* t_2; and *objective total number of times logging onto E-learning during* t_1 *and* t_2) as a predictor of *calculated performance expectancy at* t_1. The required statistical conditions and assumptions for this analysis were checked and found not to be violated (see Appendix 7-U). The linear combination of the four measurements of actual continued use of E-learning at t_2 was significantly related to *the calculated performance expectancy at* t_1: $F(4, 71) = 7.9$, $p < .001$ (see Table 7-24). The multiple correlation coefficient was .55, indicating that approximately 31 per cent of the variance in the linear combination of four measurements of actual continued use of E-learning at t_2 was accounted for by *the calculated performance expectancy at* t_1. According to the work of Cohen (1992), the ECM model had great predictive power for the continued use of E-learning. Among the four measurements of actual continued use of E-learning at t_2, only the *objective time spent on E-learning during* t_1 *and* t_2 contributed significantly to the *calculated performance expectancy at* t_1: $\beta = .59$, $t(75) = 2.4$, $p = .02$.

Table 7-24: Multiple regression analysis result between the ECM model variable at t_1 and the four measurements of actual continued use of E-learning at t_2

Independent variables	Non-standardized coefficients		Standardized coefficients	t	Sig.
	B	SE	β		
Constant	4.9	.70		7.0	< .001
Percentage (subjective) during t_1 and t_2	.01	.01	.16	.99	.32
Time spent (subjective) during t_1 and t_2	.37	.38	.14	.96	.34
Time spent (objective) during t_1 and t_2	.58	.24	.59	2.4	.02
Number of times logging on (objective) during t_1 and t_2	-1.2	.88	-.29	-1.3	.19
a. Dependent variable: calculated performance expectancy at t_1					
R = .55; R^2 = .31; F(4, 71) = 7.9; p-value < .001					

Comparisons of the square of multiple correlation coefficient of the relationship between model variables at t_1 and the four measurements of E-learning actual continued use at t_2 between EC sub-model and TAM, UTAUT, ECM

The predictive power of the model variables on continued use of E-learning (R^2) was not statistically significantly different between the EC sub-model and the three comparative models: *EC sub-model* and *ECM* ($R^2_{difference}$= .12, p = .30); *EC sub-model* and *UTAUT* ($R^2_{difference}$= .08, p = .52); *EC sub-model* and *TAM* ($R^2_{difference}$= .20, p = .11) (see Table 7-25). These suggested that the EC sub-model variables did as well at predicting the continued use of E-learning as existing models.

Table 7-25: z-score comparing EC sub-model's an predictive power on continued use of E-learning with TAM, UTAUT and ECM

		Model 1		Model 2				
Model 1	**Model 2**	**λ**	**R^2**	**λ**	**R^2**	**$R^2_{difference}$**	**P-value (two-tail)**	**Conclusion (alpha = .017)**
EC sub-model	**ECM**	.57	.43	.69	.31	.12	.30	No sig. diff
	UTAUT	.57	.43	.65	.35	.08	.52	No sig. diff
	TAM	.57	.43	.77	.23	.20	.11	No sig. diff

7.3 Validation of Relationships between the EUCH model Variables (RQ6)

To answer Research Question RQ6, which was to *validate the relationships between EUCH model variables*, there were four sub-research questions to be answered:

7.3.1 The influences of five initial expectations on the uptake of E-learning (RQ6a)

This research question was answered by conducting canonical correlation analysis using the five initial expectations at time t_0 as a predictor of the five measurements of actual E-learning uptake measured at time t_1 (see section 7.1.3). The result from the canonical analysis suggested were four variables statistically significantly influenced the E-learning uptake (h^2 > .20): *initial performance expectancy at* t_0 (PE_{t_0}); *initial effort expectancy at* t_0 (EE_{t_0}), *initial facilitating condition expectancy at* t_0 (FCE_{t_0}); and *initial learning consistency expectancy at* t_0 (LCE_{t_0}).

Most researchers in earlier studies reported that *performance expectancy* is the most important variable influencing the uptake of E-learning, since *performance expectancy* had a higher beta weight than other variables in the same study (Saadé and Bahli, 2005, Lee et al., 2009, Liu et al., 2010a, Šumak et al., 2011b). However, this group of researchers did not check whether *performance expectancy*'s beta weight was significantly higher than other predictors. The interesting research question was now '*What is the most important variable influencing the uptake of E-learning among the four significant variables?*'

Since there were two canonical functions considered noteworthy (see section 7.1.3), the sum square of part-correlation across two functions for each contributing uptake variable (h^2) were compared, rather than the beta. Fisher's *z*-score technique was applied and the procedure was worked in the following way. First, the sum square of part-correlation for each contributing variable was taken as the square root in order to obtain the sum of part-correlation across two functions. Fisher's *z*-score technique was then conducted to calculate the Z-value for each contributing variable and the difference of the Z-value between two variables (Equations 7-1 and 7-2). As there were multiple results, the Bonferroni correction was applied in order to reduce the risk of cumulative Type I error. The significance level for this analysis was set at .008 (.05/6) (see Table 7-26).

Table 7-26: Z-score comparing sum square of part-correlation between contributing variables on the uptake of E-learning

		$h^2{}_1$	$h^2{}_2$	r_{p1}	r_{p2}	Z_1	Z_2	$Z_{difference}$	P-value	Conclusion (alpha = .05/6)
PE_{t_0}	EE_{t_0}	.42	.20	.65	.44	.77	.48	2.1	.04	No sig. difference
	FCE_{t_0}	.42	.39	.65	.63	.77	.73	0.27	.78	No sig. difference
	LCE_{t_0}	.42	.23	.65	.48	.77	.52	1.78	.08	No sig. difference
EE_{t_0}	FCE_{t_0}	.20	.39	.44	.63	.48	.73	-1.8	.07	No sig. difference
	LCE_{t_0}	.20	.23	.44	.48	.48	.52	-0.31	.76	No sig. difference
FCE_{t_0}	LCE_{t_0}	.39	.23	.63	.48	.73	.52	1.5	.13	No sig. difference

The result suggested that there was no significant different in h^2 value between contributing E-learning uptake variables (p > .008): it could be concluded that all four initial expectations (PE_{t_0}, EE_{t_0}, FCE_{t_0} and LCE_{t_0}) contributed equally to uptake of E-learning.

7.3.2 Change of five expectations after using the system in the first time period (RQ6b)

The second sub-research question (RQ6b) to be answered was, *Do the levels of five expectations change over the time as student use E-learning*? To answer this research question, data analysis proceeded in two stages. First, the mean scores of each expectation variable measured at time t_0 and t_1 were compared pair-wise, using a dependent-samples *t*-test. The independent samples *t*-test used a 95 per cent confidence level: α (alpha) was set at 0.05. The null and alternative hypotheses first were set as follows:

H₀: The mean scores of expectation variable is equal between time t_0 and t_1

H₁: The mean scores of expectation variable is different between time t_0 and t_1

The *t*-test indicated only that there was a significant difference in the mean score of each expectation variable at time t_0 and t_1 in the sample: the result could not suggest the consistency of each expectation between t_0 and t_1. To realize this, the consistency of each expectation variable between time t_0 and t_1 was tested using the Pearson product-moment correlation coefficient (Pearson's correlation). Cohen's effect was applied to assess the degree of consistency. The scale was set as follows:

r = 0.1 represented *small* consistency between expectation at time t_0 and t_1

r = 0.3 represented *moderate* consistency between expectation at time t_0 and t_1

r = 0.5 represented *large* consistency between expectation at time t_0 and t_1

If the degree of consistency (r) between each expectation variable at time t_0 and t_1 was less than moderate (r = 0.3), it was concluded that there was a change in expectation between time t_0 and $t_1$on that expectation variables: less than 10 per cent of the expectation at time t_1 accounted for by its expectation at time t_0.

Dependent-samples T-test between each expectation variable at t_0 and t_1

Before conducting an analysis, the statistical condition and assumption required for a dependent-samples *t*-test were checked and found not to be violated (see Appendix 7-V).

Using an alpha level of .05, a dependent-samples *t*-test was conducted to assess whether students' mean aggregated scores of each expectation variable at t_0 and t_1 differed significantly (see Table 7-27).

Table 7-27: Dependent-samples *t*-test result of the comparison of mean aggregated scores between each expectation between t_0 and t_1

	Paired differences					t	df	Effect size	Sig. (2-tailed)
	Mean	Std. deviation	Std error mean	95% Confidence interval of the difference					
				Lower	Upper				
PE_{t_0} - PE_{t_1}	.41	1.6	.18	.05	.76	2.3	76	.26	.03
EE_{t_0} - EE_{t_1}	.12	1.6	.18	-.24	.49	.66	76	.08	.51
SEE_{t_0} - SEE_{t_1}	.25	1.4	.16	-.08	.57	1.5	76	.17	.14
FCE_{t_0} - FCE_{t_1}	.37	1.5	.17	.03	.70	2.2	76	.25	.03
LCE_{t_0} - LCE_{t_1}	.59	1.5	.17	.24	.93	3.4	76	.39	.001

The result showed that students' average *performance expectancy* dropped significantly from 7.2 (*SD* = 1.1) at time t_0 to 6.8 (*SD* = 1.3) at time t_1 ($t(76) = 2.3$, p = .03). It represented a small-size effect, d = 0.26. Similarly, on average, students' *facilitating condition expectancy* at time t_1 (*M* = 6.9, *SD* = 1.3) dropped from time t_0

(M = 7.3, SD = 1.6). The difference was significant, as $t(76) = 2.2$, $p = .03$, and represented a small effect size, $d = 0.25$. The students' average *learning consistency expectancy* at time t_1 (M = 6.7, SD = 1.5) dropped significantly from time t_0 (M = 7.3, SD = 1.2), with $t(76) = 3.4$, $p = .001$, and represented a small effect size $d = 0.39$. However, from time t_0 to t_1, the change in *effort expectancy* means (from 6.7 to 6.6) and *social encouragement expectancy* means (from 7.0 to 6.8) were both non-significant, $t(76) = .66$ and $t(76) = 1.5$ respectively.

The results from the dependent-samples *t*-test (above) suggested that there was no difference in the mean value between t_0 and t_1 for *effort expectancy* and *social encouragement expectancy*. Even though the results showed a significant difference in the mean value between time t_0 and t_1 for three expectation variables (*performance expectancy*, *facilitating condition expectancy* and *learning consistency expectancy*), the effect size of the difference in the mean value for these three variables was quite small. With these results, it may be concluded that there was a very small difference in the mean value of students' five expectations towards E-learning between time t_0 and t_1.

Correlation analysis between each expectation variable at time t_0 and t_1

The Pearson product-moment correlation coefficient (Pearson's correlation) was conducted to check the consistency between value measured at time t_0 and t_1 for each expectation variable. Pearson's correlation requires the data to satisfy one condition and one assumption (see Appendix 7-W). As the required condition and assumption were not violated, Pearson's correlation was conducted (see Table 7-28).

Table 7-28: Correlation analysis result of each pair of measured expectations at time t_0 and t_1

		N	Correlation	Sig.
Pair 1	PE_{t_0} - PE_{t_1}	77	.16	.17
Pair 2	EE_{t_0} - EE_{t_1}	77	.12	.29
Pair 3	SEE_{t_0} - SEE_{t_1}	77	.28	.01
Pair 4	FCE_{t_0} - FCE_{t_1}	77	.35	.002
Pair 5	LCE_{t_0} - LCE_{t_1}	77	.39	< .001

The result showed that there was no significant relationship between the value of students' *performance expectancy* measured at time t_0 and t_1, $r = .16, p = .17$. Similarly, students' *effort expectancy* measured at t_0 was not significantly related to the value measured at t_1, r = .12, p = .29. The significant relationship between expectations at t_0 and $t_1$were found in the pair of *social encouragement expectancy* (r = .28, p = .01), the pair of *facilitating condition expectancy* (r = .35, p = .002) and the pair of *learning consistency expectancy* (r = .39, p < .001). Even though the strength of the relationship for these three pairs was significantly different from zero, the size of strength (effect size) was quite small, according to the work of Cohen (1992).

The results from Pearson's correlation above suggested that there was a very low degree of consistency between the value measured at time t_0 and t_1 for each expectation variable: a high level of expectation at t_0 did guarantee a high level of expectation at t_1. Although the mean value of each expectation variable measured at t_0 and $t_1$was a small difference, with a very low degree of consistency between them, it may be concluded that students' five expectations towards E-learning usage changed over time as they use the E-learning system. This finding led us to investigate further the cause of the change in each expectation variable.

7.3.3 Factors influencing the change of each expectation (RQ6c)

To answer this research question, a stepwise regression analysis was conducted using difference of each expectation as the dependent variable and 22 variables as the independent variables: four other initial expectations at t_0; five perceived performances at t_1; five expectancy confirmation at t_1; four other new measured expectations at t_1; and change in four other expectations between t_0 and t_1. The reason why neither its initial expectation at t_0 nor its new measured expectation at t_1 were included in the analysis is that the difference of each expectation was the discrepancy between the initial expectation at t_0 and new expectation at t_1. If it were included, the R-square would be higher than 1.

Factors influencing the change of performance expectancy between t_0 and t_1

The required statistical conditions and assumptions were not violated (see Appendix7-X). The regression model contained four of 22 predictors, reached in four steps with no variables removed. The model was statistically significant, $F(4,72) = 101.4$, p < .001, and accounted for approximately 85 per cent of the variance in the *change in performance expectancy between* t_0 and t_1 (R-square = .85). The *change of performance expectancy between* t_0 and t_1 was significantly influenced by: *performance expectancy confirmation at*

t_1 (β = 1.1, *t*(76) = 15.5, *p* < .001); *facilitating condition expectancy at* t_1 (β = .20, *t*(76) = 2.8, *p* = .006); *perceived performance of the system at* t_1 (β = -.60, *t*(76) = -7.0, *p* < .001); and *social encouragement expectancy at* t_1 (β = .25, *t*(76) = 3.1, *p* = .003) (see Table 7-29).

Table 7-29: Stepwise regression result of the factors influencing the change of performance expectancy between t_0 and t_1

Independent variables	**Unstandardized Coefficients**		**Standardized Coefficients**	**Correlations**			**t**	**Sig.**
	B	SE_b	β	Zero-order	Partial	Part		
Constant	-9.3	.48					-19.4	< .001
Performance expectancy confirmation at t_1	9.9	.64	1.1	.84	.88	.71	15.5	< .001
Facilitating condition expectancy at t_1	.24	.08	.20	.50	.32	.13	2.8	.006
Perceived performance of the system at t_1	-.62	.09	-.60	.51	-.64	-.32	-7.0	< .001
Social encouragement expectancy at t_1	.31	.10	.25	.51	.34	.14	3.1	.003

a. Dependent variable: Change in performance expectancy between t_0 and t_1

R = . 92[a]; R^2 = .85; $F(4, 72)$ = 101.4; *p*-value < .001

Even though *social encouragement expectancy at* t_1 and *facilitating condition expectancy at* t_1 contributed significantly to the model, their unique contribution (square of part-correlation) was just around 2 per cent: a very small effect size.

A sizable increase in the beta weight from the zero order correlation of *performance expectancy confirmation at* t_1 (from r_s = .84 to *beta* = 1.1) and *perceived performance of the system at* t_1 (from r_s = .51 to *beta* = -.60) indicated the occurrence of suppression in the regression model (Tzelgov and Henik, 1991). The suspected suppressor variable was the *perceived performance of the system at* t_1, because of the difference in the sign between its zero order correlation (positive) and its beta (negative) (Thompson and Levine, 1997).

To investigate whether the *perceived performance of the system at* t_1 was a suppressor variable, multiple regression analysis was carried out. The *change in performance expectancy between* t_0 *and* t_1 regressed with all significant dependent variables apart from *perceived performance of the system at* t_1. Also, the *change in performance expectancy between* t_0 *and* t_1 regressed with all significant dependent variables including the *perceived performance of the system at* t_1(Paulhus et al., 2004) (see Table 7-30).

Table 7-30: Multiple regression analysis result between the change in performance expectancy between t_0 and t_1 and significant variables before and after adding the perceived performance of the system at t_1

Variable	(i) Before adding	(ii) After adding	Change in beta
	beta	beta	
Performance expectancy confirmation at t_1	.76	1.1	.34
Facilitating condition expectancy at t_1	.22	.20	-.02
Perceived performance of system at t_1	-	-.60	-
Social encouragement expectancy at t_1	-.001	.25	.25
	R^2 = .75	R^2= .85	R^2_{change} = .10

When the *perceived performance of the system at* t_1 was added to the equation of ii: (a) it was a contributing variable (*beta* = -.60); (b) it removed or suppressed criterion-irrelevant variance from *performance expectancy confirmation at* t_1 (increased the beta weight from *beta* = .76 to *beta* = 1.1) and *social encouragement expectancy at* t_1 (from *beta* = -.001 to *beta* = .25); and (c) the variance of *change in performance expectancy between* t_0 *and* t_1 accounted for by a set of dependent variables increased by 10 per cent. The result confirmed that *perceived performance of the system at* $t_1$was a suppressor variable for the *performance expectancy confirmation at* t_1, and the *social encouragement expectancy at* t_1.

Since the *social encouragement expectancy at* t_1 had a very small unique effect on the *change in performance expectancy between* t_0 *and* t_1 ($r_p{}^2$ = .002), the suppression effect on this variable was not a focus. To understand better the effect of suppressor *perceived performance of system at* t_1 on the variable *performance expectancy confirmation at* t_1, further examination divided the *perceived performance of system at* t_1 data into two groups: low (less than mean) and high (equal to or greater than mean). Multiple regression analysis was then conducted, regressing the *change in performance expectancy between* t_0 *and* t_1 with the *performance expectancy confirmation at* $t_1$in the low and high *perceived performance of the system at* t_1 group of participants (see Table 7-31).

Table 7-31: Multiple regression result between the change in performance expectancy between t_0 and t_1 and performance expectancy confirmation at t_1 in low and high perceived performance of system at t_1 group of participants

Variable	Low perceived performance group		High perceived performance group		Change in beta
	beta	Sig.	beta	Sig.	
Performance expectancy confirmation	.77	< .001	.87	< .001	.10
	R^2 = .60		R^2= .75		R^2_{change} = .25

The results indicated that the *performance expectancy confirmation at* t_1 had an important influence on the *change in performance expectancy between* t_0 *and* t_1 in both the high and low *perceived performance of system* groups, because the beta weight of this variable was significant in both groups (lower group, *beta* = .77, *p* < .001, higher group *beta* = .87, *p* < .001). The R-square in the high *perceived performance of system* group (.75) was higher than the lower group (.60). The increase in R-square was because the *performance expectancy confirmation*'s beta weight increased from *beta* = .77, *p* < .001 to *beta* = .87, *p* < .001. This implied that the *performance expectancy confirmation at* t_1 was an important factor influencing the *change in performance expectancy* in both the high and low *perceived performance groups*. However, the *performance expectancy confirmation at* t_1 would be more influential on the *change in performance expectancy when* a student's *perceived performance of the system* is high.

Factors influencing the change of effort expectancy between t_0 ***and*** t_1

The required statistical conditions and assumptions were not violated in this analysis (see Appendix 7-Y). The regression model contained four of 22 predictors and was reached in four steps with no variables removed. The model was statistically significant, *F*(4,72) = 93.6, *p* < .001, and accounted for approximately 84 per cent of the variance of the *change in effort expectancy between* t_0 and t_1 (*R*-square = .84). The *change in effort expectancy between* t_0 and t_1 was significantly influenced by: *effort expectancy confirmation at* t_1 (*beta* = 1.0, *t*(76) = 11.4, *p* < .001); *change in social encouragement expectancy between* t_0 *and* t_1 (*beta* = .44, *t*(76) = 6.1, *p* < .001); *perceived ease of use at* t_1 (*beta* = -.43, *t*(76) = -4.5 *p* < .001); and *social encouragement expectancy at* t_0 (*beta* = .28, *t*(76) = 3.9. *p* < .001) (see Table 7-32).

Table 7-32: Stepwise regression result of the factors influencing the change of effort expectancy between t_0 and t_1

Independent variables	Unstandardized Coefficients		Standardized Coefficients	Correlations			t	Sig.
	B	SE_b	β	Zero-order	Partial	Part		
Constant	-8.5	.84					-10.1	< .001
Effort expectancy confirmation at t_1	9.1	.80	1.0	.86	.80	.54	11.4	< .001
Change in social encouragement expectancy between t_0 and t_1	.50	.08	.44	.68	.58	.29	6.1	< .001
Perceived ease of use at t_1	-.50	.11	-.43	.58	-.47	-.21	-4.5	< .001
Social encouragement expectancy at t_0	.41	.10	.28	-.31	.42	.19	3.9	< .001

a. Dependent variable: Change in effort expectancy between t_0 and t_1

$R = .92^a$; $R^2 = .84$; $F(4, 72) = 93.6$; p-value < .001

Even though the *change in social encouragement expectancy between* t_0 *and* t_1, the *perceived ease of use at* t_1, and the *social encouragement expectancy at* t_0 had a significant influence on the *change in effort expectancy between* t_0 *and* t_1, these variables' influence was small, according to the work of Cohen (1992): the part-correlation was lower than 0.3.

Factors influencing the change of social encouragement expectancy between t_0 and t_1

The statistical conditions and assumptions were not violated in this analysis (see Appendix 7-Z). The regression model contained five of 22 predictors and was reached in five steps with no variables removed. The model was statistically significant, $F(5,71) = 106.5$, $p < .001$, and accounted for approximately 88 per cent of the variance of the *change in social encouragement expectancy between* t_0 and t_1 (R-square = .88). The *change in social encouragement expectancy between* t_0 and t_1 was significantly influenced by: *social encouragement expectancy confirmation at* t_1 (*beta* = 1.1, $t(76) = 16.8$, $p < .001$); *effort expectancy at* t_1 (*beta* = .22, $t(76) = 3.6$, $p = .001$); *perceived social encouragement at* t_1 (*beta* = -.75, $t(76) = -7.8$, $p < .001$); *learning consistency expectancy at* t_1 (*beta* = .35, $t(76) = 4.7$, $p < .001$); and *performance expectancy at* t_1 (*beta*= .16, $t(76) = 2.2$, $p = .03$) (see Table 7-33).

Table 7-33: Stepwise regression result of the factors influencing the change of social encouragement expectancy between t_0 and t_1

Independent variables	Unstandardized Coefficients		Standardized Coefficients	Correlations			t	Sig.
	B	SE_b	β	Zero-order	Partial	Part		
Constant	-9.4	.42					-22.4	< .001
Social encouragement expectancy confirmation at t_1	9.4	.56	1.1	.86	.89	.69	16.8	< .001
Effort expectancy at t_1	.25	.07	.22	.57	.39	.15	3.6	.001
Perceived social encouragement at t_1	-.75	.09	-.75	.59	-.69	-.33	-7.8	< .001
Learning consistency expectancy at t_1	.33	.07	.35	.53	.49	.19	4.7	< .001
Performance expectancy at t_1	.18	.08	.16	.56	.26	.09	2.2	.03

a. Dependent variable: Change in social encouragement expectancy

$R = .94^a$; $R^2 = .88$; $F(5, 71) = 106.5$; p-value < .001

According to the work of Cohen (1992), although the *effort expectancy at* t_1, the *learning consistency expectancy at* t_1 and the *performance expectancy at* t_1 were significant predictors of the *change in social encouragement expectancy between* t_0 *and* t_1, these variables' effect sizes were small (r_p < .3). The *social encouragement expectancy confirmation at* t_1 had a significant major effect on the *change in social encouragement expectancy between* t_0 and t_1 (r_p > .5), while the *perceived social encouragement at* t_1 had a moderate yet significant effect.

A sizable increase in the beta weight from the zero order correlation of *social encouragement expectancy confirmation at* t_1 (from r_s = .86 to *beta* = 1.1) and *perceived social encouragement at* t_1 (from r_s = .59 to *beta* = -.75) indicated suppression in the regression model (Tzelgov and Henik, 1991). With a difference in sign between its zero order correlation (positive) and its beta (negative), the suspected suppressor variable was *perceived social encouragement at* t_1 (Thompson and Levine, 1997).

To investigate whether *perceived social encouragement at* t_1 was a suppressor variable, multiple regression analysis was carried out: (i) the *change in social encouragement expectancy between* t_0 and t_1 regressed with all significant dependent variables apart from *perceived social encouragement at* t_1; and (ii) the *change in social encouragement expectancy between* t_0 and t_1 regressed with all significant dependent variables including the *perceived social encouragement at* t_1 (Paulhus et al., 2004) (see Table 7-34).

Table 7-34: Multiple regression analysis result between the change in social encouragement expectancy between t_0 and t_1 and significant variables before and after adding perceived social encouragement at t_1

Variable	**(i) Before adding beta**	**(ii) After adding beta**	**Change in beta**
Social encouragement expectancy confirmation at t_1	.75	1.1	.35
Effort expectancy at t_1	.16	.22	.06
Perceived social encouragement at t_1	-	-.75	-
Learning consistency expectancy at t_1	.10	.35	.25
Performance expectancy at t_1	-.02	.16	.18
	R^2 = .78	R^2= .88	R^2_{change} = .10

When the *perceived social encouragement at* t_1 was added to the equation of ii: (a) it was a contributing variable (*beta* = -.75, *p* < .001); (b) it removed or suppressed criterion-irrelevant variance from the *social encouragement expectancy confirmation at* t_1 (increased the beta weight from *beta* = .75 to *beta* = 1.1), the *effort expectancy at* t_1 (increased the beta weight from *beta* = .16 to *beta* = .22), the *learning consistency expectancy at* t_1 (increased the beta weight from *beta* = .10 to *beta* = .35) and the *performance expectancy at* t_1 (increased the beta weight from *beta* = -.02 to *beta* = .16); and (c) the variance of the *change in social encouragement expectancy between* t_0 and t_1 accounted for by a set of dependent variables was increased by 10 per cent. The result confirmed that *perceived social encouragement at* t_1 was a suppressor variable for all significant predictors of *change in social encouragement expectation between* t_0 and t_1.

Since the *effort expectancy at* t_1, *learning consistency expectancy at* t_1 and *performance expectancy at* t_1 had a very small unique effect on the *change in social encouragement expectancy between* t_0 and t_1, the suppression effect on these variables was not regarded as a focus.

To understand better the effect of the suppressor of *perceived social encouragement at* t_1 on the variable *social encouragement expectancy confirmation at* t_1, further examination divided the *perceived social encouragement at* t_1 data into two groups: low (less than mean) and high (equal to or greater than mean). Multiple regression analysis was then conducted, regressing the *change in social encouragement expectancy between* t_0 and t_1, with the *social encouragement expectancy confirmation at* t_1 in the low and high *perceived social encouragement at* t_1 groups of participants (see Table 7-35).

Table 7-35: Multiple regression analysis result between the change in social encouragement expectancy between t_0 and t_1 and social encouragement expectancy confirmation at t_1 in the low and high perceived social encouragement at t_1 groups of participants

Variable	**Low perceived social encouragement group**		**High perceived social encouragement group**		**Change in beta**
	beta	**Sig.**	**beta**	**Sig.**	
Social encouragement expectancy confirmation at t_1	.90	< .001	.72	< .001	-.18
	R^2 = .80		R^2= .52		R^2_{chnage} = -.28

The result indicated that the *social encouragement expectancy confirmation at* t_1 played an important influence on the *change in social encouragement expectancy between* t_0 and t_1 in both high and low *perceived social encouragement* groups, because the beta weight of this variable was significant in both groups (lower group, *beta* = .90, $p <$ .001, higher group, *beta* = .72, $p <$ .001). The R-square in the low *perceived social encouragement* group (.80) was higher than in the higher group (.52). This implied that the *social encouragement expectancy confirmation* was an important factor affecting the *change in social encouragement* in both the high and low *perceived social encouragement* groups. However, the *social encouragement confirmation* will be more influential on the *change in social encouragement* if a student has low level of *perceived social encouragement*.

Factors influencing the change of facilitating condition expectancy between t_0 ***and*** t_1

The required conditions and assumptions were not violated (see Appendix 7-ZA). The regression model contained six of 22 predictors, and was reached in six steps with no variables removed. The model was statistically significant, $F(6,70) = 54.4$, $p < .001$, and accounted for approximately 82 per cent of the variance of the *change in facilitating* *condition expectancy between t_0 and t_1* (R-square = .82). The *change in facilitating condition expectancy between t_0 and t_1* was significantly influenced by: *facilitating condition expectancy confirmation at t_1* (*beta* = 1.1, *t*(76) = 9.5, *p* < .001); *change in learning consistency expectancy between t_0* and t_1 (*beta* = .86, *t*(76) = 6.5, *p* < .001); *perceived facilitating condition at t_1* (*beta*= -.76, *t*(76) = -5.6, *p* < .001); *learning consistency expectancy at t_0* (*beta* = .46, *t*(76) = 4.5, *p* < .001); *change in performance expectancy between t_0* and t_1 (*beta* = .34, *t*(76) = 3.4, *p* = .001); and *performance expectancy confirmation at t_1* (*beta* = -.22, *t*(76) = -2.3, *p* = .03) (see Table 7-36).

Table 7-36: Stepwise regression analysis result of the factors influencing the change of facilitating condition expectancy between t_0 and t_1

Independent variables	**Unstandardized Coefficients**		**Standardized Coefficients**	**Correlations**			**t**	**Sig.**
	B	SE_b	β	Zero-order	Partial	Part		
Constant	-5.5	1.3					-4.2	< .001
Facilitating condition expectancy confirmation at t_1	8.9	.94	1.1	.76	.75	.48	9.5	< .001
Change in learning consistency expectancy between t_0 and t_1	.57	.06	.86	.70	.61	.33	6.5	< .001
Perceived facilitating condition at t_1	-.76	.14	-.76	.47	-.56	-.28	-5.6	< .001
Learning consistency expectancy at t_0	.55	.12	.46	-.35	.47	.23	4.5	< .001
Change in performance expectancy between t_0 and t_1	.33	.10	.34	.60	.38	.17	3.4	.001
Performance expectancy confirmation at t_1	-1.9	.83	-.22	.46	-.26	-.11	-2.3	.026

a. Dependent variable: Change in facilitating condition expectancy between t_0 and t_1

$R = .91^a$; $R^2 = .82$; $F(6, 70) = 54.4$; p-value < .001

According to the work of Cohen (1992), the *facilitating condition expectancy confirmation at t_1* and the *change in learning consistency expectancy between t_0* and t_1 had a moderate yet significant effect on the *change in facilitating condition expectation between t_0* and t_1 ($.3 \leq r_p \leq .5$). However, the *perceived facilitating condition at t_1*, the *learning consistency expectancy at t_0*, the *change in performance expectancy between t_0 and t_1*, and the *performance expectancy confirmation at t_1* showed little effect.

Factors influencing the change of learning consistency expectancy between t_0 and t_1

The required condition and assumption were not violated (see Appendix 7-ZB). The regression model contained four of 22 predictors and was reached in four steps with no variables removed. The model was statistically significant, $F(4,72) = 110.8$, $p < .001$, and accounted for approximately 86 per cent of the variance of the *change in learning consistency expectancy* between t_0 and t_1 (R-square = .86). The *change in learning consistency expectancy* between t_0 and t_1 was significantly influenced by: *learning consistency expectancy confirmation at* t_1 (*beta* = 1.0, $t(76) = 15.6$, $p < .001$); *facilitating condition expectancy at* t_1 (*beta* = .41, $t(76) = 5.6$, $p < .001$); *perceived learning consistency expectancy at* t_1 (*beta* = -.77, $t(76) = -8.1$, $p < .001$); and *social encouragement expectancy at* t_1 (*beta*= .38, $t(76) = 4.7$, $p < .001$) (see Table 7-37).

Table 7-37: Stepwise regression analysis result of the factors influencing the change in learning consistency expectancy between t_0 and t_1

Independent variables	**Unstandardized Coefficients**		**Standardized Coefficients**	**Correlations**			**t**	**Sig.**
	B	SE_b	β	Zero-order	Partial	Part		
Constant	-10.4	.49					-21.4	< .001
Learning consistency expectancy confirmation at t_1	9.2	.59	1.0	.81	.88	.69	15.6	< .001
Facilitating condition expectancy at t_1	.47	.08	.41	.60	.55	.25	5.6	< .001
Perceived learning consistency at t_1	-.75	.09	-.77	.55	-.69	-.36	-8.1	< .001
Social encouragement expectancy at t_1	.45	.10	.38	.56	.48	.21	4.7	< .001

a. Dependent variable: Change in learning consistency expectancy between t_0 and t_1

$R = .93^a$; $R^2 = .86$; $F(4, 72) = 110.8$; p-value < .001

Based on the work of Cohen (1992), *learning consistency expectancy confirmation at* t_1 had a significantly large effect on the change of *learning consistency expectancy between* t_0 *and* t_1, while *perceived learning consistency at* t_1 showed a moderate effect. The other two variables (*facilitating condition expectancy at* t_1 and *social encouragement expectancy at* t_1) had a small effect.

A sizable increase in the beta weight from the zero order correlation of the *learning consistency expectancy confirmation at* t_1 (from r_s = .81 to *beta* = 1.0) and *perceived learning consistency at* t_1 (from r_s = .55 to *beta* = -.77) indicated suppression in the regression model (Tzelgov and Henik, 1991). With a difference in sign between its zero order correlation (positive) and its beta (negative), the suspected suppressor variable was *perceived learning consistency at* t_1(Thompson and Levine, 1997).

To investigate whether the *perceived learning consistency at* t_1 was a suppressor variable, multiple regression analysis was carried out: (i) *the change in learning consistency expectancy between* t_0 *and* t_1 regressed with all significant dependent variables apart from *perceived learning consistency at* t_1; (ii) *the change in learning consistency expectancy between* t_0 *and* t_1 regressed with all significant dependent variables including *perceived learning consistency at* t_1 (Paulhus et al., 2004) (see Table 7-38).

Table 7-38: Multiple regression analysis result between the change in learning consistency expectancy between t_0 and t_1 and significant variables before and after adding perceived learning consistency at t_1

Variable	(i) Before adding beta	(ii) After adding beta	Change in beta
Learning consistency expectancy confirmation at t_1	.68	1.0	.32
Facilitating condition expectancy at t_1	.25	.41	.16
Perceived learning consistency at t_1	-	-.77	-
Social encouragement expectancy at t_1	.06	.38	.28
	R^2 = .73	R^2= .86	R^2_{change} = .13

When *perceived learning consistency at* $t_1$was added to the equation of ii: (a) it was a contributing variable (*beta* = -.77, p < .001); (b) it removed or suppressed criterion-irrelevant variance from the *learning consistency expectancy confirmation at* t_1 (increased the beta weight from *beta* = .68 to *beta* = 1.0), the *facilitating condition expectancy at* t_1 (increased the beta weight from *beta* = .25 to *beta* = .41) and the *social encouragement expectancy at* t_1 (increased the beta weight from *beta* = .06 to *beta* = .38); and (c) the variance of *change in learning consistency expectancy between* t_0 *and* t_1 accounted for by a set of dependent variables was increased by 13 per cent. The result showed that *perceived learning consistency at* t_1 was a suppressor variable for all significant predictors of *change in learning consistency expectancy between* t_0 *and* t_1.

Since the *facilitating condition expectancy at* t_1 and *social encouragement expectancy at* t_1 had a very small unique effect on the *change in learning consistency expectancy between* t_0 *and* t_1, the suppression effect on these variables was not a focus.

To understand better the effect of suppressor *perceived learning consistency at* t_1 on the variable *learning consistency expectancy confirmation at* t_1, further examination divided the *perceived learning consistency at* t_1 data into two groups: low (less than mean) and high (equal to or greater than mean). Multiple regression analysis was then conducted, regressing the *change in learning consistency expectancy between* t_0 *and* t_1 with *learning consistency expectancy confirmation at* t_1 in the low and high *perceived learning consistency* group of participants (see Table 7-39).

Table 7-39: Multiple regression result between the change in learning consistency expectancy between t_0 and t_1 and learning consistency expectancy confirmation at t_1 in low and high perceived learning consistency at t_1 group of participants

Variable	**Low perceived learning consistency group**		**High perceived learning consistency group**		**Change in beta**
	beta	**Sig.**	**beta**	**Sig.**	
Learning consistency confirmation	.76	< .001	.71	< .001	-.05
	R^2 = .57		R^2= .50		R^2_{change} = -.07

The results indicated that *learning consistency expectancy confirmation at* t_1 played an important influence on the *change in learning consistency expectancy between* t_0 *and* $t_1$in both high and low *perceived learning consistency* group, because the beta weight of this variable was significant in both groups (lower group, *beta* = .76, $p < .001$, higher group *beta* = .71, $p < .001$). The R-square in the low *perceived learning consistency* group (.57) was higher than in the high group (.50). This implied that the *learning consistency expectancy confirmation at* $t_1$was an important factor influencing the *change in learning consistency expectancy between* t_0 *and* $t_1$in both the high and low *perceived learning consistency groups*. However, the *learning consistency expectancy confirmation at* t_1 would be more influential on the *change in learning consistency expectancy between* t_0 *and* t_1 if a student had a low level of *perceived learning consistency*.

7.3.4 *The influence of the change in expectations on the change of E-learning actual usage (RQ6d)*

After checking the required conditions and assumptions (see Appendix 7-ZC), canonical correlation analysis was conducted using the change of five expectation variables between t_0 and t_1 (*change in performance expectancy*; *change in effort expectancy*; *change in social encouragement expectancy*; *change in facilitating condition expectancy*; and *change in learning consistency expectancy*) as independent variables and the change of five E-learning actual usages between first (t_0- t_1) and second usage (t_1- t_2) time period (*change in percentage (subjective) between first and second usage period*; *change in time spent (subjective) between first and second usage period*; *change in time spent (objective) between first and second usage period*; *change in number of times logging on (objective) between first and second usage period*; and *change in number of activities involving (objective) between first and second usage period*) as dependent variables.

The set of dependent and independent variables was statistically significant, using the Wilks' λ criterion = .44, $F(25, 235.5) = 2.4$, $p < .001$. Accordingly, there was at least one significant relationship between the change of expectation variables and the change of E-learning actual usage measurements. Wilks' λ represented the variance in the combination of dependent variables unexplained by the set of independent variables. It can be concluded that 56 per cent (1- λ) of variance in the change of E-learning actual usage was accounted for by the change of expectation variables.

The canonical correlation analysis yielded five functions with squared canonical correlations (${R_c}^2$) of .46, .09, .07, .03 and .008 respectively for each successive function (see Table 7-40).

Table 7-40: Canonical correlation analysis of the relationship between the change in five expectations and the change in five E-learning actual usages

Function	Eigenvalue	%	Cumulative %	Canonical Correlation	Squared Correlation
1	.86	79.4	79.4	.68	.46
2	.10	9.5	89.0	.31	.09
3	.07	7.1	96.1	.27	.07
4	.03	3.2	99.2	.18	.03
5	.008	.76	100.0	.09	.008

The dimension reduction analysis was used to test the hierarchal arrangement of functions for statistical significance in order to determine which should be interpreted. Function 1 to 5 was statistically significant, as F(25, 235.5) = 2.4, $p < .001$ (see Table 7-41). The cumulative effects of Functions 2 to 5, Functions 3 to 5, Functions 4 to 5 and Function 5 in isolation were not statistically significant. According to this result, the first function was considered noteworthy in the context of this study (46% of shared variance). Functions 2, 3, 4 and 5 were not chosen to be interpreted, as they explained only 9 per cent, 7 per cent, 3 per cent and .8 per cent of the remaining variance in the variable sets after extraction of the prior functions.

Table 7-41: Dimension reduction analysis for canonical functions of the relationship between the change of five expectations and the change of five E-learning actual usages

Roots	Wilks' λ	F	Hypothesis DF	Error DF	Significance of F
1 to 5	.44	2.4	25	235.5	< .001
2 to 5	.81	.89	16	196.2	.59
3 to 5	.89	.86	9	158.3	.57
4 to 5	.96	.70	4	132.0	.59
5 to 5	.99	.55	1	67.0	.46

Three dependent variables contributed to the Function 1-dependent variate ($|r_p|$ > .30): (a) *the change in percentage (subjective) between first and second usage period* (r_p = -.70); (b) *the change in time spent (subjective) between first and second usage period* (r_p = .30); and (c) *the change in time spent (objective) between the first and second usage period* (r_p = -.31) (see Table 7-42). A sizable increase in the beta weight from the zero order correlation of the change of percentage of E-learning usage in education subjective measure (from r_s = -.87 to *beta* = -1.0) indicated suppression in the Function 1 dependent variate (Tzelgov and Henik, 1991). The *change in time spent (subjective) between the first and second usage period* was a suppressor, because of the difference in sign between its zero order correlation (negative) and its beta (positive) (Thompson and Levine, 1997). However, there was no single independent variable that showed a significant effect on the change of E-learning actual usage, because the part-correlation was lower than .3: together they contributed to the change in the actual usage of E-learning.

Table 7-42: Canonical solution of the relationship between the change of five expectations and the change of five E-learning actual usages

		Function 1				
		Coef	r_s	r_p	r_p^2 (%)	*Summary*
Dependent	Change in percentage (subjective) between first and second usage period	-1.0	−.87	−.70†	.49	Contributed
	Change in time spent (subjective) between first and second usage period	.38	−.23	.30†	.09	Contributed
	Change in time spent (objective) between first and second usage period	-.52	−.64	−.31†	.09	Contributed
	Change in number of times logging on (objective) between first and second usage period	-.15	−.51	-.12	.02	No
	Change in number of activities involving (objective) between first and second usage period	.47	−.44	.27	.07	No
Independent	Change in performance expectancy	-.44	−.80	-.28	.08	No
	Change in effort expectancy	-.40	−.76	-.28	.08	No
	Change in social encouragement expectancy	.44	−.64	.25	.06	No
	Change in facilitating condition expectancy	-.25	−.80	-.17	.03	No
	Change in learning consistency expectancy	-.50	−.88	-.29	.09	No

Coef = Standardized coefficient (beta) between variable and with variate;
r_s = Zero order correlation
r_p = Part-correlation († greater than $|.30|$)
r_p^2 = Squared part-correlation
h^2 = sum squared part-correlation

7.4 Validation of a relationship between E-learning usage and a student's learning performance (RQ7)

The dependent variable was a student's *relative standardized score of the final exam in General Statistics, measured at* t_2. Five measurements of E-learning usage in General Statistics during t_0 to t_2 were used as the independent variable: (a) *subjective percentage of E-learning usage in education during* t_0 *and* t_2; (b) *subjective time spent learning with E-learning during* t_0 *and* t_2; (c) *objective time spent on E-learning during* t_0 *and* t_2; (d) *objective total number of times logging onto E-learning during* t_0 *and* t_2; and (e) *objective total number of activities involving E-learning during* t_0 *and* t_2. As students do not perform equally in learning, a student's *relative standardized score of the midterm exam in general statistics measured at* t_0 was used as another independent variable. Multiple regression analysis was conducted to detect what was a significant predictor of a student's relative standardized score in the final exam in general statistics. A student's relative standardized score in the final exam in general statistics measured at t_2 was regressed with five measurements of E-learning usage during t_0 and t_2 and a student's relative standardized score of midterm exam measured at t_0. The assumptions required were checked and are described in Appendix 7-ZD.

The linear combination of relative standardized midterm score and the five measurements of E-learning actual usage at during t_0 and t_2 was significantly related to *relative standardized score of the final exam in general statistics measured at* t_2: $F(6, 69) = 11.9$, $p < .001$ (see Table 7-43). The multiple correlation coefficient was .71, indicating that approximately 51 per cent of the variance of *relative standardized score of the final exam in General Statistics measured at* $t_2$was accounted for by the linear combination of relative standardized midterm score and the five measurements of E-learning actual usage at during t_0 and t_2. Among the six dependent variables, *relative standardized score of the midterm exam in general statistics measured at* t_0 was the only significant contributing predictor: *beta* = .72, $t(75) = 7.9$, $p < .001$.

Table 7-43: Multiple regression analysis result for relative standardized final exam score with relative standardized final midterm score and the five measurements of E-learning usage during t_0 and t_2

Independent variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	SE_b	β		
Constant	-.78	.79		-.98	.33
Relative standardized of midterm score	.72	.09	.72	7.9	< .001
Percentage (subjective) during t_0 and t_2	.002	.005	.04	.35	.73
Time spent (subjective) during t_0 and t_2	.26	.30	.09	.86	.39
Time spent (objective) during t_0 and t_2	-.11	.34	-.06	-.33	.74
Number of times logging on (objective) during t_0 and t_2	.51	.41	.14	1.3	.21
Number of activities (objective) during t_0 and t_2	-.05	.39	-.02	-.13	.90

a. Dependent variable: relative standardized of final score

$R = .71^a$; $R^2 = .51$; $F(6, 69) = 11.9$; p-value < .001

This result suggested that students who achieve high scores midterm will always achieve a high score in the final exam, and that the level of E-learning usage (5 measurements) does not affect performance in the final exam.

7.5 Summary of Chapter 7

This chapter presented the results and statistical analyses of the model validation phase to help answer the four research questions, RQ4, RQ5, RQ6 and RQ7. The chapter started with an assessment of the EU sub-model performance (RQ4) and the results indicated that statistically it did as well in predicting the uptake of E-learning as the two comparative models (TAM and UTAUT). For assessing the performance of the EC sub-model (RQ5), reported in the second section of the chapter, the results showed that its equation performance and variables' predictive power on continued use of E-learning was statistically equal to that of the TAM, UTAUT and ECM models. The third section reported on the results about the validations of relationships between the EUCH model variables (RQ6), suggesting that: (a) four of the five proposed initial expectations statistically contributed to the uptake of E-learning; (b) all five expectations changed statistically during the first usage time period (t_0 to t_1); (c) the change in each expectation was mainly statistically influenced by the level of its expectation confirmation; and (d) the change in the level of these expectation variables collectively had a significant influence, with a corresponding change in level of E-learning usage. The fourth section provided the relationship between E-learning usage and a student's learning performance (RQ7), suggesting that the relative standardized score in the midterm exam in general statistics (previous academic capability) was the only significant contributing variable for the relative standardized score of the final exam in General Statistics. No influence from E-learning usage was found. The next chapter discusses all the obtained statistical results.

Chapter 8 Discussion of EUCH Model Validation Findings

This chapter discusses the statistical results from the model validation phase, including possible reasons for each finding for research questions RQ4, RQ5, RQ6 and RQ7. In addition, the implications of the findings are suggested for higher education policy makers, practitioners and further studies. A summary of the discussion is provided at the end of the chapter.

8.1 EU sub-model's Performance of the Uptake of E-learning (RQ4)

The intent of the model validation phase was first to compare the EU sub-model equation and variables to the TAM and UTAUT in terms of their contribution to predicting and explaining E-learning uptake. The degree of consistency between the model equation's prediction of E-learning uptake at t_0 and the actual level of E-learning uptake as gauged by the five measurements at t_1 was taken to be an indicator of equation's performance. The equation's performance was calculated by multiple regression analysis. The overall ability of model predictors (variables) to fit actual uptake data, expressed by a goodness-of-fit measure R^2, was used as the indicator of model variables predictive power and was calculated by canonical correlation analysis. Fisher's (1921) Z-transform technique was used to compare the EU sub-model equation's performance and model variables' predictive power for E-learning uptake with that of the two comparative models (TAM and UTAUT).

The results of multiple regression analysis showed a significant degree of consistency between the model equation's prediction of E-learning uptake at t_0 and the level of actual E-learning uptake as measured by five measurements at $t_{1,}$ in both the

EU sub-model and the two comparative models (TAM and UTAUT). Cohen's (1992) effect size was applied to assess all three model equations' performance (degree of consistency) regarding E-learning uptake, and the results suggested that they showed a moderate predictive performance in terms of E-learning uptake: all three predicted the uptake of E-learning quite well. The result of Fisher's Z-transform showed that the EU sub-model equation's performance of E-learning uptake was not statistically significantly different from that provided by the TAM and UTAUT equations: they predicted the uptake of E-learning equally well.

The results from canonical correlation analysis showed that the variables in all three models (EU sub-model, TAM and UTAUT) accounted for a significant degree of variance in the actual of E-learning uptake. According to the work of Cohen (1992), the EU sub-model variables had a high level of predictive power of E-learning uptake, while the TAM and UTAUT had moderate predictive power. However, the difference was not large enough to conclude that the EU sub-model was better at predicting the uptake of E-learning than TAM and UTAUT: the result of Fisher's Z-transform reported that the EU sub-model's predictive power was not statistically significantly different from the other two.

With the addition of three variables (*social encouragement expectancy*, *facilitating condition expectancy* and *learning consistency expectancy*) to the TAM variables and one variable (*learning consistency expectancy*) to the UTAUT variables in the EU sub-model, it was anticipated that the EU sub-model would provide the highest predictive power of E-learning uptake. Although the EU sub-model had a higher degree of predictive power than TAM and UTAUT in E-learning uptake, as expected, the result of Fisher's Z-transform suggested that the difference was not large enough to conclude that the EU sub-model was better than the other two on statistical grounds. A possible explanation for such a finding might be due to overlap between variables in the variance in uptake of E-learning. To give an example from the EU sub-model, when *learning consistency expectancy* was added to four UTAUT variables (*performance expectancy*, *effort expectancy*, *social encouragement expectancy* and *facilitating condition expectancy*), the unique contribution to the uptake of E-learning for all four UTAUT variables was reduced from that found in UTAUT: there was a commonality between *learning consistency expectancy* and the four UTAUT variables. This might be the reason why, when *learning consistency expectancy* was incorporated, the contribution of this variable did not show a significant difference between the EU sub-model and the UTAUT. This might also be an explanation for the lack of significant difference between the EU sub-model and the TAM in terms of their predictive power.

Typically, when predictive power is equivalent, the 'best' model may be the most parsimonious, demonstrating good prediction while using the fewest predictors (Mulaik et al., 1989; Bagozzi, 1992). Therefore, if the sole goal is prediction of E-learning uptake, the TAM is the model of choice: it allows a quick and inexpensive way to gather data and make a prediction. However, if the goal is to devise a strategy to support the uptake of E-learning at a university, the EU sub-model is recommended, since the model provides a more complete profile of the determinants of E-learning uptake than the two other models.

The result from the canonical correlation analysis of the relationship between the five initial expectation factors at t_0 and the five measurements of actual E-learning uptake at t_1 suggested that, apart from the two system design factors (*performance expectancy*, $h^2 = .42$, and *effort expectancy*, $h^2 = .20$) as suggested by TAM and the resource factor (*facilitating condition expectancy*, $h^2 = .39$) as suggested by UTAUT, the additional learning motivation factor (*learning consistency expectancy*, $h^2 = .23$) suggested by EU sub-model also practically influences the uptake of E-learning (see Table 7-8). Moreover, the result from Z-score comparing the contribution of these four influential factors on the uptake of E-learning showed that these four expectations contributed statistically equally to uptake of E-learning: the additional *learning consistency expectancy* factor is as important as the factors from TAM and UTAUT (see Table 7-26). On this basis, the EU sub-model improves the understanding of E-learning uptake by adding a learning motivation factor.

8.2 EC sub-model's Performance of the Continued Use of E-learning (RQ5)

The other aim of the model validation phase was to compare the EC sub-model to the three comparative models (TAM, UTAUT and ECM) in terms of their contribution to the prediction and explanation of continued use of E-learning. The degree of consistency between the model equation prediction of continued use of E-learning at t_1 and the actual level of continued use of E-learning as measured at t_2 was used as an indicator of the model equations' performance. This was calculated by multiple regression analysis. The overall ability of model predictors (variables) to fit actual continued use data, R^2, was used as the indicator of model variables predictive power and was calculated by canonical correlation analysis. Fisher's (1921) Z-transform technique was used to compare the equation performance and model variables' predictive power of the EC sub-model with that of the three comparative models.

The result of multiple regression analysis showed a significant degree of consistency between the model equation's prediction of continued use of E-learning at t_1 and the actual level of continued use of E-learning at t_2 in all four models (EC sub-model, ECM, TAM and UTAUT). According to the work of Cohen (1992), the two specific continuance model equations (EC sub-model, and ECM) had a high level of predictive performance, while the two general technology usage model equations (TAM and UTAUT) had moderate predictive performance. Since there was a difference in predictive capability between the specific continuance models and the general technology usage models, the Z-transform technique was again conducted to compare the predictive performance of continued use E-learning among the four model equations to test whether two kinds of models were significantly different (see Appendix 8-A). The results indicated that performance was not statistically significantly different among the four model equations: this implied that the specific models of continuance (EC sub-model and ECM) and two general technology usage models (TAM and UTAUT) were similarly effective in predicting continued use.

The results from canonical correlation analysis were that the variables of all four models (EC sub-model, ECM, TAM and UTAUT) accounted for a significant percentage of variance in the actual level of continued use of E-learning. According to Cohen (1992), the variables in all four models of interest had a high level of predictive power for continued use of E-learning. The result of Fisher's Z-transform reported that the EC sub-model's predictive power was not statistically significantly different from the other three models. With this result, it can be concluded that the model variables in the EC sub-model and the other three comparative models predicted the continued use of E-learning equally well.

The high degree of consistency between each pair of calculated and measured expectations at t_1 might be why the models using calculated expectations (the EC sub-model and ECM) and the models using measured expectations (TAM and UTAUT) were not statistically significantly different in terms of their predictive power (see Appendix 8-B). A possible explanation for the lack of statistically significant difference in predictive power, even though the four model variables (*calculated EE*, *calculated SEE*, *calculated FCE*, and *calculated LCE*) were added to a ECM model variable (*calculated PE*) in the EC sub-model, might be due to overlap in the variance in continued use of E-learning between variables: when a variable was added to the model, it provided the predictive power that had already been given by other variables (commonality). To illustrate this point, even though the additional four variables alone had a strong influence on continued use of E-learning (r_s > .5), the unique contribution (r_p) of each variable was less than .3. This indicated overlap of the variance in continued use of E-learning between the *calculated PE* and the additional four variables. This is the reason why the inclusion of four additional variables did not make the EC sub-model significantly better than ECM at predicting E-learning continued usage.

The results from the longitudinal study indicated that all four models were similarly effective at predicting and explaining the continued use of E-learning. To be parsimonious, and if the sole goal is the prediction of E-learning continued use, TAM is the model of choice. However, if the goal is to devise a strategy to support the continued use of E-learning at university, the EC sub-model is recommended since it provides a more complete profile of the determinants of continued use of E-learning than other models.

In the EC sub-model, the level of each expectation factor at t_1 is calculated as the product of its initial level at t_0 and its expectancy confirmation at t_1 (see Equation 5-7). The result of the longitudinal study confirmed that there was statistically significant consistency between measured and calculated expectation at t_1 (see Appendix 8-B). By using calculated expectation at t_1, the EC sub-model relates antecedent initial level and expectancy confirmation to high or low expectation at t_1 which is not possible in the TAM and UTAUT models. ECM starts at t_1 and emphasises the post acceptance variables only: this model does not take initial expectation into account (Bhattacherjee, 2001). Apart from bad experience during usage (low expectancy confirmation), low expectation at t_1 could also be due to low initial expectation at t_0. On this basis, the EC sub-model provides more understanding of E-learning continued use than existing comparative models.

8.3 Relationships between EUCH Model Variables (RQ6)

The intent of the study was also to investigate relationships between the proposed EUCH model variables. The results are discussed in the following sections.

8.3.1 Factors influencing the uptake of E-learning (RQ6a)

Canonical correlation analysis was conducted between the five EUCH initial expectation variables measured at time t_0 (performance expectancy at t_0, effort expectancy at t_0, social encouragement expectancy at t_0, facilitating condition expectancy at t_0, and learning consistency expectancy at t_0) and the five measurements of actual uptake of E-learning at time t_1. This was to check whether was there a significant relationship between each initial expectation variable and the linear combination of the five measurements of actual E-learning uptake.

Influence of performance expectancy on the uptake of E-learning

The result of the canonical correlation analysis revealed that *performance expectancy* was a statistically significant contributing variable in the uptake of E-learning. This meant that a student who had a high level of expectation that usage of E-learning system could support him/her to learn more quickly and achieve better grades normally showed a higher level of uptake of E-learning than a student with a low expectation.

Several studies on higher education in Thailand and other countries have also revealed that *performance expectancy* plays an important role in influencing students' uptake of E-learning (Liu et al., 2009; Gaitán et al., 2011; Bhrommalee, 2012). This was not a surprising finding since E-learning is viewed as technology that facilitates learning: students will spend more time on this technology if they expect that E-learning helped them to learn better. This finding has important implications for E-learning system designers and developers in that the functionality of E-learning should provide facilitate learning effectively in order to encourage student users to learn more quickly and achieve better learning performance than other possible self-learning techniques. If the design and development of an E-learning system complies with this prerequisite, it can be expected that students will tend to spend more time using it.

Influence of effort expectancy on the uptake of E-learning

The results confirmed that *effort expectancy* was a variable that contributed statistically significantly to the uptake of E-learning among students in higher education. This indicated that a student who had a high expectation that the use of E-learning system would be easy normally demonstrated a higher level of E-learning uptake than a student with a low expectation.

A similar finding has been reported by many studies concerned with E-learning uptake in higher education in Thailand (Teo et al., 2011; Premchaiswadi et al., 2012; Punnoose, 2012) and other countries (Lee, 2006; Franco, 2010; Sánchez and Hueros, 2010). A possible explanation might be that, if an E-learning system is too hard for students to use, the benefits of using it to learn faster may be dropped because of the time and effort needed to use the system. Eventually, students may be reluctant to use the system or may reduce the time spent doing so. This finding contradicts the research reported by Šumak et al. (2010) in Slovenia, which found no effect of effort expectancy on the uptake of E-learning. However, in Šumak's research, all the participants were computer science students; these may be expected to have an attained high level of IT skill. This might be why this group of students felt that system ease of use was not an important variable in their uptake of E-learning. This would suggest that future research investigates the impact of effort expectancy on E-learning uptake among students in different areas of study.

The above finding has important implications for E-learning designers and developers in that E-learning system should be designed to be easy to navigate and understand. When E-learning is designed and developed in a more user-friendly form, it may be expected that students will tend to use it, and spend more time doing so. A further implication is for the heads of universities. They should provide structured training on the use of E-learning in order to help students become familiar with the system. When students have some experience of the system, their personal belief that the use of E-learning is hard may diminish, boosting the level of their uptake of E-learning.

Influence of social encouragement expectancy on the uptake of E-learning

There was a surprising result; the influence of *social encouragement expectancy* on the uptake of E-learning did not lead to a statistically significance. This was a departure from the findings of many prior studies that have suggested that students will use and tend to increase their level of use if this is recommended and encouraged by their important persons such as parents, teachers and friends (Jong and Wang, 2009; McGill and Klobas, 2009; Bhrommalee, 2012). Perhaps the explanation for the contradictory finding is due to the particular participants in this study. The earlier studies indicated that social encouragement and recommendation directly affects uptake of E-learning when a student has no prior experience with the system but that the effect was not significant among experienced students (Hartwick and Henri, 1994; Venkatesh and Davis, 2000; Raaij and Schepers, 2008). In our study, the participants were second-year students, so most of them might be experienced users. Prior experience with the system may have enabled this group of students to undertake E-learning without needing encouragement from other people. This might be why the effect of social encouragement was not found in this study. The inconsistent finding would suggest that future research should investigate the effect of social encouragement on the usage of E-learning among both experienced and inexperienced users in the same study. Even though the effect of social encouragement on E-learning uptake was not supported in our research, due to confirmation from many other studies the E-learning stakeholders in universities should not overlook this variable, especially regarding inexperienced users or first year undergraduates.

Influence of facilitating condition expectancy on the uptake of E-learning

The results confirmed that *facilitating condition expectancy* statistically significantly influenced the uptake of E-learning among students in HEIs, consistent with many previous studies (Ndubisi, 2004; Jong and Wang, 2009; Abbad, 2011). This suggested that students who had the necessary IT resources (e.g. a computer and internet), or who studied at a university that provided both these resources for E-learning and the IT staff to assist them with its use, normally had a higher level of E-learning uptake than students who did not. A possible reason why the facilitating conditions were important if Thai students were to take up E-learning might be the Thai IT infrastructure. In 2013, the Thai National Statistic Office reported that only 35 per cent of Thai people had a personal computer and only 23.5 per cent of households had personal internet. This problem of a lack of IT resources prevents many Thai students from taking up E-learning, and this might have been why the participants in our study confirmed that the *facilitating condition expectancy* was important to their taking it up. In order to increase the uptake of E-learning in Thai higher education, we cannot forget that not all Thai parents are able to provide their children with the necessary IT resources to use it, so the finding from this research would suggest that the Thai government should subsidize universities to provide the both the necessary IT infrastructure (such as computers, internet system) and the staff to assist with its use.

Influence of learning consistency expectancy on the uptake of E-learning

Interestingly, the empirical results confirmed that the additional variable, *learning consistency expectancy*, was one of the four variables that statistically significantly influenced the uptake of E-learning. This result was consistent with Chen's (2011) research: this is the single study that also focused on the impact of learning motivation on the uptake of E-learning. The contribution of this research to Chen's study was the addition of the variable of the student's learning goal to those of his/her learning style and capability in what he/she will study. The results indicated that students who had a high expectation that the E-learning instructional environment was relevant to their goals, learning styles and past experience about what they were to study normally took up E-learning to a greater extent than those with a lower expectancy.

E-learning is a learning environment. A low level of learning motivation may lead students to forego teaching and learning activities in E-learning, ultimately neglecting it. Since the three sub-variables within *learning consistency expectancy* were confirmed by previous studies to be variables influencing student learning motivation, there was no doubt why the *learning consistency expectancy* variable contributed to the uptake of E-learning (Atkinson, 1957; Keller and Suzuki, 2004; Schunk, 2012). The finding from this research suggested that future research should investigate the impact of learning motivation in countries other than Thailand and Taiwan in order to confirm the impact of this variable on E-learning uptake. The implication of this finding for lecturers and system designers is that it is necessary to provide a learning environment that conforms to the aforementioned educational expectancy.

Overview factors influencing the uptake of E-learning

The result of canonical correlation analysis between the five EUCH initial expectation variables at t_0 and the five measurements of actual measured E-learning uptake at t_1 suggested that four of the five variables contributed statistically significantly to E-learning uptake: *performance expectancy*; *effort expectancy; facilitating condition expectancy;* and *learning consistency expectancy*.

To establish the most important E-learning uptake variable, each significant variable's sum of square part-correlation with its variate in canonical correlation Function 1 and 2 (h^2) was compared using Fisher's Z-transform technique. The results showed that there was no significant difference in the sum square of part-correlation between the four significant variables. This suggested that all four variables were equally important in increasing the uptake of E-learning effectively. This contrasted with the finding of earlier studies that *performance expectancy* was the most important variable affecting its uptake (Saadé and Bahli, 2005; Lee et al., 2009b; Liu et al., 2010a; Šumak et al., 2011b). With the highest beta weight of *performance expectancy*, compared with other variables, researchers concluded that *performance expectancy* was the most important predictor: they did not check whether *performance expectancy*'s beta weight was significantly higher than the other variables. Consistently, without checking the significant difference, results from the current study showed that *performance expectancy* had the highest sum of square part-correlation with its variate (h^2). h^2 was used to represent the unique contribution for each variable on E-learning uptake in this study because there were two canonical functions that needed to be interpreted. Interestingly, however, when Fisher's Z-transform technique was used to test the significant difference, the results then suggested that the contribution of the four significant variables (*performance expectancy*, *effort expectancy*, *facilitating condition expectancy* and *learning consistency expectancy*) on E-learning uptake were not statistically significantly different: the four significant variables were statistically equal in terms of their contribution to the uptake of E-learning. This might be the reason behind the inconsistency in findings between this research and other studies.

A further explanation might be the IT infrastructure in Thailand. In developing countries such as Thailand, with limited access to IT resources, students have a low level of experience with IT and lack the necessary IT resources to undertake E-learning, hence *effort expectancy* and *facilitating condition expectancy* were found to be as important as *performance expectancy*. Similar to students everywhere, students take part in an E-learning if they have the motivation to learn: hence, *learning consistency expectancy* was found as important as IT motivational variables (*performance expectancy*, *effort expectancy* and *facilitating condition expectancy*).

8.3.2 Factors influencing the continued use of E-learning (RQ6b, RQ6c and RQ6d)

Previous research has revealed that users' expectations of information technology (IT) changes over time as they use IT and learn from its use (Karahanna et al., 1999; Venkatesh and Morris, 2000). Any change in expectations will probably have a corresponding impact on users' continuance of that technology (Bhattacherjee and Premkumar, 2004). This might be a possible reason why users subsequently opted out. Since previous research was not conducted in E-learning technology, to understand better the factors affecting continued use of E-learning the three research questions of interest to this study are:

> *RQ6b: Do the level of five expectations change over the time as students use E-learning?*

and, if a change in expectation was found:

> *RQ6c: What are the factors influencing the change of each expectation?*
>
> *RQ6d: Do the changes in the level of five expectations affect change in the level of E-learning usage?*

The results of longitudinal study on the three research questions are discussed in the following sections.

The changes of five expectations over the time as students use E-learning (RQ6b)

To investigate whether students' five expectations changed from time t_0 to t_1, two statistical test techniques were conducted to: (a) compare the mean aggregated scores pair-wise using a dependent-samples *t*-test; (b) check the consistency of each expectation variable between time t_0 and t_1 using Pearson's correlation.

The results from a dependent-samples *t*-test suggested that there was no significant difference between t_0 and t_1 in terms of the mean value for *effort expectancy* and *social encouragement expectancy*. Even though the results showed a significant difference in the mean value between time t_0 and t_1 for three expectation variables (*performance expectancy*, *facilitating condition expectancy* and *learning consistency expectancy*), the effect size of the difference in the mean value for these three variables was quite small. With these results, it may be concluded that there was a small difference in the mean value of students' five expectations of E-learning between t_0 and t_1.

The results of correlation suggested that there was no significant consistency between *performance expectancy* at t_0 and t_1, and *effort expectancy* at t_0 and t_1. A significant degree of consistency between expectations at t_0 and t_1 was found in *social encouragement expectancy*, *facilitating condition expectancy* and *learning consistency expectancy*. According to the work of Cohen (1992), although the consistency degree for these three pairs was statistically significantly different from zero, the consistency degree was quite small. With these results, it may be inferred that there was a low degree of consistency between the values measured at time t_0 and at time t_1, for each expectation variable: a high degree of expectation at t_0 did not guarantee a high degree of expectation at t_1.

Although the mean value of each expectation variable measured at t_0 and t_1 showed a small difference, with a low degree of consistency between them, it can be concluded that students' five expectations towards E-learning usage changed over time as they used the E-learning system. The same finding was reported in previous research (Taylor and Todd, 1995; Karahanna et al., 1999; Venkatesh and Morris, 2000; Bhattacherjee and Premkumar, 2004).

A possible explanation for this finding of a change in expectation might be that the students' expectations before taking up E-learning were typically based on others' opinions or information disseminated through mass media. Such communicated information may have been exaggerated or unrealistic, resulting in cognitions that were less reliable. Over time, as the users gained first-hand experience with IT usage or learned from it, they evaluated the extent to which their initial expectation was consonant or dissonant with actual experience. They may have revised their initial expectation, hence their five expectations on E-learning changed. This finding suggested the need to investigate further the cause of the change in each expectation variable.

The factors drive the change of expectations (RQ6c)

To answer this research question, stepwise regression was conducted using 22 variables as predictors of the change in each of the five expectations towards E-learning. In total, there were five regression models.

The results showed that the change in each expectation was mainly affected by its *expectation confirmation* level. Even though there were other significant variables, their effect on the change of each expectation was quite small. The empirical findings were that students' five expectations towards the use of E-learning were adjusted by their extent of *expectancy confirmation*: students' expectations of E-learning tended to increase when the expectation confirmation level was high, and low expectation confirmation levels may have affected a small increase or drop in expectations. This was consistent with the research conducted by Szajna and Scamell (1993) that found that users' expectations of technology changed over time from unrealistically high or low (*expectancy confirmation* in our research): unrealistically low levels effected a decrease in expectation. Bhattacherjee (2001) and prior research in E-learning (Roca et al., 2006; Ho, 2010; Lee, 2010; Lin and Wang, 2012; Alraimi et al., 2015) also found that post-expectations towards the use of technology were influenced by a user's confirmation level, and high post-expectations were the result of a high confirmation level after using the technology.

Theoretical support for these findings comes from Cognitive Dissonance theory (Festinger, 1962). Users may experience cognitive dissonance if their expectations (before take up) are disconfirmed (unrealistic high or low) during actual use. Dissonance produces discomfort and, correspondingly, applies pressure to reduce the dissonance. Festinger (1962) suggested three ways of reducing dissonance; of the three, users may distort or modify their expectations to be more consistent with reality. Another possible explanation of such findings is Helson's (1948) Adaptation Level theory. Users' expectations (before take up) of E-learning serve as their reference level. When users adopted the technology, there was a cognitive comparison between the expectation level (reference level) and actual performance of that technology, creating the new expectation (reference level). Users will continue using IT if they have high new expectations, and the new expectation will be used as a reference level in the evaluation of future performance.

Influence of the change in expectations on E-learning usage (RQ6d)

To answer this research question, a canonical correlation was conducted using changes between t_0 and t_1 in the five variables of students' expectations as a predictor of the change in five variables of their level of E-learning usage between the first ($t_0 - t_1$) and second (t_1 - t_2) usage time periods. The results showed that there was a significant relationship between the change in expectation and the change in level of E-learning usage. No individual expectation change demonstrated a significant unique contribution in the change in the level of E-learning usage. With these results, it may be concluded that the change in the five expectations towards E-learning collectively effected a corresponding change in the level of E-learning use. A similar finding was reported by Bhattacherjee and Premkumar (2004), suggesting that users' level of intention to use technology altered when they changed their performance expectancy, in that positive change in performance expectancy positively affected their intention.

Overview factors influencing the continued use of E-learning

Since the change of expectations towards E-learning had a significant effect on the change in level of E-learning usage, expectations were good predictors of the continued use of E-learning. The change of each expectation was affected by their confirmation level. Therefore, the factor behind the continued use of E-learning was expectancy confirmation. The finding suggested that E-learning stakeholders in HEIs should make the environment for E-learning better than students' expectations before they take it up. If this is done, students will have a positive experience that can aid positive confirmation. This will increase their expectations, and it may be expected that they will tend both to continue to use the E-learning system and spend more time on it.

8.4 Relationship between E-learning Usage and Students' Learning Performance (RQ7)

The aim of the longitudinal study was also to investigate the relationship between the level of E-learning usage and students' learning performance. The dependent variable was *a student's relative standardized score in the final exam in General Statistics measured at* t_2. The five measurements of E-learning usage of General Statistics during t_0 to t_2 were used as an independent variable: (a) *subjective percentage of E-learning usage in general statistics*; (b) *subjective time spent learning with E-learning in general statistics*; (c) *objective time spent in general statistics E-learning;* (d) *objective total number of times logging onto General Statistics E-learning;* and (e) *objective total number of activities involving General Statistics E-learning*. As students did not have equal prior academic performance, *a student's relative standardized score of the midterm exam in General Statistics measured at* t_0 was used as another independent variable. Multiple regression analysis was conducted to identify a significant predictor of a student's relative standardized score in the final exam in General Statistics.

The results showed a statistically significant relationship between *a student's relative standardized score in the midterm exam in General Statistics measured at* t_0 and *a student's relative standardized score in the final exam in General Statistics measured at* t_2, while the five measurements of E-learning usage during midterm and final exam were not significantly associated with the student's relative standardized final exam score. This suggested that: (a) a student who has a high prior academic ability in the subject (high relative standardized score on midterm) will usually have a high score in the final exam; and (b) the reported beneficial effects of E-learning are unlikely to improve students' learning performance automatically, since those who used E-learning more frequently and spent more time on the system in this study did not significantly improve to achieve better and higher relative scores in the subject. This finding appears to contradict both E-learning stakeholders' expectations (university policy makers, E-learning designers and developers) and the prior studies in the field (Graff, 2006; Palmer et al., 2008; Rodgers, 2008; Madar and Ibrahim, 2011; Oye et al., 2012) that found that more use of E-learning supported students to achieve better learning performance. However, some prior studies obtained the same finding as our research (Arbaugh, 2000; Davies and Graff, 2005; Lei and Zhao, 2007).

Even though the consequence of E-learning usage on a student's learning performance was not confirmed by the empirical results of this study, it could be argued that E-learning usage is an *initial* condition for realizing the benefits of E-learning on students and HEI: if there is no use, there will be no benefit. The findings also suggest that the volume of E-learning usage alone is not critical to students' learning performance, if its quality and that of the teaching expertise is not ensured. While the literature on E-learning usage has traditionally focused on the quantity (how much technology was used), in future studies should focus on the quality of use.

8.5 Summary of Chapter 8

This chapter discussed the findings from the statistical results in the model validation phase to help answer four research questions: RQ4, RQ5, RQ6, and RQ7. The chapter started with an assessment of the EU sub-model's performance (RQ4). The key findings on this research question were that the EU sub-model's performance in predicting the uptake of E-learning was not different from that provided by TAM and UTAUT. The second section of the chapter discussed the performance of the EC sub-model (RQ5) on the continued use of E-learning, and the main findings were that the EC sub-model's predictive power on the continued use of E-learning were as good as those of TAM, UTAUT and ECM. The improvement however was found in its explanation of E-learning uptake and continuance. The third section discussed the results about the validations of relationships between the EUCH model variables (RQ6), and the findings were that: (a) four of the five proposed initial expectations influenced students' uptake of E-learning (*performance expectancy*, *effort expectancy*, *facilitating condition expectancy,* and *learning consistency expectancy*); (b) the five expectations towards the use of E-learning changed over time as students experienced and learned from using the system; (c) the change in each expectation was mainly influenced by the level of its expectation confirmation; (d) the changes of these expectations collectively gave a corresponding change in the level of E-learning usage. The fourth section, which discussed the relationship between E-learning usage and a student's learning performance (RQ7), suggested that the level of E-learning usage was unlikely to improve students' learning performance automatically.

The next chapter provides the conclusion of the research, presents its contribution and suggests the direction future work should take.

Chapter 9 Conclusion, Contribution, and Future Work

This chapter starts by providing the conclusion of the research and the contribution made by this work is then discussed. It next gives the direction for future work. A number of concluding remarks are given at the end.

9.1 Conclusion

E-learning cannot fully provide benefits to individual students and HEIs if the students who are the end users do not use the technology. However, the use of E-learning by students is not guaranteed; they are sometimes unwilling to take up the technology, even if it provides them with benefits (Nickerson, 1981; Chen, 2011), and those who do start to use it sometimes opt out later (Hsu and Chiu, 2004; Lee, 2010). To better predict and explain E-learning usage in higher educational institutes (HEIs), this research conceptualized E-learning usage as two steps, E-learning uptake and continuance, and the aim was to construct the model of effective uptake and continuance of E-learning in HEIs, or 'EUCH'.

The research was divided into two phases: model construction and model validation. A data triangulation technique (literature, expert and end-user review) was used in the model construction phase to find the factors likely to affect a student's uptake (RQ1) and continued use of E-learning (RQ2). The research started with an examination of existing theories and related research (see Chapter 3). The research was grounded in five theories: Unified Theory of Acceptance and Use of Technology (UTAUT); Keller's ARCS model; Theory of Reasoned Action (TRA); Cognitive Dissonance Theory (CDT); and Adaptation Level Theory (ALT). The preliminary study was conducted with experts and end users (students) to confirm the factors of E-learning uptake and continuance that were synthesised from the literature (see Chapter 4). With confirmation from at least two as triangulation, five factors were found likely to affect a student's uptake of E-learning: *performance expectancy; effort expectancy; social encouragement expectancy; facilitating condition expectancy;* and *learning consistency expectancy*. Five factors were likely to affect the continued use of E-learning: *performance expectancy confirmation; effort expectancy confirmation; social encouragement expectancy confirmation; facilitating condition expectancy confirmation;* and *learning consistency expectancy confirmation.* The confirmed factors of E-learning uptake and continuance from the data triangulation technique were then integrated to construct the model of E-learning uptake and continuance in HEIs (EUCH), as expressed in research question RQ3 (see Chapter 5).

Longitudinal study was used in the model validation phase (see Chapter 6). Its aim was first to assess the EUCH model's predictive power and explanatory power on E-learning uptake (RQ4) and continued use (RQ5). Compared with the existing models, the EUCH model was equally effective in predicting the uptake and continued use of E-learning as the models of TAM, UTAUT and ECM. To be parsimonious, TAM is the model of choice provided the sole goal is the prediction of E-learning uptake and continued use. However, if the goal is to devise a strategy to support the uptake and continued use of E-learning at university, the EUCH model is recommended since it provides a more complete profile of the determinants of uptake and continued use of E-learning than the other models. Following the analysis of the performance of the EUCH model overall, the aim of the longitudinal study was further to validate the relationships between the proposed EUCH model variables (RQ6). The results showed that four of the five proposed initial expectation variables had a significant relationship with actual E-learning uptake: *performance expectancy; effort expectancy; facilitating condition expectancy;* and *learning consistency expectancy.* The change in the level of these expectation variables level collectively had a significant influence on the change in level of E-learning usage. Additionally, the change in each expectation was mainly influenced by the level of its expectation confirmation.

The findings have important implications for the various E-learning stakeholders in increasing usage of E-learning in HEIs: (a) system designers and developers should provide functionalities in E-learning that encourage student users to learn more quickly and achieve better learning performance – *performance expectancy*; (b) E-learning designers and developers should design systems to be easy to navigate, *or* universities should provide structured training in the use of E-learning – *effort expectancy;* (c) the Thai government, universities and or parents should provide the necessary IT equipment (such as computers and internet) for students – *facilitating condition expectancy*; and (d) learning content providers or lectures should provide a learning environment that conforms to the aforementioned educational expectancy (such as a learner's learning goal, learning style and existing competency) – *learning consistency expectancy*. By achieving these conditions, it may be expected that students will have high initial expectations towards the system and will tend to take up E-learning. During the usage period, it may be anticipated that their expectations will be confirmed or exceeded, and they will tend to continue to use the E-learning system.

In the final step of the model validation phase, E-learning usage, the main dependent variable in this research was set as a predictor of the dependent variable, the consequence of E-learning usage (a student's academic performance). Sadly, no significant relationship between E-learning usage and a student's academic performance was detected.

9.2 Contributions

This research may be considered to have contributed in three areas, through: (a) its practical contribution; (b) its theoretical contribution; and (c) its research methodological contribution. These are discussed as follows.

9.2.1 Practical contribution: the EUCH model

E-learning usage (uptake and continued use) is an initial condition for ensuring the benefits of E-learning for students and HEIs (Davis, 1989; Mathieson, 1991; Taylor and Todd, 1995). The EUCH model has practical value for HEIs in terms of evaluating E-learning systems and guiding managerial interventions aimed at reducing the problem of a low level of uptake and continuing use of E-learning.

When planning a new system or continuing to invest on E-learning technology in HEIs, policy makers should like to be able to predict whether a new system will be used, and continue to be used, by their students: *early-warning techniques*. Being able to predict E-learning failure in uptake and continuing use before implementation, or reinvestment afterwards, could facilitate changes leading to success (Szajna and Scamell, 1993). The results showed that the EUCH model predicted the uptake and continued use of E-learning quite well. This model may be used by HEIs to predict E-learning failure at any time before implementation (uptake) or after implementation (continued use), rather than using the separate existing models for uptake (TAM, UATUT) or continued use (ECM).

By combining E-learning uptake and continued use models, the EUCH model provides an improved and more comprehensive understanding of the cognitive processes and behaviours relating to E-learning usage (since students start using a system, then continue using it) than either theory alone. When the predicted level of uptake or continued use of E-learning among students at university is low, the EUCH model diagnoses why the planned E-learning system will not be used. Therefore, E-learning stakeholders can take corrective action or devote more targeted effort to obtaining the productivity benefits promised by E-learning (Karahanna et al., 1999, Parker, 1999).

9.2.2 Theoretical contribution

There are three theoretical contributions of this research to the field; these are discussed in the following:

Combining E-learning uptake and continued use models into one E-learning usage model

In the area of E-learning research, researchers view the uptake and continued use of E-learning as an extension of acceptance behaviour: it is assumed that students will take up and continue using E-learning technology if they accept the technology. These studies are therefore unable to explain why some students discontinue their use of E-learning after accepting and taking it up initially. To understand E-learning usage better, this research conceptualizes a distinction between E-learning uptake and continuance behaviours.

From the review of literature, it was found that, since E-learning uptake and continued use are in different research areas, no study has yet theoretically combined uptake and continued use factors into a single model. The primary contribution of this study is the integration of E-learning uptake and continued use factors. In the EUCH model, apart from serving to provide the motivation (intention) to take up E-learning, initial expectation (factors from E-learning uptake research area) perform two functions in the continued use of E-learning: (a) it serves as a student's reference level for making cognitive comparison with perceived actual performance to determine expectancy confirmation; (b) it is adjusted by its expectancy confirmation to determine the new expectation towards the continued use of E-learning. The model gives both practitioners and researchers an increased understanding of students' cognitive processes and behaviours in the use of E-learning from before take up through to continued use of the system: how expectations affect the uptake and how expectations change when individual students use the system, and the effect of the changes in expectations on the continued use of E-learning.

Incorporating learning motivational factor into technical motivational factors for predicting and explaining the E-learning usage

Since researchers have almost unanimously viewed E-learning as a type of technology, most have grounded their research in acceptance of technology models (the TAM and UTAUT models) and the technology continuance model (ECM) to construct the model of E-learning uptake and continued use: much effort has usually been devoted to identifying the factors of the technological motivation of students (Šumak et al., 2011a). 'E-learning' has two aspects to its definition, 'learning' (referring to teaching and learning activities) and 'E' (referring to technology). Focusing only on technological motivation may not enough.

This research has filled the gap left by other researchers by adding a 'learning motivational factor' to the model, termed the *learning consistency expectancy*. The statistical results from the model validation phase confirm that an additional variable, the *learning consistency expectancy*, is as important to the uptake of E-learning as technological motivation factors (*performance expectancy*, *effort expectancy* and *facilitating condition expectancy*). Also, the change of *learning consistency expectancy* with the change of technological expectancies collectively results in a corresponding change in the level of E-learning usage (continuance). With this finding, the contribution of this research to the field is that, aside from technological motivation, the usage of an E-learning system (both uptake and continued use) also depends on learning motivation.

E-learning usage and students' learning performance

Following the model of Information Systems Success (DeLone and McLean, 1992) and the Task-Technology Fit model (Goodhue and Thompson, 1995), which state that if technology is compatible with the tasks then the use of the system could lead to individual user performance impact, prior research has concentrated on identifying the determinants of E-learning usage (both uptake and continuance). However, investigation into the outcomes of E-learning usage on student's learning performance has received little attention (Islam, 2013). Among these, there were contradictory results: some research had found that greater use of E-learning had a positive impact on students' academic scores (Palmer et al., 2008; Rodgers, 2008; Madar and Ibrahim, 2011), while another group had found no effect (Arbaugh, 2000; Davies and Graff, 2005). Apart from its construction of the model of E-learning usage in HEIs, this current study is one of the few that has investigated the consequence of E-learning usage on users' learning performance. It finds that the use of E-learning is not associated with students' learning performance: more frequent and longer time spent on the system does not guarantee better and higher learning performance. The implication of this research is that we should pause to identify E-learning usage determinants by investigating carefully the impact of its usage (the dependent variable) on a student's learning performance before moving to the next step of E-learning usage research.

9.2.3 Research methodological contribution

The measurement of E-learning actual usage rather than intention to use is a methodological contribution from this research to the field. Studies in the area of E-learning usage usually measure behavioural intention to use E-learning to investigate the factors influencing the uptake and continued use of E-learning, rather than actual use. This is for two main reasons: limitations of time, and the researchers' belief in the ability of intention to predict future behaviour (Šumak et al., 2011a). However, there is empirical evidence that intention may not always accurately predict behaviour, or may do so in an inconsistent manner: the time period between the measurement of intention and actual usage could be full of uncertainties and other factors that may affect students' decision to adopt or change their level of use (Davis et al., 1989; Chuttur, 2009). It is important to examine fully the extent to which the model can help in predicting and explaining usage behaviour rather than merely intention to use. In this study, the EUCH and other models (TAM, UTAUT and ECM) were compared in terms of actual E-learning usage. The first contribution is the confirmation that the EUCH model and the comparative existing models work in the real world situation to explain and predict E-learning usage. The second is that models previously validated by using intention (TAM, UTAUT and ECM) seem to work as well in the real world.

9.3 Future Work

The future work in this area was suggested by: (a) the limitations of this study; (b) its findings; and (c) other research areas that might affect the uptake and use of E-learning.

9.3.1 Limitations

As is typical in many empirical studies, this study is not without its limitations. The improvements can be made in future studies in the following areas.

The model prediction of continued use of E-learning

There was a limitation to the EC sub-model regarding predicting continued use of E-learning when initial expectations were zero. In this case, according to Equation 5-7, at t_1 all predicted new expectations at will be zero for any level of perceived performance: the calculation of the new expectations is not influenced by the level of perceived performance. Even though this zero level of initial expectation is so low that these students may not take up E-learning, future work should focus on improving this case of prediction.

Multiple steps model of E-learning usage

Change is an inevitable part of human life: human continually adjust their personal beliefs and their own behaviour as they learn more about environments (Bhattacherjee and Premkumar, 2004). Likewise, from the empirical evidence of this study and other research, users' expectations about usage of information technology (IT) and E-learning change over time as they experience IT usage at first hand and learn from this use (Szajna and Scamell, 1993; Venkatesh and Morris, 2000). The EUCH is two-step model: uptake (t_0) and continued use (t_1). To predict and explain E-learning usage better, future work should develop EUCH to be a multiple-step model, extending its prediction from t_1 to t_n.

Participants for the study of E-learning uptake

E-learning uptake is a student's behaviour in accepting and starting to employ the E-learning technology available at their university. In the longitudinal study, however, the participants might be both experienced and inexperienced users. This is a limitation for the study of E-learning uptake. Nowadays, many students will have had the chance to use E-learning to support their education from high school onwards. For this reason, we may need to redefine the definition of E-learning uptake as the first time period of model usage, otherwise we may need to conduct an experiment with students who have never used E-learning before to meet the definition of E-learning uptake.

Generalization

The model validation phase was conducted at a single Thai university (RMUTT). The use of a single data collection site was to control for the potential effects of organizational variables (e.g. the type of E-learning system and infrastructure readiness) on individual use behaviour (Bhattacherjee, 2001). Since the data were obtained from students in a single country (Thailand), they may not reflect of the adoption process in contrasting cultural environments. Caution needs to be used when generalizing the findings to different countries.

According to Linjun (2003), '*Information systems research reveals that there are different technology adoption and usage patterns when cultural difference is taken into account*'. Consistent with Linjun's research, the researchers also found an effect of culture on the factors affecting E-learning uptake and continued use (Roca et al., 2006; Zhao and Tan, 2010). Because of this, factors affecting the uptake and continued use among students in various countries may be different. A cross-cultural validation of the model represents future work for the development of the EUCH. There is a need to understand the cross-cultural adoption and use of the systems. A comparison study can give us more insight into the impact of different cultures on the uptake and continued use of E-learning.

9.3.2 Findings to be added to other factors to the model

From the findings, the EUCH accounted for half the variance in the uptake and continued use of E-learning. This implies that there are other factors that are not considered in this research that influence students to take it up and continue to use it. In future work, new variables should be used to extend the EUCH model. These might include individual background factors (such as gender, age, how voluntary is their use, and experience with IT), since the moderate effect of these variables of technology usage had been detected in IT literature (Venkatesh et al., 2003).

9.3.3 *Other research areas, such as teachers' usage of E-learning*

Teachers are also users of E-learning technology. A number of studies have suggested that the successful use of E-learning in HEIs also depends on teachers' usage of this technology (Mahdizadeh et al., 2008; Yuen et al., 2008). The use of E-learning by the teachers is important as a matter of their role as initiators and facilitators to students' usage of E-learning: teachers' lack of willingness to use E-learning and low efforts to make a good content in E-learning may lead to underutilization by students and low learning outcome from the use of E-learning (Sorebo et al., 2009; Wang and Wang, 2009). It is therefore plausible to believe that factors influence a teacher's usage of E-learning in the subjects for which they are responsible should be established.

9.4 Concluding Remarks

E-learning usage is an *initial* condition for realizing the benefits to students and HEIs of E-learning. However, the use of E-learning by students is not guaranteed. To predict and explain E-learning usage in HEIs better, this research has conceptualized E-learning usage as two steps, namely its uptake and continuance, and the aim was to construct a model of effective uptake and continuance of E-learning in HEIs, or 'EUCH'. Even though the EUCH model's explanatory power and predictive performance on E-learning uptake and continuance was not superior to other models on purely statistical grounds, it bridges the existing gap between the uptake and continuance of E-learning, and permits improved understanding of the processes of E-learning usage and its prediction at any given point within a single model.

Appendix 3-A: Review of E-learning acceptance (uptake) in HEI literature

No.	Researcher	Grounded theories	Factors inflecting s intention to take up E-learning					Factors inflecting actual uptake		Contribution & other research findings
			PE	EE	SEE	FCE	Other	Intention	Other	
1.	Brown (2002)	TAM and using technology (ease of finding, ease of understanding) and user characteristics (self-efficacy, computer anxiety) as prior factors of EE		✓						Contribution: Prior factors of EE: ease of finding, ease of understanding and computer anxiety Other findings: The relationship between EE and PE
2.	Lee et al. (2003)	TAM and adding social expectation	✓				attitude			Contribution: Adding social factors, however the influence was not found Other findings: The relationship between: ▪ PE and attitude ▪ EE and PE
3.	Selim (2003)	Validation of TAM model variables	✓							Other findings: The relationship between EE and PE
4.	Yi and Hwang (2003)	TAM and extended TAM by adding enjoyment, self-efficacy and learning goal orientation	✓	✓				✓	Self-efficacy	Contribution: Using enjoyment and learning goal as prior TAM factors; and using self-efficacy as key factor Other findings: The relationship between: ▪ efficacy and EE ▪ enjoy and PE, EE and efficacy ▪ learning goal and efficacy

Where: PE is performance expectancy; EE is effort expectancy; SEE is social encouragement expectancy; and FCE is facilitating condition expectancy

No.	Researcher	Grounded theories	Factors inflecting s intention to take up E-learning					Factors inflecting actual uptake		Contribution & other research findings
			PE	EE	SEE	FCE	Other	Intention	Other	
5.	Ndubisi (2004)	Validation of decomposed TPB		✓		✓	attitude			Contribution: The validation of decomposed TPB Other findings: The relationship between: ▪ PE and attitude ▪ EE and attitude
6.	Lee et al. (2005)	TAM and extended TAM by adding enjoyment	✓				attitude enjoyment			Other findings: The relationship between: ▪ PE and attitude ▪ enjoyment and attitude ▪ EE and PE ▪ EE and enjoyment
7.	Liu et al. (2005)	TAM and Flow theory	✓				attitude concentration			Contribution: The application of flow theory Other findings: The relationship between: ▪ PE and attitude ▪ EE and attitude ▪ EE and PE
8.	Saadé and Bahli (2005)	TAM and adding cognitive absorption as prior TAM factors	✓	✓						Contribution: Using cognitive absorption as prior TAM factors Other findings: The relationship between: ▪ Cognitive absorption and PE ▪ Cognitive absorption and EE ▪ EE and PE

Where: PE is performance expectancy; EE is effort expectancy; SEE is social encouragement expectancy; and FCE is facilitating condition expectancy

No.	Researcher	Grounded theories	Factors inflecting s intention to take up E-learning					Factors inflecting actual uptake		Contribution & other research findings
			PE	EE	SEE	FCE	Other	Intention	Other	
9.	Lee (2006)	TAM and extended TAM by adding subjective norm; and using four factors (content quality, network externality, computer self-efficacy, course attribute) as a prior TAM factor	✓	✓			network externality	✓		<u>Contribution</u>: Prior of TAM factors <u>Other findings:</u> The relationship between: ▪ EE and PE ▪ content quality and PE ▪ SEE and PE ▪ network externality and PE ▪ course attributes and PE ▪ network externality and EE ▪ computer self-efficacy and EE
10.	Pituch and Lee (2006)	Extended TAM and adding prior factors: system functionality (SF), system interactivity (SI), system response (SR), self-efficacy and internet experience	✓	✓						<u>Contribution</u>: Prior of TAM factors <u>Other findings:</u> The relationship between: ▪ SF and PE ▪ SI and PE ▪ SR and PE ▪ SF and EE ▪ SR and EE ▪ SE and EE
11.	Ngai et al. (2007)	Extended TAM by adding technical support into the model							PE, EE	<u>Contribution</u>: The incorporate the technical support <u>Other findings:</u> The relationship between: ▪ EE and PE ▪ PE and Attitude ▪ EE and Attitude ▪ Technical support and PE ▪ Technical support and EE

Where: PE is performance expectancy; EE is effort expectancy; SEE is social encouragement expectancy; and FCE is facilitating condition expectancy

No.	Researcher	Grounded theories	Factors inflecting s intention to take up E-learning					Factors inflecting actual uptake		Contribution & other research findings
			PE	EE	SEE	FCE	Other	Intention	Other	
12.	Lee (2008)	Extended TAM by adding organization resource factor	✓	✓						Contribution: The incorporation of the organizational resource Other findings: The relationship between: ▪ EE and PE ▪ organizational resource and PE ▪ organizational resource and EE
13.	Liao and Lu (2008)	Applying TAM and Roger's innovation diffusion of theory (IDT)					compatibility, trialability	✓		Contribution: The validation of IDT theory
14.	Raaij and Schepers (2008)	Extended TAM by social norm, personal innovativeness and computer anxiety	✓							Contribution: Extended TAM using three variables Other findings: The relationship between: ▪ EE and PE ▪ social norm and PE ▪ personal innovativeness and EE ▪ computer anxiety and EE
15.	Shih (2008)	TPB and social cognitive theory (SCT)					attitude, outcome expectation, perceived behavioural control			Contribution: The integration of TPB and SCT Other findings: The relationship between: ▪ perceived behavioural control and attitude ▪ outcome expectation and attitude ▪ self-efficacy and attitude

Where: PE is performance expectancy; EE is effort expectancy; SEE is social encouragement expectancy; and FCE is facilitating condition expectancy

No.	Researcher	Grounded theories	Factors inflecting s intention to take up E-learning					Factors inflecting actual uptake		Contribution & other research findings
			PE	EE	SEE	FCE	Other	Intention	Other	
16.	Theng et al. (2008)	Extended TAM by adding student's awareness of E-learning and self-efficacy	✓	✓						Contribution: Prior factors for TAM Other findings: The relationship between: ▪ EE and PE ▪ awareness of E-learning and PE ▪ self-efficacy and EE
17.	Jong and Wang (2009)	UTAUT and adding attitude, anxiety and self-efficacy	✓		✓	✓	attitude, self-efficacy	✓	attitude, SEE	Contribution: Extended UTAUT with additional three factors
18.	Lee et al. (2009a)	Extended TAM by adding instructor characteristic, teaching materials, design of learning contents and playfulness	✓	✓			playfulness			Contribution: Extended UTAUT with additional four factors Other findings: The relationship between: ▪ EE and PE ▪ instructor characteristic and PE ▪ teaching material and PE ▪ design of learning content and EE
19.	Liu et al. (2009)	TAM, Flow theory and Media richness theory	✓				attitude, concentration			Other findings: The relationship between: ▪ EE and PE ▪ PE and attitude ▪ EE and attitude

Where: PE is performance expectancy; EE is effort expectancy; SEE is social encouragement expectancy; and FCE is facilitating condition expectancy

No.	Researcher	Grounded theories	Factors inflecting s intention to take up E-learning					Factors inflecting actual uptake		Contribution & other research findings
			PE	EE	SEE	FCE	Other	Intention	Other	
20.	McGill and Klobas (2009)	Task-technology fit theory and UTAUT for explaining uptake of E-learning; the consequence of use on student's grade	✓		✓		attitude, instruction norm			Contribution: The investigation of task-technology fit and consequence of use Other findings: No relationship between use and student grade
21.	Park (2009)	Extended TAM by adding self-efficacy, subjective norm, and organizational factor	✓	✓	✓		attitude			Other findings: The relationship between: ▪ PE and attitude ▪ EE and attitude ▪ SEE and attitude ▪ EE and PE ▪ self-efficacy and PE ▪ SEE and PE ▪ self-efficacy and EE ▪ organization and EE
22.	Duan et al. (2010)	The validation of innovation diffusion of theory (IDT)					compatibility, trialability			
23.	Liu et al. (2010a)	TAM and adding perceived interaction (PI), course design (CD), interface design (ID), pervious online learning experience (POLE)	✓	✓			PI and POLE			Contribution: The integration of system characteristic as an external variable of TAM factors Other findings: The relationship between: ▪ EE and PE ▪ EE and PI ▪ CD and PE ▪ POLE and PE ▪ CD and EE ▪ POLE and EE ▪ CD and PI ▪ ID and PI

Where: PE is performance expectancy; EE is effort expectancy; SEE is social encouragement expectancy; and FCE is facilitating condition expectancy

No.	Researcher	Grounded theories	Factors inflecting s intention to take up E-learning					Factors inflecting actual uptake		Contribution & other research findings
			PE	EE	SEE	FCE	Other	Intention	Other	
24.	Liu et al. (2010b)	Extended TAM with personal innovativeness	✓	✓			personal innovativeness			Other findings: The relationship between: ▪ EE and PE ▪ personal innovativeness and PE ▪ personal innovativeness and EE
25.	Franco (2010)	Extended TAM by adding flow and perceive affective quality (PAQ)	✓	✓			Flow			Contribution: The integration of PAQ Other findings: The relationship between: ▪ PAQ and PE ▪ PAQ and EE ▪ PAQ and flow
26.	Sánchez and Hueros (2010)	Extended TAM by adding computer self-efficacy and technique support	✓	✓						Other findings: The relationship between: ▪ PE and attitude ▪ EE and attitude ▪ EE and PE ▪ technique support and PE ▪ technique support and EE
27.	Šumak et al. (2010)	The validation of UTAUT			✓			✓	FCE	Other findings: The relationship between: ▪ PE and attitude ▪ SEE and attitude ▪ EE and PE ▪ technique support and PE ▪ technique support and EE

Where: PE is performance expectancy; EE is effort expectancy; SEE is social encouragement expectancy; and FCE is facilitating condition expectancy

No.	Researcher	Grounded theories	Factors inflecting s intention to take up E-learning					Factors inflecting actual uptake		Contribution & other research findings
			PE	EE	SEE	FCE	Other	Intention	Other	
28.	Zhao and Tan (2010)	Extended TAM by adding intrinsic motivation and comparing the between different cultures (China and Canada)	✓	✓			intrinsic motivation			<u>Contribution</u>: Cross-validation of TAM between two countries <u>Other findings:</u> The relationship between: ▪ EE and PE ▪ EE and intrinsic motivation Couture significantly impact on uptake: PEU seem to have a more significant impact on Chinese students to take up E-learning than Canadian
29.	Abbad (2011)	Extended TAM by adding: subjective norm, internet experience, system interactivity, self-efficacy and technical support	✓	✓	✓	✓				
30.	Gaitán et al. (2011)	Validation TAM between Hofstede's culture different countries	✓	✓				✓		<u>Contribution</u>: The application of Hofstede's culture dimension on E-learning uptake <u>Other findings</u> The same uptake factors (PE and EE) was found in both countries: culture has no effect
31.	Chen (2011)	Extended UTAUT by adding educational compatibility	✓			✓	educational compatibility			<u>Contribution</u>: The integration of educational compatibility factor

Where: PE is performance expectancy; EE is effort expectancy; SEE is social encouragement expectancy; and FCE is facilitating condition expectancy

No.	Researcher	Grounded theories	Factors inflecting s intention to take up E-learning					Factors inflecting actual uptake		Contribution & other research findings
			PE	EE	SEE	FCE	Other	Intention	Other	
32.	Hong et al. (2011)	Extended TAM and interface design and playfulness concern	✓				Interface design			<u>Other findings:</u> The relationship between: ▪ PE and attitude ▪ EE and attitude ▪ EE and PE ▪ playfulness and PE ▪ interface design and EE
33.	Terzis and Economides (2011)	Extended UTAUT by adding content, playfulness and goal expectancy		✓			playfulness			<u>Contribution</u>: The additional of content and goal expectancy <u>Other findings:</u> The relationship between: ▪ goal expectancy and PE ▪ SEE and PE ▪ FCE and EE ▪ EE and PE
34.	Aulamie et al. (2012)	Extended TAM adding enjoyment and playfulness		✓	✓					<u>Other findings:</u> The relationship between: ▪ EE and PE ▪ enjoyment and PE ▪ playfulness and PE ▪ enjoyment and EE
35.	Bhrommalee (2012)	The validation of UTAUT in Thai HEIs	✓	✓	✓	✓				<u>Contribution</u>: The validation of UTAUT in Thailand

Where: PE is performance expectancy; EE is effort expectancy; SEE is social encouragement expectancy; and FCE is facilitating condition expectancy

No.	Researcher	Grounded theories	Factors inflecting s intention to take up E-learning					Factors inflecting actual uptake		Contribution & other research findings
			PE	EE	SEE	FCE	Other	Intention	Other	
36.	Rodriguez and Lozano (2012)	Extended TAM by adding perceived useful of professor, compatibility with learning task, training	✓	✓	✓		perceived useful of professor			Other findings: The relationship between: ▪ perceived usefulness of lecture and PE ▪ training and PE ▪ compatibility with learning task and EE
37.	Lai et al. (2012)	TRA, TA, TPB, UTAUT, PCU and adding educational compatibility (EC), self-efficacy	✓				Self-efficiency, facilitating condition, attitude			Other findings: The relationship between: ▪ EC and Attitude ▪ EC and PE ▪ EC and self-efficiency ▪ EC and facilitating conditions ▪ facilitating conditions and PE
38.	Cheung and Vogel (2013)	Using TAM, TPB and adding the prior factors such as compatibility, sharing, perceived resource	✓	✓	✓		Sharing and self-efficacy	✓		Other findings: The relationship between: ▪ PE and Attitude ▪ EE and Attitude ▪ EE and PE ▪ compatibility and EE ▪ perceived resource and EE ▪ sharing and PE
39.	Meléndez et al. (2013)	Extended TAM by adding playfulness; also studying the moderate effect of gender					Attitude			Other findings: Playfulness and EE are more important for women than men

Where: PE is performance expectancy; EE is effort expectancy; SEE is social encouragement expectancy; and FCE is facilitating condition expectancy

No.	Researcher	Grounded theories	Factors inflecting s intention to take up E-learning					Factors inflecting actual uptake		Contribution & other research findings
			PE	EE	SEE	FCE	Other	Intention	Other	
40.	Lin et al. (2013)	Validation UTAUT across teachers and students	✓	✓						Contribution: The validation of UTAUT across teachers and students group Other findings: Type of user affects adoption pattern differently ▪ EE affects students' uptake more than teacher ▪ FCE affects teachers more than students
41.	Sawang et al. (2014)	Investigating the moderate effect of subjective norm on TPB factors		✓	✓	✓	Attitude, perceived behaviour control			Contribution: The validation of a moderating role for subjective norm on technology attitude and perceived control on adoption intention Other findings: A moderating effect of subjective norm was found on both technology attitude and perceived control on adoption intention
42.	Merhi (2015)	TAM and innovation diffusion of theory (IDT)	✓	✓			Image, perceived enjoyment, perceived self-efficacy, relative advantage			Other findings: The relationship between: ▪ mobility and PE ▪ mobility and EE ▪ mobility and Image ▪ mobility and perceived enjoyment ▪ PE and relative advantage ▪ self-efficacy and PE

Where: PE is performance expectancy; EE is effort expectancy; SEE is social encouragement expectancy; and FCE is facilitating condition expectancy

Appendix 3-B: Review of E-learning continuance in HEI literature

No.	Researcher	Grounded theories	Factors influencing expectation			Factors influencing satisfaction			Factors influencing intention to continue use			Contribution & other research findings
			IE	PP	EC	IE	PP	EC	S	ME	Other	
1.	Chiu et al. (2005)	Extended EDT by decomposing the perceived performance component into *usability*, *quality* and *value* from IS success model					✓	✓	✓			Contribution: Decomposing perceived performance into three dimension Other findings: The relationship between PP and EC
2.	Roca et al. (2006)	This research grounded in three theories: (1) TPB; (2) TAM; (3) EDT; decomposing perceived performance component into *usability*, *quality* and *value* from IS success model			✓		✓	✓	✓			Contribution: Integrated three theories (TPB, TAM and EDT) for explaining continued use intention Other findings: The relationship between PP and EC
3.	Chiu et al. (2007)	Using satisfaction and subjective task value factors (utility, attainment, intrinsic value and cost) as a predictor of continued use of E-learning. Additionally, fairness theory was applied as a predictor of satisfaction.						✓	✓	✓		Contribution: Used fairness theory as a set of predictors for satisfaction Combined subjective task value and satisfaction as a predictor of continued use
4.	Levy (2007)	This study compared level of satisfaction between groups of students who opted out and completed E-learning course.							✓			Contribution: Compared satisfaction between two group of students Other findings: Completed group has significantly higher satisfaction level than drop-out group

Where: IE is initial expectation; PP is perceived performance; EC is expectancy confirmation; S is satisfaction; and ME is modified (new) expectation

No.	Researcher	Grounded theories	Factors influencing expectation			Factors influencing satisfaction			Factors influencing intention to continue use			Contribution & other research findings
			IE	PP	EC	IE	PP	EC	S	ME	Other	
5.	Chiu and Wang (2008)	Extended UTAUT by introducing the components from subjective task value for explaining intention to continuance								✓		Contribution: Extended UTAUT with subjective task value
6.	Liaw (2008)	Using performance expectancy (TAM) and satisfaction as a predictor of intention to continued use; learner characteristics and environmental factors as a prior factor							✓	✓		Contribution: Prior factors of expectation and satisfaction Other findings: Learner characteristics and environmental factors as a prior factor
7.	Liao and Lu (2008)	Using PCI theory and comparing the strange of the relationships between experienced and inexperience users								✓		Contribution: Compared expectations of two groups of students Other findings: The relationship between intention and the use of E-learning
8.	Cho et al. (2009)	Using TAM (performance expectancy, effort expectancy) and satisfaction as a predictor of continued use intention; user interface design (UID) as prior factor of performance and effort expectancy							✓	✓		Contribution: Prior factors of performance and effort expectancy Other findings: The relationship between UID and modified expectation
9.	Tao et al. (2009)	Using EDT and decomposing perceived performance into four dimensions: two from TAM (perceived usefulness, ease of use) and another two (perceived attractiveness and playfulness)					✓	✓	✓			Contribution: Decomposing perceived performance into four dimensions
10.	Ho (2010)	Using TAM and ECM as a set of continued use of E-learning predictors; self-determination model (SDM) factors as prior factors of TAM and ECM factors			✓			✓	✓	✓	Attitude	Contribution: Using SDM factors as prior factors of TAM and ECM

Where: IE is initial expectation; PP is perceived performance; EC is expectancy confirmation; S is satisfaction; and ME is modified (new) expectation

No.	Researcher	Grounded theories	Factors influencing expectation			Factors influencing satisfaction			Factors influencing intention to continue use			Contribution & other research findings
			IE	PP	EC	IE	PP	EC	S	ME	Other	
11.	Lee (2010)	Using TPB, TAM, ECM and flow theory for explaining continued use of E-learning			✓			✓	✓	✓	Attitude	Contribution: Applying flow theory as perceived performance factor Other findings: Relationship between perceived enjoyment on attitude
12.	Almahamid and Rub (2011)	EDT and decomposing perceived performance into 6 dimensions: perceived usefulness, information content, intrinsic motivation, system quality, service quality and perceived self-efficacy					✓		✓			Contribution: Decomposing perceived performance
13.	Lin (2011)	EDT and TAM for explaining continued use of E-learning									Attitude	Other findings: Attitude is a function of expectation (performance expectancy) and satisfaction
14.	Sun et al. (2011)	UATUT and ECM							✓	✓		
15.	Lin and Wang (2012)	ECM, TAM, and decomposing perceived performance into four dimensions: task-technology fit, information quality, knowledge quality and system quality			✓			✓	✓	✓		Contribution: Decomposing perceived performance Other findings: The relationship between PP and EC
16.	Islam (2013)	TAM for explaining continued use and investigate the impact of use on academic performance								✓		Contribution: The consequence of use on performance Other findings: The relationship between use and academic performance

Where: IE is initial expectation; PP is perceived performance; EC is expectancy confirmation; S is satisfaction; and ME is modified (new) expectation

No.	Researcher	Grounded theories	Factors influencing expectation			Factors influencing satisfaction			Factors influencing intention to continue use			Contribution & other research findings
			IE	PP	EC	IE	PP	EC	S	ME	Other	
17.	Terzis et al. (2013)	ECM, UTAUT and adding confirmed content and playfulness									Expectancy confirmation	Contribution: Decomposing expectancy confirmation into 6 dimensions
18.	Hong et al. (2014)	Liking, enjoyment and engagement as predictors of continued use intention									Liking, enjoyment and engagement	Contribution: Student feeling for explaining continued use
19.	Alraimi et al. (2015)	ECM, performance expectancy and enjoyment			✓			✓	✓	✓	Enjoyment	

Where: IE is initial expectation; PP is perceived performance; EC is expectancy confirmation; S is satisfaction; and ME is modified (new) expectation

Appendix 4-A: Translation of a Thai questionnaire used at preliminary study

Questionnaire number | | | | |

Questionnaire

Model of E-learning uptake and continued use in Higher Education Institutions

The main aim of this research is to construct the model of E-learning uptake and continued use in Higher Education Institutions. You have been chosen because you are a university student and this research is trying to obtain your opinion about which factors affect your decision to take up and continue using E-learning. This research is under the direction of Electronics and Computer Science, University of Southampton. I would appreciate your responses to the following questions. Your information will be used for this research purpose only. Thank you very much for your time in completing this questionnaire.

Explanation

1. There are 17 questions in this questionnaire. In addition, all of these questions are divided in to three parts. The first part is designed for collecting general information. The second part is designed only for *students who have never used E-learning* to explore the factors that influence students to take up E-leaning. The third part is designed only for *students who have used E-learning before* for finding out the factors that affect the uptake and continued use of E-learning.
2. This questionnaire is designed only for undergraduate students who study at Rajamangala University of Technology Thanyaburi (RMUTT).
3. Please try to answer all the questions, as the information you give will be valuable in our research.
4. Please tick only one answer to each question.

Section A: General information

Explanation: This section is used to collect your general information. Please consider all the options in each question carefully, and tick only one answer.

1. Are you currently studying at a Thai University?

☐ (1) Yes ☐ (2) No

2. Have you ever used E-learning?

☐ (1) Yes

☐ (2) No

If you have never used E-learning at all, *please skip the next question of this section, and continue with Section B*

3. Do you currently use E-learning?

☐ (1) Yes

☐ (2) No

If you have ever used E-learning before *(whether you continued using it or opted out), please skip Section B and go on to answer Section C*

Section B: Factors affecting the uptake of E-learning

Explanation: This section is designed only for *students who have never used E-learning*. Please consider all options in each question carefully, and tick only one answer.

Items	No not at all (1)	Partially no (2)	Not sure (3)	Partially yes (4)	Yes absolutely (5)
Would your decision to take up E-learning be influenced by its usefulness for your education?					
Would your decision to take up E-learning be influenced by its ease of use?					
Would your decision to take up E-learning be influenced by encouragement from other people who are important to you?					
Would your decision to take up E-learning be influenced by the availability of IT resources and staff?					
Would your decision to take up E-learning be influenced by how relevant the content is?					
Would your decision to take up E-learning be influenced by your learning preferences?					
Would your decision to take up E-learning be influenced by your present competency in what is being learned?					

Section C: Factors affecting the uptake and continued use of E-learning

Explanation: This section is designed only for *students who have used E-learning before*. Please consider all options in each question carefully, and tick only one answer.

Items	**No not at all** (1)	**Partially no** (2)	**Not sure** (3)	**Partially yes** (4)	**Yes absolutely** (5)
Would your decision to take up E-learning be influenced by its usefulness for your education?					
Would your decision to take up E-learning be influenced by its ease of use?					
Would your decision to take up E-learning be influenced by encouragement by other people who are important to you?					
Would your decision to take up E-learning be influenced by the availability of IT resources and staff?					
Would your decision to take up E-learning be influenced by how relevant the content is?					
Would your decision to take up E-learning be influenced by your learning preferences?					
Would your decision to take up E-learning be influenced by your present competency in what is being learned?					
Would your decision to continue using E-learning be influenced by how useful you perceive it to be for your education?					
Would your decision to continue using E-learning be influenced by how easy you think it is to use?					
Would your decision to continue using E-learning be influenced by continuing encouragement from your important person?					
Would your decision to continue using E-learning be influenced by the availability of IT resources and staff?					
Would your decision to continue using E-learning be influenced by its having content relevant to you?					
Would your decision to continue using E-learning be influenced by how closely you think its learning activities match your learning styles?					
Would your decision to continue using E-learning be influenced by how closely you think its content matches your present competencies?					

Appendix 6-A: Translation of a Thai questionnaire used at the first data collection of a longitudinal study (time t_0)

UNIVERSITY OF Southampton

Questionnaire

Model of E-learning uptake and continuance in Higher Education Institutions

The main purpose of this questionnaire is to measure students' expectations about the use of the RMUTT online classroom in General Statistics. You have been chosen because you are a student on the General Statistics course. This research is under the direction of Electronics and Computer Science, University of Southampton. I would appreciate your responses to the following questions. Your information will be used for this purpose only. Thank you very much for your time in completing this questionnaire.

Explanation

1. This questionnaire is designed for only undergraduate students on the General Statistics course at Rajamangala University of Technology Thanyaburi (RMUTT)
2. There are 16 questions in the questionnaire
3. Please try to answer all the questions and tick only one option in each question.

If you agree to take part in this research, *please give your name and username of RMUTT online classroom.*

Name of participant (print name)…………………………………………………………………….

Username of RMUTT online classroom…………………………………………………………..

Please consider all options in each question carefully, and tick only one answer.

		Not at all					Somewhat					Very much
1.	Before using the RMUTT online classroom in general statistics next month, how much do you expect that the system will be useful to your study of General Statistics?	0	1	2	3	4	5	6	7	8	9	10
2.	Before using the RMUTT online classroom in general statistics next month, how much do you expect that the system will allow you to learn General Statistics more quickly?	0	1	2	3	4	5	6	7	8	9	10
3.	Before using the RMUTT online classroom in general statistics next month, how much do you expect that the system will improve your score in General Statistics?	0	1	2	3	4	5	6	7	8	9	10
4.	Before using the RMUTT online classroom in general statistics next month, how much do you expect that learning to operate the system will be easy?	0	1	2	3	4	5	6	7	8	9	10
5.	Before using the RMUTT online classroom in general statistics next month, how much do you expect that you will become skilful at using the system (capable of asking the system to do what you want it to do)?	0	1	2	3	4	5	6	7	8	9	10
6.	Before using the RMUTT online classroom in general statistics next month, how much do you expect that the system will be easy to use?	0	1	2	3	4	5	6	7	8	9	10
7.	Before using the RMUTT online classroom in general statistics next month, how much do you expect that your parents will encourage the use of the system?	0	1	2	3	4	5	6	7	8	9	10
8.	Before using the RMUTT online classroom in general statistics next month, how much do you expect that the director of your university will encourage the use of the system?	0	1	2	3	4	5	6	7	8	9	10
9.	Before using the RMUTT online classroom in general statistics next month, how much do you expect that your lecturers will encourage the use of the system?	0	1	2	3	4	5	6	7	8	9	10
10.	Before using the RMUTT online classroom in general statistics next month, how much do you expect that your friends will encourage the use of the system?	0	1	2	3	4	5	6	7	8	9	10
11.	Before using the RMUTT online classroom in general statistics next month, how much do you expect that you will have necessary IT resources (e.g. a computer and internet) to use the system?	0	1	2	3	4	5	6	7	8	9	10

		Not at all					Somewhat					Very much
12.	Before using the RMUTT online classroom in general statistics next month, how much do you expect that the university will provide you with the necessary IT resources to use the system?	0	1	2	3	4	5	6	7	8	9	10
13.	Before using the RMUTT online classroom in general statistics next month, how much do you expect that IT staffs will assist you with the use of the system when you need help?	0	1	2	3	4	5	6	7	8	9	10
14.	Before using the RMUTT online classroom in general statistics next month, how much do you expect that the system will provide the content that is relevant to you?	0	1	2	3	4	5	6	7	8	9	10
15.	Before using the RMUTT online classroom in general statistics next month, how much do you expect that the system will provide teaching and learning activities that suit the way you learn?	0	1	2	3	4	5	6	7	8	9	10
16.	Before using the RMUTT online classroom in general statistics next month, how much do you expect that the system will provide content that is appropriate for your present competencies (neither too easy nor too hard)?	0	1	2	3	4	5	6	7	8	9	10

Appendix 6-B: Translation of a Thai questionnaire used at the second data collection of a longitudinal study (time t_1)

Questionnaire

Model of E-learning uptake and continuance in Higher Education Institutions

The aim of the questionnaire is to measure: (a) time spent on learning activities outside the class in General Statistics; (b) perceived actual performance of RMUTT online classroom in General Statistics; (c) new expectations towards the use of RMUTT online classroom in General Statistics next month. You have been chosen because you were a participant in the first data collection (last month). This research is under direction of Electronics and Computer Science, University of Southampton. I would appreciate your responses to the following questions. Your information will be used for this purpose only. Thank you very much for your time in completing this questionnaire.

Explanation

1. There are 47 questions in this questionnaire. The first section has 15 questions measuring time spent on learning activities outside classroom for General Statistics. The second section has 16 questions measuring perceived actual performance of RMUTT online classroom in General Statistics. The third section has 16 questions measuring new expectations towards the use of RMUTT online classroom in General Statistics.
2. This questionnaire is designed only for students on the General Statistics course at RMUTT who undertook the research last month.
3. All participants should complete the first section. The second and third sections are for those who used the RMUTT online classroom in General Statistics last month.
4. Please try to answer all questions, as the information you give will be valuable for our research.
5. Please tick only one answer in each question.

If you agree to take part in this research, *please give your name and username of RMUTT online classroom.*

Name of participant (print name)……………………………………………………………………….

Username of RMUTT online classroom……………………………………………………………..

Section 1 Please indicate below how many times per week and the average hours each time that you spent on each of the following kinds of activities during the previous month.

	Activity	**How often** (Times)	**How long** (hours)
1.	Reviewing lecture notes of General Statistics		
2.	Reading General Statistics documents from RMUTT online classroom		
3.	Reading documents related to General Statistics from other sources *(please specify)*……………………………………………………..		
4.	Watching the General Statistics video from RMUTT online classroom		
5.	Watching the video related to General Statistics from other sources *(please specify)*……………………………………………………..		
6.	Doing General Statistics exercises from RMUTT online classroom		
7.	Doing General Statistics exercises from other sources *(please specify)*………………………………………………………………..		
8.	Discussing General Statistics with friends face-to-face		
9.	Discussing General Statistics with friends using the RMUTT online classroom		
10.	Discussing General Statistics with friends using social media (Facebook, Twitter) or other communication tools *(please specify)*………………………………………………………………		
11.	Discussing with lecturers face-to-face about General Statistics		
12.	Discussing General Statistics with lecturers using the RMUTT online classroom		
13.	Discussing General Statistics with lecturers using social media (Facebook, Twitter) and online communication tools *(please specify)*………………………………………………………………..		
14.	Name of Personal Tutor for General Statistics		
15.	Other *(please specify)*…………………………………………………………		

Section 2 Only for students who used RMUTT online classroom in General Statistics last month, please consider all the options in each question carefully, and tick only one answer

		Not at all					Somewhat					Very much
1.	After using RMUTT online classroom in general statistics last month, how much do you think that the system was useful for your study in General Statistics?	0	1	2	3	4	5	6	7	8	9	10
2.	After using RMUTT online classroom in general statistics last month, how much do you think that the system allowed you to learn General Statistics more quickly?	0	1	2	3	4	5	6	7	8	9	10
3.	After using RMUTT online classroom in general statistics last month, how much do you think that the system improved your scores in general statistics?	0	1	2	3	4	5	6	7	8	9	10
4.	After using RMUTT online classroom in general statistics last month, how much do you think that learning to operate the system was easy?	0	1	2	3	4	5	6	7	8	9	10
5.	After using RMUTT online classroom in general statistics last month, how much do you think that you became skilful at using the system (capable of asking the system to do what you want it to do)?	0	1	2	3	4	5	6	7	8	9	10
6.	After using RMUTT online classroom in general statistics last month, how much do you think that the system was easy to use?	0	1	2	3	4	5	6	7	8	9	10
7.	After using RMUTT online classroom in general statistics last month, how much did your parents encourage the use of the system?	0	1	2	3	4	5	6	7	8	9	10
8.	After using RMUTT online classroom in general statistics last month, how much did the director of your university encourage the use of the system?	0	1	2	3	4	5	6	7	8	9	10
9.	After using RMUTT online classroom in general statistics last month, how much did your lecturers encourage the use of the system?	0	1	2	3	4	5	6	7	8	9	10
10.	After using RMUTT online classroom in general statistics last month, how much did your friends encourage the use of the system?	0	1	2	3	4	5	6	7	8	9	10
11.	After using RMUTT online classroom in general statistics last month, how much do you think that you have necessary IT resources (e.g. a computer and internet) to use the system?	0	1	2	3	4	5	6	7	8	9	10

		Not at all					Somewhat					Very much
12.	After using RMUTT online classroom in general statistics last month, how much did the university provide you with the necessary IT resources to use the system?	0	1	2	3	4	5	6	7	8	9	10
13.	After using RMUTT online classroom in general statistics last month, how much did the IT staff assist you with the use of the system when you needed help?	0	1	2	3	4	5	6	7	8	9	10
14.	After using RMUTT online classroom in general statistics last month, how much do you think that E-learning provided content that is relevant to you?	0	1	2	3	4	5	6	7	8	9	10
15.	After using RMUTT online classroom in general statistics last month, how much do you think that E-learning provided teaching and learning activities that suit the way you learn?	0	1	2	3	4	5	6	7	8	9	10
16.	After using RMUTT online classroom in general statistics last month, how much do you think that E-learning provided the content that is appropriate for your present competencies (neither too easy nor too hard)?	0	1	2	3	4	5	6	7	8	9	10

Section 3 Only for students who used RMUTT online classroom in General Statistics last month, please consider all of options in each question carefully, and tick only one answer

		Not at all					Somewhat					Very much
1.	Before using RMUTT online classroom in general statistics next month, how much do you expect that the system will be useful your study in General Statistics?	0	1	2	3	4	5	6	7	8	9	10
2.	Before using RMUTT online classroom in general statistics next month, how much do you expect that the system will allow you to learn General Statistics more quickly?	0	1	2	3	4	5	6	7	8	9	10
3.	Before using RMUTT online classroom in general statistics next month, how much do you expect that the system will improve your score in general statistics?	0	1	2	3	4	5	6	7	8	9	10
4.	Before using RMUTT online classroom in general statistics next month, how much do you expect that learning to operate the system will be easy?	0	1	2	3	4	5	6	7	8	9	10
5.	Before using RMUTT online classroom in general statistics next month, how much do you expect that you will become skilful at using the system (capable of asking the system to do what you want it to do)?	0	1	2	3	4	5	6	7	8	9	10

		Not at all					Somewhat					Very much
6.	Before using RMUTT online classroom in general statistics next month, how much do you expect that the system will be easy to use?	0	1	2	3	4	5	6	7	8	9	10
7.	Before using RMUTT online classroom in general statistics next month, how much do you expect that your parents will encourage the use of the system?	0	1	2	3	4	5	6	7	8	9	10
8.	Before using RMUTT online classroom in general statistics next month, how much do you expect that the director of your university will encourage the use of the system?	0	1	2	3	4	5	6	7	8	9	10
9.	Before using RMUTT online classroom in general statistics next month, how much do you expect that your lecturers will encourage the use of the system?	0	1	2	3	4	5	6	7	8	9	10
10.	Before using RMUTT online classroom in general statistics next month, how much do you expect that your friends will encourage the use of the system?	0	1	2	3	4	5	6	7	8	9	10
11.	Before using RMUTT online classroom in general statistics next month how much do you expect that you will have necessary IT resources (e.g. a computer and internet) to use the system?	0	1	2	3	4	5	6	7	8	9	10
12.	Before using RMUTT online classroom in general statistics next month, how much do you expect that the university will provide you with the necessary IT resources to use the system?	0	1	2	3	4	5	6	7	8	9	10
13.	Before using RMUTT online classroom in general statistics next month, how much do you expect that IT staffs will assist you with the use of the system when you need help?	0	1	2	3	4	5	6	7	8	9	10
14.	Before using RMUTT online classroom in general statistics next month, how much do you expect that the system will provide content that is relevant to you?	0	1	2	3	4	5	6	7	8	9	10
15.	Before using RMUTT online classroom in general statistics next month, how much do you expect that the system will provide teaching and learning activities that suit the way you learn?	0	1	2	3	4	5	6	7	8	9	10
16.	Before using RMUTT online classroom in general statistics next month, how much do you expect that the system will provide the content that is appropriate for your present competencies (neither too easy nor too hard)?	0	1	2	3	4	5	6	7	8	9	10

Appendix 6-C: Translation of Thai questionnaire used at the third data collection of a longitudinal study (time t_2)

UNIVERSITY OF Southampton

Questionnaire

Model of E-learning uptake and continuance in Higher Education Institutions

The main purpose of this questionnaire is to measure the time spent on learning activities for General Statistics outside the classroom during the past month. You have been chosen because you were a participant in the first two data collections and used the RMUTT online classroom for General Statistics during January and February. This research is under the direction of Electronics and Computer Science, University of Southampton. I would appreciate your responses to the following questions. Your information will be used for this research purpose only. Thank you very much for your time in completing this questionnaire.

Explanation

1. There are 15 questions in this questionnaire, measuring the time you spent on learning activities outside classroom for General Statistics in the past month.
2. This questionnaire is designed only for students who participated in the first two data collections and used the RMUTT online classroom for General Statistics during January and February.
3. Please try to answer all the questions as the information you give will be valuable in our research.
4. Please tick only one option to each question.

If you agree to take part in this research, *please give your name and username for the RMUTT online classroom.*

Name of participant (print name)…………………………………………………………………….

Username of RMUTT online classroom…………………………………………………………..

Section 1 Please indicate below how many times and average hours per each time a week, you spent in each of the following kinds of activities during the previous month.

	Activity	**How often** (times)	**How long** (hours)
1.	Reviewing lecture notes of General Statistics		
2.	Reading General Statistics documents from RMUTT online classroom		
3.	Reading documents related to General Statistics from other sources *(please specify)*………………………………………………..		
4.	Watching the General Statistics video from RMUTT online classroom		
5.	Watching the video related to General Statistics from other sources *(please specify)*………………………………………………..		
6.	Doing General Statistics exercises from RMUTT online classroom		
7.	Doing General Statistics exercises from other sources *(please specify)*……………………………………………………….		
8.	Discussing General Statistics with friends face-to-face		
9.	Discussing General Statistics with friends using RMUTT online classroom		
10.	Discussing General Statistics with friends using social media (Facebook, Twitter) or other communication tools *(please specify)*………………………………………………………………		
11.	Discussing General Statistics with lecturers face-to-face		
12.	Discussing General Statistics with lecturers using RMUTT online classroom		
13.	Discussing General Statistics with lecturers using social media (Facebook, Twitter) and online communication tool *(please specify)*…………………………………………………………….		
14.	Name of Personal Tutor for General Statistics		
15.	Other *(please specify)*…………………………………………………		

Appendix 6-D: Results of consistency translation test

Expectation questions

	Question (English)	Question (Thai)	Language consistency score					Total score	Comment
			Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
1.	How much do you expect that E-learning will be useful for your education?	ระดับความคาดหวังของท่านว่า ระบบ E-learning จะมีประโยชน์ต่อการศึกษาของท่านนั้นอยู่ในระดับใด	1	1	1	1	1	5	**No**
2.	How much do you expect that E-learning will allow you to learn more quickly?	ระดับความคาดหวังของท่านว่า ระบบ E-learning จะที่ช่วยให้ท่านเรียนรู้ได้เร็วขึ้นนั้นอยู่ในระดับใด	1	1	1	1	1	5	**No**
3.	How much do you expect that E-learning will improve your grades?	ระดับความคาดหวังของท่านว่า ระบบ E-learning จะช่วยให้ท่านมีผลการเรียนที่ดีขึ้นนั้นอยู่ในระดับใด	1	1	1	1	1	5	**No**
4.	How much do you expect that learning to operate E-learning system will be easy?	ระดับความคาดหวังของท่านว่า การเรียนรู้การใช้งานระบบ E-learning จะง่ายนั้นอยู่ในระดับใด	1	1	1	1	1	5	**No**
5.	How much do you expect that you will become skilful at using E-learning?	ระดับความคาดหวังของท่านว่า ท่านจะมีความเชี่ยวชาญในการใช้งานระบบE-learning นั้นอยู่ในระดับใด	1	1	1	1	1	5	**No**
6.	How much do you expect that E-learning will be easy to use?	ระดับความคาดหวังของท่านว่าระบบ E-learning จะเป็นระบบที่ง่ายต่อการใช้งานนั้นอยู่ในระดับใด	1	1	1	1	1	5	**No**
7.	How much do you expect that your parents will encourage the use of E-learning?	ระดับความคาดหวังของท่านว่า ผู้ปกครองของท่านจะมีส่วนสนับสนุนในการใช้งานระบบ E-learning นั้นอยู่ในระดับใด	1	1	1	1	0	4	**Cut some words for clear statement** *ระดับความคาดหวังของท่านว่าผู้ปกครองของท่านจะ~~มีส่วน~~สนับสนุน~~ใน~~การใช้งานระบบ E-learning นั้นอยู่ในระดับใด*
8.	How much do you expect that the directors of your university will encourage the use of E-learning?	ระดับความคาดหวังของท่านว่า ผู้บริหารสถาบันการศึกษาของท่านจะมีส่วนสนับสนุนในการใช้งานระบบ E-learning นั้นอยู่ในระดับใด	1	1	1	1	0	4	**Cut some words for clear statement** *ระดับความคาดหวังของท่านว่าผู้บริหารสถาบันการศึกษาของท่านจะ~~มีส่วน~~สนับสนุน~~ใน~~การใช้งานระบบ E-learning นั้นอยู่ในระดับใด*

	Question (English)	Question (Thai)	Language consistency score					Total score	Comment
			Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
9.	How much do you expect that your lecturers will encourage the use of E-learning?	ระดับความคาดหวังของท่านว่าอาจารย์ประจำวิชาของท่านจะมีส่วนสนับสนุนในการใช้งานระบบ E-learning นั้นอยู่ในระดับใด	1	1	1	1	0	4	**Cut words for clear statement** *ระดับความคาดหวังของท่านว่าอาจารย์ประจำวิชาของท่านจะ~~มีส่วน~~สนับสนุน~~ใน~~การใช้งานระบบ E-learning นั้นอยู่ในระดับใด*
10.	How much do you expect that your friends will encourage the use of E-learning?	ระดับความคาดหวังของท่านว่านักศึกษาของท่านจะมีส่วนสนับสนุนในการใช้งานระบบ E-learning นั้นอยู่ในระดับใด	1	1	1	1	0	4	**Cut words for clear statement** *ระดับความคาดหวังของท่านว่าเพื่อนนักศึกษาของท่านจะ~~มีส่วน~~สนับสนุน~~ใน~~การใช้งานระบบ E-learning นั้นอยู่ในระดับใด*
11.	How much do you expect that you will necessary IT resources (e.g. a computer and internet) to use E-learning?	ระดับความคาดหวังของท่านในเชิงอุปกรณ์ IT ที่จำเป็นต่อการใช้งานระบบ(เช่น คอมพิวเตอร์ และอินเตอร์เน็ต) ของท่านนั้นอยู่ในระดับใด	0	1	1	1	1	4	**Should add *'E-learning'* to the statement** *ระดับความคาดหวังของท่านในเชิงอุปกรณ์ IT ที่จำเป็นต่อการใช้งานระบบ E-learning (เช่น คอมพิวเตอร์ และอินเตอร์เน็ต) ของท่านนั้นอยู่ในระดับใด*
12.	How much do you expect that the university will provide you with the necessary IT resources to use E-learning?	ระดับความคาดหวังของท่านว่ามหาวิทยาลัยของท่านจะมีการจัดเตรียมอุปกรณ์ IT ที่จำเป็นต่อการใช้งานระบบนั้นอยู่ในระดับใด	0	1	1	1	1	4	**Should add *'E-learning'* to statement** *ระดับความคาดหวังของท่านว่ามหาวิทยาลัยของท่านจะมีการจัดเตรียมอุปกรณ์ IT ที่จำเป็นต่อการใช้งานระบบ E-learning นั้นอยู่ในระดับใด*

	Question (English)	Question (Thai)	Language consistency score					Total score	Comment
			Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
13.	How much do you expect that IT staff will assist you with the use of E-learning system when you need help?	ระดับความคาดหวังของท่านว่าบุคคากรด้าน IT ในมหาวิทยาลัยจะสนับสนุนและมีส่วนช่วยแก้ปัญหาที่เกิดขึ้นในระหว่างการใช้งานระบบ E-learningนั้นอยู่ในระดับใด	0	1	0	1	1	3	**Cut words for clear statement** *ระดับความคาดหวังของท่านว่าบุคคากรด้าน IT ในมหาวิทยาลัยจะ~~สนับสนุน~~และมีส่วนช่วยแก้ปัญหาที่เกิดขึ้นใน~~ระหว่าง~~การใช้งานระบบ E-learningนั้นอยู่ในระดับใด*
14.	How much do you expect that E-learning will provide content that is relevant to you?	ระดับความคาดหวังของท่านว่าว่าระบบ E-learning จะมีตัวเนื้อหาที่ตรงกับความต้องการของท่านนั้นอยู่ในระดับใด	1	1	1	1	0	4	**Cut words and add new for clear statement** *ระดับความคาดหวังของท่านว่า~~ว่า~~ระบบ E-learning จะ~~มี~~เตรียม ตัวเนื้อหาที่ตรงกับความต้องการของท่านนั้นอยู่ในระดับใด*
15.	How much do you expect that E-learning will provide teaching and learning activities that suit the way you learn?	ระดับความคาดหวังของท่านว่าว่าระบบ E-learning จะมีกิจกรรมการเรียน (learning activity) และวิธีการสอน (teaching activity) ที่สอดคล้องกับวิธีการเรียนของท่าน (learning preference)นั้นอยู่ในระดับใด	1	1	0	0	0	2	1. **Cut words for clear sentence** (Expert 4 and 5) 2. **Change words to make precise meaning** (Expert3) *ระดับความคาดหวังของท่านว่า~~ว่า~~ระบบ E-learning จะมีกิจกรรมการเรียน (learning activity) และ~~วิธีการ~~กิจกรรมการสอน (teaching activity) ที่สอดคล้องกับวิธีการเรียนของท่าน (learning preference)นั้นอยู่ในระดับใด*

	Question (English)	Question (Thai)	Language consistency score					Total score	Comment
			Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
16.	How much do you expect that E-learning will provide the content that is appropriate for your present competencies (not too easy or not too hard)?	ระดับความคาดหวังของท่านว่าระบบ E-learning จะเป็นระบบที่มีเนื้อหาเหมาะสมกับระดับความรู้ที่ท่านมีอยู่ในปัจจุบันนั้นอยู่ในระดับใด	1	1	1	0	1	4	**Change and add some words for making clearer statement** *ระดับความคาดหวังของท่านว่าระบบ E-learning จะ~~เป็นระบบที่มี~~ จัดเตรียมเนื้อหาที่หมาะสมกับระดับความรู้~~ที่~~ของท่าน~~มีอยู่~~ในปัจจุบันนั้นอยู่ในระดับใด*

Perceived performance questions

	Question (English)	Question (Thai)	Language consistency score					Total score	Comment
			Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
1.	How much do you think that E-learning was useful for your education?	ท่านคิดว่าระบบ E-learning มีประโยชน์ต่อการศึกษาของท่านมากน้อยเพียงใด	1	1	1	1	1	5	**No**
2.	How much do you think that E-learning allowed you to learn more quickly?	ท่านคิดว่าระบบ E-learning ช่วยให้ท่านเรียนรู้ได้เร็วขึ้นมากน้อยเพียงใด	1	1	1	1	1	5	**No**
3.	How much do you think that E-learning improved your grades?	ท่านคิดว่าระบบ E-learning ช่วยให้ท่านมีผลการเรียนดีขึ้นมากน้อยเพียงใด	1	1	1	1	1	5	**No**
4.	How much do you think that learning to operate E-learning system was easy?	ท่านคิดว่าการเรียนรู้การใช้งานระบบ E-learning นั้นง่ายอยู่ในระดับใด	1	1	-1	1	1	3	**Should change statement to make easier to understand** *หลังจากได้ใช้งานระบบ E-learning ท่านคิดว่าการเรียนรู้การใช้งานระบบ E-learning นั้นง่ายมากน้อยเพียงใด*
5.	How much do you think that you became skilful at using E-learning?	ท่านคิดว่าท่านมีความเชี่ยวชาญในการใช้งานระบบมากน้อยเพียงใด	1	1	1	1	1	5	**No**
6.	How much do you think that E-learning was easy to use?	ท่านคิดว่าระบบ E-learning มีความง่ายต่อการใช้งานมากน้อยเพียงใด	1	1	1	1	1	5	**No**
7.	How much did your parents encourage the use of E-learning?	ผู้ปกครองของท่านได้มีส่วนสนับสนุนในการใช้งานระบบมากน้อยเพียงใด	1	1	1	1	0	4	**Cut some words and add ‘*E-learning*’ to statement for clearer statement** *ผู้ปกครองของท่าน~~ได้มีส่วน~~สนับสนุน~~ใน~~การใช้งานระบบ E-learning มากน้อยเพียงใด*

	Question (English)	Question (Thai)	Language consistency score					Total score	Comment
			Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
8.	How much did the directors of your university encourage the use of E-learning?	ผู้บริหารสถาบันการศึกษาของท่านได้มีส่วนสนับสนุนในการใช้งานระบบมากน้อยเพียงใด	1	1	1	1	0	4	**Cut words and add *'E-learning'* to statement for more clear statement** *ผู้บริหารสถาบันการศึกษาของท่าน~~ได้มีส่วน~~สนับสนุน~~ใน~~การใช้งานระบบ E-learning มากน้อยเพียงใด*
9.	How much did your lectures encourage the use of E-learning?	อาจารย์ประจำวิชาของท่านได้มีส่วนสนับสนุนในการใช้งานระบบมากน้อยเพียงใด	1	1	1	1	0	4	**Cut words and add *'E-learning'* to statement for clearer statement** *อาจารย์ประจำวิชาของท่าน~~ได้มีส่วน~~สนับสนุน~~ใน~~การใช้งานระบบ E-learning มากน้อยเพียงใด*
10.	How much did your friends encourage the use of E-learning?	เพื่อนนักศึกษาของท่านได้มีส่วนสนับสนุนในการใช้งานระบบมากน้อยเพียงใด	1	1	1	1	0	4	**Cut some words off and add the word *'E-learning'* to the statement for more clear statement** *เพื่อนนักศึกษาของท่าน~~ได้มีส่วน~~สนับสนุน~~ใน~~การใช้งานระบบ E-learning มากน้อยเพียงใด*
11.	How much do you think that you have necessary IT resources (e.g. a computer and internet) to use E-learning?	ท่านคิดว่าท่านมีอุปกรณ์ IT ที่จำเป็นต่อการใช้งานระบบ(เช่น คอมพิวเตอร์ และ อินเตอร์เน็ต) อยู่ในระดับใด	1	1	1	1	1	5	**No**

	Question (English)	Question (Thai)	Language consistency score					Total score	Comment
			Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
12.	How much did the university provide you with the necessary IT resources to use E-learning?	ท่านคิดว่าระดับความพร้อมของอุปกรณ์ IT ที่จำเป็นต่อการใช้งานระบบ E-learning ในมหาวิทยาลัยของท่านอยู่ในระดับใด	1	1	1	1	1	5	**No**
13.	How much did the IT staff assist you with the use of E-learning system when you needed help?	ท่านคิดว่าบุคคากรด้าน IT ในมหาวิทยาลัยได้สนับสนุนและมีส่วนช่วยแก้ปัญหาที่เกิดขึ้นในระหว่างการใช้งานระบบ E-learning มากน้อยเพียงใด	1	1	0	1	1	4	**Cut words for clearer statement** *ท่านคิดว่าบุคคากรด้าน IT ในมหาวิทยาลัย~~ได้สนับสนุนและมีส่วน~~ช่วยแก้ปัญหาที่เกิดขึ้นในระหว่างการใช้งานระบบ E-learning มากน้อยเพียงใด*
14.	How much do you think that E-learning provided the content that is relevant to you?	ท่านคิดว่าระบบ E-learning เป็นระบบที่สร้างตัวเนื้อหาที่ตรงกับความต้องการของท่านมากน้อยเพียงใด	1	1	1	1	0	4	**Cut words and add new for clearer statement** *ท่านคิดว่าระบบ E-learning เป็นระบบที่~~สร้างตัว~~ จัดเตรียมเนื้อหาที่ตรงกับความต้องการของท่านมากน้อยเพียงใด*
15.	How much do you think that E-learning provided teaching and learning activities that suit the way you learn?	ท่านคิดว่าระบบ E-learning มีกิจกรรมการเรียน (learning activity) และวิธีการสอน (teaching activity) ที่สอดคล้องกับวิธีการเรียนของท่าน (learning preference) มากน้อยเพียงใด	1	1	0	0	0	2	1. **Cut words for make clearer** (Experts 4 & 5) 2. **Change wording to make more precise** (Expert 3) *ท่านคิดว่าระบบ E-learning ~~มี~~ เป็นระบบที่จัดเตรียมกิจกรรมการเรียน (learning activity) และ ~~วิธีการ~~ กิจกรรมการสอน (teaching activity) ที่สอดคล้องกับวิธีการเรียนของท่าน (learning preference) มาก*

	Question (English)	Question (Thai)	Language consistency score					Total score	Comment
			Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
16.	How much do you think that the content in E-learning was appropriate for your present competencies (not too easy or not too hard)?	ท่านคิดว่าระบบ E-learning มีเนื้อหาที่เหมาะสมกับระดับความรู้ของท่านในปัจจุบัน มากน้อยเพียงใด	1	1	1	0	1	4	**Change and add some words for making clearer statement** *ท่านคิดว่าระบบ E-learning ~~มี~~เป็นระบบที่จัดเตรียมเนื้อหาที่เหมาะสมกับระดับความรู้ของท่านในปัจจุบัน มากน้อยเพียงใด*

Part 3: Time spent on learning activities outside classroom

	Question (English)	Question (Thai)	Language consistency score					Total score	Comment
			Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
1.	Reviewing lecture notes	ทบทวนสมุดจดบันทึกในห้องเรียน (Lecture note)	1	1	1	1	1	5	**No**
2.	Reading course related documents from E-learning	อ่านเอกสารประกอบการสอนจากระบบ E-learning	1	1	1	1	1	5	**No**
3.	Reading course related documents from other sources *(please specify)*	อ่านตำราวิชาการจากแหล่งการเรียนรู้อื่นที่ไม่ใช่ระบบ E-learning *(โปรดระบุแหล่งที่มาของตำราวิชาการ)*	1	1	1	1	1	5	**No**
4.	Watching the course video from E-learning	ดูวีดีทัศ เพื่อการศึกษาจากระบบ RMUTT online classroom	1	1	0	1	0	3	**Wrong spelling** (Expert 5) **and should change the word for making more specific meaning** (Expert 3) *ดูวีดีทัศน์ เพื่อการศึกษาที่เกี่ยวข้องกับรายวิชาจากระบบ E-learning*

	Question (English)	Question (Thai)	Language consistency score					Total score	Comment
			Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
5.	Watching the course related video from other sources *(please specify)*	ดูวีดีทัศ เพื่อการศึกษาจากแหล่งเรียนรู้อื่นที่ไม่ใช่ E-learning *(โปรดระบุแหล่งที่มาของวีดีทัศ)*	1	1	0	1	0	3	**Wrong spelling** (Expert 5) **and should change wording to make more specific meaning** (Expert 3) ดูวีดีทัศน์ เพื่อการศึกษา*ที่เกี่ยวข้องกับรายวิชา*จากแหล่งเรียนรู้อื่นที่ไม่ใช่ E-learning *(โปรดระบุแหล่งที่มาของวีดีทัศน์)*
6.	Doing course exercise from E-learning	ทำแบบฝึกหัดจากระบบ E-learning	1	1	1	1	1	5	**No**
7.	Doing course related exercise from other sources *(please specify)*	ทำแบบฝึกหัดจากแหล่งการเรียนรู้อื่นที่ไม่ใช่ระบบ E-learning *(โปรดระบุแหล่งที่มาของแบบฝึกหัด)*	1	1	1	1	1	5	**No**
8.	Discussing with friends face-to-face	ปรึกษาหารือกับเพื่อนของท่านโดยตรง (face-to-face)	0	1	1	1	1	4	**Should add some words for making clearer statement** *ปรึกษาหารือกับเพื่อนของท่านโดยการพบปะพูดคุยโดยตรง (face-to-face)*
9.	Discussing with friends using E-learning	ปรึกษาหารือกับเพื่อนของท่านผ่านทางระบบ E-learning	1	1	1	1	1	5	**No**
10.	Discussing with friends using social media (Facebook, Line) or other communication tools *(please specify)*	ปรึกษาหารือกับเพื่อนของท่านผ่านทาง social media (เช่น Facebook, twitter) และ วิธีการสื่อสารแบบอื่นๆ (โปรดระบุ)	1	1	1	1	1	5	**No**
11.	Discussing with lecturers face-to-face	ปรึกษาหารือกับอาจารย์ของท่านโดยตรง (face-to-face)	0	1	1	1	1	4	**Should add words to make clearer statement** ปรึกษาหารือกับอาจารย์ของท่าน*โดยการพบปะพูดคุย*โดยตรง *(face-to-face)*

	Question (English)	Question (Thai)	Language consistency score					Total score	Comment
			Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
12.	Discussing with lecturers using E-learning	ปรึกษาหารือกับอาจารย์ของท่านผ่านทางระบบ E-learning	1	1	1	1	1	5	**No**
13.	Discussing with lecturers using social media (Facebook, Line) and online communication tool *(please specify)*	ปรึกษาหารือกับอาจารย์ของท่านผ่านทาง social media (เช่น Facebook, twitter) และวิธีการสื่อสาร online แบบอื่นๆ (โปรดระบุ)	1	1	1	1	1	5	**No**
14.	Personal tutor	การเรียนพิเศษ	1	1	1	1	1	5	**Should add some words for make a statement easier to understand** *การเรียนเพิ่มเติม* (การเรียนพิเศษ) *จากอาจารย์นอกมหาวิทยาลัยในวิชาสถิติทั่วไป*
15.	Other (please specify)	กิจกรรมการเรียนนอกห้องเรียนอื่นๆ (โปรดระบุ)	1	1	1	1	1	5	**No**

Appendix 6-E: Results of content validity test

Part 1: Expectation questions

Performance expectancy

Q	Improved Thai question (after language consistency test)	Content validity score					CVR value	Comment
		Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
1.	ระดับความคาดหวังของท่านว่า ระบบ E-learning จะที่ช่วยให้ท่านเรียนรู้ได้เร็วขึ้นนั้นอยู่ในระดับใด	+1	+1	+1	+1	+1	1	Accepted
2.	ระดับความคาดหวังของท่านว่า ระบบ E-learning จะช่วยให้ท่านมีผลการเรียนที่ดีขึ้นนั้นอยู่ในระดับใด	+1	+1	+1	+1	+1	1	Accepted
3.	ระดับความคาดหวังของท่านว่า ระบบ E-learning จะมีประโยชน์ต่อการศึกษาของท่านนั้นอยู่ในระดับใด	+1	+1	+1	+1	+1	1	Accepted

Effort expectancy

Q	Improved Thai question (after language consistency test)	Content validity score					CVR value	Comment
		Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
4.	ระดับความคาดหวังของท่านว่า การเรียนรู้การใช้งานระบบ E-learning จะง่ายนั้นอยู่ในระดับใด	+1	+1	+1	+1	+1	1	**Accepted**
5.	ระดับความคาดหวังของท่านว่า ท่านจะมีความเชี่ยวชาญในการใช้งานระบบE-learning นั้นอยู่ในระดับใด	+1	+1	0	+1	0	0.2	**Accepted** *but should clarify what skilful is in the statement* ระดับความคาดหวังของท่านว่า ท่านจะมีความเชี่ยวชาญในการใช้งานระบบ E-learning (ใช้งานระบบได้คล่องแคล่วรวดเร็ว) นั้นอยู่ในระดับใด
6.	ระดับความคาดหวังของท่านว่าระบบ E-learning จะเป็นระบบที่ง่ายต่อการใช้งานนั้นอยู่ในระดับใด	+1	+1	+1	+1	+1	1	**Accepted**

Social encouragement expectancy

Q	Improved Thai question (after language consistency test)	Content validity score					CVR value	Comment
		Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
7.	ระดับความคาดหวังของท่านว่าผู้ปกครองของท่านจะสนับสนุนการใช้งานระบบ E-learning นั้นอยู่ในระดับใด	+1	+1	+1	+1	+1	1	**Accepted**
8.	ระดับความคาดหวังของท่านว่าผู้บริหารสถาบันการศึกษาของท่านจะสนับสนุนการใช้งานระบบ E-learning นั้นอยู่ในระดับใด	+1	+1	+1	+1	+1	1	**Accepted**
9.	ระดับความคาดหวังของท่านว่าอาจารย์ประจำวิชาของท่านจะสนับสนุนการใช้งานระบบ E-learning นั้นอยู่ในระดับใด	+1	+1	+1	+1	+1	1	**Accepted**
10.	ระดับความคาดหวังของท่านว่าเพื่อนนักศึกษาของท่านจะมีส่วนสนับสนุนในการใช้งานระบบ E-learning นั้นอยู่ในระดับใด	+1	+1	+1	+1	+1	1	**Accepted**

Facilitating condition expectancy

Q	Improved Thai question (after language consistency test)	Content validity score					CVR value	Comment
		Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
11.	ระดับความพร้อมในเชิงอุปกรณ์ IT ที่จำเป็นต่อการใช้งานระบบ E-learning (เช่น คอมพิวเตอร์ และ อินเตอร์เน็ต) ของท่านนั้นอยู่ในระดับใด	+1	+1	+1	+1	+1	1	**Accepted**
12.	ระดับความคาดหวังของท่านว่ามหาวิทยาลัยของท่านจะมีการจัดเตรียมอุปกรณ์ IT ที่จำเป็นต่อการใช้งานระบบ E-learning นั้นอยู่ในระดับใด	+1	+1	+1	+1	+1	1	**Accepted**
13.	ระดับความคาดหวังของท่านว่าบุคลากรด้าน IT ในมหาวิทยาลัยจะช่วยแก้ปัญหาที่เกิดขึ้นในการใช้งานระบบ E-learningนั้นอยู่ในระดับใด	+1	+1	+1	+1	+1	1	**Accepted**

Learning consistency expectancy

Q	Improved Thai question (after language consistency test)	Content validity score					CVR value	Comment
		Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
14.	ระดับความคาดหวังของท่านว่าระบบ E-learning จะ เตรียม ตัวเนื้อหาที่ตรงกับความต้องการของท่านนั้นอยู่ในระดับใด	+1	+1	+1	+1	+1	1	**Accepted**
15.	ระดับความคาดหวังของท่านว่าระบบ E-learning จะมีกิจกรรมการเรียน (learning activity) และ กิจกรรมการสอน (teaching activity) ที่สอดคล้องกับวิธีการเรียนของท่าน (learning preference)นั้นอยู่ในระดับใด	+1	+1	+1	+1	+1	1	**Accepted**
16.	ระดับความคาดหวังของท่านว่าระบบ E-learning จะจัดเตรียมเนื้อหาที่หมาะสมกับระดับความรู้ที่ของท่านในปัจจุบันนั้นอยู่ในระดับใด	+1	+1	+1	+1	+1	1	**Accepted**

Part 2: Perceived performance questions

Perceived performance of the system

Q	Improved Thai question (after language consistency test)	Content validity score					CVR value	Comment
		Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
1.	ท่านคิดว่าระบบ E-learning ช่วยให้ท่านเรียนรู้ได้เร็วขึ้นมากน้อยเพียงใด	+1	+1	+1	+1	+1	1	**Accepted**
2.	ท่านคิดว่าระบบ E-learning ช่วยให้ท่านมีผลการเรียนดีขึ้นมากน้อยเพียงใด	+1	+1	+1	+1	+1	1	**Accepted**
3.	ท่านคิดว่าระบบ E-learning มีประโยชน์ต่อการศึกษาของท่านมากน้อยเพียงใด	+1	+1	+1	+1	+1	1	**Accepted**

Perceived ease of use

Q	Improved Thai question (after language consistency test)	Content validity score					CVR value	Comment
		Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
4.	หลังจากได้ใช้งานระบบ E-learning ท่านคิดว่าการเรียนรู้การใช้งานระบบ E-learning นั้นง่าย มากน้อยเพียงใด	+1	+1	+1	+1	+1	1	**Accepted**
5.	ท่านคิดว่าท่านมีความเชี่ยวชาญในการใช้งานระบบมากน้อยเพียงใด	+1	+1	0	+1	0	0.2	**Accepted** *but should clarify what skilful is in :* ท่านคิดว่าท่านมีความเชี่ยวชาญชำนาญในการใช้งานระบบ E-learning (ใช้งานระบบได้คล่องแคล่ว รวดเร็ว) มากน้อยเพียงใด
6.	ท่านคิดว่าระบบ E-learning มีความง่ายต่อการใช้งานมากน้อยเพียงใด	+1	+1	+1	+1	+1	1	**Accepted**

Perceived social encouragement

Q	Improved Thai question (after language consistency test)	Content validity score					CVR value	Comment
		Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
7.	ผู้ปกครองของท่านสนับสนุนการใช้งานระบบ E-learning มากน้อยเพียงใด	+1	+1	+1	+1	+1	1	**Accepted**
8.	ผู้บริหารสถาบันการศึกษาของท่านสนับสนุนการใช้งานระบบ E-learning มากน้อยเพียงใด	+1	+1	+1	+1	+1	1	**Accepted**
9.	อาจารย์ประจำวิชาของท่านสนับสนุนการใช้งานระบบ E-learning มากน้อยเพียงใด	+1	+1	+1	+1	+1	1	**Accepted**
10.	เพื่อนนักศึกษาของท่านสนับสนุนการใช้งานระบบ E-learning มากน้อยเพียงใด	+1	+1	+1	+1	+1	1	**Accepted**

Perceived facilitating conditions

Q	Improved Thai question (after language consistency test)	Content validity score					CVR value	Comment
		Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
11.	ท่านคิดว่าท่านมีอุปกรณ์ IT ที่จำเป็นต่อการใช้งานระบบ(เช่น คอมพิวเตอร์ และ อินเตอร์เน็ต) อยู่ในระดับใด	+1	+1	+1	+1	+1	1	**Accepted**
12.	ท่านคิดว่าระดับความพร้อมของอุปกรณ์ IT ที่จำเป็นต่อการใช้งานระบบ E-learning ในมหาวิทยาลัยของท่านอยู่ในระดับใด	+1	+1	+1	+1	+1	1	**Accepted**
13.	ท่านคิดว่าบุคลากรด้าน IT ในมหาวิทยาลัยช่วยแก้ปัญหาที่เกิดขึ้นในระหว่างการใช้งานระบบ E-learning มากน้อยเพียงใด	+1	+1	+1	+1	+1	1	**Accepted**

Learning consistency

Q	Improved Thai question (after language consistency test)	Content validity score					CVR value	Comment
		Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
14.	ท่านคิดว่าระบบ E-learning เป็นระบบที่-จัดเตรียม เนื้อหาที่ตรงกับความต้องการของท่านมากน้อยเพียงใด	+1	+1	+1	+1	+1	1	**Accepted**
15.	ท่านคิดว่าระบบ E-learning เป็นระบบที่จัดเตรียมกิจกรรมการเรียน (learning activity) และกิจกรรมการสอน (teaching activity) ที่สอดคล้องกับวิธีการเรียนของท่าน (learning preference) มากน้อยเพียงใด	+1	+1	+1	+1	+1	1	**Accepted**
16.	ท่านคิดว่าระบบ E-learning เป็นระบบที่จัดเตรียมเนื้อหาที่เหมาะสมกับระดับความรู้ของท่านในปัจจุบัน มากน้อยเพียงใด	+1	+1	+1	+1	+1	1	**Accepted**

Part 3: Time spent on learning activities outside classroom

Q	Improved Thai question (after language consistency test)	Content validity score					CVR value	Comment
		Expert 1	Expert 2	Expert 3	Expert 4	Expert 5		
1.	ทบทวนสมุดจดบันทึกในห้องเรียน (Lecture note)	+1	+1	+1	+1	+1	1	**Accepted**
2.	อ่านเอกสารประกอบการสอนจากระบบ E-learning	+1	+1	+1	+1	+1	1	**Accepted**
3.	อ่านตำราวิชาการจากแหล่งการเรียนรู้อื่นที่ไม่ใช่ระบบ E-learning (โปรดระบุแหล่งที่มาของตำราวิชาการ)	+1	+1	+1	+1	+1	1	**Accepted**
4.	ดูวีดีทัศน์ เพื่อการศึกษาที่เกี่ยวข้องกับรายวิชาจากระบบ E-learning	+1	+1	+1	+1	+1	1	**Accepted**
5.	ดูวีดีทัศน์ เพื่อการศึกษาที่เกี่ยวข้องกับรายวิชาจากแหล่งเรียนรู้อื่นที่ไม่ใช่ E-learning (โปรดระบุแหล่งที่มาของวีดีทัศน์)	+1	+1	+1	+1	+1	1	**Accepted**
6.	ทำแบบฝึกหัดจากระบบ E-learning	+1	+1	+1	+1	+1	1	**Accepted**
7.	ทำแบบฝึกหัดจากแหล่งการเรียนรู้อื่นที่ไม่ใช่ระบบ E-learning (โปรดระบุแหล่งที่มาของแบบฝึกหัด)	+1	+1	+1	+1	+1	1	**Accepted**
8.	ปรึกษาหารือกับเพื่อนของท่าน โดยการพบปะพูดคุยโดยตรง (face-to-face)	+1	+1	+1	+1	+1	1	**Accepted**
9.	ปรึกษาหารือกับเพื่อนของท่านผ่านทางระบบ E-learning	+1	+1	+1	+1	+1	1	**Accepted**
10.	ปรึกษาหารือกับเพื่อนของท่านผ่านทาง social media (เช่น Facebook, Line) และ วิธีการสื่อสารแบบอื่นๆ (โปรดระบุ)	+1	+1	+1	+1	+1	1	**Accepted**
11.	ปรึกษาหารือกับอาจารย์ของท่าน โดยการพบปะพูดคุยโดยตรง (face-to-face)	+1	+1	+1	+1	+1	1	**Accepted**
12.	ปรึกษาหารือกับอาจารย์ของท่านผ่านทางระบบ E-learning	+1	+1	+1	+1	+1	1	**Accepted**
13.	ปรึกษาหารือกับอาจารย์ของท่านผ่านทาง social media (เช่น Facebook, Line) และวิธีการสื่อสาร online แบบอื่นๆ (โปรดระบุ)	+1	+1	+1	+1	+1	1	**Accepted**
14.	การเรียนเพิ่มเติม (การเรียนพิเศษ) จากอาจารย์นอกมหาวิทยาลัยในวิชาสถิติทั่วไป	+1	+1	+1	+1	+1	1	**Accepted**
15.	กิจกรรมการเรียนนอกห้องเรียนอื่นๆ (โปรดระบุ)	+1	+1	+1	+1	+1	1	**Accepted**

Appendix 6-F: Sample size design for a longitudinal study

In the experimental design phase, the G*power 3.1.5 program was used to calculate the optimum sample size for each data analysis to yield acceptable Type I and Type II errors.

Analysis of the data collected during the first time period (t_0 and t_1)

Study of the EU sub-model's predictive performance for E-learning uptake

In this data analysis, three regression multiple regression models are required: (a) the EU sub-model's prediction of E-learning uptake at t_0 and the five measurements of actual E-learning uptake at t_1; (b) the TAM model's prediction of E-learning uptake at t_0 and the five measurements of actual E-learning uptake at time t_1; and (c) the UTAUT model's prediction of E-learning uptake at t_0 and the five measurements of actual E-learning uptake at time t_1. To detect the degree of consistency (effect size) of 0.35 with less than conventional Type I and II errors, the minimum number of participants required for each regression model was found to be 43 (see Table 1).

Table 1: Computing sample size for regression analysis of the model prediction of E-learning uptake at t_0 and measurements of actual E-learning uptake at t_1

Required variable	Setting value	Why
What type of data analysis will be used?	Regression analysis	The aim of this data analysis was to: calculate the degree of consistency between model prediction and measurements of actual E-learning uptake (*R*)
What is the expected effect size (f^2)?	0.35	Since the prior research confirmed that the predictors of the three models of interest are all significant, we could expect that each model's prediction will have high consistency degree and Cohen's large effect size was selected (f^2 = .35)
What is the number of predictors?	5	In each regression model, there are five predictors: subjective percentage at t_1, subjective time spent at t_1, objective time spent at t_1, objective logging on at t_1, and objective number of activity at t_1
At what level do we want to avoid a Type I error?	0.95	A Type I error is a false positive: detecting the significant consistency when it does not exist in reality (Sheskin, 2004). 5% of this error type, as conventional, is acceptable for this research.
At what level do we want to avoid a Type II error?	0.80	The power was set as conventional power (.08)
Total sample size	43	

Since the three models predicted the uptake of E-learning for a same group of students in this study, at least 43 participants were needed to investigate the model's predictive performance in terms of uptake of E-learning.

The EUCH model's explanatory power of E-learning uptake

In this data analysis, three canonical models were required: (a) the five EU sub-model initial expectation variables at t_0 (PE_{t_0}, EE_{t_0}, SEE_{t_0}, FCE_{t_0} and LCE_{t_0}) and the five measurements of actual E-learning uptake at t_1; (b) the two TAM variables at t_0 (PE_{t_0}, EE_{t_0}) and the five measurements of actual E-learning uptake at t_1; (c) the four UTAUT variables at t_0 (PE_{t_0}, EE_{t_0}, SEE_{t_0}, FCE_{t_0}) and the five measurements of actual E-learning uptake at t_1. Although there is no function to calculate the sample size of canonical correlation analysis (CCA), the estimate provided for a multiple regression analysis was adjusted and simply used the total number of variables in CCA as the number of predictors. This might be a possible way to approach obtaining the reasonable sample size for CCA. As data from the same group of students were used in all three CCA canonical models, the model with the largest number of predictors (EU sub-model variables and the measurements of actual E-learning uptake) was selected to calculate the sample size (see Table 2).

Table 2: Computing sample size for CCA of the EU sub-model variables at t_0 and the measurements of E-learning actual usage at t_1

Required variable	Setting value	Why
What type of data analysis will be used?	Regression analysis	Since there was no function for estimating sample size of CCA, the estimation of sample size for multiple regression analysis was applied
What is the expected effect size (f^2)?	0.67	The Cohen's f^2 effect size measure for multiple regression is defined as: $f^2 = \frac{R^2}{1-R^2}$ (Cohen, 1992) where R^2 is the squared multiple correlation: percent variance of the outcome (y) that can be explained by the linear regression model. Based on previous studies, a rough estimate of squared multiple correlations from existing models is 0.40 (Venkatesh et. at., 2003; Sumak, 2011). As the EU sub-model was constructed by synthesizing the factors from the existing model, the expected minimum R^2 to be detected is 40. Thus: $f^2 = \frac{0.40}{1-0.40} = 0.67$
What is the number of predictors?	10	Five EUCH uptake model variables and the five measurements of E-learning actual uptake
At what level do we want to avoid a Type I error?	0.95	5% of Type I error, as conventional, is set
At what level do we want to avoid a Type II error?	0.80	The power was set as conventional power (.08)
Total sample size	35	

The required minimum participants for CCA for five EU sub-model variables and the five measurements of actual E-learning uptake was 35. Since this analysis had the highest number of model variables, at least 35 participants were needed to investigate the model's explanatory power in terms of uptake of E-learning compared with TAM and UTAUT.

The change in students' five expectations towards E-learning usage over time

To investigate whether students' five expectations changed from time t_0 to t_1, the mean aggregated scores of each expectation at time t_0 to t_1 was compared pair-wise, using a dependent-samples t-test. The consistency of each expectation variable at time t_0 and t_1 was checked. The required minimum number of participants for a dependent-samples *t*-test was found to be 15 (see Table 3).

Table 3: Computing sample size for a dependent-samples *t*-test between each expectation

Required variable	Setting value	Why
What type of data analysis will be used?	a dependent-samples *t*-test	To detect the difference in the mean value of each expectation at time t_0 and t_1 measured from the same group
What is the expected effect size (d)?	0.8	To explore whether the mean value of each expectation is different between time t_0 and t_1, Cohen's large effect's size (.8) was set.
At what level do we want to avoid a Type I error?	0.95	Type I and II error was set as conventional
At what level do we want to avoid a Type II error?	0.80	
Total sample size	15	

The required minimum number of participants for a correlation analysis is 53 (see Table 4).

Table 4: Computing sample size for correlation analysis between each expectation

Required variable	Setting value	Why
What type of data analysis will be used?	Correlation analysis	To investigate the relationship between each expectation at time t_0 and t_1
What is the expected effect size (r)?	0.5	To explore whether there is a relationship between each expectation at time t_0 and t_1, never before conducted, Cohen's large effect's size (.5) was set.
At what level do we want to avoid a Type I error?	0.95	Type I and II error was set as conventional
At what level do we want to avoid a Type II error?	0.80	
Total sample size	53	

The effect of expectancy confirmation on the change of each expectation

In this data analysis, there were five regression models: (a) the expectancy confirmation of PE regressed against the change of PE; (b) the expectancy confirmation of EE regressed against the change of EE; (c) the expectancy confirmation of SEE regressed against the change of SEE; (d) the expectancy confirmation of FCE regressed against the change of FCE; and (e) the expectancy confirmation of LCE regressed against the change of LCE. To detect the effect size of .35 with 95% of power, the required number of each regression model was found to be 25 (see Table 5).

Table 5: Computing sample size for regression analysis of the expectancy confirmation at t_1 and the change of expectation between t_0 and t_1

Required variable	Setting value	Why
What type of data analysis will be used?	Regression analysis	The aim of this data analysis was to investigate the effect of expectancy confirmation on the change of each expectation
What is the expected effect size (f^2)?	0.35	To explore whether there is a relationship between expectancy confirmation and the change of each expectation, which were not before studied, Cohen's large effect size was selected (f^2 = .35).
What is the number of predictors?	1	The predictor was expectancy confirmation of each expectation
At what level do we want to avoid a Type I error?	0.95	Type I and II error was set as conventional
At what level do we want to avoid a Type II error?	0.80	
Total sample size	25	

Analysis of the data collected during the second time period (t_1 and t_2)

Study of EUCH model's predictive performance of continued use of E-learning

In this data analysis, four regression models were required: (a) the EC sub-model's prediction at time t_1 and the five measurements of actual E-learning uptake at time t_2; (b) TAM model's prediction at time t_1 and the five measurements of actual E-learning uptake at time t_2; (c) UTAUT model's prediction at time t_1 and the five measurements of actual E-learning uptake at time t_2; and (d) ECM model's prediction at time t_1 and the five measurements of actual E-learning uptake at time t_2. To detect the degree of consistency (effect size) of 0.35 with fewer than conventionally acceptable Type I and II errors, the minimum number of participants required for each regression model was 43 (see Table 6).

Table 6: Computing sample size for regression analysis of the model prediction at t_1 and the measurements of E-learning actual usage at t_2

Required variable	Setting value	Why
What type of data analysis will be used?	Regression analysis	The aim of this data analysis was to: (a) calculate the degree of consistency between model prediction and measurements of actual E-learning continued use *R*
What is the expected effect size (f²)?	0.35	Since the prior research confirmed that the predictors of the four models of interest are all significant, we could expect that each model's prediction will have high consistency degree and Cohen's large effect size was selected (f^2 = .35)
What is the number of predictors?	5	In each regression model, there are five predictors: (1) subjective percentage at t_1; (2) subjective time spent at t_1; (3) objective time spent at t_1; (4) objective logging on at t_1 and (5) objective number of activity at t_1
At what level do we want to avoid a Type I error?	0.95	A Type I error is a false positive: detecting the significant consistency when it does not exist in reality (Sheskin, 2004). 5% of this error type, as conventional, is acceptable for this research.
At what level do we want to avoid a Type II error?	0.80	The power was set as conventional power (.08)
Total sample size	43	

The EC sub-model's explanatory power of E-learning uptake

In this data analysis, four canonical models were required: (a) the five EC sub-model variables at t_1 and the five measurements of actual continued use of E-learning at t_2; (b) the two TAM variables at t_1 and the five measurements of actual continued use of E-learning at t_2; (c) the four UTAUT variables at t_1 and the five measurements of actual continued use of E-learning at t_2; and (d) the one for ECM variables at t_1 and the five measurements of actual continued use of E-learning at t_2. As data from the same group of students were used for all four CCA, the canonical model having the largest number of predictors (EC sub-model variables and measurements of actual continued use) was selected to calculate the sample size (see Table 7).

To detect the explanatory power (effect size) of .67 with 80% power, the required minimum number of participants for CCA between five EUCH EC sub-model variables and the five measurements of actual continued use of E-learning was 35. Since the EUCH had the highest number of model variables, at least 35 participants were needed to investigate the model's explanatory power on the continued use of E-learning.

Table 7: Computing the sample size for CCA of the model variables at t_1 and the measurements of E-learning actual usage at t_2

Required variable	Setting value	Why
What type of data analysis will be used?	Regression analysis	Since there was no function for estimating sample size of CCA, the estimation of sample size for multiple regression analysis was applied
What is the expected effect size (f^2)?	0.67	The Cohen's f^2 effect size measure for multiple regressio where R^2 is the squared multiple correlation: percent variance of the outcome (y) that can be explained by the linear regression model. Based on previous studies, a rough estimate of squared multiple correlations from existing models is 0.40. As the EUCH model was constructed by synthesizing the factors from the existing model, the expected minimum R^2 to be detected is 40. Thus: $f^2 = \frac{0.40}{1-0.40} = 0.67$
What is the number of predictors?	10	Five EC sub-model variables and the five measurements of E-learning actual continued use
At what level do we want to avoid a Type I error?	0.95	as conventional
At what level do we want to avoid a Type II error?	0.8	
Total sample size	47	

The effect of the change in expectations on the change in level of E-learning usage

Canonical correlation analysis was conducted using the change of five expectation variables (PE, EE, SEE, FCE and LCE) as independent variables and the change of five E-learning actual usages (percentage of E-learning usage, time spent subjective measure, time spent objective measure, number of time logging onto E-learning and number of activity taking part) as dependent variables. The estimation of multiple regression analysis was applied to calculate the sample size (see Table 8).

Table 8: Computing sample size for CCA of the change in expectations and the change in level of E-learning usage

Required variable	Setting value	Why
What type of data analysis will be used?	Regression analysis	Since there was no function for estimating the sample size of CCA, the estimation of sample size for multiple regression analysis was applied
What is the expected effect size (f^2)?	0.35	To explore, Cohen's large effect size for multiple regression was selected
What is the number of predictors?	10	Five changes in expectation variables and five changes in E-learning actual uptake
At what level do we want to avoid a Type I error?	0.95	5% of Type I error, as conventional, is set
At what level do we want to avoid a Type II error?	0.80	The power was set .8 as conventional
Total sample size	57	

To detect the explanatory power (effect size) of .35 with 80% power, the required minimum number of participants for CCA for the change of expectations and the change in level of E-learning usage was found to be 57.

The study of the relationship between E-learning usage and learning outcome

Multiple regression analysis was conducted between students' final score in General Statistics and six predictors (midterm score, five measurements of E-learning usage during t_0 and t_2). The sample size of this analysis was 46 (see Table 9).

Table 9: Computing sample size for regression analysis between students' final score in General Statistics and the six predictors

Required variable	Setting value	Why
What type of data analysis will be used?	Regression analysis	The aim of this data analysis was to find the relationship between students' final score and the six predictor
What is the expected effect size (f²)?	0.35	Since there was no existing investigation, Cohen's large effect size was selected (f^2 = .35).
What is the number of predictors?	6	Six predictors: midterm score, subjective percentage during t_0 and t_2, subjective time spent during t_0 and t_2, objective time spent during t_0 and t_2, objective logging on during t_0 and t_2, and the objective number of activity during t_0 and t_2
At what level do we want to avoid a Type I error?	0.95	as conventional
At what level do we want to avoid a Type II error?	0.80	
Total sample size	46	

Appendix 7-A: Statistical conditions and assumptions checking of the multiple regression analysis between the EU sub-model's prediction of E-learning uptake at t_0 and the five measurements of actual E-learning uptake at t_1

The multiple regression analysis required two conditions and five assumptions to be passed, as follows:

Condition 1**:** Dependent variable is continuous data

In this data analysis, the dependent variable was a *EU sub-model prediction of E-learning uptake at* t_0. The model prediction of E-learning uptake data was continuous, ranging from 0 to 100. Thus, this condition was met.

Condition 2**:** At least two independent variables, and continuous data

There were five independent variables in this regression analysis: (a) *subjective percentage of E-learning usage in education during* t_0 *and* t_1; (b) *subjective time spent learning with E-learning during* t_0 *and* t_1; (c) *objective time spent on E-learning during* t_0 *and* t_1; (d) *objective total number of times logging onto E-learning during* t_0 *and* t_1; and (e) *objective total number of activities involving E-learning during* t_0 *and* t_1. As the data from all five independent variables were continuous, the second condition was met.

Assumption 1**:** Sampling distribution of the sample mean for each variable is normal

- *EU sub-model prediction of E-learning uptake at* t_0

A review of the Shapiro-Wilk test for normality (SW = .97, df = 102, p = .02) and skewness (-1.7) and kurtosis (-1.2) statistics suggested that the *EU sub-model prediction of E-learning uptake at* t_0 data did not deviate significantly from normal (see Table 1).

Table 1: Normality test for EU sub-model prediction of E-learning uptake at t_0 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\lvert Z\rvert \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\lvert Z\rvert \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
EC sub-model prediction at t_0	102	69.5 ± 11.2	-.40	.24	-1.7	no skewness	-.58	.47	-1.2	no kurtosis	.97	102	.02	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *EU sub-model prediction of E-learning uptake at* t_0 data suggested that normality was reasonable (see Figure 1). The boxplot indicated no outliers in the data. As the *EU sub-*

model prediction of E-learning uptake at t_0 data were distributed normally, the sampling distribution of the sample mean for this data was normal.

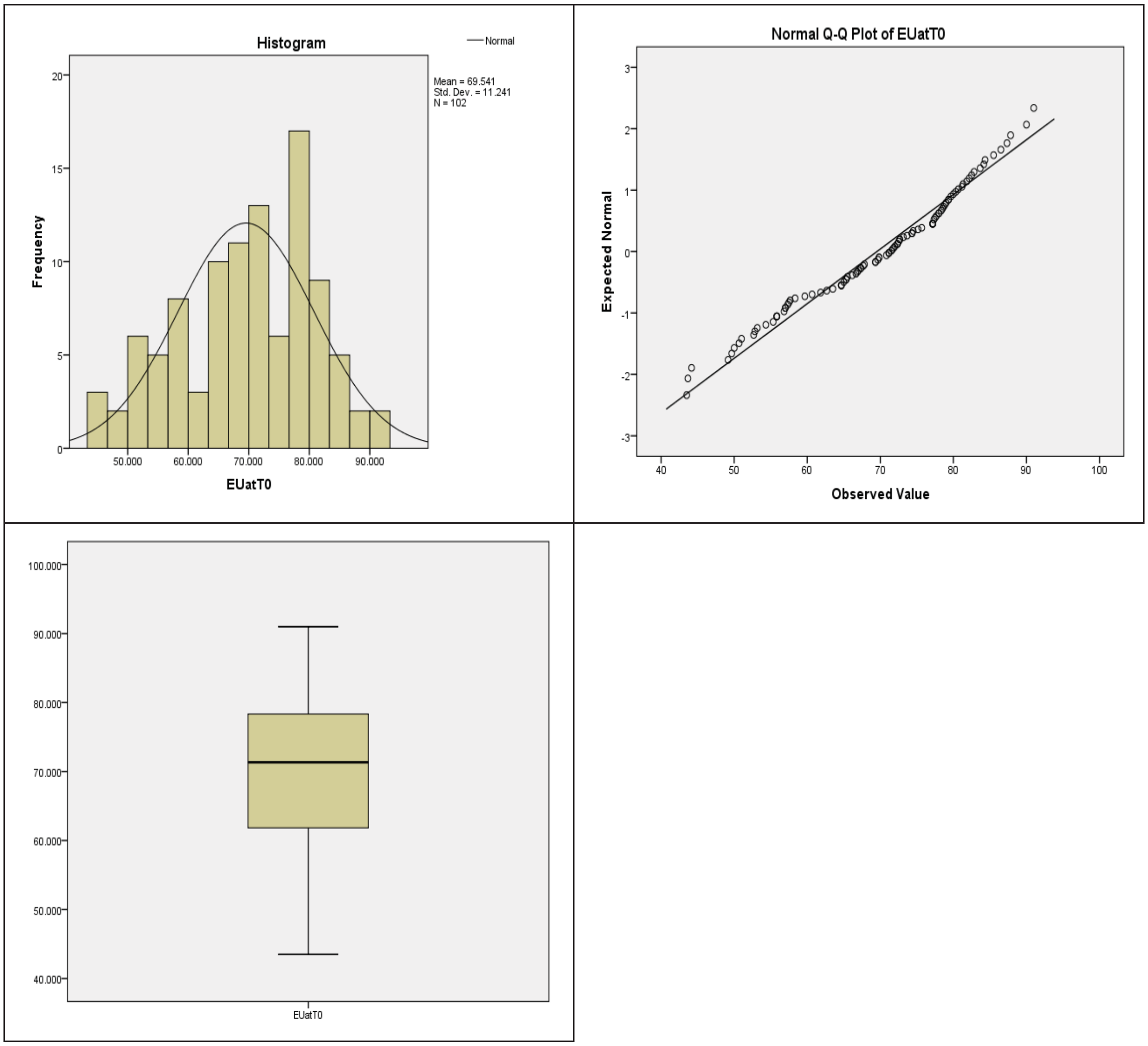


Figure 1: Histogram, Q-Q plot and boxplot for EU sub-model prediction of E-learning uptake at t_0 data

- *Subjective percentage of E-learning usage in Education at* t_1

The *subjective percentage of E-learning usage in education at* t_1 data did not deviate significantly from normal (*SW* = .99, *df* = 102, *p* = .45) (see Table 2).

Table 2: Normality test for subjective percentage of E-learning usage in education at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\lvert Z\rvert \le 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\lvert Z\rvert \le 2.56$)	Statistic	df	P-value	Conclusion ($p \le .01$)
Percentage of E-learning usage at T1	102	37.9 ± 16.7	.27	.24	1.1	no skewness	.15	.47	.31	no kurtosis	.99	102	.45	normal

The histogram and Q-Q plot also suggested that normality was reasonable (see Figure 2). Although the boxplot indicated two outliers (Case 89 and 102), these two values were not considered as outliers in this research because their values were lower than Q_3 + 3×IQR. According to the central limited theorem, as the *subjective percentage of E-learning usage in education at* t_1 data were distributed normally, the sampling distribution of the sample mean for this variable data was normal.

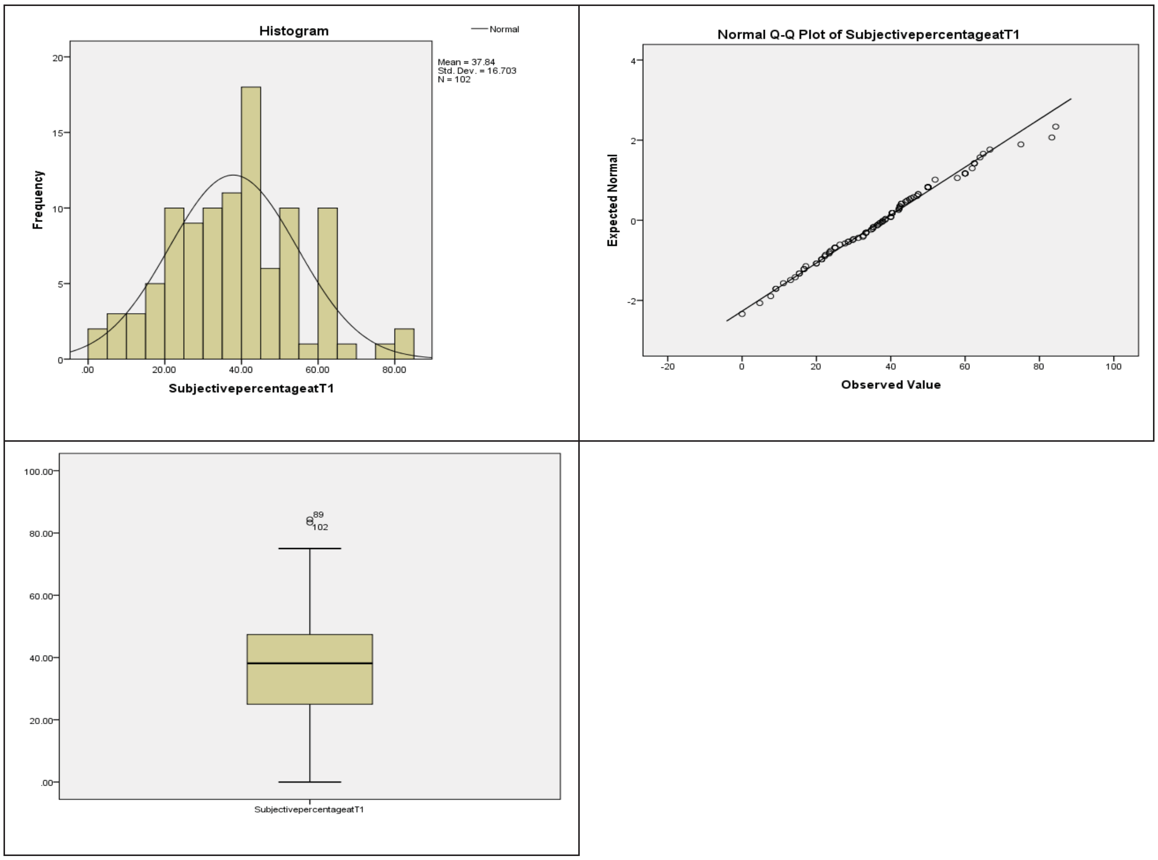


Figure 2: Histogram, Q-Q plot and boxplot for subjective percentage of E-learning usage in education at t_1 data

- *Subjective time spent learning with E-learning at* t_1

A review of the Shapiro-Wilk test for normality (*SW* = .43, *df* = 102, *p* = < .001) and skewness (23.3) and kurtosis (79) statistics suggested that the *subjective time spent learning with E-learning at* t_1 data deviated significantly from normal (see Table 3).

Table 3: Normality test for subjective time spent learning with E-learning at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Time spent (subjective) at T1	102	301.2 ± 536.6	5.6	.24	23.3	positive skewness	37.5	.47	79.0	positive kurtosis	.43	102	<.001	not normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *subjective time spent learning with E-learning at* t_1 data suggested that assuming normality was not reasonable, with positive skewness and kurtosis (see Figure 3).

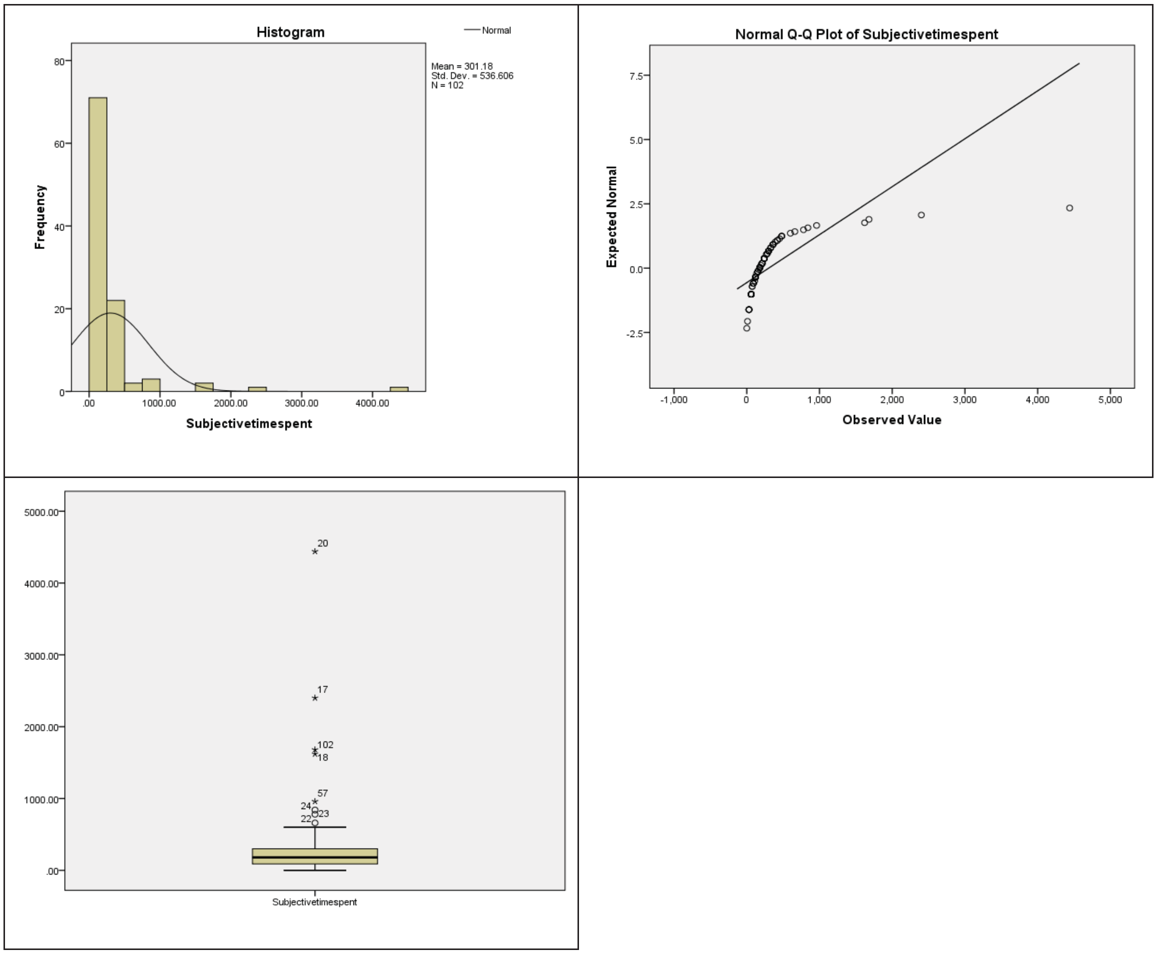


Figure 3: Histogram, Q-Q plot and boxplot for subjective time spent learning with E-learning at t_1 data

As the data had positive skewness and kurtosis, Log (X+1) was used to transform the data in order to improve the normality. The result of normality test after transforming the data is shown in Table 4.

Table 4: Normality test for subjective time spent learning with E-learning at t_1 data after transformation

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\lvert Z \rvert \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\lvert Z \rvert \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Log total time spent (subjective) at T1	102	2.2 ± .48	-.61	.24	-2.56	no skewness	4.1	.47	8.7	positive kurtosis	.94	102	<.001	not normal

The results from the Shapiro-Wilk test indicated that the transformed data of this variable still deviated significantly from normal (SW = .94, df = 102, p = < .001). The result from the histogram, Q-Q plot and boxplot suggested that the majority of data seemed normal but there was an extreme outlier: its value was less than Q_1 - 3×IQR (see Figure 4). Thus, the data for this variable from Participant 19 was cut.

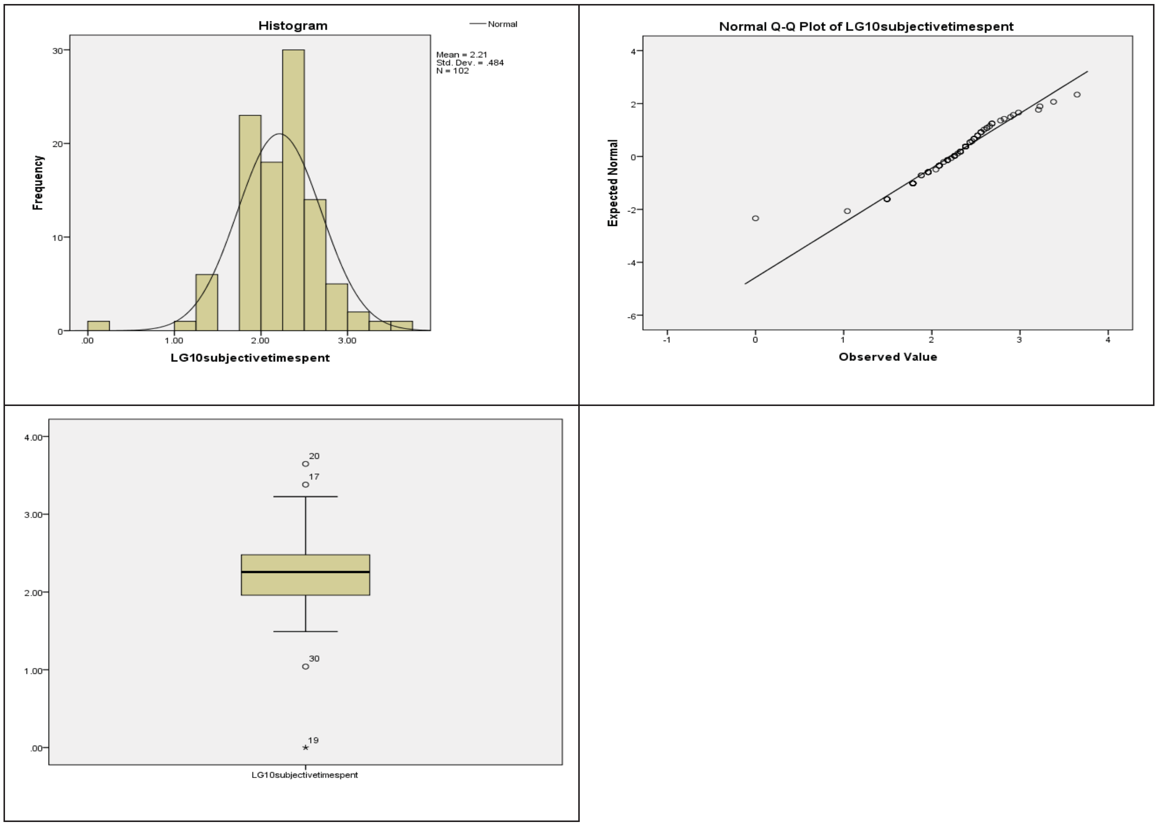


Figure 4: Histogram, Q-Q plot and boxplot for subjective time spent learning with E-learning at t_1 data after transformation

After cutting an extreme outlier (Case 19), the S-W test for normality (SW = .98, df = 101, p = .05), skewness (1.5) and kurtosis (2.1) statistics suggested that normality was now a reasonable assumption (see Table 5). The histogram and Q-Q plot also suggested this (see Figure 5).

Table 5: Normality test for subjective time spent learning with E-learning at t_1 data after transformation and cutting an extreme outlier

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion (|Z| ≤ 2.56)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion (|Z| ≤ 2.56)	Statistic	df	P-value	Conclusion (p ≤ .01)
Total time spent at T1 (Log and cut extreme outlier)	101	2.2 ± .43	.35	.24	1.5	no skewness	.98	.48	2.1	no kurtosis	.98	101	.05	normal

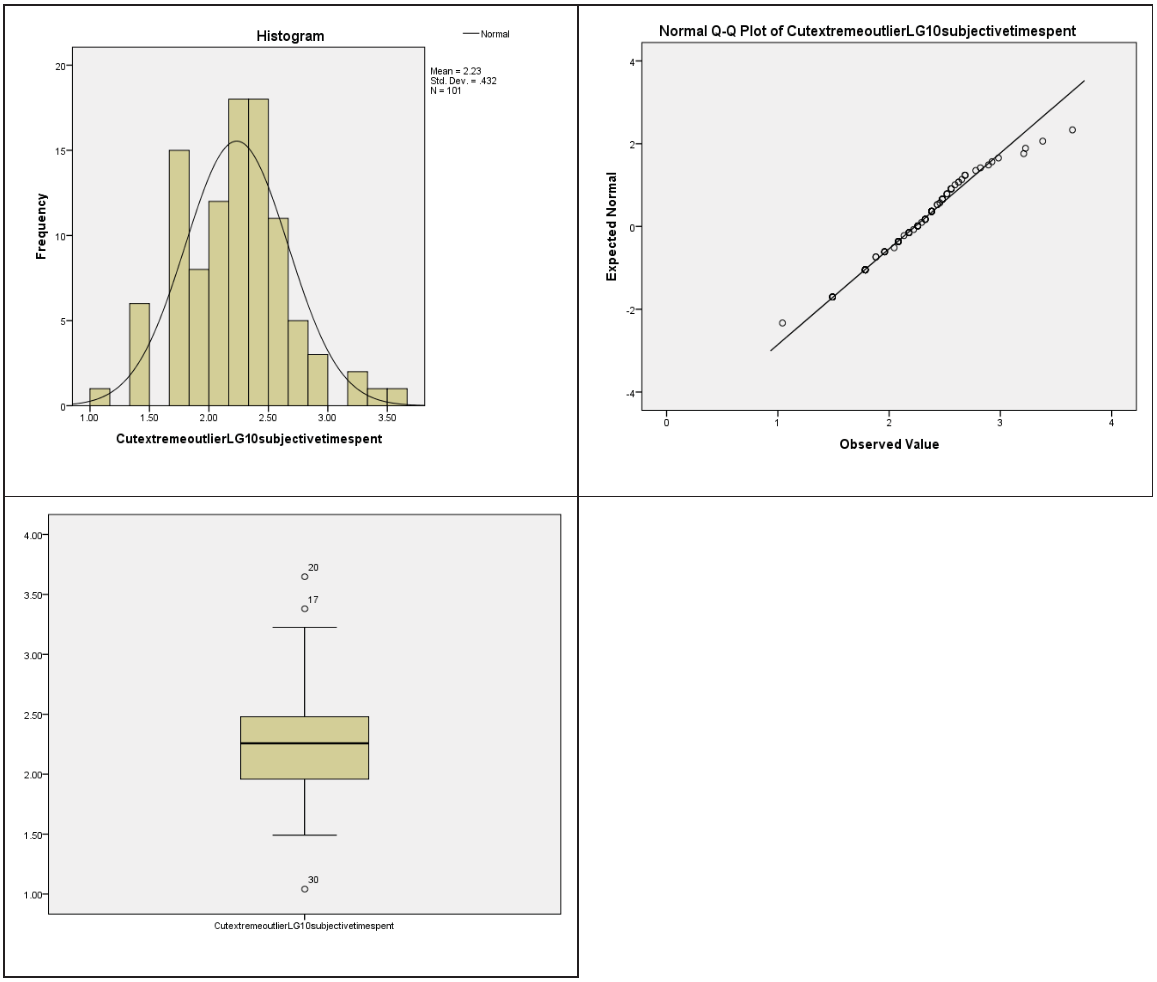


Figure 5: Histogram, Q-Q plot and boxplot for subjective time spent learning with E-learning at t_1 data after transformation and cutting an extreme outlier

- *Objective time spent on E-learning at* t_1

A review of the Shapiro-Wilk test for normality (SW = .61, df = 102, p = < .001) and skewness (15.9) and kurtosis (41.1) statistics suggested that the *objective time spent on E-learning at* t_1 data deviated significantly from normal (see Table 6).

Table 6: Normality test for objective time spent on E-learning system at $t_1$data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion (|Z| ≤ 2.56)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion (|Z| ≤ 2.56)	Statistic	df	P-value	Conclusion (p ≤ .01)
Total time spent (objective) at T1	102	63.2 ± 91.7	3.8	.24	15.9	positive skewness	19.5	.47	41.1	positive kurtosis	.61	102	< .001	not normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *objective time spent on E-learning at* t_1 data suggested it was not reasonable to assume normality, with positive skewness and kurtosis (see Figure 6).

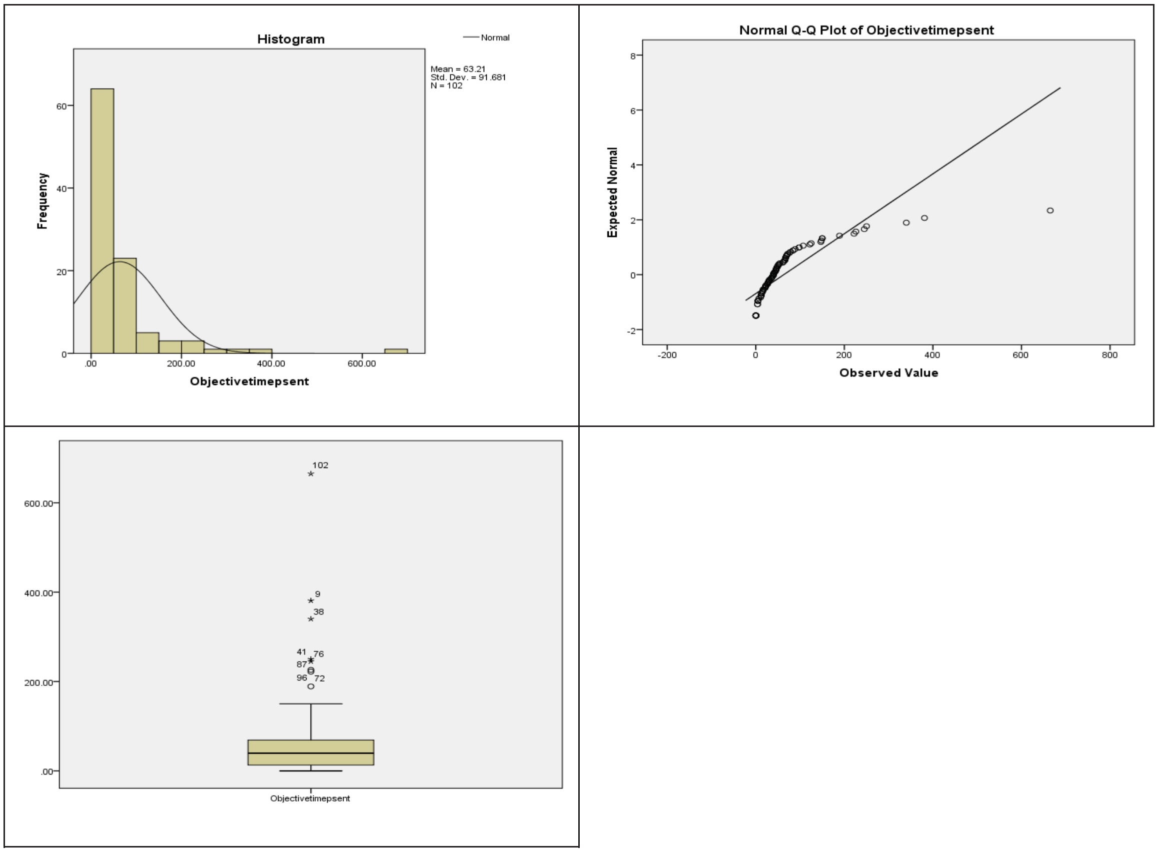


Figure 6: Histogram, Q-Q plot and boxplot for objective time spent on E-learning at t_1 data

As the data had positive skewness and kurtosis, Log (X+1) was used to transform the data in order to improve the normality. The result of normality test after transforming the data is shown in Table 7.

Table 7: Normality test for objective time spent on E-learning at t_1 data after transformation

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\lvert Z\rvert \le 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\lvert Z\rvert \le 2.56$)	Statistic	df	P-value	Conclusion ($p \le .01$)
Log total time spent (objective) at T1	102	1.4 ± .69	-.85	.24	-3.5	negative skewness	.21	.47	.44	no kurtosis	.90	102	<.001	not normal

The result from Shapiro-Wilk test indicated that the transformed data still deviated significantly from normal (*SW* = .90, *df* = 102, *p* = < .001) with negative skewness (-.3.5) (see Figure 7).

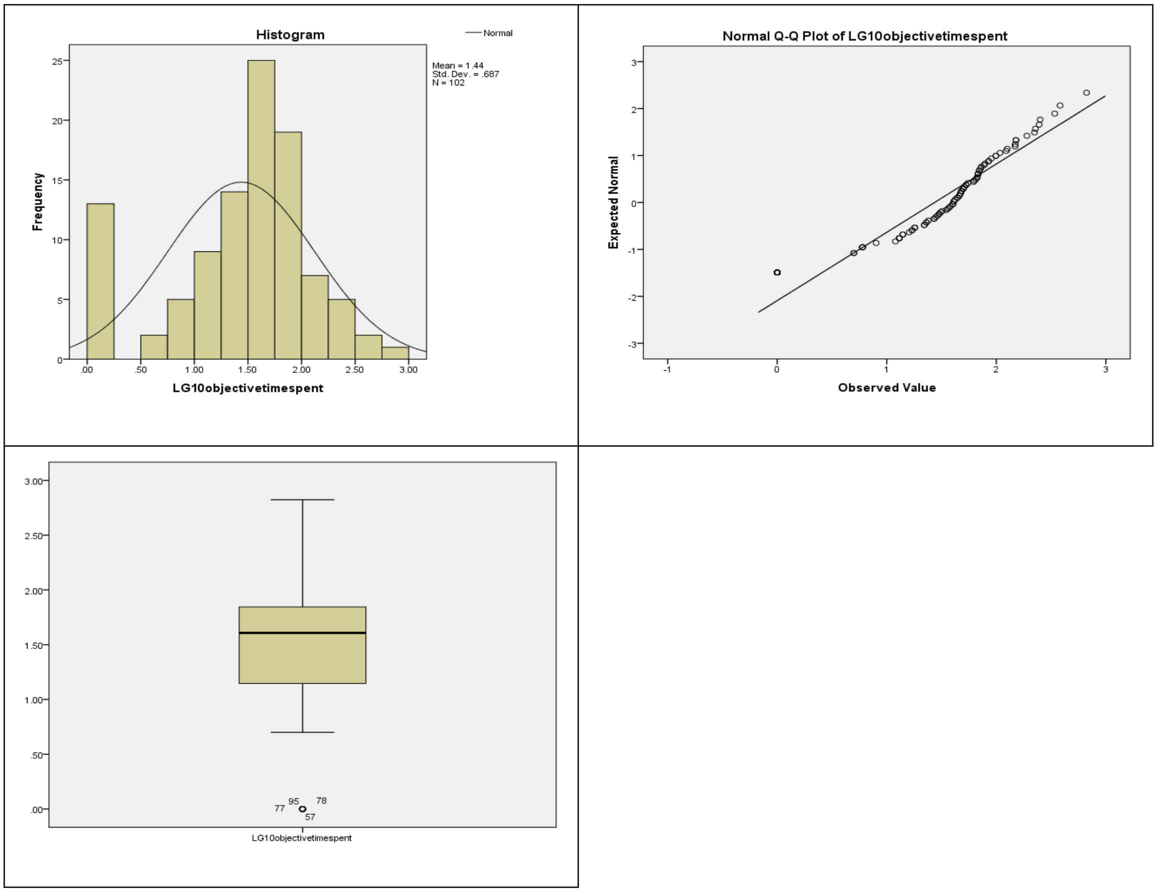


Figure 7: Histogram, Q-Q plot and boxplot for objective time spent on E-learning at t_1 data after transformation

Even though the boxplot indicated four outliers, these data were not cut because the value of these data was not less than Q_1 - 3×IQR so they were not extreme outliers. According to the central limit theorem, even though this measurement of the data was not distributed normally, its sampling distribution of the sample mean is normal since the sample size of this study was higher than 30.

- *Objective total number of times logging onto E-learning at t_1*

A review of the Shapiro-Wilk test for normality (*SW* = .87, *df* = 102, *p* = < .001) statistics suggested that the *objective total number of times logging onto E-learning at* t_1 data deviated significantly from normal with positive skewness (4.7) (see Table 8).

Table 8: Normality test for objective total number of times logging onto E-learning at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion (|Z| ≤ 2.56)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion (|Z| ≤ 2.56)	Statistic	df	P-value	Conclusion (p ≤ .01)
Total number of time logging on (objective) at T1	102	1.7 ± 1.5	1.1	.24	4.7	positive skewness	1.1	.47	2.3	no kurtosis	.87	102	<.001	not normal

Consistent with the Shapiro-Wilk test, the histogram for this data suggested an assumption of normality was not reasonable, with positive skewness (see Figure 8).

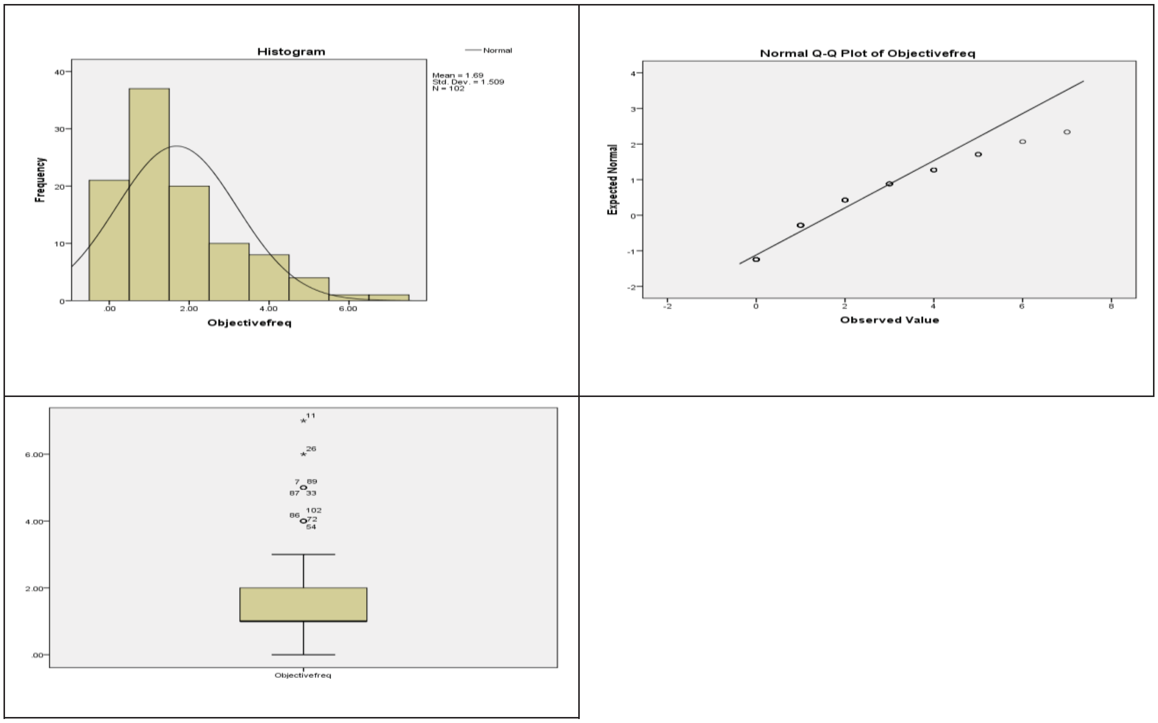


Figure 8: Histogram, Q-Q plot and boxplot for objective total number of times logging onto E-learning at t_1 data

To improve the normality, as the data had positive skewness, Log (X+1) was used to transform the data. The result of the normality test after transforming the data is shown in Table 9.

Table 9: Normality test for objective total number of times logging onto E-learning at t_1 data after transformation

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion (|Z| ≤ 2.56)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion (|Z| ≤ 2.56)	Statistic	df	P-value	Conclusion (p ≤ .01)
Log total number of time logging on (objective) at T1	102	.36 ± .24	-.01	.24	.03	no skewness	-.71	.47	1.5	no kurtosis	.91	102	< .001	not normal

After transformation, the data were still not normal distribution (*SW* = .91, *df* = 102, *p* = < .001). The histogram and Q-Q plot indicated gaps between data (see Figure 9). That is why the result from S-W test showed non-normality, even though there was no skewness (.03) or kurtosis (1.51). The boxplot showed there were 10 outliers, however these data were not cut because they were not higher or lower than 3IQR, and cutting them would lose more than 10 per cent of the data. Although this variable data was not normal, it was used for investigation by virtue of the central limit theorem and regression robustness.

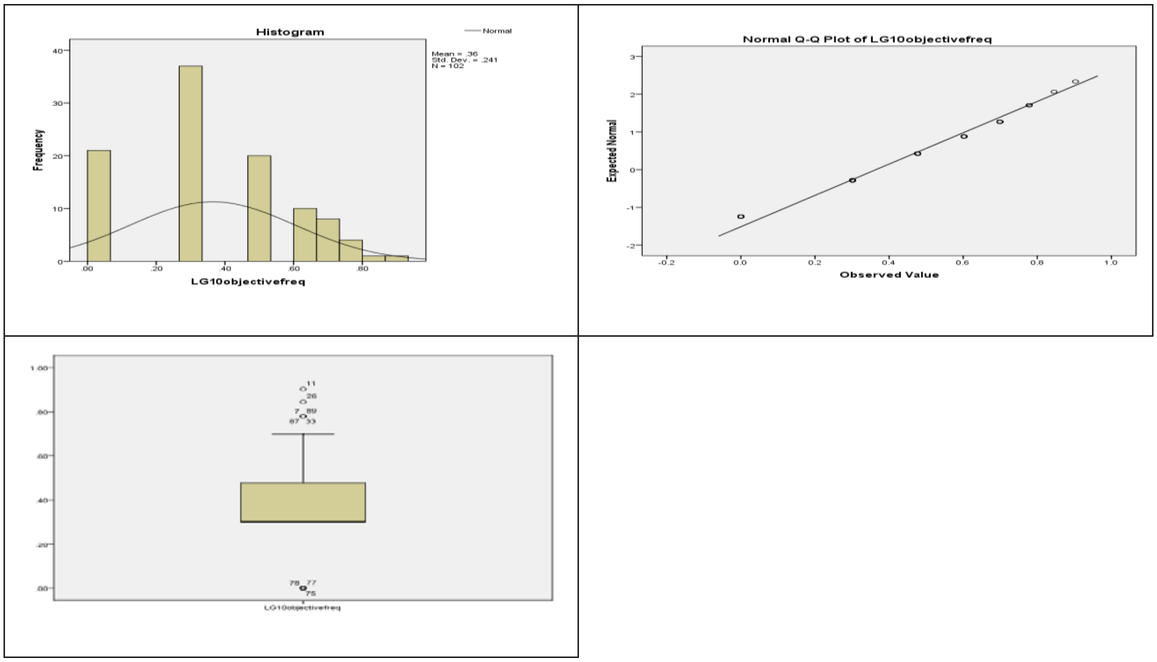


Figure 9: Histogram, Q-Q plot and boxplot for objective total number of times logging onto E-learning at t_1 data after transformation

- *Objective total number of activities involving E-learning at t_1*

The *objective total number of activities involving E-learning at t_1* data deviated significantly from normal (*SW* = .53, *df* = 102, *p* = < .001) (see Table 10).

Table 10: Normality test for objective total number of activities involving E-learning at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{Kurtosis}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Total number of activity (objective) at T1	102	4.2 ± 6.5	5.1	.24	21.3	positive skewness	34.5	.47	72.7	positive kurtosis	.53	102	<.001	not normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for this data suggested the assumption of normality was not reasonable, with positive skewness and kurtosis (see Figure 10).

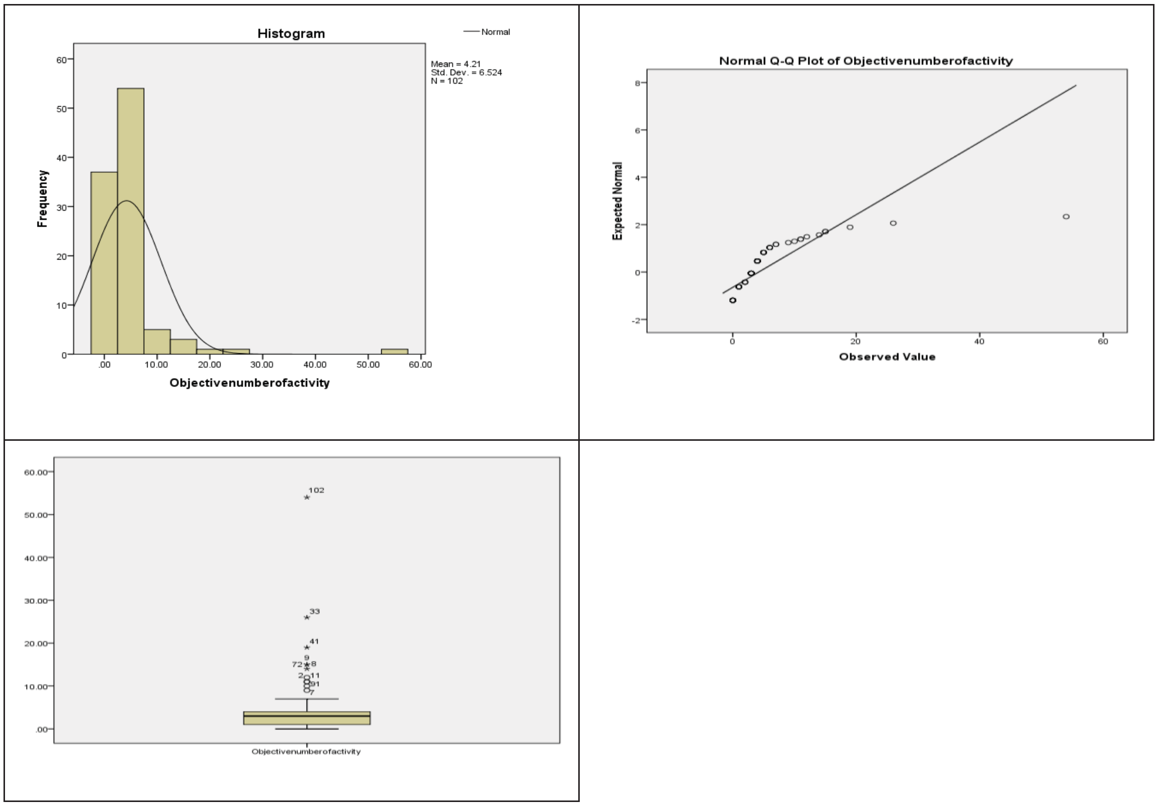


Figure 10: Histogram, Q-Q plot and boxplot for objective total number of activities involving E-learning at t_1 data

As the data had positive skewness (21.3) and kurtosis (72.7), Log(X+1) was used to transform the data in order to improve the normality. The result of normality test after transforming the data is shown in Table 11.

Table 11: Normality test for objective total number of activities involving E-learning at t_1 data after transformation

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion (|Z| ≤ 2.56)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion (|Z| ≤ 2.56)	Statistic	df	P-value	Conclusion (p ≤ .01)
Log total number of activity (objective) at T1	102	.54 ± .38	.17	.24	0.70	no skewness	.12	.47	.24	no kurtosis	.53	102	<.001	not normal

After transformation, the data still did not have normal distribution (SW = .53, df = 102, p = < .001). Accordingly, the histogram, Q-Q plot and boxplot suggested an assumption of normality was not reasonable (see Figure 11). Although this variable's data were not normal, they were used for investigation by virtue of the central limit theorem and regression robustness.

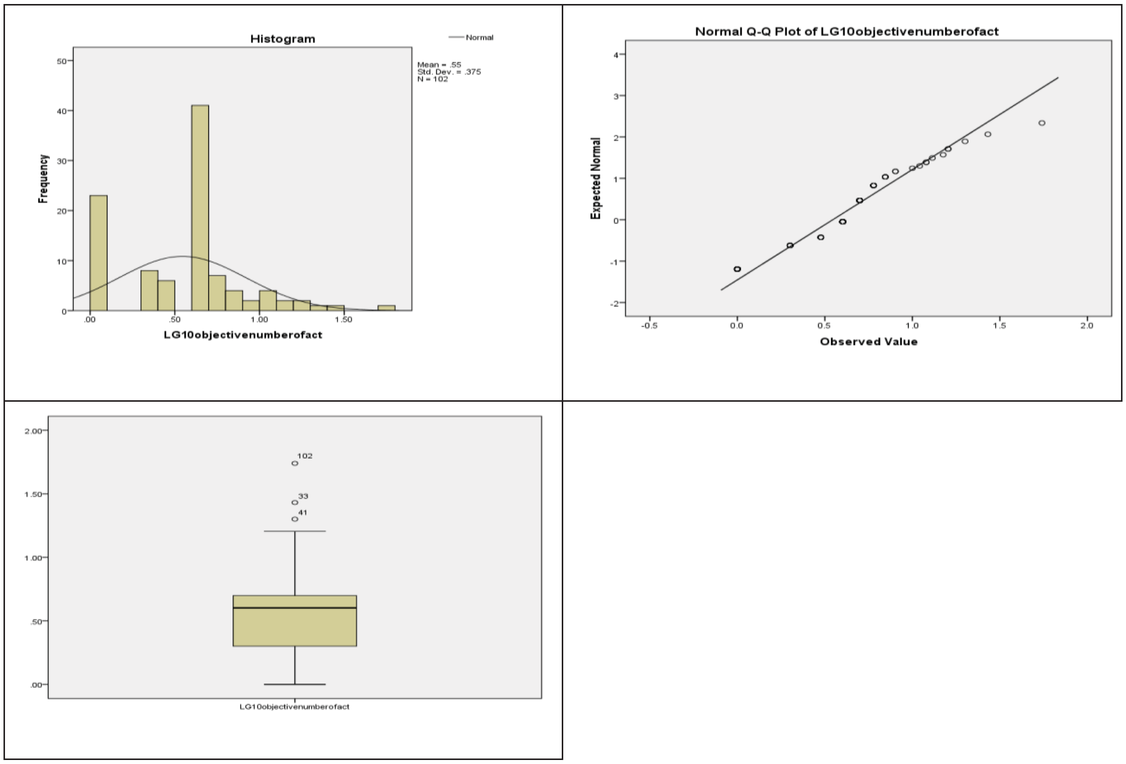


Figure 11: Histogram, Q-Q plot and boxplot objective total number of activities involving E-learning at t_1 data after transformation

<u>Assumption 2</u>: Linear relationship between the dependent and independent variables

To check the linearity assumption, a scatterplot of the standardized residual as a function of standardized predicted value was drawn (see Figure 12). A scatterplot of the residual showed that the points were symmetrically distributed about a horizontal line, the linearity assumption therefore was not violated.

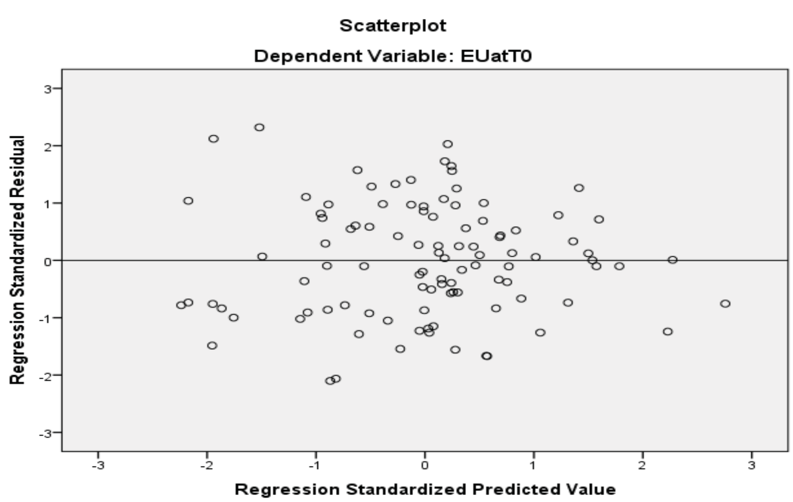


Figure 12: Scatterplot of residual for the relationship between the five measurements of actual E-learning uptake at t_1 and the EC-sub-model prediction of E-learning uptake at t_0

Assumption 3: Homoscedasticity

The assumption is that the residuals at each level of the independent variables had the same variance, known as '*homoscedasticity*'. To check this assumption, the scatterplot of standardized residuals against the standardized predicted value was used again (see Figure 12). The spread of residuals appeared fairly constant across the range of standardized predicted values. It may be inferred that this assumption was met.

Assumption 4: Independence of residual (error)

The assumption is that the error is not correlated with any independent variables (lack of autocorrelation). The Durbin-Watson test was used to evaluate the independence of the residuals. According to a conservative rule of thumb, as the Durbin-Watson statistic for this regression model was 2.2, within the range of 1–3, this assumption was not violated.

Assumption 5: Multicollinearity

This assumption is that independent variables are not highly correlated with each other. To detect multicollinearity between the five measurements of actual E-learning uptake at t_0 (independent variables in this regression model), the VIF test was used. According to the general rule of thumb, as the VIF for each independent variable was lower than 10, multicollinearity was not a concern (see Table 12).

Table 12: Collinearity test for the five measurements of actual E-learning uptake at t_1

Independent variable	**VIF**
Percentage (subjective) during t_0 and t_1	1.6
Time spent (subjective) during t_0 and t_1	1.2
Time spent (objective) during t_0 and t_1	4.0
Number of times logging on (objective) during t_0 and t_1	3.1
Number of activities (objective) during t_0 and t_1	4.1

Appendix 7-B: Statistical conditions and assumptions checking of the multiple regression analysis between the TAM model's prediction of E-learning uptake at t_0 and the five measurements of actual E-learning uptake at t_1

The multiple regression analysis required two conditions and five assumptions to be passed, as follows:

<u>Condition 1</u>**:** Dependent variable is continuous data

The dependent variable was the *TAM model's prediction of E-learning uptake at* t_0. The model prediction of E-learning uptake data was continuous, ranging from 0 to 100. Thus, this condition was met.

<u>Condition 2</u>**:** At least two independent variables and continuous data

There were five independent variables (five measurements of actual E-learning uptake at t_1) in this analysis and the data of five independent variables were continuous. The second condition was therefore met.

<u>Assumption 1</u>**:** Sampling distribution of the sample mean for each variable is normal

- *TAM mode's prediction of E-learning uptake at* t_0

A review of the Shapiro-Wilk test for normality (*SW* = .96, *df* = 102, *p* = .05), and skewness (-1.8) and kurtosis (.82) statistics suggested that the *TAM model's prediction of E-learning uptake at* t_0 data did not deviate significantly from normal (see Table 1).

Table 1: Normality test for TAM model's prediction of E-learning uptake at t_0 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
TAM model result at T0	102	67.4 ± 12.1	-.43	.24	-1.8	no skewness	.39	.47	.82	no kurtosis	.96	102	.05	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *TAM model's prediction of E-learning uptake at* t_0 data suggested normality was reasonable (see Figure 1). The boxplot indicated no outliers in this data. As the *TAM model's prediction of E-learning uptake at* t_0 data were distributed normally, the sampling distribution of the sample mean for this variable data was normal.

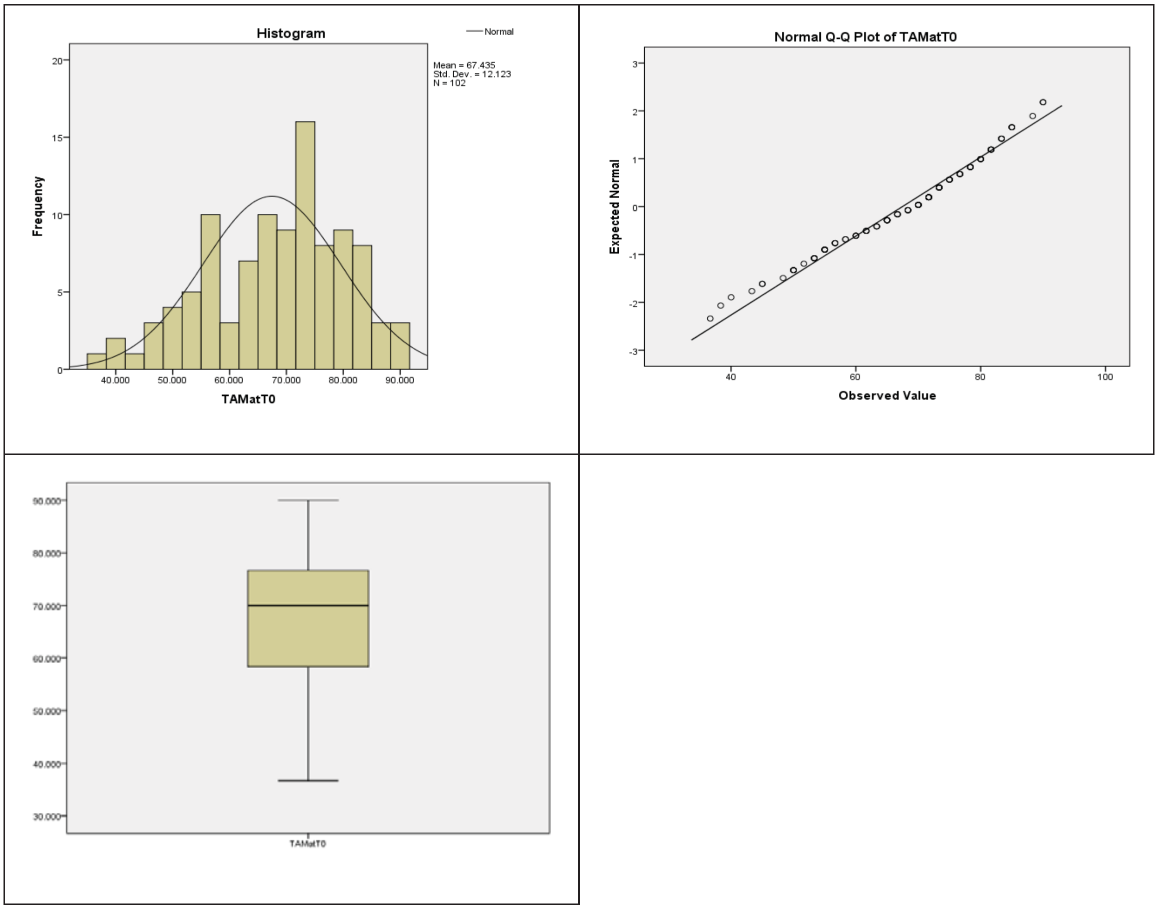


Figure 1: Histogram, Q-Q plot and boxplot for TAM model's prediction of E-learning uptake at t_0 data

- *Five independent variables (measurements of actual E-learning uptake at t_1)*

The normality of five independent variables had been checked previously when conducting the multiple regression analysis of the relationship between the EU sub-model's prediction of E-learning uptake at t_0 and the five measurements of E-learning actual uptake at t_1 (see Appendix 7-A). The results suggested that this assumption was not violated.

<u>Assumption 2</u>: Linear relationship between the dependent and independent variables

To check the linearity assumption, a scatterplot of the standardized residual as a function of standardized predicted value was used (see Figure 2). The scatterplot of the residual indicated the linear relationship between the dependent and independent variables in this regression model: the points were symmetrically distributed about a horizontal line. Therefore, the linearity assumption was not violated.

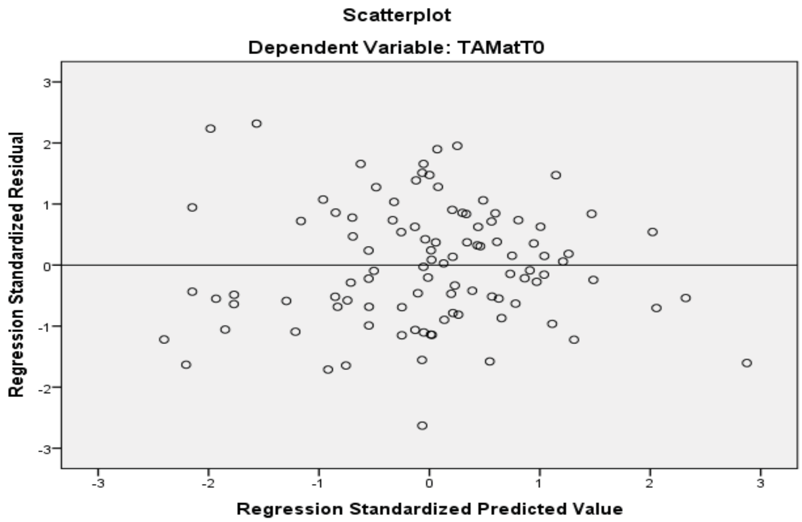


Figure 2: Scatterplot of residual for the relationship between the five measurements of actual E-learning uptake at t_1 and the TAM models' prediction of E-learning uptake at t_0

Assumption 3: Homoscedasticity

To check this assumption, the scatterplot of standardized residuals against the standardized predicted value was used again (see Figure 2). In this regression model, since the spread of residuals appeared fairly constant over the range of standardized predicted value, it could be inferred that the assumption was met.

Assumption 4: Independence of residual (error)

The Durbin-Watson test was used to evaluate the independence of the residual. As the Durbin-Watson statistic for this regression model was 1.9, within a range of 1–3, this assumption was not violated.

Assumption 5: Multicollinearity

This assumption was checked previously (see Appendix 7-A), and the results suggested that the assumption was not violated.

Appendix 7-C: Statistical conditions and assumptions checking of the multiple regression analysis between the UTAUT model's prediction of E-learning uptake at t_0 and the five measurements of actual E-learning uptake at t_1

The multiple regression analysis required two conditions and five assumptions to be passed as follows:

Condition 1**:** Dependent variable is continuous data

Dependent variable was a *UTAUT model's prediction of E-learning uptake at* t_0. The model prediction of E-learning uptake data is continuous, ranging from 0 to 100. Thus, this condition was met.

Condition 2**:** At least two independent variables comprising continuous data

Five independent variables (measurements of actual E-learning uptake at t_1) in regression model were continuous, the second condition was therefore met.

Assumption 1**:** Sampling distribution of the sample mean for each variable is normal

- *UTAUT model's prediction of E-learning uptake at* t_0

A review of the Shapiro-Wilk test for normality (*SW* = .98, *df* = 102, *p* = .05) and skewness (-1.5) and kurtosis (1.2) statistics suggested that the *UTAUT model's prediction of E-learning uptake at* t_0 data did not deviate significantly from normal (see Table 1).

Table 1: Normality test for UTAUT model's prediction of E-learning uptake at t_0 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\|Z\| \le 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\|Z\| \le 2.56$)	Statistic	df	P-value	Conclusion ($p \le .01$)
UTAUT model result at T0	102	69.1 ± 11.1	-.36	.24	-1.5	no skewness	.56	.47	1.2	no kurtosis	.98	102	.05	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *UTAUT model's prediction of E-learning uptake at* t_0 data suggested normality was reasonable (see Figure 1). The boxplot indicated no outliers in this data. As the *UTAUT model's prediction of E-learning uptake at* t_0 data were distributed normally, the sampling distribution of the sample mean for this data is normal.

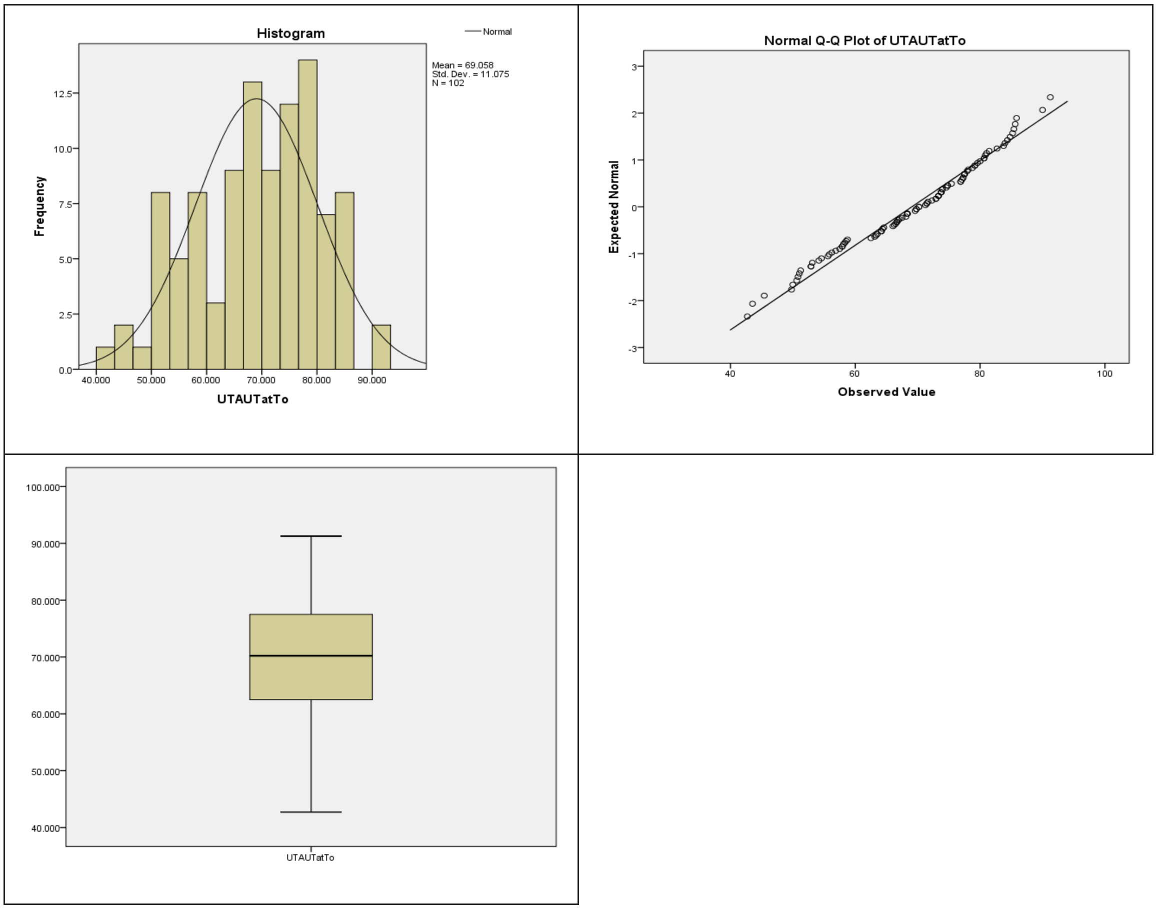


Figure 1: Histogram, Q-Q plot and boxplot for UTAUT model's prediction of E-learning uptake at t_0 data

- *Five independent variables (the measurements of E-learning uptake at t_1)*

The normality of five independent variables (the five measurements of E-learning actual uptake at t_1) was checked previously since conducting multiple regression analysis of the relationship between the EU sub-model prediction of E-learning uptake at t_0 and the five measurements of E-learning actual uptake at t_1 (see Appendix 7-A). The result suggested that this assumption was not violated.

<u>Assumption 2</u>: Linear relationship between the dependent and independent variables

To check the linearity assumption, a scatterplot of the standardized residual as a function of standardized predicted value was used (see Figure 2). A scatterplot of the residual indicated linear relationship between the dependent and independent variables in this regression model: the points were symmetrically distributed around a horizontal line. Therefore, the linearity assumption was not violated.

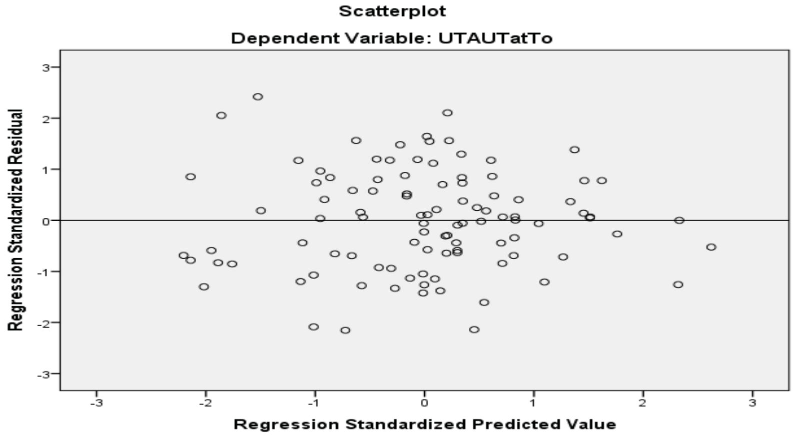


Figure 2: Scatterplot of residual plot for the relationship between the five measurements of actual E-learning uptake at t_1 and the UTAUT models' prediction of E-learning uptake at t_0

Assumption 3: Homoscedasticity

To check this assumption, the scatterplot of standardized residuals against the standardized predicted value was used again (see Figure 2). In this regression model, since the spread of residuals appeared fairly constant over the range of standardized predicted value, it could be inferred that the assumption was met.

Assumption 4: Independence of residual (error)

The Durbin-Watson test was used to evaluate the independence of residual. As Durbin-Watson statistic for this regression model was 2.2, this assumption was not violated.

Assumption 5: Multicollinearity

This assumption was checked previously when conducting multiple regression analysis of the relationship between EU sub-model prediction of E-learning uptake at t_0 and the five measurements of E-learning actual uptake at t_1 (see Appendix 7-A). The result suggested that the assumption was not violated.

Appendix 7-D: Concept and procedure works of canonical correlation analysis

Canonical correlation analysis was developed to facilitate the researcher in simultaneously investigating the relationship between a set of dependent and independent variables (Kuylen and Verhallen, 1981). It is conceptualized as a simple bivariate correlation (Pearson's r) between the two linear equations (variate): the linear composite of the dependent variables and the linear composite of the independent variables. Because only one test is performed to evaluate simultaneously the relationship between multiple dependent variables and multiple independent variables, it can reduce the risk of Type I error and will also produce multivariate results (Hair et al., 2010). The procedure works in the following way (Sherry and Henson, 2005).

In canonical correlation analysis, multivariate test (Wilks' lambda) is first carried out to: (a) determine whether two sets of variables are statistically dependent of each other in a linear sense; and (b) measure the percentage of variance in the combination of dependent variables not accounted for by the group of independent variables (Meyers et al., 2006). The canonical correlation analysis then derives a linear equation for each set of variables to create a canonical variate that best explains the relationship between them. These two linear equations (dependent and independent variate) are created to yield the largest possible canonical correlation (R_c) between the dependent and independent canonical variate (Manly, 2005). This set of two linear equations (canonical variate) is the canonical function. The number of canonical functions depends on the number of variables in the smaller of the two variable sets. Dimension reduction analysis is then conducted to determine which functions should be included for interpretation (Sherry and Henson, 2005). In order to investigate which dependent and independent variables contribute to the selected canonical function, part-correlations between a variable and its variate are calculated. Part-correlation is a correlation between a variable and its variate when the effect of other variables within the same variate has been removed from that variable (Field, 2013). It gives us the unique contribution of each variable for its variate. According to Cohen's effect size (1992), a correlation coefficient of 0.3 is considered a moderate correlation: the variable accounts for approximately ten percent (0.3^2) of total variation in its variate. Thus, the contributing variable in each canonical variate is the variable that has a part-correlation coefficient between itself and its variate greater than or equal to 0.3.

To yield insight into the relationship between variables within each variate, canonical weights and canonical loadings are used (Kuylen and Verhallen, 1981). Canonical weights (*Beta*) are comparable with beta-weights from multiple regression analysis between a variable and its variate. On the other hand, canonical loadings (r_s) are comparable with the factor loadings from factor analysis or zero-order correlation between a variable and its variate. When variables within a variate are uncorrelated with each other, each variable's *Beta* weight is equal to its canonical loading (Courville and Thompson, 2001). However, if correlations between variables within a variate are found, there are two possible outcomes: if a variable's *Beta* weight is lower than its canonical loading, it indicates the shared predictive power among variables within a variate; conversely, when the *Beta* weight is higher than canonical loading, a suppressor effect is indicated.

A suppressor variable is a variable that alone has a very small or no zero order correlation with its variate, but it is correlated with the other variables within the same variate (Tzelgov and Henik, 1991). When a suppressor variable is added to the equation (variate), it removed or suppressed criterion-irrelevant variance from the correlated variable. This results in: (a) a sizable increase in the beta weight of the correlated variable from zero order correlation; (b) an increase in its beta weight from zero order correlation with the different in the sign; and (c) a boost in the value of R square. Finally, to investigate the important predictors and relevant outcomes for the canonical model, the sum square of the part-correlation for each variable across functions (h^2) was used to indicate the amount of variance for which each variable was reproducible across the function.

Appendix 7-E: Statistical conditions and assumptions checking of the canonical correlation analysis between the five EU sub-model initial expectations t_0 and the five measurements of actual E-learning uptake at t_1

Before running the canonical correlation analysis, the two required conditions and three required assumptions were checked as follows.

Condition 1**:** At least two independent and two dependent variables

There were five independent variables in this data analysis: *performance expectancy at* t_0; *effort expectancy at* t_0; *social encouragement expectancy at* t_0; *facilitating condition expectancy at* t_0; and *learning consistency expectancy at* t_0. The five dependent variables were: *subjective percentage of E-learning usage in education during time* t_0 *to* t_1; *subjective time spent learning with E-learning during time* t_0 *to* t_1; *objective time spent on E-learning during time* t_0 *to* t_1; *objective total number of times logging onto E-learning during time* t_0 *to* t_1; and *objective total number of activities involving E-learning during time* t_0 *to* t_1. This condition therefore was met.

Condition 2**:** Dependent and independent variables are continuous data

The independent variables (five initial expectations at t_0) were continuous, ranging from 0 to 10. The five independent variables (five measurements of actual E-learning uptake at t_1) were also continuous. This condition therefore was met.

Assumption 1**:** Sampling distribution of the sample mean for each variable is normal

- *Performance expectancy at* t_0

A review of the Shapiro-Wilk test for normality (SW = .98, df = 102, p = .06) and skewness (-1.7) and kurtosis (-.49) statistics suggested that the *performance expectancy at* t_0 data did not deviate significantly from normal (see Table 1).

Table 1: Normality test for performance expectancy at t_0 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\lvert Z\rvert \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\lvert Z\rvert \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Performance expectancy at T0	102	7.0 ± 1.3	-.41	.24	-1.7	no skewness	-.23	.47	-.49	no kurtosis	.98	102	.06	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for this variable data suggested the assumption of normality was reasonable. The boxplot suggested no outliers in the *performance expectancy at* t_0 data (see Figure 1). As the *performance expectancy at* t_0 data were distributed normally, the sampling distribution of the sample mean for this data was normal.

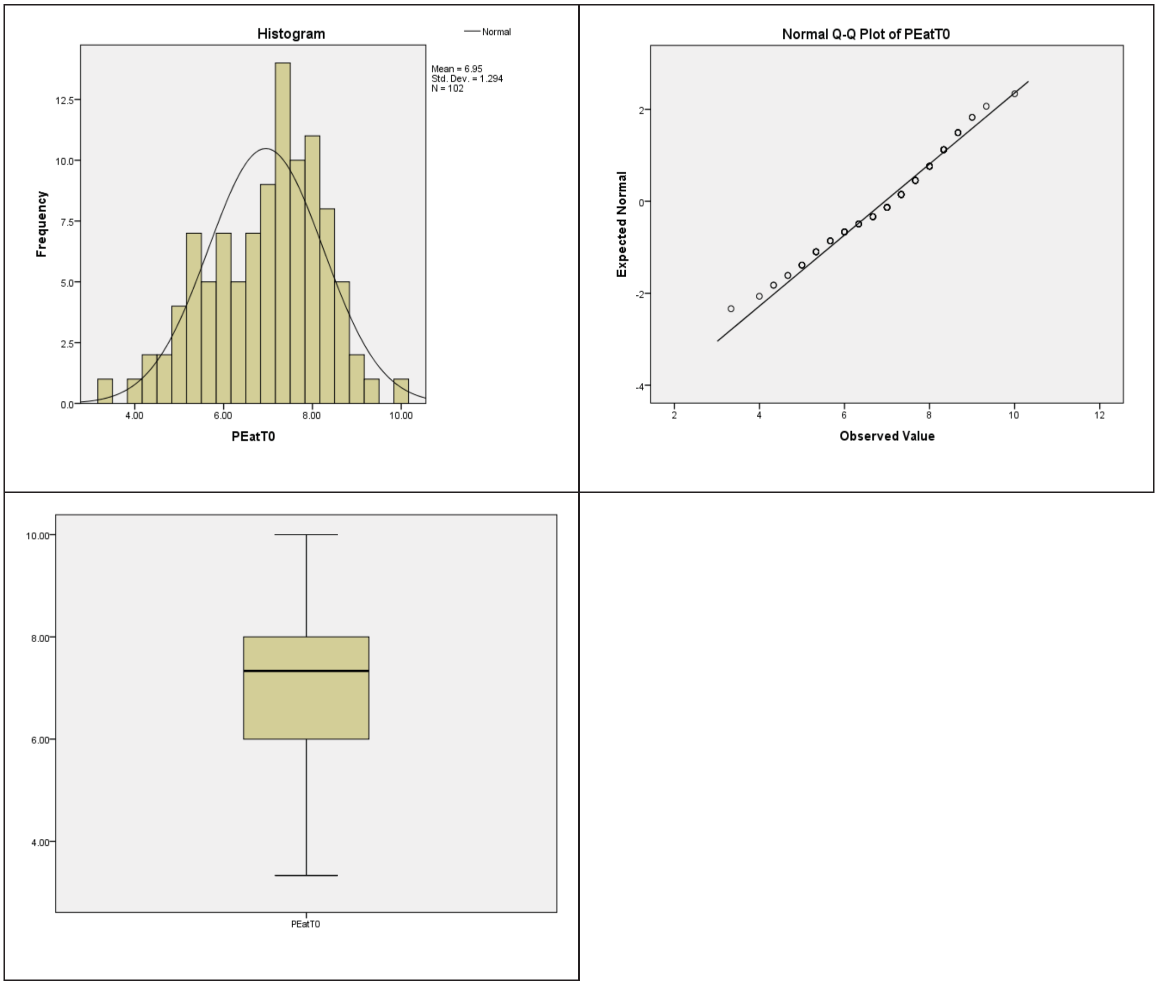


Figure 1: Histogram, Q-Q plot and boxplot for performance expectancy at t_0 data

- *Effort expectancy at* t_0

A review of the Shapiro-Wilk test for normality (SW = .97, df = 102, p = .012) and skewness (-.20) and kurtosis (-.74) statistics suggested that the *effort expectancy at* t_0 data did not deviate significantly from normal (see Table 2).

Table 2: Normality test for effort expectancy at t_0 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion (|Z |≤ 2.56)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion (|Z| ≤ 2.56)	Statistic	df	P-value	Conclusion (p ≤ .01)
Effort expectancy at T0	102	6.5 ± 1.4	-.49	.24	-2.0	no skewness	-.35	.47	-.74	no kurtosis	.97	102	.012	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *effort expectancy at* t_0 data suggested the assumption of normality was reasonable. The boxplot suggested no outliers in this variable data (see Figure 2). According to the central limit theorem, as the *effort expectancy at* t_0 data were distributed normally, the sampling distribution of the sample mean for this data is normal.

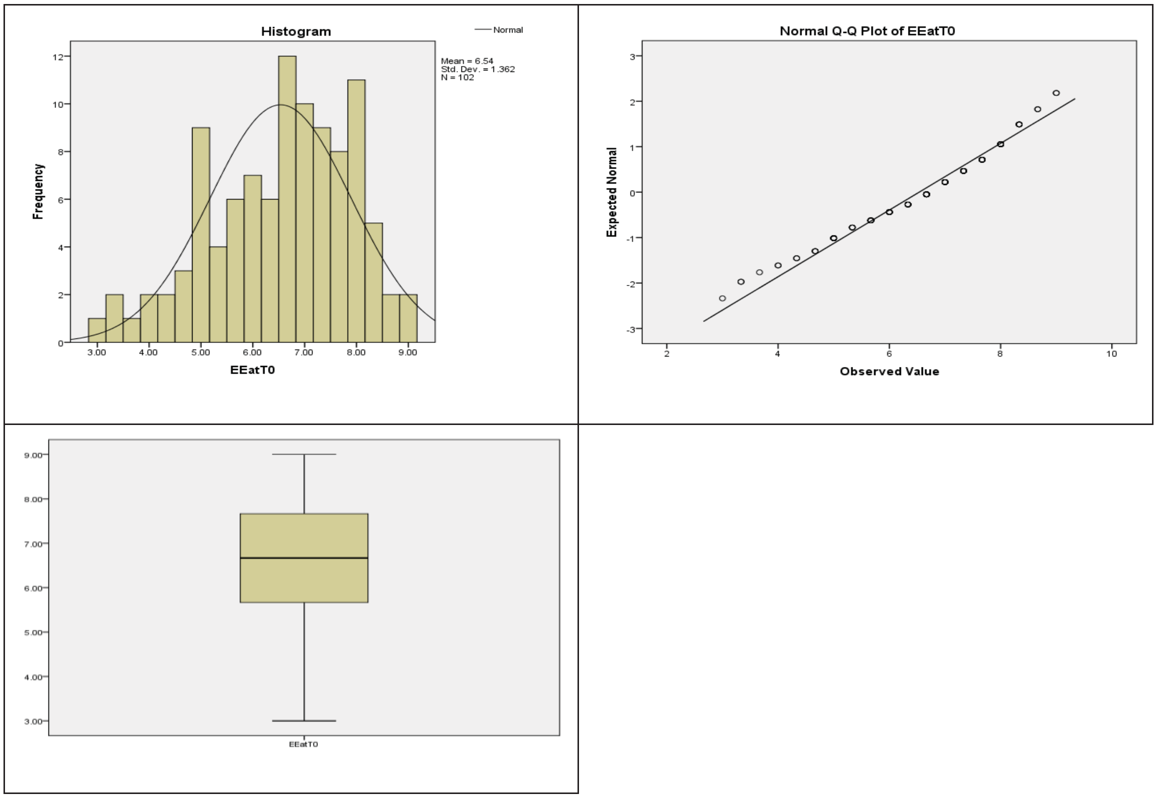


Figure 2: Histogram, Q-Q plot and boxplot for effort expectancy at t_0 data

- *Social encouragement expectancy at* t_0

A review of the Shapiro-Wilk test for normality (SW = .98, df = 102, p = .11) and skewness (-1.2) and kurtosis (-.77) statistics suggested that the *social encouragement expectancy at* t_0 data did not deviate significantly from normal (see Table 3).

Table 3: Normality test for social encouragement expectancy at t_0 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Social encouragement expectancy at T0	102	6.9 ± .12	-.29	.24	-1.2	no skewness	-.36	.47	-.77	no kurtosis	.98	102	.11	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *social encouragement expectation at* t_0 data suggested the assumption of normality was reasonable. The boxplot suggested no outliers in this s data (see Figure 3). According to the central limit theorem, as the *social encouragement expectancy at* t_0 data were distributed normally, the sampling distribution of the sample mean for this data is normal.

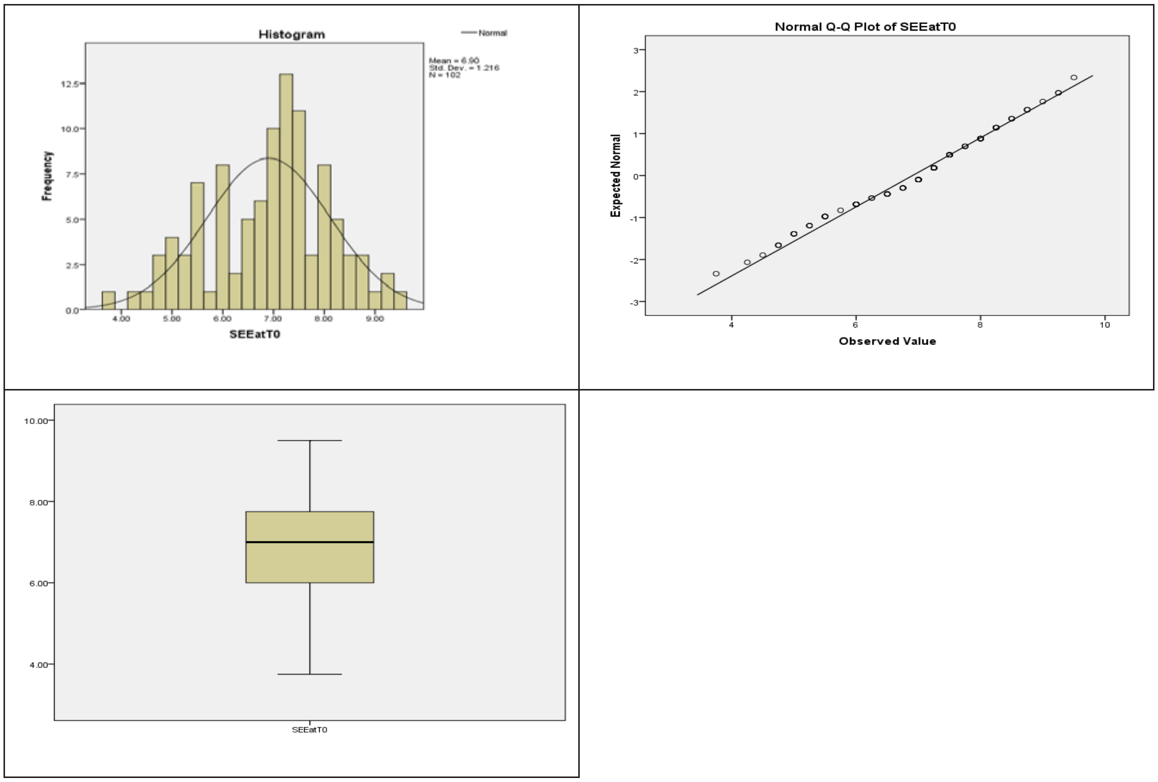


Figure 3: Histogram, Q-Q plot and boxplot for social encouragement expectancy at t_0 data

- *Facilitating condition expectancy at* t_0

A review of the Shapiro-Wilk test for normality (SW = .98, df = 102, p = .16) and skewness (-1.2) and kurtosis (-.49) statistics suggested that the *facilitating condition expectancy at* t_0 data did not deviate significantly from normal (see Table 4).

Table 4: Normality test for facilitating condition expectancy at t_0 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Facilitating condition expectancy at T0	102	7.2 ± .13	-.29	.24	-1.2	no skewness	-.23	.47	-.49	no kurtosis	.98	102	.16	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *facilitating condition expectancy at* t_0 data suggested the assumption of normality was reasonable. Although the boxplot indicated an outlier (Case 74), it was not considered as such in this research because its value was not lower than Q_1 - 3×IQR (see Figure 4).

According to the central limit theorem, as the *facilitating condition expectancy at* t_0 data were distributed normally, the sampling distribution of the sample mean for this data is normal.

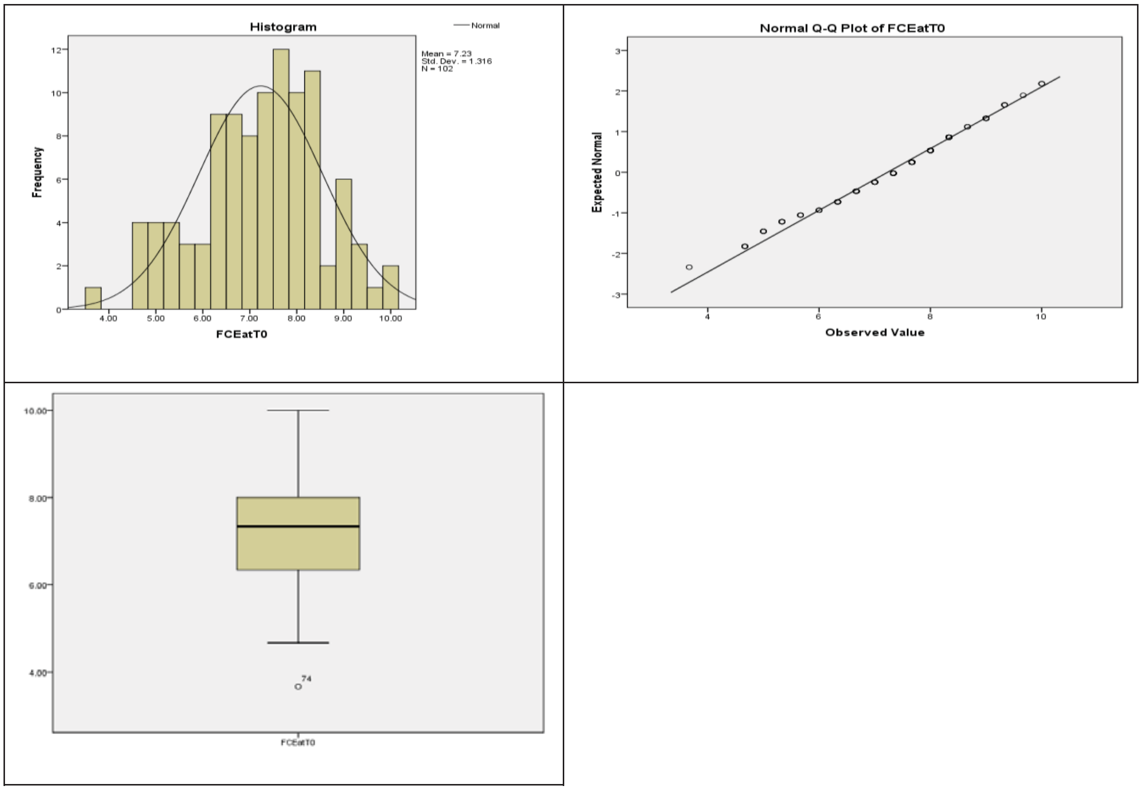


Figure 4: Histogram, Q-Q plot and boxplot for facilitating condition expectancy at t_0 data

- *Learning consistency expectancy at* t_0

A review of the Shapiro-Wilk test for normality (*SW* = .98, *df* = 102, *p* = .06) and skewness (-1.6) and kurtosis (-.77) statistics suggested that the *learning consistency expectancy at* t_0 data did not deviate significantly from normal (see Table 5).

Table 5: Normality test for learning consistency expectancy at t_0 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Learning consistence expectancy at T0	102	7.2 ± .14	-.39	.24	-1.6	no skewness	-.37	.47	-.77	no kurtosis	.98	102	.06	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *learning consistency expectancy at* t_0 data suggested the assumption of normality was reasonable (see Figure 5). The boxplot of this data showed no outlier. According to the central limit theorem, as the *learning consistency expectancy at* t_0 data were distributed normally, the sampling distribution of the sample mean for this data is normal.

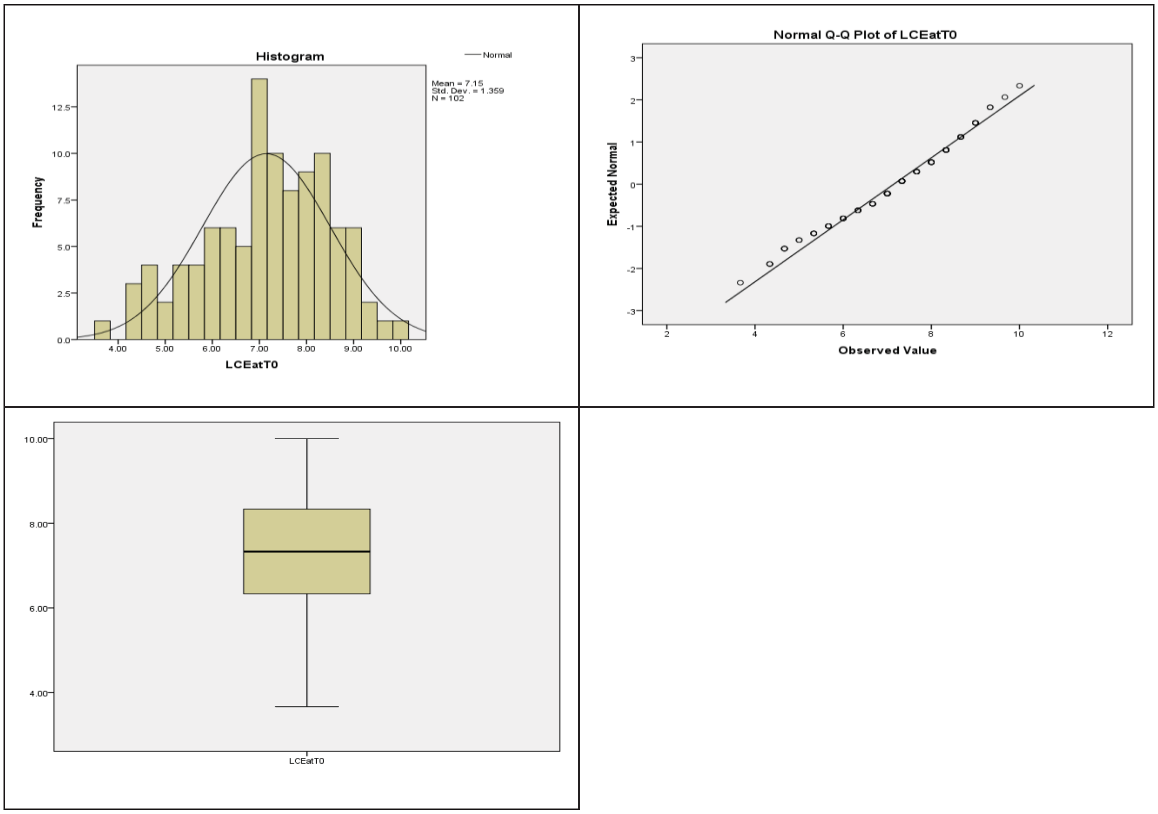


Figure 5: Histogram, Q-Q plot and boxplot for learning consistency expectancy at t_0 data

- *Dependent variables*

The normality check and outlier detection for five dependent variables (the five measurements of actual E-learning uptake) was carried out previously and the results suggested that the normality assumption was not violated (see Appendix 7-A).

<u>Assumption 2</u>: Linear relationship between the dependent and independent variables

The canonical correlation analysis is conceptualized as the linear relationship (correlation) between two variates. The assumption of linearity was required because the relationship between two variates cannot be accurately captured by this data analysis technique if the variates relate in nonlinear manner (Hair et al. 2010). Since there is no method for checking this assumption before conducting canonical analysis, linearity was checked afterwards by plotting a scatterplot between the standardized predicted value and the standardized residual of the Function 1 dependent and independent variates (see Figure 6). The result showed that there was no pattern of residual dots in this data analysis. Accordingly, linearity assumption was not violated.

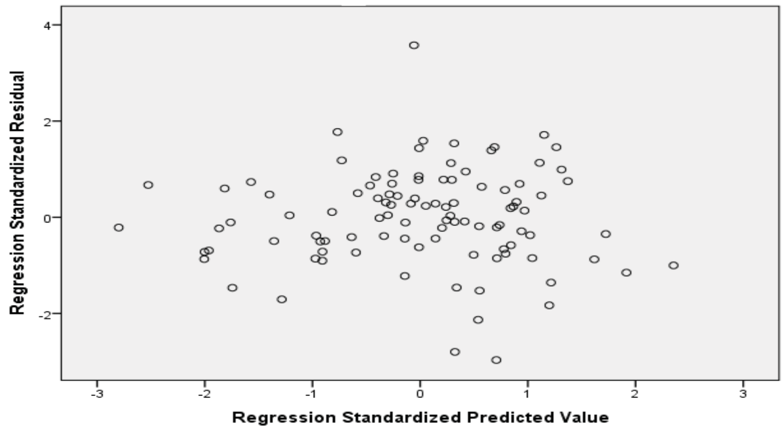


Figure 6: Scatterplot of residual plot for the relationship between the five measurements of actual E-learning uptake at t_1 and the five EU sub-model initial expectation variables at t_0

<u>Assumption 3:</u> Multicollinearity

To detect multicollinearity among dependent variables and among independent variables, the test of the VIF test was used (see Table 6). As VIF for each variable in this study was lower than 10, multicollinearity was not a concern (Field, 2013).

Table 6: Multicollinearity test for the five measurements of actual E-learning uptake at t_1 and the five EU sub-model initial expectation variables at t_0

		VIF
Dependent variable	Percentage (subjective) during t_0 and t_1	1.6
	Time spent (subjective) during t_0 and t_1	1.2
	Time spent (objective) during t_0 and t_1	4.0
	Number of times logging on (objective) during t_0 and t_1	3.1
	Number of activity taking part (objective) during t_0 and t_1	4.1
Independent variable	Performance expectancy at t_0	2.7
	Effort expectancy at t_0	2.3
	Social encouragement expectancy at t_0	3.4
	Facilitating condition expectancy at t_0	2.8
	Learning consistency expectancy at t_0	3.8

Appendix 7-F: Statistical conditions and assumptions checking of the canonical correlation analysis between the two TAM model variables at t_0 and the five measurements of actual E-learning uptake at t_1

Before running the canonical correlation analysis, the two required conditions and three required assumptions were checked as follows.

Condition 1**:** At least two independent and two dependent variables

There were two independent variables in this data analysis: *performance expectancy at* t_0, and *effort expectancy at* t_0. The five dependent variables were: *subjective percentage of E-learning usage in education during time* t_0 *to* t_1; *subjective time spent learning with E-learning during time* t_0 *to* t_1; *objective time spent on E-learning during time* t_0 *to* t_1; *objective total number of times logging onto E-learning during time* t_0 *to* t_1; and *objective total number of activities involving E-learning during time* t_0 *to* t_1. This condition therefore was met.

Condition 2**:** Dependent and independent variables are continuous data

Independent variables (two initial expectations at t_0) were continuous ranging from 0 to 10. Five dependent variables (measurements of actual E-learning uptake at t_1) were also continuous. This condition therefore was met.

Assumption 1**:** Sampling distribution of the sample mean for each variable is normal.

The normality check and outlier detection for the five dependent variables (the five measurements of E-learning actual uptake) were carried out previously and the results suggested that the normality assumption was not violated (see Appendix 7-A). The normality check and outlier detection for two independent variables (performance expectancy at t_0, and effort expectancy at t_0) were carried out previously and the results suggested that the normality assumption was not violated (see Appendix 7-E).

Assumption 2: Linear relationship between the dependent and independent variables

The linearity was checked afterwards by a scatterplot of the standardized predicted value and the standardized residual of Function 1 dependent and independent variates (see Figure 1). The result showed that there was no pattern of residual dots in this data analysis. Accordingly, the linearity assumption was not violated.

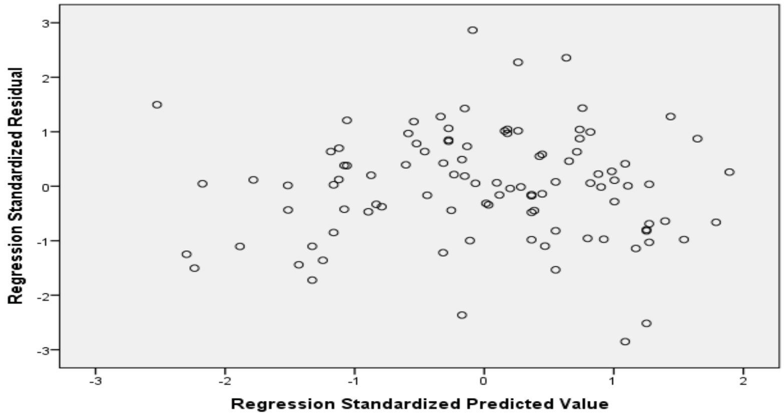


Figure 1: Scatterplot of residual for the relationship between the five measurements of actual E-learning uptake at t_1 and the two TAM model variables at t_0

Assumption 3: Multicollinearity

This assumption was tested previously (see Appendix 7-E). As the VIF for each variable in this data analysis was less than 10, multicollinearity was not a concern (Field, 2013).

Appendix 7-G: Explanation of the canonical solution of the relationship between the two TAM model variables at t_0 and the five measurements of actual E-learning uptake at t_1

The independent variables were the two measured expectations from TAM model at t_0: (1) *performance expectancy at* t_1, and (2) *effort expectancy at* t_1. Dependent variables were the five measurements of actual E-learning uptake at t_1: (1) *subjective percentage of E-learning usage in education during time* t_0 *to* t_1; (2) *subjective time spent learning with E-learning during time* t_0 *to* t_1; (3) *objective time spent on E-learning during time* t_0 *to* t_1; (4) *objective total number of times logging onto E-learning during time* t_0 *to* t_1; and (5) *objective total number of activities involving E-learning during time* t_0 *to* t_1.

The relationship between the set of TAM model variables at t_0 and the measurements of actual E-learning uptake at t_1 was statistically significant, Wilks' λ criterion =.68, $F(10, 188) = 4.1$, $p < .001$. Accordingly, there was at least one significant relationship between the TAM variables at t_0 and actual E-learning uptake measurements at t_1. Because Wilks' λ represents the variance in the combination of dependent variables unexplained by the set of independent variables, 32% (1- λ) of variance in E-learning actual uptake was accounted for by TAM variables.

The canonical correlation analysis yielded two functions with squared canonical correlations (${R_c}^2$) of .24 and .12 respectively for each successive function (see Table 1).

Table 1: Canonical correlation analysis of the relationship between the two TAM model variables at t_0 and the five measurements of actual E-learning uptake at t_1

Function	Eigenvalue	%	Cumulative %	Canonical Correlation	Squared Correlation
1	.31	70.4	70.4	.49	.24
2	.13	29.6	100	.34	.12

Functions 1 to 2 and Function 2 in isolation were statistically significant, $F(10, 188) = 4.1$, $p < .001$, and $F(4, 95) = 3.1$, $p = 0.19$, respectively (see Table 2). Because of this, Function 1 and 2 were both interpreted.

Table 2: Dimension reduction analysis for canonical functions of the relationship between the two TAM model variables at t_0 and the five measurements of E-learning actual uptake at t_1

Roots	Wilks' λ	F	Hypothesis DF	Error DF	Significance of F
1 to 2	.68	4.1	10	188	< .001
2 to 2	.89	3.1	4	95	.019

The canonical weight (*beta*), canonical loading (r_s), part-correlation between variable and its variate (r_p), square of part-correlation (${r_p}^2$) and sum square of part-correlation for each variable across the two selected functions (h^2) were showed in Table 3.

Table 3: Initial canonical solution for canonical Function 1 and 2 of the relationship between the two TAM model variables at t_0 and the five measurements of actual E-learning uptake at t_1

	Variable	Function 1					Function 2					Overall	
		β	r_s	r_p	${r_p}^2$ (%)	*Summary*	β	r_s	r_p	${r_p}^2$ (%)	*Summary*	h^2(%)	Summary
DV (s)	Percentage (subjective) during t_0 and t_1	.65	.91	.51†	.26	Contributed	-.05	-.18	-.04	.001	No	.26	Relevant
	Time spent (subjective) during t_0 and t_1	.06	.43	.05	$2.8*10^{-3}$	No	-.21	-.26	-.19	.04	No	.04	No
	Time spent (objective) during t_0 and t_1	.76	.79	.39†	.15	Contributed	1.3	-.13	.68†	.46	Suppressor contributed	.61	Relevant
	Number of times logging (objective) during t_0 and t_1	-.26	.42	-.15	.02	No	.09	−.37	.05	.003	No	.03	No
	Number of activities (objective) during t_0 and t_1	-.21	.55	-.10	.01	No	-1.8	−.66	−.87†	.75	Contributed	.76	Relevant
IV (S)	Performance expectancy at t_0	.32	.82	.23	.06	No	-1.3	−.57	−.97†	.95	Contributed	1.0	Important
	Effort expectancy at t_0	.76	.97	.57†	.32	Contributed	1.1	.24	.82†	.67	Contributed	1.0	Important

β = Standardized coefficient between variable and with its variate
r_s = Zero order correlation between variable and with its variate
r_p = Part correlation († greater than |. 30|)
${r_p}^2$ = Squared part correlation between variable and with its variate
h^2 = sum squared part correlation across two CCA function (greater than .20 or 20 % is underlined)

In canonical Function 2, the high part-correlation (higher than .30) and the difference in the sign between zero order correlation and beta, *objective time spent on E-learning during* t_0 *and* t_1 was suspected as a suppressor (Friedman and Wall, 2005). It is not easy to interpret the effect of suppressor variable on a contributing variable within the Function 2-dependent variate *(objective total number of activities involving E-learning during* t_0 *and* t_1) if this contributing variable has negative beta and canonical loading. To make it easier, the variable *objective total number of activities involving E-learning during* t_0 *and* $t_1$was inverted: inversion consisted of subtracting the variable from a constant being the maximum of the variable. The resulting inverted variable can be said to measure total number of non E-learning activities involving. A final canonical analysis was carried out using the inverted variable (see Table 4).

Table 4: Final canonical solution for canonical Function 1 and 2 of the relationship between the two TAM model variables at t_0 and the five measurements of actual E-learning uptake at t_1

	Variable	Function 1					Function 2					Overall	
		β	r_s	r_p	r_p^2 (%)	*Summary*	β	r_s	r_p	r_p^2 (%)	*Summary*	h^2(%)	Summary
DV(s)	Percentage (subjective) during t_0 and t_1	-.65	-.91	-.51†	.26	Contributed	-.05	-.18	-.04	.001	No	.26	Relevant
	Time spent (subjective) during t_0 and t_1	-.06	-.43	-.05	$2.8*10^{-3}$	No	-.21	-.26	-.19	.04	No	.04	No
	Time spent (objective) during t_0 and t_1	-.76	-.79	-.39†	.15	Contributed	1.3	-.13	.68†	.46	Suppressor contributed	.61	Relevant
	Number of times logging on (objective) during t_0 and t_1	.26	-.42	.15	.02	No	.09	−.37	.05	.003	No	.03	No
	Inverted number of activities (objective) during t_0 and t_1	-.21	.55	-.10	.01	No	1.8	.66	.87†	.75	Contributed	.76	Relevant
IV(S)	Performance expectancy at t_0	-.32	-.82	-.23	.06	No	-1.3	−.57	−.97†	.95	Contributed	1.0	Important
	Effort expectancy at t_0	-.76	.97	.57†	.32	Contributed	1.1	.24	.82†	.67	Contributed	1.0	Important

β = Standardized coefficient between variable and with its variate
r_s = Zero order correlation between variable and with its variate
r_p = Part correlation († greater than |.30|)
r_p^2 = Squared part correlation between variable and with its variate
h^2 = sum squared part correlation across two CCA function (greater than .20 or 20 % is underlined)

Summary of CCA Function 1

In Function 1, there was a positive relationship between the dependent and the independent variates because the canonical correlation coefficient between the dependent and the independent variates (.49) in Function 1 was positive. There were two dependent variables which contributed to the Function 1-dependent variate ($|r_p| > .3$): *subjective percentage of E-learning usage in education during t_0 and t_1* (r_p = .51) and *objective time spent on E-learning during t_0 and t_1* (r_p = .39). Since the canonical loading (r_s) for these two contributing dependent variables had a same sign, these two dependent variables positively related to one another. *Effort expectancy at t_1* (r_p = .57) was a contributing independent variable in the Function 1 (see Figure 1)

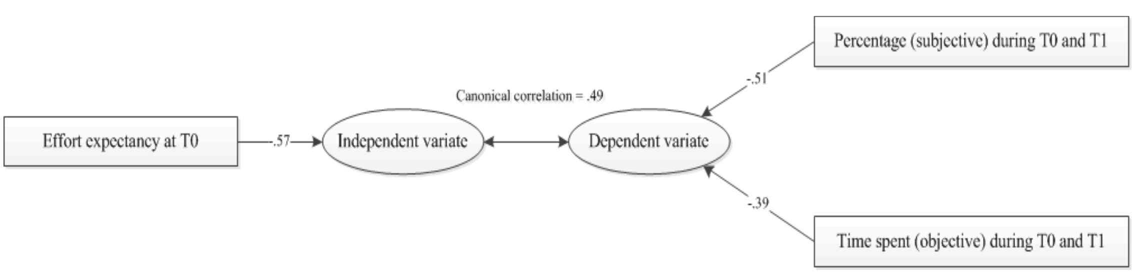


Figure 1: Summary of canonical correlation analysis Function 1 of the relationship between the two TAM model variables at t_0 and the five measurements of actual E-learning uptake at t_1

Dependent variate Function 2

There were two dependent variables which contributed to the Function 2-dependent variate ($|r_p| > .3$): (a) *inverted objective total number of activities involving E-learning during t_0 and t_1* (r_p = .87); (b) *objective time spent on E-learning during t_0 and t_1* (r_p = .68). A sizable increase in the beta weight from the zero order correlation of *inverted objective total number of activities involving E-learning during t_0 and t_1* (from r_s =.66 to *beta* = 1.8) and *objective time spent on E-learning during t_0 and t_1* (from r_s = -.13 to *beta* = 1.3*)* indicated the occurrence of suppression in Function 2-dependent variate (Tzelgov and Henik, 1991). The suspected suppressor variable was *objective time spent on E-learning during t_0 and t_1* because of the difference in the sign between its zero order correlation (negative) and beta (positive) (Thompson and Levine, 1997).

To investigate whether *objective time spent on E-learning during t_0 and t_1* was a suppressor variable, multiple regression analysis was carried out: (i) Function 2-dependent variate regressed with all dependent variables except *objective time spent on E-learning during t_0 and t_1*; (ii) Function 2-dependent variate regressed with all dependent variables included *objective time spent on E-learning during t_0 and t_1* (Paulhus et al., 2004) (see Table 5).

Table 5: Multiple regression analysis result between Funtion2-dependent variate and dependent variables before and after adding objective time spent on E-learning during t_0 and t_1

Variable	**(i) Before adding beta**	**(ii) After adding beta**	**Sizable change in beta**
Percentage (subjective) during t_0 and t_1	-.23	-.05	.18
Time spent (subjective) during t_0 and t_1	-.16	-.21	-.05
Time spent (objective) during t_0 and t_1	-	1.3	-
Number of times logging on (objective) during t_0 and t_1	.42	.09	-.31
Inverted number of activities (objective) during t_0 and t_1	1.1	1.8	.70
	R^2 = .60	R^2= 1	R^2_{chnage} = .40

Even though *objective time spent on E-learning during t_0 and t_1*had a smallest value of zero order correlation with its variate, when this variable was added to the equation of ii: (a) it was a contributing variable (*beta* = 1.3); (b) it removed or suppressed criterion-irrelevant variance from *inverted objective total number of activities involving E-learning during t_0 and t_1* (increased the beta weight from *beta* =

1.1 to *beta* = 1.8) and (c) the variance of dependent variate accounted for by a set of dependent variables was increased 40%. The result helped us to confirm that *objective time spent on E-learning during* t_0 *and* t_1 was a suppressor variable for *inverted objective total number of activities involving E-learning during* t_0 *and* t_1.

Having noticed the appearance of a suppressor, we further examined what was taking place by dividing *objective time spent on E-learning during* t_0 *and* t_1 data into two groups: low (less than mean) and high (equal to and greater than mean). Multiple regression analysis then conducted: regressing the dependent variate with *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 in low and high *objective time spent on E-learning during* t_0 *and* t_1 group of participants (see Table 6).

Table 6: Multiple regression analysis result between Funtion2-dependent variate and inverted objective total number of activities involving E-learning during t_0 and t_1 in low and high objective time spent on E-learning during t_0 and t_1 groups of participants

Variable	**Low time spent objective group**		**High time spent objective group**		**Sizable change in beta**
	beta	**Sig.**	**beta**	**Sig.**	
Inverted number of activities (objective) during t_0 and t_1	.65	< .001	.91	< .001	.26
	R^2 = .42		R^2= .83		R^2_{chnage} = .41

The result indicated that *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 was an important outcome in both high and low *objective time spent on E-learning during* t_0 *and* t_1 group because the beta weight of this variable was significant in both groups: in lower group (*beta* = .65, *p* < .001), in higher group (*beta* = .91, *p* < .001). The R-square in *objective total time spent on E-learning during* t_0 *and* t_1 group (.83) was higher than the lower group (.42). It indicated that *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 was a relevant outcome of TAM variables within Function 2 in both high and low *objective time spent on E-learning during* t_0 *and* t_1 groups, but this measurement became more relevant outcome with TAM factors when participants spent a greater amount of time on E-learning by the objective measure.

Independent variate Function 2

There were two dependent variables that contributed to the Function 2 dependent variate ($|r_p|$ > .31): (a) *performance expectancy at* t_0 (r_p = -.97) and (b) *effort expectancy at* t_0 (r_p = .82). The canonical loading (r_s) for the two contributing independent variables had a different sign: that meant these two variables were negatively related to one another.

Summary of CCA Function 2

In Function 2, since the canonical correlation coefficient between the dependent and the independent variates was positive (.34), there was a positive relationship between the dependent and independent variate. The two contributing independent variables were *performance expectancy at* t_0 and *effort expectancy at* t_0, while contributing dependent were *inverted objective total number of activities involving E-learning during* t_0 *and* t_1, *objective time spent on E-learning during* t_0 *and* t_1. The *objective time spent on E-learning during* t_0 *and* t_1 was a suppressor variable for *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 (see Figure 2).

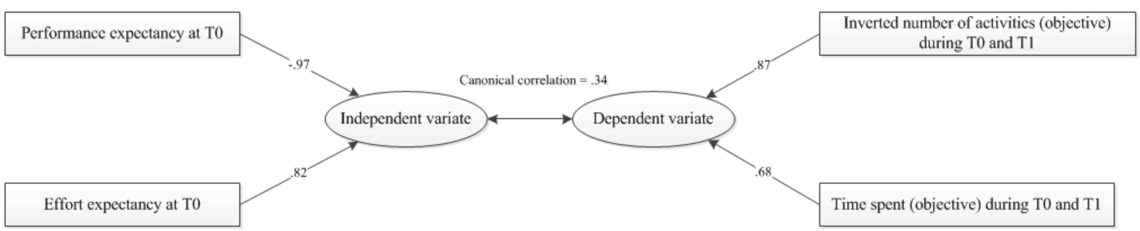


Figure 2: Summary of canonical correlation analysis Function 2 of the analysis of the relationship between two TAM model variables at t_0 and the five measurements of actual E-learning uptake at t_1

Summary of CCA of the relationship between the two TAM model variables at t_0 *and the five measurements of actual E-learning uptake at* t_1

Subjective time spent learning with E-learning during t_0 *and* $t_1$and *objective total number of times logging onto E-learning during time* t_0 *to* t_1 did not contribute to any canonical functions. Because of this, sum square of part-correlation for these two dependent variables across 2 functions was lower than criterion (h^2 = .2): *subjective time spent learning with E-learning during* t_0 *and* $t_1$and *objective total number of times logging onto E-learning during time* t_0 *to* t_1 were an irrelevant outcome for the TAM model variables at t_0. There were three measurements of actual E-learning uptake that related with a set of TAM model variables: (a) *inverted objective total number of* *activities involving E-learning during t_0 and t_1* (h^2 = .76); (b) *objective total time spent on E-learning during t_0 and t_1* (h^2 = .61) and (c) *subjective percentage of E-learning usage in education during time t_0 to t_1* (h^2 = .26). The results from canonical correlation analysis recommended that all the two TAM variables (PE and EE) affecting the uptake of E-learning (h^2 > .20). Both variables significantly related to *inverted objective total number of activities involving E-learning during t_0 and t_1* and *objective time spent on E-learning during t_0 and t_1*, while *effort expectancy* was more related to *subjective percentage of E-learning usage in education during time t_0 to t_1* (see Figure 3).

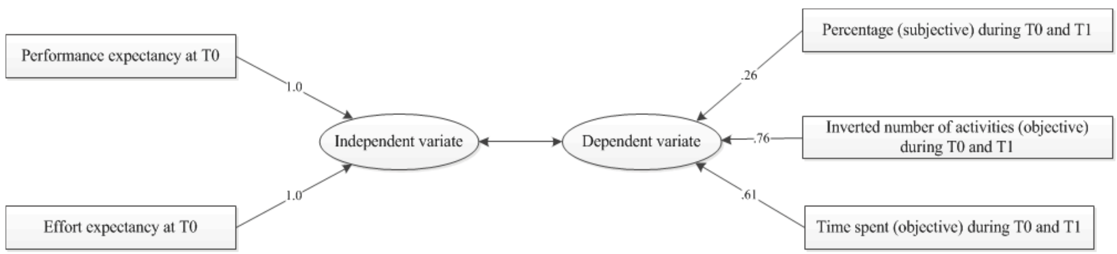


Figure 3: Summary of canonical correlation analysis of the relationship between the two TAM model variables at t_0 and the five measurements of actual E-learning uptake at t_1

Appendix 7-H: Statistical conditions and assumptions checking of the canonical correlation analysis between the four UTAUT model variables at t_0 and the five measurements of actual E-learning uptake at t_1

Before running the canonical correlation analysis, the two required conditions and three required assumptions were checked as follows.

<u>Condition 1</u>**:** At least two independent and two dependent variables

There were four independent variables in this data analysis*: performance expectancy at* t_0, *effort expectancy at* t_0, *social encouragement expectancy at* t_0, and *facilitating condition expectancy at* t_0. The five dependent variables were: *subjective percentage of E-learning usage in education during time* t_0 *to* t_1; *subjective time spent learning with E-learning during time* t_0 *to* t_1; *objective time spent on E-learning during time* t_0 *to* t_1; *objective total number of times logging onto E-learning during time* t_0 *to* t_1; and *objective total number of activities involving E-learning during time* t_0 *to* t_1. This condition therefore was met.

<u>Condition 2</u>**:** Dependent and independent variables are continuous data

Independent variables (four initial expectations at t_0) were continuous ranging from 0 to 10. Five independent variables (measurements of actual E-learning uptake at t_1) were also continuous. This condition therefore was met.

<u>Assumption 1</u>**:** Sampling distribution of the sample mean for each variable was normal

The normality check and outlier detection for the five dependent variables (the five measurements of E-learning actual uptake) was carried out previously and the results suggested that the normality assumption was not violated (see Appendix 7-A). The normality check and outlier detection for four independent variables (performance expectancy at t_0, effort expectancy at t_0, social encouragement expectancy at t_0, and facilitating condition expectancy at t_0) was carried out previously and the results suggested that the normality assumption was not violated (see Appendix 7-E).

Assumption 2: Linear relationship between the dependent and independent variables

Linearity was checked afterwards by a scatterplot between the standardized predicted value and the standardized residual of Function 1 dependent and independent variates (see Figure 1). The result showed that there was no pattern of residual dots in this data analysis. Accordingly, the linearity assumption was not violated.

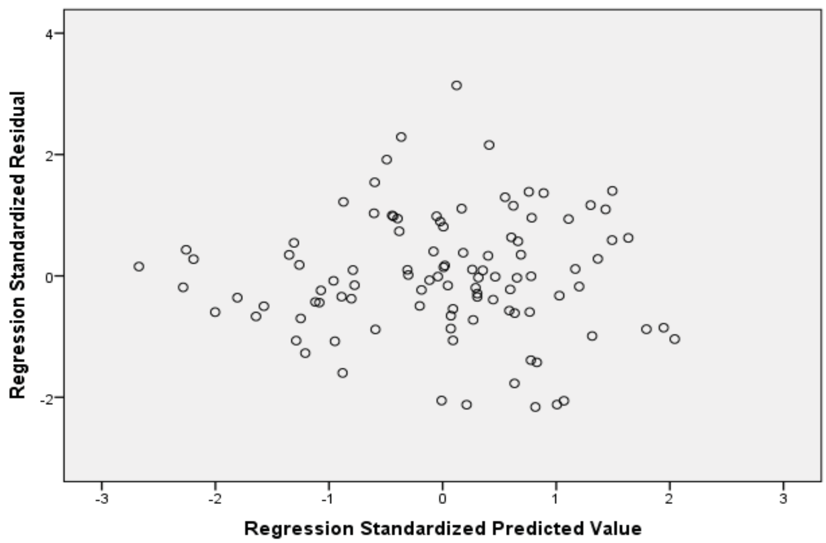


Figure 1: Scatterplot of residual plot for the relationship between the five measurements of actual E-learning uptake at t_0 and the four UTAUT model variables at t_1

Assumption 3: Multicollinearity

This assumption was test previously (see Appendix 7-E). As VIF for each variable in this data analysis was lower than 10, multicollinearity was not a concern (Field, 2013).

Appendix 7-I: Explanation of the canonical solution of the relationship between the four UTAUT model variables at t_0 and the five measurements of actual E-learning uptake at t_1

Canonical correlation analysis was conducted using the four UTAUT factors (PE, EE, SEE and FCE) measured at time t_0 as predictors of the five measurements of actual E-learning uptake measured at time t_1. The relationship between the set of UTAUT model variables at time t_0 and the measurements of actual E-learning uptake at time t_0 was statistically significant, Wilks' λ criterion = .55, $F(20, 306.1) = 3.0$, $p < .001$. Accordingly, there was at least one significant relationship between the UTAUT variables and the measurements of actual E-learning uptake. Wilks' λ represents the variance in the combination of dependent variables unexplained by the set of independent variables: 45% (1- λ) of variance in E-learning actual uptake was accounted for by UTAUT variables.

The canonical correlation analysis yielded four functions with squared canonical correlations ($R_c{}^2$) of .27, .21, .04 and .01 respectively for each successive function (see Table 1).

Table 1: Canonical correlation analysis of the relationship between the four UTAUT model variables at t_0 and the five measurements of actual E-learning uptake at t_1

Function	Eigenvalue	%	Cumulative %	Canonical Correlation	Squared Correlation
1	.36	53.5	53.5	.52	.27
2	.26	38.5	92.0	.46	.21
3	.04	5.9	97.8	.20	.04
4	.02	2.2	100.0	.12	.01

Functions 1 to 4 and Functions 2 to 4 were statistically significant, $F(20, 306.1) = 3.0$, $p < .001$, and $F(12, 246.4) = 2.3$, $p = 0.07$, respectively (see Table 2). However, the cumulative effects of Functions 3 to 4 and Function 4 in isolation were not statistically significant. Because of this, the first two functions were considered noteworthy in the context of this study (27% and 21% of shared variance, respectively). Functions 3and 4 were not interpreted, as they only explained 4% and 1% of the remaining variance in the variable sets after the extraction of the prior functions.

Table 2: Dimension reduction analysis for canonical functions of the relationship between the four UTAUT model variable at t_0 and the five measurements of E-learning actual uptake at t_1

Roots	**Wilks' λ**	**F**	**Hypothesis DF**	**Error DF**	**Significance of F**
1 to 4	.55	3.0	20.0	306.1	< .001
2 to 4	.75	2.3	12.0	246.4	.007
3 to 4	.95	.85	6.0	188.0	.53
4 to 4	.99	.70	2.0	95.0	.50

The canonical weight (*Beta*), canonical loading (r_s), part-correlation between variable and its variate (r_p), square of part-correlation ($r_p{}^2$) and sum square of part-correlation for each variable across the two selected functions (h^2) are shown in Table 3.

Table 3: Initial canonical solution for canonical Function 1 & 2 of the relationship between the four UTAUT initial expectation variables at t_0 and the five measurements of actual E-learning uptake at t_1

	Variable	**Function 1**					**Function 2**					**Overall**	
		β	r_s	r_p	$r_p{}^2$ (%)	*Summary*	β	r_s	r_p	$r_p{}^2$ (%)	*Summary*	h^2(%)	Summary
Dependent variable	Percentage (subjective) during t_0 and t_1	.66	.69	.51‡	.26	Contributed	-.25	−.61	-.19	.04	No	.30	Relevant
	Time spent (subjective) during t_0 and t_1	-.03	.27	-.03	$.09\times10^{-2}$	No	-.16	−.40	-.15	.02	No	.02	No
	Time spent (objective) during t_0 and t_1	1.1	.51	.55‡	.30	Contributed	.24	−.63	.12	.02	No	.31	Relevant
	Number of times logging (objective) during t_0 and t_1	.24	.21	.14	.02	No	.67	−.43	.38‡	.15	Suppressor	.17	No
	Number of activities (objective) during t_0 and t_1	-1.4	.03	−.68‡	.46	Contributed	-1.4	−.86	−.71‡	.50	Contributed	.96	Relevant
Independent variable	Performance expectancy at t_0	-.32	.41	-.20	.04	No	-1.1	−.85	−.66‡	.43	Contributed	.47	Important
	Effort expectancy at t_0	.91	.81	.63‡	.39	Contributed	.02	−.51	.01	$.01\times10^{-2}$	No	.39	Important
	Social encouragement expectancy at t_0	-.39	.51	-.22	.05	No	-.26	−.58	-.14	.02	No	.07	No
	Facilitating condition expectancy at t_0	.76	.78	.56‡	.31	Contributed	.70	-.05	.51‡	.26	Suppressor	.57	Important

β = Standardized coefficient between variable and with its variate
r_s = Zero order correlation between variable and with its variate
r_p = Part correlation (‡ greater than |.30|)
$r_p{}^2$ = Squared part correlation between variable and with its variate
h^2 = sum squared part correlation across two CCA function (greater than .20 or 20 % is underlined)

In canonical Function 2-dependent variate, the high part-correlation (higher than .30) and the difference in the sign between zero order correlation and beta, *objective total number of times logging onto E-learning during t_0 to t_1* was suspected to be a suppressor. It would not be easy to interpret the effect of a suppressor variable on a contributing variable within the dependent variate *(objective total number of activities involving E-learning during t_0 to t_1)* if this contributing variable had a negative beta and canonical loading. To make it easier, the variable *objective total number of activities involving E-learning during t_0 to t_1* was inverted: inversion consisted of subtracting the variable from a constant being the maximum of the variable. The resulting inverted variable can be said to measure total number of non E-learning activities involving. Moreover, the suppressor effect was also found in the Function 2-independent variate, to be easier for interpreting the effect of suppressor, the variable *performance expectancy* was inverted: inversion consisted of subtracting the variable from a constant 10 (the highest number). A final canonical analysis was carried out using the inverted variable (see Table 4).

Table 4: Final canonical solution for canonical Function 1 & 2 of the relationship between the four UTAUT variables at t_0 and the five measurements of actual E-learning uptake at t_1

	Variable	Function 1					Function 2					Overall	
		β	r_s	r_p	r_p^2 (%)	*Summary*	β	r_s	r_p	r_p^2 (%)	*Summary*	h^2(%)	Summary
Dependent variable	Percentage (subjective) during t_0 and t_1	.66	.69	.51†	.26	Contributed	-.25	−.61	-.19	.04	No	.30	Relevant
	Time spent (subjective) during t_0 and t_1	-.03	.27	-.03	$.09 \times 10^{-2}$	No	-.16	−.40	-.15	.02	No	.02	No
	Time spent (objective) during t_0 and t_1	1.1	.51	.55†	.30	Contributed	.24	−.63	.12	.02	No	.31	Relevant
	Number of times logging on (objective) during t_0 and t_1	.24	.21	.14	.02	No	.67	−.43	.38†	.15	Suppressor	.17	No
	Inverted number of activities (objective) during t_0 and t_1	1.4	-.03	.68†	.46	Suppressor	1.4	.86	.71†	.50	Contributed	.96	Relevant
Independent variable	Inverted performance expectancy at t_0	-.32	.41	-.20	.04	No	1.1	.85	.66†	.43	Contributed	.47	Important
	Effort expectancy at t_0	.91	.81	.63†	.39	Contributed	.02	−.51	.01	$.01 \times 10^{-2}$	No	.39	Important
	Social encouragement expectancy at t_0	-.39	.51	-.22	.05	No	-.26	−.58	-.14	.02	No	.07	No
	Facilitating condition expectancy at t_0	.76	.78	.56†	.31	Contributed	.70	-.05	.51†	.26	Suppressor	.57	Important

β = Standardized coefficient between variable and with its variate
r_s = Zero order correlation between variable and with its variate (* correlation is significant at the 0.05 level, ** correlation is significant at the 0.01 level)
r_p = Part correlation († greater than |.30|)
r_p^2 = Squared part correlation between variable and with its variate
h^2 = sum squared part correlation across two CCA function (greater than .20 or 20 % is underlined)

Dependent variate Function 1

There were two dependent variables which contributed to the Function 1-dependent variate ($|r_p| > .3$): (a) *subjective percentage of E-learning usage in education during t_0 to t_1* (r_p = .51); (b) *objective time spent on E-learning during t_0 to t_1* (r_p = .55) and *inverted objective total number of activities involving E-learning during t_0 to t_1* (r_p = .68). A sizable increase in the beta weight from the zero order correlation of *objective time spent on E-learning during t_0 to t_1* (from r_s =.51 to *beta* = 1.1) and *inverted objective total number of activities involving E-learning during time* t_0 *to* t_1 (from r_s = -.03 to *beta* = 1.4) indicated the occurrence of suppression in Function 1-dependent variate (Tzelgov and Henik, 1991). The suspected suppressor variable was *inverted objective total number of activities involving E-learning during* t_0 *to* t_1 because of the difference in the sign between its zero order correlation (negative) and beta (positive).

To investigate whether *inverted objective total number of activities involving E-learning during time* t_0 *to* t_1 was a suppressor variable, multiple regression analysis was carried out: (i) dependent variate regressed with all dependent variables except *inverted objective total number of activities involving E-learning during* t_0 *to* t_1; (ii) dependent variate regressed with all dependent variables *inverted objective total number of activities involving E-learning during* t_0 *to* t_1 (Paulhus et al., 2004) (see Table 5).

Table 5: Multiple regression result of the relationship between Funtion1-dependent variate and dependent variables before and after adding inverted objective total number of activities involving E-learning during t_0 to t_1

Variable	**(i) Before adding beta**	**(ii) After adding beta**	**Sizable change in beta**
Percentage (subjective) during t_0 and t_1	.57	.66	.09
Time spent (subjective) during t_0 and t_1	-.01	-.03	-.02
Time spent (objective) during t_0 and t_1	.43	1.1	.67
Number of times logging on (objective) during t_0 and t_1	.43	.24	-.19
Inverted number of activities (objective) during t_0 and t_1	-	1.4	-
	R^2 = .53	R^2= 1	R^2_{chnage} = .47

When the *inverted objective total number of activities involving E-learning during* t_0 *to* t_1 was added to the equation: (a) this variable was a contributing variable (*beta* = 1.4) even though its zero order correlation was very small (r_s = -.03); (b) it increased *objective time spent on E-learning during* t_0 *to* t_1 beta from *beta* = .43 to *beta* = 1.1 (c) it helped in the improvement of the prediction (boosted to 47% of R-square). Thus, the *inverted objective total number of activities involving E-learning during* t_0 *to* t_1 was a suppressor variable for *objective total time spent using E-learning during* t_0 *to* t_1.

Having noticed the appearance of a suppressor, we further examined what was taking place by dividing *inverted total number of activities involving E-learning* data into two groups: low (less than mean) and high (equal to or greater than mean). Multiple regression analysis then conducted: regressing the dependent variate with *objective time spent on E-learning during* t_0 *to* t_1 and *percentage of E-learning usage in education during* t_0 *to* t_1 (two contributed variables) in low and high *inverted total number of activities involving E-learning* group (Thompson and Levine, 1997) (see Table 6).

Table 6: Multiple regression analysis result between Funtion1-dependent variate and two contributing dependent variables (percentage of E-learning usage in education during t_0 to t_1, objective time spent on E-learning during t_0 to t_1) in low and high inverted total number of activities involving E-learning during t_0 to $t_1$groups of participants

Variable	**Low inverted number of activities group**		**High inverted number of activities group**		**Sizable change in beta**
	beta	**Sig.**	**beta**	**Sig.**	
Percentage (subjective) during t_0 and t_1	.51	< .001	.72	< .001	.21
Time spent (objective) during t_0 and t_1	.64	< .001	.04	.69	.60
	R^2 = .87		R^2= .56		R^2_{chnage} = .31

The result indicated that *subjective percentage of E-learning usage in education during* t_0 *to* t_1 plays an important measurement in both high and low *inverted objective total number of activities involving E-learning during* t_0 *to* t_1 group because the beta weight of this variable was significant in both groups: in lower group (*beta* = .51, $p <$ .001), in higher group (*beta* = .72, $p <$ .001). The R-square in low *inverted objective total number of activities involving E-learning during* t_0 *to* t_1 (.87) was higher than the higher group (.56). A decrease in the amount of R-square was because *objective total time spent using E-learning during* t_0 *to* t_1's beta weight in the higher group (*beta* = .04, *p* = .69) was dropped from the lower group (*beta* = .64, $p <$ .001).It implied that *objective total time spent using E-learning during* t_0 *to* t_1 was not an important relevant outcome of UTAUT model variables with Function 1 in the low number of activity group (high inverse),whereas it was an important measurement when students had high number of activity (low inverse).

Independent variate Function 1

There were two dependent variables which contributed to the Function 1: *effort expectancy at* t_0 (r_p = .63) and *facilitating condition expectancy at* t_0 (r_p = .56). Since the canonical loading (r_s) for these two contributing dependent variables had a same sign, these two dependent variables positively related to one another

Summary of CCA Function 1

In Function 1, there was a positive relationship between the dependent and the independent variates because the canonical correlation coefficient between the dependent and the independent variates (.52) was positive. The two contributing independent variables are *effort expectancy at* t_0 and *facilitating condition expectancy at* t_0, while contributing dependent were *subjective percentage of E-learning usage in education during* t_0 *to* t_1, *objective time spent on E-learning during* t_0 *to* t_1 and *inverted objective total number of activities involving E-learning during* t_0 *to* t_1. The *inverted objective total number of activities involving E-learning during time* t_0 *to* t_1 was a suppressor variable for the *objective total time spent using E-learning during* t_0 *to* t_1 (see Figure 1).

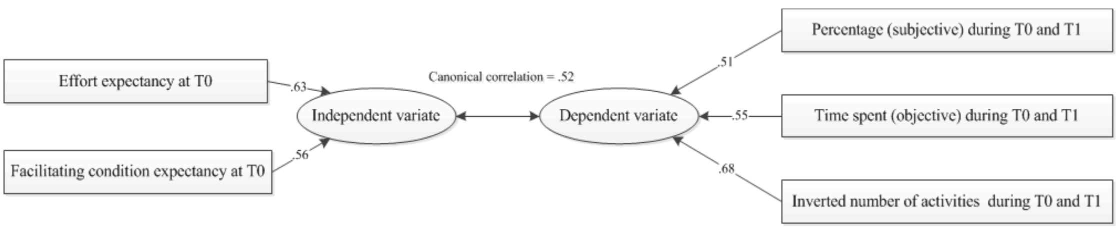


Figure 1: Summary of canonical correlation analysis Function 1 of the analysis of the relationship between the four UTAUT model variables at t_0 and the five measurements of actual E-learning uptake at t_1

Dependent variate Function 2

There were two dependent variables which contributed to the Function 2 dependent variate: *inverted objective total number of activities involving E-learning during* t_0 *to* t_1 (r_p =.71) and *objective total number of times logging onto E-learning during* t_0 *to* t_1 (r_p = .38). A sizable increase in the beta weight from the zero order correlation of these two contributing dependent variables indicated the occurrence of suppression in the Function 2-dependent variate (Tzelgov and Henik, 1991). The difference in the sign between its zero order correlation and beta led us to suspect that *objective total number of times logging onto E-learning during* t_0 *to* t_1 a suppressor variable (Thompson and Levine, 1997).

To investigate whether *objective total number of times logging onto E-learning during* t_0 *to* t_1 is a suppressor variable for the Function 2-dependent variate, multiple regression analysis was carried out: (a) dependent variate regressed with all dependent variables except *objective total number of times logging onto E-learning during* t_0 *to* t_1; (b) dependent variate regressed with all dependent variables included *objective total number of times logging onto E-learning during* t_0 *to* t_1 (Paulhus et al., 2004) (see Table 7).

Table 7: Multiple regression result of the relationship between Function 2 dependent variate and dependent variables before and after adding objective total number of times logging onto E-learning during t_0 to t_1

Variable	**Before adding**	**After adding**	**Sizable change in beta**
	beta	**beta**	
Percentage (subjective) during t_0 and t_1	-.32	-.25	.07
Time spent (subjective) during t_0 and t_1	-.13	-.16	-.03
Time spent (objective) during t_0 and t_1	.48	.24	-.24
Number of times logging on (objective) during t_0 and t_1	-	.67	-
Inverted number of activities (objective) during t_0 and t_1	1.05	1.4	.35
	R^2 = .85	R^2= 1	$R^2{}_{chnage}$ = .15

When *objective total number of times logging onto E-learning during* t_0 *to* t_1 was added to the equation: (a) this variable was a contributing variable (*beta* = .67) even though its zero order correlation was smallest; (b) it increased *inverted objective total number of activities involving E-learning during* t_0 *and* t_1's beta from *beta* = 1.05 to *beta* = 1.4 (c) it helped in the improvement of prediction (boosted to 15% of R-square). Thus, *objective total number of times logging onto E-learning during* t_0 *to* t_1 was a suppressor variable for *inverted objective total number of activities involving on E-learning during* t_0 *and* t_1.

Having noticed the appearance of a suppressor, we further examined what was taking place by dividing *objective total number of times logging onto E-learning during* t_0 *to* t_1 data into two groups: low (lower than mean) and high (higher than mean). Multiple regression analysis then conducted: regressing Function 2 dependent variate with *inverted objective total number of activities taking part on E-learning during* t_0 *and* t_1 in low and high *objective total number of times logging onto E-learning during* t_0 *to* t_1 (Thompson and Levine, 1997) (see Table 8).

Table 8: Multiple regression result of the relationship between Function 2 dependent variate and inverted objective total number of activities taking part on E-learning during t_0 and t_1 in low and high objective total number of times logging onto E-learning during t_0 to t_1 groups of participants

variable	Low time logging on group		High time logging on group		Sizable change in beta
	beta	Sig.	beta	Sig.	
Inverted number of activities (objective) during t_0 and t_1	.90	< .001	.93	< .001	.03
	R^2 = .81		R^2= .87		R^2_{chnage} = .06

The result indicated that *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 played an important measurement in both high and low *objective total number of times logging onto E-learning during* t_0 *to* t_1 group because the beta weight of this variable was significant in both groups: in lower group (*beta* = .90, *p* < .001), in higher group (*beta* = .93, *p* < .001). The R-square in high *objective total number of times logging onto E-learning during* t_0 *to* t_1 group (.87) was higher than the lower group (.81). It implied that *inverted objective total number of activities involving E-learning during* t_0 *and* t_1 has the stronger relationship with UTAUT factors if students have high number of time logging onto E-learning.

Independent variate Function 2

There were two dependent variables contributing to the Function 2: *inverted performance expectancy at* t_0 (r_p =.66) and *facilitating condition expectancy at* t_0 (r_p = .51). A sizable increase in the beta weight from the zero order correlation of these two contributing dependent variables indicated the occurrence of suppression in the Function 2 dependent variate (Tzelgov and Henik, 1991). According to the difference in the sign between its zero order correlation and beta, *facilitating condition expectancy at* t_0 was a suspected suppressor variable (Thompson and Levine, 1997).

To investigate whether *facilitating condition expectancy at* t_0 was a suppressor variable for the Function 2 independent variate, multiple regression analysis was carried out: (a) dependent variate regressed with all dependent variables apart from the *facilitating condition expectancy at* t_0; (b) dependent variate regressed with all dependent variables including *facilitating condition expectancy at* t_0 (Paulhus et al., 2004) (see Table 9).

Table 9: Multiple regression result of the relationship between Function 2-independent variate and independent variables before and after adding facilitating condition expectancy at t_0

Variable	Before adding	After adding	Sizable change in beta
	beta	beta	
Inverted performance expectancy at t_0	1.0	1.1	.10
Effort expectancy at t_0	.06	.02	-.04
Social encouragement expectancy at t_0	.13	-.26	-.39
Facilitating condition expectancy at t_0	-	.70	-
	R^2 = .75	R^2= 1	$R^2{}_{chnage}$ = .25

When the *facilitating condition expectancy at* t_0 was added to the equation: (a) this variable was a contributing variable (*beta* = .70) even though its zero order correlation was very small (r_s = -.05); and (b) it helped in the improvement of the prediction (boosted to 25% of R-square). The result confirmed that *facilitating condition expectancy at* $t_0$was a suppressor variable for the Function 2 independent variate.

Having noticed the appearance of a suppressor, we further examined what was taking place by dividing *facilitating condition expectancy at* t_0 data into two groups: low (lower than mean) and high (higher than mean). Multiple regression analysis was then conducted, regressing Function 2 independent variate with *inverted performance expectancy at* t_0 in low and high *facilitating condition expectancy at* t_0 (Thompson and Levine, 1997) (see Table 8).

Table 8: Multiple regression result of the relationship between Function 2-independent variate and inverted performance expectancy at t_0 in low and high facilitating condition expectancy at t_0 groups of participants

Variable	Low FCE group		High FCE group		Sizable change in beta
	beta	Sig.	beta	Sig.	
Inverted performance expectancy at t_0	.92	< .001	.95	< .001	.03
	R^2 = .84		R^2= .89		$R^2{}_{chnage}$ = .05

The result indicated that *inverted performance expectancy at* t_0 played an important measurement in both high and low *facilitating condition expectancy at* t_0 group because the beta weight of this variable was significant in both groups: in lower group (*beta* = .92, $p < .001$), in higher group (*beta* = .95, $p < .001$). The R-square in high *facilitating condition expectancy at* t_0 group (.89) was higher than the lower group (.84). It implied that *inverted performance expectancy at* t_0 has the stronger relationship with the measurements of E-learning actual uptake if students have high facilitating condition expectation.

Summary of CCA Function 2

There was a positive relationship between the dependent and the independent variates in Function 2 (R_c = .46). There were two dependent variables that contributed to the Function 2 dependent variate: *inverted objective total number of activities involving E-learning during t_0 to t_1*, and *objective total number of times of logging onto E-learning during t_0 to t_1*. The *objective total number of times logging onto E-learning during t_0 to t_1* was a suppressor variable for *inverted objective total number of activities involving E-learning during time t_0 to t_1*. There were two dependent variables that contributed to Function 2: *inverted performance expectancy at t_0* and *facilitating condition expectancy at t_0*. The *facilitating condition expectancy at t_0* was a suppressor variable for the Function 2-dependent variate (see Figure 2).

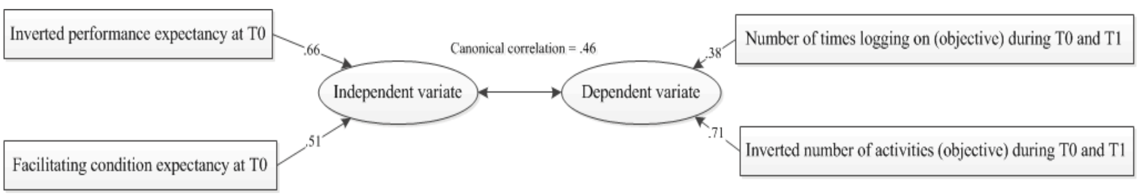


Figure 2: Summary of canonical correlation analysis Function 2 of the analysis of the relationship between the UTAUT variables at t_0 and the five measurements of E-learning actual uptake at t_1

Summary of CCA of the relationship between the two UTAUT variables at t_0 and the five measurements of actual E-learning uptake at t_1

Subjective total time spent learning with E-learning during t_0 to t_1 did not contribute to any canonical functions. Because of this, the sum square of part-correlation for this dependent variable across two functions was lower than the criterion (h^2 = .2): *subjective total time spent learning with E-learning during t_0 to t_1* was thus an irrelevant outcome in the UTAUT model's explanation. Even though the *objective total number of times logging onto E-learning during t_0 to t_1* itself acted as a suppressor in canonical Function 2, with very small contributing (${r_p}^2$ = .02) to Function 1, this outcome was not relevant to the UTAUT factors. There were three E-learning uptake outcomes that related to the set of UTAUT factors: (a) *inverted objective total number of activities involving E-learning during t_0 to t_1* (h^2 = .96);(b) *objective total time spent using E-learning during t_0 to t_1* (h^2 = .31); and (c) *subjective percentage of E-learning* *usage in education during* t_0 *to* t_1 (h^2 = .30). In the independent variable set, *social encouragement expectancy at* t_0 was the only predictor that did not contribute to any functions. Accordingly, this variable was not an important UTAUT factor affecting the uptake of E-learning. The results from canonical correlation analysis suggested that there were three variables (*performance expectancy at* t_0, *effort expectancy at* t_0 and *facilitating condition expectancy at* t_0) affecting the uptake of E-learning (h^2 > .20). All three factors significantly related to the *inverted objective total number of activities taking part in E-learning during* t_0 *to* t_1. *Effort expectancy at* t_0 and *facilitating condition expectancy at* t_0 were also significantly related to the *subjective percentage of E-learning usage in education during* t_0 *to* t_1*and objective total time spent using E-learning during* t_0 *to* t_1, while *performance expectancy at* t_0 and *facilitating condition expectancy at* t_0 showed up as significant predictors of *objective total number of times logging onto E-learning during time* t_0 *to* t_1 (see Figure 3).

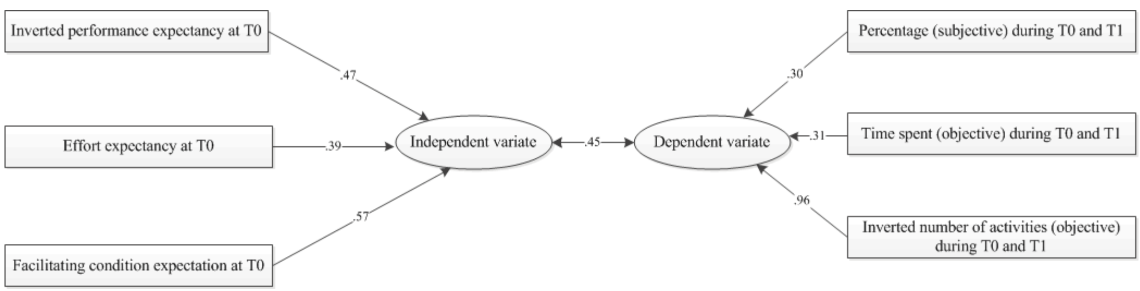


Figure 3: Summary of canonical correlation analysis of the relationship between the between the four UTAUT variable at t_0 and the five measurements of E-learning actual uptake at t_1

Appendix 7-J: Correlation matrix of the five measurements of actual continued use of E-learning at t_2

	Percentage	**Time (subjective)**	**Time (objective)**	**Logging on (objective)**	**Number of activity (objective)**
Percentage (subjective) during t_1 and t_2	1	.72**	.58**	.45**	.49**
Time spent (subjective) during t_1 and t_2	.72**	1	.44**	.37**	.37**
Time spent (objective) during t_1 and t_2	.58**	.44**	1	.89**	.93**
Number of times logging on (objective) during t_1 and t_2	.45**	.37**	.89**	1	.87**
Number of activities (objective) during t_1 and t_2	.45**	.37**	.93**	.87**	1

**. Correlation was significant at the 0.01 level (2-tailed).

Appendix 7-K: Stepwise regression analysis between the EC sub-model prediction of continued use of E-learning at t_1 and the five measurements of actual continued use of E-learning at t_2

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	number of activities (objective) at t_2, time spent (subjective) at t_2, percentage (subjective) at t_2, number of times logging on (objective) at t_2, time spent (objective) at t_2	-	Enter
2	-	number of activities (objective) at t_2	Backward (criterion: Probability of F-to-remove >= .100).
3	-	percentage (subjective) at t_2	Backward (criterion: Probability of F-to-remove >= .100).

a. Dependent Variable: EC sub-model prediction of continued use of E-learning at t_1

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.51[a]	.26	.21	8. 9
2	.51[b]	.26	.21	8.8
3	.49[c]	.24	.21	8.9

a. Predictors: (Constant), number of activities (objective) at t_2, time spent (subjective) at t_2, percentage (subjective) at t_2, number of times logging on (objective) at t_2, time spent (objective) at t_2
b. Predictors: (Constant), time spent (subjective) at t_2, percentage (subjective) at t_2, number of times logging on (objective) at t_2, time spent (objective) at t_2

c. Predictors: (Constant), time spent (subjective) at t_2, number of times logging on (objective) at t_2, time spent (objective) at t_2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1927.5	5	385.5	4.9	.001[b]
	Residual	5510.9	70	78.7		
	Total	7438. 2	75			
2	Regression	1904.9	4	476.2	6.1	<.001[c]
	Residual	5533.3	71	77.9		
	Total	7438. 2	75			
3	Regression	1774.9	3	591.6	7.5	<.001[d]
	Residual	5663.3	72	78. 7		
	Total	7438. 2	75			

a. Dependent Variable: EC sub-model prediction of continued use of E-learning at t_1
a. Predictors: (Constant), number of activities (objective) at t_2, time spent (subjective) at t_2, percentage (subjective) at t_2, number of times logging on (objective) at t_2, time spent (objective) at t_2

b. Predictors: (Constant), time spent (subjective) at t_2, percentage (subjective) at t_2, number of times logging on (objective) at t_2, time spent (objective) at t_2

c. Predictors: (Constant), time spent (subjective) at t_2, number of times logging on (objective) at t_2, time spent (objective) at t_2

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	49.1	6.5		7.6	.000		
	percentage (subjective) at t_2	.11	.09	.21	1.2	.22	.38	2.6
	time spent (subjective) at t_2	4.7	3.5	.20	1.3	.19	.47	2.1
	time spent (objective) at t_2	4.8	3.0	.55	1.6	.12	.09	11.3
	number of times logging on (objective) at t_2	-10.6	8.3	-.30	-1.3	.21	.19	5.2
	number of activities (objective) at t_2	-2.3	4.3	-.16	-.54	.59	.12	8.3
2	(Constant)	48.9	6.44		7.6	.000		
	percentage (subjective) at t_2	.12	.09	.21	1.3	.20	.38	2.6
	time spent (subjective) at t_2	4.7	3.5	.20	1.4	.18	.47	2.1
	time spent (objective) at t_2	3.7	2.2	.42	1.7	.09	.17	5.9
	number of times logging on (objective) at t_2	-11.6	8.1	-.33	-1.4	.15	.20	5.0
3	(Constant)	45.6	5.9		7.7	.000		
	time spent (subjective) at t_2	7.6	2.7	.32	2.8	.006	.81	1.2
	time spent (objective) at t_2	4.8	2.0	.55	2.4	.02	.20	5.0
	number of times logging on (objective) at t_2	-13.9	7.9	-.39	-1.8	.08	.21	4.7

a. Dependent Variable: EC sub-model prediction of continued use of E-learning at t_1

Appendix 7-L: Statistical conditions and assumptions checking of the multiple regression analysis between the EC sub-model prediction of continued use of E-learning at t_1 and the four measurements of actual continued use of E-learning at t_2 (exclude *objective total number of activities involving E-learning during t_1 and t_2*)

The multiple regression required two conditions and five assumptions to be passed, as follows:

Condition 1**:** Dependent variable comprises continuous data

In this data analysis, the dependent variable was a *EC sub-model prediction of continued use of E-learning at t_1*. The model prediction data were continuous, ranging from 0 to 100. Thus, this condition was met.

Condition 2**:** At least two independent variables comprising continuous data

There were four independent variables in this regression model: (a) *subjective percentage of E-learning usage in education during t_1 and t_2*; (b) *subjective time spent learning with E-learning during t_1 and t_0*; (c) *objective time spent on E-learning during t_1 and t_2*; (d) *objective total number of times logging onto E-learning during t_1 and t_2*. As the data from all four independent variables were continuous, the second condition was met.

Assumption 1**:** Sampling distribution of the sample mean for each variable is normal

- *The EC sub-model's prediction of continued use of E-learning at t_1*

A review of the Shapiro-Wilk test for normality (SW = .99, df = 77, p = .76) and skewness (-.17) and kurtosis (-.81) statistics suggested that the *EC sub-model's prediction of continued use of E-learning at t_1* data did not deviate significantly from normal (see Table 1).

Table 1: Normality test for EC sub-model's prediction of continued use of E-learning at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
EUCU continued use model's result at T1	77	65.6 ± 9.9	-.05	.27	-.17	no skewness	-.44	.54	-.81	no kurtosis	.99	77	.76	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *EC sub-model's prediction of continued use of E-learning at t_1* data suggested that the assumption of normality was reasonable (see Figure 1). The boxplot indicated no outliers in this data. As the *EC sub-model's prediction of continued use of E-learning at* t_1 data were distributed normally, the sampling distribution of the sample mean for this variable data was normal.

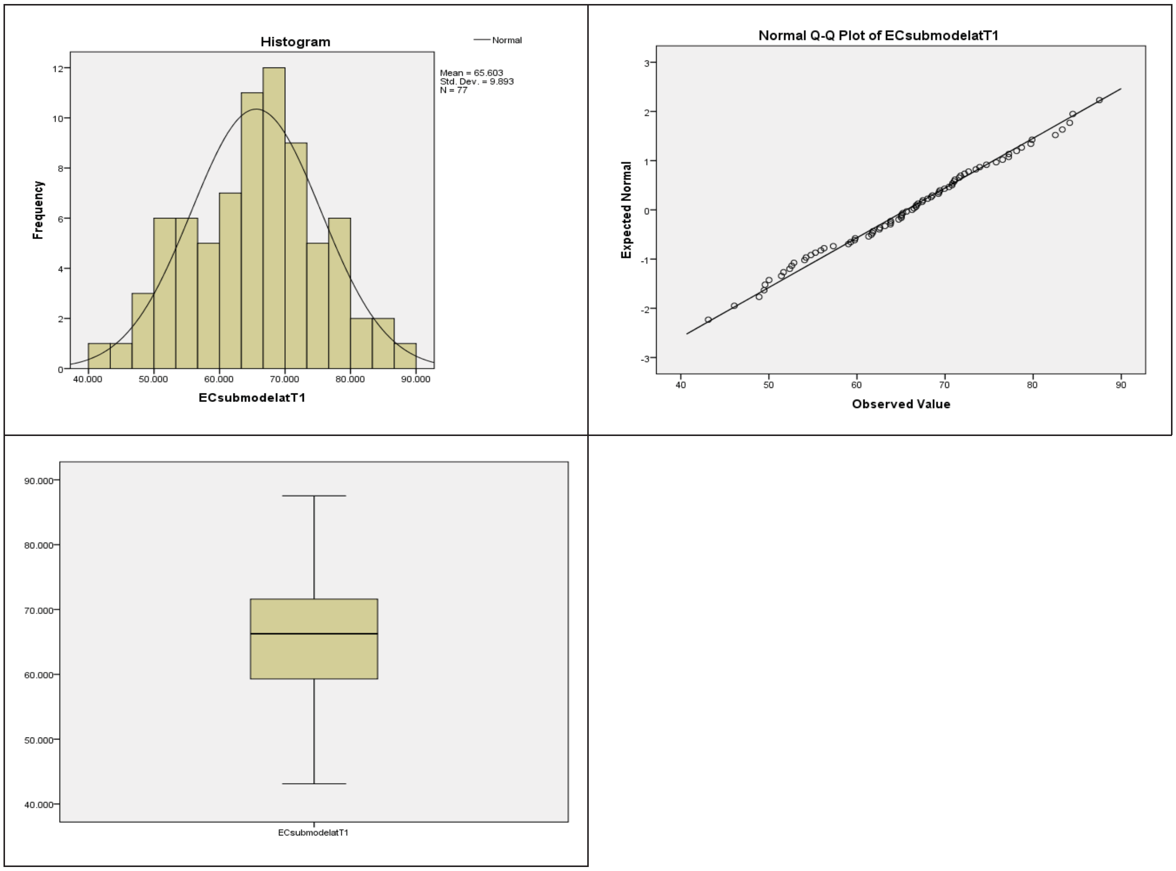


Figure 1: Histogram, Q-Q plot and boxplot for EC sub-model's prediction of continued use of E-learning at t_1 data

- *Subjective percentage of E-learning usage in Education at* t_2

A review of the Shapiro-Wilk test for normality (SW = .98, df = 77, p = .22) and skewness (.86) and kurtosis (-.50) statistics suggested that this measurement data did not deviate significantly from normal (see Table 2).

Table 2: Normality test for subjective percentage of E-learning usage in education at t_2 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\lvert Z\rvert \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\lvert Z\rvert \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Percentage of E-learning usage subjective at T1	77	35.9 ± 18.5	.24	.27	.86	no skewness	-.24	.54	-.50	no kurtosis	.98	77	.22	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *subjective percentage of E-learning usage in education* at t_2 data suggested the assumption of normality was reasonable (see Figure 2). The boxplot suggested there was an outlier (Case 43). As Case 45 was not an extreme outlier (Q_3 + 3×IQR), it was not considered as such in this research. The *subjective percentage of E-learning usage in education* at t_2 data were distributed normally, thus the sampling distribution of the sample mean for this variable was normal.

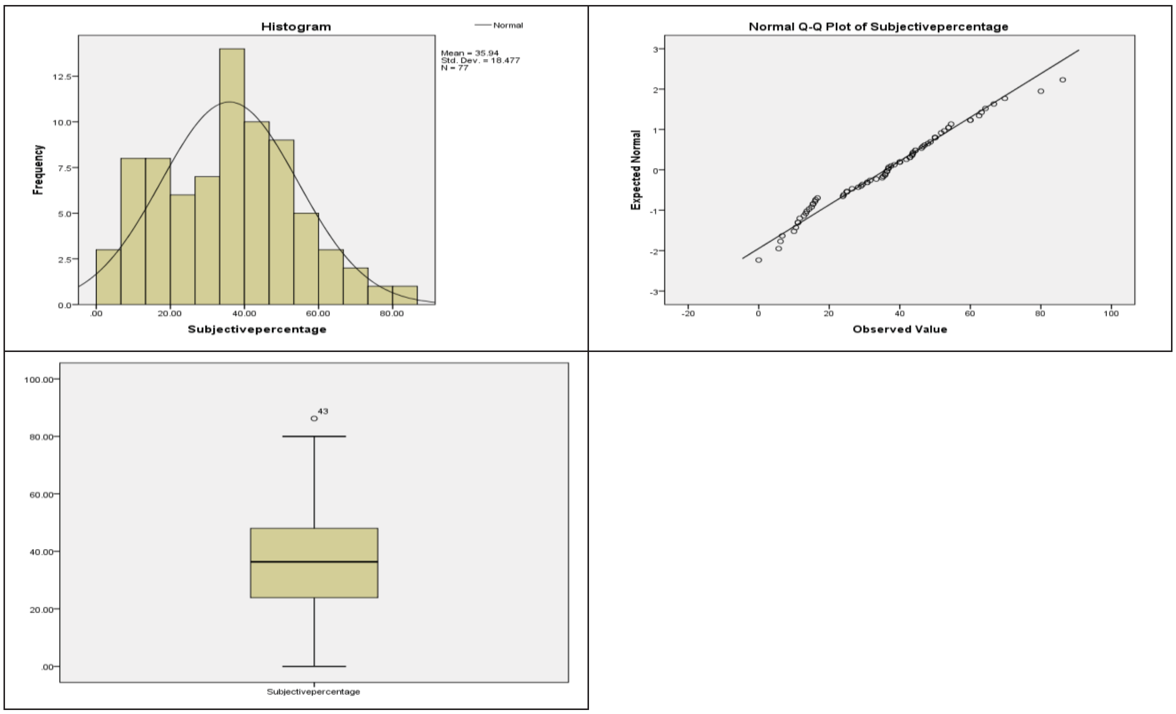


Figure 2: Histogram, Q-Q plot and boxplot for subjective percentage of E-learning usage in education at t_2 data

- *Subjective time spent learning with E-learning during at* t_2

The *subjective time spent learning with E-learning at* t_2 data deviated significantly from normal (SW = .82, df = 77, p < .001) (see Table 3).

Table 3: Normality test for subjective time spent learning with E-learning at t_2 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\lvert Z\rvert \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\lvert Z\rvert \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Time spent with E-learning subjective at T2	77	339.5 ± 327.8	1.5	.27	5.5	positive skewness	1.8	.54	3.5	positive kurtosis	.82	77	< .001	Not normal

To improve the normality, as the data had positive skewness (5.5) and kurtosis (3.5), $\text{Log}_{10}(X + 1)$ was used to transform the data. The result of normality test after transforming the data is shown in Table 4.

Table 4: Normality test for subjective time spent learning with E-learning subjective at t_2 data after transformation

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\lvert Z\rvert \le 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\lvert Z\rvert \le 2.56$)	Statistic	df	P-value	Conclusion ($p \le .01$)
Time spent with E-learning subjective at T2 (after transformation)	77	2.3 ± .50	-1.3	.27	-4.6	negative skewness	4.7	.54	8.7	positive kurtosis	.92	77	< .001	Not normal

The data still deviated significantly from normal (*SW* = .92, *df* = 77, *p* = < .001) after transformation. The boxplot, Q-Q plot and histogram suggested cutting an extreme outlier (Case 67) from the data to improve the normality (see Figure 3).

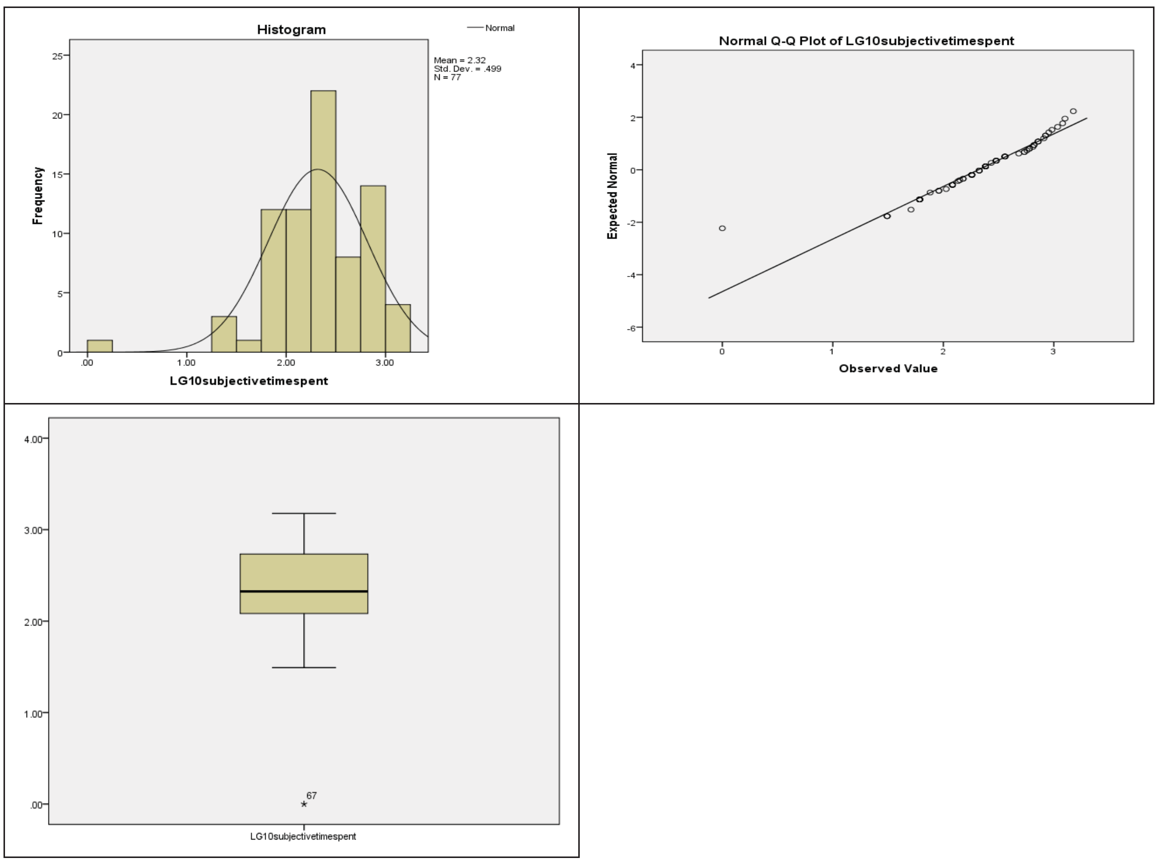


Figure 3: Histogram, Q-Q plot and boxplot for subjective time spent learning with E-learning at t_2 data after transformation

After setting Case 67 data as missing data, the Shapiro-Wilk test for normality suggested that this measurement data did not deviated significantly from normal (*SW* = .97, *df* = 76, *p* = .11) (see Table 5).

Table 5: Normality test for subjective time spent learning with E-learning at t_2 data after transformation and cutting extreme outliers

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Time spent with E-learning subjective at T2 (after transformation and cut extreme outlier)	76	2.4 ± .42	-.05	.28	.18	no skewness	-.77	.55	1.4	no kurtosis	.97	76	.11	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for this measurement data after transformation and cutting the extreme outlier suggested the assumption of normality was now reasonable (see Figure 4). The boxplot suggested there was no outlier. As the data of *subjective time spent learning with E-learning during at* t_2 after transformation and cutting the extreme outlier were distributed normally, the sampling distribution of the sample mean for this variable data was normal.

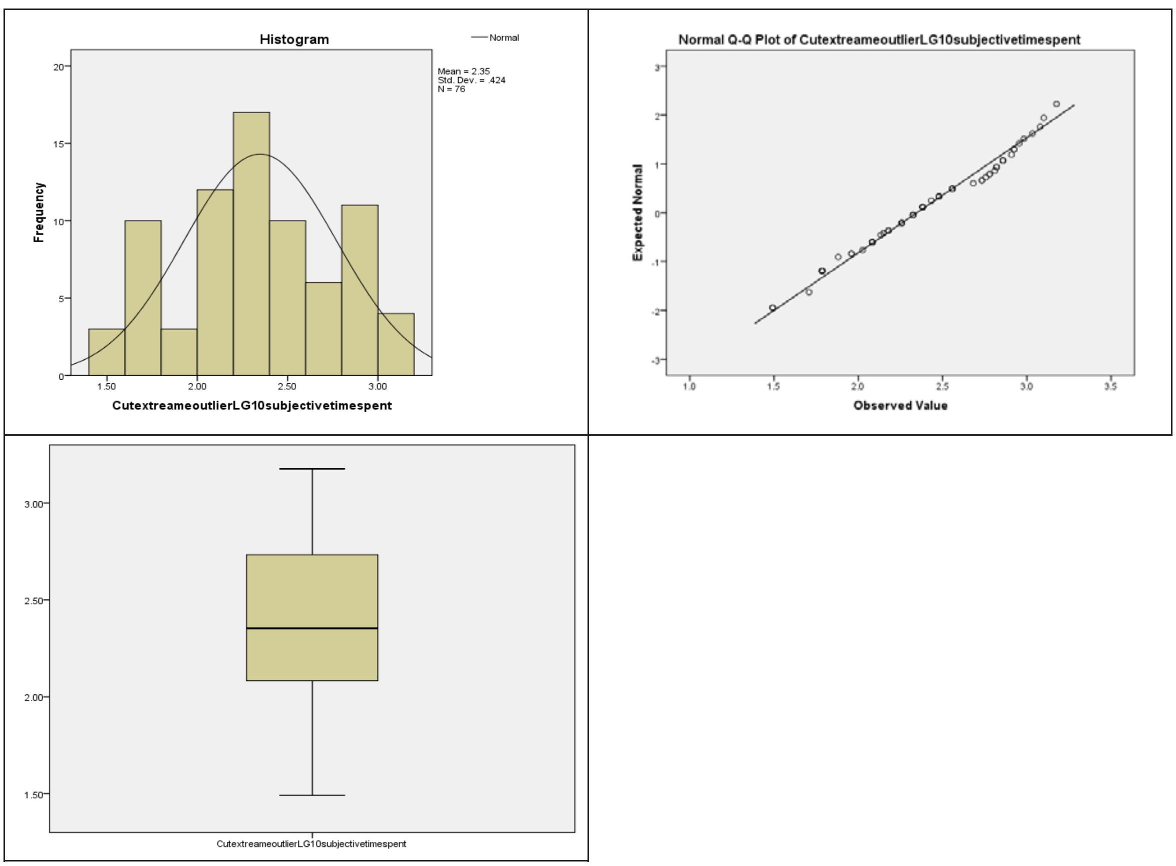


Figure 4: Histogram, Q-Q plot and boxplot for subjective time spent learning with E-learning at t_2 data after transformation and cutting the extreme outlier

- *Objective time spent on E-learning at t_2*

The objective total time spent on E-learning at t_2 data deviated significantly from normal (*SW* = .67, *df* = 77, *p* < .001) (see Table 6).

Table 6: Normality test for objective total time spent on E-learning at t_2 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\lvert Z\rvert \le 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\lvert Z\rvert \le 2.56$)	Statistic	df	P-value	Conclusion ($p \le .01$)
Time spent on E-learning objective at T2	77	200.8 ± 327.9	2.0	.27	7.5	positive skewness	3.6	.54	6.6	positive kurtosis	.67	77	< .001	Not normal

As the data had positive skewness (7.5) and kurtosis (6.6), $\text{Log}_{10}(X + 1)$ was used to transform the data in order to improve the normality of the data. The result of normality test after transforming the data is shown in Table 7.

Table 7: Normality test for objective total time spent on E-learning at t_2 data after transformation

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\lvert Z\rvert \le 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\lvert Z\rvert \le 2.56$)	Statistic	df	P-value	Conclusion ($p \le .01$)
Time spent on E-learning objective at T2 (after transformation)	77	1.4 ± 1.2	-.06	.27	-.20	no skewness	-1.6	.54	-3.0	negative kurtosis	.85	77	< .001	Not normal

The result suggested that the data after transformation data still deviated significantly from normal (*SW* = .85, *df* = 77, *p* < .001): negative kurtosis (3.0). Consistently, the histogram and Q-Q plot indicated that the assumption of normality was not reasonable (see Figure 5). The boxplot suggested there was no outlier. According to the central limit theorem, even though this measurement data did not distribute normally, its sampling distribution of the sample mean was normal: this was because the sample size of this study was higher than 30.

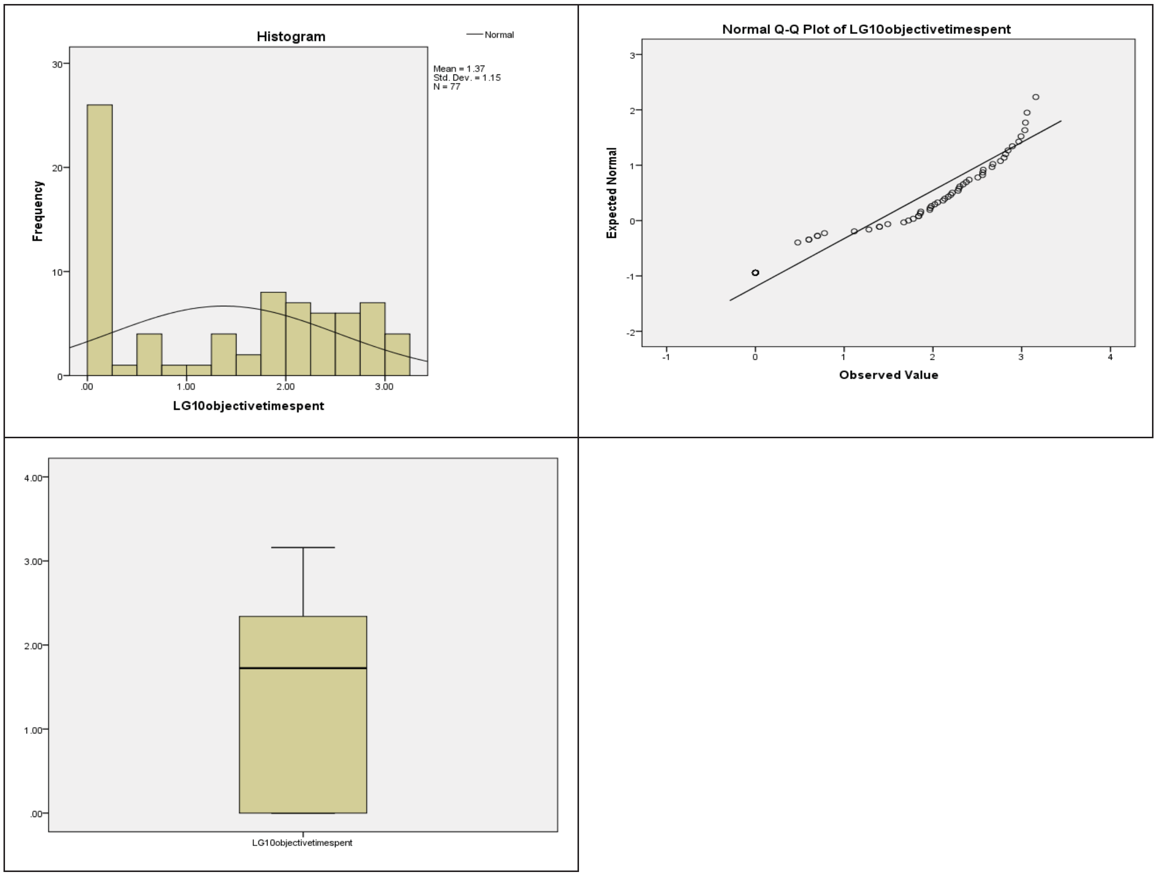


Figure 5: Histogram, Q-Q plot and boxplot for objective total time spent on E-learning during t_1 and t_2 after transformation

- *Objective total number of times logging onto E-learning at* t_2

The *objective total number of time logging onto E-learning at* t_2 data deviated significantly from normal (*SW* = .68, *df* = 77, *p* < .001) (see Table 8).

Table 8: Normality test for objective total number of times logging onto E-learning at t_2 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion (|Z| ≤ 2.56)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion (|Z| ≤ 2.56)	Statistic	df	P-value	Conclusion (p ≤ .01)
Number of time logging on objective at T2	77	1.6 ± 1.7	.89	.27	3.2	positive skewness	-.22	.54	-.41	no kurtosis	.85	77	< .001	Not normal

With the positive skewness (3.2), the data of this measure was then transformed with $\text{Log}_{10}(X+1)$ in order to improve the normality of the data (see Table 9).

Table 9: Normality test for objective total number of times logging onto E-learning at t_2 data after transformation

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Number of time logging on objective at T2 (after transformation)	77	.32 ± .28	.17	.27	.60	no skewness	-1.4	.54	-2.5	no kurtosis	.86	77	< .001	Not normal

After transformation, the data were still not normally distributed (*SW* = .86, *df* = 77, *p* < .001). The histogram and Q-Q plot indicated gaps between data (see Figure 6). That is why the results from the S-W test showed non-normality, even if there was neither skewness (.60) nor kurtosis (-2.5). The boxplot showed there was no outlier. Although the measurement data were not normal, the sampling distribution of the sample mean of this measurement was normal since the number of participants in this experiment was higher than 30.

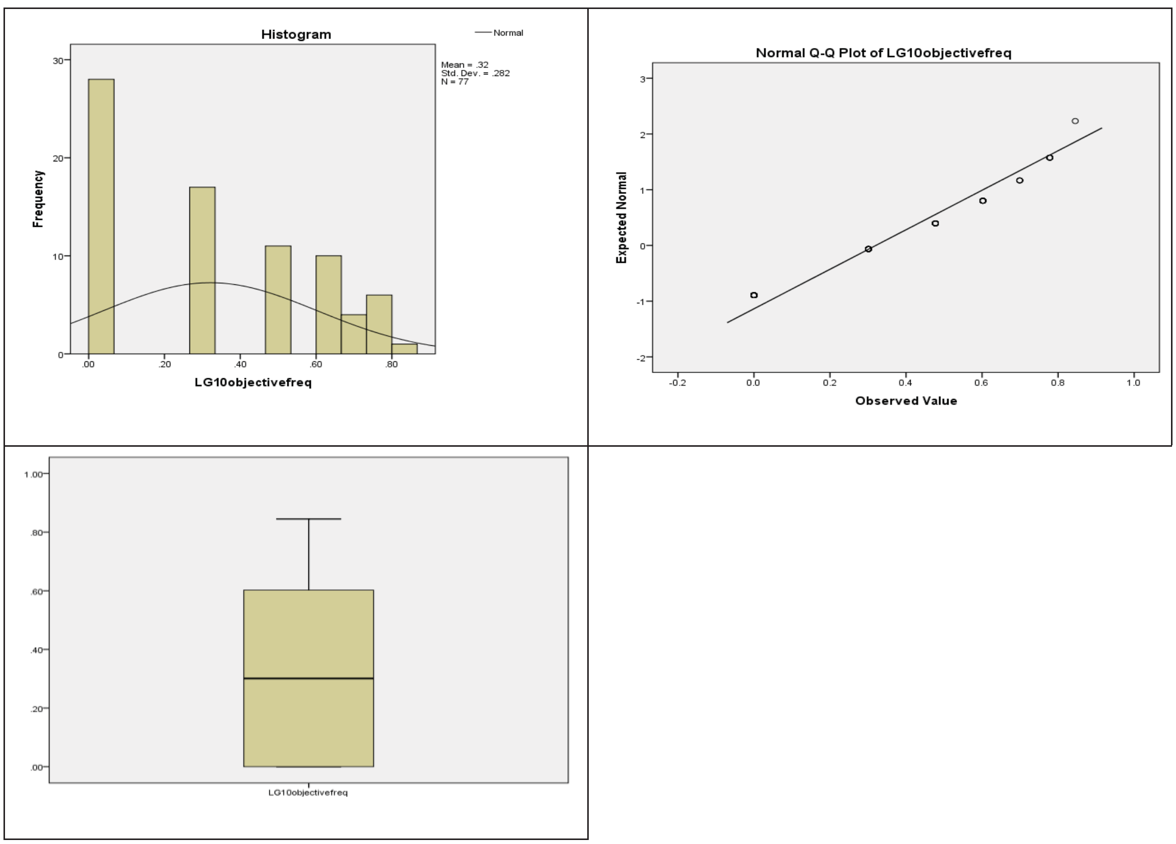


Figure 6: Histogram, Q-Q plot and boxplot for objective total number of times logging onto E-learning at t_2 data after transformation

Assumption 2 and 3: Linearity and Homoscedasticity

To check the linearity and homoscedasticity assumption, a scatterplot of the standardized residual and standardized predicted value was created (see Figure 7). The result suggested that the assumption of linearity and homoscedasticity for the regression models between EC sub-model prediction at t_1 and the four measurements of actual continued use of E-learning was not violated, since there was no systematic relationship between the standardized residual and standardized predicted value.

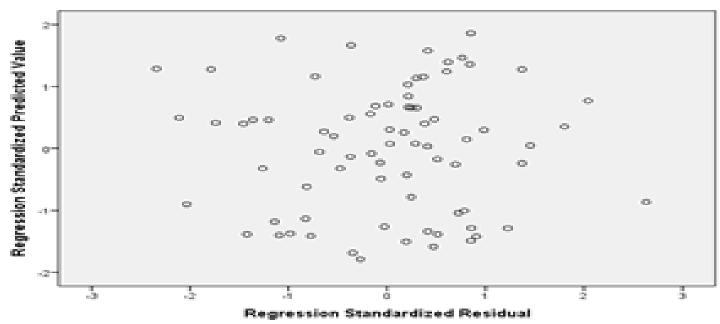


Figure 7: Scatterplot of residual and predicted value of the relationship between the EC sub-model prediction at t_1 and the four measurements of actual continued use of E-learning at t_2

Assumption 4: Independence of residual (error)

The Durbin-Watson test was used to evaluate the independence of residual. The result showed that the statistic for this data analysis was within the range of 1–2 (1.9), which was considered acceptable. This suggested that the assumption of independent errors has been met.

Assumption 5: Multicollinearity

To detect multicollinearity between four measurements of actual continued use of E-learning at t_2 (independent variables in each regression model), the VIF test was used. According to the general rule of thumb, as the VIF for each independent variable was lower than 10, multicollinearity was not a concern (see Table 10).

Table 10: Collinearity test for the four measurements of actual continued use of E-learning at t_2

Independent variable	VIF
Percentage (subjective) during t_1 and t_2	2.6
Time spent (subjective) during t_1 and t_2	2.1
Time spent (objective) during t_1 and t_2	5.9
Number of times logging on (objective) during t_1 and t_2	5.0

Appendix 7-M: Statistical conditions and assumptions checking of the multiple regression analysis between the TAM prediction of continued use of E-learning at t_1 and the four measurements of actual continued use of E-learning at t_2(exclude *objective total number of activities involving E-learning during t_1 and t_2*)

The multiple regression required two conditions and five assumptions to be passed, as follows:

<u>Condition 1</u>**:** Dependent variable is continuous data

In this data analysis, the dependent variable was *a TAM prediction of continued use of E-learning at t_1*. The model prediction data were continuous, ranging from 0 to 100. Thus, this condition was met.

<u>Condition 2</u>**:** At least two independent variables comprising continuous data

There were four independent variables in each regression model: (a) *subjective percentage of E-learning usage in education during t_1 and t_2*,(b) *subjective time spent learning with E-learning during t_1 and t_2*; (c) *objective total time spent on E-learning during t_1 and t_2*; and(d) *objective total number of activities involving E-learning during t_1 and t_2*. As the data from all four independent variables were continuous, the second condition was met.

<u>Assumption 1</u>**:** Sampling distribution of the sample mean for each variable is normal

- *The TAM's prediction of continued use of E-learning at t_1*

A review of the Shapiro-Wilk test for normality (SW = .98, df = 77, p = .20) and skewness (.51) and kurtosis (-.83) statistics suggested that the *TAM model's prediction of continued use of E-learning at t_1* data did not deviate significantly from normal (see Table 1).

Table 1: Normality test for TAM model's prediction of continued use of E-learning at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion (|Z| ≤ 2.56)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion (|Z| ≤ 2.56)	Statistic	df	P-value	Conclusion (p ≤ .01)
TAM model result at T1	77	66.6 ± 11.3	.14	.27	.51	no skewness	-.45	.54	-.83	no kurtosis	.98	77	.20	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *TAM model's prediction of continued use of E-learning at* t_1 data suggested the assumption of normality was reasonable (see Figure 1). Even though the boxplot indicated one outlier, this data (Case 75) was not cut: because the value of this data was not higher than Q_3 + 3×IQR. As the *TAM model's prediction of continued use of E-learning at* $t_1$data were distributed normally, the sampling distribution of the sample mean for this data was normal.

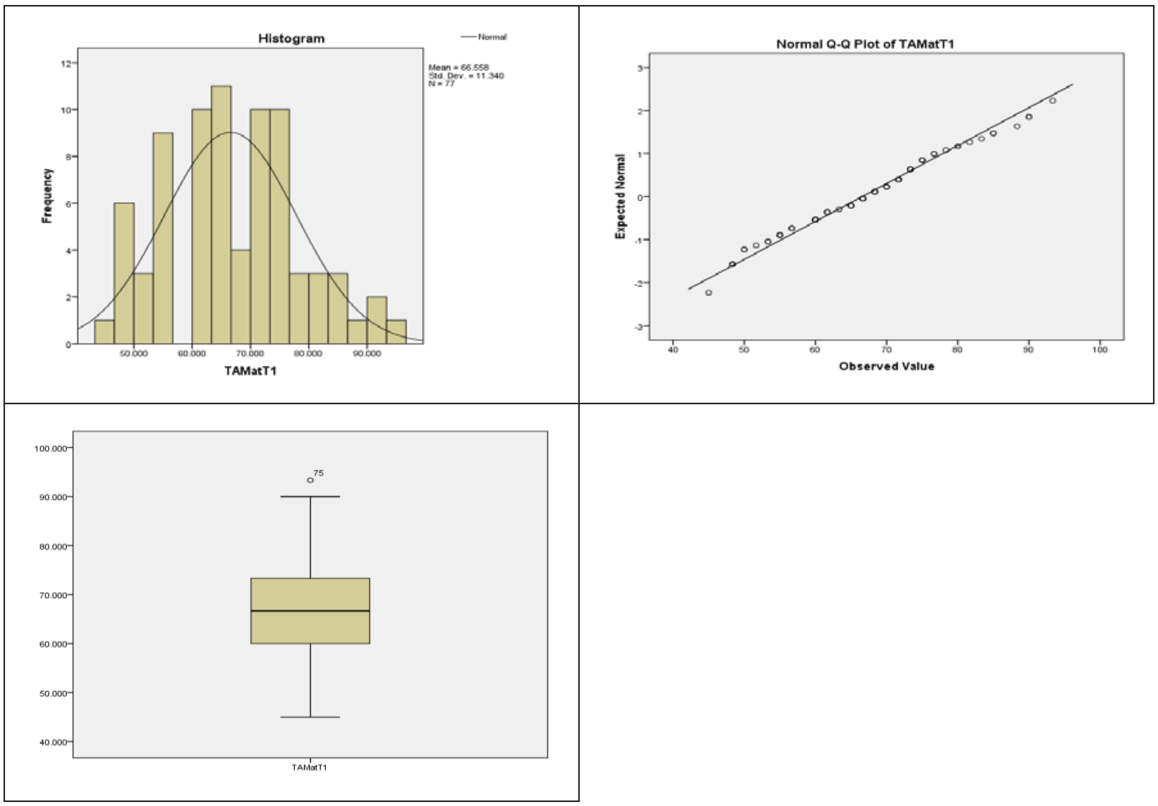


Figure 1: Histogram, Q-Q plot and boxplot for TAM model's prediction of continued use of E-learning at t_1 data

- *Independent variables*

The normality check and outlier detection for four independent variables (the four measurements of actual continued use of E-learning) were carried out previously and the results suggested that the normality assumption was not violated (see Appendix 7-L).

Assumption 2 and 3: Linearity and Homoscedasticity

To check the linearity and homoscedasticity assumption, a scatterplot of the standardized residual and standardized predicted value was created (see Figure 2). The result suggested that the assumption of linearity and homoscedasticity for the regression models between TAM model prediction at t_1 and the four measurements of actual continued use of E-learning was not violated, since there was no systematic relationship between the standardized residual and the standardized predicted value.

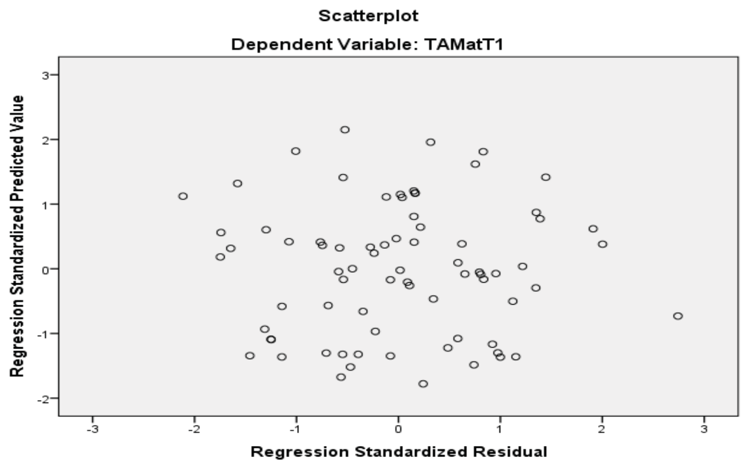


Figure 2: Scatterplot of residual and predicted value of the relationship between the TAM model prediction at t_1 and the four measurements of actual continued use of E-learning at t_2

Assumption 4: Independence of residual (error)

The Durbin-Watson test was used to evaluate the independence of residual. The result showed that the statistic for this data analysis was within the range of 1–2 (1.7), which was considered acceptable. This suggested that the assumption of independent errors was met.

Assumption 5: Multicollinearity

This assumption was checked previously (see Appendix 7-L) and the result suggested that the assumption was not violated.

Appendix 7-N: Statistical conditions and assumptions checking of the multiple regression analysis between the UTAUT prediction of continued use of E-learning at t_1 and the four measurements of actual continued use of E-learning at t_2 (exclude *objective total number of activities involving E-learning during t_1 and t_2*)

The multiple regression required two conditions and five assumptions to be passed:

Condition 1**:** Dependent variable is continuous data

In this data analysis, the dependent variable was a *UTAUT model prediction of continued use of E-learning at t_1*. The model prediction data were continuous, ranging from 0 to 100. Thus, this condition was met.

Condition 2**:** At least two independent variables and these comprise continuous data

There were four independent variables in each regression model: (a) *subjective percentage of E-learning usage in education during t_1 and t_2*,;(b) *subjective time spent learning with E-learning during t_1 and t_2*; (c) *objective time spent on E-learning during t_1 and t_2*; and (d) *objective total number of times logging on during t_1 and t_2*. As the data from all four independent variables were continuous, the second condition was met.

Assumption 1**:** Sampling distribution of the sample mean for each variable was normal

- *UTAUT's prediction of continued use of E-learning at t_1*

A review of the Shapiro-Wilk test for normality (*SW* = .98, *df* = 77, *p* = .44), and skewness (1.0) and kurtosis (-.45) statistics suggested that the *UTAUT model's prediction of continued use of E-learning at t_1* data did not deviate significantly from normal (see Table 1).

Table 1: Normality test for UTAUT model's prediction of continued use of E-learning at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\lvert Z \rvert \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\lvert Z \rvert \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
UTAUT model's result at T1	77	67.5 ± 11.4	.28	.27	1.0	no skewness	-.25	.54	-.45	no kurtosis	.98	77	.44	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *UTAUT model's prediction of continued use of E-learning at* t_1 data suggested the assumption of normality was reasonable (see Figure 1). The boxplot indicated one outlier (Case 45) in this data. However, that outlier was not cut since its value was not higher than Q_3 + 3×IQR. According to the central limit theorem, since the *UTAUT model's prediction of continued use of E-learning at* t_1 data were distributed normally, the sampling distribution of the sample mean for this data was normal.

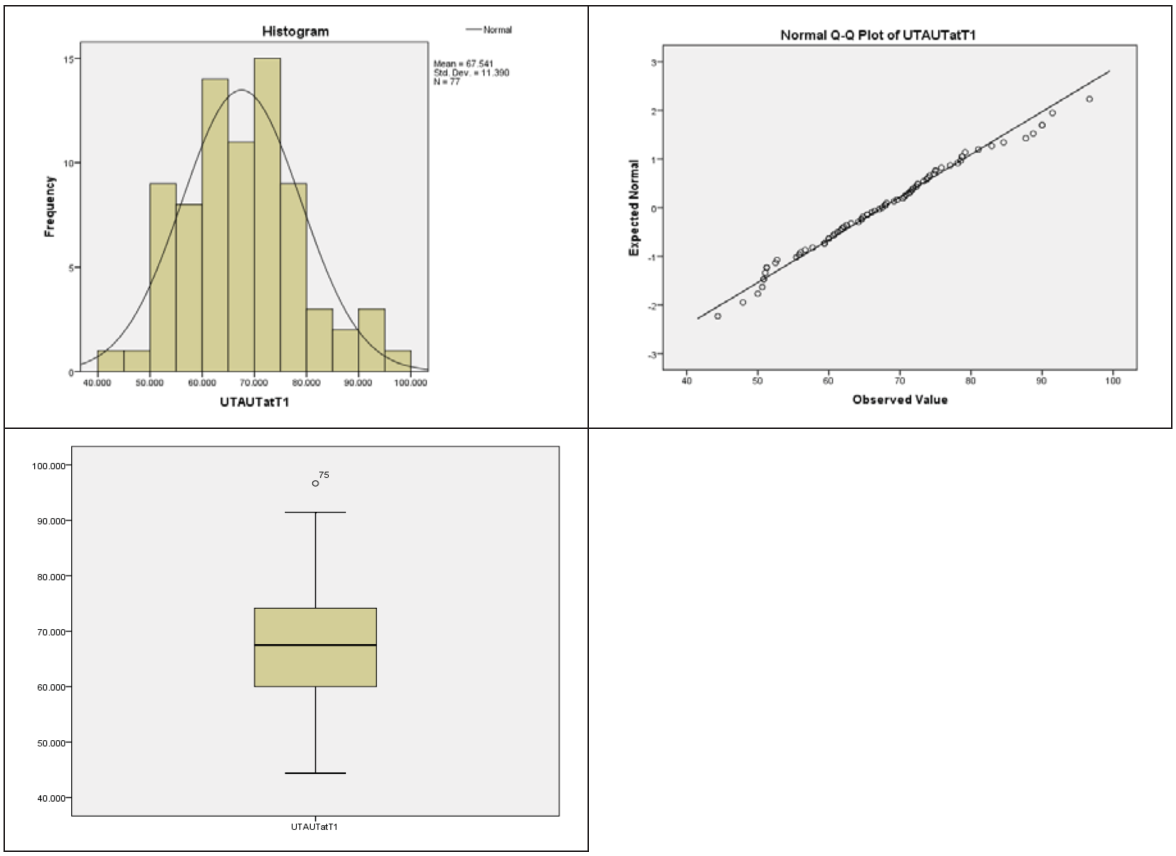


Figure 1: Histogram, Q-Q plot and boxplot for UTAUT model's prediction of continued use of E-learning at t_1 data

- *Independent variables*

The normality check and outlier detection for the four independent variables (the four measurements of actual continued use of E-learning) were carried out previously and the results suggested that the normality assumption was not violated (see Appendix 7-L).

Assumption 2 and 3: Linearity and Homoscedasticity

A scatterplot of the standardized residual and standardized predicted value was created to check the linearity and homoscedasticity assumption (see Figure 2). The result suggested that the assumption of linearity and homoscedasticity for the regression models between the UTAUT model prediction at t_1 and the four measurements of actual continued use of E-learning was not violated, since there was no systematic relationship between the standardized residual and standardized predicted value.

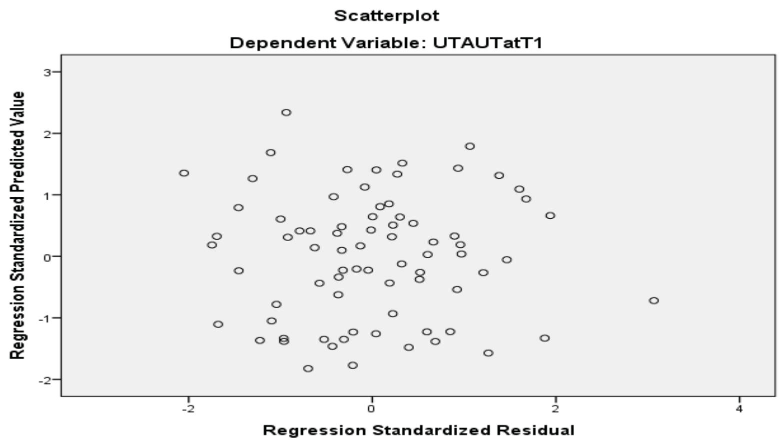


Figure 2: Scatterplot of residual and predicted value of the relationship between the UTAUT model prediction at t_1 and the four measurements of actual continued use of E-learning at t_2

Assumption 4: Independence of residual (error)

The Durbin-Watson test was used to evaluate the independence of residual. The result showed that the statistic for this data analysis was within the range of 1-2 (1.6), which was considered acceptable. This suggested that the assumption of independent errors has been met.

Assumption 5: Multicollinearity

This assumption was checked previously (see Appendix 7-L) and the result suggested that the assumption was not violated.

Appendix 7-O: Statistical conditions and assumptions checking of the multiple regression analysis between the ECM prediction of continued use of E-learning at t_1 and the four measurements of actual continued use of E-learning t_2 (exclude *objective total number of activities involving E-learning during t_1 and t_2*)

The multiple regression required two conditions and five assumptions to be passed, as follows:

<u>Condition 1</u>**:** Dependent variable is continuous data

In this data analysis, the dependent variable was a *ECM model's prediction of continued use of E-learning at t_1*. The model prediction data were continuous, ranging from 0 to 100. Thus, this condition was met.

<u>Condition 2</u>**:** At least two independent variables comprising continuous data

There were four independent variables in this regression model: (a) *subjective percentage of E-learning usage in education during t_1 and t_2*; (b) *subjective time spent learning with E-learning during t_1 and t_2*; (c) *objective time spent on E-learning during t_1 and t_2*; (d) *objective total number of times logging onto E-learning during t_1 and t_2*. As the data from all four independent variables were continuous, the second condition was met.

<u>Assumption 1</u>**:** Sampling distribution of the sample mean for each variable was normal

- *The ECM's prediction of continued use of E-learning at t_1*

A review of the Shapiro-Wilk test for normality (SW = .99, df = 77, p = .72) and skewness (-.37) and kurtosis (-.91) statistics suggested that the *ECM model prediction of continued use of E-learning at t_1* data did not deviate significantly from normal (see Table 1).

Table 1: Normality test for ECM model's prediction of continued use of E-learning at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\lvert Z\rvert \le 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\lvert Z\rvert \le 2.56$)	Statistic	df	P-value	Conclusion ($p \le .01$)
ECM model's result at T1	77	65.8 ± 11.2	-.10	.27	-.38	no skewness	-.49	.54	-.91	no kurtosis	.99	77	.72	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *ECM model prediction of continued use of E-learning at* t_1 data suggested the assumption of normality was reasonable (see Figure 1). The boxplot indicated no outliers in this data. The sampling distribution of the sample mean for the *ECM model prediction of continued use of E-learning at* t_1 data was normal because this data distributed normally.

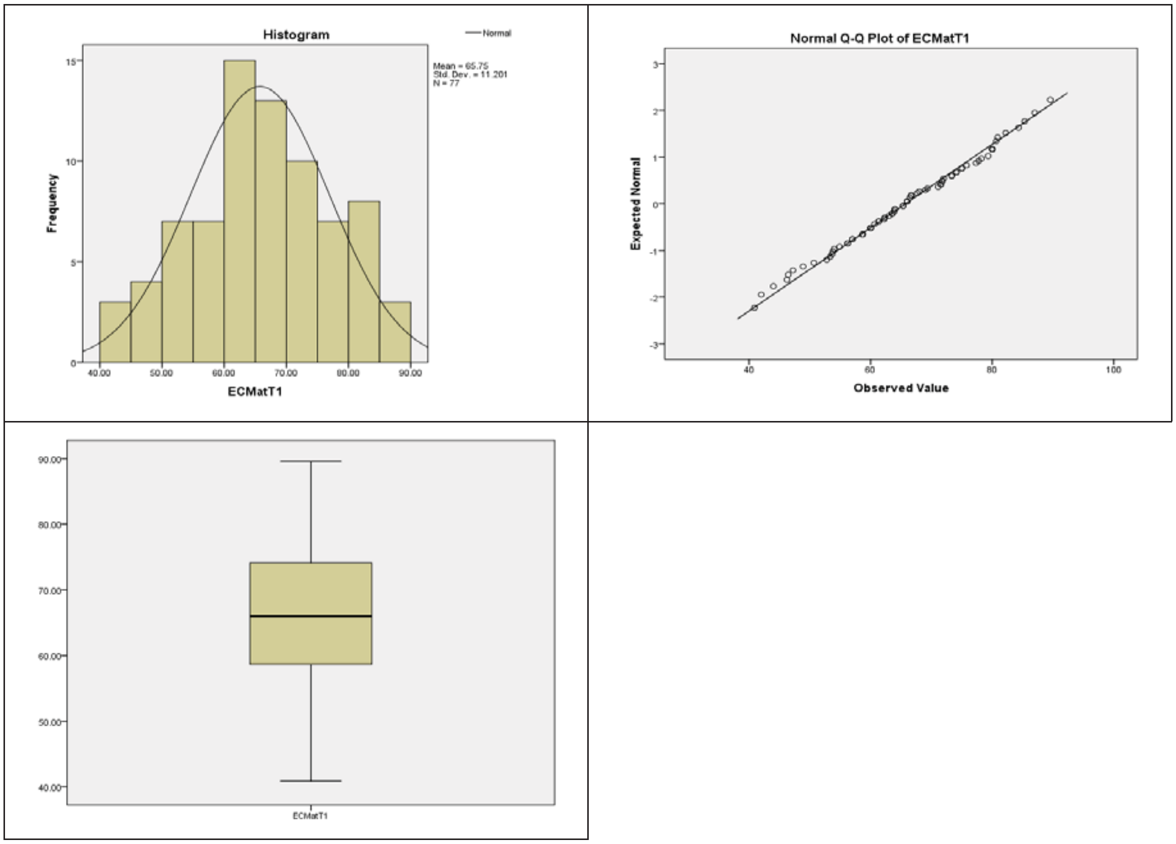


Figure 1: Histogram, Q-Q plot and boxplot for ECM model’s prediction of continued use of E-learning at t_1 data

- *Independent variables*

The normality check and outlier detection for four independent variables (the four measurements of actual continued use of E-learning) were carried out previously and the results suggested that the normality assumption was not violated (see Appendix 7-L).

Assumption 2 and 3: Linearity and Homoscedasticity

A scatterplot of the standardized residual and standardized predicted value was created to check the linearity and homoscedasticity assumption (see Figure 2). The result suggested that the assumption of linearity and homoscedasticity for the regression models between the ECM model prediction at t_1 and the four measurements of actual continued use of E-learning at t_2 was not violated, since there was no systematic relationship between the standardized residual and the standardized predicted value.

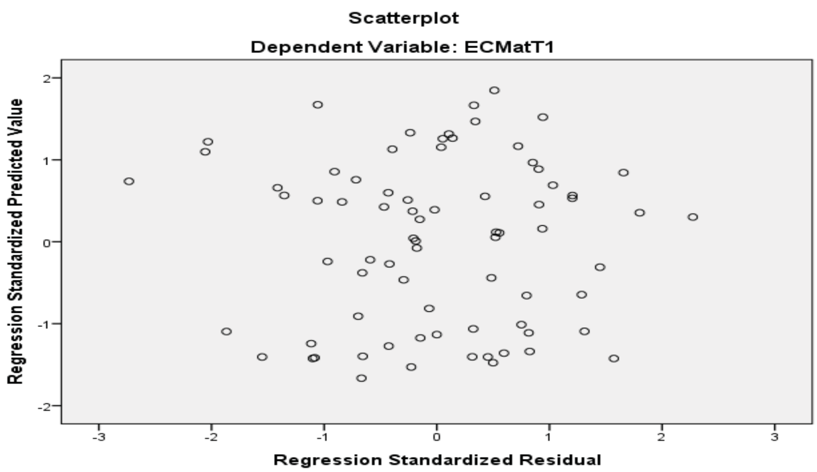


Figure 2: Scatterplot of residual and predicted value of the relationship between the ECM model prediction at t_1 and the four measurements of actual continued use of E-learning at t_2

Assumption 4: Independence of residual (error)

The Durbin-Watson test was used to evaluate the independence of residual. The result showed that the statistic for this data analysis was within the range of 1–2 (1.8), which was considered acceptable. This suggested that the assumption of independent errors was met.

Assumption 5: Multicollinearity

This assumption was checked previously (see Appendix 7-L) and the result suggested that the assumption was not violated.

Appendix 7-P: Statistical conditions and assumptions checking of the canonical correlation analysis between the five EC sub-model variables at t_1 and the four measurements of actual continued use of E-learning at t_2 (exclude *objective total number of activities involving E-learning during t_1 and t_2*)

Before running the canonical correlation analysis, the two required conditions and three required assumptions were checked, as follows.

Condition 1**:** At least two independent and two dependent variables

There were five independent variables in this data analysis: *calculated performance expectancy at t_1*; *calculated effort expectancy at t_1; calculated social encouragement expectancy at t_1*; *calculated facilitating condition expectancy at t_1*; and *calculated learning consistency expectancy at t_1*. The four dependent variables were: *subjective percentage of E-learning usage in education during time t_1 to t_2*; *subjective time spent learning with E-learning during time during time t_1 to t_2*; *objective time spent on E-learning during time during time t_1 to t_2*; and *objective total number of times logging onto E-learning during time during time t_1 to t_2*. This condition, therefore, was met.

Condition 2**:** Dependent and independent variables are continuous data

The independent variables (calculated new expectations at t_1) were continuous, ranging from 0 to 10. The four independent variables (measurements of actual continued use of E-learning at t_2) in were also continuous. This condition, therefore, was met.

Assumption 1**:** Sampling distribution of the sample mean for each variable is normal

- *Calculated performance expectancy at t_1*

A review of the Shapiro-Wilk test for normality (*SW* = .99, *df* = 77, *p* = .72) and skewness (-.37) and kurtosis (-.91) statistics suggested that the *calculated performance expectancy at t_1* data did not deviate significantly from normal (see Table 1).

Table 1: Normality test for calculated performance expectancy at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Calculated PE at T1	77	6.6 ± 1.1	-.10	.27	-.37	no skewness	-.49	.54	-.91	no kurtosis	.99	77	.72	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *calculated performance expectancy at* t_1 data suggested the assumption of normality was reasonable (see Figure 1). The boxplot indicated no outliers in this data. As the *calculated performance expectancy at* t_1 data were distributed normally, the sampling distribution of the sample mean for this variable was normal.

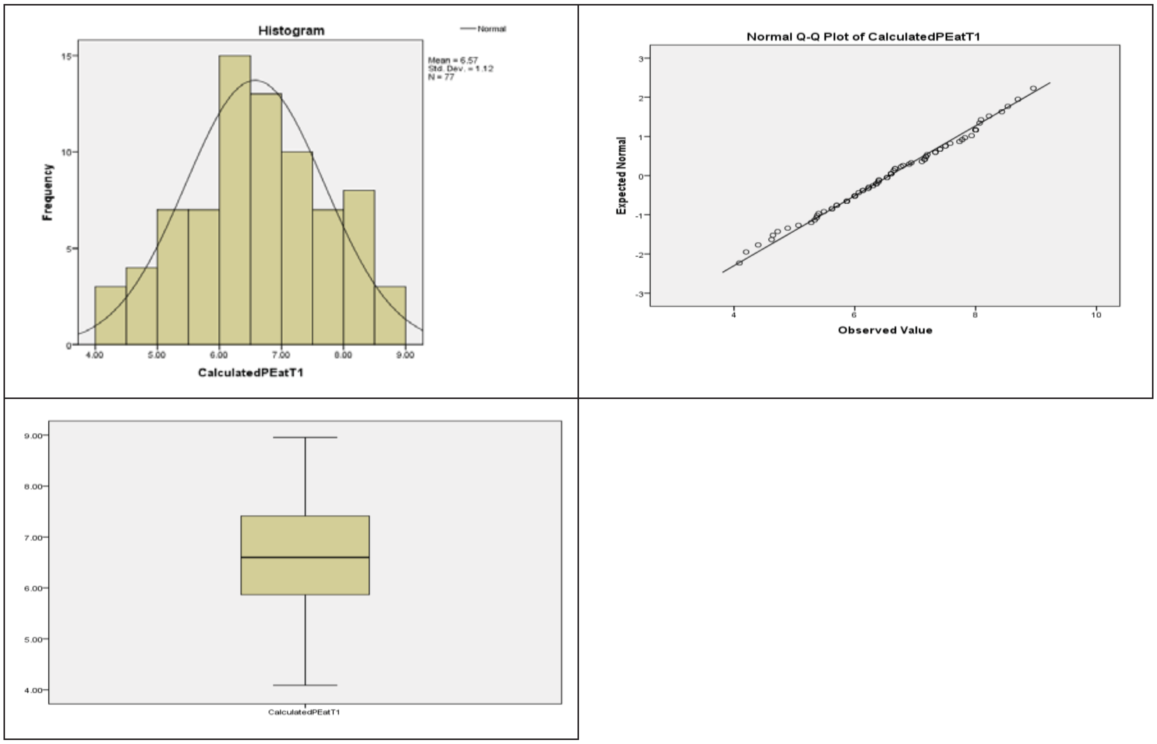


Figure 1: Histogram, Q-Q plot and boxplot for calculated performance expectancy at t_1 data

- *Calculated effort expectancy at* t_1

A review of the Shapiro-Wilk test for normality (SW = .99, df = 77, p = .79) and skewness (.78) and kurtosis (.02) statistics suggested that the *calculated effort expectancy at* t_1 data did not deviate significantly from normal (see Table 2).

Table 2: Normality test for calculated effort expectancy at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Calculated EE at T1	77	6.4 ± 1.4	.21	.27	.78	no skewness	.008	.54	.02	no kurtosis	.99	77	.79	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *calculated effort expectancy at* t_1 data suggested the assumption of normality was reasonable (see Figure 2). The boxplot indicated no outliers in this data. Since the *calculated effort expectancy at* t_1 data were distributed normally, the sampling distribution of the sample mean for this variable was normal.

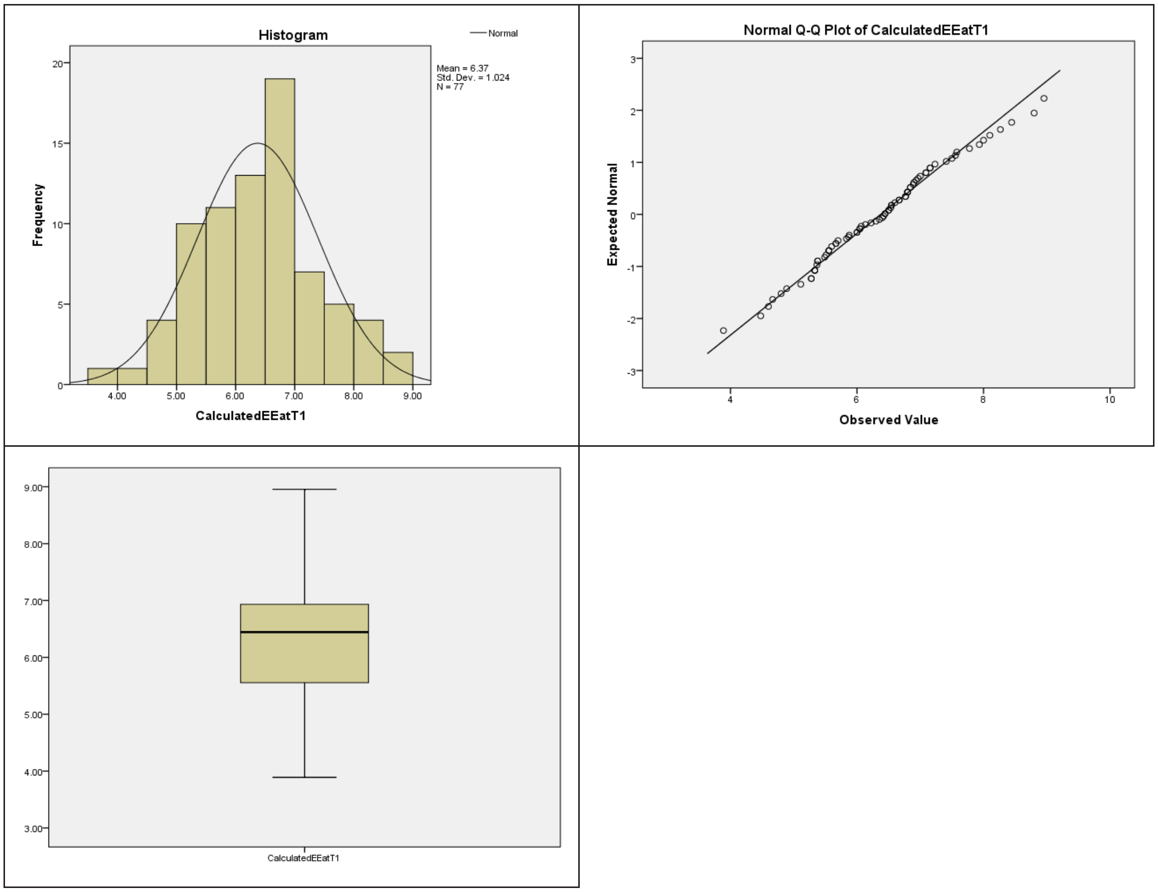


Figure 2: Histogram, Q-Q plot and boxplot for calculated effort expectancy at t_1 data

- *Calculated social encouragement expectancy at* t_1

A review of the Shapiro-Wilk test for normality (*SW* = .97, *df* = 77, *p* = .11) and skewness (1.5) and kurtosis (-.56) statistics suggested that the *calculated social encouragement at* t_1 data did not deviate significantly from normal (see Table 3).

Table 3: Normality test for calculated social encouragement expectancy at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Calculated SEE at T1	77	6.7 ± 1.1	.40	.27	1.5	no skewness	-.30	.54	-.56	no kurtosis	.97	77	.11	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *calculated social encouragement at* t_1 data suggested the assumption of normality was reasonable (see Figure 3). The boxplot indicated no outliers in this data. Since the *calculated social encouragement at* t_1 data were distributed normally, the sampling distribution of the sample mean for this variable was normal.

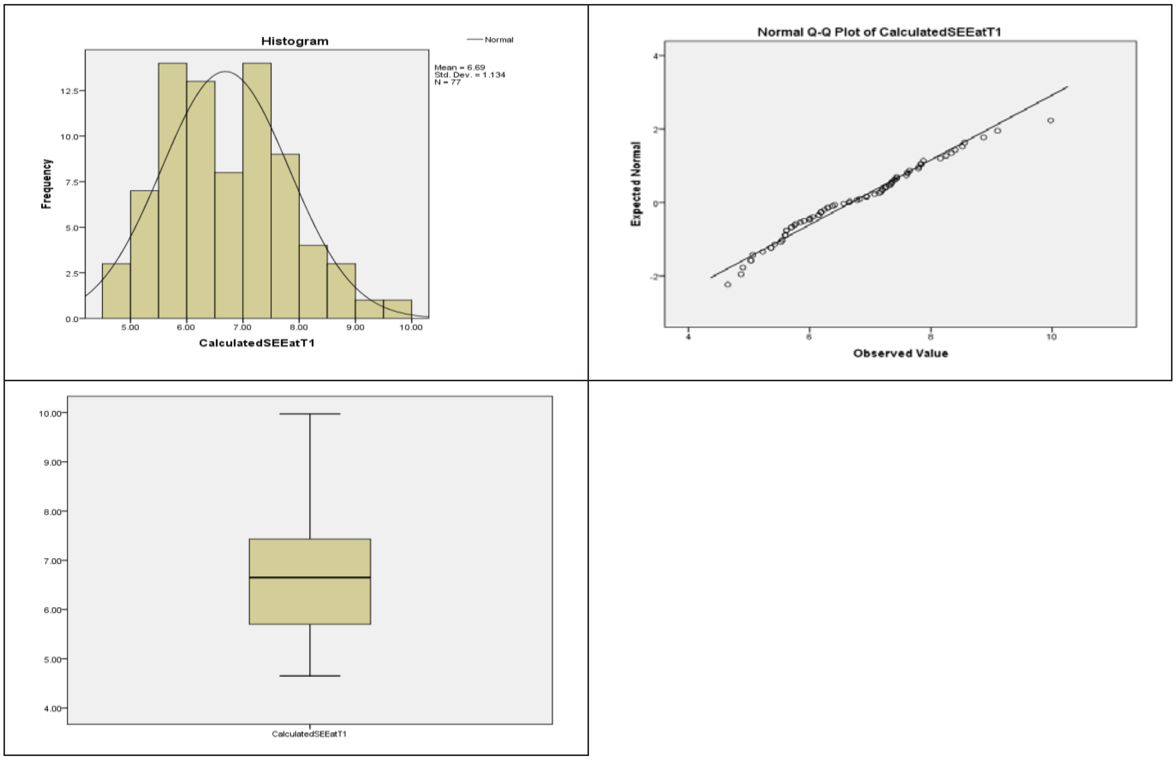


Figure 3: Histogram, Q-Q plot and boxplot for calculated social encouragement expectancy at t_1 data

- *Calculated facilitating condition expectancy at* t_1

A review of the Shapiro-Wilk test for normality (*SW* = .98, *df* = 77, *p* = .21) and skewness (-1.6) and kurtosis (-.41) statistics suggested that the *calculated facilitating condition expectancy at* t_1 data did not deviate significantly from normal (see Table 4).

Table 4: Normality test for calculated facilitating condition expectancy at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Calculated FCE at T1	77	6.6 ± 1.2	-.45	.27	-1.6	no skewness	-.22	.54	-.41	no kurtosis	.98	77	.21	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *calculated facilitating condition expectancy at* $t_1$data suggested the assumption of normality was reasonable (see Figure 4). The boxplot indicated one outlier in this data. However, that outlier was not cut since its value was not lower than Q_1 - 3×IQR. As the *calculated facilitating condition expectancy at* $t_1$data were distributed normally, the sampling distribution of the sample mean for this variable was normal.

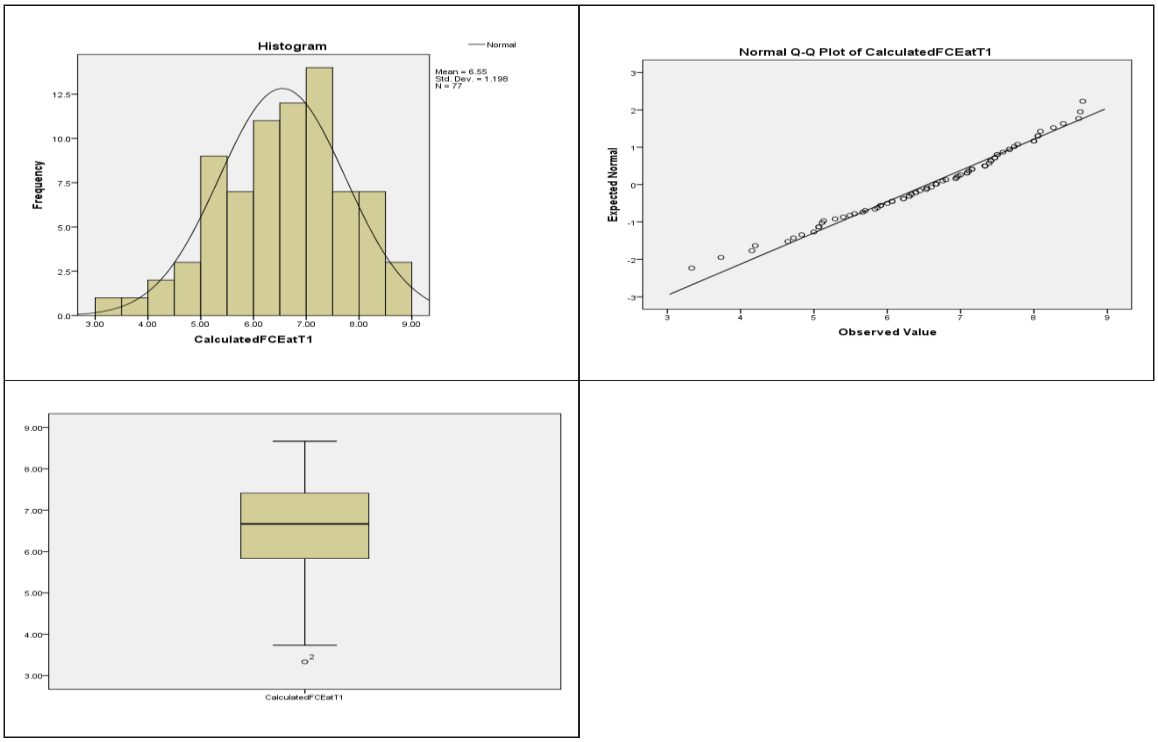


Figure 4: Histogram, Q-Q plot and boxplot for facilitating condition expectancy at t_1 data

- *Calculated learning consistency expectancy at* t_1

A review of the Shapiro-Wilk test for normality (SW = .98, df = 77, p = .35) and skewness (.56) and kurtosis (-1.3) statistics suggested that the *calculated learning consistency expectancy at* $t_1$data did not deviate significantly from normal (see Table 5).

Table 5: Normality test for calculated learning consistency expectancy at $t_1$data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Calculated LCE at T1	77	6.6 ± 1.2	.15	.27	.56	no skewness	-.69	.54	-1.3	no kurtosis	.98	77	.35	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *calculated learning consistency expectancy at* t_1 data suggested the assumption of normality was reasonable (see Figure 5). The boxplot indicated no outliers in this data. Since the *calculated learning consistency expectancy at* t_1 data were distributed normally, the sampling distribution of the sample mean for this variable was normal.

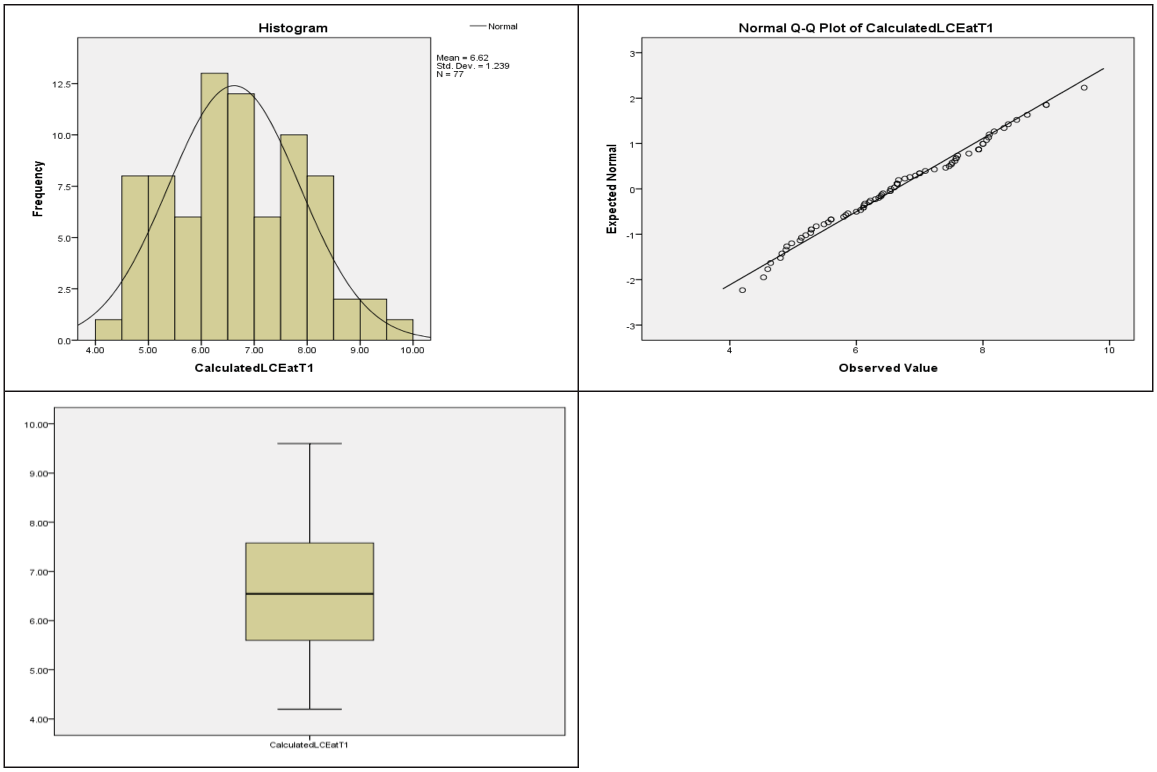


Figure 5: Histogram, Q-Q plot and boxplot for calculated learning consistency expectancy at t_1 data

- *Dependent variables*

The normality check and outlier detection for four dependent variables (the four measurements of actual continued use of E-learning) was carried out previously and the results suggested that the normality assumption was not violated (see Appendix 7-L).

<u>Assumption 2</u>: Linear relationship between the dependent and independent variables

Linearity was checked by plotting a scatterplot between standardized predicted value and standardized residual of Function 1 dependent and independent variates (see Figure 6). The result showed that there was no pattern of residual dots in this data analysis. Accordingly, linearity assumption was not violated.

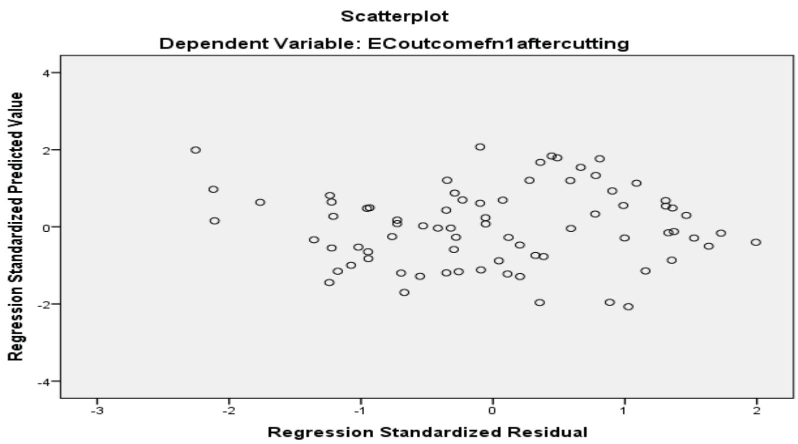


Figure 6: Scatterplot of residual plot for the relationship between the five EC sub-model at t_1 variables and the four measurements of actual continued use of E-learning t_2

<u>Assumption 3:</u> Multicollinearity

To detect multicollinearity among dependent variables and among independent variables the VIF test was used (see Table 6). As VIF for each variable in this study was lower than 10, multicollinearity was not a concern.

Table 6: Collinearity test for four measurements of actual continued use of E-learning at t_2 and five calculated expectations at t_1

		Variance inflation factors (VIF)
Dependent	Percentage (subjective) during t_1 and t_2	2.6
	Time spent (subjective) during t_1 and t_2	2.1
	Time spent (objective) during t_1 and t_2	5.9
	Number of times logging on (objective) during t_1 and t_2	5.0
Independent	CalculatedPEatT1	2.6
	CalculatedEEatT1	2.0
	CalculatedSEEatT1	2.7
	CalculatedFCEatT1	2.9
	CalculatedLCEatT1	4.3

Appendix 7-Q: Statistical conditions and assumptions checking of the canonical correlation analysis between the two TAM model variables at $t_1$and the four measurements of actual continued use of E-learning at t_2 (excluding *objective total number of times logging onto E-learning during t_1 and t_2*)

Before running the canonical correlation analysis, the two required conditions and three required assumptions were checked as follows.

Condition 1**:** At least two independent and two dependent variables

There were two independent variables in this data analysis: *measured performance expectancy at t_1*, and *measured effort expectancy at t_1*. The four dependent variables were: *subjective percentage of E-learning usage in education during time t_1 and t_2*; *subjective total time spent learning with E-learning during time during time t_1 and t_2*; *objective time spent on E-learning during time during time t_1 and t_2*; and *objective total number of activities involving E-learning during t_1 and t_2*. This condition therefore was met.

Condition 2**:** Dependent and independent variables are continuous data

Independent variables (two measured expectations at t_1) were continuous, ranging from 0 to 10. Four independent variables (measurements of actual continued use of E-learning at t_2) in were also continuous. This condition therefore was met.

Assumption 1**:** Sampling distribution of the sample mean for each variable is normal

- *Measured performance expectancy at t_1*

A review of the Shapiro-Wilk test for normality (*SW* = .97, *df* = 77, *p* = .05) and skewness (-.66) and kurtosis (-1.4) statistics suggested that the *measured performance expectancy at t_1* data did not deviate significantly from normal (see Table 1).

Table 1: Normality test for measured performance expectancy at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Measured PE at T1	77	6.8 ± 1.3	-.18	.27	-.66	no skewness	-.75	.54	-1.4	no kurtosis	.97	77	.05	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *measured performance expectancy at* t_1 data suggested normality was reasonable (see Figure 1). The boxplot indicated no outliers in this data. As the *measured performance expectancy at* t_1 data were distributed normally, the sampling distribution of the sample mean for this variable is normal.

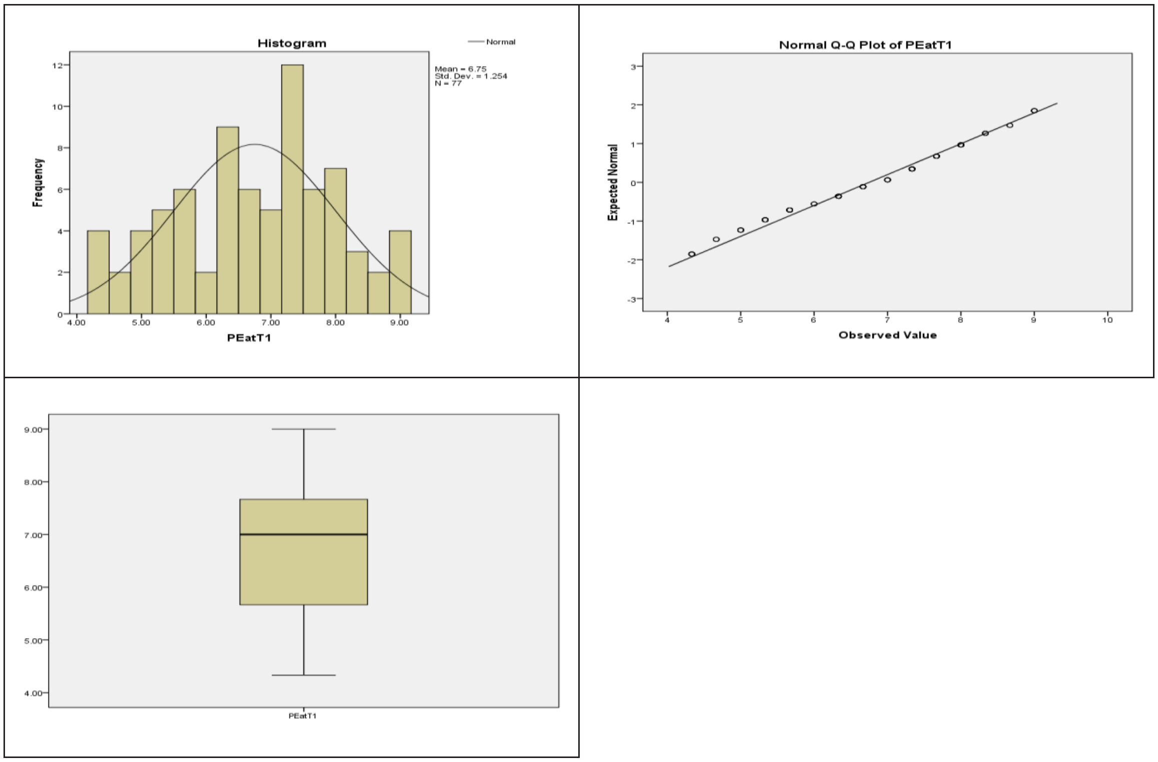


Figure 1: Histogram, Q-Q plot and boxplot for measured performance expectancy at t_1 data

- *Measured effort expectancy at* t_1

A review of the Shapiro-Wilk test for normality (SW = .97, df = 77, p = .09) and skewness (1.6) and kurtosis (.007) statistics suggested that the *measured effort expectancy at* t_1 data did not deviate significantly from normal (see Table 2).

Table 2: Normality test for measured effort expectancy at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion (Z ≤ 2.56)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion (Z ≤ 2.56)	Statistic	df	P-value	Conclusion (p ≤ .01)
Measured EE at T1	77	6.6 ± 1.2	.43	.27	1.6	no skewness	.004	.54	.007	no kurtosis	.97	77	.09	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *measured effort expectancy at* $t_1$data suggested the assumption of normality was reasonable (see Figure 2). The boxplot indicated one outlier in this data (Case 75). However, that outlier was not cut since its value was not higher than Q_3 + 3×IQR: Case 75 was not an extreme outlier. As the *measured effort expectancy at* $t_1$data were distributed normally, the sampling distribution of the sample mean for this variable was normal.

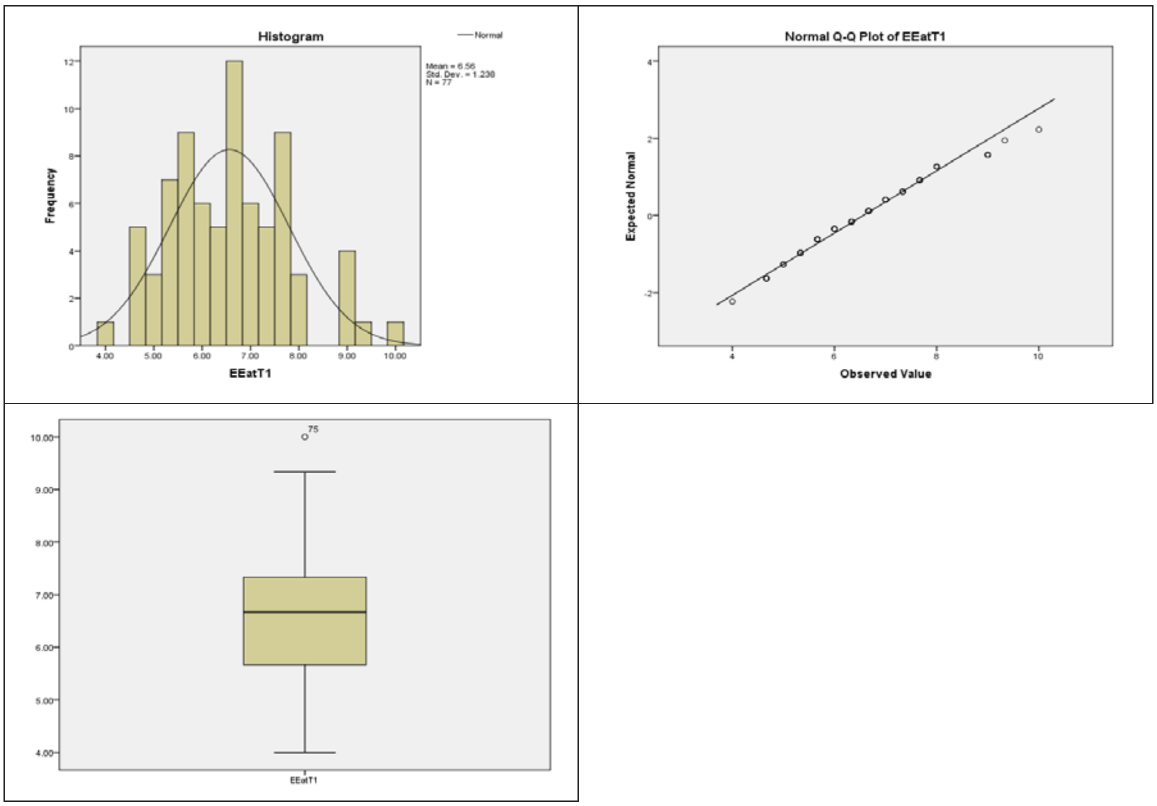


Figure 2: Histogram, Q-Q plot and boxplot for measured effort expectancy at t_1 data

- *Objective total number of activities involving E-learning at* t_2

The *objective total number of activities involving E-learning at* t_2 data deviated significantly from normal (*SW* = .78, *df* = 77, *p* = < .001) (see Table 3).

Table 3: Normality test for objective total number of activities involving E-learning at t_2 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\lvert Z\rvert \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\lvert Z\rvert \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Number of activity taking part objective at T2	77	15.4 ± 20.4	1.5	.27	5.4	positive skewness	1.8	.54	3.4	positive kurtosis	.78	77	< .001	Not normal

With the positive skewness (5.4) and kurtosis (3.4), $\text{Log}_{10}(X+1)$ was used for transforming this measurement data in order to improve the normality. The result of normality test after transforming the data is shown in Table 4.

Table 4: Normality test for objective total number of activities involving E-learning at t_2 data after transformation

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Number of activity taking part objective at T2 (after transformation)	77	0.77 ± 0.69	.11	.27	.38	no skewness	-1.6	.54	-3.0	negative kurtosis	.84	77	< .001	Not normal

The result suggested that the data after transformation still deviated significantly from normal (SW = .84, df = 77, p = < .001). Consistently, the histogram and Q-Q plot suggested the assumption of normality was not reasonable (see Figure 3). Although this variable data was not normal distributed, as the sample size was greater than 30, the central limit theorem asserts that the sampling distribution of the sample mean was normal. Therefore, this measurement data did not violate the assumption of normality.

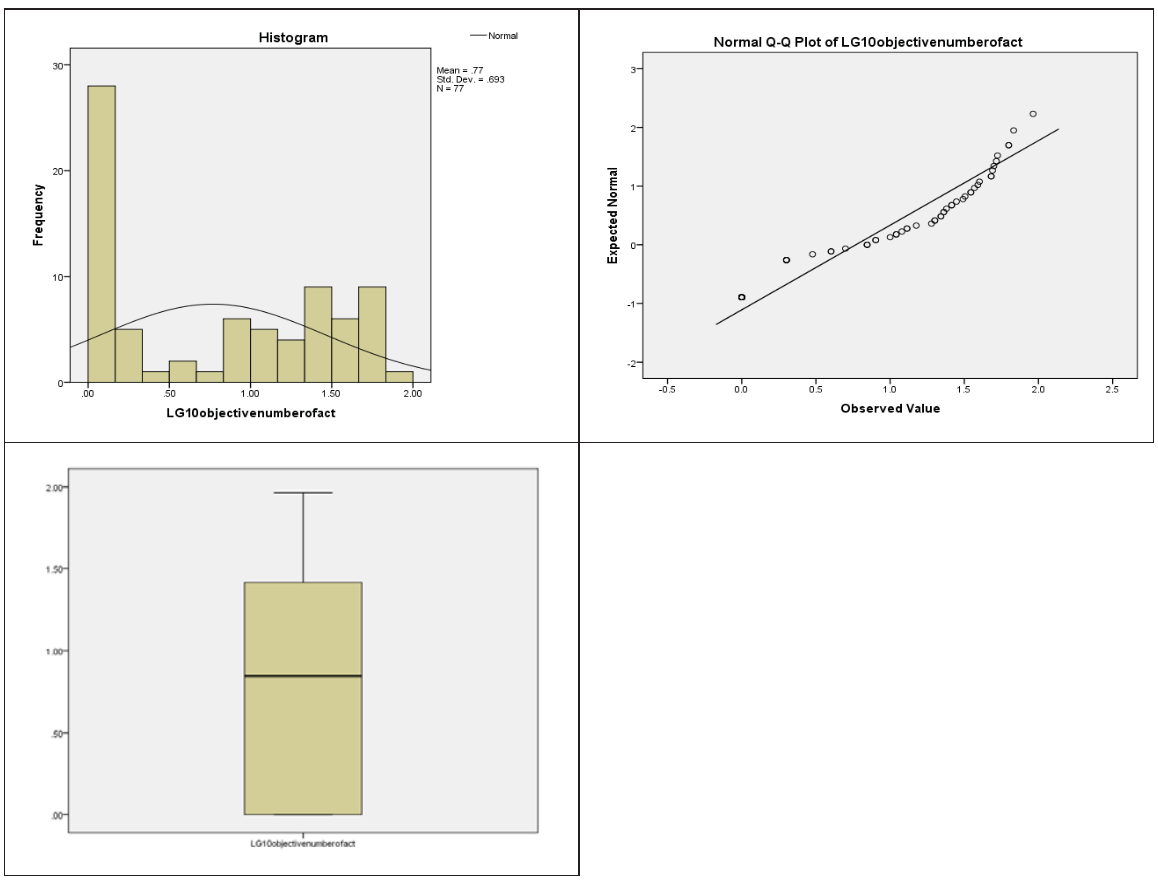


Figure 3: Histogram, Q-Q plot and boxplot for objective total number of activities involving E-learning at t_2 after transformation

- *Other dependent variables*

The normality check and outlier detection for another three dependent variables (*subjective percentage of E-learning usage in education during* t_1 *and* t_2, *subjective time spent learning with E-learning during* t_1 *and* t_2, *objective time spent on E-learning during* t_1 *and* t_2) were carried out previously and the results suggested that the normality assumption was not violated (see Appendix 7-L).

Assumption 2: Linear relationship between the dependent and independent variables

The linearity was checked afterwards by a scatterplot between the standardized predicted value and the standardized residual of Function 1 dependent and the independent variates (see Figure 4). The result showed that there was no pattern of residual dots in this data analysis. Accordingly, the linearity assumption was not violated.

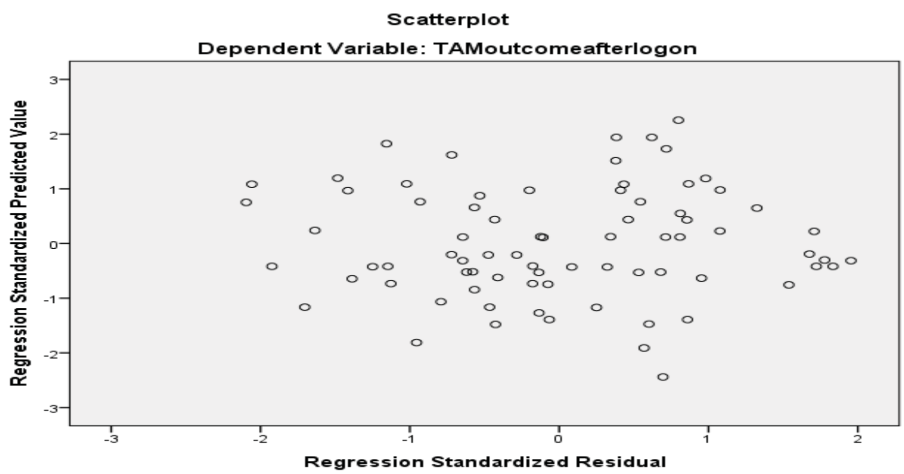


Figure 4: Scatterplot of residual plot for the relationship between the two TAM variables at t_1 and the four measurements of actual continued use of E-learning t_2

Assumption 3: Multicollinearity

Multicollinearity among dependent variables and among independent variables was checked (see Table 5). As the VIF for each variable in this study was lower than 10, multicollinearity was not a concern.

Table 6: Collinearity test for four measurements of actual continued use of E-learning at t_2 and two TAM measured expectations at t_1

		Variance inflation factors (VIF)
Dependent	Percentage (subjective) during t_1 and t_2	2.0
	Time spent (subjective) during t_1 and t_2	1.6
	Time spent (objective) during t_1 and t_2	3.2
	Number of activities (objective) during t_1 and t_2	3.1
Independent	Measured PE at T1	1.7
	Measured EE at T1	1.7

Appendix 7-R: Explanation of the canonical solution of the relationship between the two TAM model variables at t_1 and the four measurements of actual continued use of E-learning at t_2 (exclude *objective total number of times logging onto E-learning during t_1 and t_2*)

The independent variables were the two measured expectations from TAM model at t_1: *measured performance expectancy* at t_1 and *measured effort expectancy* at t_1. Dependent variables were the four measurements of E-learning actual usage at t_2: (a) *subjective percentage of E-learning usage in education during t_1 and t_2*;(b) *subjective time spent learning with E-learning during t_1 and t_2*; (c) *objective time spent on E-learning system during t_1 and t_2*; and (d) *objective total number of activities involving E-learning during t_1 and t_2*.

The relationship between the set of dependent and independent variables was statistically significant, Wilks' λ criterion = .77, *F*(8, 140.0) = 2.5, *p* = .014. Accordingly, there was at least one significant relationship between the TAM variables at t_1 and the measurements of E-learning actual continued use at t_2. Because Wilks' λ represents the variance in the combination of dependent variables unexplained by the set of independent variables, 33% (1- λ) of variance in actual continued use of E-learning was accounted for by the TAM model variables.

The canonical correlation analysis yielded two functions with squared canonical correlations (R_c^2) of .20 and .04 respectively for each successive function (see Table 1).

Table 1: Canonical correlation analysis of the relationship between the two TAM variables at t_1 and the four measurements of actual continued use of E-learning at t_2

Function	Eigenvalue	%	Cumulative %	Canonical Correlation	Squared Correlation
1	.26	86.4	86.4	.45	.20
2	.04	13.7	100	.20	.04

Dimension reduction analysis was used to determine which functions should be interpreted (see Table 2). Functions 1 to 2 was statistically significant, *F*(8, 140) = 2.5, *p* = .01. The Function 2 in isolation was not statistically significant. According to this result, the first function was considered noteworthy in the context of this study (20% of shared variance).

Table 2: Dimension reduction analysis for canonical functions of the relationship between the two TAM variables at t_1 and the four measurements of actual continued use of E-learning at t_2

Roots	Wilks' λ	F	Hypothesis DF	Error DF	Significance of F
1 to 2	.77	2.5	8.0	140.0	.01
2 to 2	.96	.96	3.0	71.0	.42

The initial canonical weight (*Beta*), canonical loading (r_s), part-correlation between variable and its variate (r_p), and square of part-correlation ($r_p{}^2$) for each variable within the selected Function are showed in Table 3.

Table 3: Initial canonical solution of the relationship between the two TAM variables at t_1 and the four measurements of actual continued use of E-learning at t_2

	Variable	Function 1				
		Coef	r_s	r_p	$r_p{}^2$ *(%)*	*Summary*
Dependent	Percentage (subjective) during t_1 and t_2	-.26	$-.83$	-.17	.03	No
Dependent	Time spent (subjective) during t_1 and t_2	-.34	$-.77$	-.23	.05	No
Dependent	Time spent (objective) during t_1 and t_2	-1.3	$-.77$	$-.44^{\dagger}$	.19	Relevant
Dependent	Number of activities (objective) during t_1 and t_2	.92	$-.57$	$.32^{\dagger}$	.10	Suppressor
Independent	performance expectancy at t_1	-1.2	$-.96$	$-.92^{\dagger}$	.85	Important
Independent	effort expectancy at t_1	.40	$-.40$	$.30^{\dagger}$	.09	Suppressor

Coef = Standardized coefficient (beta) between variable and with variate;
r_s = Zero order correlation
r_p = Part-correlation († greater than $|.30|$)
$r_p{}^2$ = Squared part-correlation

In canonical Function 1, the high part-correlation (higher than .30) and the difference in the sign between zero order correlation and beta, *measured effort expectancy* at t_1, and *objective total number of activities involving E-learning during* t_1 *and* t_2 were suspected as a suppressor (Friedman and Wall, 2005) It was not easy to interpret the effect of suppressor variable on contributing variables within the Function 1-independent variate (*measured performance expectancy* at t_1) and dependent variate (*objective time spent on E-learning system during* t_1 *and* t_2) if these contributing variables are all have negative beta and canonical loading. To make it easier, the variable *measured performance expectancy* at $t_1$and *objective total time spent on E-learning system during* t_1 *and* t_2 was inverted: inversion consisted of subtracting the variable from a constant being the maximum of the variable. A canonical analysis was carried out using the inverted variable (see Table 4).

Table 4: Final canonical solution of the relationship between the two TAM variables at t_1 and the four measurements of actual continued use of E-learning at t_2 after inversion

	Variable	**Function 1**				
		Coef	r_s	r_p	r_p^2 ***(%)***	***Summary***
Dependent	Percentage (subjective) during t_1 and t_2	-.26	$-.83$	-.17	.03	No
	Time spent (subjective) during t_1 and t_2	-.34	$-.77$	-.23	.05	No
	Inverted time spent (objective) during t_1 and t_2	1.3	$.77$	$.44^{\dagger}$	<u>.19</u>	Relevant
	Number of activities (objective) during t_1 and t_2	.92	$-.57$	$.32^{\dagger}$	<u>.10</u>	Suppressor
Independent	Inverted performance expectancy at t_1	1.2	$.96$	$.92^{\dagger}$	<u>.85</u>	Important
	Effort expectancy at t_1	.40	$-.40$	$.30^{\dagger}$	<u>.09</u>	Suppressor

Coef = Standardized coefficient (beta) between variable and with variate
r_s = Zero order correlation
r_p = Part-correlation († greater than $|.30|$)
r_p^2 = Squared part-correlation

Dependent variate Function 1

There were two dependent variables which contributed to the Function 1 dependent variate, where $|r_p| > .3$ *Inverted objective time spent on E-learning during t_1 and t_2* (r_p = .44) and *objective total number of activities involving E-learning during t_1 and t_2* (r_p = .32). Because of the difference in the sign between its zero order correlation (negative) and beta (positive), *objective total number of activities involving E-learning during t_1 and t_2* was the suspected suppressor variable.

To investigate whether *objective total number of activities involving E-learning during t_1 and t_2* was a suppressor variable, multiple regression analysis was carried out: (i) dependent variate regressed with all dependent variables except *objective total number of activities involving E-learning during t_1 and t_2*; (ii) dependent variate regressed with all dependent variables included *objective total number of activities involving E-learning during t_1 and t_2* (see Table 5).

Table 5: Multiple regression result of the relationship between funtion1 dependent variate and dependent variables before and after adding objective number of activities involving E-learning during t_1 and t_2

Variable	(i) Before adding beta	(ii) After adding beta	Sizable change in beta
Percentage (subjective) during t_1 and t_2	-.33	-.26	.07
Time spent (subjective) during t_1 and t_2	-.35	-.35	0
Inverted time spent (objective) during t_1 and t_2	.45	1.4	.95
Number of activities (objective) during t_1 and t_2	-	.92	-
	R^2 = .89	R^2= 1	$R^2{}_{chnage}$ = .11

Even though *objective total number of activities involving E-learning during t_1 and t_2* had the smallest value of zero order correlation with its variate, when this variable was added to the equation of ii: (a) it was a contributing variable (*beta* = .92); (b) it removed or suppressed criterion-irrelevant variance from *inverted objective time spent on E-learning during t_1 and t_2* (increased the beta weight from *beta* = .45 to *beta* = 1.4); and (c) increased 11% the variance of dependent variate accounted for by a set of dependent variables. The result confirmed that *objective total number of activities involving E-learning during t_1 and t_2* was a suppressor variable for *inverted objective total time spent on E-learning during t_1 and t_2*.

Following the appearance of the suppressor, further examination divided the *objective total number of activities involving E-learning during t_1 and t_2* data into two groups: low (less than mean) and high (equal to or greater than mean). Multiple regression analysis was then conducted: regressing the dependent variate with the *inverted objective total time spent on E-learning during t_1 and t_2* (the contributing variable for the Function 1 dependent variate) in the low and high *objective total number of activities involving E-learning during t_1 and t_2* group (see Table 6).

Table 6: Multiple regression result of the relationship between Funtion1-dependent variate and inverted objective time spent on E-learning during t_1 and t_2 in low and high objective total number of activities involving E-learning during t_1 and t_2 groups of participants

Variable	Low number of activity		High number of activity		Change in beta
	beta	Sig.	beta	Sig.	
Inverted time spent (objective) during t_1 and t_2	.75	< .001	.68	< .001	.07
	R^2 = .56		R^2= .46		$R^2{}_{chnage}$ = .10

The result indicated that *inverted objective time spent on E-learning during* t_1 *and* t_2 had an important influence in both the high and low *objective total number of activities involving on E-learning during* t_1 *and* t_2 groups because the beta weight of this variable was significant in both groups (lower group, *beta* = .75, *p* < .001, higher group *beta* = .68, *p* < .001). The R-square in the lower group (.56) was higher than the higher group (.46). It implied that the *inverted objective time spent on E-learning during* t_1 *and* t_2 was an influential variable in both the high and low activity group, whilst it would be more influential when students took part in few activities.

Independent variate Function 1

There were two dependent variables contributing to the Function 1-dependent variate, where $|r_p|$ > .3 *inverted measured performance expectancy at* t_1 (r_p = .92) and *measured effort expectancy at* t_1 (r_p = .30). A sizable increase in the beta weight from the zero order correlation of the *inverted measured performance expectancy at* t_1 (from r_s = .96 to *beta* = 1.2) indicated suppression in the Function 1-independent variate (Tzelgov and Henik, 1991) The suspected suppressor variable was *measured effort expectancy at* t_1 because of the difference in the sign between its zero order correlation (negative) and beta (positive). To investigate whether *measured effort expectancy at* t_1 was a suppressor variable, multiple regression analysis was carried out: (i) the dependent variate regressed with all dependent variables except *measured effort expectancy at* t_1; (ii) the dependent variate regressed with all dependent variables including *measured effort expectancy at* t_1 (see Table 7).

Table 7: Multiple regression result of the relationship between Funtion1-independent variate and independent variables before and after adding measured effort expectancy at t_1

Variable	**(i) Before adding**	**(ii) After adding**	**Sizable change in beta**
	beta	beta	
Measured inverted performance expectancy at T1	.95	1.2	.25
Measured effort expectancy at T1	-	.40	-
	R^2 = .91	R^2= 1	R^2_{chnage} = .09

When *measured effort expectancy at* t_1 (suspected suppressor variable) was added to the equation of ii: (a) it was a contributing variable (*beta* = .40, *p* < .001); (b) it removed or suppressed criterion-irrelevant variance from the *inverted measured performance expectancy at* t_1 (increased the beta weight from *beta* = .95 to *beta* = 1.2); and (c) the variance of dependent variate accounted for by a set of dependent variables was increased by 9%. The result confirmed that *measured effort expectancy at* t_1 was a suppressor variable for *inverted measured performance expectancy at* t_1.

Following the appearance of a suppressor, to examine what was taking place, *measured effort expectancy at* t_1 data was divided into two groups: low (less than mean) and high (equal to or greater than mean). Multiple regression analysis was then conducted: regressing the independent variate with *inverted measured performance expectancy at* t_1 (the contributing variable for the Function 1-independent variate) in the low and high *measured effort expectancy at* t_1 groups (see Table 8).

Table 8: Multiple regression result of the relationship between Funtion1-independent variate and inverted measured performance expectancy at t_1 in low and high measured effort expectancy at t_1 groups of participants

Variable	**Low effort expectancy**		**High effort expectancy**		**Change in beta**
	beta	Sig.	beta	Sig.	
Inverted performance expectancy at T1	.99	< .001	.95	< .001	.04
	R^2 = .98		R^2= .91		$R^2{}_{chnage}$ = .07

The result indicated that *inverted performance expectancy at* t_1 had an important influence in both the high and low *effort expectancy at* t_1 groups, because the beta weight of this variable was significant in both groups (lower group, *beta* = .99, $p < .001$, higher group *beta* = .95, $p < .001$). The R-square in the lower group (.98) was higher than the high group (.91). It implied that the *inverted performance expectancy at* t_1 was an influential variable in both the high and low *effort expectancy at* t_1 groups of students, whilst it would be more influential when students had low *effort expectancy at* t_1.

Summary of CCA of the relationship between the two TAM model variables at t_1 *and the four measurements of actual E-learning continued use at* t_2

It can be concluded that: (a) there was a positive relationship between the dependent and independent variates, since the canonical correlation between the dependent and the independent variates (R_c = .45) in Function 1 was positive; (b) the *inverted performance expectancy at* t_1 and *effort expectancy at* t_1 contributed to the Function 1-independent variate, while; (c) the *inverted objective time spent on E-learning during* t_1 *and* t_2 and *objective total number of activities involving E-learning during* t_1 *and* t_2 contributed to the Function 1 dependent variate; (d) the *effort expectancy at* t_1 was a suppressor variable for *inverted performance expectancy at* t_1 and; (e) the *objective total number of activities involving E-learning during* t_1 *and* t_2 was a suppressor variable for the *inverted objective total time spent on E-learning during* t_1 *and* t_2 (see Figure 1).

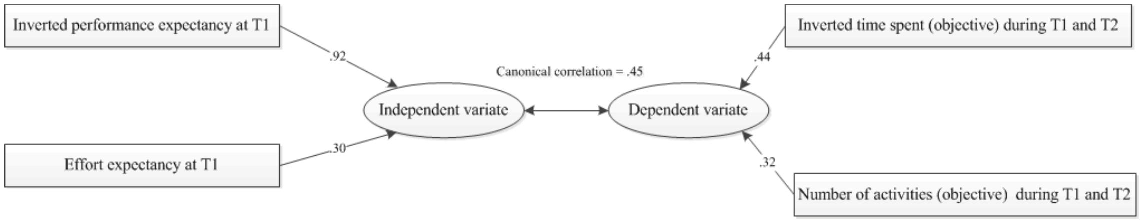


Figure 1: Summary of canonical correlation analysis of the relationship between the two TAM variables at t_1 and the four measurements of actual continued use of E-learning at t_2

Appendix 7-S: Statistical conditions and assumptions checking of the canonical correlation analysis between the four UTAUT model variables at $t_1$and the four measurements of actual continued use of E-learning at t_2 (excluding *objective total number of times logging onto E-learning during t_1 and t_2*)

Before running the canonical correlation analysis, the two required conditions and three required assumptions were checked, as follows.

Condition 1**:** At least two independent and two dependent variables

There were four independent variables in this data analysis: *measured performance expectancy at t_1*, *measured effort expectancy at t_1*, *measured social encouragement expectancy at t_1*, and *measured facilitating condition expectancy at t_1*. The four dependent variables were: *subjective percentage of E-learning usage in education during time t_1 to t_2*; *subjective time spent learning with E-learning during time during time t_1 to t_2*; *objective time spent using E-learning during time during time t_1 to t_2*; and *objective total number of activities involving E-learning during t_1 and t_2*. This condition, therefore, was met.

Condition 2**:** Dependent and independent variables are continuous data

The independent variables (four measured expectations at t_1) were continuous, ranging from 0 to 10. The four independent variables (measurements of actual continued use of E-learning at t_2) were also continuous. This condition therefore was met.

Assumption 1**:** Sampling distribution of the sample mean for each variable is normal

- *Measured social encouragement expectancy at t_1*

A review of the Shapiro-Wilk test for normality (*SW* = .99, *df* = 77, *p* = .51) and skewness (1.0) and kurtosis (.23) statistics suggested that the *measured social encouragement expectancy at t_1* data did not deviate significantly from normal (see Table 1).

Table 1: Normality test for measured social encouragement expectancy at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Measured SEE at T1	77	6.8 ± 1.3	.28	.27	1.0	no skewness	.13	.54	.23	no kurtosis	.99	77	.51	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *measured social encouragement expectancy at* t_1 data suggested the assumption of normality was reasonable (see Figure 1). The boxplot indicated two outliers in this data (Cases 25 and 75). As these two outliers were not extreme, they were not cut from the data analysis. Since the *measured social encouragement expectancy at* t_1 data were distributed normally, the sampling distribution of the sample mean for this variable was normal.

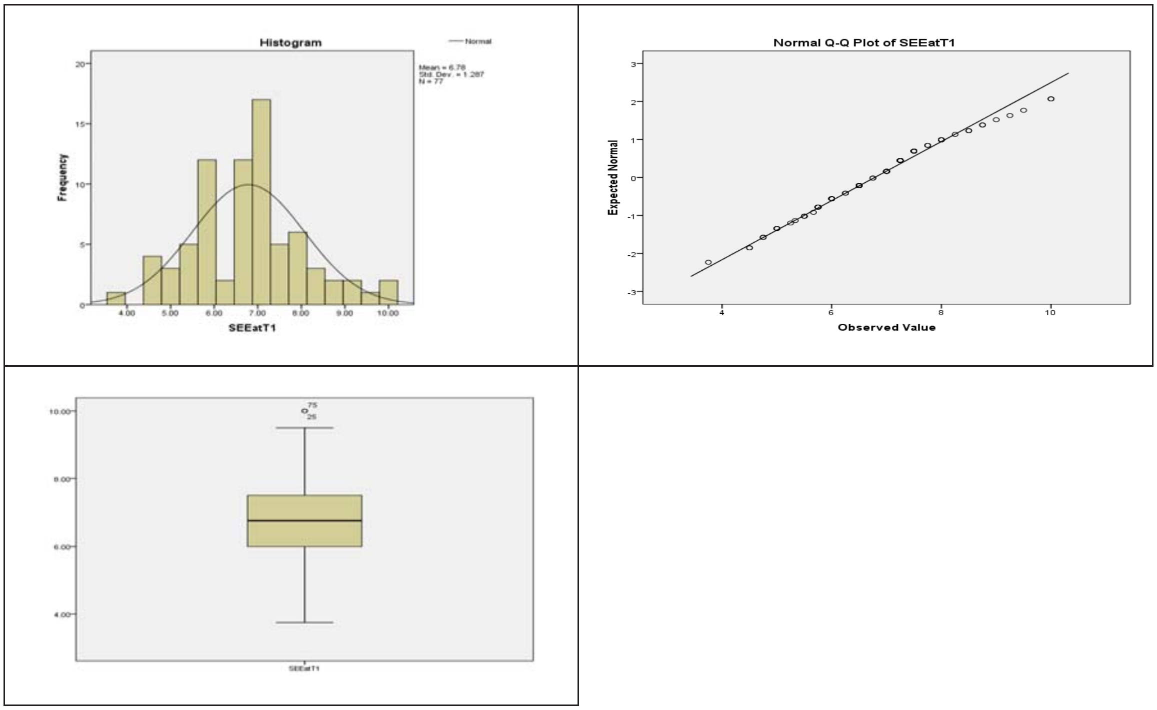


Figure 1: Histogram, Q-Q plot and boxplot for measured social encouragement expectancy at t_1 data

- *Measured facilitating condition expectancy at* t_1

A review of the Shapiro-Wilk test for normality (SW = .97, df = 77, p = .080) and skewness (1.2) and kurtosis (-.79) statistics suggested that the *measured facilitating condition expectancy at* t_1 data did not deviate significantly from normal (see Table 2).

Table 2: Normality test for facilitating condition expectancy at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Measured FCE at T1	77	6.9 ± 1.3	.34	.27	1.2	no skewness	-.43	.54	-.79	no kurtosis	.97	77	.08	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *measured facilitating condition expectancy at* t_1 data suggested the assumption of normality was reasonable (see Figure 2). The boxplot indicated no outliers in this data. As the *measured facilitating condition expectancy at* t_1 data were distributed normally, the sampling distribution of the sample mean for this variable was normal.

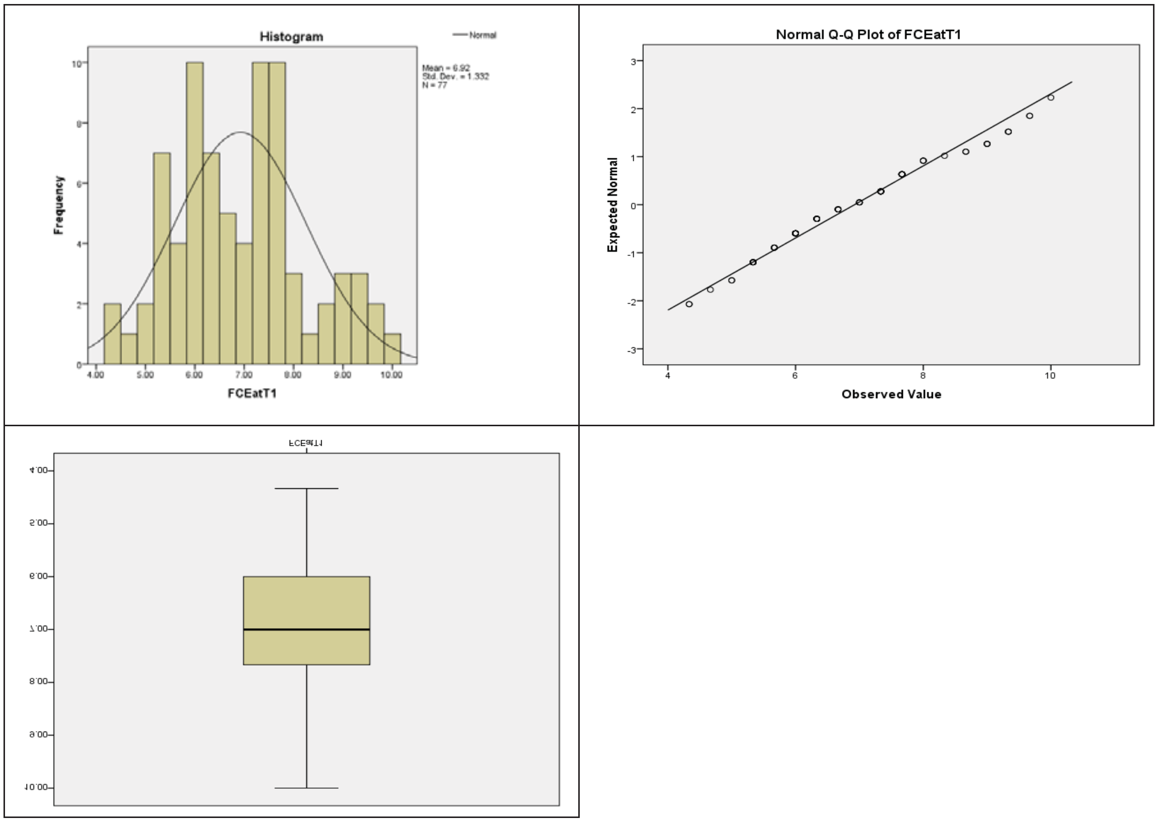


Figure 2: Histogram, Q-Q plot and boxplot for facilitating condition expectancy at t_1 data

- *Other independent variables*

The normality check and outlier detection for another two independent variables (*measured performance expectancy at* t_1, and *measured effort expectancy at* t_1) were carried out previously (see Appendix 7-Q) and the results suggested that the assumption of normality assumption was not violated.

- *Other dependent variables*

The normality check and outlier detection for another three dependent variables (*subjective percentage of E-learning usage in education during time t_1 to t_2; subjective time spent learning with E-learning during time during time t_1 to t_2; objective time spent on E-learning during time during time t_1 to t_2;* and *objective total number of activities taking part on E-learning during t_1 and t_2*) were carried out previously (see Appendix 7-L and 7-Q) and the results suggested that the assumption of normality assumption was not violated.

<u>Assumption 2</u>: Linear relationship between the dependent and independent variables

The linearity was checked afterwards by plotting a scatterplot between standardized predicted value and standardized residual of Function 1 dependent and the independent variates (see Figure 3). The result showed no pattern of residual dots in this data analysis. Accordingly, the linearity assumption was not violated.

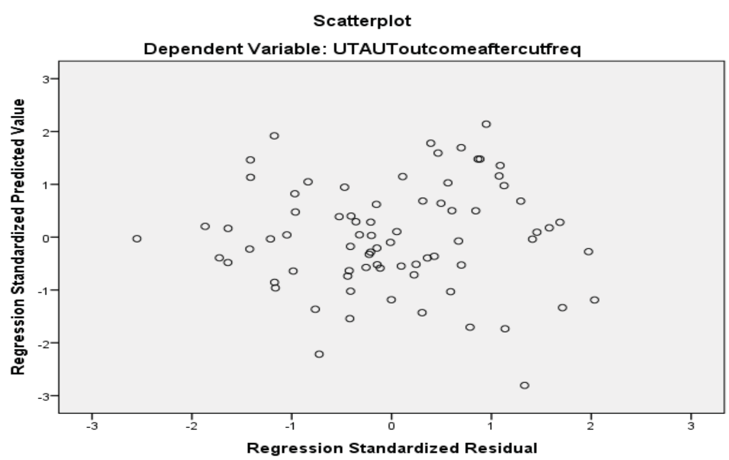


Figure 3: Scatterplot of residual plot for the relationship between the four UTAUT variables at t_1 and the four measurements of actual continued use of E-learning at t_2

<u>Assumption 3:</u> Multicollinearity

Multicollinearity among dependent variables and among independent variables was checked (see Table 3). As VIF for each variable in this study was lower than 10, multicollinearity was not a concern.

Table 3: Collinearity test for four measurements of actual continued use of E-learning at t_2 and four UTAUT measured expectations at t_1

		Variance inflation factors (VIF)
Dependent	Percentage (subjective) during t_1 and t_2	2.0
	Time spent (subjective) during t_1 and t_2	1.6
	Time spent (objective) during t_1 and t_2	3.2
	Number of activities (objective) during t_1 and t_2	3.1
Independent	Measured PE at T1	3.0
	Measured EE at T1	2.6
	Measured SEE at T1	4.7
	Measured FCC at T1	2.7

Appendix 7-T: Explanation of the canonical solution of the relationship between the four UTAUT model variables at t_1 and the four measurements of actual continued use of E-learning at t_2 (exclude *objective total number of times logging onto E-learning during t_1 and t_2*)

The independent variables were the four measured expectations from UTAUT model at t_1: *measured performance expectancy at t_1*, *measured effort expectancy at t_1*, *measured social encouragement expectancy at t_1*, and *measured facilitating condition expectancy at t_1*. Dependent variables are the four measurements of E-learning actual usage at t_2: *subjective percentage of E-learning usage in education during t_1 and t_2*, *subjective time spent learning with E-learning during t_1 and t_2*, *objective time spent on E-learning during t_1 and t_2*, and *objective total number of activities involving E-learning during t_1 and t_2*.

The relationship between the set of dependent and independent variables was statistically significant, Wilks' λ criterion = .65, F(16, 208.4) = 2.0, p = .014. Accordingly, there was at least one significant relationship between the UTAUT variables at t_1 and the measurements of actual continued use of E-learning at t_2. Because Wilks' λ represents the variance in the combination of dependent variables unexplained by the set of independent variables, 35% (1- λ) of variance in actual continued use of E-learning was accounted for by the UTAUT model variables.

The canonical correlation analysis yielded four functions with squared canonical correlations (${R_c}^2$) of .28, .07, .04 and .001 respectively for each successive function (see Table 1).

Table 1: Canonical correlation analysis of the relationship between the four UTAUT variables at t_1 and the four measurements of actual continued use of E-learning at t_2

Function	Eigenvalue	%	Cumulative %	Canonical Correlation	Squared Correlation
1	.38	76.5	76.5	.53	.28
2	.08	15.5	92.1	.27	.07
3	.04	7.8	99.8	.19	.04
4	.001	.19	100.0	.03	.001

Functions 1 to 4 was statistically significant, $F(16, 208.4) = 2.01$, $p = .01$ (see Table 2). However, the cumulative effects of Functions 2 to 4, Functions 3 to 4 and Function 4 in isolation were not statistically significant. Because of this, the first functions were considered noteworthy in the context of this study (28% of shared variance).

Table 2: Dimension reduction analysis for canonical functions of the relationship between the four UTAUT variables at t_1 and the four measurements of actual continued use of E-learning at t_2

Roots	Wilks' λ	F	Hypothesis DF	Error DF	Significance of F
1 to 4	.65	2.01	16.0	208.4	.01
2 to 4	.89	.90	9.0	168.1	.53
3 to 4	.96	.69	4.0	140.0	.60
4 to 4	1.0	.07	1.0	71.0	.79

The initial canonical weight (*Beta*), canonical loading (r_s), part-correlation between variable and its variate (r_p), square of part-correlation (${r_p}^2$) for each variable are showed in Table 3.

Table 3: Initial canonical solution for canonical Function 1 of the relationship between the four UTAUT variables at t_1 and the four measurements of actual continued use of E-learning at t_2

	Variable	Function 1				
		Coef	r_s	r_p	${r_p}^2$ (%)	*Summary*
Dependent	Percentage (subjective) during t_1 and t_2	.15	.81	.09	$8.1*10^{-3}$	No
	Time spent (subjective) during t_1 and t_2	.66	.91	.46†	.21	Relevant
	Time spent (objective) during t_1 and t_2	1.0	.64	.34†	.12	Relevant
	Number of activity taking part (objective) during t_1 and t_2	-.81	.46	-.29	.08	No
Independent	Performance expectancy at t_1	-.44	−.79	-.26	.07	No
	Effort expectancy at t_1	.64	−.35	.39†	.15	Suppressor
	Social encouragement expectancy at t_1	-.25	−.71	-.12	.01	No
	Facilitating condition expectancy at t_1	-.78	−.89	−.48†	.23	Important

Coef = Standardized coefficient (beta) between variable and with variate
r_s = Zero order correlation
r_p = Part correlation († greater than |.30|)
${r_p}^2$ = Squared part correlation

In canonical Function 1, the high part-correlation (higher than .30) and the difference in the sign between zero order correlation and beta, *effort expectancy at* t_1 was suspected as a suppressor (Friedman and Wall, 2005). It was not easy to interpret the effect of suppressor variable on contributing variables within the Function 1independent variate (*facilitating condition expectancy at* t_1) if the contributing variable all has negative beta and canonical loading. To make it easier, the variable *facilitating condition expectancy at* t_1 was inverted: inversion consisted of subtracting the variable from a constant 10 (the maximum of the variable). A canonical analysis was carried out using the inverted variable (see Table 4).

Table 4: Final canonical solution for canonical Function 1 of the relationship between the four UTAUT variables at t_1 and the four measurements of actual continued use of E-learning at t_2 after inversion

	Variable	**Function 1**				
		Coef	r_s	r_p	r_p^2 ***(%)***	***Summary***
Dependent	Percentage (subjective) during t_1 and t_2	-.15	-.81	-.09	$8.1*10^{-3}$	No
	Time spent (subjective) during t_1 and t_2	-.66	$-.91$	$-.46^{\dagger}$	.21	Relevant
	Time spent (objective) during t_1 and t_2	-1.0	$-.64$	$-.34^{\dagger}$	.12	Relevant
	Number of activity taking part (objective) during t_1 and t_2	.81	$-.46$	.29	.08	No
Independent	Performance expectancy at t_1	-.44	$-.79$	-.26	.07	No
	Effort expectancy at t_1	.64	$-.35$	$.39^{\dagger}$	.15	Suppressor
	Social encouragement expectancy at t_1	-.25	$-.71$	-.12	.01	No
	Inverted facilitating condition expectancy at t_1	.78	.89	$.48^{\dagger}$	.23	Important

Coef = Standardized coefficient (beta) between variable and with variate
r_s = Zero order correlation (* correlation is greater than $|.30|$, ** correlation is greater than $|.50|$)
r_p = Part correlation († greater than $|.30|$)
r_p^2 = Squared part correlation

Dependent variate Function 1

There were two dependent variables which contributed to the Function 1-dependent variate, where $|r_p| > .3$ *subjective time spent learning with E-learning during* t_1 *and* t_2 (r_p = -.46) and *objective time spent on E-learning during* t_1 *and* t_2 (r_p = -.34). The canonical loading (r_s) for the two contributing independent variables had a same sign: these two variables positively related to one another.

Independent variate Function 1

There were two independent variables which contributed to the Function 1 independent variate, where $|r_p| > .3$: *inverted facilitating condition expectancy at* t_1 (r_p = .48) and *effort expectancy at* t_1 (r_p = .39). Because of the difference in the sign between its zero order correlation (negative) and beta (positive), *effort expectancy at* t_1 was a suspected suppressor variable. To investigate whether *effort expectancy at* t_1 was a suppressor variable, multiple regression analysis was carried out: (i) independent variate regressed with all dependent variables except *effort expectancy at* t_1; (ii) independent variate regressed with all dependent variables included *effort expectancy at* t_1 (see Table 5).

Table 5: Multiple regression result of the relationship between Funtion1-independent variate and independent variables before and after adding effort expectancy at t_1

Variable	**(i) Before adding beta**	**(ii) After adding beta**	**Sizable change in beta**
Performance expectancy at t_1	-.39	-.44	-.05
Effort expectancy at t_1	-	.64	-
Social encouragement expectancy at t_1	.18	-.25	-.43
Inverted facilitating condition expectancy at t_1	.75	.78	.03
	R^2 = .84	R^2= 1	R^2_{chnage} = .16

Even though *effort expectancy at* t_1 had the smallest value of zero order correlation with its variate (r_s = -.35), when this variable was added to the equation of ii: (a) it was a contributing variable (*beta* = .64); (b) it removed or suppressed criterion-irrelevant variance from *inverted facilitating condition expectancy at* t_1 (increased the beta weight for from *Beta* = .75 to *Beta* = .78) and (c) the variance of dependent variate accounted for by a set of dependent variables was increased 16%. The result confirmed that *effort expectancy at* t_1 was a suppressor variable for *inverted facilitating condition expectancy at* t_1.

To examine what was taking place, *measured effort expectancy at* t_1 data was divided into two groups: low (less than mean) and high (equal to or greater than mean). Multiple regression analysis was then conducted: regressing the independent variate with *inverted facilitating condition expectancy at* t_1 (the contributing variable for the Function 1 independent variate) in the low and high *measured effort expectancy at* t_1 groups (see Table 6).

Table 6: Multiple regression result of the relationship between Function 1-independent variate and inverted measured facilitating condition expectancy at t_1 in low and high measured effort expectancy at t_1 groups of participants

Variable	Low effort expectancy		High effort expectancy		Change in beta
	beta	Sig.	beta	Sig.	
Inverted facilitating condition expectation at t_1	.88	< .001	.94	< .001	.06
	R^2 = .78		R^2= .88		$R^2{}_{chnage}$ = .10

The result indicated that *inverted facilitating condition expectancy at* t_1 played an important influence in both the high and low *effort expectancy at* t_1 groups because the beta weight of this variable was significant in both groups (lower group, *beta* = .88, $p < .001$, higher group *beta* = .94, $p < .001$). The R-square in the higher group (.88) was higher than the lower group (.78). It implied that the *inverted facilitating condition expectancy at* $t_1$was an influential variable in both the high and low effort expectancy groups of students, whilst it would be more influential when students had high effort expectancy.

Summary of CCA of the relationship between the four UTAUT model variables at t_1 *and the four measurements of actual E-learning continued use at* t_2

Even though there was a positive relationship between the dependent and the independent variates (R_c = .53). The contributing dependent variables were *subjective time spent learning with E-learning during* t_1 *and* t_2 and *objective time spent on E-learning during* t_1 *and* t_2. The contributing independent variables were *inverted facilitating condition expectancy at* t_1 and *effort expectancy at* t_1. The *effort expectancy at* $t_1$was a suppressor variable for *inverted facilitating condition expectancy at* t_1 (see Figure 1).

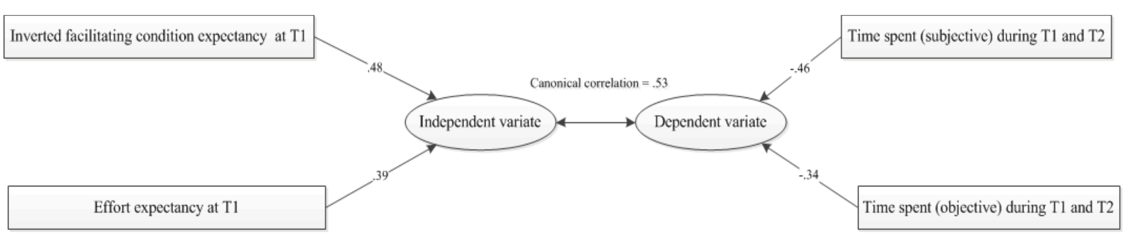


Figure 1: Summary of canonical correlation analysis of the relationship between the four UTAUT variables at t_1 and the four measurements of actual continued use of E-learning at t_2

Appendix 7-U: Statistical conditions and assumptions checking of the multiple regression analysis between the ECM model variable at t_1 and the four measurements of actual continued use of E-learning at t_2 (exclude *objective total number of activities involving E-learning during t_1 and t_2*)

The multiple regression required two conditions and five assumptions to be passed, as follows:

Condition 1**:** Dependent variable is continuous data

In this data analysis, the dependent variable was a *calculated performance expectancy at t_1*. This variable data was continuous, ranging from 0 to 10. Thus, this condition was met.

Condition 2**:** At least two independent variables comprising continuous data

There were four independent variables in each regression model: (a) *subjective percentage of E-learning usage in education during t_1 and t_2*; (b) *subjective time spent learning with E-learning during t_1 and t_2*; (c) *objective time spent on E-learning during t_1 and t_2*; (d) *objective total number of times logging onto E-learning during t_1 and t_2*. As the data from all four independent variables were continuous, the second condition was met.

Assumption 1**:** Sampling distribution of the sample mean for each variable is normal

The normality check and outlier detection for four independent variables (the four measurements of actual continued use of E-learning) and dependent variable (*calculated performance expectancy at t_1*) was carried out previously and the results suggested that the assumption of normality assumption was not violated (see Appendix 7-P).

Assumption 2 and 3: Linearity and Homoscedasticity

A scatterplot of the standardized residual and standardized predicted value was created to check the linearity and homoscedasticity assumption (see Figure 2). The result suggested that the assumption of linearity and homoscedasticity for the regression models between *calculated performance expectancy at t_1* and the four measurements of actual continued use of E-learning was not violated, since there was no systematic relationship between the standardized residual and standardized predicted value.

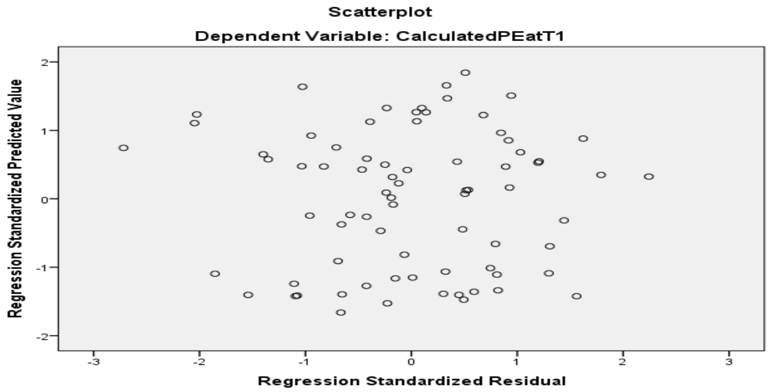


Figure 2: Scatterplot of residual and predicted value of the relationship between the calculated performance expectancy at t_1 and the four measurements of actual continued use of E-learning at t_2

Assumption 4: Independence of residual (error)

The Durbin-Watson test was used to evaluate the independence of residual. The result showed that the statistic for this data analysis was within the range of 1-2 (1.8), which was considered acceptable. This suggested that the assumption of independent errors has been met.

Assumption 5: Multicollinearity

This assumption was checked previously (see Appendix 7-P) and the result suggested that the assumption was not violated.

Appendix 7-V: Statistical conditions and assumptions checking of the dependent sample *t*-test between each expectation variable at t_0 and t_1

The dependent-sample *t* test required one condition and one assumption to be passed as follows:

Condition 1**:** Variables are continuous data

In this data analysis, there were 10 variables: the five measured expectations at t_0 and the five measured expectations at t_1. Expectation in this research was measured on a scale of 0 to 10. This condition there was met.

Assumption 1**:** Sampling distribution of the sample mean for each variable is normal

The normality check and outlier detection for the five initial expectations at t_0 and the five expectations at t_1 were checked previously. The results suggested that the assumption of normality assumption was not violated.

Appendix 7-W: Statistical conditions and assumptions checking of the correlation analysis between each expectation variable at t_0 and t_1

The correlation analysis required one condition and one assumption to be passed as follows:

Condition 1**:** Variables are continuous data

In this data analysis, there were 10 variables: the five measured expectation at t_0 and the five measured expectation at t_1. Expectation in this research was measured on a scale of 0 to 10. This condition, therefore, was met.

Assumption 1**:** Sampling distribution of the sample mean for each variable is normal

The normality check and outlier detection for the five initial expectations at t_0 and the five expectations at t_1 were checked previously. The results suggested that the assumption of normality assumption was not violated.

Appendix 7-X: Statistical conditions and assumptions checking of the stepwise regression analysis between the change of performance expectancy and related variables

The stepwise regression required two conditions and five assumptions to be passed, as follows:

<u>Condition 1</u>**:** Dependent variable is continuous data

In this data analysis, the dependent variable was a *change in performance expectancy between* t_0 *and* t_1. This variable data was continuous, ranging from -10 to 10. Thus, this condition was met.

<u>Condition 2</u>**:** At least two independent variables comprising continuous data

There were four independent variables in the regression model: (a) *performance expectancy confirmation at* t_1; (b) *perceived performance of the system at* t_1; (c) *facilitating condition expectancy at* t_1, and (d) *social encouragement expectancy at* t_1. As the data from all four independent variables were continuous, the second condition was met.

<u>Assumption 1</u>**:** Sampling distribution of the sample mean for each variable is normal

- *Change in performance expectancy between* t_0 *and* t_1

A review of the Shapiro-Wilk test for normality (*SW* = .99, *df* = 77, *p* = .71) and skewness (-.62) and kurtosis (-.1) statistics suggested that the *change in performance expectancy between* t_0 *and* t_1 data did not deviate significantly from normal (see Table 1).

Table 1: Normality test result for the change in performance expectancy between t_0 and t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Change of performance expectancy between t_0 and t_1	77	-.41 ± 1.6	-.17	.27	.63	no skewness	-.05	.54	- 0.1	no kurtosis	.99	77	.71	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *change in performance expectancy between* t_0 *and* t_1 data suggested that the assumption of normality was reasonable (see Figure 1). The boxplot indicated no outliers in the data. According to the central limit theorem, since the *change in performance* *expectancy between t_0 and t_1* data were distributed normally, the sampling distribution of the sample mean for this data was normal.

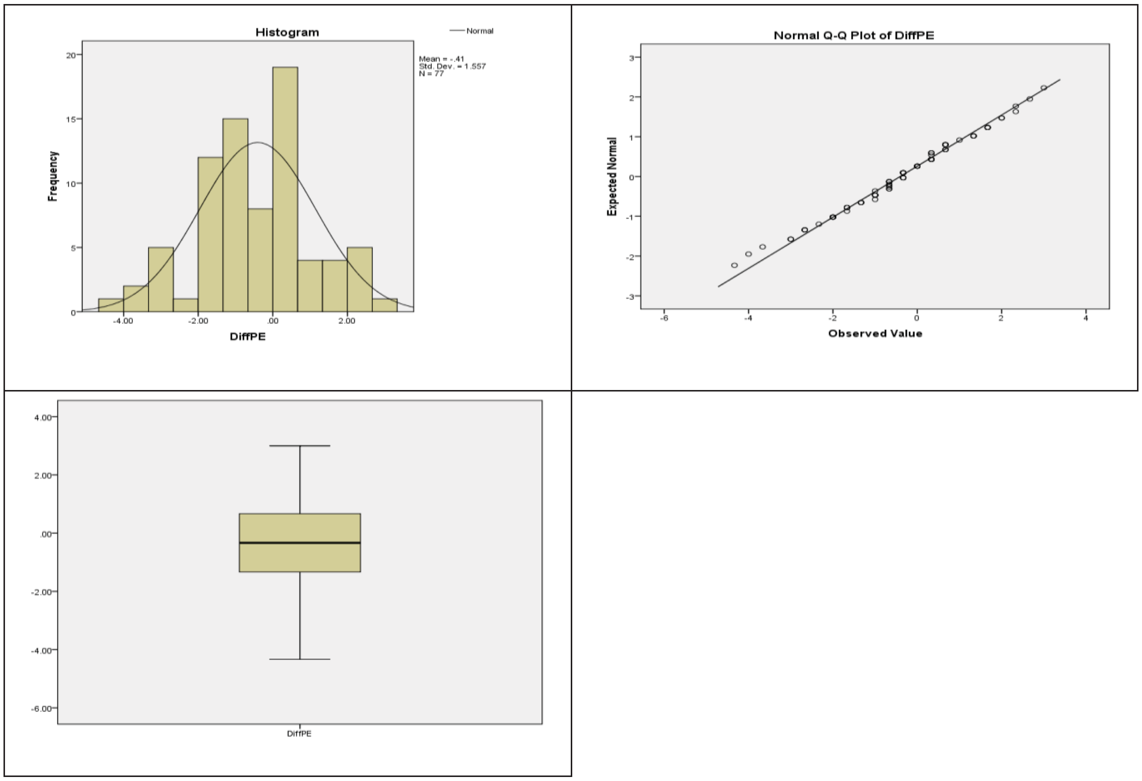


Figure 5: Histogram, Q-Q plot and boxplot for the change in performance expectancy between t_0 and t_1 data

- *Performance expectancy confirmation at t_1*

A review of the Shapiro-Wilk test for normality (*SW* = .98, *df* = 77, *p* = .26) and skewness (1.5) and kurtosis (1.1) statistics suggested that the *performance expectancy confirmation at t_1* data did not deviate significantly from normal (see Table 2)

Table 2: Normality test result for performance expectancy confirmation at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Performance expectancy confirmation at t_1	77	.93 ± .17	.42	.27	1.5	no skewness	.59	.54	1.1	no kurtosis	.98	77	.26	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *performance expectancy confirmation at t_1* data suggested the assumption of normality was reasonable (see Figure 2). The boxplot indicated one outlier (Case 47). As Case 47 data was not an extreme outlier, it was not excluded from data analysis. According to the central limit theorem, since the *performance expectancy confirmation at* t_1 data were distributed normally, the sampling distribution of the sample mean for this data was normal.

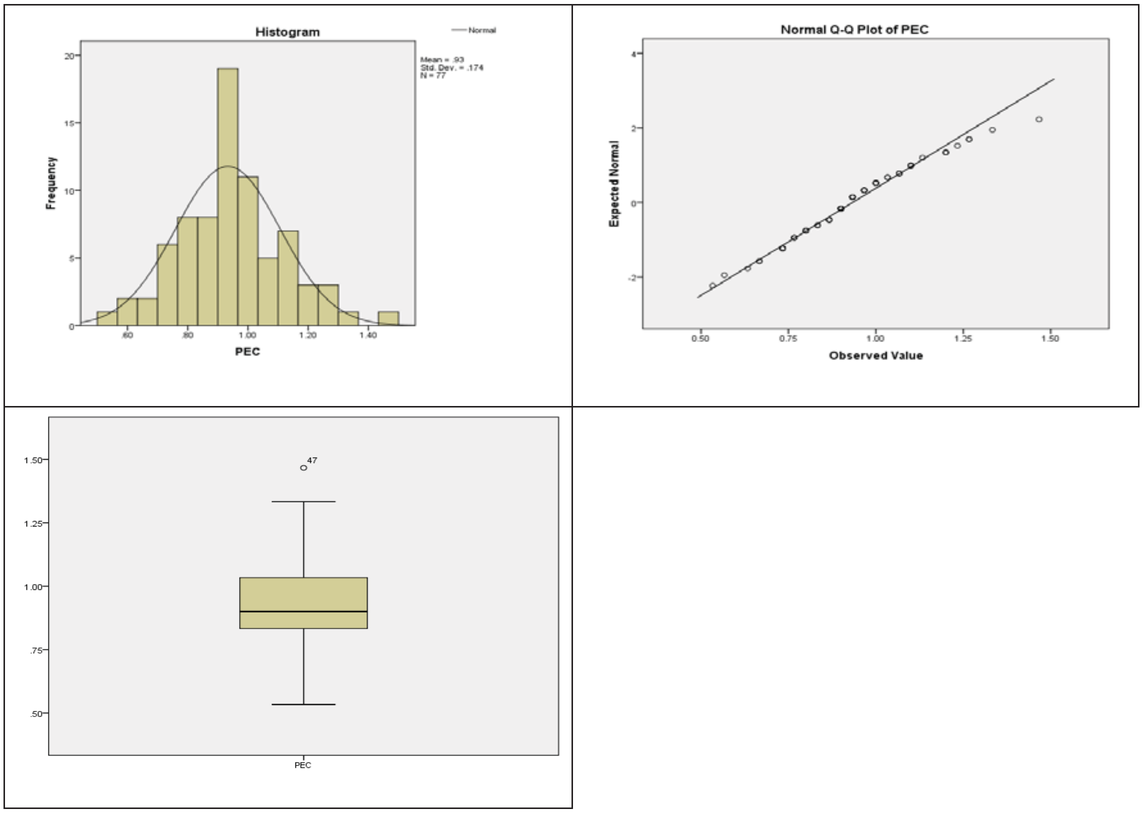


Figure 2: Histogram, Q-Q plot and boxplot for performance expectancy confirmation at t_1 data

- *Perceived performance of the system at* t_1

A review of the Shapiro-Wilk test for normality (*SW* = .99, *df* = 77, *p* = .87) and skewness (-.06) and kurtosis (-.75) statistics suggested that the *perceived performance of the system at* t_1 data did not deviate significantly from normal (see Table 3).

Table 3: Normality test result for perceived performance of the system at t_1

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Perceived performance of the system at t_1	77	6.5 ± 1.5	-.02	.27	-.06	no skewness	-.41	.54	-.75	no kurtosis	.99	77	.87	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *perceived performance of the system at* t_1 data suggested the assumption of normality was reasonable (see Figure 3). The boxplot indicated no outliers in this data. According to the central limit theorem, since the *perceived performance of the system at* t_1 data were distributed normally, the sampling distribution of the sample mean for this data was normal.

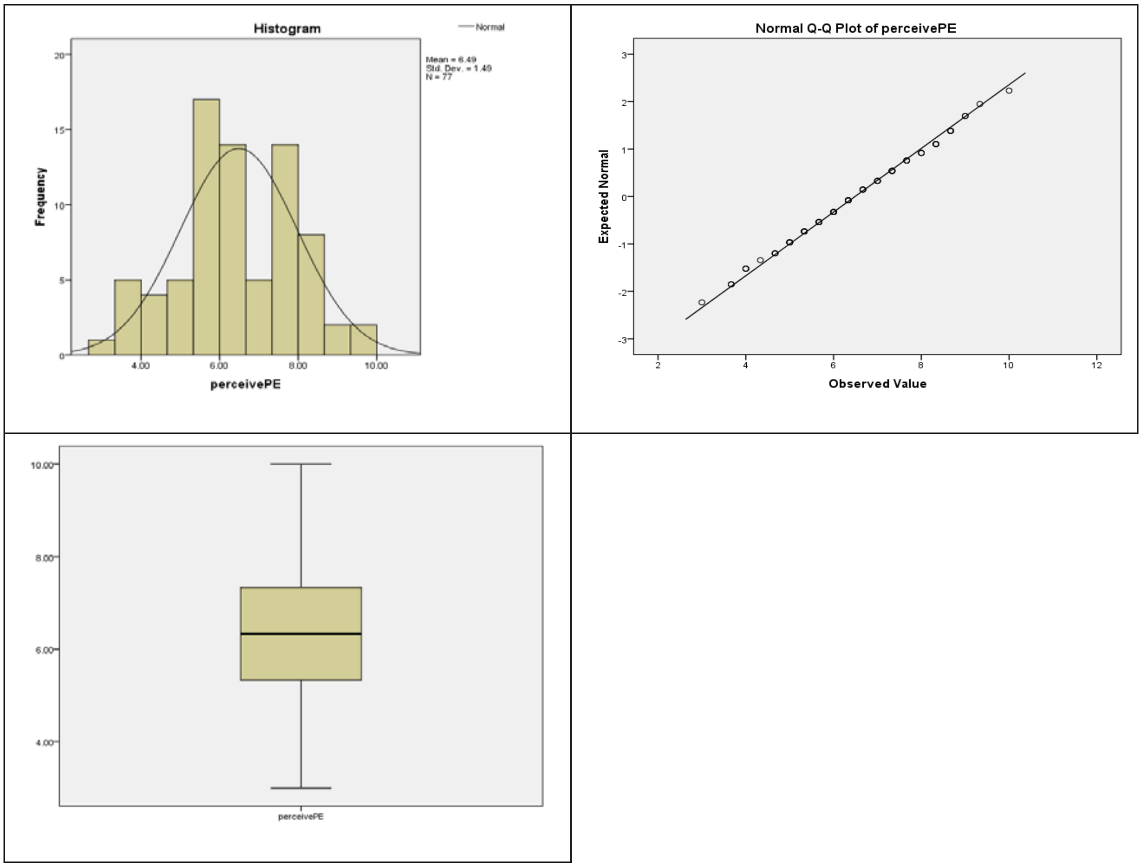


Figure 3: Histogram, Q-Q plot and boxplot for perceived performance of the system at t_1 data

- *Facilitating condition expectancy at* t_1

A review of the Shapiro-Wilk test for normality (*SW* = .97, *df* = 77, *p* = .08) and skewness (1.2) and kurtosis (-.79) statistics suggested that the *facilitating condition expectancy at* t_1 data did not deviate significantly from normal (see Table 4).

Table 4: Normality test for facilitating condition expectancy at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Measured FCE at T1	77	6.9 ± 1.3	.34	.27	1.2	no skewness	-.43	.54	-.79	no kurtosis	.97	77	.08	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *facilitating condition expectancy at* t_1 data suggested the assumption of normality was reasonable (see Figure 4). The boxplot indicated no outliers in this data. As the data of *facilitating condition expectancy at* $t_1$distributed normally, the sampling distribution of the sample mean for this variable was normal.

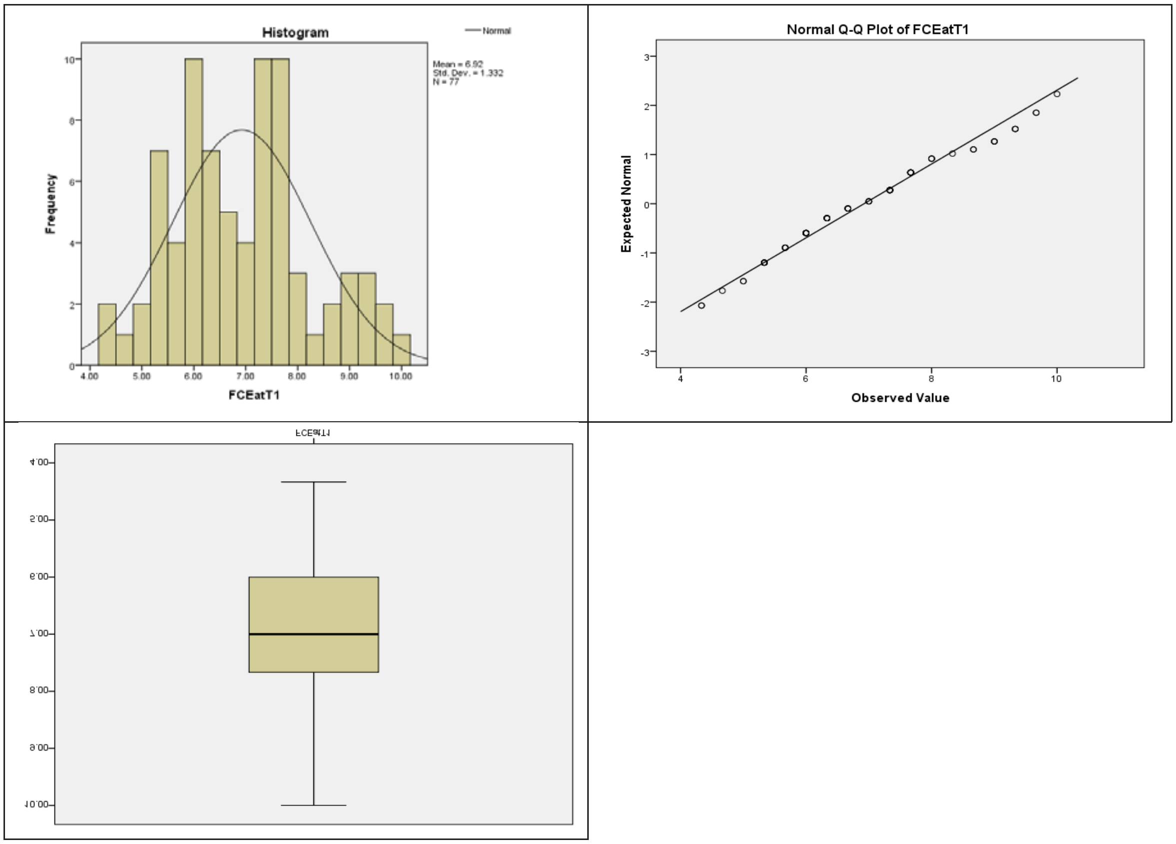


Figure 4: Histogram, Q-Q plot and boxplot for facilitating condition expectancy at t_1 data

- *Social encouragement expectancy at* t_1

A review of the Shapiro-Wilk test for normality (SW = .99, df = 77, p = .51) and skewness (1.0) and kurtosis (.23) statistics suggested that the *social encouragement expectancy at* t_1 data did not deviate significantly from normal (see Table 5).

Table 5: Normality test for measured social encouragement expectancy at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Measured SEE at T1	77	6.8 ± 1.3	.28	.27	1.0	no skewness	.13	.54	.23	no kurtosis	.99	77	.51	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *social encouragement expectancy at* t_1 data suggested the assumption of normality was reasonable (see Figure 5). The boxplot indicated two outliers in this data (Cases 25 and 75). As these two outliers were not extreme, they were not cut from the data analysis. Since the *social encouragement expectancy at* t_1 data were distributed normally, the sampling distribution of the sample mean for this variable was normal.

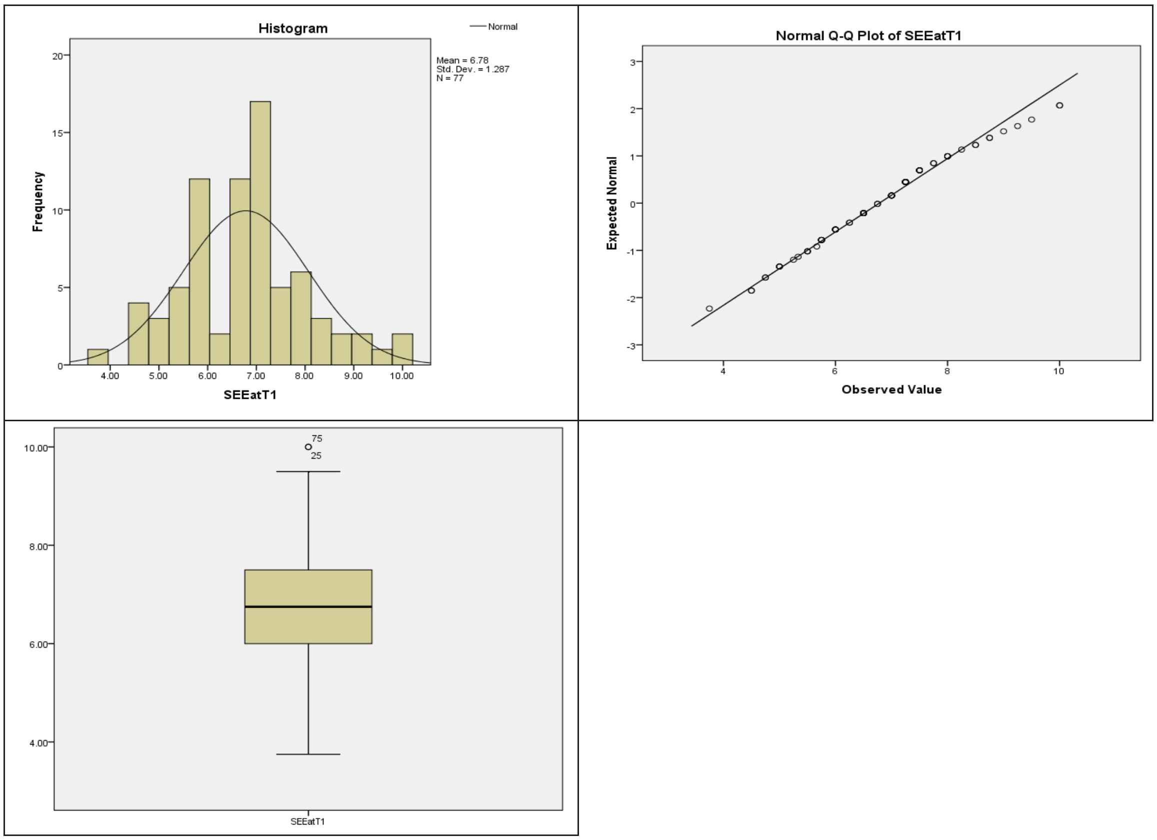


Figure 5: Histogram, Q-Q plot and boxplot for measured social encouragement expectancy at t_1 data

<u>Assumption 2 and 3</u>: Linearity and Homoscedasticity

A scatterplot of the standardized residual and standardized predicted value was created to check the linearity and homoscedasticity assumption (see Figure 6). The result suggested that the assumption of linearity and homoscedasticity for this regression model was not violated, since there was no systematic relationship between the standardized residual and standardized predicted value.

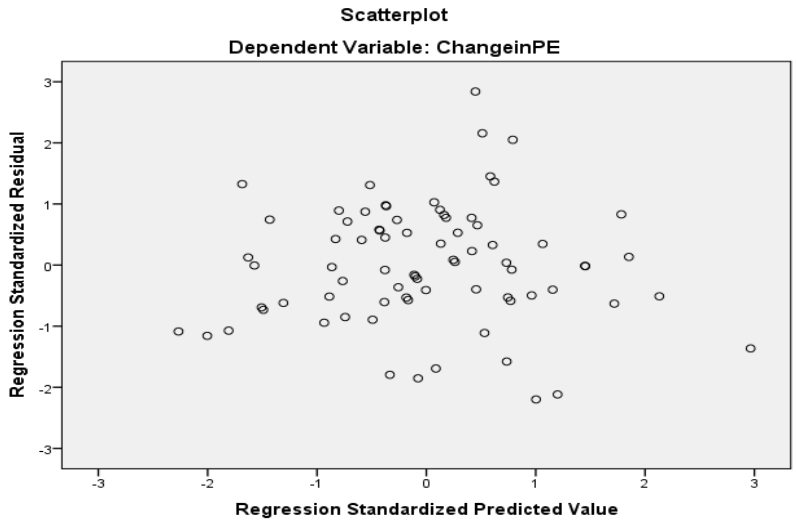


Figure 6: Scatterplot of residual of the relationship between the change of performance expectancy between t_0 and t_1 and four contributing variables

Assumption 4: Independence of residual (error)

The Durbin-Watson statistic was computed to evaluate independence of errors and was 2.2 which was considered acceptable. This suggests that the assumption of independent error has been met.

Assumption 5: Multicollinearity

The VIF test was applied to detect multicollinearity between four contributing variables of the change of performance expectancy between t_0 and t_1. According to the general rule of thumb, as VIF for each independent variable was lower than 10, multicollinearity was not a concern (see Table 6).

Table 6: Collinearity test for the four contributing variables of the change of performance expectancy between t_0 and t_1

Independent variable	VIF
performance expectancy confirmation at t_1	2.4
perceived performance of the system at t_1	3.4
facilitating condition expectancy at t_1	2.5
social encouragement expectancy at t_1	3.3

Appendix 7-Y: Statistical conditions and assumptions checking of the stepwise regression analysis between the change of effort expectancy and related variables

The multiple regression required two conditions and five assumptions to be passed:

<u>Condition 1</u>**:** Dependent variable comprises continuous data

In this data analysis, the dependent variable was a change in *effort expectancy between* t_0 *and* t_1. This variable data was continuous, ranging from -10 to 10. Thus, this condition was met.

<u>Condition 2</u>**:** At least two independent variables comprising continuous data

There were four independent variables in each regression model: (a) *effort expectancy confirmation at* t_1; (b) *perceived ease of use at* t_1; (c) *change in social encouragement expectancy* between t_0 *and* t_1; (d) *social encouragement expectancy at* t_0. As the data from all four independent variables were continuous, the second condition was met.

<u>Assumption 1</u>**:** Sampling distribution of the sample mean for each variable is normal

- *Change in effort expectancy between* t_0 *and* t_1

A review of the Shapiro-Wilk test for normality (*SW* = .98, *df* = 77, *p* = .24) and skewness (1.5) and kurtosis (.49) statistics suggested that the *change in effort expectancy between* t_0 *and* t_1 data did not deviate significantly from normal (see Table 1).

Table 1: Normality test result for change in effort expectancy between t_0 and t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Change in effort expectancy between t_0 and t_1	77	-.12 ± 1.6	.42	.27	1.5	no skewness	.26	.54	.49	no kurtosis	.98	77	.24	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for this data suggested the assumption of normality was reasonable (see Figure 1). The boxplot indicated one outlier in this data (Case 25). Case 25 data was not cut from the data analysis because it was not an extreme outlier. According to the central limit theorem, since the *change in effort expectancy between* t_0 *and* $t_1$data were distributed normally, the sampling distribution of the sample mean for this data was normal.

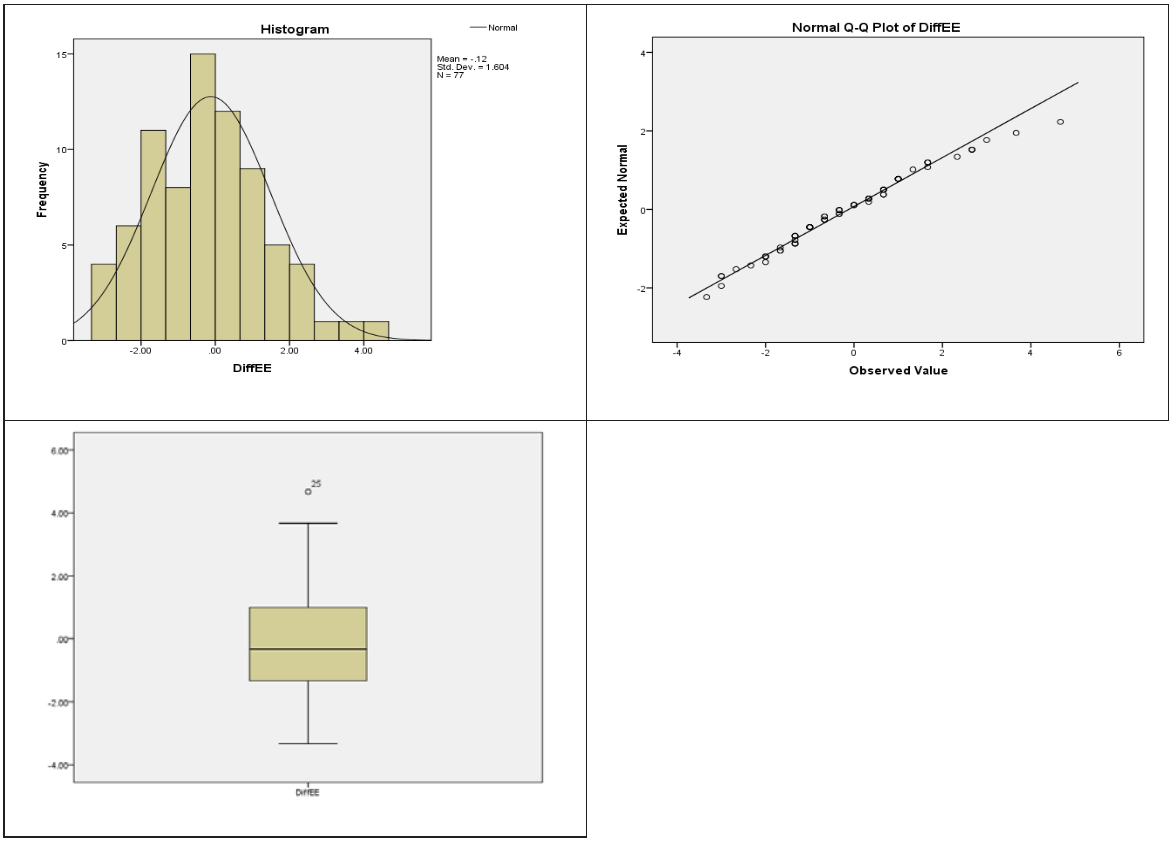


Figure 1: Histogram, Q-Q plot and boxplot for change in effort expectancy between t_0 and t_1 data

- *Effort expectancy confirmation at* t_1

A review of the Shapiro-Wilk test for normality (*SW* = .99, *df* = 77, *p* = .54) and skewness (.53) and kurtosis (-.29) statistics suggested that the *effort expectancy confirmation at* t_1 data did not deviate significantly from normal (see Table 2).

Table 2: Normality test result for effort expectancy confirmation at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Effort expectancy confirmation at t_1	77	.97 ± .18	.14	.27	.53	no skewness	-.15	.54	-.29	no kurtosis	.99	77	.54	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *effort expectancy confirmation at* t_1 data suggested the assumption of normality was reasonable (see Figure 2). The boxplot indicated no outliers in this data. According to the central limit theorem, since the *effort expectancy confirmation at* t_1 data were distributed normally, the sampling distribution of the sample mean for this data was normal.

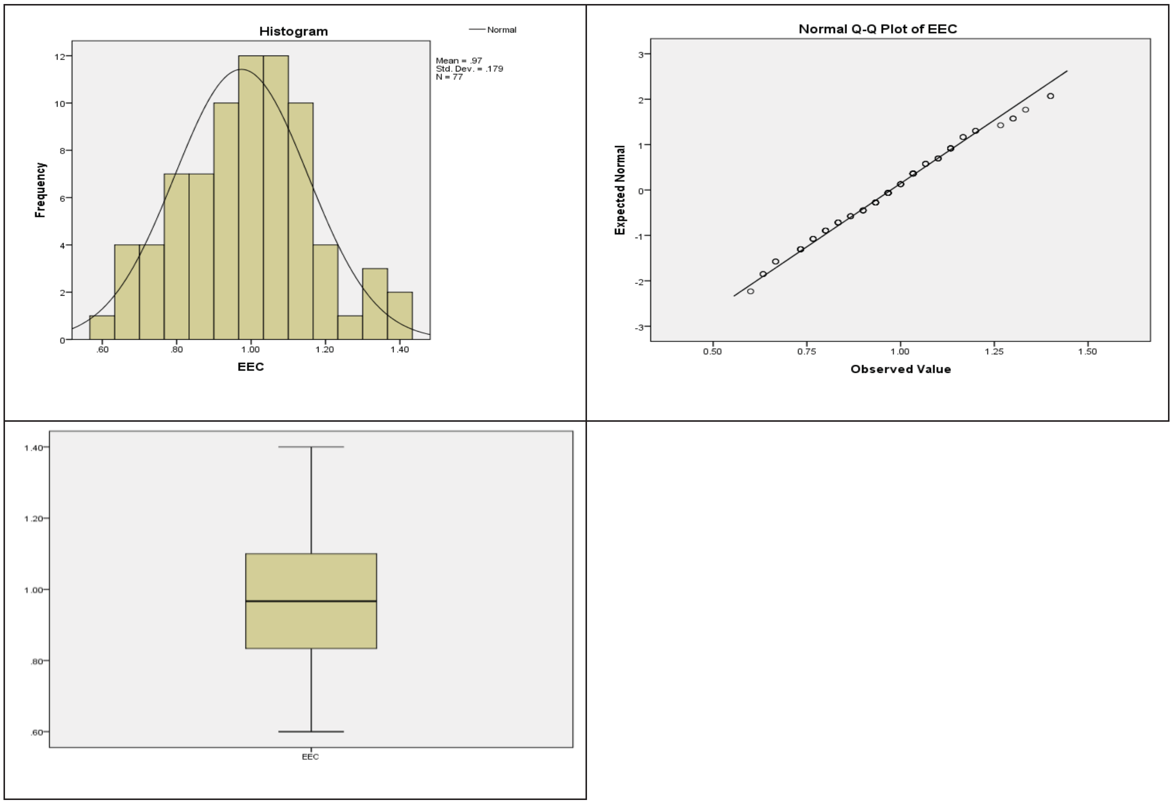


Figure 2: Histogram, Q-Q plot and boxplot for effort expectancy confirmation at t_1 data

- *Perceived ease of use at t_1*

A review of the Shapiro-Wilk test for normality (*SW* = .97, *df* = 77, *p* = .12) and skewness (.73) and kurtosis (-.56) statistics suggested that the *perceived ease of use at t_1* data did not deviate significantly from normal (see Table 3).

Table 3: Normality test result for perceived ease of use at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Perceived ease of use at t_1	77	6.42 ± 1.4	.20	.27	.73	no skewness	-.31	.54	-.56	no kurtosis	.97	77	.12	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *perceived ease of use at t_1* data suggested the assumption of normality was reasonable (see Figure 3). The boxplot indicated no outliers in this data. According to the central limit theorem, since the *perceived ease of use at t_1* data were distributed normally, the sampling distribution of the sample mean for this data was normal.

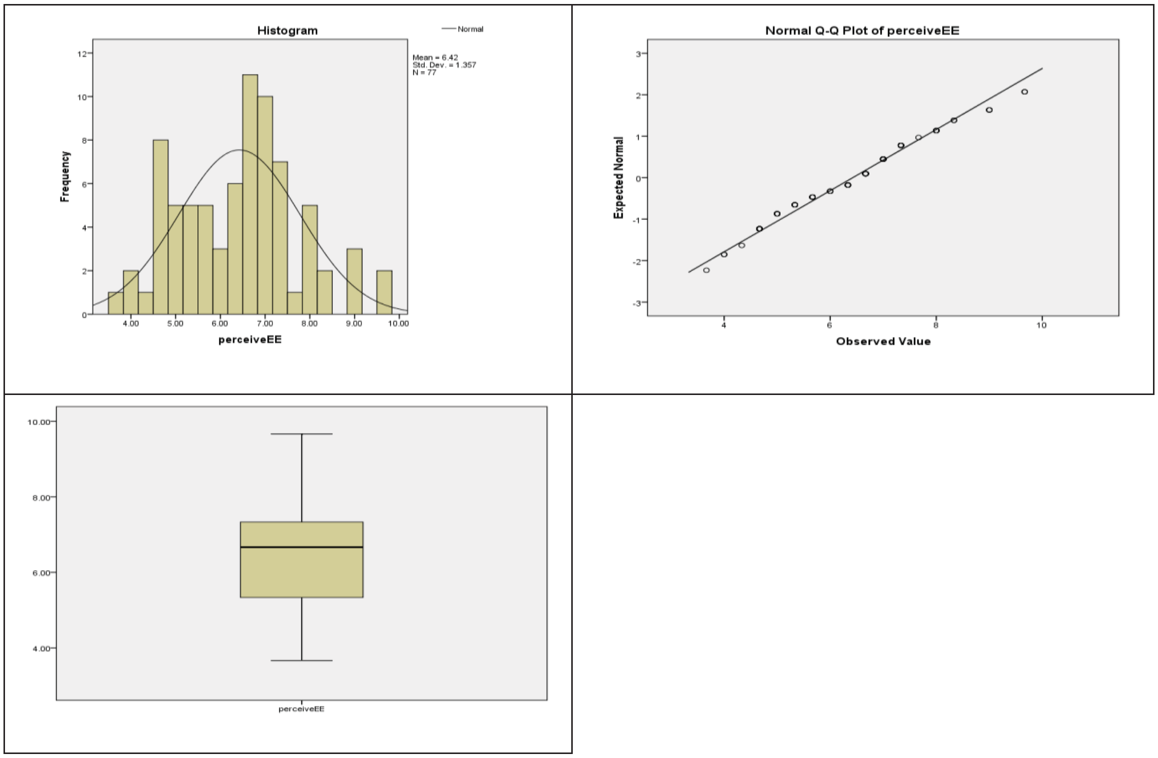


Figure 3: Histogram, Q-Q plot and boxplot for perceived ease of use at t_1 data

- *Change in social encouragement expectancy between t_0 and t_1*

A review of the Shapiro-Wilk test for normality (*SW* = .99, *df* = 77, *p* = .70) and skewness (-.46) and kurtosis (.46) statistics suggested that the *change in social encouragement expectancy between t_0 and t_1* data did not deviate significantly from normal (see Table 4).

Table 4: Normality test result for change in social encouragement expectancy between t_0 and t_1

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \le 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \le 2.56$)	Statistic	df	P-value	Conclusion ($p \le .01$)
Change in social encouragement expectancy between t_0 and t_1	77	-.25 ± 1.4	-.13	.27	-.46	no skewness	.25	.54	.46	no kurtosis	.99	77	.70	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *change in social encouragement expectancy between t_0 and t_1* data suggested the assumption of normality was reasonable (see Figure 4). The boxplot indicated two outliers in this data (Cases 8 and 47). These two outliers were not cut from the data analysis; they were not extreme. Since the *change in social encouragement expectancy between t_0 and t_1* data were distributed normally, the sampling distribution of the sample mean for this data was normal.

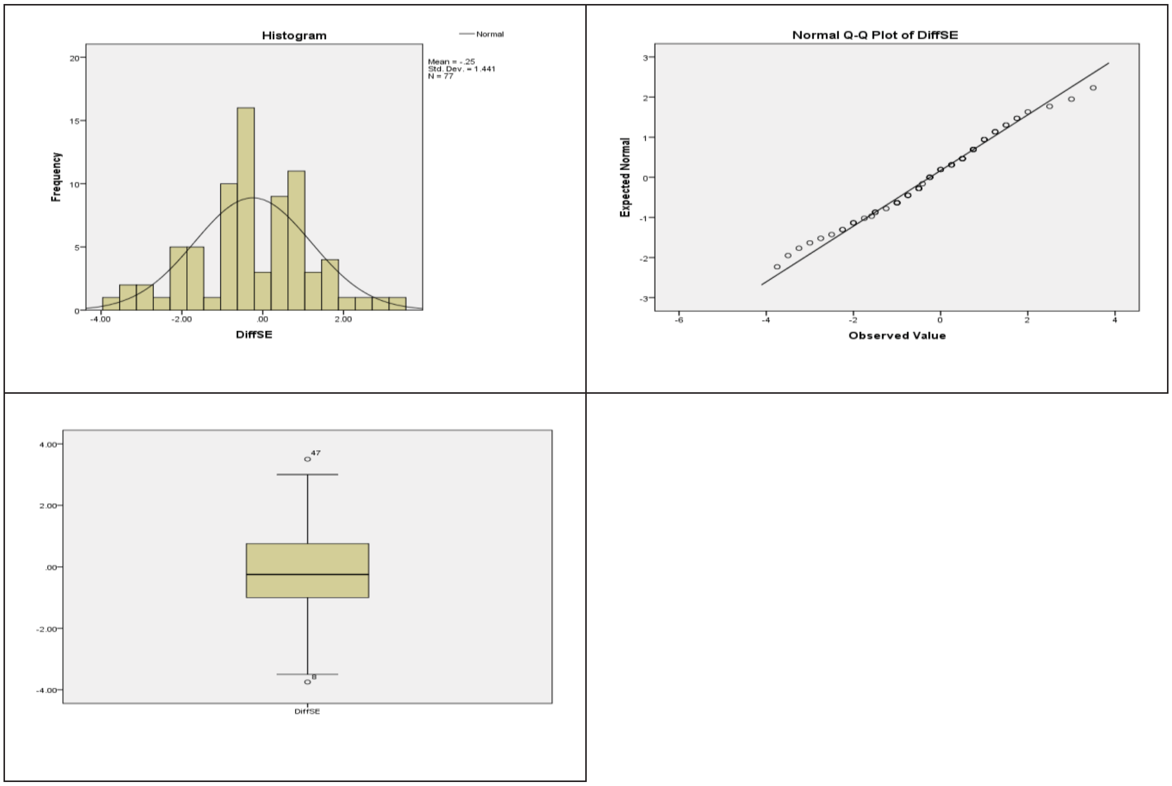


Figure 4: Histogram, Q-Q plot and boxplot for change in social encouragement expectancy between t_0 and t_1 data

- *Social encouragement expectancy at t_0*

A review of the Shapiro-Wilk test for normality (*SW* = .98, *df* = 102, *p* = .11) and skewness (-1.2) and kurtosis (-.77) statistics suggested that the *social encouragement expectancy at t_0* data did not deviate significantly from normal (see Table 5).

Table 5: Normality test for social encouragement expectancy at t_0 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{Kurtosis}$	Conclusion ($\|Z\| \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Social encouragement expectancy at T0	102	6.9 ± .12	-.29	.24	-1.2	no skewness	-.36	.47	-.77	no kurtosis	.98	102	.11	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for social encouragement expectation data at t_0 suggested the assumption of normality was reasonable. The boxplot suggested no outliers in this variable data (see Figure 5). According to the central limit theorem, as the *social encouragement expectation at t_0* data were distributed normally, the sampling distribution of the sample mean for this data was normal.

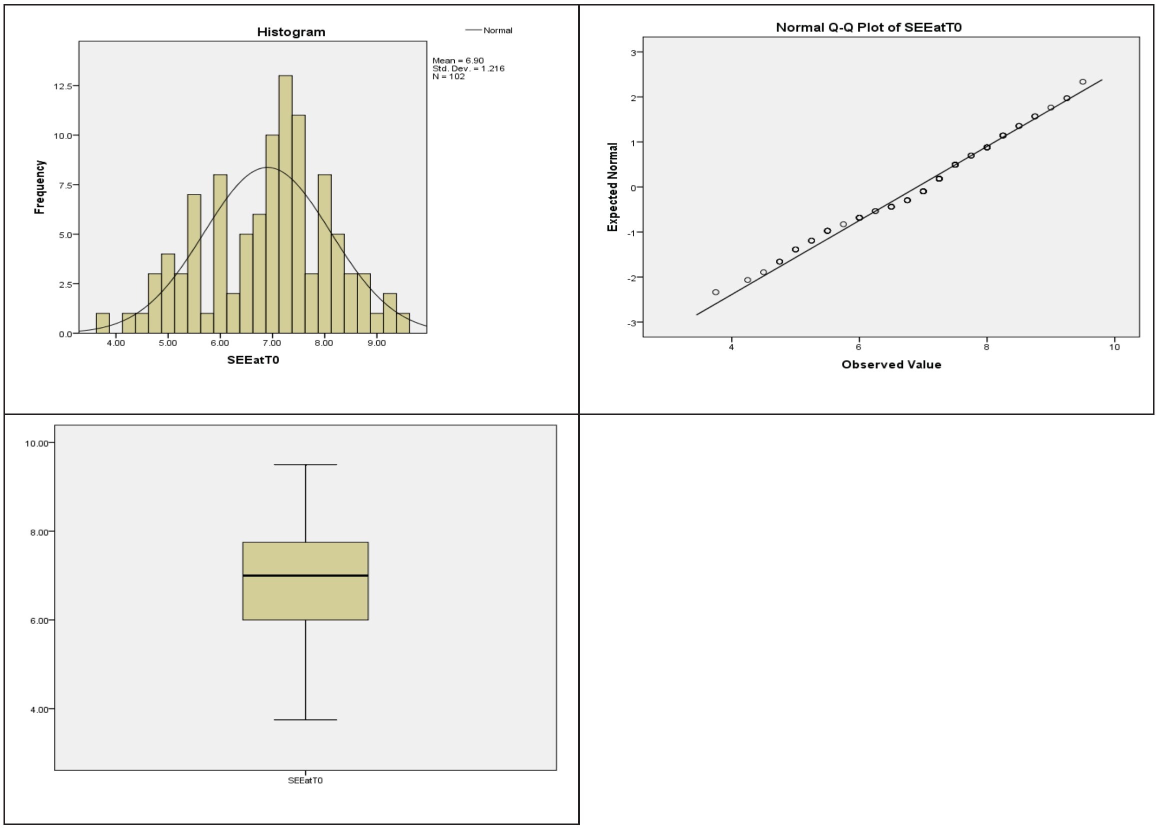


Figure 5: Histogram, Q-Q plot and boxplot for social encouragement expectancy at t_0 data

<u>Assumptions 2 and 3</u>: Linearity and Homoscedasticity

A scatterplot of the standardized residual and standardized predicted value was created to check the linearity and homoscedasticity assumption (see Figure 6). The result suggested that the assumption of linearity and homoscedasticity for this regression model was not violated, since there was no systematic relationship between the standardized residual and standardized predicted value.

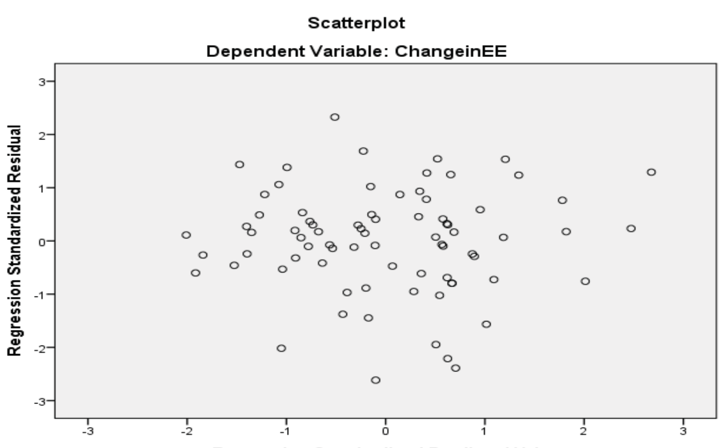


Figure 6: Scatterplot of residual of the relationship between the change of effort expectancy between t_0 and t_1 and four contributing variables

Assumption 4: Independence of residual (error)

The Durbin-Watson statistic was computed to evaluate independence of errors and was 2.2, which was considered acceptable. This suggests that the assumption of independent error has been met.

Assumption 5: Multicollinearity

The VIF test was applied to detect multicollinearity between four contributing variables of the change of effort expectancy between t_0 and t_1. According to the general rule of thumb, as VIF for each independent variable was lower than 10, multicollinearity was not a concern (see Table 6).

Table 6: Collinearity test for the four contributing variables of the change of effort expectancy between t_0 and t_1

Independent variable	**VIF**
effort expectancy confirmation at t_1	3.6
perceived ease of use at t_1	4.0
change in social encouragement expectancy between t_0 and t_1	2.3
social encouragement expectancy at t_0	2.3

Appendix 7-Z: Statistical conditions and assumptions checking of the stepwise regression analysis between the change of social encouragement expectancy and related variables

The multiple regression required two conditions and five assumptions to be passed as follows:

<u>Condition 1</u>**:** Dependent variable comprises continuous data

In this data analysis, the dependent variable was a *change in social encouragement expectancy between* t_0 *and* t_1. This variable data was continuous, ranging from -10 to 10. Thus, this condition was met.

<u>Condition 2</u>**:** At least two independent variables comprising continuous data

There were five independent variables in each regression model: (a) *social encouragement expectancy confirmation at* t_1; (b) *perceived social encouragement at* t_1; (c) *learning consistency expectancy at* t_1; (d) *effort expectancy at* t_1, and (e) *performance expectancy at* t_1. As the data from all five independent variables were continuous, the second condition was met.

<u>Assumption 1</u>**:** Sampling distribution of the sample mean for each variable is normal

- *Change in social encouragement expectancy between* t_0 *and* t_1

A review of the Shapiro-Wilk test for normality (*SW* = .99, *df* = 77, *p* = .70) and skewness (-.46) and kurtosis (.46) statistics suggested that the *change in social encouragement expectancy between* t_0 *and* t_1 data did not deviate significantly from normal (see Table 1).

Table 1: Normality test result for change in social encouragement expectancy between t_0 and t_1

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Change in social encouragement expectancy between t_0 and t_1	77	-.25 ± 1.4	-.13	.27	-.46	no skewness	.25	.54	.46	no kurtosis	.99	77	.70	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *change in social encouragement expectancy between* t_0 *and* t_1 data suggested the assumption of normality was reasonable (see Figure 1). The boxplot indicated two outliers in this data (Cases 8 and 47). These two outliers were not cut from the data analysis; they were not extreme. Since the *change in social encouragement expectancy between* t_0 *and* t_1 data were distributed normally, the sampling distribution of the sample mean for this data was normal.

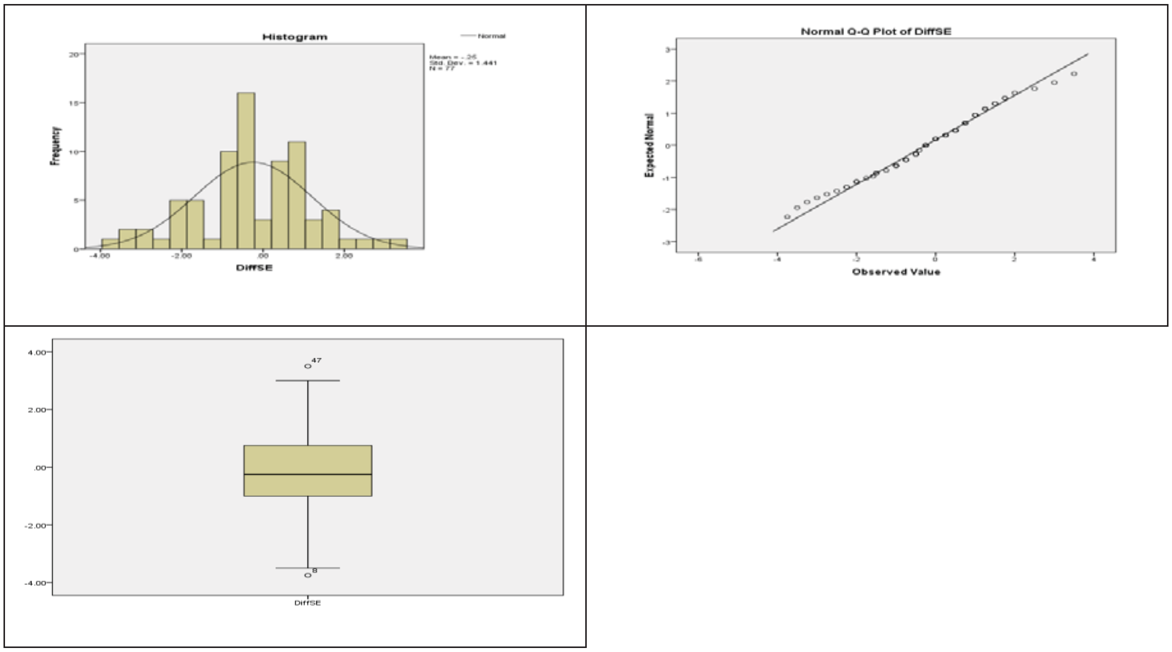


Figure 1: Histogram, Q-Q plot and boxplot for change in social encouragement expectancy between t_0 and t_1

- *Social encouragement expectancy confirmation at* t_1

A review of the Shapiro-Wilk test for normality (*SW* = .99, *df* = 77, *p* = .79) and skewness (.56) and kurtosis (.33) statistics suggested that the *social encouragement expectancy confirmation at* t_1 data did not deviate significantly from normal (see Table 2).

Table 2: Normality test result for social encouragement expectancy confirmation at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \le 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \le 2.56$)	Statistic	df	P-value	Conclusion ($p \le .01$)
Social encouragement expectancy confirmation at t_1	77	.97 ± .17	.15	.27	.56	no skewness	.18	.54	.33	no kurtosis	.99	77	.79	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *social encouragement expectancy confirmation at* t_1 data suggested the assumption of normality was reasonable (see Figure 2). The boxplot indicated two outliers in this data (Cases 28 and 65). As these two outliers were not extreme, they were not cut from the data analysis. According to the central limit theorem, since the *social encouragement* *expectancy confirmation at* t_1 data were distributed normally, the sampling distribution of the sample mean for this data was normal.

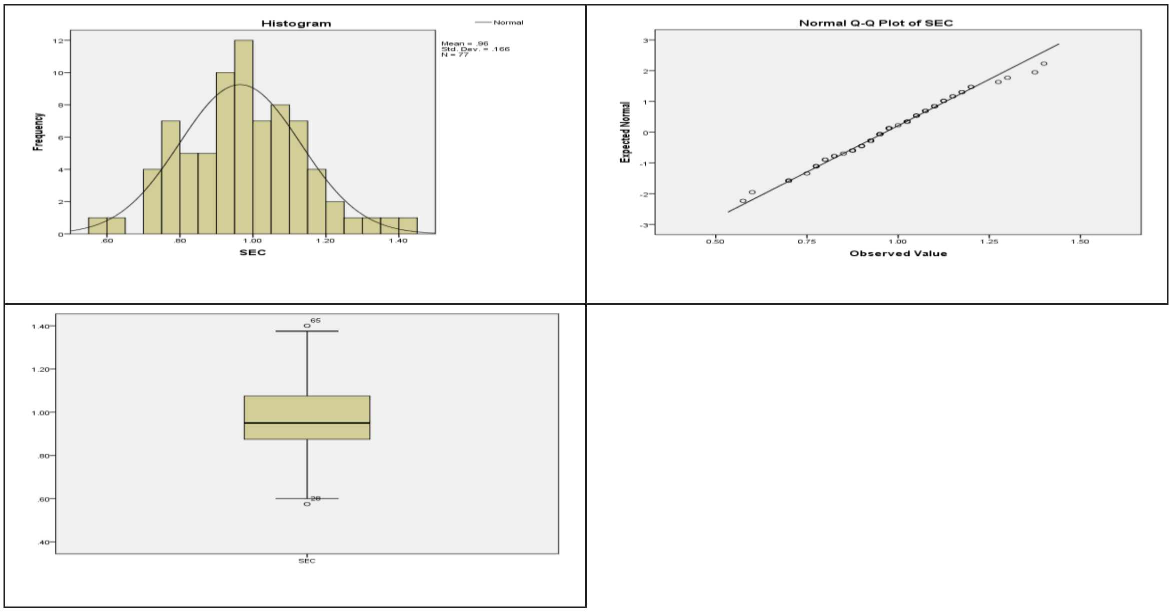


Figure 4: Histogram, Q-Q plot and boxplot for social encouragement expectancy confirmation at t_1 data

- *Perceived social encouragement at* t_1

A review of the Shapiro-Wilk test for normality (*SW* = .98, *df* = 77, *p* = .33) and skewness (.79) and kurtosis (-.87) statistics suggested that the *perceived social encouragement at* t_1 data did not deviate significantly from normal (see Table 3).

Table3: Normality test result for perceived social encouragement at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \le 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \le 2.56$)	Statistic	df	P-value	Conclusion ($p \le .01$)
Perceived social encouragement at t_1	77	6.68 ± 1.4	.22	.27	.79	no skewness	-.47	.54	-.87	no kurtosis	.98	77	.33	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *perceived social encouragement at* t_1 data suggested the assumption of normality was reasonable (see Figure 3). The boxplot indicated no outliers in this data. According to the central limit theorem, since the *perceived social encouragement at* t_1 data were distributed normally, the sampling distribution of the sample mean for this data was normal.

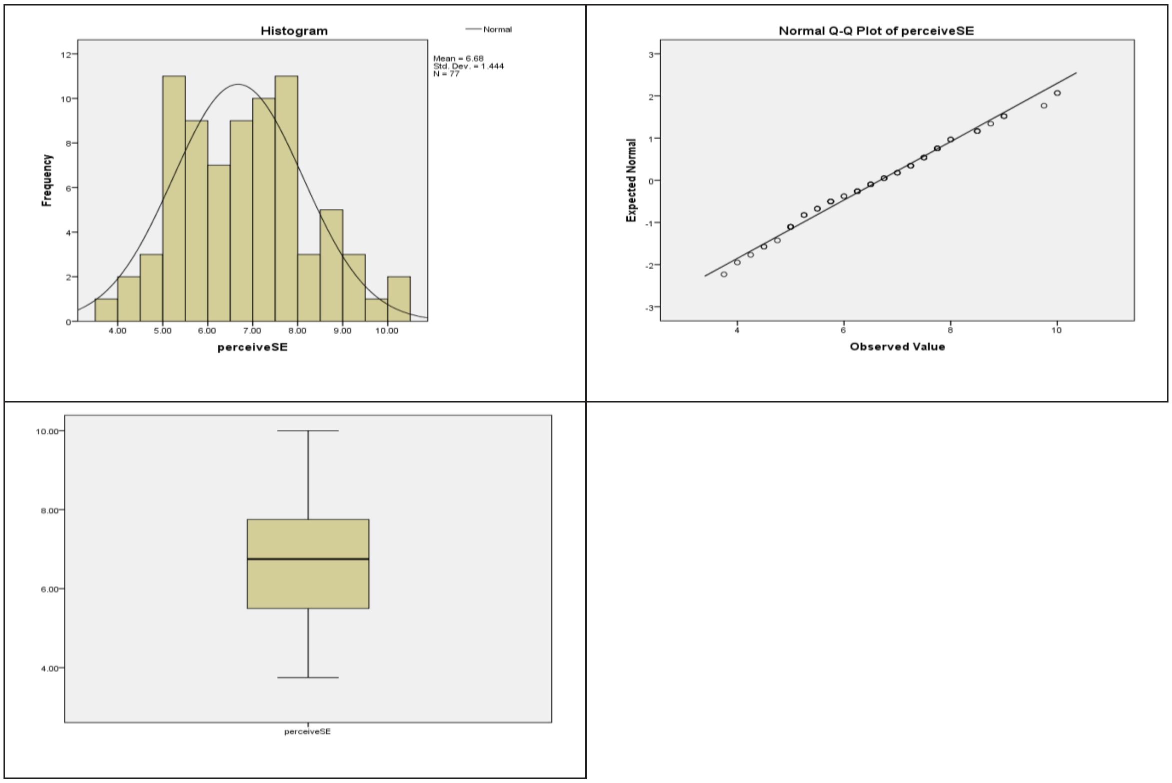


Figure 3: Histogram, Q-Q plot and boxplot for perceived social encouragement at t_1 data

- *Learning consistency expectancy at t_1*

A review of the Shapiro-Wilk test for normality (*SW* = .98, *df* = 77, *p* = .16) and skewness (.42) and kurtosis (1.0) statistics suggested that the *learning consistency expectancy at t_1* data did not deviate significantly from normal (see Table 4).

Table 4: Normality test for learning consistency expectancy at t_1

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Learning consistence expectancy at t_1	77	6.7 ± 1.5	.12	.27	.42	no skewness	-.56	.54	1.0	no kurtosis	.98	77	.16	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *learning consistency expectancy at t_1* data suggested the assumption of normality was reasonable (see Figure 4). The boxplot indicated no outliers in this data. As the data of *learning consistency expectancy at t_1* distributed normally, the sampling distribution of the sample mean for this variable was normal.

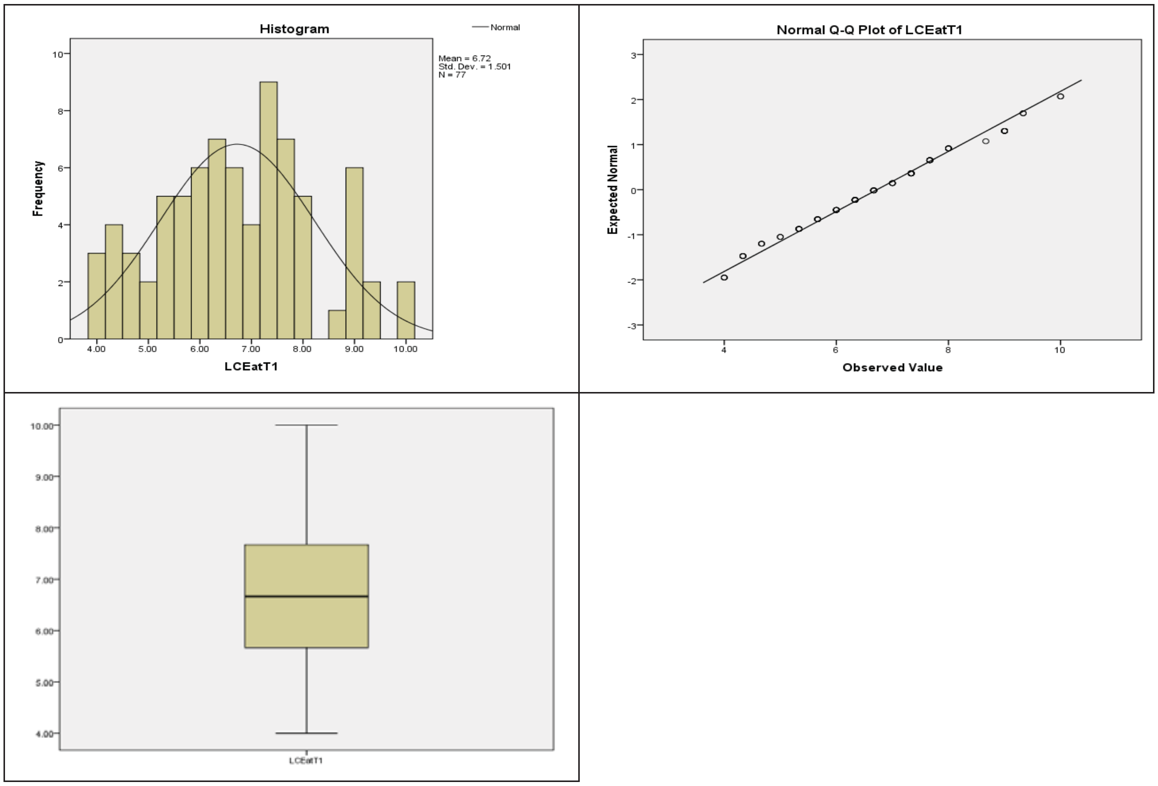


Figure 4: Histogram, Q-Q plot and boxplot for learning consistency expectancy at t_1 data

- *Effort expectancy at* t_1

A review of the Shapiro-Wilk test for normality (*SW* = .97, *df* = 77, *p* = .09) and skewness (1.6) and kurtosis (.007) statistics suggested that the *measured effort expectancy at* t_1 data did not deviate significantly from normal (see Table 5).

Table 5: Normality test for measured effort expectancy at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Measured EE at T1	77	6.6 ± 1.2	.43	.27	1.6	no skewness	.004	.54	.007	no kurtosis	.97	77	.09	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *measured effort expectancy at* t_1 data suggested the assumption of normality was reasonable (see Figure 5). The boxplot indicated one outlier in this data (Case 75). However, that outlier was not cut since its value was not higher than Q_3 + 3×IQR: it was not an extreme outlier. As the *measured effort expectancy at* t_1 data were distributed normally, the sampling distribution of the sample mean for this variable was normal.

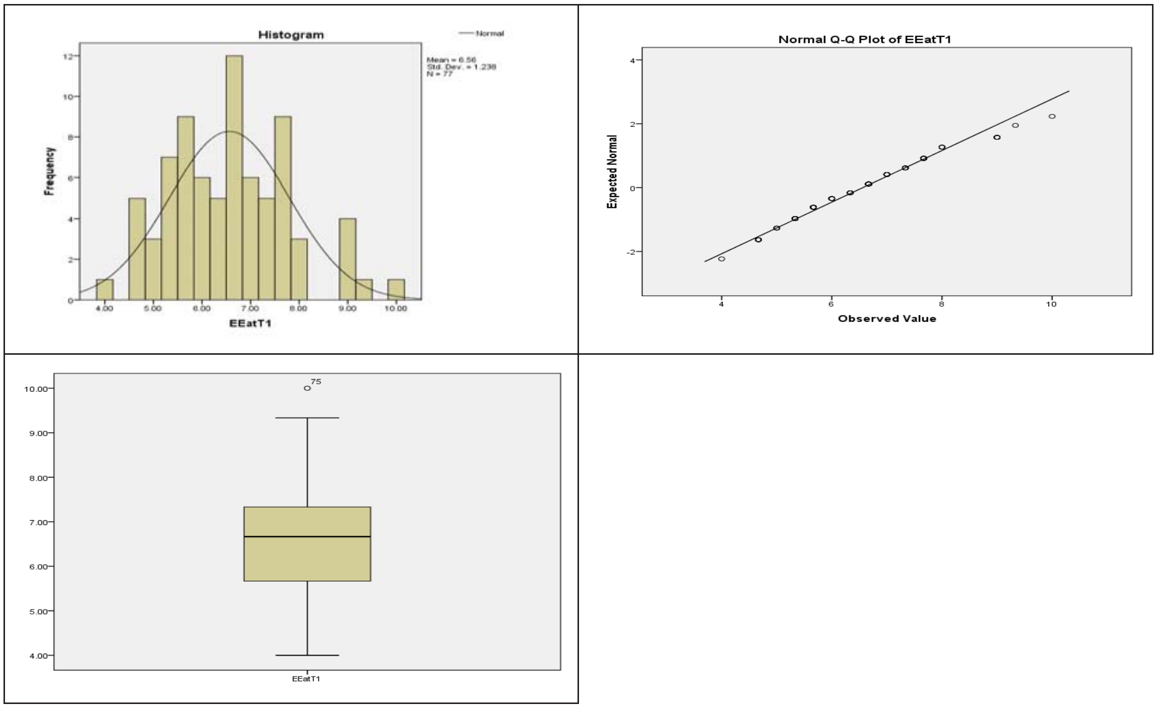


Figure 5: Histogram, Q-Q plot and boxplot for measured effort expectancy at t_1 data

- *Performance expectancy at* t_1

A review of the Shapiro-Wilk test for normality (*SW* = .97, *df* = 77, *p* = .05) and skewness (-.66) and kurtosis (-1.4) statistics suggested that the *measured performance expectancy at* t_1 data did not deviate significantly from normal (see Table 6).

Table 6: Normality test for measured performance expectancy at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Measured PE at T1	77	6.8 ± 1.3	-.18	.27	-.66	no skewness	-.75	.54	-1.4	no kurtosis	.97	77	.05	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *measured performance expectancy at* t_1 data suggested the assumption of normality was reasonable (see Figure 6). The boxplot indicated no outliers in this data. As the data of *measured performance expectancy at* t_1 distributed normally, the sampling distribution of the sample mean for this variable was normal.

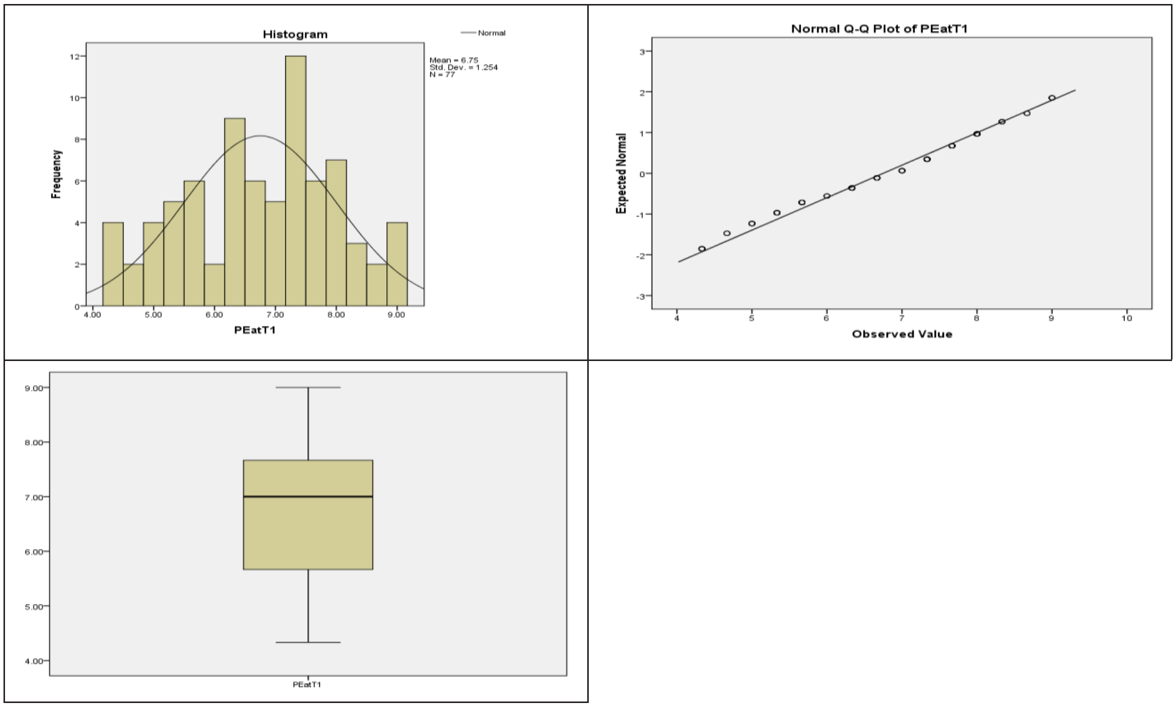


Figure 6: Histogram, Q-Q plot and boxplot for measured performance expectancy at t_1 data

<u>Assumptions 2 and 3</u>: Linearity and Homoscedasticity

A scatterplot of the standardized residual and standardized predicted value was created to check the linearity and homoscedasticity assumption (see Figure 7). The result suggested that the assumption of linearity and homoscedasticity for this regression model was not violated, since there was no systematic relationship between the standardized residual and standardized predicted value.

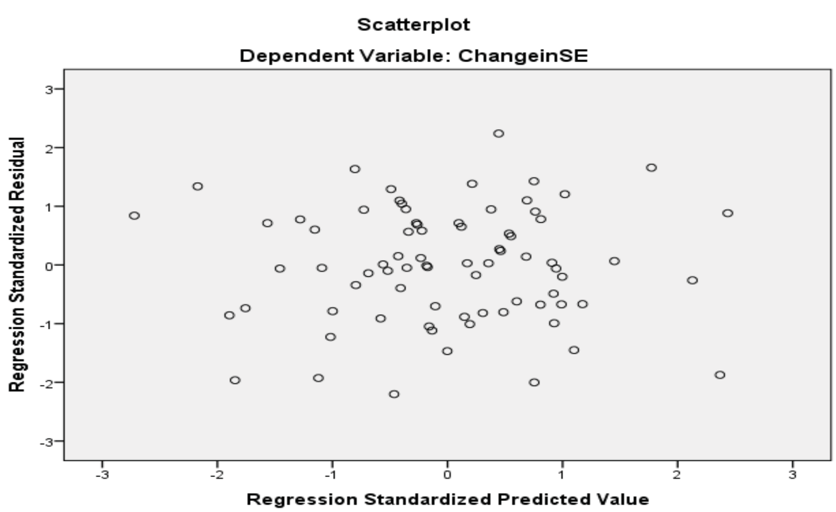


Figure 7: Scatterplot of residual and predicted value of the relationship between the change of social encouragement expectancy between t_0 and t_1 and five contributing variables

Assumption 4: Independence of residual (error)

The Durbin-Watson statistic was computed to evaluate independence of errors and was 2.4, which was considered acceptable. This suggests that the assumption of independent error has been met.

Assumption 5: Multicollinearity

The VIF test was applied to detect multicollinearity between the five contributing variables of the change of social encouragement expectancy between t_0 and t_1. According to the general rule of thumb, as VIF for each independent variable was lower than 10, multicollinearity was not a concern (see Table 7).

Table 7: Collinearity test for the five contributing variables of the change of social encouragement expectancy between t_0 and t_1

Independent variable	**VIF**
social encouragement expectancy confirmation at t_1	2.5
perceived social encouragement at t_1	5.3
learning consistency expectancy at t_1	3.3
effort expectancy at t_1	2.2
performance expectancy at t_1	2.9

Appendix 7-ZA: Statistical conditions and assumptions checking of the stepwise regression analysis between the change of facilitating condition expectancy and related variables

The multiple regression required two conditions and five assumptions to be passed as follows:

Condition 1**:** Dependent variable is continuous data

In this data analysis, the dependent variable was a *change in facilitating condition expectancy between t_0 and t_1*. This variable data was continuous, ranging from -10 to 10. Thus, this condition was met.

Condition 2**:** At least two independent variables comprising continuous data

There were six independent variables in each regression model: (a) *facilitating condition expectancy confirmation at t_1*; (b) *change in learning consistency expectancy between t_0* and t_1; (c) *perceived facilitating condition at t_1*; (d) *learning consistency expectancy at t_0*; (e) *change in performance expectancy between t_0* and t_1; and (f) *performance expectancy confirmation at t_1*. As the data from all five independent variables were continuous, the second condition was met.

Assumption 1**:** Sampling distribution of the sample mean for each variable is normal

- *Change in facilitating condition expectancy between t_0 and t_1*

A review of the Shapiro-Wilk test for normality (*SW* = .99, *df* = 77, *p* = .49) and skewness (.98) and kurtosis (.69) statistics suggested that the *change in facilitating condition expectancy between t_0 and t_1* data did not deviate significantly from normal (see Table 1).

Table 1: Normality test result for the change in facilitating condition expectancy between t_0 and t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Change in facilitating condition expectancy between t_0 and t_1	77	-.37 ± 1.5	.27	.27	.98	no skewness	.37	.54	.69	no kurtosis	.99	77	.49	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *change in facilitating condition expectancy between t_0 and t_1* data suggested the assumption of normality was reasonable (see Figure 1). The boxplot indicated one outlier (Case 16). As Case 16 data was not an extreme outlier, it was not cut from the data analysis. According to the central limit theorem, the sampling distribution of the sample mean for the *change in facilitating condition expectancy between t_0 and t_1* data was normal since this data at T1 distributed normally.

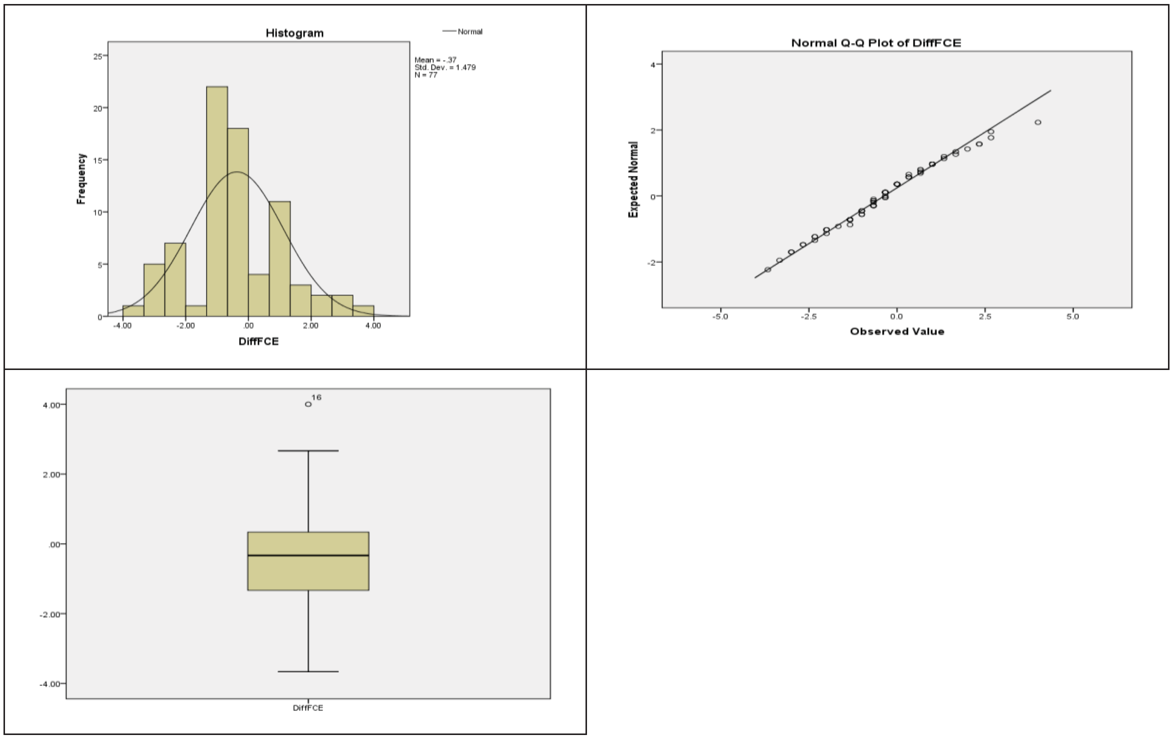


Figure 1: Histogram, Q-Q plot and boxplot for the change in facilitating condition expectancy between t_0 and t_1 data

- *Facilitating condition expectancy confirmation at t_1*

A review of the Shapiro-Wilk test for normality (*SW* = .98, *df* = 77, *p* = .15) and skewness (-1.2) and kurtosis (1.3) statistics suggested that the *facilitating condition expectancy confirmation at t_1* data did not deviate significantly from normal (see Table 2).

Table 2: Normality test result for facilitating condition expectancy confirmation at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Facilitating condition expectancy confirmation at t_1	77	.92 ± .18	-.36	.27	-1.2	no skewness	.68	.54	1.3	no kurtosis	.98	77	.15	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *facilitating condition expectancy confirmation at t_1* (see Figure 2). The boxplot indicated five outliers in this data (Cases 2, 7, 22, 42 and 47). As these outliers were not extreme, they were not cut from the data analysis. According to the central limit theorem, since the *facilitating condition expectancy confirmation at* $t_1$data were distributed normally, the sampling distribution of the sample mean for this data was normal.

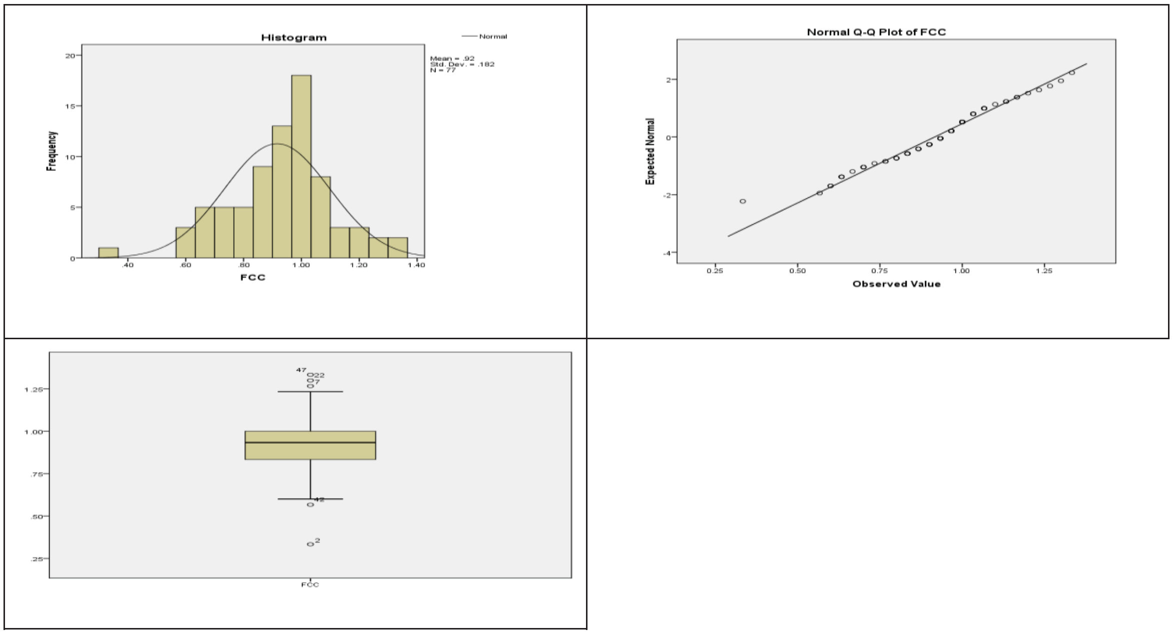


Figure 2: Histogram, Q-Q plot and boxplot for facilitating condition expectancy confirmation at t_1 data

- *Change in learning consistency expectancy between* t_0 and t_1

A review of the Shapiro-Wilk test for normality (*SW* = .98, *df* = 77, *p* = .25) and skewness (-1.4) and kurtosis (1.7) statistics suggested that the *change in learning consistency expectancy between* t_0 and t_1 data did not deviate significantly from normal (see Table 3).

Table 3: Normality test result for change in learning consistency expectancy between t_0 and t_1

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Change in learning consistence expectancy between t_0 and t_1	77	-.56 ± 1.5	-.38	.27	-1.4	no skewness	.90	.54	1.7	no kurtosis	.98	77	.25	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *change in learning consistency expectancy between* t_0 and t_1 data suggested the assumption of normality was reasonable (see Figure 3). The boxplot indicated three outliers in this data (Cases 2, 28 and 47). As these three outliers were not extreme, they were not cut from the data analysis. Since the *change in learning consistency expectancy between* t_0 and t_1 data were distributed normally, the sampling distribution of the sample mean for this data was normal.

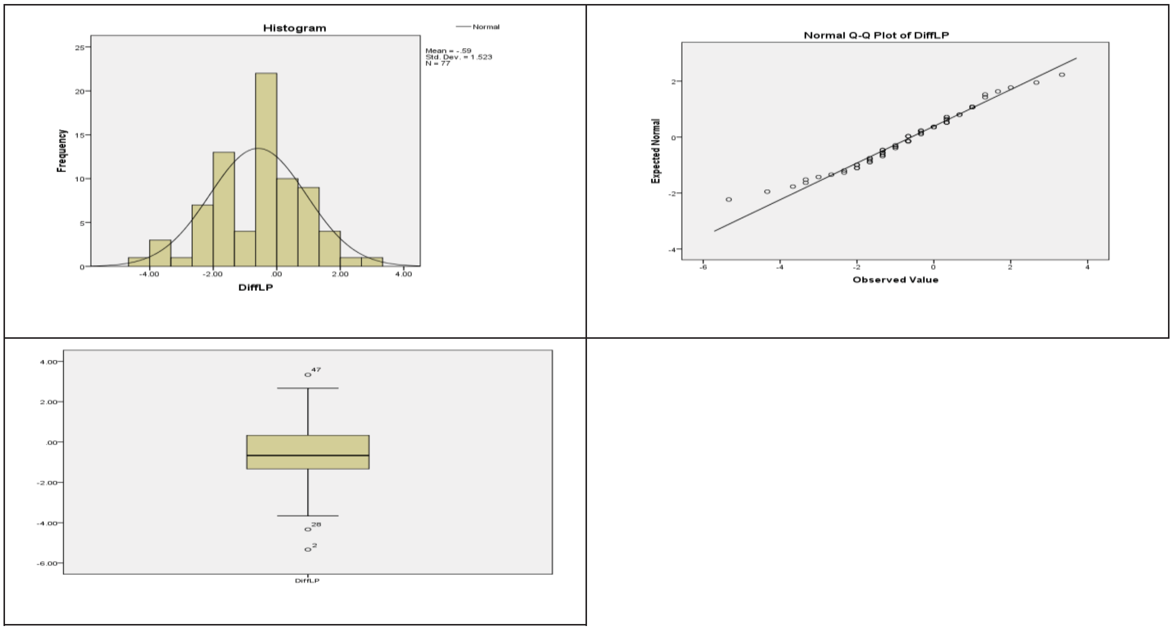


Figure 3: Histogram, Q-Q plot and boxplot for change in learning consistency expectancy between t_0 and t_1 data

- *Perceived facilitating condition at* t_1

A review of the Shapiro-Wilk test for normality (*SW* = .96, *df* = 77, *p* = .03) and skewness (-2.0) and kurtosis (-.26) statistics suggested that the *perceived facilitating condition at* t_1 data did not deviate significantly from normal (see Table 4).

Table 4: Normality test result for perceived facilitating condition at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Perceived facilitating condition at t_1	77	6.5 ± 1.5	-.54	.27	-2.0	no skewness	-.14	.54	-.26	no kurtosis	.96	77	.03	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *perceived facilitating condition at* t_1 data suggested the assumption of normality was reasonable (see Figure 4). The boxplot indicated no outliers in this data. According to the central limit theorem, since the *perceived facilitating condition at* t_1 data were distributed normally, the sampling distribution of the sample mean for this data was normal.

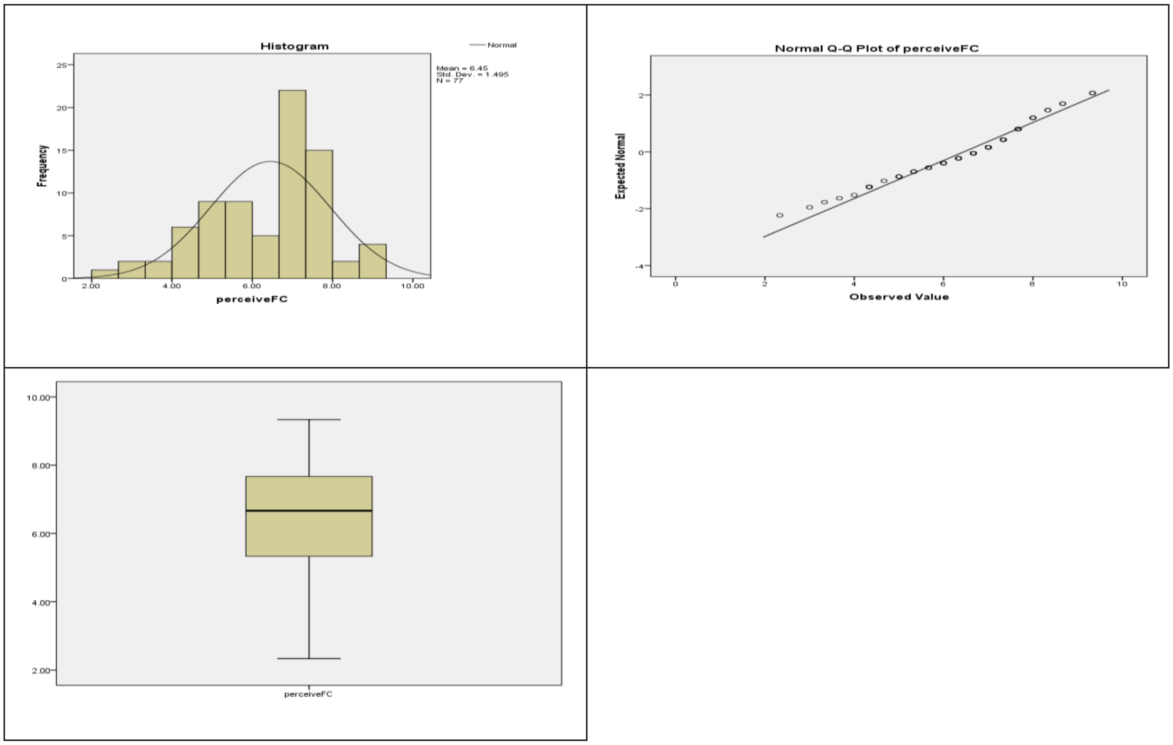


Figure 4: Histogram, Q-Q plot and boxplot for perceived facilitating condition at t_1 data

- *Learning consistency expectancy at* t_0

A review of the Shapiro-Wilk test for normality (*SW* = .98, *df* = 102, *p* = .06) and skewness (-1.2) and kurtosis (-.49) statistics suggested that the *learning consistency expectancy at* t_0 data did not deviate significantly from normal (see Table 5).

Table 5: Normality test for learning consistency expectation at t_0 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($\|Z\| \le 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($\|Z\| \le 2.56$)	Statistic	df	P-value	Conclusion ($p \le .01$)
Learning consistence expectancy at T0	102	7.2 ± .14	-.39	.24	-1.6	no skewness	-.37	.47	-.77	no kurtosis	.98	102	.06	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *learning consistency expectancy at* t_0 data suggested the assumption of normality was reasonable with no outliers (see Figure 5). The boxplot of this data showed no outlier. According to the central limit theorem, as the *learning consistency expectancy at* t_0 data were distributed normally, the sampling distribution of the sample mean for this data was normal.

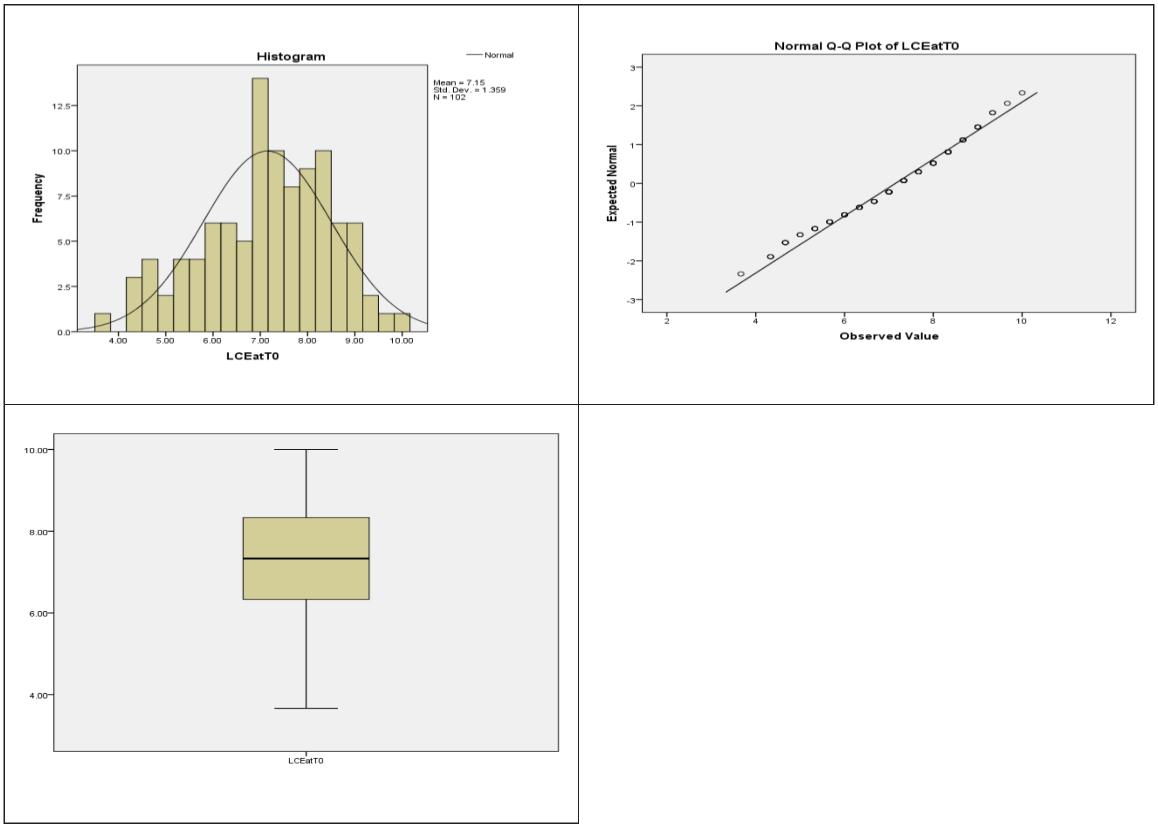


Figure 5: Histogram, Q-Q plot and boxplot for learning consistency expectation at t_0

- *Change in performance expectancy between t_0 and t_1*

A review of the Shapiro-Wilk test for normality (*SW* = .99, *df* = 77, *p* = .71) and skewness (-.62) and kurtosis (-.1) statistics suggested that the *change in performance expectancy between t_0 and t_1* data did not deviate significantly from normal (see Table 6).

Table 6: Normality test result for the change in performance expectancy between t_0 and t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Change of performance expectancy between t_0 and t_1	77	-.41 ± 1.6	-.17	.27	.63	no skewness	-.05	.54	- 0.1	no kurtosis	.99	77	.71	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *change in performance expectancy between t_0 and t_1* data suggested the assumption of normality was reasonable (see Figure 6). The boxplot indicated no outliers in this data. According to the central limit theorem, since the *change in performance expectancy between* t_0 *and* t_1 data were distributed normally, the sampling distribution of the sample mean for this data was normal.

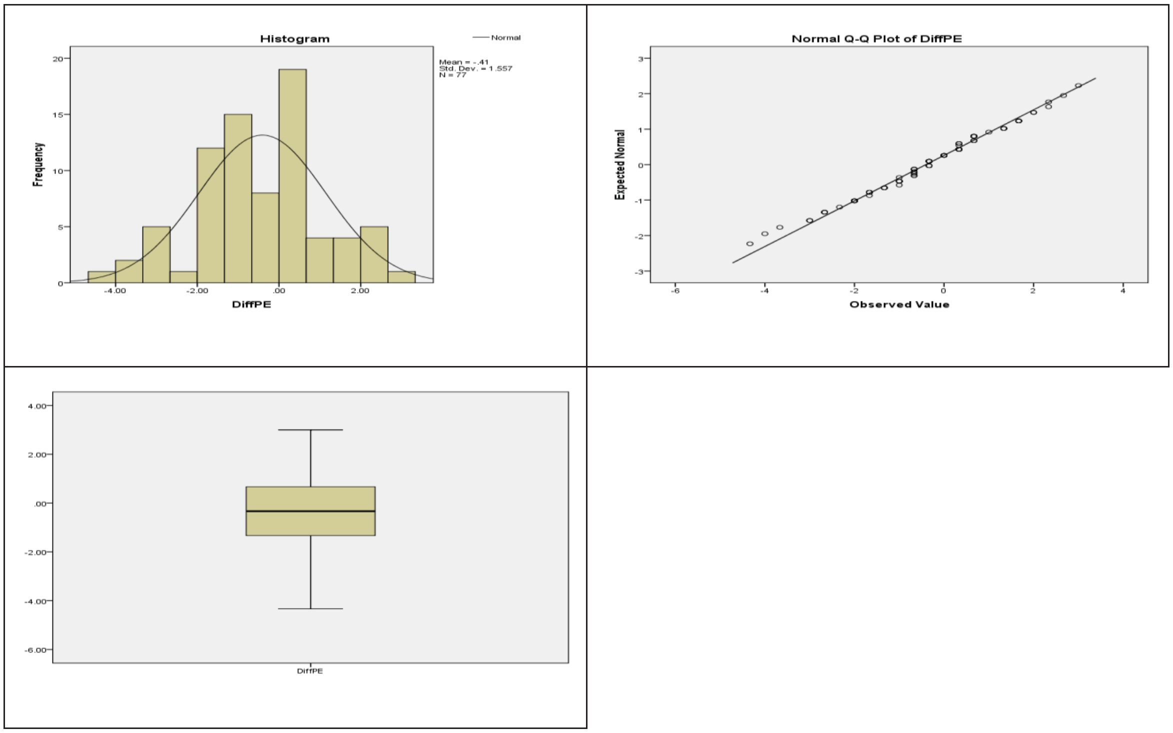


Figure 6: Histogram, Q-Q plot and boxplot for the change in performance expectancy between t_0 and t_1 data

- *performance expectancy confirmation at* t_1

A review of the Shapiro-Wilk test for normality (SW = .98, df = 77, p = .26) and skewness (1.5) and kurtosis (1.1) statistics suggested that the *performance expectancy confirmation at* t_1 data did not deviate significantly from normal (see Table 7)

Table 7: Normality test result for performance expectancy confirmation at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{Kurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Performance expectancy confirmation at t_1	77	.93 ± .17	.42	.27	1.5	no skewness	.59	.54	1.1	no kurtosis	.98	77	.26	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *performance expectancy confirmation at* t_1 data suggested the assumption of normality was reasonable (see Figure 2). The boxplot indicated one outlier (Case 47). As Case 47 data was not an extreme outlier, it was not cut from the data analysis. According to the central limit theorem, since the *performance expectancy confirmation at* $t_1$data were distributed normally, the sampling distribution of the sample mean for this data was normal.

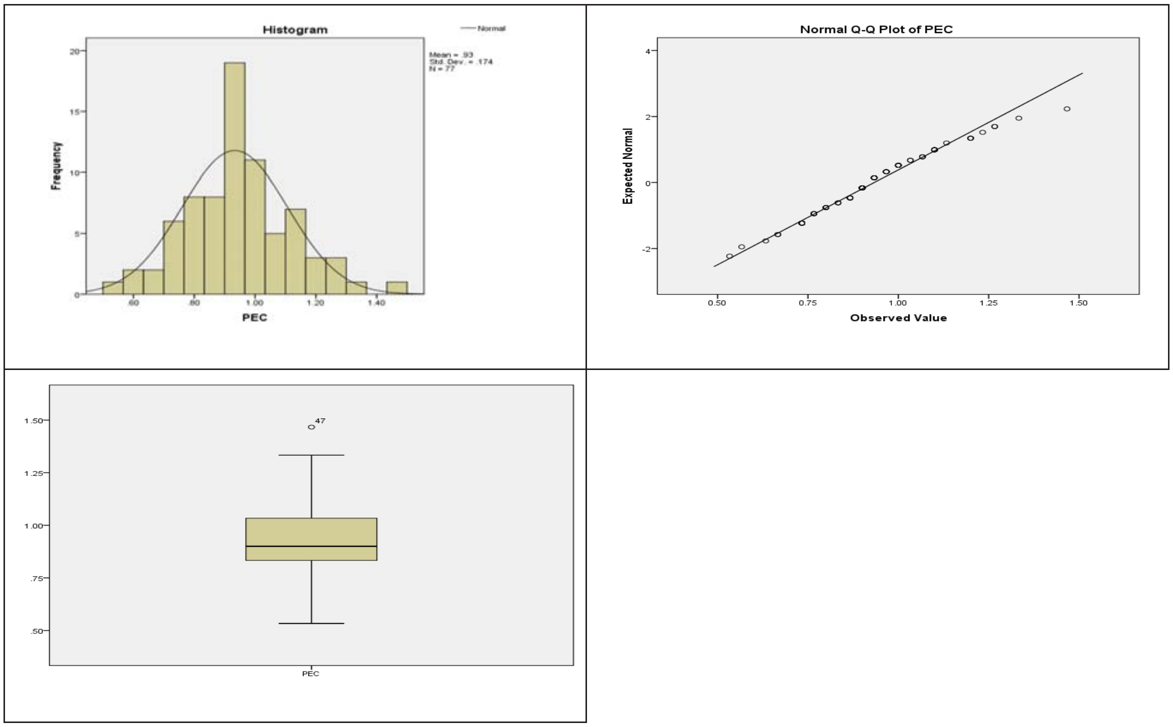


Figure 7: Histogram, Q-Q plot and boxplot for performance expectancy confirmation at t_1

<u>Assumption 2 and 3</u>: Linearity and Homoscedasticity

To check the linearity and homoscedasticity assumption, a scatterplot of the standardized residual and standardized predicted value was created (see Figure 8).

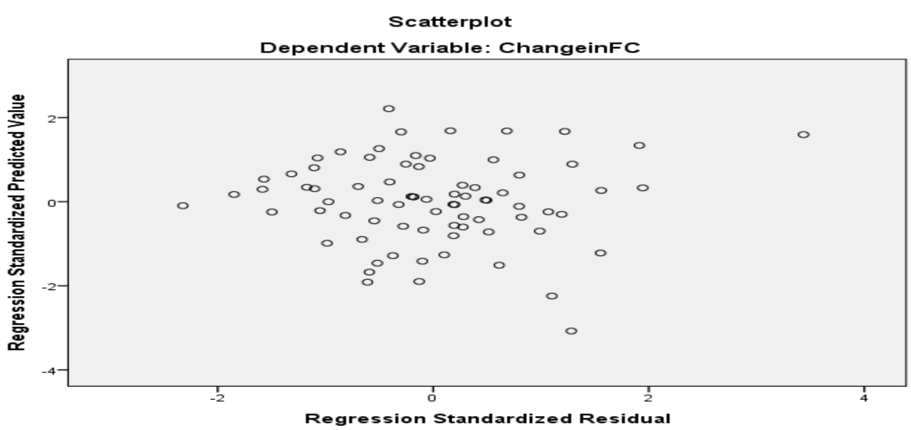


Figure 8: Scatterplot of residual and predicted value of the relationship between the change of facilitating condition expectancy between t_0 and t_1 and six contributing variables

Since there was no systematic relationship revealed between the standardized residual and standardized predicted value, this suggested that the assumption of linearity and homoscedasticity for this regression model was not violated.

Assumption 4: Independence of residual (error)

The Durbin-Watson test was used to evaluate the independence of residual. The result showed that Durbin-Watson statistic for this regression models was 2.0: it suggested that the assumption of independent errors has been met.

Assumption 5: Multicollinearity

According to the general rule of thumb, as the VIF for each significant predictor was lower than 10, the multicollinearity assumption was not violated (see Table 8).

Table 8: Collinearity test for the five contributing variables of the change of facilitating condition expectancy between t_0 and t_1

Independent variable	**VIF**
facilitating condition expectancy confirmation at t_1	5.3
change in learning consistency expectancy between t_0 and t_1	3.2
perceived facilitating condition at t_1	7.3
learning consistency expectancy at t_0	4.1
change in performance expectancy between t_0 and t_1	4.0
performance expectancy confirmation at t_1	3.7

Appendix 7-ZB: Statistical conditions and assumptions checking of the stepwise regression analysis between the change of learning consistency expectancy and related variables

The multiple regression required two conditions and five assumptions to be passed as follows:

Condition 1**:** Dependent variable comprises continuous data

In this data analysis, the dependent variable was a *change in learning consistency expectancy between* t_0 *and* t_1. This variable data were continuous, ranging from -10 to 10. Thus, this condition was met.

Condition 2**:** At least two independent variables comprising continuous data

There were four independent variables in each regression model: (a) *learning consistency expectancy confirmation at* t_1; (b) *facilitating condition expectancy at* t_1; (c) *perceived learning consistency expectancy at* t_1, and (d) *social encouragement expectancy at* t_1. As the data from all five independent variables were continuous, the second condition was met.

Assumption 1**:** Sampling distribution of the sample mean for each variable is normal

- *Change in learning consistency expectancy between* t_0 *and* t_1

A review of the Shapiro-Wilk test for normality (*SW* = .98, *df* = 77, *p* = .25) and skewness (-1.4) and kurtosis (1.7) statistics suggested that the *change in learning consistency expectancy between* t_0 *and* t_1 data did not deviate significantly from normal (see Table 1).

Table 1: Normality test result for change in learning consistency expectancy between t_0 and t_1

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Change in learning consistence expectancy between t_0 and t_1	77	-.56 ± 1.5	-.38	.27	-1.4	no skewness	.90	.54	1.7	no kurtosis	.98	77	.25	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *change in learning consistency expectancy between* t_0 and t_1 data suggested the assumption of normality was reasonable (see Figure 1). The boxplot indicated three outliers in this data (Cases 2, 28 and 47). As these three outliers were not extreme, they were not cut from the data analysis. Since the *change in learning consistency* *expectancy between* t_0 and t_1 data were distributed normally, the sampling distribution of the sample mean for this data was normal.

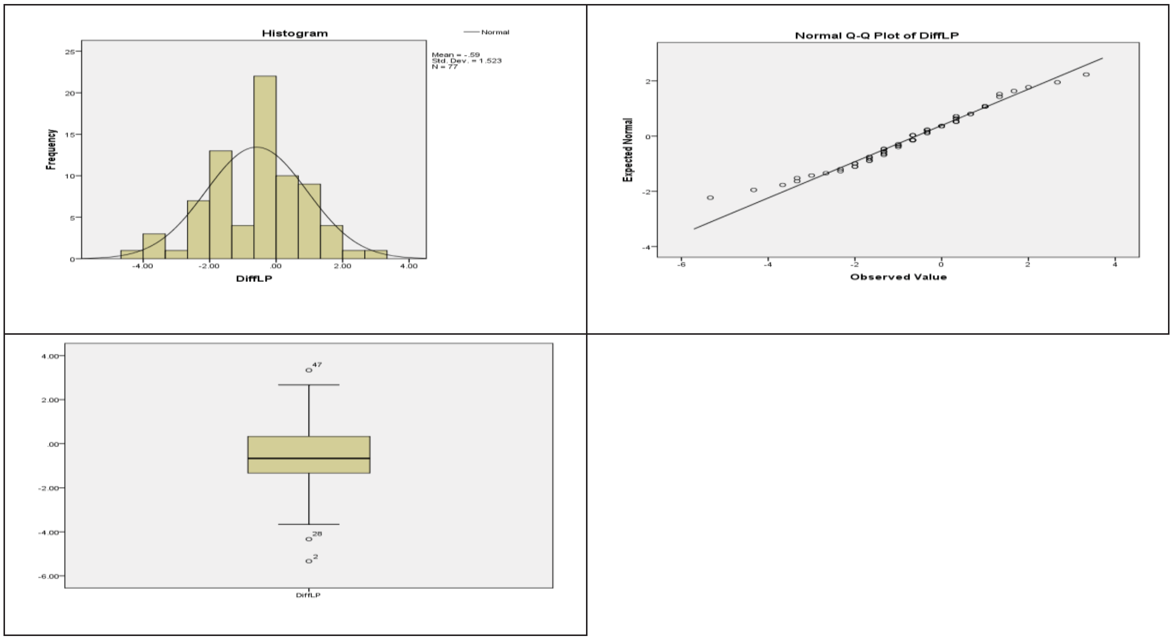


Figure 1: Histogram, Q-Q plot and boxplot for change in learning consistency expectancy between t_0 and t_1

- *Learning consistency expectancy confirmation at* t_1

A review of the Shapiro-Wilk test for normality (*SW* = .92, *df* = 77, *p* = .23) and skewness (1.2) and kurtosis (.89) statistics suggested that *learning consistency expectancy confirmation at* t_1 data did not deviate significantly from normal (see Table 2).

Table 2: Normality test result for learning consistency expectancy confirmation at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{Kurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Learning consistence expectancy confirmation at t_1	77	.92 ± .17	.33	.27	1.2	no skewness	.48	.54	.89	no kurtosis	.98	77	.23	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *learning consistency expectancy confirmation at* t_1 data suggested the assumption of normality was reasonable (see Figure 2). The boxplot indicated two outliers in this data (Cases 16 and 47). As these two outliers were not extreme, they were not cut from the data analysis. According to the central limit theorem, since the *learning consistency* *expectancy confirmation at* t_1 data were distributed normally, the sampling distribution of the sample mean for this data was normal.

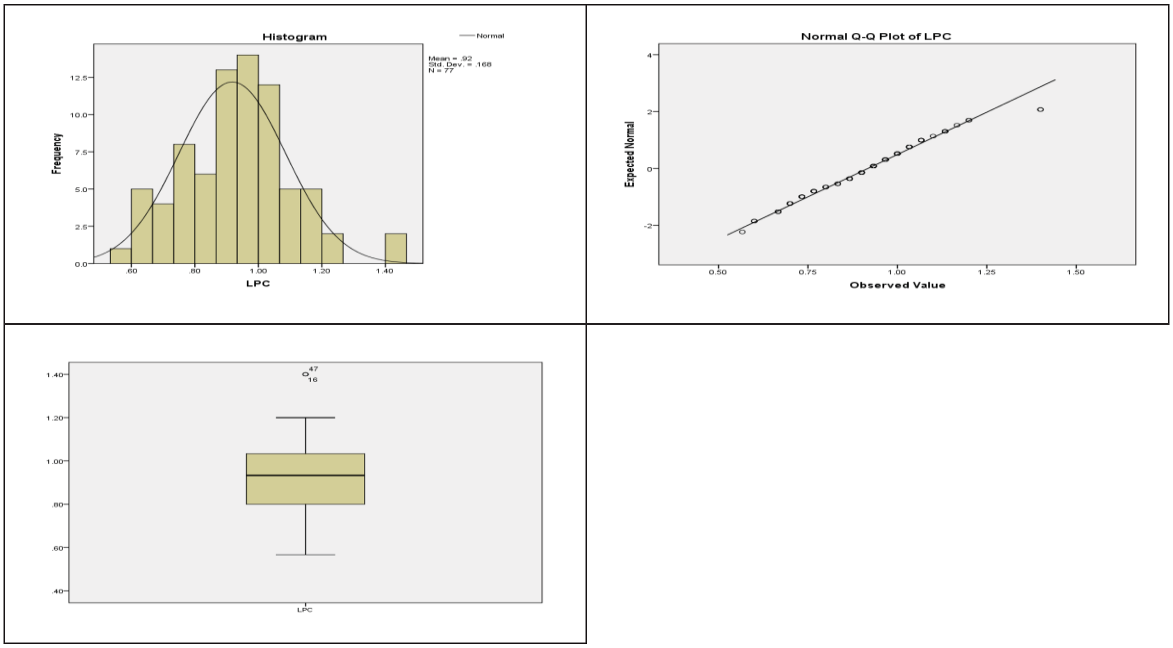


Figure 2: Histogram, Q-Q plot and boxplot for learning consistency expectancy confirmation at t_1 data

- *Facilitating condition expectancy at* t_1

A review of the Shapiro-Wilk test for normality (SW = .97, df = 77, p = .08) and skewness (1.2) and kurtosis (-.79) statistics suggested that the *facilitating condition expectancy at* t_1 data did not deviate significantly from normal (see Table 3).

Table 3: Normality test for facilitating condition expectancy at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	SE_{skewne}	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Measured FCE at T1	77	6.9 ± 1.3	.34	.27	1.2	no skewness	-.43	.54	-.79	no kurtosis	.97	77	.08	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *facilitating condition expectancy at* t_1 data suggested the assumption of normality was reasonable (see Figure 3). The boxplot indicated no outliers in this data. As the data of *facilitating condition expectancy at* $t_1$distributed normally, the sampling distribution of the sample mean for this variable was normal.

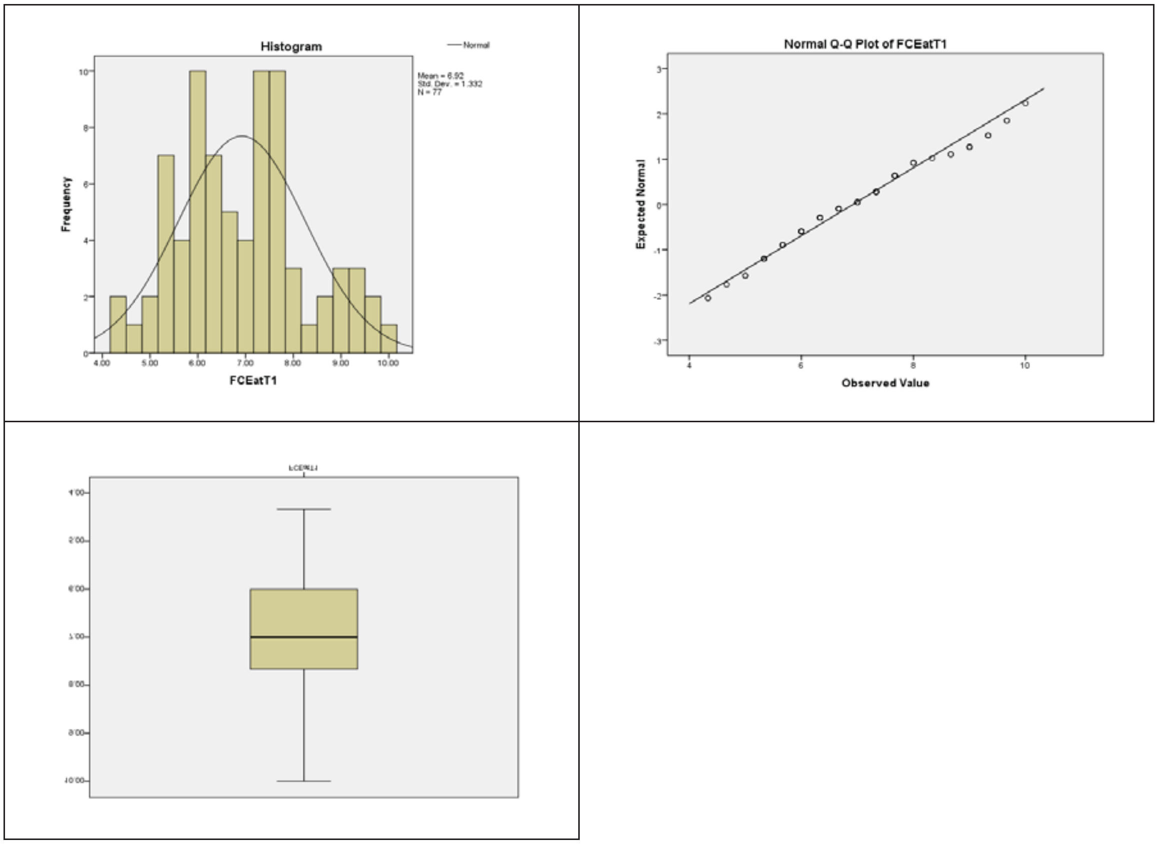


Figure 3: Histogram, Q-Q plot and boxplot for facilitating condition expectancy at t_1 data

- *Perceived learning consistency at* t_1

A review of the Shapiro-Wilk test for normality (SW = .98, df = 77, p = .28) and skewness (-.30) and kurtosis (-1.34) statistics suggested that the *perceived learning consistency at* t_1 data did not deviate significantly from normal (see Table 4).

Table 4: Normality test result for perceived learning consistency at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Perceived learning consistence at t_1	77	6.5 ± 1.6	-.08	.27	-.30	no skewness	-.75	.54	-1.4	no kurtosis	.98	77	.28	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *perceived learning consistency at* t_1 data suggested the assumption of normality was reasonable (see Figure 4). The boxplot indicated no outliers in this data. According to the central limit theorem, since the *perceived learning consistency at* t_1 data were distributed normally, the sampling distribution of the sample mean for this data was normal.

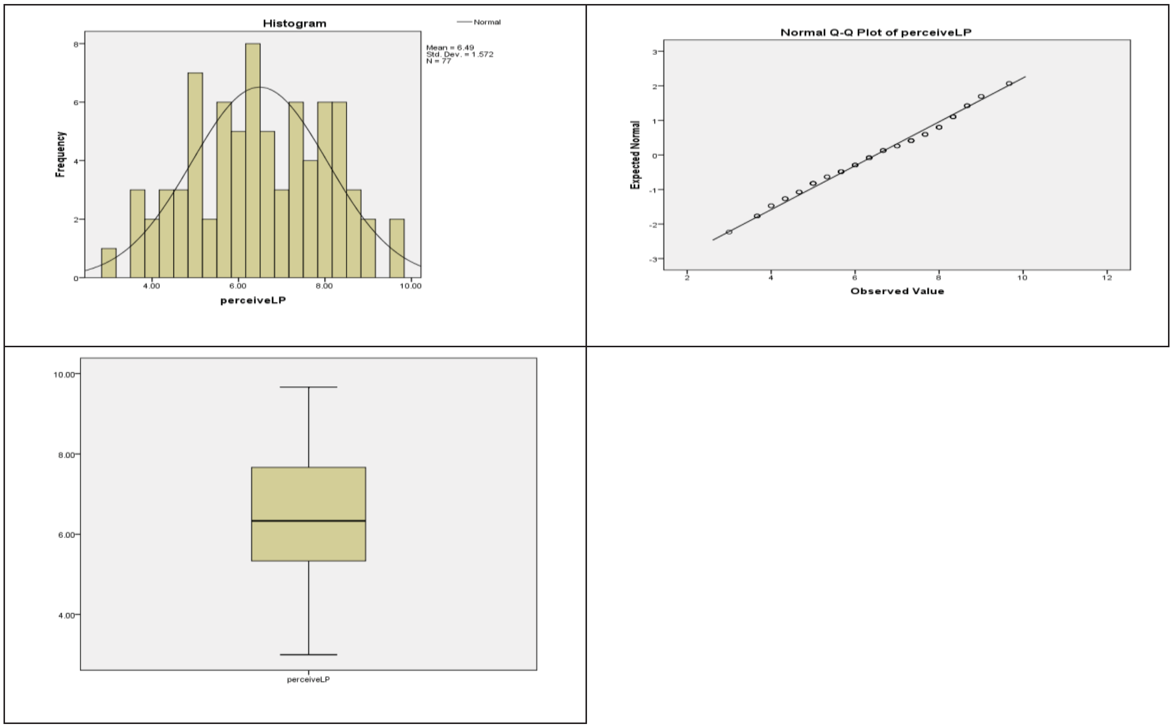


Figure 4: Histogram, Q-Q plot and boxplot for perceived learning consistency at t_1 data

- *Social encouragement expectancy at* t_1

A review of the Shapiro-Wilk test for normality (*SW* = .99, *df* = 77, *p* = .51) and skewness (1.0) and kurtosis (.23) statistics suggested that the *social encouragement* expectancy at t_1 did not deviate significantly from normal (see Table 5).

Table 5: Normality test for measured social encouragement expectancy at t_1 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \le 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \le 2.56$)	Statistic	df	P-value	Conclusion ($p \le .01$)
Measured SEE at T1	77	6.8 ± 1.3	.28	.27	1.0	no skewness	.13	.54	.23	no kurtosis	.99	77	.51	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *social encouragement* expectancy at t_1 suggested the assumption of normality was reasonable (see Figure 5). The boxplot indicated two outliers in this data (Cases 25 and 75). As these two outliers were not extreme, they were not cut from the data analysis. Since the *social encouragement* expectancy at t_1 was distributed normally, the sampling distribution of the sample mean for this variable was normal.

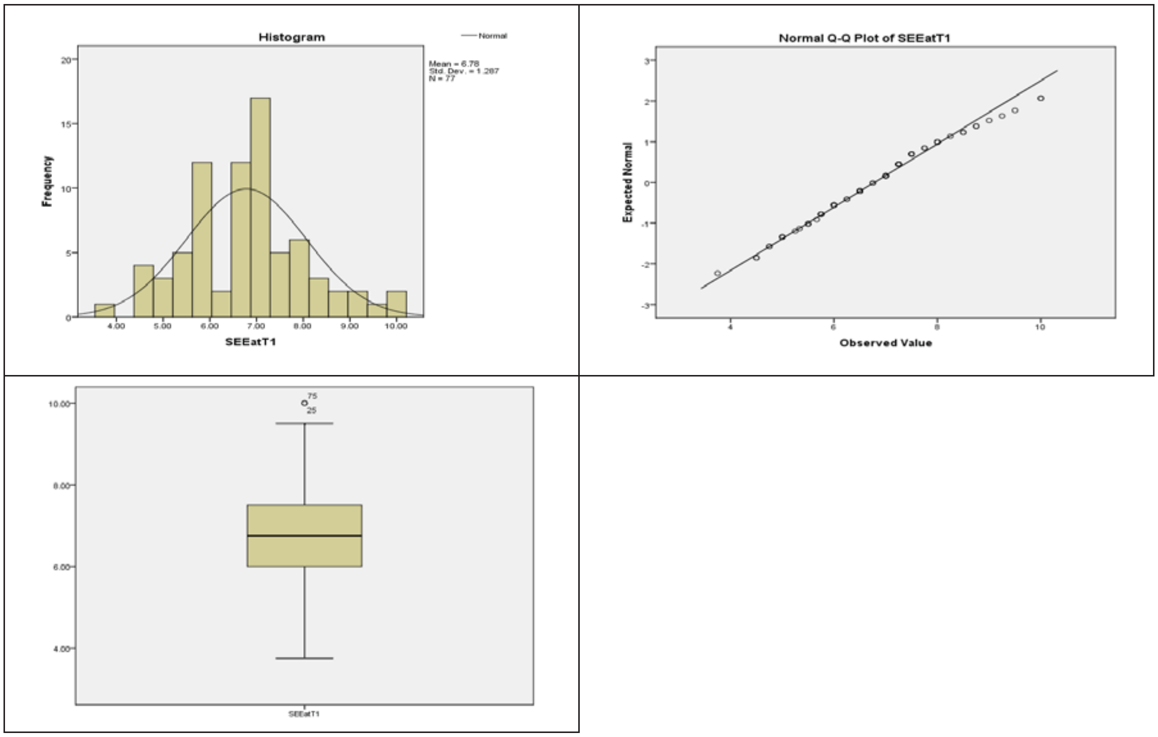


Figure 5: Histogram, Q-Q plot and boxplot for measured social encouragement expectancy at t_1 data

Assumption 2 and 3: Linearity and Homoscedasticity

To check the linearity and homoscedasticity assumption, a scatterplot of the standardized residual and standardized predicted value was created (see Figure 6). Since there was no systematic relationship between the standardized residual and standardized predicted value, this suggested that the assumption of linearity and homoscedasticity for this regression model was not violated.

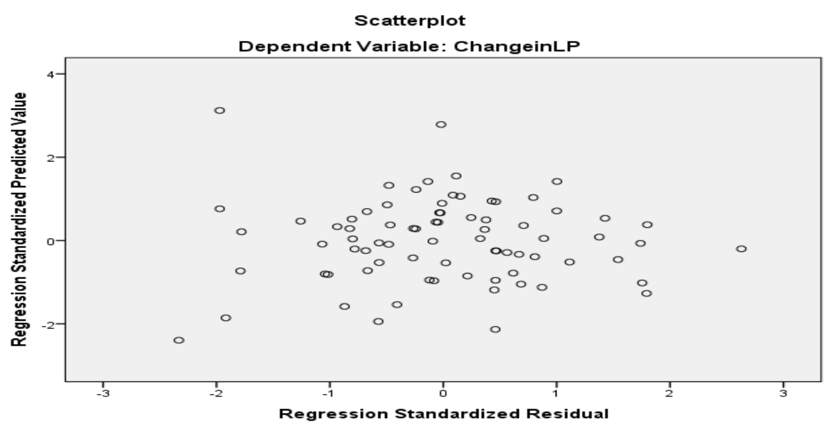


Figure 6: Scatterplot of residual and predicted value of the relationship between the change of learning consistency expectancy between t_0 and t_1 and four contributing variables

Assumption 4: Independence of residual (error)

The Durbin-Watson test was used to evaluate the independence of residual. The result showed that Durbin-Watson statistic for this regression models was 2.0: it suggested that the assumption of independent errors has been met.

Assumption 5: Multicollinearity

According to the general rule of thumb, as the VIF for each significant predictor was lower than 10, the multicollinearity assumption was not violated (see Table 6).

Table 8: Collinearity test for the five contributing variables of the change of facilitating condition expectancy between t_0 and t_1

Independent variable	**VIF**
learning consistency expectancy confirmation at t_1	2.2
facilitating condition expectancy at t_1	2.7
perceived learning consistency expectancy at t_1	4.6
social encouragement expectancy at t_1	3.4

Appendix 7-ZC: Statistical conditions and assumptions checking of the canonical correlation analysis between the change of five expectations and the change in E-learning usage

Before running the canonical correlation analysis, the two required conditions and three required assumptions were checked, as follows.

<u>Condition 1</u>**:** At least two independent and two dependent variables

There were five independent variables in this data analysis: change in performance expectancy between t_0 and t_1, change in effort expectancy between t_0 and t_1, change in social encouragement expectancy between t_0 and t_1, change in facilitating condition expectancy between t_0 and t_1, and change in learning consistency expectancy between t_0 and t_1. The five dependent variables were: change in percentage (subjective) between first and second usage period; change in time spent (subjective) between first and second usage period; change in time spent (objective) between first and second usage period; change in number of times of logging on (objective) between first and second usage period; and change in number of activities involving (objective) between first and second usage period. This condition therefore was met.

<u>Condition 2</u>**:** Dependent and independent variables are continuous data

All variables were continuous, this condition therefore was met.

<u>Assumption 1</u>**:** Sampling distribution of the sample mean for each variable is normal

- *Change in percentage (subjective) between first and second usage period*

A review of the Shapiro-Wilk test for normality (*SW* = .99, *df* = 77, *p* = .83) and skewness (.04) and kurtosis (-.55) statistics suggested that the *change in percentage of E-learning usage in education* data did not deviate significantly from normal (see Table 1).

Table 1: Normality test result for the change in percentage of E-learning usage in education

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Change in the percentage of E-learning usage in education	77	-5.5 ± 24.4	.01	.27	.04	no skewness	-.30	.54	-.55	no kurtosis	.99	77	.83	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *change in percentage of E-learning usage in education* data suggested normality was reasonable (see Figure 1). The boxplot indicated no outliers in this data. According to the central limit theorem, since the *change in percentage of E-learning usage in education* data were distributed normally, the sampling distribution of the sample mean for this data is normal.

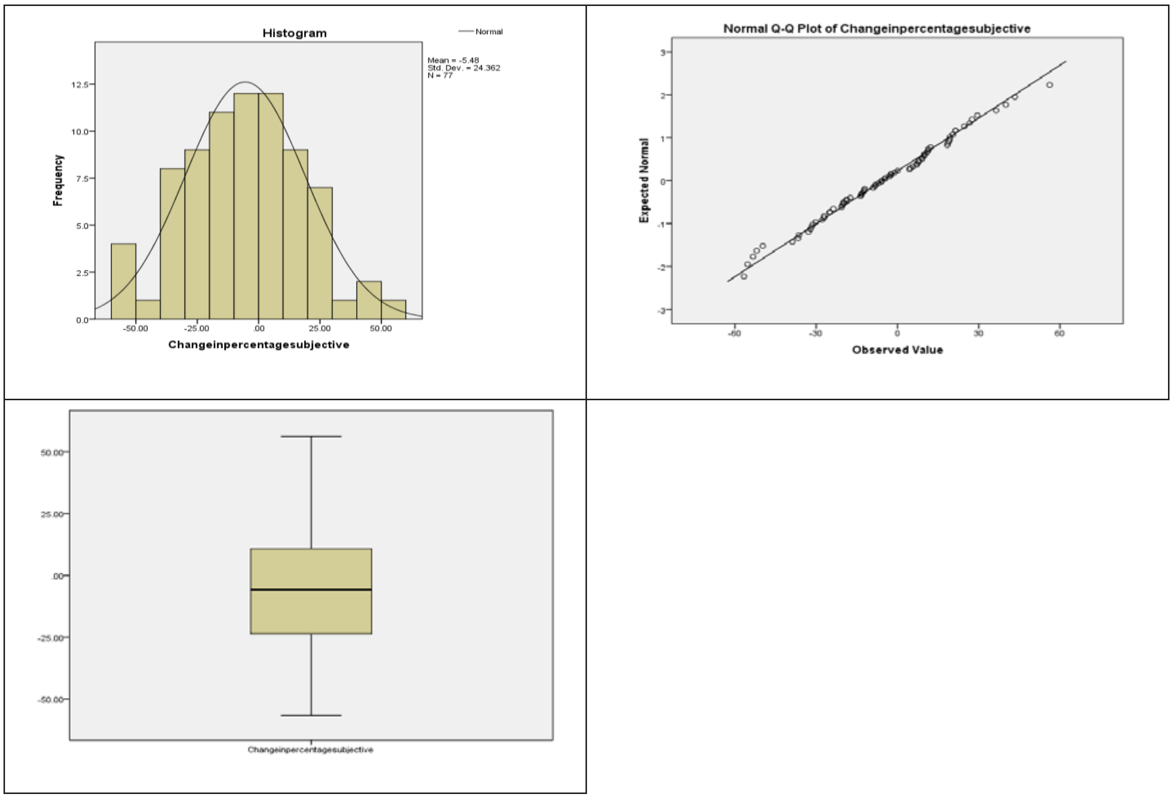


Figure 6: Histogram, Q-Q plot and boxplot for the change in percentage of E-learning usage in education

- *Change in time spent (subjective) between first and second usage period*

A review of the Shapiro-Wilk test for normality (SW = .60, df = 77, p < .001) suggested that the *change in time spent learning with E-learning* data deviated significantly from normal, with negative skewness (-16.4) and positive kurtosis 62.4) (see Table 2).

Table 2: Normality test result for the change in time spent learning with E-learning data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Change in time spent learning with E-learning (subjective measure)	77	39.8 ± 538.4	-4.5	.27	-16.4	negative skewness	33.7	.54	62.4	positive kurtosis	.60	77	< .001	not normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *change in time spent learning with E-learning* data suggested the assumption of normality was not reasonable (see Figure 2). The boxplot indicated two extreme outliers in this data (Cases 13 and 43).

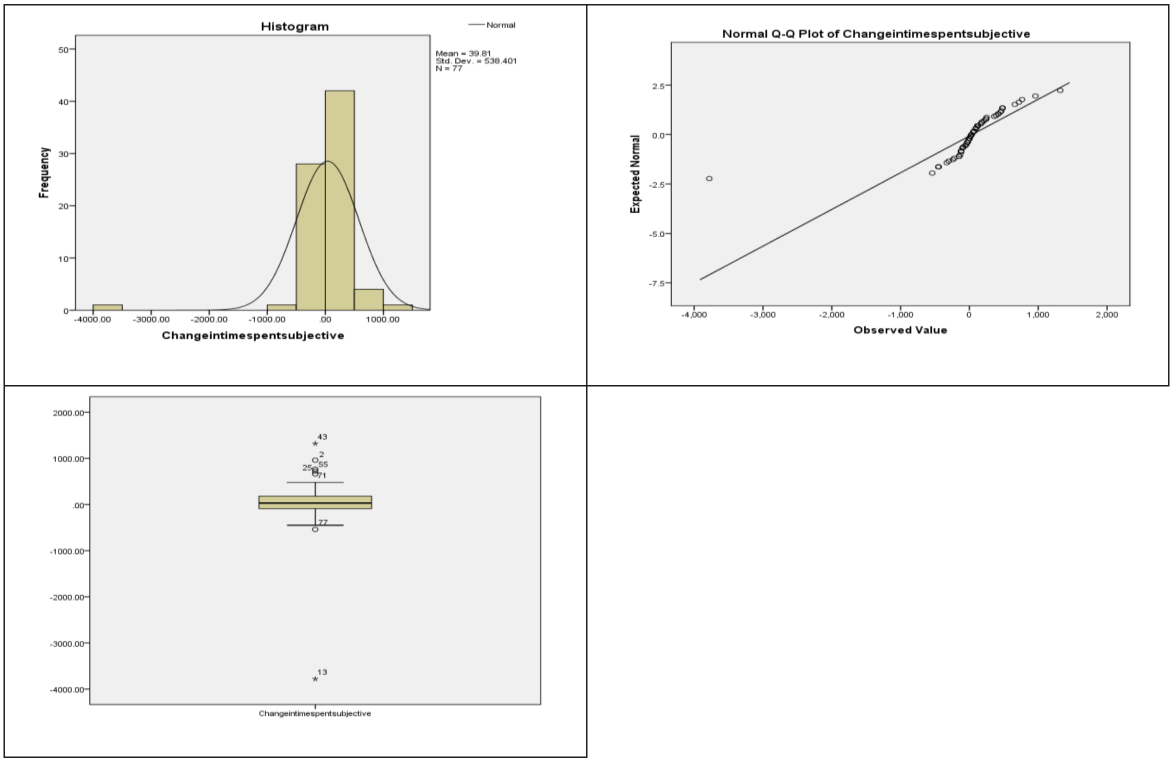


Figure 2: Histogram, Q-Q plot and boxplot for the change in time spent learning with E-learning data

To improve the normality, the two extreme outliers (Cases 13 and 43) were set as missing data (see Table 3).

Table 3: Normality test result for the change in time spent learning with E-learning data after cutting extreme outlier

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Change in time spent learning with E-learning (subjective measure) after cut extreme outliers	75	73.7 ± 227.9	.67	.28	2.4	no skewness	1.2	.55	2.2	no kurtosis	.95	75	.005	not normal

After the two extreme outliers were cut, the skewness (2.4) and kurtosis (2.2) improved. However, the data were still not normally distributed (SW = .95, df = 75, p =.005) (see Figure 3).

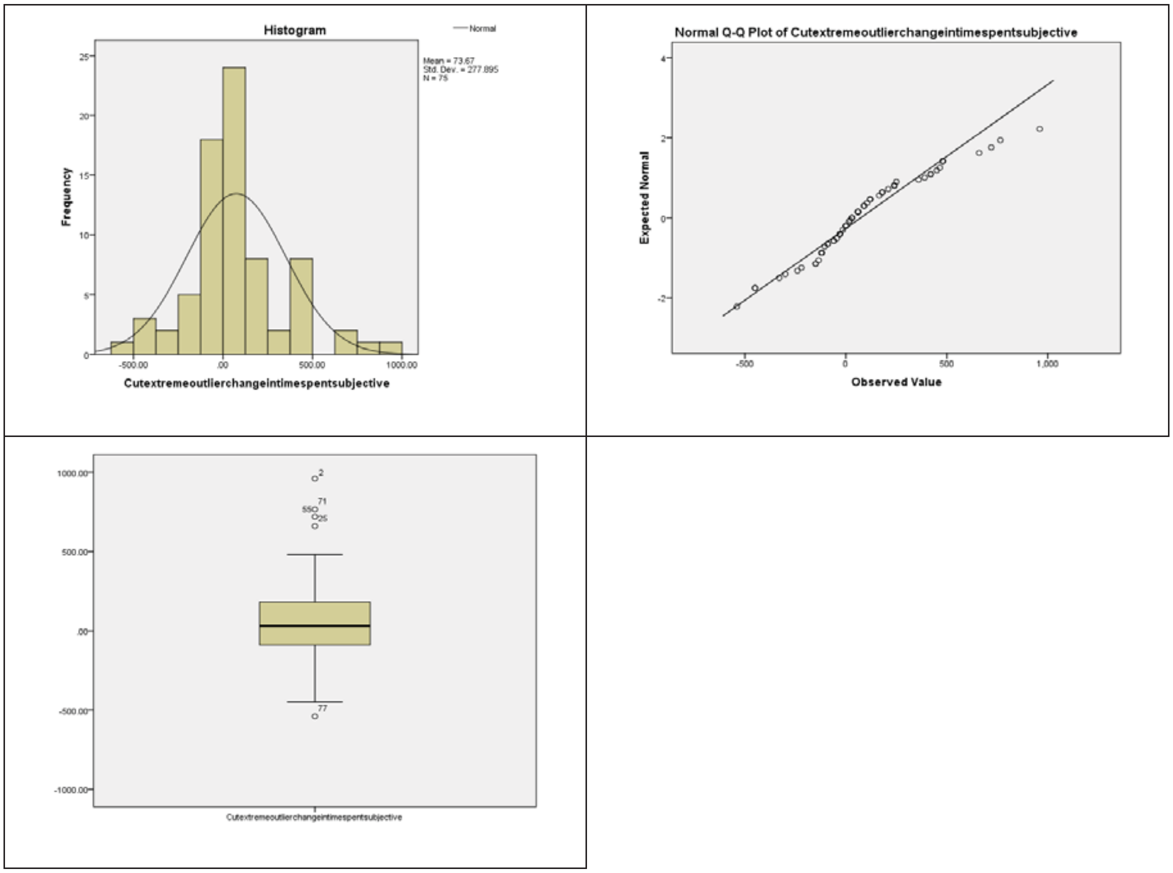


Figure 3: Histogram, Q-Q plot and boxplot for the change in time spent learning with E-learning data after cutting extreme outliers

Although the change in time spent learning with E-learning after cutting the extreme outliers data was still not normal, the sampling distribution of the sample mean of this data was normal since the number of participants in this experiment was higher 30.

- *Change in time spent (objective) between first and second usage period*

A review of the Shapiro-Wilk test for normality (*SW* = .76, *df* = 77, *p* < .001) suggested that the *change in time spent using E-learning* data deviated significantly from normal: positive skewness (6.5) and positive kurtosis (5.5) (see Table 4).

Table 4: Normality test result for the change in time spent using E-learning data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Change in time spent using E-learning (objective measure)	77	118.5 ± 324.6	1.8	.27	6.5	positive skewness	3.0	.54	5.5	positive kurtosis	.76	77	< .001	not normal

With the positive skewness and kurtosis, this data was then transformed with Log (X+1) in order to improve the normality (see Table 5).

Table 5: Normality test result for the change in time spent using E-learning data after transformation

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Change in time spent using E-learning (objective measure) after transformation	77	2.7 ± .36	-5.8	.27	-21.3	negative skewness	45.7	.54	84.6	positive kurtosis	.47	77	< .001	not normal

The result suggested that the data after transformation still deviated significantly from normal (*SW* = .47, *df* = 77, *p* = < .001). Consistently, the histogram and Q-Q plot suggested the assumption of normality was not reasonable (see Figure 4). The boxplot indicated one extreme outlier (Case 77).

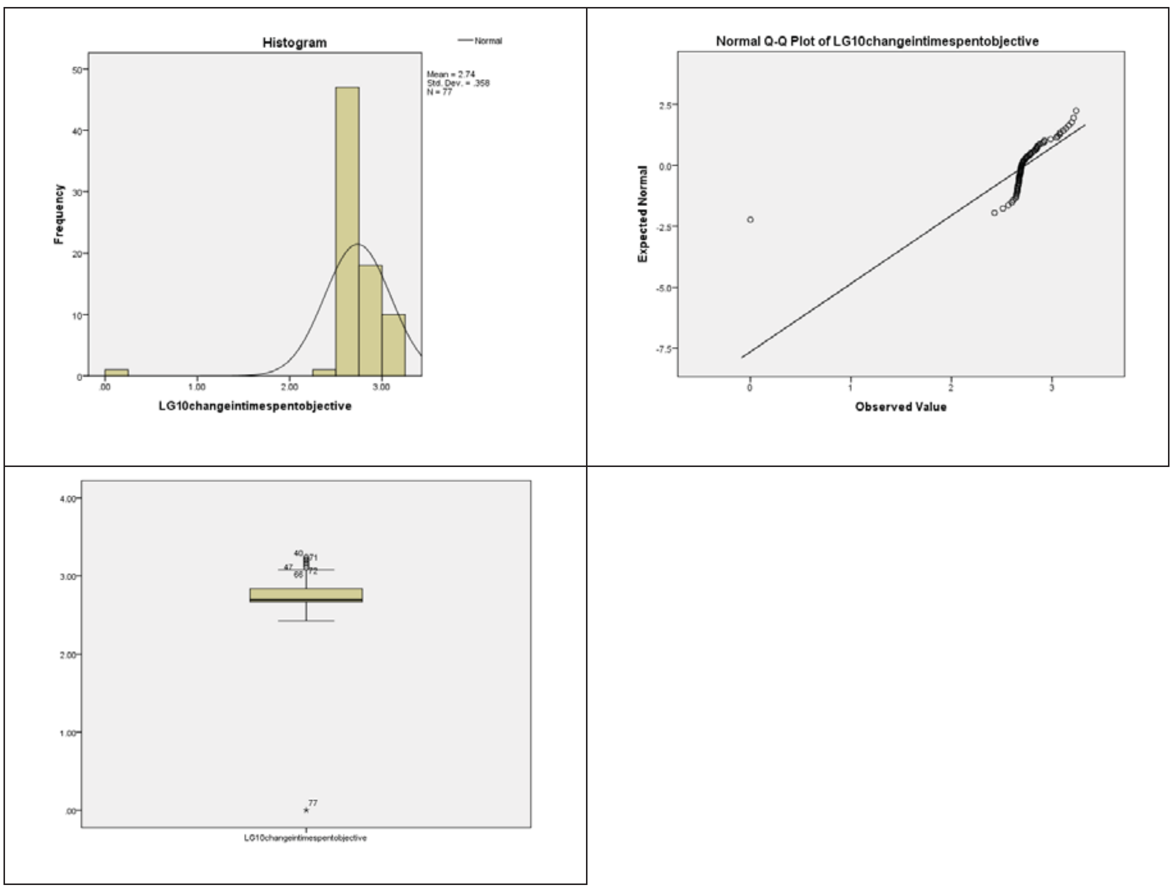


Figure 4: Histogram, Q-Q plot and boxplot for the change in time spent using E-learning after transformation

Since Case 77 data was an extreme outlier, it was set as missing data and the normality test was conducted again (see Table 6).

Table 6: Normality test result for the change in time spent using E-learning data after transformation and cutting an extreme outlier

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Change in time spent using E-learning (objective measure) after transformation and cutting extreme outlier	76	2.8 ± .17	1.2	.28	4.4	positive skewness	.98	.55	1.8	no kurtosis	.85	76	<.001	not normal

The result suggested that the data after transformation and cutting an extreme outlier still deviated significantly from the normal (SW = .85, df = 76, p = < .001). Consistently, the histogram and Q-Q plot suggested the assumption of normality was not reasonable (see Figure 5).

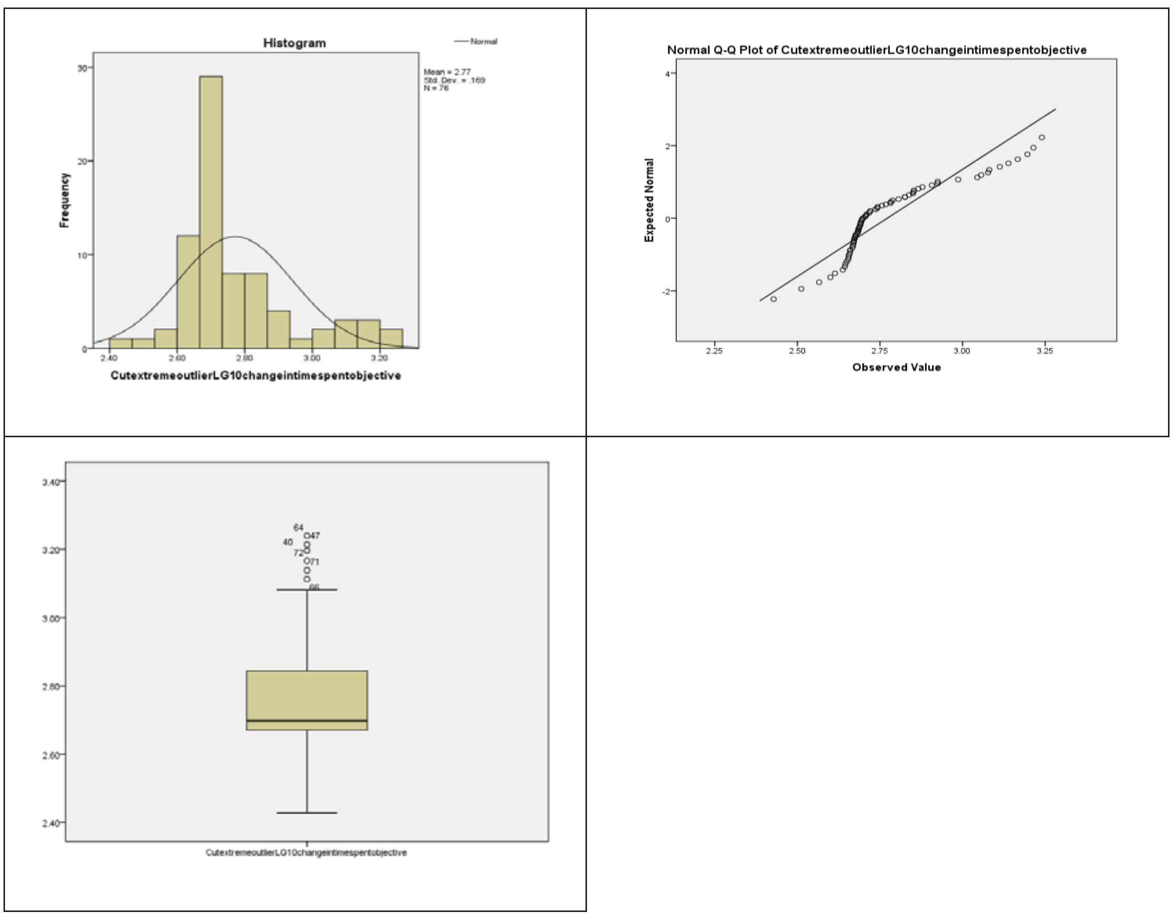


Figure 5: Histogram, Q-Q plot and boxplot for the change in time spent using E-learning data after transformation and cutting an extreme outlier

Although this variable data was not normal distribution, with the sample size higher than 30, the central limit theorem asserts that the sampling distribution of the sample mean was normal. Therefore, this measurement data did not violate the assumption of normality.

- *Change in number of times logging on (objective) between first and second usage period*

A review of the Shapiro-Wilk test for normality (*SW* = .94, *df* = 77, *p* = .001) suggested that the *change in number of time logging onto E-learning* data deviated significantly from normal, even though there was no skewness (1.6) and kurtosis (1.2) (see Table 7 and Figure 6). Although this variable data was not normal distribution, with the sample size higher than 30, the central limit theorem asserts that the sampling distribution of the sample mean was normal.

Table 7: Normality test result for the change in number of times logging onto E-learning data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Change in number of time logging on E-learning system	77	-.61 ± 1.8	.44	.27	1.6	no skewness	.62	.54	1.2	no kurtosis	.94	77	.001	not normal

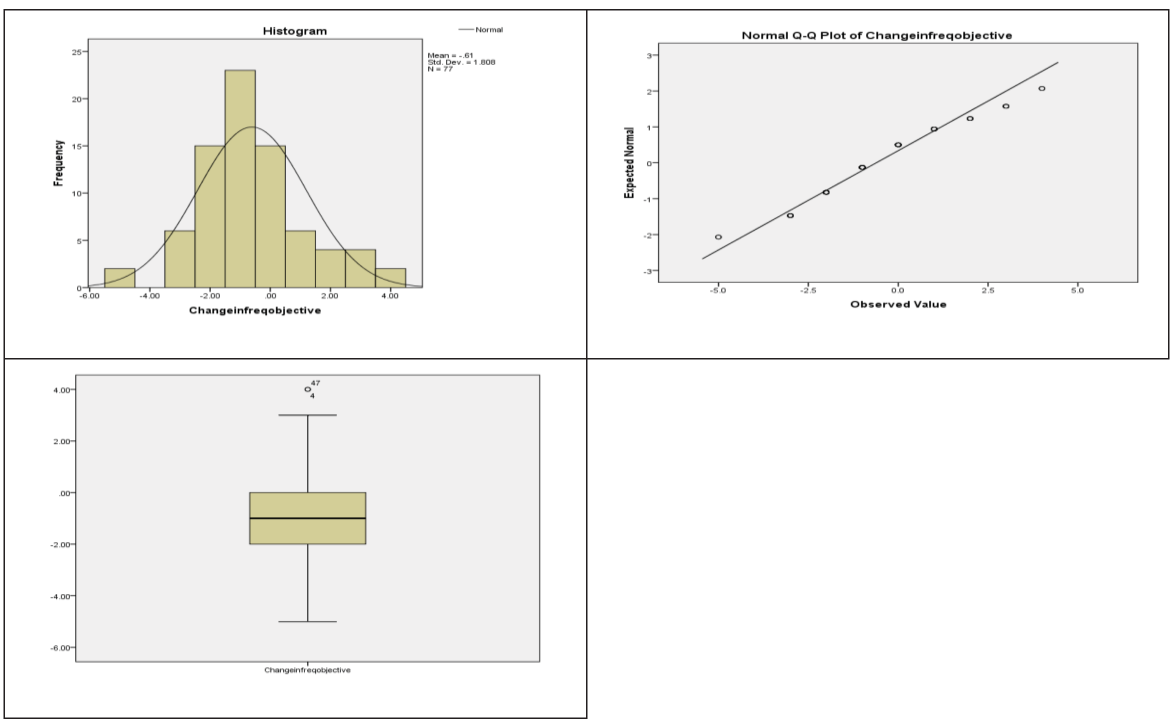


Figure 6: Histogram, Q-Q plot and boxplot for the change in number of times logging onto E-learning data

Change in number of activities involving E-learning (objective) between first and second usage period

The *change in number of activities involving E-learning* data deviated significantly from normal (SW = .85, df = 77, p < .001) (see Table 8).

Table 8: Normality test result for the change in number of activities involving E-learning data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Change in number of activity taking part on E-learning	77	9.9 ± 21.2	1.4	.27	4.9	positive skewness	1.9	.54	3.5	positive kurtosis	.86	77	< .001	not normal

To improve the normality of the data with the positive skewness (4.9) and kurtosis (3.5), the data of the change in number of activities involving E-learning was transformed with Log (X+1) (see Table 9).

Table 9: Normality test result for the change in number of activities involving E-learning after transformation

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Change in number of activity taking part on E-learning after transformation	77	1.5 ± .30	-2.3	.27	-8.3	negative skewness	10.3	.54	19.1	positive kurtosis	.77	77	< .001	not normal

After transformation, the data was still not normally distributed (SW = .77, df = 77, p < .001). Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *change in number of activities involving E-learning* data after transformation suggested the assumption of normality was not reasonable (see Figure 7). The boxplot indicated two extreme outliers (Cases 24 and 77) in this data.

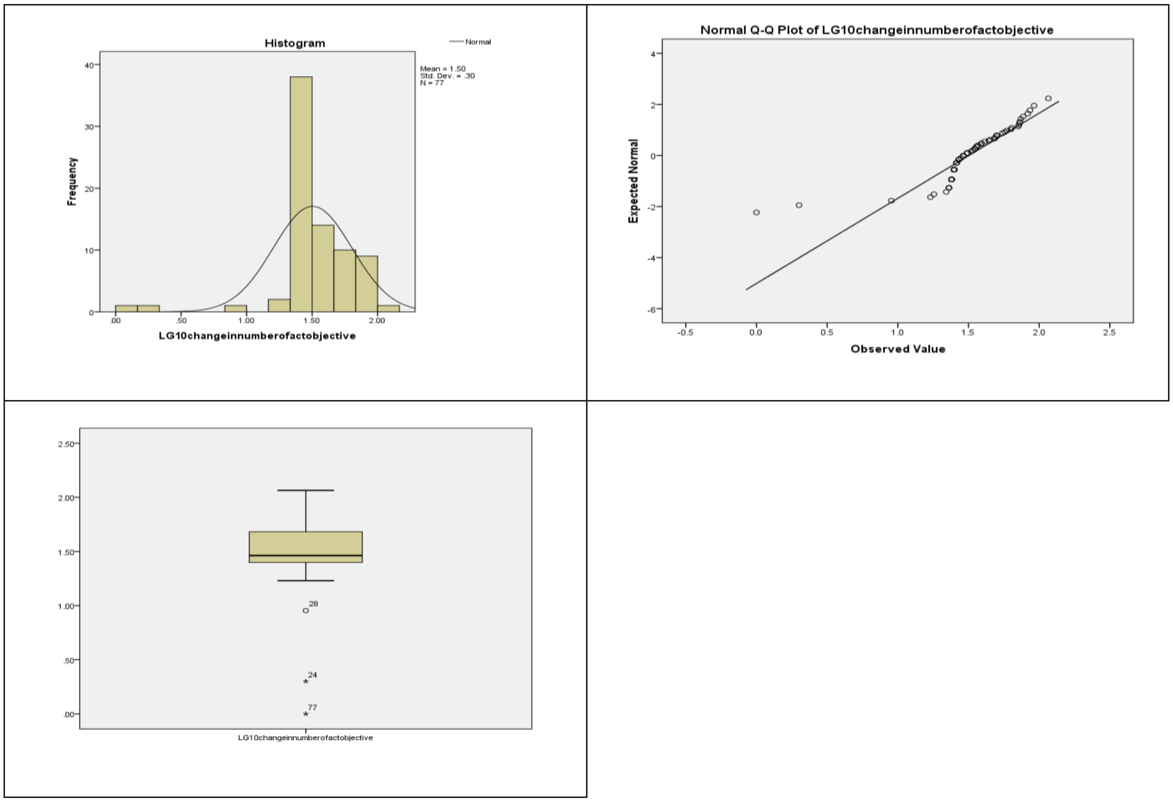


Figure 7: Histogram, Q-Q plot and boxplot for the number of activities involving E-learning data after transformation

Since Cases 24 and 77 were extreme outliers, they were set as missing data and the normality test was conducted again (see Table 10 and Figure 8).

Table 10: Normality test result for the change in number of activities involving E-learning data after transformation and cutting extreme outliers

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Change in number of activity taking part on E-learning after transformation and cut extreme outliers	75	1.5 ± .20	.46	.28	1.7	no skewness	.46	.28	1.7	no kurtosis	.92	75	< .001	not normal

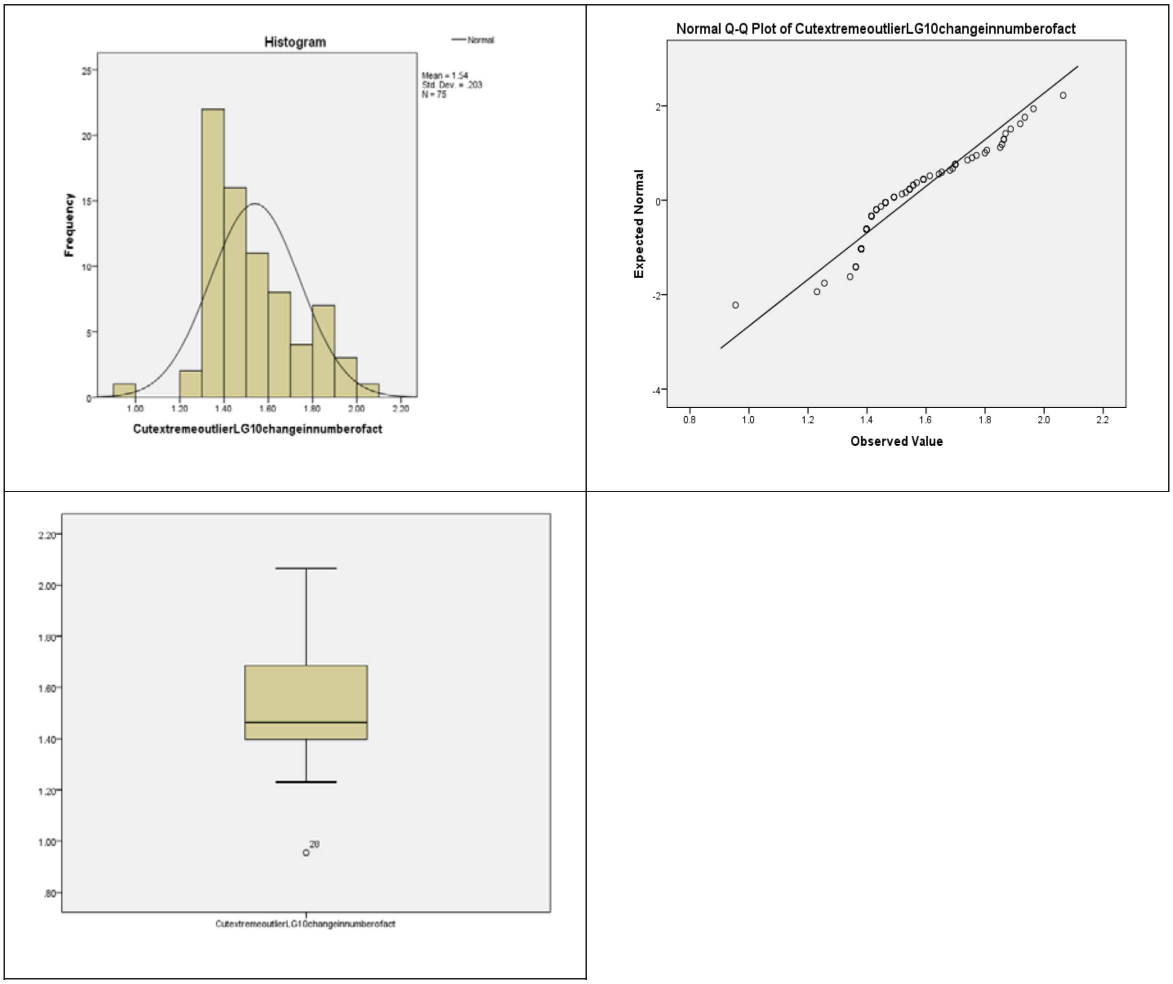


Figure 8: Histogram, Q-Q plot and boxplot for change in number of activities involving E-learning data after transformation and cutting extreme outliers

Although this measurement data was not normal, the sampling distribution of the sample mean of this measurement was normal since the number of participants in this experiment was higher than 30.

- *Independent variables*

The normality check and outlier detection for five independent variables (the change in five expectations between t_0 and t_1) was carried out previously and the results suggested that the normality assumption was not violated.

<u>Assumption 2</u>: Linear relationship between the dependent and independent variables

The linearity assumption was checked by a scatterplot of the standardized predicted value and the standardized residual of the relationship; between the change of five expectations and the change in the level of usage of E-learning between the first time period (t_0 - t_1) and the second time period (t_1 - t_2) in each of the five measurements (subjective percentage, subjective time spent, objective time spent, objective logging on and objective activities) (see Figure 9). As there was no pattern of residual dots, it was concluded the linearity assumption was not violated.

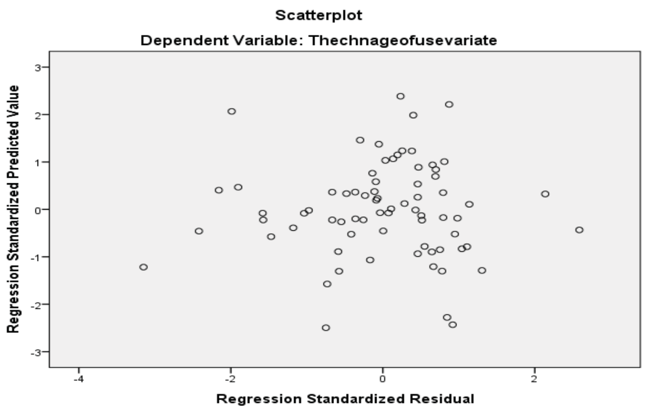


Figure 7: Scatterplot of residual between the change of five expectations and the change in five E-learning actual usage

Assumption 3: Multicollinearity

The VIF test was used to detect multicollinearity among the dependent and the independent variables (see Table 11). The result showed that VIF value for each variable in this study was lower than 10, thus multicollinearity was not a concern.

Table 11: Collinearity test for the change of the five expectations and the change in the five E-learning actual usage

		Variance inflation factors (VIF)
Dependent	Change in percentage of E-learning usage in education (subjective)	2.0
	Change in total time spent learning with E-learning (subjective)	1.6
	Change in total time spent using E-learning (objective)	3.2
	Change in total number of time logging onto E-learning (objective)	1.6
	Change in total number of activity taking part on E-learning (objective)	3.4
Independent	Change in performance expectancy	2.4
	Change in effort expectancy	2.0
	Change in social encouragement expectancy	3.2
	Change in facilitating condition expectancy	2.1
	Change in learning consistency expectancy	2.9

Appendix 7-ZD: Statistical conditions and assumptions checking of the multiple regression analysis between the relative standardized score of the final exam in general statistics measured at t_2 and six predictors

The multiple regression required two conditions and five assumptions to be passed:

<u>Condition 1</u>**:** Dependent variable is continuous data

In this data analysis, the dependent variable was a *relative standardized score of the final exam in General Statistics at* t_2. This variable data was continuous, this condition therefore was met.

<u>Condition 2</u>**:** At least two independent variables comprising continuous data

There were six independent variables in this regression model: (a) *relative standardized score of the midterm exam in General Statistics at* t_0; (b) *subjective time spent learning with E-learning during* t_0 *and* t_2; (c) *subjective percentage of E-learning usage in education during* t_0 *and* t_2; (d) *objective total time spent on E-learning system during* t_0 *and* t_2; € *objective total number of activities involving E-learning during* t_0 *and* t_2, and (f) *objective total number of times logging onto E-learning during* t_0 *and* t_2. As the data from all six independent variables were continuous, the second condition was met.

<u>Assumption 1</u>**:** The sampling distribution of the sample mean for each variable data is normal

- *Relative standardized score of the final exam in General Statistics.*

A review of the Shapiro-Wilk test for normality (*SW* = .96, *df* = 76, *p* = .02) and skewness (1.3) and kurtosis (-1.6) statistics suggested that the *relative standardized score of the final exam in general statistics at* t_2 did not deviate significantly from normal (see Table 1).

Table 1: Normality test for relative standardized score of the final exam in general statistics *at* t_2

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p \leq .01$)
Zscore on final exam	76	0 ± 1.0	.36	.28	1.3	no skewness	-.88	.55	-1.6	no kurtosis	.96	76	.02	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *relative standardized score of the final exam in general statistics at* t_2 data suggested the assumption of normality was reasonable (see Figure 1). The boxplot indicated no outliers in this data. As the data of *relative standardized score of the final exam in general statistics at* t_2 distributed normally, the sampling distribution of the sample mean for this variable is normal.

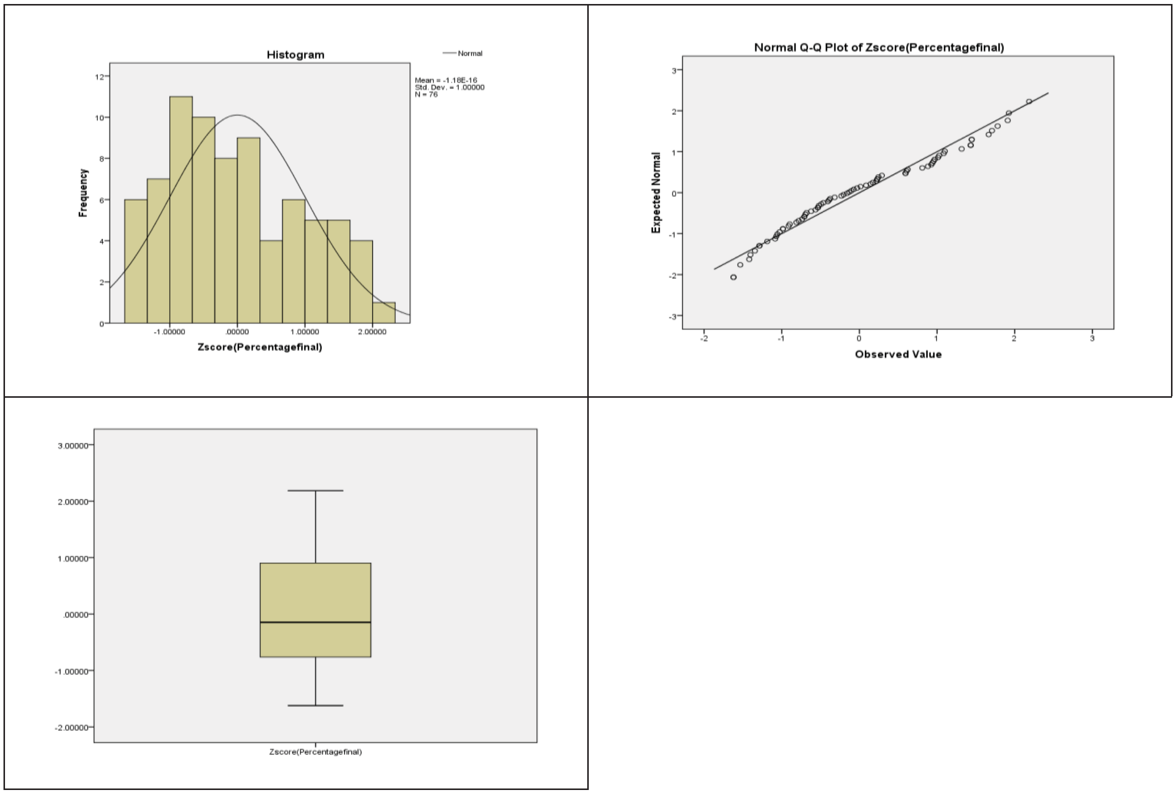


Figure 1: Histogram, Q-Q plot and boxplot for relative standardized score of the final exam in general statistics at t_2 data

- *Relative standardized score of the midterm exam in general statistics.*

A review of the Shapiro-Wilk test for normality (*SW* = .96, *df* = 76, *p* = .01) and skewness (1.9) and kurtosis (-.88) statistics suggested that the *relative standardized score of the midterm exam in General Statistics at* t_0 data did not deviate significantly from normal (see Table 2).

Table 2: Normality test for relative standardized score of the midterm exam in general statistics at t_0 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p < .01$)
Zscore on midterm exam	76	0 ± 1.0	-.51	.28	-1.9	no skewness	-.48	.55	-.88	no kurtosis	.96	76	.01	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for the *relative standardized score of the midterm exam in General Statistics at* t_0 data suggested the assumption of normality was reasonable (see Figure 2). The boxplot indicated no outliers in this data. As the data of *relative standardized score of the midterm exam in General Statistics at* t_0 distributed normally, the sampling distribution of the sample mean for this variable was normal.

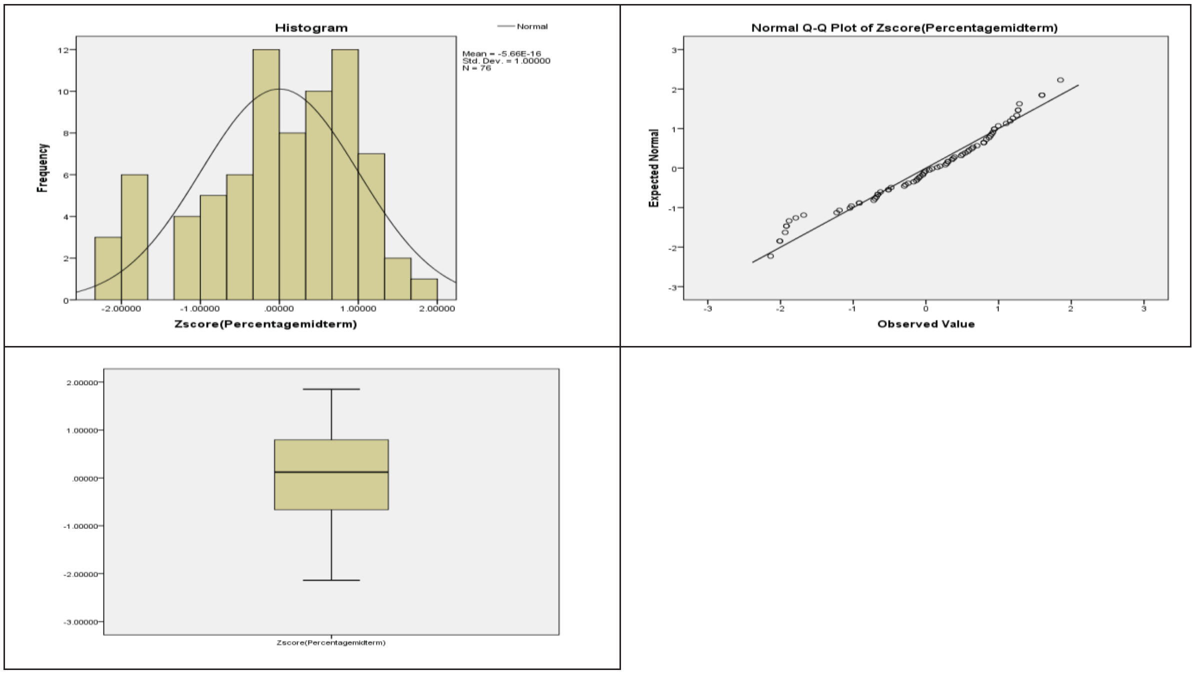


Figure 2: Histogram, Q-Q plot and boxplot for relative standardized score of the midterm exam in General Statistics at t_0 data

- *Subjective percentage of E-learning usage in education during* t_0 *and* t_2

A review of the Shapiro-Wilk test for normality (*SW* = .98, *df* = 77, *p* = .39) and skewness (1.3) and kurtosis (-.80) statistics suggested that *subjective percentage of* E-*learning usage in education during* t_0 *and* t_2 data did not deviate significantly from normal (see Table 3).

Table 3: Normality test for subjective percentage of E-learning usage in education during t_0 and t_2 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{Kurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p < .01$)
Total percentage of E-learning usage during t_0 and t_2	77	77.4 ± 23.6	.34	.27	1.3	no skewness	.43	.54	.80	no kurtosis	.98	77	.39	normal

Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for *subjective percentage of E-learning usage in education during* t_0 *and* t_2 data suggested the assumption of normality was reasonable (see Figure 3). Even though the boxplot indicated one outlier, this data was not cut, because the value of this data was not higher than Q_3 + 3×IQR (this was not an extreme outlier). As the data of *subjective percentage* *of E-learning usage in education during* t_0 *and* t_2 distributed normally, the sampling distribution of the sample mean for this variable data was normal.

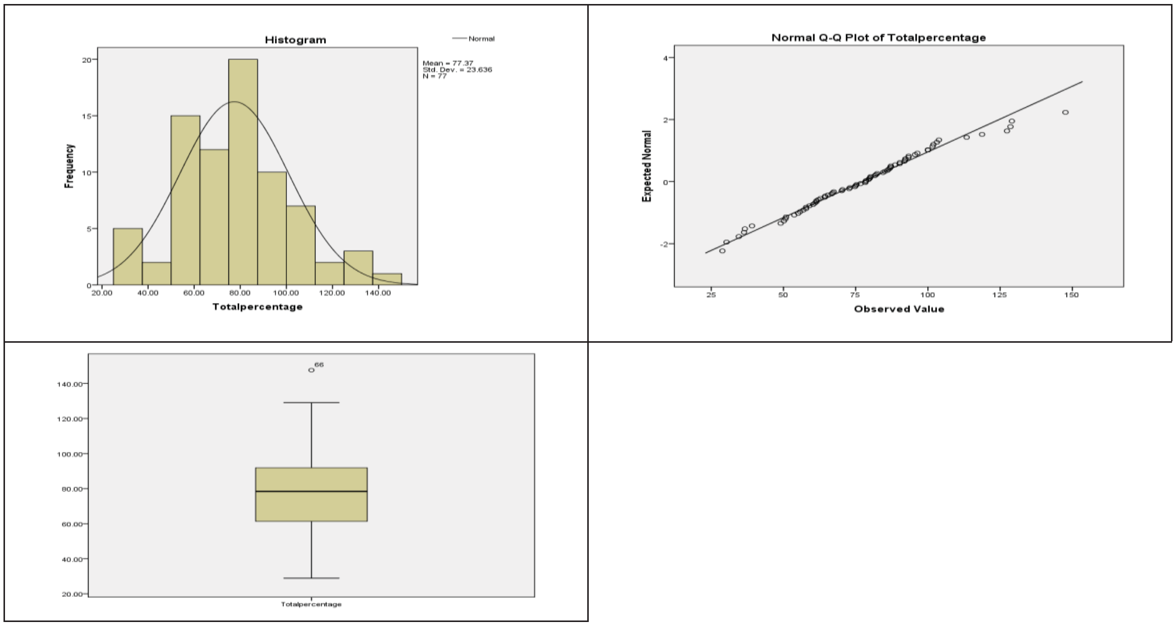


Figure 3: Histogram, Q-Q plot and boxplot for subjective percentage of E-learning usage in education during t_0 and t_2 data

- *Subjective time spent learning with E-learning during* t_0 *and* t_2

The *subjective time spent learning with E-learning during* t_0 *and* t_2 data deviated significantly from normal (*SW* = .61, *df* = 77, *p* < .001) (see Table 4).

Table 4: Normality test for subjective time spent learning with E-learning during t_0 and t_2 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p < .01$)
Total time spent learning with E-learning subjective during t_0 and t_2	77	639.2 ± 698.3	4.0	.27	14.7	positive skewness	22.2	.54	41	positive kurtosis	.61	77	< .001	not normal

To improve the normality, as the data had positive skewness (14.7) and kurtosis (41), $\text{Log}_{10}(\text{X} + 1)$ was used to transform the data. The result of normality test after transforming the data is shown in Table 5.

Table 5: Normality test for subjective time spent learning with E-learning during t_0 and t_2 data after transformation

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p < .01$)
Total time spent learning with E-learning subjective during t_0 and t_2 (after transformation)	77	2.7 ± .34	.47	.27	1.7	no skewness	.31	.54	.58	no kurtosis	.98	77	.18	not normal

The data of this variable now did not deviated significantly from normal, (*SW* = .98, *df* = 77, *p* = .18) and skewness (1.7) and kurtosis .58) statistics. Consistent with the

Shapiro-Wilk test, the histogram and Q-Q plot for *subjective time spent learning with E-learning during* t_0 *and* t_2 after transformation suggested the assumption of normality was reasonable (see Figure 4). Even though the boxplot indicated one outlier (Case 13), this data was not cut, because it was not extreme. As the data *subjective time spent learning with E-learning during* t_0 *and* t_2 after transformation was distributed normally, the sampling distribution of the sample mean for this variable data was normal.

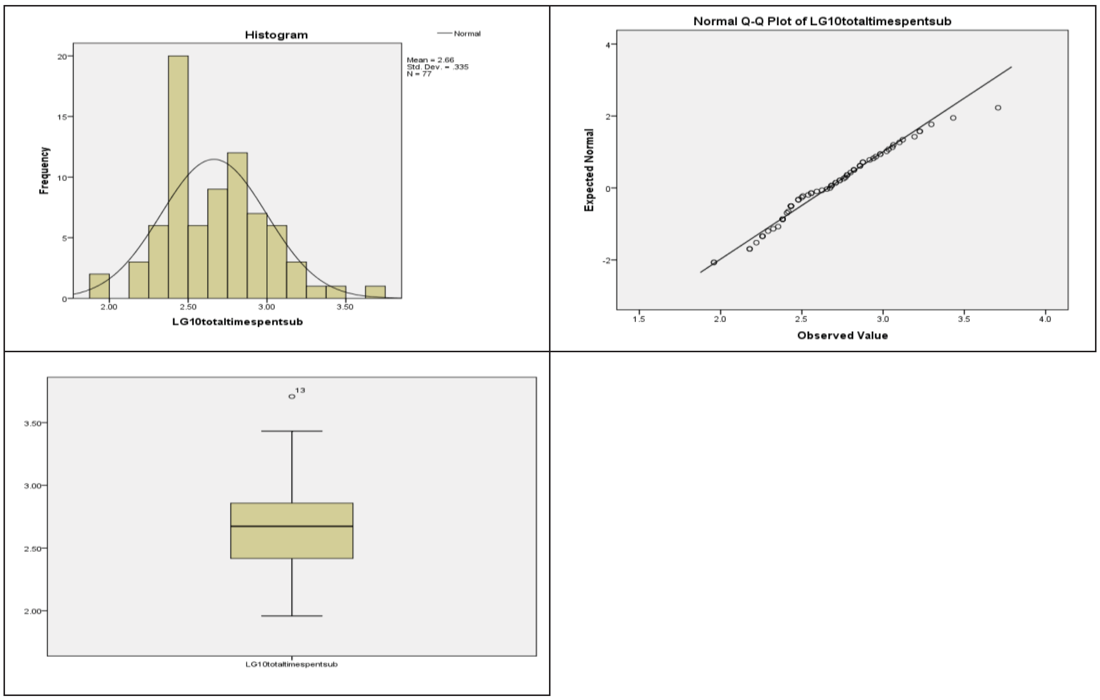


Figure 4: Histogram, Q-Q plot and boxplot for subjective time spent learning with E-learning during t_0 and t_2 data after transformation

- *Objective total time spent on E-learning system during* t_0 *and* t_2

Objective total time spent on E-learning system during t_0 and t_2 data deviated significantly from normal (SW = .72, df = 77, p < .001) (see Table 6).

Table 6: Normality test for objective total time spent on E-learning system during t_0 and t_2 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion (p < .01)
Total time spent with E-learning objective during t_0 and t_2	77	283.1 ± 359.1	1.9	.27	7.0	positive skewness	3.1	.54	5.8	positive kurtosis	.72	77	< .001	not normal

To improve the normality, as the data had positive skewness (7.0) and kurtosis (5.8), $\text{Log}_{10}(X + 1)$ was used to transform the data. The result of normality test after transforming the data is shown in Table 7.

Table 7: Normality test for objective total time spent on E-learning system during t_0 and t_2 data after transformation

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p < .01$)
Total time spent with E-learning objective during t_0 and t_2 (after transformation)	77	2.2 ± .52	.29	.27	1.1	no skewness	-.91	.54	-1.7	no kurtosis	.96	77	.02	normal

After transformation, the result showed that this variable data now did not deviate significantly from normal (*SW* = .96, *df* = 77, *p* = .02) and skewness (1.1) and kurtosis (-1.7) statistics. Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for *objective total time spent on E-learning system during* t_0 *and* t_2 after transformation suggested the assumption of normality was reasonable (see Figure 5). The boxplot indicated no outliers in this data. As the data of *Objective total time spent on E-learning system during* t_0 *and* t_2 after transformation distributed normally, the sampling distribution of the sample mean for this variable was normal.

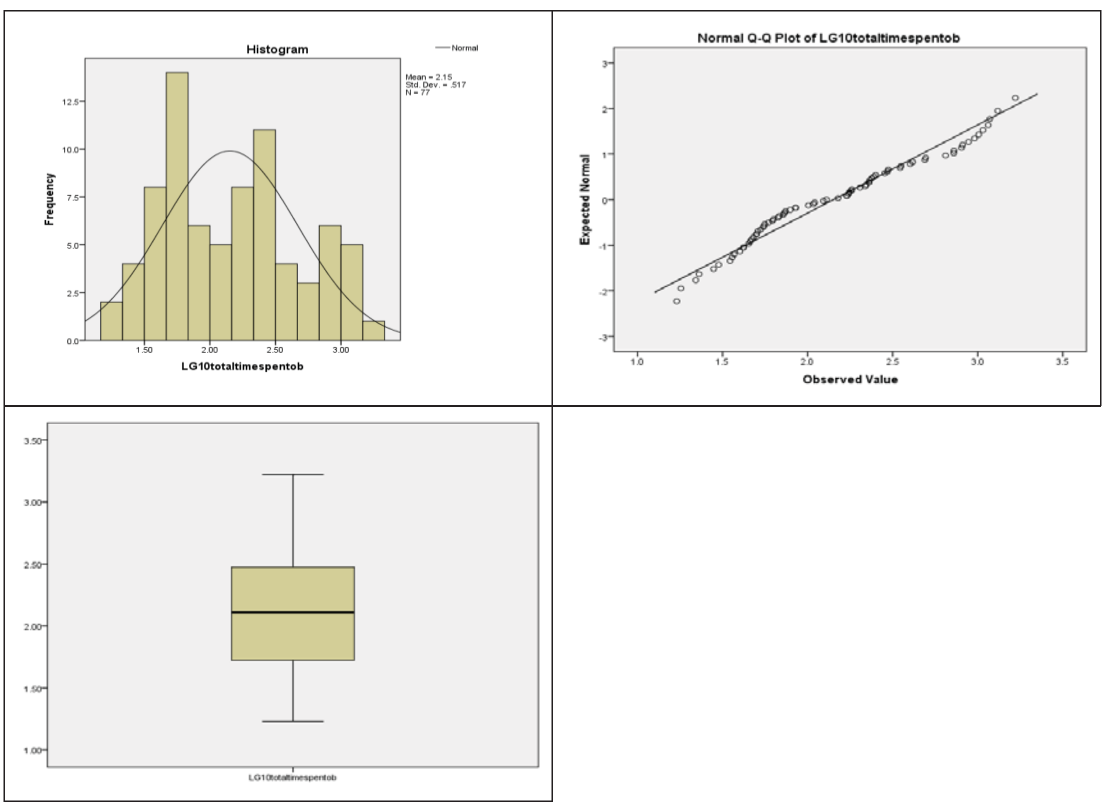


Figure 5: Histogram, Q-Q plot and boxplot for objective total time spent on E-learning system during t_0 and t_2 data after transformation

- *Objective total number of times logging onto E-learning during t_0 and t_2*

Objective total number of time logging onto E-learning during t_0 and t_2 data deviated significantly from normal (*SW* = .89, *df* = 77, $p < .001$) (see Table 8).

Table 8: Normality test for objective total number of times logging onto E-learning during t_0 and t_2 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p < .01$)
Total number of time logging on E-learning objective during t_0 and t_2	77	3.1 ± 2.5	1.3	.27	4.6	positive skewness	2.3	.54	4.3	positive kurtosis	.89	77	< .001	not normal

To improve the normality, as the data had positive skewness (4.6) and kurtosis (4.2), $\text{Log}_{10}(X+1)$ was used to transform the data. The result of normality test after transforming the data is shown in Table 9.

Table 9: Normality test for objective total number of times logging onto E-learning during t_0 and t_2 data after transformation

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p < .01$)
Total number of time logging on E-learning objective during t_0 and t_2 (after transformation)	77	.53 ± .28	-.25	.27	-.89	no skewness	-.47	.54	-.87	no kurtosis	.95	77	.006	not normal

After transformation, the result suggested that skewness (-.89) and kurtosis (-.87), was improved. However, Shapiro-Wilk test suggested that *objective total number of times logging onto E-learning during t_0 and t_2* data after transformation still deviated significantly from normal (*SW* = .95, *df* = 77, $p = .006$). The histogram and Q-Q plot for this variable data after transformation showed gaps between data, and this was why the data after transformation was still not normally distributed (see Figure 6). The boxplot indicated no outliers in this data. Even though this measurement data did not distribute normally, the sampling distribution of the sample mean was normal: this was because the sample size of this study was higher than 30.

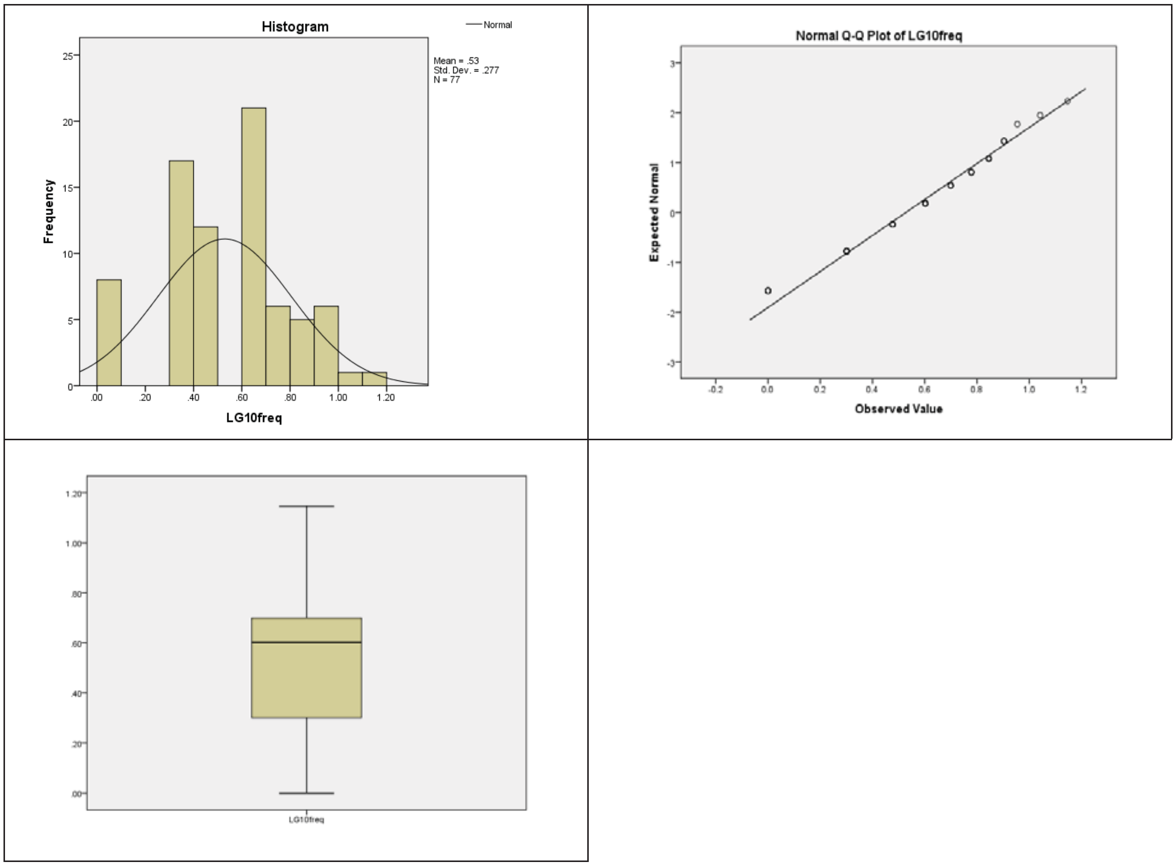


Figure 6: Histogram, Q-Q plot and boxplot for objective total number of times logging onto E-learning during t_0 and t_2 data after transformation

- *Objective total number of activities involving E-learning during t_0 and t_2*

Objective total number of activities involving E-learning during t_0 and t_2 data deviated significantly from normal (SW = .82, df = 77, p < .001) (see Table 10).

Table 10: Normality test for objective total number of activities involving E-learning during t_0 and t_2 data

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{Skewness}$	$Z_{Skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{Kurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p < .01$)
Total number of activity taking part on E-learning objective during t_0 and t_2	77	20.9 ± 21.9	1.3	.27	4.8	positive skewness	1.1	.54	2.0	no kurtosis	.82	77	< .001	not normal

To improve the normality, as the data had positive skewness (4.8), $\text{Log}_{10}(X + 1)$ was used to transform the data. The result of normality test after the transforming data is shown in Table 11.

Table 11: Normality test for objective total number of activities involving E-learning during t_0 and t_2 data after transformation

	No.	Mean ± SD	Skewness Test				Kurtosis Test				Shapiro-Wilk Test			
			Statistic	$SE_{skewness}$	$Z_{skewness}$	Conclusion ($Z \leq 2.56$)	Statistic	$SE_{Kurtosis}$	$Z_{sKurtosis}$	Conclusion ($Z \leq 2.56$)	Statistic	df	P-value	Conclusion ($p < .01$)
Total number of activity taking part on E-learning objective during t_0 and t_2 (after transformation)	77	1.1 ± .46	.12	.27	.43	no skewness	-1.3	.54	2.4	no kurtosis	.93	77	.001	not normal

The result after transformation suggested that the data still deviated significantly from normal (*SW* = .93, *df* = 77, *p* = .001). Consistent with the Shapiro-Wilk test, the histogram and Q-Q plot for *objective total number of activities involving E-learning during* t_0 *and* t_2 after transformation suggested the assumption of normality was not reasonable (see Figure 7). The boxplot indicated no outliers in this data. As the sample size of this study was higher than 30, its sampling distribution of the sample mean was normal, even though this measurement data did not distribute normally.

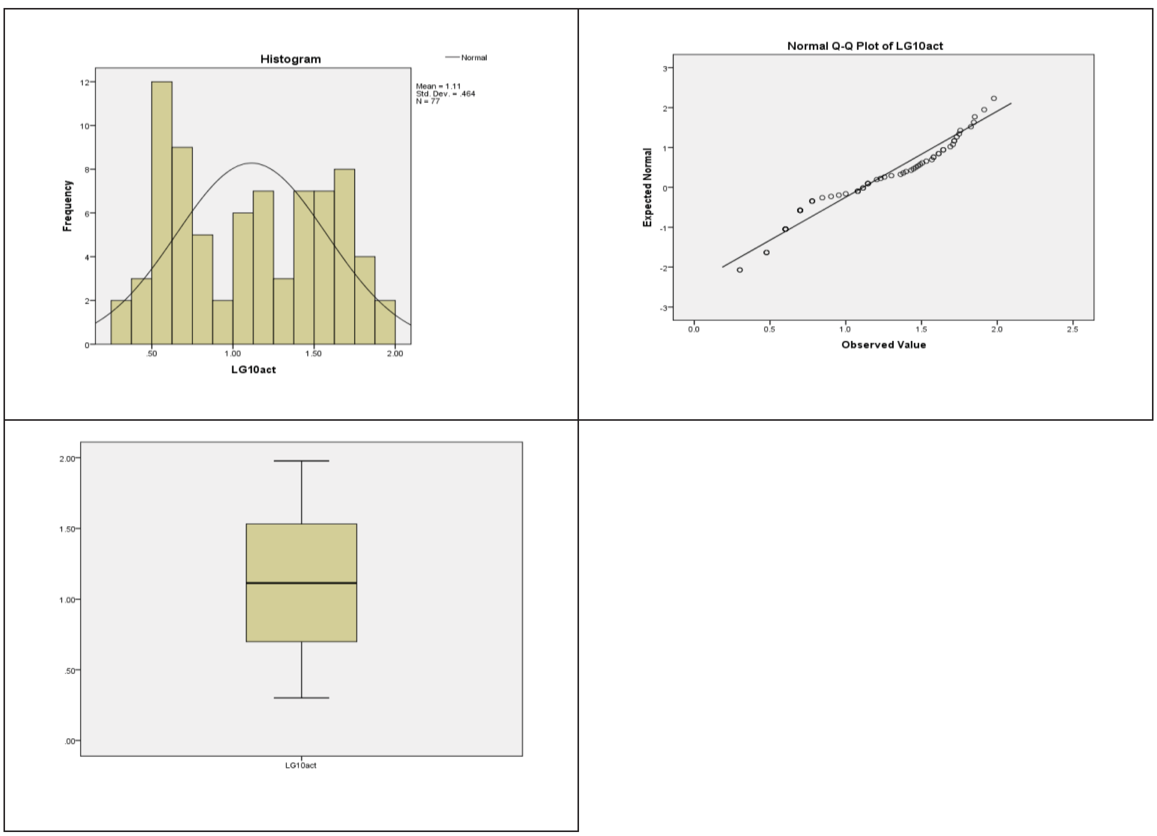


Figure 7: Histogram, Q-Q plot and boxplot for objective total number of activities involving E-learning during t_0 and $t_2$after transformation

Assumptions 2 and 3: Linearity and Homoscedasticity

To check the linearity and homoscedasticity assumption, a scatterplot of the standardized residual and standardized predicted value was drawn (see Figure 8). The result suggested that the assumption of linearity and homoscedasticity for this data analysis was not violated, because there was no systematic relationship between the standardized residual and the standardized predicted value.

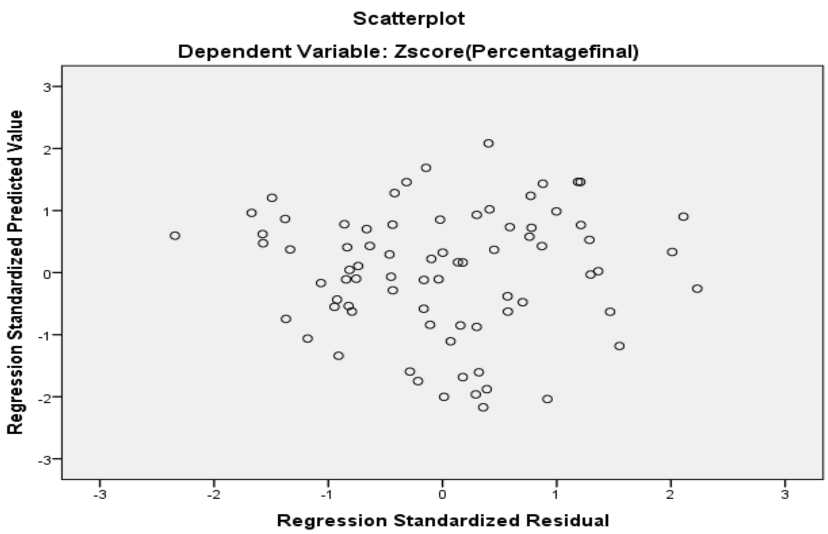


Figure 8: Scatterplot of residual plot and predicted value for the regression model of relative standardized final exam score with relative standardized final midterm score and the five measurements of E-learning usage during t_0 and t_2

Assumption 4: Independence of residual (error)

The Durbin-Watson test was used to evaluate the independence of residual. The result showed that Durbin-Watson statistic for all this data analysis was 1.7, which was considered acceptable. It suggested that the assumption of independent errors has been met.

Assumption 5: Multicollinearity

To detect multicollinearity among independent variables, the VIF test was used (see Table 12). According to the general rule of thumb, as the VIF for each independent variable was lower than 10, multicollinearity was not a concern.

Table 12: Collinearity test for the relative standardized final midterm score and the five measurements of E-learning usage during t_0 and t_2

Independent variable	**Variance inflation factors (VIF)**
Relative standardized midterm score	1.2
Percentage (subjective) during t_0 and t_2	1.7
Time spent (subjective) during t_0 and t_2	1.4
Time spent (objective) during t_0 and t_2	4.4
Number of time logging (objective) during t_0 and t_2	1.8
Number of activity talking part (objective) during t_0 and t_2	4.6

Appendix 8-A: Z-transform comparing predictive performance of continued use of E-learning among four models of interest

To compare the predictive performance of continued use of E-learning (degree of consistency), Fisher's Z-score technique was conducted between the four models (EC sub-model, ECM, TAM and UTAUT). As there were multiple tests, the Bonferroni correction was applied in order to reduce the risk of cumulative Type I error. The significance level for this analysis was set at .008 (.05/6) (see Table 1).

Table1: z-score comparing a degree of consistency with actual continued use of E-learning among the four models of interest (EC sub-model, ECM, TAM and UTAUT)

Pair 1	Pair 2	R1	R2	Z_{R1}	Z_{R2}	P-value	Conclusion (P < .008)
ECM	EC sub-model	.55	.51	.62	.56	.69	Not sig. different
	UTAUT	.55	.44	.62	.48	.37	Not sig. different
	TAM	.55	.37	.62	.39	.16	Not sig. different
EC sub-model	UTAUT	.51	.44	.56	.48	.62	Not sig. different
	TAM	.51	.37	.56	.39	.31	Not sig. different
UTAUT	TAM	.44	.37	.48	.39	.61	Not sig. different

The degree of consistency between the model's prediction of continued use of E-learning at t_1 and the actual continued use of E-learning at at t_2 was not significantly different between the four models: the ECM and EC sub-model (R different = .04, *p* = .69); the ECM and UTAUT (R different = .11, *p* = .37); the ECM and TAM (R different = .18, *p* = .16); the EC sub-model and UTAUT (R different = .07, *p* = .62); the EC sub-model and TAM (R different = .14, *p* = .31); and the UTAUT and TAM (R different = 0.7, *p* = .61). The result suggested that the four models do equally well in predicting the continued use of E-learning.

Appendix 8-B: Consistency between calculated and measured expectations

The consistency between each measured and calculated expectation was tested using the Pearson product-moment correlation coefficient. There was one condition and one assumption for this analysis.

Condition 1**:** Variables are continuous data

In this data analysis, there were 10 variables: five measured expectations at t_1 and five calculated expectations at t_1. These variables were within the range of 0–10. This condition therefore was met.

Assumption 1**:** Sampling distribution of the sample mean for each variable is normal

The normality check and outlier detection for the five measured expectations at t_1 and the five calculated expectations at t_1 were checked previously. The results suggested that the normality assumption was not violated.

Correlation analysis between each measured and calculated expectation at time t_1

The Pearson product-moment correlation coefficient (Pearson's correlation) was conducted to check the consistency between the measured and calculated expectation variable (see Table 1).

Table 1: Correlation table for the pair of measured and calculated expectation

		N	Correlation	Sig.
Pair 1	mPE - cPE	77	.76	< .001
Pair 2	mEE - cEE	77	.72	< .001
Pair 3	mSEE - cSEE	77	.82	< .001
Pair 4	mFCE - cFCE	77	.67	< .001
Pair 5	mLCE - cLCE	77	.82	< .001

The result showed that there was a statistically significant relationship between measured and calculated expectation in all five expectation variables: *performance expectancy* ($r = .76$, $p < .001$); *effort expectancy* ($r = .72$, $p < .001$); *social encouragement expectancy* ($r = .82$, $p < .001$); *facilitating condition expectancy* ($r = .67$, $p < .001$); and *learning consistency expectancy* ($r = .82$, $p < .001$).

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