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Faculty of Engineering and Physical Science

Electronic and Computer Science (Web and Internet Science)

MPM Model: A Cross-Platform Massive Open Online Course (MOOC) Performance Monitoring and Measurement Model Based on MOOC Learning Analytics

by

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Abstract

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Over the past ten years, most higher education institutions have employed Massive Open Online Courses (MOOCs) to deliver educational materials and activities. MOOC learning analytics data is readily available, which is one of its primary characteristics. Sadly, there are still problems with student dropout, retention, and engagement on MOOCs, which reduces their usefulness as a learning tool. More research is urgently needed to determine how to monitor, assess, and enhance learning delivered through online platforms. The researchers designed the research to solve specific practical problems and answer certain questions. The Ministry of Education Malaysia's requirement partly motivates this study, and the semantic web concept inspires it to investigate learning analytics in different MOOC platforms. The aim is to find a way to utilise the existing learning analytics data from MOOCs for monitoring and measuring a course or learner performance. An initial study led this research to three main research questions and research objectives. The first research objective is identifying parameters and algorithms for measuring course and learner performance using existing learning analytics. The second research objective is to propose a generic model for monitoring course and learner performance at macro and micro levels using MOOC learning analytics, which resembles the cross-platform features. The third objective is to observe and evaluate the MPM Model's usability. This study used Applied research using mixed methods. The researchers designed the research to solve specific practical problems and answer certain questions. A combination of various research methods and activities, such as observation, simulations, experiments, and surveys, are used throughout different phases of this research study. Phase 1 is a literature review and preliminary study. Phase 2 is data analysis and algorithm development. Phase 3 is the MPM model design, development and experiments. Phase 4 is MPM Model user usability testing and feedback. Phase 5 is results, discussion and report preparation. A Series of simulations provides us with the information to consider in completing the algorithm design and development of the MPM Model. The MPM Model experiments showed more insight from analysed MOOC learning analytics data. User usability testing conducted with 20 selected participants indicates good feedback on how a user can use the MPM model, what information it gives them to justify their MOOCs course or learner performance, and what to consider for future improvement. As this study ends, I have effectively addressed and met the established goals and research questions. I assert that MOOC learning analytics will now be more accessible to comprehend and utilise thanks to the MPM Model. This work advances the fields of data science and MOOC education research, particularly in the areas of cross-platform MOOC analytic monitoring and performance reporting.

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Wan Saifudin, Wendy Hall, Lesli Carr. (6 December 2022) Doctoral Research Showcase.

https://sotonac.sharepoint.com/teams/PGREventsProgramme/SitePages/Faculty.aspx

Research Thesis: Declaration of Authorship

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Title of thesis: MPM Model: A Cross-Platform Massive Open Online Course (MOOC) Performance Monitoring and Measurement Model Based on MOOC Learning Analytics

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

I confirm that:

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2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
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7. None of this work has been published before submission.

Signature: .... Date:........................

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"He gives wisdom (useful knowledge) to whom He wills; and whoever is blessed with wisdom, then indeed he benefits greatly; and no one can take lessons except those who have understanding." (Al-Baqarah: 269)

Definitions and Abbreviations

MOOC .... Massive Open Online Course

LA .... Learning Analytics

DePAN .... Infrastructure & Infostructure Domain of Malaysian National e-Learning Policy

ICT.................................. Information and Communication Technology

RQ1 .... Research Question 1

RQ2 .... Research Question 2

RQ3 .... Research Question 3

RO1 .... Research Objective 1

RO2 .... Research Objective 2

RO3 .... Research Objective 3

EDM................................ Educational Data Mining

LAK .... International Conference on Learning Analytics and Knowledge

CFA .... Correct on the First Attempt

SRL .... Self-Regulated Learning

ODL .... Open and Distance Learning

MDS................................ Module Difference Score

WDS .... Widget Difference Score

ADS .... Assignment Difference Score

API.................................. Application Programming Interface

W3C .... World Wide Web Consortium

RDF .... Resource Description Framework

OWL .... Web Ontology Language

SKOS .... Simple Knowledge Organization System

MPM .... MOOC Performance Measurement

RNN................................ Recurrent Neural Network

OIL.................................. Ontology Inference Layer

DAML-ONT....................... DARPA Agent Markup Language - ontology language

RDFS .... Resource Description Framework Schema

SLR................................. Systematic Literature Review

ERGO............................... Ethical Research Governance Guidelines

UUT .... User Usability Testing

UK .... United Kingdom

CSV .... Comma-separated values

JSON................................ JavaScript Object Notation

HTML .... HyperText Markup Language

Chapter 1 Introduction

1.1 Motivation

Concern about the escalating cost of education, during an interview in 1997 by Forbes, Peter Druker, a management consultant, educator and author, was quoted saying, "Thirty years from now, the big university campuses will be relics. Universities will not survive" (van Baalen, P.J., Moratis, L.T., 2001). Druker also suggested that video delivery could reduce costs and obviate campus building needs. The thirty-year prediction runs until 2027, and it gives us approximately five years to be prepared and carefully re-evaluate how our education system works best in today's challenging environment, especially at the high-learning institution levels.

Chronologically, good infrastructure and technology readiness supported the introduction of Massive Open Online Courses (MOOC) in 2008, approximately 11 years after Druker interviews. Most institutions of higher learning and organizations have used MOOC to deliver learning content and learning activities for almost 15 years now. MOOC enables learning providers to offer online courses to learners worldwide, primarily for free. As each technological innovation has come and gone within the educational scope, it has left education feeling that something good has happened but that nothing fundamental has changed (Noss, R. and Pachler, N. 1999). I describe this scenario as technological innovation changing how people learn, but how we teach, assess, and evaluate hardly changes.

Besides being driven by rich video presentation content, MOOCs offer a solid proposition to attract a new generation of learners as MOOCs incorporate the evolution of how people use the internet. This proposition includes social interaction in digital platforms, online collaborative learning and hype within the supply and demands where everyone could start their MOOC learning with prestigious universities and get certified for future career advantages or satisfactory self-achievement. MOOCs offer researchers, content providers, and users significant advantages by providing systematic learning analytics (LA) data. Log data and user interaction information on most MOOC platforms were recorded and made available. I consider this data as another variable that can be leveraged.

Noss and Pachler (1999) highlight that introducing a new variable into the teaching and learning process has considerable implications for the role of the teacher and her relationship with the learner. Educators need not only to possess the requisite technical skills but also to understand the relationship between the system and the learners and the implicit and explicit values and assumptions of ICT applications about how learning happens and how technology might contribute. This demand is one of the fundamental challenges of information and communication technology (ICT) for educational purposes to ensure that it enhances the learning experience's quality. I believe learning analytics can address this concern with insight. Analytic data is the knowledge in this digital era, and we build a massive collection of 'knowledge'. It is time to understand it.

Another challenge to consider is when we look at an array of today's MOOC platform providers where each provider does share the most MOOC similarities but is distinct in some detailed features. This challenge gives higher learning institutions and users options to decide which platform best suits them. Therefore, we now experience that users are highly likely to use more than one MOOC platform to start learning, while content providers might focus on using one or two platforms or even changing platforms over time to offer their courses.

Learning analytic data from the MOOC platform is a way to help understand how the offered course contributes to learning performance. This situation led to issues where it is challenging to analyse learning performances. To my knowledge, there is no standard consensus between MOOC platform providers on how the learning analytics should be structured, the meaning of each data represented, or to what extent data will be harvested and made available.

On the other hand, I see a trend where higher learning institutions use MOOC to offer free courses and apply fees for an option to get a professional certificate or even accreditation towards a final qualification degree from universities. In some countries, such as Malaysia, the Education Ministry and e-learning experts published policies and guidelines to ensure MOOCs are developed and aligned with the national agenda (Dasar e-Pembelajaran Negara., 2011). This research study is partly motivated by the target set in the Malaysian government's National e-Learning Policy (DePAN). The Ministry of Education Malaysia requires all MOOC platforms at higher learning institutions to be learning analytic-ready by 2025 (Executive Summary Malaysia Education Blueprint 2015-2025, Higher Education., 2013).

Table 1: Infrastructure & Infostructure Domain of Malaysian National e-Learning Policy (DePAN)

Domain	**Focus Area**	**Phase 1: 2015**	**Phase 2: 2016-2020**	**Phase 3: 2021-2025**
Infrastructure & Infostructure	eLearning Platform	eLearning platform 2.0 and MOOC ready	eLearning platform 2.0, MOOC and mobile-ready	eLearning platform 2.0, MOOC, mobile and learning analytics ready

The requirement indicates that we must monitor and use MOOCs accordingly, regardless of which MOOC platforms were used. This trend indicates the MOOC technology cycle and the future of education, where there is an initiative to utilise the existing learning analytics information fully.

In a study, Ferguson et al. (2016) reveal a set of nine priority areas for MOOC research and development. Table 2 below describes all nine areas and brief descriptions of how this study contributes and plays both direct and indirect roles in the stated areas.

Table 2: Nine Priority Areas for MOOC Research and Development

Areas	**Description**	**This Study**
Develop a strategic approach to MOOCs.	This involves creating a comprehensive plan for the role of MOOCs in education, both in the present and future and establishing lasting collaborations.	Using the MPM Model, the course admin or provider can monitor course and learner performance in standard and systematic methods. This will enable the course admin or provider to develop a strategic approach to how their MOOC can be improved.
Expand the benefits of teaching and learning in MOOCs.	Focuses on maximizing the advantages of teaching and learning within the MOOC environment.	Part of the advantages of teaching and learning within an MOOC environment are that learning can happen at any time and location, the use of different content and interaction types, such as quizzes, forums, video Using the MPM Model, the course admin or provider can monitor and measure course and learner performance in each module or chapter.
Offer well-designed assessment and accreditation.	Involves creating effective methods for assessing and accrediting learning within MOOCs.	Achievement scores or completion scores, are two common methods for assessing and accrediting learning with MOOCs. Performance measurement method design in this study

		is another method for assessing that can be use, which includes the Consideration Factor Indicator.
Widen participation and extend access.	Aims to increase the inclusivity of MOOCs and make learning opportunities more accessible to a broader audience.	It is challenging to design and deliver MOOC courses for wider learners' preferences. However, learning analytics data can help course admin and course providers to understand their learner characteristics, and with good analysis methods, MOOC courses can be designed according to their learners.
Develop and make effective use of appropriate pedagogies.	Focuses on the development and utilization of suitable teaching methods within the MOOC context.	This study was designed in the context of using data science knowledge to understand existing MOOC learning analytics data. A data model, measurement algorithms, metrics, and indicators were designed in this study to answer all research questions and meet research objectives, which eventually give MOOC course admin and provider insight and capabilities to make data-driven decisions on how they can apply effective and appropriate pedagogies.
Support the development of educators.	Involves providing support and resources for educators involved in MOOCs.	It is challenging for a non-data science background MOOC course admin to utilize or understand existing MOOC learning analytics data. The development of the MPM Model, which includes algorithms and indicators provides support for the development of MOOC course admin.

Make effective use of learning design.	Emphasizes the importance of designing learning materials and experiences effectively within the MOOC framework.	The MPM Model is designed to allow MOOC course admin to monitor each module or chapter. This will give a more accurate analysis, of how each module or chapter performs, and what learning design and structure used can be compared for improvement with additional reference to proposed Consideration Factor Indicators.
Develop methods of quality assurance.	Involves establishing processes to ensure the quality and effectiveness of MOOCs.	The MPM Model is currently tested on two different MOOC platforms and has demonstrated the ability to produce a standard performance measurement analysis. This cross-platform characteristic is one of the key features of the MPM Model and potential to be a standard method of quality assurance.
Address issues related to privacy and ethics.	Focuses on addressing ethical and privacy concerns related to the use of learner data and the conduct of research within the MOOC environment.	Not directly. However, the MPM model identified parameters that are essential to monitor and measure MOOC course and learner performance. Therefore, only specific datasets are required.

In general, this study justified that the data-driven decisions can be made more accurately based on MOOC learning analytics data analysis, as the study's key contribution towards the nine priority areas for MOOC research and development. Detailed justifications are provided in Section 8.4.

My observation of MOOC research studies in the early years indicates there are substantial unknown areas to explore, and research is focusing more on the MOOC technical setup, connectivity, learning design, MOOC implementation experience and feedback from selected groups of users or MOOC courses. The primary data for most of this study, which relied on observation and interviews, did not come from the MOOC analytics itself. The number of studies in the MOOC learning analytics field is relatively small and new for us to understand the needs of learners better. A systematic review of MOOC learning analytics studies published from 2011 until the end of April 2021 shows only around 166 learning analytics empirical studies conducted in a MOOC setting (Zhu, Sari and Lee, 2022).

Considering we now have massive learning analytics data from various MOOC platforms, it is logical to revisit some of the problems in MOOCs and try to solve them using learning analytics information and a semantic web approach. At this stage, we should do more research that will utilise existing MOOC learning analytics and understand what this data tells us and how we can improve with cross-platform capabilities.

Therefore, at the beginning of this research study, I underline the plan for research to be within the MOOC learning analytics areas. I considered the issues the Ministry of Education Malaysia raised concerning MOOC usage and my initial study of some global real-case scenario problems. I identified a research gap and three research problems for this research, which I explain in the following sections in this chapter.

1.2 Research Questions

This section described and justified the research gap and questions addressed in this study. The broad topic of MOOC undeniably emphasizes the essential use of this online-based learning method, especially in today's learning environment, and a strong belief exists that future dependency on it will be high. Both growth in the number of universities or learning providers that offer MOOC content and growth in the number of MOOC platform providers can also justify positive feedback on MOOC usage. Coursera, edX, Udacity, FutureLearn, NovoEd, Canvas, and OpenLearning are examples of MOOC platforms that offer the same key features of MOOC with slightly different approaches and other additional features between them. This diversity gives learning content providers various options for which platform they want to use. Some learning content providers even use multiple platforms or change platforms based on their current needs, policies or other circumstances.

Nonetheless, MOOCs are subject to the following three primary educational criticisms, according to Waks (2016): (1) MOOC completion rates are low; (2) MOOCs cannot take the place of necessary teaching functions; and (3) MOOCs are isolating while learning is social.

Experienced as a university lecturer in Malaysia where part of the work involves MOOC-related activity, the primary researcher in this study has background ideas and initial hypotheses on the possible research gap addressed in this research study. Later, I conducted a preliminary study on MOOC research areas to observe related research issues. Conducted systematic literature review discovers that a high user dropout rate and learner engagement remain MOOCs concerning issues (Sunar et al., 2016). I also found that assessing courses, learning evaluation, instructional design and methods of evaluating the success of MOOC programs and compelling content for diverse groups of learners remain popular issues in MOOCs-related research areas.

These findings support my initial hypothesis research gap: we still lack understanding and underutilizing MOOC learning analytics, especially in cross-platform data source events. I believe that more effort should be made to understand these alarming conditions by designing a practical, usable data model using learning analytic data that will help us better understand the knowledge behind the existing MOOC learning analytics data in a more universal approach, that is not limited to specific MOOC platforms analytics data. Based on thesis findings and with clear intention by the Malaysian education ministry to ensure the use of MOOC by local higher learning institutions is supported with learning analytics components as an essential feature, my observation then narrowed down to MOOC learning analytics usage at higher learning institution research areas.

Most higher learning institutions have used MOOCs to deliver learning content and activities over the past ten years. One of the critical features of MOOCs for course providers is the availability of MOOC learning analytics data that keep intensive log data related to learner interaction and activity on MOOCs. As a result, we can see a growing number of cases over the years of MOOC learning analytics research on how these valuable data can be fully utilized and benefit us, especially when addressing known issues related to retention, engagement, and dropout learners that undermine the effectiveness of learning on MOOCs.

However, despite the existing studies on MOOC learning analytics data, including developing a dashboard to utilize existing learning analytics data, little is known about the MOOC platform-dependent learning analytics model that can work on different MOOC platforms to measure performance. Therefore, the present study contributes to the design and development of the MOOC Performance Measurement Model (MPM Model) by introducing a MOOC Performance Theory that applies learning analytics and time series analysis method in the measurement algorithms development for cross-platform capabilities.

The research study then identified three research questions. The first research question (RQ1) is: what parameters can we use to measure course and learner performance at macro and micro levels using MOOCs cross-platform friendly learning analytics?

A vast collection of datasets with various information is available from MOOC platforms. The usability of each dataset provided depends on the purpose. Existing data must be carefully selected to ensure the information used is relevant to the purpose of the monitoring or measuring. Determining which data to use presents another challenge because different MOOC platforms can represent the same information under different names in their datasets. As I observed, various MOOC platforms were made available for the content provider and learners, and it is essential to acknowledge that each platform collects and stores learning analytics data in its standard or name that refers to the same data between different platforms. Studying and identifying data from various platforms is critical to ensure the measurement algorithm is compatible with datasets from different MOOC platforms and will work as a cross-platform algorithm. This requirement poses specific challenges, and I aim to overcome this challenge using the uniform dataset creation approach.

The second research question (RQ2) is how can monitoring and measuring course and learner performance at macro and micro levels be performed using MOOC learning analytics?

In general, not all MOOC course admin are well trained with the skills of data science or statistics. Therefore, it is understandable that most of them have difficulty understanding and using information from MOOC learning analytics data. Without a proper tool on how course admin can effectively use the learning analytics data, it is nearly impossible for them to benefit from it. From the MOOC platform providers' end, they have done their part in designing, collecting, storing, and making learning analytics data available to course admins. Some platforms provide a data visualisation based on learning analytics, but the information is basic yet limited. Considering the lists of well-established and acknowledged issues in MOOCs, it is crucial for MOOC learning analytics data to be understood and used, especially by course admin, to help them plan improvement on their MOOCs.

The third research question (RQ3) is: how do we evaluate the usability of the proposed MOOC Performance Measurement (MPM) model design?

There are two aspects considered when I plan to evaluate the proposed model. The first aspect is the algorithm design. This research study evaluates algorithm design using a sample dataset from targeted MOOC platforms. The second aspect considered is from the user perspective, which is the course admin and user in this scenario. I plan and conduct MPM User Usability

Testing with MOOC course admin and users from Malaysia who represent OpenLearning users and users from the United Kingdom who represent FutureLearn users.

1.3 Research Scope

Research motivation and questions described in previous sections help shape the research scope. Here, I explain how much this research study will be explored and limited. I was expected to provide an insight into the aim of the study and what we should anticipate at the end of this section. The timeframe of this study is within four years of a PhD term at the School of Electronics and Computer Science (Web and Internet Science), University of Southampton, United Kingdom.

RQ1 emphasise the parameters to be identified and used for monitoring and measuring the performances of a course or a learner on MOOCs. I also described the urge for a measurement model to work on cross-platform demand earlier. With these requirements, I plan to use sample datasets from two MOOC platforms to simulate the cross-platform scenario. Initially, I am not limiting which datasets to use as all available datasets will be explored and studied to find suitable parameters for designing the measurement algorithms. The two MOOC platforms used in this study are FutureLearn, a MOOC platform widely used in the United Kingdom, and OpenLearning, a MOOC platform widely used in Malaysia. The design of the measurement algorithm will focus on course performance as a whole and student performance as an individual.

Although many measurement methods can be possible using existing MOOC learning analytics data, in RQ2, I emphasize using learning analytics to monitor and measure course and learner performance. Therefore, I am designing and developing two measurement algorithms in this research study: the Course Performance Algorithm and the Learner Performance Algorithm. I will also design and propose measurement metrics and indicators to complete the MPM model.

In RQ3, I describe the need to evaluate the MPM model usability. For this, I am not planning to develop a complete system or project based on the designed MPM model. Instead, I will prepare a Microsoft Excel-based tool document embedded with the proposed MPM model. This tool will enable users to learn and experience using the MPM model. A series of experiments using actual data samples are conducted to evaluate the usability of the proposed model. Finally, I conducted sessions of user usability testing where participants are selected from Malaysia and the United Kingdom. Participants selected are individuals with experience using one of the MOOC platforms used in this study, either as course admin or MOOC course content developer.

1.4 Research Objectives

With the high user dropout rate and learner engagement remaining as MOOCs concerning issues (Sunar et al., 2016), it was identified that learning analytics could make a significant contribution as a tool for quality assurance and quality improvement, tools to improve teaching, and tools that could offer more extensive benefits (Sclater, Peasgood and Mullan, 2016). Based on the preliminary study, I believe that using learning analytics data to monitor and measure MOOC performances will provide better insight for the course admin to improve their MOOC content or instructional design.

Three research objectives are set to help answer the research questions mentioned in the previous section of this chapter. The first Research Objective (RO1) is to identify parameters and algorithms for measuring course and learner performance using learning analytics from MOOCs. The second Research Objective (RO2) proposes a cross-platform data model for monitoring course and learner performance at macro and micro levels using learning analytics from MOOCs. The third Research Objective (RO3) is to conduct a series of experiments using the MPM Model with sample datasets and a session of user usability testing with the MOOC course admin or MOOC content developer to validate the proposed model.

Table 3: Research Questions and Research Objectives

Research Questions	Research Objectives
RQ1: What are the parameters for measuring course and learner performance at macro and micro levels using learning analytics from cross-platform MOOCs?	RO1: To identify parameters and algorithms for measuring course and learner performance using learning analytics from MOOCs.
RQ2: How can monitoring course and learner performance at macro and micro levels be performed using MOOC learning analytics?	RO2: To propose a cross-platform model for monitoring course and learner performance at macro and micro levels using learning analytics from MOOCs.
RQ3: how do we evaluate the usability of the proposed MOOC Performance Measurement (MPM) model design?	RO3: To conduct a series of experiments using the MPM Model with sample datasets and a session of user usability testing with the MOOC course admin or MOOC content developer.

1.5 Research Contribution

Since their introduction in 2008, people have used MOOCs for almost 15 years to describe free, easily accessible, completely online courses. Continuous effort must be drawn towards online learning and MOOCs. MOOC platforms have demonstrated their capabilities in preparing learning analytic data and making it available to course admin. This vastly available data contains information and knowledge on MOOCs and how each MOOC course has been used. Now is the critical time for us to understand the data and learn from it to improve how MOOCs deliver to learners. This research study successfully achieved the stated objectives. This report highlights the use of MOOC learning analytics data and a the approach undertake to understanding data from different platforms. This research contributes to the cross-platform MOOC analytic monitoring and performance measurement research area with a novel MOOC performance theory. Two measurement algorithms proposed in this research study can be seen as a novel approach for MOOC performance measurement. The proposed measurement metrics and an indicator that completes the MPM Model are another novel contribution of this research study towards the data model and MOOC learning analytic research areas.

Another significant contribution of this research study is that the MPM model helps users monitor and measure their MOOC performances based on the existing dataset. This available learning analytic data gives the motivation to overcome existing issues in MOOCs, such as high dropout rates, weak engagement, course design and effectiveness, by better understanding how current MOOC offerings affect the learner. This thesis's last chapter presents details of theoretical, practical, ontological, and methodological contributions.

1.6 Thesis Organization

This thesis is structured into eight chapters.

- Chapter 1, Introduction
- Chapter 2, Background and Literature Review
- Chapter 3, Research Design and Methodology
- Chapter 4, Identifying parameters from an existing MOOC learning analytics
- Chapter 5, Designing and Development of the MPM Model
- Chapter 6, MPM Model Experiments
- Chapter 7, MPM Model User Usability
- Chapter 8, Research Conclusions and Future Works.

Chapter 2 Background and Literature Review

2.1 Introduction

Since the introduction of Massive Open Online Courses (MOOCs), the educational landscape has undergone significant change. MOOCs, as a novel platform for delivering educational content, have attracted a lot of interest and funding from academic institutions, businesses, and governments. MOOCs were first introduced in developed nations, but their use and acceptance have spread throughout the world, providing learning opportunities for people from all socioeconomic backgrounds and places.

Millions of students worldwide now have access to education thanks to MOOCs, which initially gained popularity in developed nations. Over time, in response to shifting market demands and careful balancing between national education policies, MOOC adoption and perception in Malaysia have changed. Influenced by factors like economic pressures, shifting educational priorities, and technological advancements, Malaysia's strategic view of MOOCs has mirrored global trends.

This research study is titled MPM Model – A cross-platform Massive Open Online Course (MOOC) Performance Monitoring and Measurement Model Based on MOOC Learning Analytics. I carry out a literature review spiral to the application of MOOC learning analytics in higher education institutions, a cross-platform learning performance measurement data model, a learning analysis method, and related data science technology to close the research gap and contribute to the resolution of research questions. Along with reviewing the semantic web concept, this chapter also covers the theoretical framework that will direct the investigation.

Information retrieval techniques and systematic literature review are the two main methods used in literature studies. I used Google Scholar as my main online library and search engine, including links to other journal publications relevant to the field. I have established general selection criteria, such as the requirement that publications be written exclusively in English or Bahasa Malaysia and published before 2021. I used print publications from university libraries in addition to those found online. Limiting the scope of the literature review to what my study will accommodate is crucial. The primary field of study is data science, and my primary goal is to create a cross-platform data model that will function within the parameters of my investigation and fill in knowledge gaps regarding learning and education.

2.2 Background Study

The word MOOC is an acronym for sentence Massive Open Online Course. The MOOC revolution commenced in the early 2010s when two American institutions, the Massachusetts Institute of Technology (MIT) and Stanford University, launched their online course offerings (Gebre-Medhin, 2018). The sheer scope of learners enrolling from all corners of the globe laid the foundation for an educational paradigm shift. MOOCs offer free and unlimited access to the intellectual holdings of the university, including access to the world’s most renowned scholars and teachers (Rieber, 2016). MOOCs are also described as courses designed for large numbers of participants that can be accessed by anyone anywhere as long they have an internet connection, are open to everyone without entry qualifications, and offer a full or complete course experience online for free (Gaebel, 2013).

The United Kingdom (UK) embraced the MOOC movement with enthusiasm, developing partnerships with renowned universities and utilizing the platform to bolster professional development and skills enhancement (Osborne and Mayes, 2014). In Malaysia, the perception and usage of MOOCs have followed suit, hinging on the nation's evolving economic needs and prioritization of education.

As the global community came face-to-face with the unprecedented challenges wrought by the COVID-19 pandemic, educational institutions worldwide adapted and incorporated online learning, including MOOCs, into their curriculums (Bozkurt et al., 2020). This shift in strategy has led to a more favorable perception of MOOCs, as the pandemic demonstrated the resilience, flexibility, and accessibility of online learning formats.

The diversity of MOOC usage also leads to a different MOOC environment setup, especially in terms of accessibility, where some of the MOOCs require learners to pay for it or are restricted to a specific group of people. Another definition of MOOC is that MOOCs are online courses in which anyone can participate anywhere, usually for free.

Vigentini and Clayphan (2015) conclude that the MOOC ‘event’ structure substantially impacts how students engage, but more analysis is necessary to determine the level of flexibility afforded. The sequence of the MOOC course ‘event’ describes the course structure. The MOOC course is generally structured in several learning units, each with content in lecture videos, textbooks, tutorial notes, blog posts and others. The course also includes assessment functionality delivered by designated components such as assignments, quizzes or exams (Chauhan and Goel, 2016). MOOC definition may change as users innovate it with the latest technology, learning style, learning instructional design, or based on the policy maker's decision. At present, I agree on the definition of MOOC as an online learning course made available over the Internet to many participants.

The use of MOOCs enables learning analytics data to be tracked and stored. It is an activity that is also described as data collection, where data by itself is a collection of facts or signals that are raw and, as such, are not helpful. Turning data into information ready to be utilised is another vital process. Consistently arranging and ordering learning analytics data makes this data collection more valuable. Knowledge is then described as a collection of information. Building knowledge and understanding it are two equally important activities.

As I perpetuate my exploration of the broader context around MOOCs, I will investigate their usage, perception, and strategic view in Malaysia and the United Kingdom, while assessing the potential usage of existing MOOC learning analytics data in monitoring and measuring MOOC courses and MOOC learner performance.

There are various MOOC learning analytics data structures exist from different MOOC platforms. For example, one platform might use learners' progress and, in another platform, use module completion, yet they have the same data meaning.

Khalil and Ebner (2016) indicate close relationships exist between Learning Analytics and Web Analytics, Educational Data Mining (EDM) and Academic Analysis. With the relationships between the areas mentioned above in mind, a general definition of learning analytics during the first LAK in 2011 is learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts for purposes of understanding and optimising learning and the environments in which it occurs (Siemens and Gasavic, 2012).

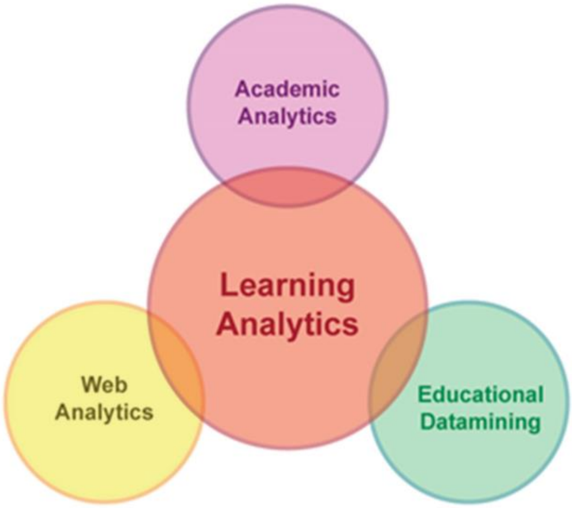


Figure 1: Learning analytics, educational data mining, web analytics and academic analytics (Siemens and Gasavic, 2012).

Although the learning analytics field has grown, and my research study is regarding MOOC learning analytics in a cross-platform context, the general definition of MOOC learning analytics itself is acceptable.

In this research study, I am looking into a way to understand MOOC learning analytics data from different MOOC platforms. I believe a better understanding of MOOC learning analytics data in a cross-platform environment will lead to the possibility of designing and developing the MOOC performance measurement model. A model that will help MOOC course admin or users justify their performance on MOOC and give insight on what aspect of changes or improvement to consider.

From the preliminary study and research motivation, I identified gaps in the current understanding of learning analytics in cross-platform MOOCs that warrant further investigation. Due to the massive nature of MOOCs, the number of learning activities (e.g. forum posts, video comments, assessment) might become very large or too complex to be tracked by the course learners (Arnold & Pistilli, 2012; Blikstein, 2011). It is not easy to provide personal feedback to many learners (Mackness, Mak, & Williams, 2010; Yousef et al., 2014b). Practical methods are needed to track and monitor learners' activities and performance to improve learning among large groups of students (Yousef et al., 2014). I, therefore, pose the three research questions. First, what parameters can be used for measuring course and learner performance at macro and micro levels using existing MOOC learning analytics data? How can we measure MOOC courses and learner performance using learning analytics? Finally, how do we evaluate the usability of the proposed model design?

2.3 Definition in Context of the Research Study

Words in general contexts could be interpreted in many ways and have a different understanding depending on the point of view, justification of facts or purpose. In more subjective circumstances, it is more likely to have various ways to explain something, and none of it is considered wrong. It is a condition where which explanation is more acceptable and clearly describes something to others and justifies the specific purpose. A definition is a way to say the meaning of something. Therefore, it is essential to have a clear definition set at the beginning of the research. This section intended to construct a definition of MOOC Courses and Learners Performance for the research on the MOOC Performance Measurement Model from an educational point of view and Cross-platform Data Model definition from a data science research point of view.

2.3.1 MOOC Course and Learners Performance

To perform is to take a complex series of actions that integrate skills and knowledge to produce a valuable result (Elger, 2007). If we consider the linguistic form of the word, the Oxford English Dictionary takes performance to be how well or badly someone does something or how well or badly something works (Ghalem et al., 2016). ‘Something’ is based on the context of how we want to distinguish performance. For example, from the business point of view, a significant number of enrolments, subscriptions, or profit income may be the best performance parameters matrix to use. Nevertheless, if we look at MOOC Performance from a technology or security point of view, the downtime or page loading time could be a more suitable performance parameters matrix.

In this study, I look at MOOC performance from an educational point of view. Education is defined as the process of facilitating learning, the acquisition of knowledge, skills, values, beliefs, and habits (Kravchenko and Payunena, 2017) or the process of receiving or giving systematic instruction, especially at a school or university (Singh and Kumari, 2017).

Therefore, from this general performance definition, if I determine ‘something’ in the context of MOOC, MOOC courses or MOOC learners, I can have MOOC performance defined as how well or badly you do MOOC course learning or how well or badly MOOC course or MOOC student learning works.

From this initial understanding and general definition, I conduct literature reviews of findings from related research publications to explore existing understanding describing MOOC performance and how performance is measured.

Table 4: Literature Reviews on MOOC Performance Definition

Publication	Definition	Definition Matric
Conijn, Van den Beemt, and Cuijpers, 2018	In the context of MOOCs, ***student performance*** is often defined as ***course completion***. However, students could have other learning objectives than MOOC completion. Therefore, we define student performance as ***obtaining personal learning objective(s)***.	Course completion Obtaining personal learning objective(s)
Alario-Hoyos et al., 2016	This article addresses the challenge of exploring top contributors' characteristics. For this purpose, we conducted a study with empirical data on participants' performance in different assessment activities and their use of five different social tools from a 9-week MOOC on educational technologies. In addition, we analyse the relationship between ***participants' overall performance*** **(*measured in terms of final scores*)** and the number of posts in the social tools under analysis.	Final score
Brinton and Chiang, 2015	Our videos are equipped with in-video quiz questions, which are short multiple-choice exercises designed to test a student's knowledge recall of the content in the video before he/she proceeds. ***Our performance measures are the scores that students obtain on their first attempts at these quizzes***, i.e., whether they are Correct on the First Attempt (CFA) or not (non-CFA).	Quizzes' fir[st] attempts score
He, J., et al., 2015	Predicted probabilities must be well-calibrated and smoothed across weeks to be effective. Based on logistic regression, we propose two transfer learning algorithms to trade off smoothness and accuracy by adding a regularization term to minimize the difference in failure probabilities between consecutive weeks. Experimental results on two Coursera MOOC offerings establish the effectiveness of our algorithms.	Use/measure weekly for each lecture and assignment.

	For example, one might use individual-level features ***for each lecture and assignment, which might be released weekly, to help understand and interpret student performance.***	
Mortenson and Witt, 1998.	***Student academic performance during the intervention was scored as the percentage of items correctly completed by each student on typical classroom assignments in the designated subject area***. Based on pretreatment academic baseline performance during screening procedures and feedback from the teacher, an academic goal was established for each student. ***The goal was established at 80% for all students***. This was consistent with ability levels and was acceptable to all teachers. This goal remained constant throughout the study.	Percentage of the item correctly completed. The goal was established at 80%
Ashby, 2004	Internally, ***it is important to monitor academic progress from registration to completion*** and understand the policy's impact on the retention milestones chosen. While ***course completion rates are important indicators of the university's performance***, such indicators are limited representations of the full range of educational services provided. It is important to note that course completion rates are a goal established by the university and may only be an imperfect representation of learners educational goals.	Monitor academic progress from registration (start) through to completion (end) Course completion rates are important indicators of performance.
de Barba, Kennedy, and Ainley, 2016.	These types of data have then been used in investigations that have related demographic variables (e.g., previous education and gender) to measures of MOOC participation (e.g., assignments completed, videos viewed and contribution to online discussions) and ***measures of performance (e.g., course completion or grades).***	Course completion or grades as a measure of performance
Admiraal, Huisman and Pilli, 2015.	Assessment in MOOC. The notion that people might sign up for a course not intending to complete the assessments is common in free courses where the barrier to entry is usually as low as clicking a registration button and entering an email address. This means that ***new measures of success and quality are required***	New measures of success and quality are required.

	because participant behaviours and intentions are so diverse.	

The literature review conducted showed an exciting finding. First, I am focusing on how other MOOC research defines Performance.

Conijn, Van den Beemt, and Cuijpers (2018) and de Barba, Kennedy, and Ainley (2016) defined student performance as course completion. Ashby (2004) then acknowledges course completion rate as an essential performance indicator. In addition to this, Mortenson and Witt (1998) define student academic performance as the percentage score of correctly completed items. This differs from Brinton and Chiang (2015) and Brinton et al.'s (2016) approaches to measuring performance. Their approach is based on scores that students obtain on their first attempts at quizzes, not on overall or any correctly completed.

These findings give us an indication of the completion-score value as a parameter to consider. Next, I explore existing studies to identify how performance was measured in another research.

Alario-Hoyos et al., (2016) describe participants' overall performance as measured by the final scores. This approach explains that performance measurement can only be done at the end of the course or semester when the final scores are available. This differs from what Ashby (2004) suggests, that it is essential to monitor academic progress from as early as registration through to the completion of the course. In other words, Ashby (2004) suggests that measuring performance is done continuously. This approach was also suggested by He, J., et al., (2015) to justify the effectiveness of smooth and well-calibrated predicted probabilities in helping course administrators understand and interpret student performance. Weekly monitoring or measuring is ideal, assuming each lecture and assignment might be released weekly.

These findings indicate that regularly monitoring available data is a good approach for effective measurement indication. A weekly learning analytic data measurement is more practical as most courses release their content or activity weekly.

Based on this information, MOOC performance from the educational point of view involves two primary responders. It can be either focusing on the course performance as an overall class or the learner's performance outcome as an individual. Completion rate and other assessment scores are suitable parameters (Conijn, Van den Beemt, and Cuijpers, 2018; Mortenson and Witt, 1998., and Ashby, 2004).

Therefore, in this research study, I define MOOC performance as the **value of improvement or the ability to maintain the highest score value throughout the learning course, either for the**

course performance or individual learner performance. The highest score value in my definition is a full mark or 100% score.

There is a possibility scenario when the score is unchanged in two or more sequential data. For example, if data record a score of 99% in the previous week and 99% in the current week. In general view, this may look like a good performance. However, in logic, this score can be improved by another 1%. Therefore, if the unchanged data is 100%, this indicates the full mark and positive performance with no possibility for improvement. If the unchanged data is 99.99% or below, this indicates negative performance, with an improvement still possible. The logic justified this condition because the course or learner maintains the achievement at the total state, with no possibility of achieving a higher score. This approach is subjective and debatable, where some others establish 80% or other value benchmark performance (Asarta and Schmidt, 2012). As in this study, I consider course or learner achievement as an essential indicator; aiming for perfection is the benchmark I set.

2.3.2 Cross-Platform Data Model

Cross-platform refers to software or hardware running on multiple platforms or operating systems. For example, a web browser that can run on Windows, Mac, and Linux is a cross-platform application. Cross-platform in mobile application development taxonomy is a cross-platform solution when a developer develops one application once and runs it on many platforms (El-Kassas et al., 2017). In data analysis taxonomy, a cross-platform approach also means that when large amounts of data are stored in different sources, repositories can be accessed and used within tools, software, or analysis models (Xia et al., 2009). In summary, cross-platform means the ability to run on multiple platforms.

Data models are central to information systems. It provides the conceptual basis for thinking about data-intensive applications and a formal basis for tools and techniques for developing and using information systems (Brodie, 1984). According to (Codd, 1980), a data model combines three components: a collection of data structure types, a collection of operators or inferencing rules, and a collection of general integrity rules. Additionally, (Brodie,1984) highlights that concepts constituting a particular data model must be precisely defined. Precise definitions aid people in understanding the data model, ensuring the soundness of the data model concepts and their interaction, developing analytical tools, and implementing related languages and techniques. Typically, data models have not been formally defined. Consequently, data models are challenging to understand, apply, compare, and analyse.

Within the context of this research study, I define a cross-platform data model as a data model specifically designed and constructed for data analysis, with the ability to source data from various data analytics platforms. A standardized cross-platform data model could provide more comprehensive solutions than a single platform can offer (Daszczyszak et al., 2019). For example, we can use the same data model in a case study to analyse performance based on data from different platforms. This approach will give standard and non-biased analysis results to the stakeholders.

Future studies on learning analytics datasets from different MOOC platforms must identify suitable measurement parameters. The next chapter will explain this study.

2.4 Factors Affecting MOOC Course Usage

The utilization of MOOCs has revolutionized the field of education by offering widespread access to learning opportunities. Despite their popularity, however, retention rates in MOOCs present a significant challenge, as many learners tend to discontinue their courses before completion. This section of the thesis is dedicated to examining and understanding the various factors that impact the usage of MOOC courses, with the aim of improving learner outcomes and the effectiveness of the platforms.

In this study, a systematic literature review was conducted to categorize and assess the factors that influence the utilization of MOOC courses. Adhering to the PRISMA guidelines, 25 peer-reviewed articles were carefully selected for inclusion, providing a comprehensive overview of the existing research in this domain. The review identified seven primary categories of factors that affect the utilization of MOOC courses, underscoring the significance of user engagement, course design, and student motivation.

The key findings from the literature review underscored the importance of addressing challenges such as research methodology, data collection techniques, subjectivity in analysis, and the generalizability of results. Recommendations for future research include a focus on understanding learner behavior, the integration of information visualization tools, and tackling the identified challenges to enhance MOOC platforms and improve learner outcomes.

The systematic assessment of factors influencing the utilization of MOOC courses lays the groundwork for comprehending the intricacies of online learning environments. By recognizing and dealing with these factors, researchers can contribute to the advancement of more efficient and captivating MOOC platforms. Improvements in learner support resources, assessment mechanisms, and educational variables are crucial for enhancing the overall user experience and retention rates in MOOCs.

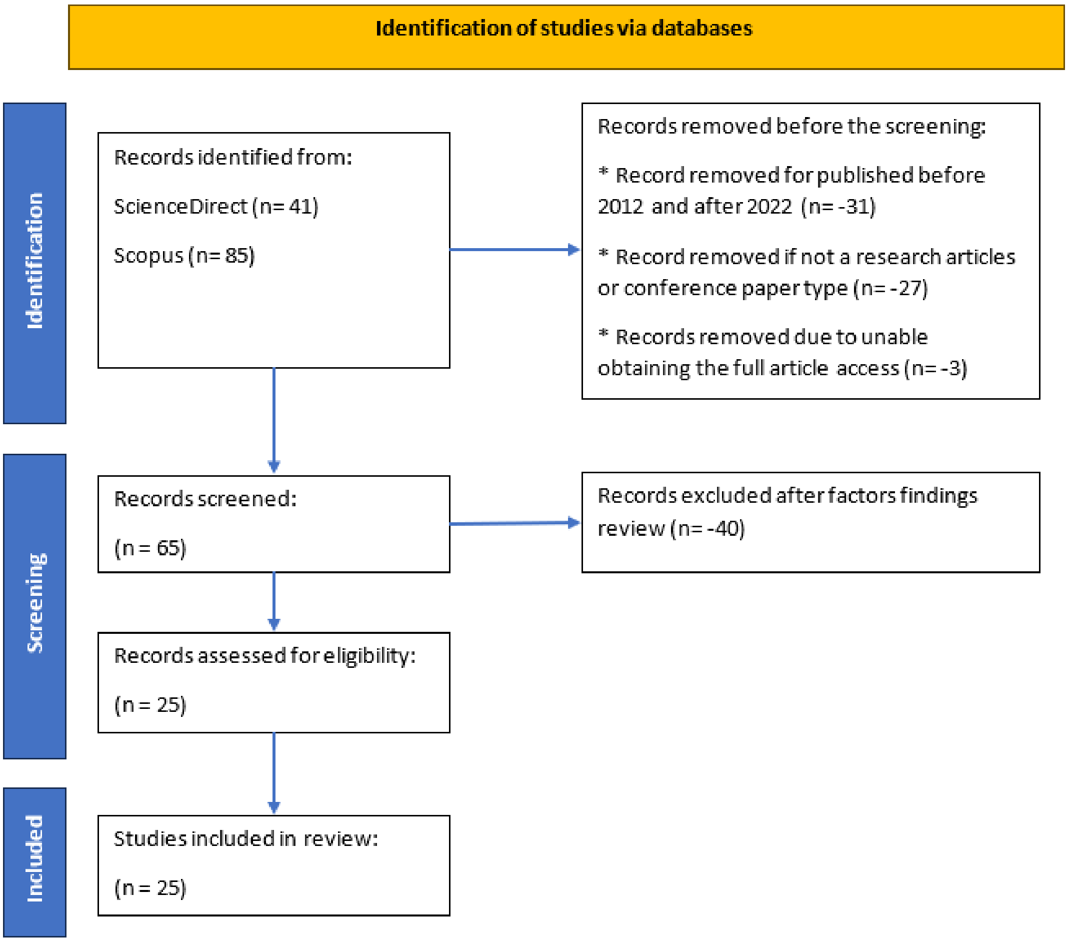


Figure 2: PRISMA flow diagram for article selection

A comprehensive review of literature was carried out to identify and assess the factors influencing the utilization of MOOC courses. The study utilized the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram as a methodological tool. PRISMA serves as a structured approach for identifying, selecting, assessing, and synthesizing research papers that investigate the existing knowledge within a specific domain.

2.4.1 Literature Search

The search strategy, selection, and data extraction were conducted in accordance with the PRISMA guidelines. We conducted a comprehensive search on the ScienceDirect and Scopus databases for articles published between 2012 and 2022. Our search strategy involved using a combination of keywords such as "MOOCs," "course usage," "retention," "dropout rate," and "student outcomes." By utilizing all search terms and available limits, we were able to determine the final number of articles in each database. This information was then entered into the top-left box of the PRISMA flow chart to complete the process. The total number of aggregated results from all databases was added to the previous value after the equal sign following "Databases (n=)."

2.4.2 Article Selection

In order to be considered for inclusion in the study, the articles had to be written in English. After applying screening parameters, we identified 126 articles that met our criteria. We implemented a search filter that required the articles to be published between 2012 and 2022 and classified as research articles or conference papers, which are complete reports on original research. Additionally, we excluded articles for which we were unable to access the full text during the study. A total of 65 articles were selected for screening. During the screening process, we identified articles that mentioned or shared findings related to factors affecting MOOC course usage. As a result, 40 articles were excluded, leaving us with a final selection of 25 articles for further data extraction and review.

2.4.3 Data Extraction

To gather comprehensive information from the articles, we employed the following criteria; (1) Identified information that addressed research questions 1, 2, and 3; (2) Considered limitations or challenges mentioned in the study; (3) Extracted data on the MOOC platforms used; and (4) Analyzed the study methods employed.

Table 5: List of Factors Overview of the Reviewed Articles

#	**Authors** (Year) and Title	**List of Factors**
1	Joo YJ,So HJ,Kim NH. (2018) Examination of relationships among students' self-determination, technology acceptance, satisfaction,	1. perceived ease of use, 2. perceived usefulness, satisfaction with the course, and 3. continuance intention to use.

	and continuance intention to use K-MOOCs	
2	Vieira C,Parsons P,Byrd V. (2018) Visual learning analytics of educational data: A systematic literature review and research agenda	1. Students' interactions with the online tool 2. Contributions to discussion forums or chat 3. Survey responses 4. Students' performance 5. Demographic data 6. Students' gaze patterns
3	Kim TD,Yang MY,Bae J,Min BA,Lee I,Kim J. (2017) Escape from infinite freedom: Effects of constraining user freedom on the prevention of dropout in an online learning context	1. perceived scarcity and 2. lack of control.
4	Hone KS,El Said GR. (2016) Exploring the factors affecting MOOC retention: A survey study	1. Course Content 2. Interaction with the Instructor 3. Information Delivery Technology
5	Dai HM,Teo T,Rappa NA,Huang F. (2020) Explaining Chinese university students' continuance learning intention in the MOOC setting: A modified expectation confirmation model perspective	1. attitude and 2. curiosity.
6	Tsai YH,Lin CH,Hong JC,Tai KH. (2018) The effects of metacognition on online learning interest and continuance to learn with MOOCs	1. metacognition skills, 2. learning interest, and 3. online learning willingness as a means of self-directed learning.
7	Zhao Y,Wang A,Sun Y. (2020) Technological environment, virtual experience, and MOOC continuance: A stimulus–organism–response perspective	1. technological environmental features such as interactivity, media richness, and sociability. 2. flow experience was identified as a mediating factor that influenced MOOC course usage.
8	Coussement K,Phan M,De Caigny A,Benoit DF,Raes A. (2020) Predicting student dropout in subscription-based online learning environments: The beneficial impact of the logit leaf model	1. demographics, 2. classroom characteristics, and cognitive, 3. academic, and 4. behavioural forms of engagement.

9	Aparicio M,Oliveira T,Bacao F,Painho M. (2019) Gamification: A key determinant of massive open online course (MOOC) success	1. service quality, 2. system quality, and 3. gamification.
10	Gregori EB,Zhang J,Galván-Fernández C,de Asís Fernández-Navarro F. (2018) Learner support in MOOCs: Identifying variables linked to completion	1. student-content interactions, 2. course schedule quality, and 3. the presence of the teacher. 4. learner engagement and social participation in MOOCs.
11	Gupta S,Sabitha AS. (2020) Designing Ontology for Massive Open Online Courses using Protégé	1. learners' profiles and 2. the necessity to create a social environment. 3. addressing the attributes of attrition in MOOCs and 4. development of a content-based recommender system using data mining and knowledge discovery in linked open datasets.
12	Tahiri JS,Bennani S,Idrissi MK. (2016) An assessment system adapted to differentiated learning within Massive Open Online Courses using psychometric testing	1. Various categories of registrants 2. Lack of prerequisites to succeed in a course 3. Learners' disinterest 4. Lack of time
13	Zheng S,Rosson MB,Shih PC,Carroll JM. (2015) Understanding student motivation, behaviors, and perceptions in MOOCs	1. High workload 2. Challenging course content 3. Lack of time 4. Lack of pressure 5. Lack of awareness features 6. Social influence 7. Lengthy course start-up 8. Learning on demand
14	Onah DF,Sinclair JE. (2015) Measuring self-regulated learning in a novel e-learning platform: ELDa	1. attitudes, 2. circumstances, 3. engagement, 4. nature of activity undertaken, 5. emotional and cognitive commitment, and 6. passive nature of learning in most MOOCs. 7. learner autonomy and the ability for learners to set their own goals and study in a self-regulated manner.

15	Rothkrantz L. (2017) Dropout rates of regular courses and moocs	1. Study commitment 2. Choice of study 3. Skills/abilities 4. Impersonal teaching
16	Wang L,Wang H. (2019) Learning behavior analysis and dropout rate prediction based on MOOCs data	1. learning objectives, 2. social interaction, 3. learning autonomy, 4. evaluation mechanisms, and 5. learning expectations. 6. lack of punitive measures and incentives to stimulate learning, 7. the willingness of learners to actively engage in the learning process
17	Zheng S. (2015) Retention in MOOCs: Understanding users' motivations, perceptions and activity trajectories	1. personal, 2. social, 3. technical, and 4. course-related reasons.
18	Rothkrantz L. (2016) Dropout rates of regular courses and MOOCs	1. Study commitment 2. Choice of study 3. Skills/abilities 4. Impersonal teaching
19	Gay G,Djafarova N,Zefi L. (2017) Teaching accessibility to the masses	1. the structure of the course, 2. class size, 3. feedback, and 4. prior experience learning online. 5. learner engagement types: active engagement, passive engagement, and disengagement, on course usage.
20	Borrella I,Caballero-Caballero S,Ponce-Cueto E. (2019) Predict and intervene: Addressing the dropout problem in a MOOC-based program	1. Learners' interaction with the online platform, including engagement with different learning activities such as videos, quick questions, and problems. 2. Learners' progress in the course, particularly their grades and achievement over time. 3. Psychological attributes, such as motivation, which were addressed through an intervention aimed at encouraging learners to complete important course activities.

21	Hakami N,White S,Chakaveh S. (2017) Motivational factors that influence the use of MOOCs: Learners' perspectives: A systematic literature review	1. Learner-related factors, including personal, social, and educational/professional development factors. 2. Institution and instructor-related factors. 3. Platform and course-related factors. 4. Perception of external control/facilitating conditions-related factors. Specific factors identified include computer self-efficacy, experience in MOOCs, self-determination (self-regulated learning), technology compatibility, perceived usefulness, perceived ease of use, extend knowledge and skills, curiosity, and earning a certificate.
22	Adamopoulos P. (2013) What makes a great MOOC? An interdisciplinary analysis of student retention in online courses	1. the sentiment of students for assignments and course material, 2. the influence of the professor, and 3. the impact of the discussion forum. 4. self-paced courses, 5. difficulty, 6. workload, and 7. duration of the course
23	Kaur PD,Malhotra J,Arora M. (2019) Role of Perseverance and Persistence for Retaining and Stimulating MOOC Learners	1. engagement, 2. persistence, 3. completion, 4. attention, 5. relevance, 6. confidence, and 7. satisfaction.
24	Kaabi K,Essalmi F,Jemni M,Qaffas AA. (2020) Personalization of MOOCs for increasing the retention rate of learners	1. learner engagement and disengagement patterns, 2. the success of students, and 3. the need for adaptive content or assistance based on learners' needs. 4. personalization parameters, such as learning styles
25	Whitmer J,Schiorring E,James P. (2014) Patterns of persistence: What	1. the nature of the course activities.

	engages students in a remedial English writing MOOC?	

2.4.4 Literature Review Findings

There are many different and complex factors that affect MOOC engagement and retention. Joo, YJ, So HJ, and Kim NH (2018) determined that the course's perceived usefulness, ease of use, satisfaction, and intention to continue using it were the most important factors.

RQ1: what are the factors affecting MOOC course usage? Factors that impact MOOC course usage fall into several categories that affect user acceptance, satisfaction, engagement, and intention to continue using the course. Joo et al. (2018) highlight the importance of perceived usefulness, ease of use, satisfaction with the course, and intention to continue using it as critical factors; Vieira et al. (2018) emphasize the significance of students' interactions with the online tool, their contributions to discussion forums or chat, their responses to surveys, their performance, their demographic information, and their gaze patterns; Hone and El Said (2016) emphasize the significance of course content, interaction with the instructor, information delivery technology, and metacognition skills. Dai et al. (2020) also underscore the role of attitude and curiosity, while Onah and Sinclair (2015) emphasize attitudes, circumstances, engagement, nature of activity undertaken, emotional and cognitive commitment, learner autonomy, and the ability for learners to set their own goals and study in a self-regulated manner.

Additionally, learner engagement and participation are critical factors in the utilization of MOOC courses. The importance of engagement, perseverance, completion, attention, relevance, confidence, and satisfaction is emphasized by Kaur et al. (2019). Furthermore, Kaabi et al. (2020) emphasize the significance of learner engagement and disengagement patterns, student success, and the requirement for assistance or adaptive content tailored to the needs of individual learners.

RQ2: what are key findings from previous study? These studies cover a wide range of previous works topics related to Massive Open Online Courses (MOOCs), including student interaction, learning outcomes, course design, motivation, and personalization.

Prior works have placed significant emphasis on user interaction and learning outcomes. According to Zhao et al. (2020), different kinds of MOOCs highlight different approaches to learning and evaluation and distinct teacher roles. This demonstrates how crucial the content and design of a course are in determining how popular and valuable MOOCs are. Additionally, identifying factors for high dropout rates in MOOCs and regular courses has been a significant study area (Rothkrantz, 2016). When addressing issues that impede MOOC course usage and completion, it is imperative to comprehend the causes of high dropout rates.

In the context of MOOCs, student motivation and engagement have also been thoroughly studied. One major factor influencing MOOC course usage has been the impact of digital evolution on education and the rise of MOOCs (Hakami et al., 2017). This emphasizes how outside variables, like technology developments, impact the uptake and application of MOOCs. Additionally, gamification has been found to be crucial to MOOC success, positively affecting use, individual impacts, and organizational impacts (Gupta and Sabitha, 2020). It is essential to consider gamification when designing and implementing MOOCs since it can significantly affect student engagement and course utilization.

Course design and content are also essential to comprehend the variables influencing MOOC course usage. According to Tsai et al. (2018), sociability features are critical in promoting interaction between instructors and learners in MOOCs. This emphasizes the impact of community development and social interaction on user engagement and course usage. To improve student engagement and sense of community, ontology has also been suggested to foster a social environment and lower dropout rates in MOOCs (Onah and Sinclair, 2015). According to Kaur et al. (2019), factors that significantly impact MOOC course usage include strategies to improve student engagement and sense of community.

In summary, various factors influence the use of MOOCs, including user interaction, student engagement, and course design. The study has shed light on the significance of gamification, social features, and personalization in shaping MOOC course utilization. MOOCs must continue to be developed and improved to serve the needs of students enrolled in online courses better.

RQ3: what is the recommendation for future works? To enhance MOOCs and comprehend the elements influencing student engagement and continuation intentions in online learning environments, the reviewed studies suggest various future research directions. According to these recommendations, future research should focus on a wide range of topics, such as the integration of information visualization and educational research fields (Vieira et al., 2018), the creation of a research agenda for visual learning analytics (Vieira et al., 2018), and the investigation of the impact of metacognition on interest in and persistence in online learning (Tsai et al., 2018).

The authors stress the significance of comprehending learner behaviour and needs (Kim et al.,2017; Rothkrantz,2016; Kaur et al., 2019) to minimize dropout rates and maximize learning outcomes in an online setting. Future studies could focus on developing an operational ontology based on essential variables that affect retention in MOOC courses (Gupta and Sabitha, 2020) and investigating creative didactic models adapted to MOOCs' particularities (Rothkrantz, 2016).

These studies also highlight the need for enhancements to learner support materials (Gregori et al.,2018), assessment systems (Tahiri et al.,2016), and educational variables like course subject, enrollment motivation, and student's prior knowledge or expectations (Gregori et al., 2018). To lessen bias and further support the study's findings, future research could also look at the effects of various learner engagement types on course usage (Gay et al., 2017) and investigate alternate longitudinal data-collection techniques (Dai et al., 2020).

In conclusion, the systematic literature review has provided a comprehensive overview of the factors affecting MOOC course usage, offering insightful information for further research. Future research recommendations include addressing literature gaps and considering the variables that affect MOOC engagement and retention (Tsai et al., 2018; Coussement et al., 2020). By acknowledging and addressing these challenges, researchers can contribute to a deeper understanding of the factors that influence MOOC usage and effectiveness, ultimately leading to the development of more effective and user-friendly MOOC platforms.

2.5 Type of MOOC

it is important to understand type of MOOCs before learning content can be design. According to McGreal et al., (2013), they can be currently classified as xMOOCs, cMOOCs and quasi-MOOCs where Alghamdi, Hall and Millard (2019) add bMOOC as described in Table 6 below.

Table 6: MOOC Types

MOOC Type	Description
xMOOCs	Replicate online the traditional model of an expert tutor and learners as knowledge consumers, with saved video tutorial and graded assignment.
cMOOCs	Based on a connectivism pedagogical model that viewer knowledge as a networked state and learning as the process of generating those networks, in
	the case using online and social tools.

Quasi-MOOCs	Encompasses a myriad of webbased tutorial as OER that are technically not courses but are intended to support learning specific tasks and consist of asynchronous of cMOOCs or the automated grading and tutorialdriven format of xMOOCs.
bMOOCs	Blended MOOC not intended to replace traditional learning method but rather to enhance them. bMOOC as the convergence of cMOOC, xMOOC, and face-to-face learning.

Most courses share common defining features such as high levels of participation, online accessibility, and the use of short video lectures with quizzes, automated assessments, and online forums for peer support. A study by Costley, Hughes, and Lange (2017) identified five crucial elements of instructional design for online learning environments that positively correlated with students' completion of video lectures: (1) designing methods, (2) setting the curriculum, (3) establishing time parameters, (4) establishing netiquette, and (5)utilizing the medium effectively

The study highlighted the importance of instructional design considerations in enhancing learner engagement, particularly in ensuring that students watch and complete video lectures. Surprisingly, the research revealed that 37% of learners dropped out within the first 3% of the video, indicating a significant challenge in retaining student interest. Instructors play a vital role in providing clear instructions on how to navigate video lecture platforms, as this can influence students' decision to engage with the course materials.

Successful instructional design in online courses hinges on factors such as setting appropriate pacing, modulating instruction, and tracking deadlines to motivate students to watch videos in their entirety. Merely relying on video content without effective guidance may not suffice in fostering learner engagement. Therefore, a well-designed MOOC should integrate video content with clear instructions and various assessment activities to keep learners motivated and reduce dropout rates. In the context of my research study, xMOOCS type is consider as the most relevant.

2.6 MOOC Learning Analytics

Apart from challenges regarding the pedagogical and learning style, the shifting and the use of a new approach, in this context, MOOC as a learning platform in higher learning institutions, lead to new challenges. According to (Fair et al., 2017),it is challenging to assess the results of incorporating MOOCs into conventional university courses for several reasons. Four of the reasons are lack of research, diverse approaches, varying roles and proportions and diverse timelines.

This situation is expected, as (Phethean et al., 2012) highlighted in the context of measuring marketing performance in the event of shifting platform methods to social media marketing. They urged the need for methods of measuring the performance of this type of marketing by analyzing data from social media. Therefore, we need to rethink how we monitor and measure MOOC courses and learner performance based on existing MOOCs learning analytic data to fully understand, realise and justify the effects and performances of this unconventional learning method.

It may ultimately be possible to discover a relationship between how MOOC courses are offered, representing MOOC course enrolment or learners' inclination to complete and progress in the MOOC course to support the learning, and the resulting 'real' performance subsequently achieved.

Topali et al., (2023) focuses on instructor-led feedback mediated by LAtools in MOOCs in their study. 21 system proposals was reviewed, with 8 tools evaluated positively. However, Topali et al., (2023) highlight the lack of in-depth design considerations. The discovery of the "Lack of in-depth design considerations" in the study pertains to a significant constraint that was identified in certain feedback proposals within the MOOC context. This constraint indicates that specific feedback interventions lacked thorough and comprehensive design considerations. Consequently, the effectiveness and impact of these feedback strategies may be compromised due to the absence of detailed planning and alignment with learning goals, feedback aims, learning topics, and the overall context of the course. In the absence of a robust design framework, feedback tools may not be optimally tailored to address the specific needs and requirements of instructors and learners in the MOOC environment. This discovery emphasizes the significance of integrating pedagogical theories and contextual factors into the design process to enhance the relevance and effectiveness of feedback interventions in online learning settings.

Learning analytics has several advantages, not the least of which is that it can guide our efforts to support our learners' success (Dietz-Uhler and Hurn, 2013). This subsection focuses on understanding how I used MOOC learning analytics data. According to (Reich and Ruipérez-Valiente, 2019), learning analytics can offer various degrees of insights; these can be offered at the level of a single course or across a series of MOOCs, for example it can provides real-time monitoring of student progress and identifies at-risk students (Xing et al., 2019).

The main goal of Learning Analytics is to improve learning efficiency and operation effectiveness and provide educators, learners, and decision-makers with actionable insight into online course-level activities (Tabaa and Medouri, 2013). This section reviews learning analytics in higher education, learning Analytical data in learning management systems (LMS) and MOOCs, problems in learning analytics using MOOCs, learning analytics in MOOCs, and learning analytics in cross-platform MOOCs.

As a preliminary study, I conduct a systematic literature review, at the beginning of this research study, reviewing publication from 2014 to 2019. Journals found were then tagged and summarised according to the keywords used during the search. Then, keywords found in each journal were counted and analysed to confirm their relevancy to the topics concerned, as shown in Table 7. Journals with keywords 'performance' and 'retention' were grouped under 'measuring MOOC performance,' while journals with keywords 'monitoring,' 'data visualisation,' 'predictive,' 'algorithm,' and 'method' were grouped under 'monitoring MOOC learning.' This group category is shown in the legend descriptions in Table 9. The final results are displayed in Table 5. We can see that three more journals were excluded since keywords for the journals only covered 'MOOCs,' and no other keywords of my concern exist. Excluded journals include (Poquet. O et al., 2018), (Sureephong. P et al., 2020), and (Henderikz M. et al., 2019).

Table 7 List the publication citation and keywords list, Table 8 is the same publication describe in a keywords matrix detail, while Table 9 describe lagend used in Table 8.

While Table 7 provide a clear keywords found in each publication, it also highigh the significant of each publication based on citation number. Next, Table 8 provide a matrix that show similarity or links between defferent publications, based on the keywords.

Table 7: Publication Search Results and Associated Keyword Analysis

	C	Keywords
(Kizilcec, Pérez-Sanagustín and Maldonado, 2017)	249	Online Learning (245), **LA (146),** Individual differences, SRL, **MOOCs (92)**
***(Jordan, 2015)**	283	Distance Education, open learning, online learning, **MOOCs (65), platform (9)**
***(Israel, 2015)**	136	Online learning, **MOOCs (193),** Higher Education (31), Hybrid Learning, **LA (2)**, **platform (6)**
(Phan, McNeil and Robin, 2016)	113	**MOOCs (147),** Student engagement (20), prior knowledge, **course performance (150),** professional development
(Alexandron et al., 2017)	13	Academic dishonesty, educational data mining, **LA (24**), **MOOCs (43), platform (10)**

***(Rayyan et al., 2016)**	11	Blended classroom, item response theory, **LA (1), MOOCs (76)**, online learning, retention (9), **platform (11)**
(Goggins et al., 2016)	11	**LA (240), MOOCs (85),** network analysis, small group, social sensors, VLE, **performance (76)**
(Conijn, Van Den Beemt and Cuijpers, 2018)	7	Blended learning (23), **LA (108), MOOCs (194),** MOOC Improvement, Predictive Modeling (14), process mining, **performance (104)**
(Greene, Oswald and Pomerantz, 2015)	168	**MOOCs (220)**, an implicit theory of intelligence, **retention (62),** motivation, **academic achievement (61)**, predictor (67)
(Fidalgo-Blanco, Sein-Echaluce and García-Peñalvo, 2015)	154	LMS, **MOOCs (183), technological framework (46),** instructive, connectivism, adaptive learning, **monitoring (5)**
(Barak, M., Watted, A., & Haick, H., 2016)	139	Higher Education, Language of instruction, **MOOCs (64)**, Motivation, Social Engagement (24), **monitoring (2)**
(Garcia-Penalvo, F.J., et al., 2017)	128	**MOOCs (152),** Informal learning, Non-formal learning, personalised learning, Adaptive system, **monitoring (0)**
(Stephens-Martinez, K., Hearst, M. A., & Fox, A., 2014)	81	**Data Visualization (67),** Instructor Support, e-learning, **MOOCs (45), Monitoring (24)**
***(Romero, C., & Ventura, S., 2017)**	22	**MOOCs (130),** Educational Data Science (113), **LA (73), performance (11), platform(13)**
***(Joksimović, S. et al., 2018)**	20	Nonformal education, learning environment, **MOOCs (156),** engagement (126), **LA (32)**
(Gašević, D. et al., 2019)	17	Social Network Analysis, Epistemic network analysis, collaborative problem solving, **LA (164), MOOCs (14)**
***(Chapman, S.A. et al., 2016)**	12	**MOOCs (64),** Online course, **monitoring (62),** evaluation, developmental evaluation, performance monitoring, **platform (18)**
(Lau, K. H. V., et al., 2017)	9	**Learning Analytics (53), MOOCs (15), retention (10**), evaluation (9)
(Moreno-Marcos, P. M., et al., 2018)	9	Prediction (126), learners grades, **indicators (22), LA (42),** edX, **MOOCs (78), performance (25)**
(Poquet, O. et al., 2018)	8	Social presence (497), **MOOCs (114),** forum participation (80), **LA (0)**
(O'Riordan, T. et al., 2016)	2	Computer-Mediated Communication, CSCL, content analysis**, LA (106), MOOCs (13),** pedagogical frameworks, measure (14), engagement(9)
(Handoko, E. et al., 2019)	0	SRL, **MOOCs (187),** MOOC completion (19), questionnaire, OSLQ, goal setting, **performance (10), LA (0)**
(Sureephong, P. et al., 2020)	0	Employee performance (29), **MOOCs (34),** VIE Theory, non-mandatory reward, **LA (0)**
(Tabaa, Y and Medouri, A, 2013)		Cloud computing, **MOOCs (73),** Hadoop, **LA (105), platform (25), learning indicator (35)**

(Yousef et al., 2014)		**LA (212), MOOCs (144)**, Blended MOOC (71), Evaluation (25), **monitoring (11),** performance (6)
(Sclater, N. et al., 2016)		**LA (503),** MOOCs (1), distance learning (28), Higher Education (161), **predictive (43), performance (21)**
(Wong, B. T. M., 2017)		Higher Education (103), **LA (225),** ODL (12), Open and Distance Education (66), **MOOCs (12), online learning (127), performance (26)**
(Khalil, M. and Ebner, M., 2016)	13	**LA (118), MOOCs (67),** student retention (11), single MOOC platform (11), **algorithm (14), indicator (9)**
(Henderikz, M. et al., 2019)	4	Online learning (203), **MOOCs (90),** open education (59), **achievement (33),** barriers to learning (141)

Legend: LA – Learning Analytics, SRL – Self-Regulated Learning, ODL – Open & Distance Learning

Table 8: Matrix Table of Publication Search Results

	C	LA	MO	PL	PE	RT	MO	DV	PR	AL	MT	DS	CP
(Kizilcec, Pérez-Sanagustín and Maldonado, 2017)	249	146	92	-	-	-	-	-	-				
***(Jordan, K., 2015)**	283	-	65	9	-	-	-	-	-				X
***(Israel, M. J., 2015)**	136	2	193	6	-	-	-	-	-				X
(Phan, T. et al., 2016)	113	-	147	-	150	-	-	-	-				
(Alexandron, G. et al., 2017)	13	24	43	10	-	-	-	-	-				
***(Rayyan et al., 2016)**	11	1	76	11	-	-	-	-	-				X
(Goggins et al., 2016)	11	240	85	-	76	-	-	-	-				
(Conijn, Van Den Beemt and Cuijpers, 2018)	7	108	194	-	104	-	-	-	14				
(Greene, Oswald and Pomerantz, 2015)	168	-	220	-	-	62	-	-	67				
(Fidalgo-Blanco, Sein-Echaluce and García-Peñalvo, 2015)	154	-	183	-	-	-	5	-	-				

(Barak, M., Watted, A., & Haick, H., 2016)	139	-	64	-	-	-	2	-	-				
(Garcia-Penalvo, F.J., et al., 2017)	128	-	152	-	-	-	0	-	-				
(Stephens-Martinez, K., Hearst, M. A., & Fox, A., 2014)	81	-	45	-	-	-	24	67	-				
***(Romero, C., & Ventura, S., 2017)**	22	73	130	13	11	-	-	-	-				X
***(Joksimović, S. et al., 2018)**	20	32	156	-	-	-	-	-	-				
(Gašević, D. et al., 2019)	17	164	14	-	-	-	-	-	-				
***(Chapman, S.A. et al., 2016)**	12	-	64	18	-	-	62	-	-				X
(Lau, K. H. V., et al., 2017)	9	53	15	-	-	10	-	-	-				
(Moreno-Marcos, P. M., et al., 2018)	9	42	78	-	25	-	-	-	-				
~~(Poquet, O. et al., 2018)~~	8	0	114	-	-	-	-	-	-				
(O'Riordan, T. et al., 2016)	2	106	13	-	-	-	-	-	-				
(Handoko, E. et al., 2019)	0	0	187	-	10	-		-	-				
~~(Sureephong, P. et al., 2020)~~	0	0	34	-	-	-	-	-	-				
(Tabaa, Y and Medouri, A, 2013)		105	73	25	-	-	-	-	-		X	X	X
(Yousef et al., 2014)		212	144	-	-	-	11	-	-				
(Sclater, N. et al., 2016)		503	1	-	21	-	-	-	-				
(Wong, B. T. M., 2017)		225	12	-	26	-	-	-	-				
(Khalil, M. and Ebner, M., 2016)	13	118	67	11	-	11	-	-	-	X			
~~(Henderikz, M. et al., 2019)~~	4	-	90	-	-	-	-	-	-				

Table 9: Legend for Acronyms Used in Table 8.

Legend			
C	Citation	The number of citations.	
LA	Learning Analytics	Keyword: MOOC + Learning Analytic	
MOOC	MOOCs	Keyword: MOOC	
PL	Platform	Keyword: Platform	
PE	Performance	Keyword: Performance	Measuring Performance
RT	Retention	Keyword: Retention	
MO	Monitoring	Keyword: Monitoring	Monitoring Learning
DV	Data Visualization	Keyword: Data Visualization	
PR	Predictive	Keyword: Predictive	
AL	Algorithm	Keyword: Algorithm	
MT	Method	List of journals that develop methods for monitoring MOOC.	
CP	Cross-Platform	Sample data/testing from more than 1 MOOC platform.	
DS	Develop Solutions	Develop a software/platform/tool used in the study.	
*	Selected Publication	Publications selected for future review. Mention cross-platform in the study/publication.	

Based on the literature search results, only the six most related publications mentioned cross-platform in their study. The details of the findings and discussion are presented in the next section of this chapter. Table 10 shows the reviews of the literature study on learning analytics, which is divided into four main subtopics: learning analytics, MOOC learning analytics, measuring MOOC performance, and monitoring MOOC learning.

Table 10: Discussions of the Literature Study on MOOC Learning Analytics

Research Topics	Research Aims	Papers
Learning Analytics in Higher Education	They are classifying usages and benefits of learning analytics in Higher Education. Details of the utilisation and benefits are presented in Table 5.	(Sclater, N. et al., 2016), (Wong, B. T. M., 2017)
MOOC Learning Analytics	Develop an analytic learning system; Investigate self-regulated learning skills; Use learning analytics to identify academic dishonesty; analyse	(Kizilcec, Pérez-Sanagustín and Maldonado, 2017), (Alexandron, G. et al., 2017), (Tabaa, Y and Medouri, A,

	MOOC comment forums using pedagogical analysis;	2013), (O'Riordan, T. et al., 2016)
Measuring MOOC Performance	Finding the relationship between course performance and student engagement; Exploring performance indicators in online groups; Predicting student performance by analysing aggregated activity frequencies, specific course item frequencies, and order of activities using correlations, multiple regressions, and process mining; Analysing how to predict course scores; Using SRL survey to understand students who completed and those who did not complete their course;	(Phan, T. et al., 2016), (Goggins et al., 2016), (Conijn, Van Den Beemt and Cuijpers, 2018), (Romero, C., & Ventura, S., 2017), (Moreno-Marcos, P. M., et al., 2018), (Handoko, E. et al., 2019)
Monitoring MOOC Learning	Develop a learning analytics module that supports self-organised and network learning and monitors the learning process; Improve students' retention and learning using an algorithm based on MOOC indicators and propose a scheme/framework to reflect the results of students' MOOC; Examine the degree to which student characteristics with MOOCs to predict retention and achievement; Surveying MOOC instructors to find out which information they find helpful for monitoring MOOCs; Developing an algorithm to identify online learners that likely to drop out;	(Yousef et al., 2014), (Khalil, M. and Ebner, M., 2016), (Greene, Oswald and Pomerantz, 2015), (Stephens-Martinez, K., Hearst, M. A. & Fox, A., 2014), (Tabaa, Y and Medouri, A., 2013),

Throughout this study, I have examined the obstacles and importance of incorporating MOOCs into traditional university classes, the significance of utilizing learning analytics data to evaluate the performance of MOOCs, and the emphasis on instructor-led feedback in MOOC environments. The development of the MPM Model, which utilizes MOOC learning analytics to monitor and assess both the performance of MOOC courses and learners, highlights the value of data-driven approaches in enhancing outcomes in online learning. By integrating the findings from this research into my work, I can further refine the MPM Model to offer practical insights for enhancing the delivery of MOOC courses, promoting learner engagement and improving performances.

2.6.1 Learning Analytics in Higher Education

Table 11 shows how higher education uses learning analytics and how much it benefits them. The study involved 49 higher education institutions in the United Kingdom, the United States, Australia, and Germany. Results of this study show that 93% (77 of 83 benefits) of the learning analytic usages are for faculty/lecturers. Only 7% (6 of 83 benefits) are intended for students as users: Table 11 and Table 12 below show details of this literature study.

Table 11: Existing learning analytics usages and benefits in higher education institutions

Benefits	ISR	SID	ICE	USL	PSP	TFI	BBS	ISS	IET	TCT	UAT	TRL	RMC	PVC
Bowie State University[1]	/													
Edith Cowan University[1]	/													
Harvard University[1]	/													
New York Institute of Technology[1,2]	/		/					/						
Northern Arizona University[1]	/													
Paul Smith's College[1]	/													
Rio Salado Community College[1]	/													
The Open University, UK[1,2]	/	/		/	/				/					
University of New England[1,2]	/				/			/						
Grand Rapids College[1]		/												
University of Adelaide[1]		/	/	/		/								

University of Edinburgh[1]		/		/		/								
University of North Bengal[1]		/		/										
University of Salamanca[1]		/												
The Technical University of Madrid[1]		/		/	/									
Bridgewater College[1]			/		/									
Drexel University[1]			/											
Georgia Institute of Technology and Carnegie Mellon University[1]			/	/										
Harvard University[1]			/											
Lancaster University[1]			/											
Open University of Catalonia[1]			/											
Portland State University[1]			/											
Purdue University[1,2]			/			/		/		/				
Rio Salado College[1]			/											
The Hong Kong Institute of Education[1]			/											
University of Michigan[1]			/		/	/								
University of Salamanca[1]			/											

University of the South Pacific[1]			/											
University of Sydney[1]			/											
Bell State University[1]				/										
McGill University[1]				/										
Oxford Brookes University[1]				/										
The Hong Kong Institute of Education[1]				/										
The University of Melbourne[1]				/										
University of Rijeka[1]				/										
University of Santiago de Compostela[1]				/										
Albany Technical College[1]					/									
Open Universities Australia[1,2]					/				/					
Edith Cowan University[1,2]						/		/						
Marist College[1]						/								
Northern Arizona University[1]						/								
San Diego State University[1]						/								
University of Wollongong[1,2]					/	/								

University of Maryland[2]									/					
Nottingham Trent University[2]	/	/					/	/		/				
University of New England[1,2]	/							/						
University of South Australia[1]						/								
Marist College, New York[2]						/								
RWTH Aachen University[3]											/	/	/	/
TOTAL	11	8	16	13	8	11	1	6	3	2	1	1	1	1

Legend: 1 – Wong, 2017 2 – Sclater et al., 2016 3 – Yousef et al., 2015

Table 12: Legends for Table 11

Acronym	Reference	Benefits of Learning Analytics	Users of Learning Analytics
ISR	Wong, 2017	Improve Student Retention	Faculty/Lecturer
SID	Wong, 2017	Supporting Informed Decision Making	University/Faculty
ICE	Wong, 2017	Increasing Cost-Effectiveness	University/Faculty
USL	Wong, 2017	Understanding Students Learning Behaviours	Faculty/Lecturer
PSP	Wong, 2017	Providing Students with Personalised Assistance	Lecturer
TFI	Wong, 2017	Timely Feedback & Intervention	Faculty/Lecturer
BBS	Sclater et al., 2016	Build Better Student-Tutor Relations	Lecturer
ISS	Sclater et al., 2016	Identify Struggling Students Earlier	Faculty/Lecturer
IET	Sclater et al., 2016	Identify Effective Teaching Strategies	Faculty/Lecturer
TCT	Sclater et al., 2016	Take Control of Their Learning	Student
UAT	Yousef et al., 2014	Track Learning Activities (User Analytics)	Student
RMC	Yousef et al., 2014	Reflect/Monitor Course Activities (Course Analytics)	Student/Lecturer

TRL	Yousef et al., 2014	Track Recent Learning Activities (Course Stream Analytics)	Students
PVC	Yousef et al., 2014	Personalised View of Courses & Video (User Courses)	Students

The amount of data available to us in educational institutions is immense. The foundation of learning analytics is our capacity to utilize this data to guide our actions in the classroom, both in-person and virtually (Dietz-Uhler and Hurn, 2013). There is no denying that learning analytic data from MOOC providers offers many benefits. However, as mentioned earlier, issues of a static dataset with limited information presentation and no standard format offered by different MOOC platforms are still a concern.

Another finding is that frequent monitoring and measuring performance could benefit both macro and micro-level users. Ministry of Education of the People's Republic of China regularly inspected MOOC courses based on six categories to earn China national recognition: team, design, content, teaching, impact, and support to ensure national high-quality MOOC content (Chinaooc.cn., 2020). Additionally, the used of learning analytics can help in reducing teachers' workload by automating data analysis and prediction models (Xing et al., 2019).

From this study, I also discovered that learning analytic data that were made available by the MOOC platform is considered raw data. The course administrator who has access to it can view or download it. This data can also be used to provide a macro-level statistical report for faculty, university, or ministry levels. At the micro-level, with the proper interpretation of data, this information can give course administrators insight into how their student performs. It will also open the possibility of teaching and learning improvement.

2.6.2 Monitoring MOOC Using Learning Analytics

According to Reich and Ruipérez-Valiente (2019), there were 261 different courses offered on the edX MOOC platform from October 2012 to May 2018, which combined 12.67 million course registrations from 5.63 million learners. FutureLearn, with nearly 10 million learners, provides the highest MOOC-based degrees, offering 23 degrees.

The Chinese government has started listing recommended online courses to boost MOOC, where the education ministry inspects the courses regarding their operation, effects and updates. Four hundred ninety premium quality MOOCs were carefully selected for their content, structure, and quality, representing China's best open online courses. Higher learning institutions that develop MOOC content will submit their course to be evaluated by (Chinaooc.cn 2020) as the authority that monitors, evaluates and lists courses considered as China Premium Quality MOOC. Courses that fail to meet the standards will be removed from the list. This initiative is excellent and helpful for all, especially the learners. However, it will be demanding many resources to keep updating and monitoring the growing numbers of courses offered by MOOC platforms unless a proper systematic tool is available and used. Malaysia government, for example, in (Dasar e-Pembelajaran Negara 2.0, 2011) clearly stated the need to have MOOC platform learning analytics ready by the year 2021-2025.

Another reason for the urge to have a MOOC monitoring tool ready is related to the issues raised by MOOC learners' consistently high dropout rate (Onah, Sinclair and Boyatt, 2014). The lack of understanding of how learners react toward courses contributes to the high dropout rate on MOOCs (Costley, Hughes and Lange, 2017). Monitoring and evaluating MOOCs is a challenging process. MOOCs' flexible nature, which leads to unpredictable outcomes, became significantly more difficult when involving multiple MOOC platforms. There is a scenario where a course instructor might find specific data helpful while others find it not due to the diverse range of instructors' preferences (Stephens-Martinez, Hearst and Fox., 2014). Based on Coursera and FutureLearn platforms, (Chapman et al., 2016) propose four performance monitoring components and a set of indicators. The four monitoring elements are coverage, participation, achievement, and quality. Data sources were acquired from the MOOC platform and participant survey.

From a technical view, (Corbi and Solans, 2014) describe three basic system-dependent monitoring techniques and how data sources can be acquired: web service, scrapping and raw database access. Each method addresses the different challenges and requires deep consideration to be implemented. Web service techniques might be suitable if an application programming interface (API) was made available, which is highly doubtful for most MOOC platforms. This situation was also faced by (Chitsaz, Vigentini, and Clayphan, 2016), which led them to use scrapping techniques instead. Another option is using existing analytic data made available by most MOOC providers as small-scale content analysis. This approach must consider how the data will be securely handled and what data access control setting will be applied (Tinati et al., 2015). It is required to conduct and share more experimental studies with different MOOC formats and variations (Yousef et al., 2014).

Another view in context using learning analytics for monitoring purposes (Drachsler, H., and Kalz, M., 2016) describes that needs specific to a single course is addressed at the course instructor and learner level. Course managers can find information at the university or institution level regarding MOOCs or structures within a curriculum. A directory of MOOCs is viewed from above by the ministry or the national level. Observing how people learn in MOOCs across different scientific disciplines can offer insights for an entire community. Different goals and pieces of information are pertinent and can be tracked based on the degree to which learning analytics are employed.

Several researchers developed MOOC dashboards at the university level to leverage the availability of learning analytic data from their MOOC platform providers. For example, Ruth Cobos et al. (2016) developed a MOOC dashboard called Open-DLA for edX and Open edX platform (M León et al., 2016, León-Urrutia, M and Darron Tang., 2017) developed University of Southampton MOOC Observatory Dashboard based on FutureLearn MOOC platform, (Chitsaz, Vigentini, and Clayphan, 2016) also developed a MOOC dashboard for FutureLearn platform. Vigentini study (2017a, 2017b) developed several dashboards (L Vigentini et al., 2017a) for UNSW MOOCs and (L Vigentini et al., 2017b) MOOC Dashboards for Coursera and FutureLearn.

A well design and use learning-analytics-dashboard could enables timely feedback to students during the learning process (Xing et al., 2019).

Faculty or the course admin may be able to identify opportunities for course improvement by keeping an eye on learner performance and involvement in the course and examining the relationship between these factors and grades (Dietz-Uhler and Hurn, 2013).

2.6.3 Learning Analytics from Cross-Platform MOOCs

The MOOC-knowladge graph aims to improve the utilization of online learning resources by organizing data from diverse sources like MOOC platforms, universities, courses, and instructors (Abu-Salih & Alotaibi, 2024). While working on MOOC data analysis from two different platforms, FutureLearn and edX, Ruth, Adriana, and Ed (2017) point out three major challenges. The initial difference between the two platforms was the underlying methodology. Aligning and comparing the gathered data was difficult due to the disparate pedagogical strategies and technological implementations used by the MOOC platforms. A second issue that made conducting comparison studies difficult was the stark technical variations in the technical implementations used by each MOOC platform. The difficulties with data alignment last. Because the two platforms' approaches and technical implementations differed, it was difficult to align the data gathered from them for comparative studies.

Table 13 shows that only a few of the latest types of research conducted on learning analytics from cross-platform MOOCs. Pérez-Berenguer and García-Molina (2016) used Learning Technology Interoperability (LTI) to enable developed content to be integrated and tracked into different e-learning platforms. Later, Quintana and Tan (2019) analysed MOOC discussion forum data from a MOOC that ran concurrently on edX and Coursera. Recently, Valiente and teams (2020a, 2020b) conducted two separate types of research involving cross-platform MOOCs: 1) to understand the differences in learners' behaviour across regional and global contexts and 2) to generate learning analytics trends at macro levels based on the country of origin, level of education, gender and age of the learners across global and regional MOOC providers.

Table 13: Literature Review - Existing research on learning analytics from cross-platform MOOCs

Author, Year	Summarized Review
Berenguer and Molina, 2016	This study presents the tracking component responsible for collecting student tracking data throughout a course. The segment also supports data visualisation and exporting to facilitate course monitoring and analysis. UPCTforma uses LTI to integrate the developed content into different e-learning platforms.
Quintana and Tan, 2019	This study analyses how technical features of MOOC platforms may impact social interaction and the formation of learner networks. It analysed MOOC discussion forum data from a single data science ethics course that ran concurrently on two MOOC platforms (edX and Coursera).
Valiente et al., 2020a	This study capitalises on the multi-platform, observational data from regional and global MOOC providers to understand the differences in learners' behaviour across the local and global contexts.
Valiente et al., 2020b	This study applies a multi-platform approach, generating a joint and comparable analysis with data from millions of learners and more than 10 MOOC providers. It allows the generation of learning analytics trends at macro levels based on the country of origin, level of education, gender, and age of their learners across global and regional MOOC providers.

As described in the previous section, most of the dashboards were developed for monitoring MOOCs that reside in one single MOOC platform, including Vigentini et al. (2017b), which developed two different MOOC dashboards as solutions for their UNSW MOOCs. Since many MOOC platforms exist and each platform provides benefits and different approaches or styles, there is a possibility for universities or MOOC content providers to have their MOOCs on multiple platforms or change MOOC platforms over time. These have increased the complexity for course administrators in monitoring their MOOCs or justifying the performances. Therefore, it is essential to consider the ability to analyse MOOC learning analytics in a cross-platform setup.

According to Drachsler and Kalz's (2016) research, it is imperative to develop a standardised assessment methodology that enables MOOC researchers to conduct consistent and comparative comparisons of the impacts of various MOOCs. The assessment framework's defined characteristics and indicators may represent a positive first step towards developing a standardised methodology for MOOC evaluation in the future.

Mangaroska, Vesin, and Giannakos (2019) in their study, highlight the need for analytics to be combined to offer broader insights into learner behaviour and experiences due to the distributed nature of the learning process. Although the scope and cross-platform problems addressed are different, we share the view that there is a need for analytics to be able to work and be used in the cross-platform scenario.

For two case studies, Ruth, Adriana, and Ed (2017) used MOOC learning analytics data to predict course attrition. They used datasets from a selected FutureLearn MOOC and an edX MOOC of comparable structure and themes. They applied Machine learning algorithms to analyze the data and predict attrition. The parameters used in the machine learning algorithm included attributes such as *number_sessions*, *number_comments*, *total_time*, and *time_problems*, which are identified as valuable for predicting course attrition in MOOCs. They suggest that additional research is necessary to assess the effectiveness of interventions by better understanding learner dropout and attrition models. They consider it essential to identify valuable attributes based on the analysis objectives and use suitable parameters data to ensure accurate results.

A series of studies deriving proof of concept showed how cross-platform analytics amplify the relevant analytics for the learning process. Such analytics could improve educators' and learners' understanding of their actions and the environments in which learning occurs (Ndukwe and Daniel., 2020). While Mangaroska, Vesin, and Giannakos (2019) focused on cross-platform architecture, where the dataset used was from a different source, my research focuses on the similarity of MOOC learning datasets at cross-platform data sources.

Additionally, a research study by Judel and Schroeder (2022) proposed an extendable and scalable infrastructure built for learning analytics that provides a central data warehouse to store learning records. A concept that allows analyses adjusted to the needs of an institution and also to analyse data from multiple platforms combined.

Theoretically, we could materialise this concept with the possibility of good database management design and web semantic approach. That was one of the considerations in this research study to explore and take advantage of the semantic web concept and the need for cross-platform friendly RDF for MOOC learning analytics.

2.6.4 Measurement and Analysis of Performance

According to a study by Fan Y. et al. (2021), they use learning analytics to demonstrate that selecting learning strategies indicative of metacognitive control and monitoring best demonstrates self-regulated learning skills. In order to identify theoretically significant learning strategies and analyse process variations among learning groups with varying academic performance, they also put forth a novel learning analytical approach.

Yassine, Kadry and Sicilia (2016) emphasised that learning analytics has potential for evaluating course learning outcomes, particularly in light of the growing institutional accreditation issue. Their research focuses on the Moodle learning management system, and they discovered that many helpful analytical tools can be enhanced, integrated, and redesigned to create a comprehensive tool for assessing learning outcomes and forecasting student performance. With MOOCs, I think the situation is comparable. The difficulties in guaranteeing the scalability and dependability of the new analytical tool are also highlighted by (Yassine, Kadry and Sicilia., 2016).

I believe that the fundamental concept of measuring performance is to get a better score by comparing the current score to the previous score. This concept also encourages the participation of learners and course admin to keep on engaging with the learning activity. According to (Apple, D.K. and Ellis, W., 2015), people who intentionally strive to become better learners are trying to perform better as learners.

To achieve this, I need to have a set of parameters that can be universal enough to be available in various MOOC platforms and have the same data meaning. These parameters are what will be used to perform the measurement. This stage is challenging due to the lack of standards in MOOC learning analytic data structure between platforms. Apart from the measurement algorithm, there are possibilities where I will be required to have a specifically designed metric or indicator to support the algorithm in measuring and analysing data.

Abu-Salih and Alotaibi, (2024) discussed the integration of knowladge graph technology in MOOCs to enhance functionalities and supports intelligent course content recommendations. MOOC learning analytics data hold valuable information that can be utilised for various discovery purposes. MOOC admin or course instructor has access to analytical data, which contains information regarding course completion, navigation patterns, and completion rates and possibly points out issues with MOOC design (Walters and Henry, 2019). Analysing the analytic learning data can provide information regarding learning design and possible improvement (Ford et al., 2019). Observing and making use of the existing data is a good practice. MOOC platforms collect complete records of learners' online activities continuously in real-time. This feature is something that was not available in a traditional learning environment. These data give better insight into learners' learning behaviour than ever before. However, the MOOC platform's advantages also give us new challenges. For example, although we have every data that describes learners, MOOC statistically shows that less than 5% of the participants have completed a course (Kizilcec, Piech and Schneider., 2013). Based on the MOOC analytic learning literature review, seven discoveries that can be formulated are:

i. **Learning analytic data availability** – Each MOOC platform does have analytic data available for course instructor use. Learning analytics provide feedback that can aid the learner evaluation of learning resources (O'Riordan T., Millard D. E., and Schulz J., 2016)
ii. **Research study for cross-platform MOOC** – Early research studies and findings are limited and only focus on MOOC learning analytics from a single MOOC platform or in cross-institution within the same MOOC platform (Chitsaz, M., Vigentini, L., & Clayphan, A.J., 2016).
iii. **Dataset standards between platforms** – There are no standards for MOOC platform learning analytic dataset design. Although the dataset is not a 100% match between platforms, it does have a fundamental similarity to datasets (Leon Urrutia et al., 2016). For example, the number of enrolments, page views, marks and others are datasets available on most MOOC platforms.
iv. **Challenge for dataset synchronisation** – It will be challenging to synchronise the dataset for analysis when considering usage at cross-platform MOOCs. Measurement parameters must be identified and defined based on the proposed synchronised analytic dataset.
v. **Data combination** – Combining MOOC learning analytics data with self-reports is considered for comprehensive evaluation (Vincent Lau et al., 2017).
vi. **Data source access** – Another issue and consideration to analyses MOOC learning analytic data shows the dataset can be obtained and managed. An uncompleted or missing part of data in the dataset could affect the analysis result. After facing limitations with data from edX to perform analysis, (Moreno-Marcos P.M. et al., 2018) suggest possibly using courses with control over all platform traces. To achieve this, options to be considered are enabling the course owner to self-perform an analysis or provide the data sources for the study.
vii. **Understanding the data** – Most of the analytic data presented was in the table list and raw data. My hypothesis for this situation is that existing MOOC learning analytic information is hard for the course instructor to interpret. Performing an analysis requires specific knowledge and skill. The situation becomes more complicated when involving data from different MOOC platforms, as the dataset design differs. With a lack of

understanding of their data, it is difficult for the course instructor to react and take action for future improvement.

There is an ongoing research study to improve the effectiveness of the learning experience on MOOC using new learning models and learning analytics tools (Yousef et al., 2014). Another effort is using MOOC learning analytics to analyse student grades prediction (Moreno-Marcos, P.M. et al., 2018), prediction of student dropout and performance (Ye, C. and Biswas, G., 2014), disengagement analysis (René F. Kizilcec et al., 2013). Despite several relevant studies, such as course completion analysis, learning behaviour analysis and student classification and engagement analysis, there are few systematic studies on modelling student learning behaviour for different categories of courses or cross-platform courses (Jiezhong Qiu et al., 2016).

2.7 MOOC Performance Measurement Model

Performance is generally defined as completing a task with an application of knowledge, skills and abilities. Based on the early observation and study, only using numbers of course completion is not the best practice or indicator to measure MOOC performance due to various reasons such as the motivation of the students and the learning design itself. An assessment must be used to test whether the learners gain knowledge or enhance their experience before the MOOC learning process is undertaken. Findings by (Stephens-Martinez, Hearst and Fox., 2014) indicate that quantitative data sources such as assignment grades are insufficient in evaluating MOOC performance. Therefore, I am are considering using a combination of data from course completion and assessment scores to analyse and measure the performances. For this research, I will initially look at and study performance measurement in two categories: learner performance and MOOC course performance.

MOOC Course Performance: There is a growing trend of research to improve user engagement, hence reducing MOOC's dropout rate problem (Sunar A.S. et al., 2016). I believe that with the available analytic data, course performance can be measured to provide better insight for course instructor in improving their content. Course performance is an evaluation of the course offered in MOOC. China evaluates MOOC courses based on six categories to earn China national recognition: team, design, content, teaching, impact, and support (Chinaooc.cn, 2020).

In this research, I initially defined Course Performance as the quality of learner engagements, number of enrolments and completion course rates.

MOOC Learner Performance: Learner engagement and MOOC completion percentage alone are not suitable learner performance indicators. Neither has assessment measurement features for individual learners. MOOC in education must have three requirements: assessment, instructor and model. Examples of e-activities used as MOOC assessments are online quizzes, essay writing, self-video presentations and audio listening assessments. A study conducted at University Teknikal Malaysia Melaka (UTeM) using learners' coursework marks and grades shows that learners using MOOC perform better than those not using MOOC (Hashim, Salam and Mohamad, 2017). (Gregor, et al. 2015) use grade book and event log data from the Coursera platform as the basis for learning performance analysis. An assessment can increase the performance of the student, and at the same time, it brings benefits to the teacher. Therefore, the numbers and frequency of assessment in MOOCs should be designed to provide adequacy and ensure better measurement and engagement.

2.7.1 Algorithm Development

An efficient, deterministic, and finite approach to problem-solving that can be put into practice as a computer program is referred to as an algorithm in computer science (Sedgewick and Wayne, 2011, p.4). An algorithm is a procedure or instructions applied to solve a particular problem and accomplish a specific task. Algorithm is the idea behind any reasonable computer program (Skiena, S.S. 2009).

Algorithm development is an activity where a measurement formula is designed and tested using parameters identified. Flowchart and pseudocode are two approaches that can be used to design an algorithm. In this research study, I will use the pseudocode approach. This activity is presented in the next chapter.

Algorithm development activity involves a series of data simulations. A simulation method is an approximate imitation of the operation of a process or system that represents its operation over time and can be designed to be more realistic in enhancing potential validity and generalizability (Dooley, K., 2002). Utilising computers to recreate complex operations can offer assistance in exploring system interactions, component performance, and theoretical limits. Simulations permit investigating the impacts of diverse parameters and may show how proposed alterations or changes would work with existing frameworks (Edgar and Manz, 2017).

In developing my MPM model, I used a combination of stages of system dynamic and agent-based simulation modelling process recommended by (Dooley, K., 2002). The four steps are to develop a conceptual design and theoretical solution, elaborate the solution, and perform analysis to create algorithm equations. Validate the algorithm against actual data and conduct any necessary updates. Finally, experimental scenarios and result analysis are performed.

The key to algorithm design is asking ourselves questions to guide our thought process (Skiena, S.S. 2009, p.368). Three design concerns to consider as I work on designing and fine-tuning algorithms using a mathematical solution to overcome a real-world problem are: is the algorithm producing results that I expected? Is this the most optional way to get these results? Moreover, how is the algorithm going to perform on larger datasets? According to Sedgewick and Wayne (2011), we can define an algorithm by writing a computer program that carries out the procedure or describing a problem-solving process in natural language.

Skiena (2009) stated that an essential and honourable technique in algorithm design is to narrow the set of allowable instances until there is a correct and efficient algorithm. Apart from knowing what problem we want to address with the algorithm, it is vital to identify and use suitable parameters in designing it, considering data variables or parameters as critical components. According to Ackoff and Sasieni (1968), the correct evaluation of a variable involves how it is defined, the type of measurements of its value that are made, the basis of the observations, and how estimates are derived from the observations.

In this research study, I am working on solutions for a data model that can be used to measure MOOC courses and learner performance using existing learning analytics data; thus, an algorithm is required. I break this section into five: algorithm parameters, measurement methods, analysis methods, algorithm development and algorithm validation.

2.7.1.1 Algorithm Parameters

In a review of the developments in performance measurement over the last 20 years, Bourne (2008), in the context of business and human resources, indicates the academic disciplines issues in which, from his point of view, performance measurement and management are by their very nature cross-disciplinary, and we do not learn from our colleagues in other disciplines as often as we should. Taking Bourne's (2008) point of view in the context of this research study, I acknowledged the cross-disciplinary relationship between computer science and education. These cross-disciplinary relationships affect the parameters selection consideration. Nevertheless, it could be extended to other fields, such as social science, economics, and security, in which parameters could include, for example, the number of learners based on region, the number of learners who pay for premium subscriptions, or the number of frequent the course cannot be accessed due to technical issues. However, when designing the measurement solutions, I believe it is essential to set a clear scope of study within computer science, which covers data science and education. With this said, the measurement parameters potentially reflect different characteristics, for example, one that measures completion or engagement and another that measures score or achievement. I have clarified what is define as performance that I want to measure in the context of my study, and the algorithm design will reflect this.

My initial findings indicate that using only numbers of course completion as a single measurement parameter is not the best practice or indicator to measure MOOC performance for various reasons, such as the motivation of the learners and the learning design itself. We need more than one parameter. Combining source of dataset approach was also used by (Gregor Kennedy et al., 2015), where they used grade book and event log data as the basis for learning performance analysis.

Analysing and measuring using more than one dataset is considered a novelty approach (Maria Carannante, Cristina Davino and Domenico Vistocco., 2020) with the simultaneous analysis of multiple factors that impact performance. I also identify issues in obtaining reliable assessment data from the MOOC platform. Therefore, my flexible approach enables the assessment score parameters to be obtained from MOOC dataset sources or any other source of assessment data, including offline assessments.

For the Learner performance, I identified the completion of the module and assessment score or marks as parameters to measure. The learner's completion percentage indicates that the learner is going through the learning content. These are important and justified parameters to ensure the learner is monitored and measured effectively (Alison Ashby., 2004; He (J. et al., 2015). Similar to using the average percentage of completion widget in course performance, in learner performance, I use average scores or marks received by learners from assessments. The course admin provides no specific number of assessments in each module or week. Therefore, using the average score is suggested.

I also suggest using the marks or score value, not the completion rate, for learner assessment parameters. Research showed that the number of assessment attempts did not significantly correlate with their final exam scores (Zhiyun Ren, Huzefa Rangwala and Aditya Johri., 2016). Assessment could be an assignment, quiz (Lorenzo Vigentini and Andrew Clayphan, 2015) or test. Assessment data give tangible value for measuring learner performance on MOOC (Jyoti Chauhan and Anita Goel., 2016). Student Assessment parameter is set to be flexible where data sources can be either from MOOC platform or not. The course admin can obtain assessment scores from offline assessments to calculate the average score to be used.

When I conduct data analysis activity, I will confirm which MOOC learning analytics data is suitable as measurement parameters in the next chapter. Assuming I had figured out what data to use as measurement parameters, the following process was determining the measurement and analysis method before the algorithm development activity.

2.7.1.2 Measurement Metric

Measurement is quantifying a characteristic or property of an object or event. According to Ackoff and Sasieni (1968), measurement allows us to compare the same properties of different things and the same property of the same thing at different times and describe how properties of the same or different things are related.

The debate over how best to measure learning or learning gains is centred on two main points of argument, according to Caspersen, Smeby, and Olaf (2017): those who support a test-based approach and those who argue that self-reported measures are appropriate. They also stressed that it's crucial to distinguish between measuring students' performance levels and measuring their learning.

I agreed with Caspersen, Smeby, and Olaf (2017) concerning distinguishing between measuring learner performance and learning. I also believe measuring performance can indicate a poor learner despite achieving higher marks or scores. If a learner scores the same 90% marks in all weeks or modules, in my understanding of performance, the learner is not good at performance. Compare this to a learner who achieves low marks or scores and improves each week or module. This understanding, measurement accuracy, and error will be considered in my algorithm development phase and explained in the next chapter.

2.7.1.3 Algorithm and Model Validation

Algorithm validation activity is an essential activity. This stage involves experts in related areas of study to evaluate the algorithm model design. According to Hand and Khan (2020), validating algorithms means confirming that they can solve the problem.

The two main methods of evaluation are classified as theoretical and experimental. The algorithm is subjected to learning tasks through experimental evaluation to examine its practical performance. Depending on the intended use, various property types may be pertinent to evaluate (Webb, G.I., 2011). Validation often involves applying the algorithm to cases where the "right" answer is known to determine whether, even in cases where the AI system functions as intended and the question is correctly formulated, the system may still not be very good (Hand and Khan., 2020).

Measurement and analysis methods are essential tools for evaluating the performance of an algorithm. Measurement examples include accuracy, precision, speed, memory usage, and error rate. Analysis methods include hypothesis testing, regression analysis, A/B testing, cross-validation, and benchmarking. Depending on the main objective, a data model can be validated using simulation, experiment or user testing. To address my RQ3, I need to understand user feedback, and user usability testing is the appropriate validation method for my model. In the context of my research study and algorithm design concern, the main objective is to design and develop a performance measurement algorithm that works in different MOOC platforms and will enable users to measure MOOC course or learner performance using existing learning analytics data. A series of simulations, experiments and user usability testing methods are considered in this study and explained in the next chapter.

2.7.2 Measurement and Analysis Indicators

The analysis method is the way of breaking down and examining the data collected through measurement. Various data analysis methods exist; each method was designed with specific considerations.

According to (Fotso, J.E.M. et al., 2020), many different types of predictive models are used in MOOCs. The most common are activity-based models. In their study on relevant algorithms for developing deep learning models to classify and predict learner behaviour in MOOC, time series data was used with the RNN (Recurrent Neural Network) analysis method. Fotso, J.E.M. et al. (2020) conclude that Simple RNNs perform the best in their experiments.

In another study, (Vankayalapati et al., 2020) presented a model for analysing learner performance that considers the K-means clustering model. With this support, students' outcomes and futures can be strengthened. Based on similar performance features, (Vankayalapati et al., 2020) learned that the K-means cluster algorithm helps classify students, as demonstrated by the results.

I am considering a time series analysis approach. My definition of performance justified this, emphasising the need for constant measuring performance throughout the MOOC course. As my measurement preference is to compare current data with previous data available, the RNN method is preferable. RNN is a type of Neural Network where the output from the previous step is fed as input to the current step. RNN works on the principle of saving the output of a particular layer and feeding this back to the input to predict the layer's output.

2.8 Theoretical Framework

In this section, I discuss key concepts applied in this research study. The concept influences my solution for the stated research questions by designing measurement algorithms, metrics and indicators that eventually form my MPM Model. This study focuses on analytic data model research, specifically for learning about MOOCs and measuring performances influenced by other existing studies or theories. This section describes and discusses the philosophical assumptions of this research study, followed by the theoretical concept and the semantic web and ontology.

2.8.1 Engagement, Improvement, and Performance in MOOCs Learning

Disengagement is a significant concern in teaching and learning, and it becomes even more complex in online teaching and learning environments. According to Refugio et al. (2018), an individual's learning style refers to the preferred way in which a student absorbs, processes, comprehends, and retains information and skills while learning. Learning design, on the other hand, refers to the type, sequence, and balance of activities that learners are set to do (Koper & Bennett, 2008).

However, the concept of Learning Style has been disproven over the last few years (Zrudlo, 2023). Additionally, in most MOOC platforms, there are no features for identifying a learner's learning style. Learners can register or browse courses and start using MOOCs, the content of which is already prepared, without knowing their learning style. In a massive environment, it is challenging to identify or predict each learner or most learners' learning styles. One of the preferable methods of study is taking advantage of the clickstream or available analytic data in MOOC platforms to predict learners' learning styles (Sunar et al., 2016; Williams et al., 2018; and Yassine & Abdellatif, 2013).

To address this issue, it is essential to focus on learner goals or objectives rather than learning styles. By understanding the learner's goals or objectives, instructors can design courses that cater to their needs and preferences. This approach can help improve engagement and retention rates in online teaching and learning environments, as describe in Table 4.

For example, if a learner's goal is to improve their writing skills, the instructor can design a course that focuses on writing techniques, grammar, and sentence structure. The course can include interactive activities, such as writing exercises, peer reviews, and feedback from the instructor. By focusing on the learner's goals or objectives, the instructor can create a more personalized and engaging learning experience.

In conclusion, it is essential to focus on learner goals or objectives in online teaching and learning environments. By understanding the learner's goals or objectives, instructors can design courses that cater to their needs and preferences, leading to improved engagement and retention rates.

2.8.2 Semantic Web and Ontology for Cross-Platform MOOC Learning Analytics Data Sources

Davies, J., Fensel, D. and van Harmelen, F. (2002) versioned the Semantic Web as a set of connected applications forming a consistent logical web of data. The semantic web is also described as an extension of the current web in which information is given well-defined meaning, better-enabling computers and people to work in cooperation. This is when an ontology is needed as a key enabling technology for the Semantic Web (Davies, J., Fensel, D. and van Harmelen, F., 2002). An ontology is an engineering artefact consisting of a vocabulary used to describe a particular view of some domain. It is an explicit specification of the intended meaning of the vocabulary. It often includes classification-based information. Ideally, an ontology should capture a shared understanding of a domain of interest. The ontology should also provide a formal and machine-manipulatable model.

Semantic web effort led to the development of resource description languages, RDF Schema (RDFS). Although RDFS is recognizable as an ontology language, it is too weak to describe resources sufficiently. Two languages, OIL and DAML-ONT, were developed to address deficiencies and problems of RDFS. OWL language is based on DAML and OIL, which are based on description logic.

An ontology is a form of knowledge management. In computer science, ontology is a formal representation of the knowledge by a set of concepts within a domain and the relationship between those concepts. Ontologies are made up of classes and relationships. Classes are concepts in the designated domain, collections of objects with similar properties.

When there is a need to use a combination or sourcing data from multiple sources, it is essential to ensure those data are represented and correctly understandable. For example, one data source uses gender while another data source uses sex, which both represent the same concepts of data. Another example is that one data source uses *Module_Name* while another uses *Week_Number*, which both represent the same concepts of data.

Due to the research scope limitation, the study focuses on incorporating the concepts of the Semantic Web and ontology to develop the MPM Model for data from two distinct MOOC platforms, FutureLearn and OpenLearning. The study will involve mapping datasets from these platforms and creating an RDF only, without proposing an actual MOOC ontology. This research aims to address the structure of datasets from different platforms and propose a performance model using RDF, as detailed in the upcoming chapter.

2.9 Chapter Conclusion

Access to learning analytic datasets and the capability to use them for measuring performance is essential and could lead to more favourable benefits, especially in MOOC and performance-related research studies. This also will help MOOC content stakeholders improve their content, offer better learning experiences to learners, and, most importantly, have a more accurate interpretation of their MOOC. As I describe, defining something can be subjective, and it is possible to have various definitions. Based on the study conducted and the justification I present in this chapter, I define MOOC Performance as the value of improvement or ability to maintain the highest score value throughout the course, either for the course performance or individual learner performance. Score values are parameter data from the MOOC learning dataset available in most MOOC platforms. In a later chapter, I will present the findings and justify the parameters used in my measurement algorithm.

Chapter 3 Research Design and Methodology

3.1 Introduction

This chapter covers the research design and methodology aligned with the research study required to answer research questions and achieve objectives. It detailed the study's research type, data collection, and analysis method. I organised this chapter starting with an introduction, followed by research design, research methodology, data collection method, data analysis method, data validity and reliability subtopic and finally, the chapter conclusion.

3.2 Epistemological Orientation

A research study is meant to contribute significantly to the body of knowledge. As a researcher, I view certain phenomena within my assumptions and interests. Then I study them as I am concerned with what constitutes valid, acceptable or legitimate knowledge. Epistemology is defined as a theory of knowledge. It deals with the question of gaining knowledge (A. Tolk et al. 2013) or how we know about something. This section explains the epistemological orientation in conducting this research study.

In this research study, I adopted the pragmatism paradigm when I viewed issues on MOOC learning in higher education. Having personal experience and observation on MOOC education as a lecturer at a university, I know two apparent phenomena: dropout MOOC learners and the increasing interest towards empowering MOOCs via the use of learning analytics.

Later, this phenomenon built my assumption and belief that MOOCs stored valuable learning analytics data that can be utilised to help improve how the MOOC is delivered effectively and could benefit its users. I also believe that each MOOC platform has its style or structure of tracking and recording learning analytics. Nevertheless, at some point, there are similarities in the data collected. Therefore, having a standard for identifying and acknowledging MOOC performance will be a good practice. Finally, I believe that a concept or theory being better than before is a justification for performance and being the same or worse than before is considered not performing.

The research issue, questions, and objectives were later identified, as explained in the previous chapter. I used mixed methods methodology to answer the research questions, combining various methods throughout the study. All the data collection and analysis methods are carefully chosen to help address specific objectives. Literature review, secondary data analysis, simulations, observation, experiments, user usability testing, demonstration, questionnaire and interview methods are used and explained in the following sections.

Reality is constantly renegotiated, debated, and interpreted in light of its usefulness in new, unpredictable situations. At the end of this research study, I conducted user usability testing involving a particular group of users as participants. I present findings and demonstrate the MPM model. Participants later experienced using the MPM model before answering questionnaires and being involved in informative feedback interview sessions. Besides answering the research questions, research findings and results also contribute towards validating my epistemology. The conclusion of this research is presented in the final chapter of this thesis.

3.3 Research Design

This study is designed as applied exploratory research with qualitative and quantitative research methods involving primary and secondary data.

Applied research best fits my research study objectives: identify solutions to specific problems and offer applicable and implementable knowledge. I begin this research study with an initial hypothesis based on personal experiences and observations. Therefore, an exploratory approach is considered appropriate as I examine what is already known about the potential of MOOC learning analytics used to measure performances. A combination of both qualitative and quantitative approaches is used and explained in the next section.

This research study aims to develop techniques, products and procedures, which is the MPM Model that includes performance measurement algorithms, measurement metrics and analysis indicators. Research design provides the strategy of investigation to answer research questions, which are:

> *RQ1:* ***What are the parameters*** *for measuring course and learner performance at macro and micro levels using learning analytics from cross-platform MOOCs?*
>
> *RQ2:* ***How can monitoring*** *course and learner performance at macro and micro levels be performed using MOOC learning analytics?*
>
> *RQ3:* ***How do we evaluate*** *the usability of the proposed MOOC Performance Measurement (MPM) model design?*

Due to the nature of this research questions, scope and objectives, I am applying an exploratory research approach to explore the main aspects of under-researched problems, using learning analytics in a cross-platform compatible model inspired by the semantic web concept. The research framework was planned and explained in the next section, followed by the visualised operational framework.

3.3.1 Research Framework

Five research phases were designed as the research frameworks. Phase 1 is a literature review and preliminary study, followed by Phase 2, Data Analysis and Algorithm Design and Development. Phase 3 is MPM Model Design, Development and Experiments. Phase 4 is MPM Model User Usability Testing, and finally, Phase 5 is Documentation and Final Report. Table 14 below details all 5 phases.

Table 14: Research Framework

METHODOLOGY PHASE		METHOD AND ACTIVITY	REMARKS
Phase 1	Literature Review and Preliminary Study	An initial study on Linked Data and Semantic Web. Literature study on MOOC learning analytics (on Learning Analytics in Higher Education, Available Data in LMS and MOOC Learning Analytics, Problems in Learning Analytics Using MOOCs, Learning Analytics in MOOCs) Literature study on learning performance (on MOOC Course Performance Measurement Using Learning Analytics) Literature study on MOOC ontologies (on Learning Analytics in Cross-Platform MOOCs)	Gap 1: The first gap concerns the availability of learning analytics from cross-platform MOOCs for student use at the micro-level and for administrator use at the macro level. Gap 2: The second gap concerns only a few research conducted on learning analytics from cross-platform MOOCs, and there is no model proposed as a solution.
Phase 2	Data Analysis and Algorithm Design and Development	Secondary data analysis Journals data collection Dataset from the FutureLearn platform Dataset from the OpenLearning platform	RQ1: What are the parameters for measuring course and learner performance at macro and micro levels using learning analytics with cross-platform MOOC compatibility?

		Algorithm Development Simulations Expert Validation	RO1: To identify parameters and algorithms for measuring course and learner performances using learning analytics from MOOCs.
	Semantic Web	Uniform Dataset Creation Analysing the dataset content and structure Select data groups Analysing and comparing at the lower granularity level	
Phase 3	MPM Model Design, Development, and Experiments	Designing the Dataset Integration Model MPM Indicator and Metrics development Model Validation (Sample Data Experiments) OpenLearning dataset experiments FutureLearn dataset experiments	RQ2: How can learning analytics from MOOC be used to monitor and measure the course or learner performances at macro and micro levels? RO2: To propose a cross-platform model for monitoring course performance at macro and micro levels using learning analytics from MOOCs.
Phase 4	*MPM Model User Usability Testing*	Conduct a series of MPM User Usability Testing: FutureLearn MOOC Users from the United Kingdom OpenLearning MOOC users from Malaysia	An additional research activity response to reviewer feedback and recommendation. RQ3: how do we evaluate the usability of the proposed MOOC Performance Measurement (MPM) model design? RO3: To conduct a series of experiments using the MPM Model with sample datasets and a session of user usability testing with the MOOC course admin or MOOC content developer.
Phase 5	Documentation and Final Report	Documentation and Publication	

3.3.2 Operational Framework

Based on the research framework detailed in the previous section, I prepare the operational framework (Figure 3), which visualises the connection between the research ideas and activity and how it relates to the research questions and objectives.

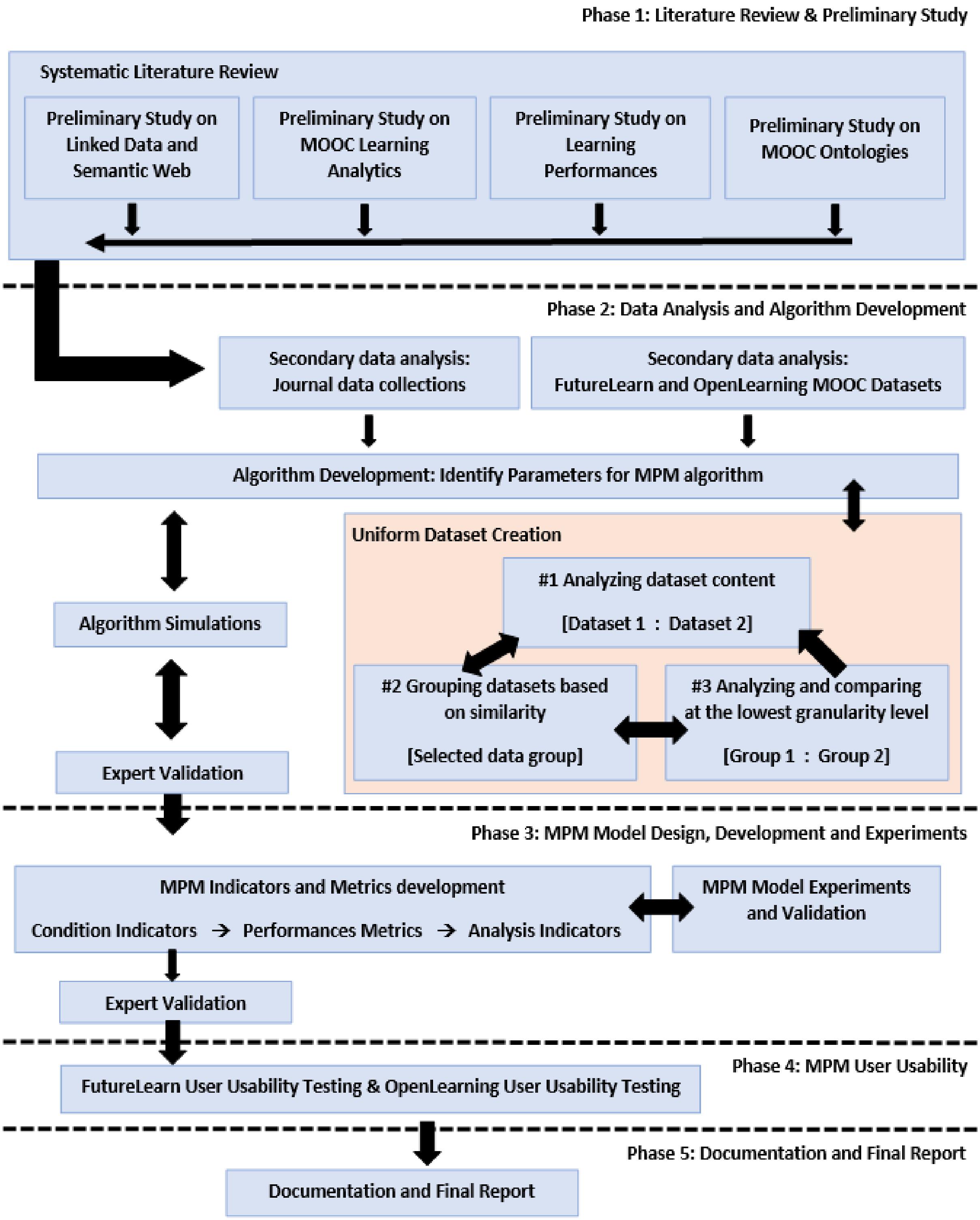


Figure 3: Operational Framework

3.4 Research Methodology

Research methodology is a system of scientific methods to address the research topic. Research methodology aims to use appropriate procedures to find solutions for the research issue or questions.

A combination of qualitative and quantitative methodology is used in this research study, considering the complexity of the data collection type to facilitate the research questions, objectives, and scope. Half of my research will depend highly on the data numbers, and the other half will look beyond the percentage numbers to understand analysed results and related viewpoints.

Thus, it is essential to highlight that appropriate research methodology lays the foundation for effective research methods and ensures that the research method is conducted correctly. This section justifies this study's quantitative and qualitative methodology by relating it to my operational framework. Data collection and data analysis methods are explained in section 3.5 and 3.6.

3.4.1 Quantitative Method

The measurement of quantity or amount is the foundation of quantitative research. The process of gathering and interpreting numerical data is known as quantitative research. Based on the research questions and as previously described, this research will collect, measure, analyse, and study existing learning analytics data from MOOC platforms. Therefore, I am using both data collection and data analysis quantitative methods as follows:

- Data Collection
    - Simulation
    - Experiment
    - Questionnaire
- Data Analysis
    - Hypothesis Testing
    - Statistical Test

3.4.2 Qualitative Method

The qualitative research method involves collecting and evaluating non-numerical data. This method helps better comprehend ideas, opinions, or experiences needed in this study to uncover intricate details about my hypothesis, the approach I undertake in analysing measurement results and looking at fresh investigation thoughts. To understand measured data and provide analysis, I use qualitative data gathering and analysis, especially during the early phase of the research phase and throughout the end of the research study when I perform user usability testing.

Both data collection and data analysis qualitative methods are as follows:

- Data Collection
    - Literature review
    - Observation
    - Interview
- Data Analysis
    - Grounded theory
    - Content analysis

3.5 Data Collection Method

Data collection is gathering information from all relevant sources to answer the research questions, test hypotheses and evaluate the findings. The data collection method for this research study is carefully planned and chosen based on my research questions and guided by my research design and methodology. Two categories of data collection methods are primary data and secondary data. I used both data collection methods, which are explained in the following sections.

3.5.1 Systematic Literature Review

Systematic Literature Review (SLR) is a secondary study data collection method used to map, identify, critically evaluate, consolidate, and collect the results of relevant primary studies on a specific research topic (A. Dresch et al. 2015). SLR becomes a standard method to obtain an answer by performing a literature review based on the previous relevant studies (Miswar et al. 2018).

I used the SLR method in Phase 1 research framework. A preliminary study was conducted on four research topics related to my research study: a Preliminary study on linked data and semantic web, a Preliminary study on MOOC learning analytics, a Preliminary study on Learning Performance and a Preliminary study on MOOC ontologies. Information and data obtained from the SLR activity give us critical insight to progress with the study.

I also conducted a combination of Information Retrieval strategy and thematic analysis by using keywords and summarising the topic discussed in the literature collected. The collection of literature was gathered by searching Microsoft Academic and Google Scholar databases. The keywords used for searching included ‘learning analytics in higher education’, ‘available data in MOOC learning analytics’, ‘problems in learning analytics using MOOCs’, ‘learning analytics in MOOCs’, ‘measuring MOOC performance’, ‘monitoring MOOC learning’, and ‘learning analytics in Cross-Platform MOOCs’. Searching was limited to journals published from 2013 to 2020, and the results were filtered to be sorted by relevance.

3.5.2 Observation

Observation is a valuable method for formulating a hypothesis. Observational methods collect relevant data during the development of a project and use them for further analysis. My research study used the observation method in my Data Analysis and Algorithm Development phase and MPM Model User Usability phase.

I collect sample datasets from two MOOC platforms in the Data Analysis and Algorithm Development phase. Using the semantic concept, I observed and identified data similarity between two sources in the Uniform Dataset Creation process. Next, I conduct a series of simulations to test my algorithm and theory.

In the MPM Model User Usability phase, the observation method was used to observe participants using the MPM Model and assist them when needed. Seeing how end-users explore and use my MPM Model gives us valuable insight into its usability.

3.5.3 Simulation

A simulation method is an approximate imitation of the operation of a process or system that represents its operation over time, which can be designed to be more realistic in enhancing potential validity and generalizability (Dooley, K., 2002).

Utilising computers to recreate complex operations can offer assistance in exploring system interactions, component performance, and theoretical limits. Simulations permit investigating the impacts of diverse parameters and seeing how proposed alterations or changes would work with existing frameworks (Edgar and Manz., 2017). Gilbert and Ahrweiler (2006) suggest that research communities have to offer and develop their own "best practices" for doing simulation research rather than having their epistemological approach dictated to them by methodologists.

In developing my MPM model, I used a combination of stages of the system dynamic and agent-based simulation modelling process recommended by (Dooley, K., 2002). The four steps are to develop the conceptual design and theoretical solution, elaborate the solution, perform analysis to create algorithm equations, validate the algorithm against actual data, conduct any necessary updates, and perform experimental scenarios and the result analysis.

Step 1: Develop a conceptual design and propose the MPM algorithm.

At the beginning of this research study, problem statements, research questions and objectives are determined. Systematic literature review activity performed. Based on the existing literature, I develop a conceptual design and propose a theoretical MPM algorithm to be tested.

Step 2: Elaborate equations based on sample data. Perform statistical analysis and create algorithm equations.

Statistical analysis of the proposed theoretical MPM algorithm using sample data was conducted. This process includes data cleaning, dataset analysis, parameter identification, and uniform dataset creation. Then, MPM algorithm equations are developed based on the early conceptual design.

Step 3: Validate the results against actual data.

Next, results from the MPM model simulation are compared and validated against actual data. At this current research stage, I conducted simulations using data from OpenLearning. Results from this step were used for corrections and updates on the MPM algorithm. This is essential as validation of the proposed MPM algorithm is necessary for the next step activity.

Step 4: Perform experimental scenarios, analysing the result and interpretation.

This final step in my research simulation involved sample data from MOOC platforms. This step gives us better consideration simulations of the overall process in using the MPM Model. Indicators and metrics were also tested as I stimulated the weekly module measurement. In this part of my research study, I conduct a series of course and learner performance simulations using made-up MOOC learning analytic data based on the proposed MPM model.

Simulation conducted in this research study served four purposes: to make a proof and theory discovery, observe performance, understand the existing process and address research questions. The simulation method can be used to prove the existence of a potential solution to a problem. It can reveal phenomena that concentrate theoretical attention in turn. Other purposes of conducting simulation are to observe performance and provide a way to investigate the effectiveness of solutions. Simulation may be used with a correctly calibrated and validated model to execute actual activities, such as diagnosis or decision-making, within an organisation or system.

A simulation was conducted to provide more general information about how complex systems work and how the proposed MPM model is used. The researcher can gain a more profound concept. Finally, this study used the simulation to address the research questions and objectives.

3.5.4 Experiment

Experimental method in computer science research was defined as measuring an apparatus to test a hypothesis (Denning, 1980). This method comprises a set of skills and techniques for minimising errors in acquiring and communicating measurements (R. Maxion, 2009). The experiment also can be used to find the optimum result. According to Nordin Abu Bakar (2018), experimental computer science is still unexplored. However, Denning (1981) describes the field of performance evaluation as a positive example of experimental computer science research.

This research used the experimental method to measure and test my MPM model hypothesis within sample data. This includes testing the measurement algorithms, metrics and indicators. A series of experiments was conducted using datasets from different MOOC platforms.

3.5.5 Usability Testing

Usability is defined as the extent to which specified users can use a product to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use (ISO 9241, 2018). The RQ3 of this research study is how do we evaluate the usability of the proposed MPM Model design? Furthermore, using the user usability testing method is appropriate to address this research question. It is a preferable method for collecting detailed and direct user feedback.

3.5.5.1 Test Run - User Usability Testing

A test run of user usability testing was performed with a research lab member with matching backgrounds required for the actual user usability testing. The main objective for the test run is to check and ensure the procedure, tools, resources, instructions, and data to be collected during the actual user usability testing are practically proven and valuable data is collected.

I conducted the test run in two settings, online and face-to-face sessions involving one participant. During the session, the tester provided direct feedback and recommendations on improving the practicality of planned user usability testing. I made some changes based on the relevant recommendation before the user usability testing.

3.5.5.2 Ethics and Research Governance (ERGO)

This research study involves human participants. Phase 4, user usability testing, involved participants from the United Kingdom and Malaysia. The usability testing activities were conducted in compliance with the ethical research governance guidelines of the University of Southampton (ERGO). Ethical approval was obtained before the usability testing activity was conducted. This process uses an online submission tool called ERGO 2 (https://ergo2.soton.ac.uk).

- ERGO Submission ID: 72071
- Project Title: MPM Model User Usability Testing (2022-04)
- Status: Approved (Category C)
- End Date: 22 January 2024

Attachments submitted with the ERGO application are the Ethics form, FEPS Consent form, Questionnaire form and FEPS Data Protection Plan form.

3.5.5.3 User Usability Testing

I conduct a series of User Usability Testing (UUT) as a user-based evaluation of my MPM Model in Phase 4 of my research study. User-based evaluations are usability evaluation methods in which users directly participate (J.M. Christian Basten. 2010). Specified end users were invited to participate as participants and instructed how the testing session would run.

The UUT is a final validation activity designed and conducted to get feedback from targeted groups of users reflecting the user scope of this research study, which are FutureLearn MOOC users and OpenLearning MOOC users.

This UUT activity involved five phases. First is the initial UUT design and planning. The second phase was conducting a Test Run of MPM Model UUT, followed by a UUT update. Once I complete an update of my UUT procedure based on results and feedback from the Test Run, I apply for ERGO before conducting the actual UUT with two main groups of participants from the United Kingdom that represent users of FutureLearn and groups of participants from Malaysia that represent users of OpenLearning.

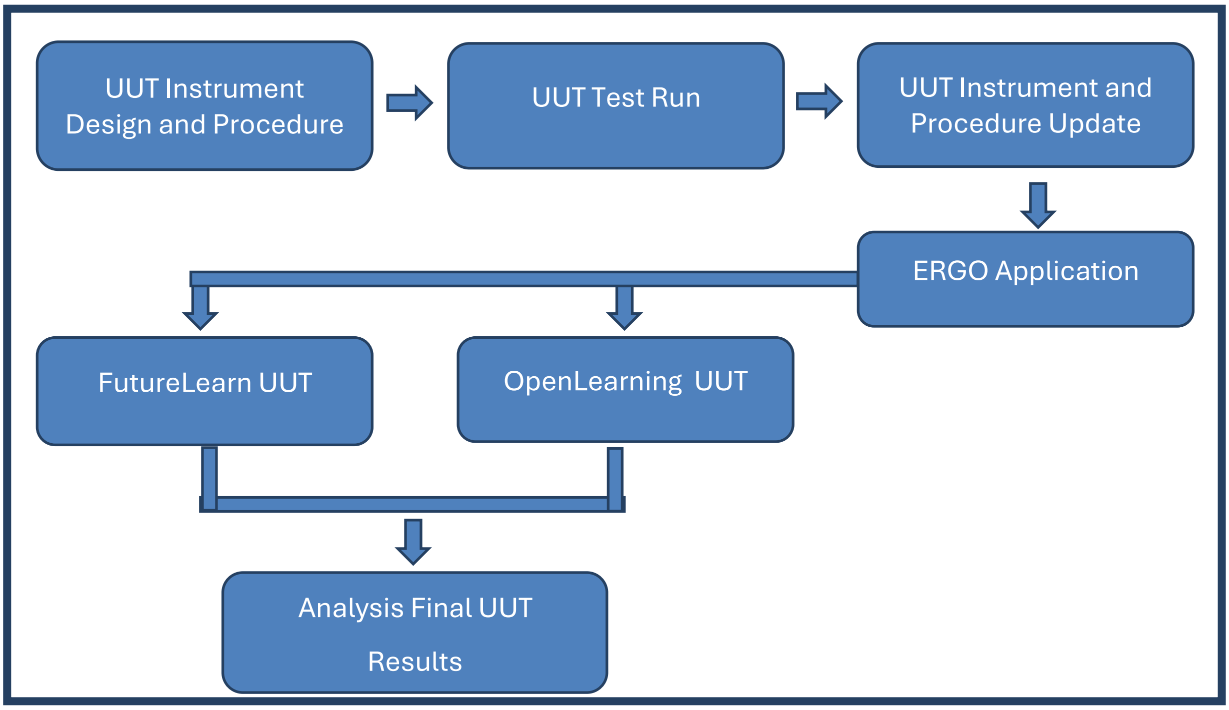


Figure 4: User Usability Process Flow

How many users do we have to test?

When inviting users to participate in a user test, the aim is to find the most flaws a product may have at the lowest cost, where cost includes the cost of participants, cost of observers, cost of laboratory facilities, and limited time to obtain data to provide to developers in a timely fashion (J.R. Lewis. 2006). Due to the nature of this study, I am required to obtain data from two different groups of participants. One group of participants will be the FutureLearn MOOC platform users, and another group will be those using the OpenLearning MOOC platform. Initially, I gathered up to 20 lists of suitable participants from both groups that were identified based on their experience and background criteria. Unfortunately, only 7 participants successfully participated due to availability issues. Three from the FutureLearn users group and four from the OpenLearning users group,

UUT Test Run

Before conducting the actual user usability testing, I conduct a test run to evaluate the method and setup used during actual user usability testing. The main objective for this test run is to observe the method used, the setup of how testing will be conducted, and the details that will be collected from the testing. Any recommendation will be considered for improvement before the user usability test.

The test procedure

Each participant will be provided with a Microsoft Excel document as the testing tool that also includes testing instructions and a questionnaire form. Next, each participant will set a one-hour session for the testing. The participants were allowed to conduct a face-to-face or online session via Microsoft Teams. For the first 30 minutes, the researcher will start by giving an introduction and demonstrate how to use the provided tool. Then, participants will explore and use the tool for the remaining time while the researcher observes and assists the participants if needed. Towards the end of the session, participants were reminded to complete the testing by answering the questionnaire form provided and emailing it to the researcher.

I include a questionnaire and an open-ended interview method, explained in the following sub-section below.

Remote usability evaluation

Remote usability evaluation refers to a situation in which the researcher and the test participants are not in the same room or location (J.M. Christian Basten., 2010). Seven online sessions were conducted remotely during the user usability testing, with all participants from Malaysia and two from the UK. One participant from the UK takes part in both online and in-person sessions. The testing session used Microsoft Teams as the online video meeting platform. The testing session was recorded with the participant's consensus.

User testing tools for the usability specialist

The main objective of the user usability testing is to test the usability of the proposed MPM Model. Due to time and resource limitations, I prepared a tool using Microsoft Excel. A spreadsheet was created with an MPM algorithm integrated to measure users' keyed-in data. The result is presented in graph and table format, ready for the user to analyse, referring to my indicator. Microsoft Excel was chosen considering it was easy to integrate my model and the Microsoft Excel software is familiar to the user.

3.5.5.4 Questionnaire

A questionnaire collects data through questions, which are either quantifying data (closed, alternative questions) or qualifying data (open and reviewing questions) (Håkansson, A. 2013). The questionnaire method is used in the Phase 4 research framework, where a questionnaire form is integrated into the MPM Model Tool document used during user usability testing to gather data from end users. The questionnaire consists of a total of 31 questions categorised into five parts. The completed questionnaire form is returned to us via email for my records and analysis.

Table 15: Questionnaire Structure

Question Part	Number of Questions	Question Type
Part 1: Demography	8	Scale rate and short answer
Part 2: MPM Usage (Monitoring)	6	Scale rate
Part 3: MPM Usage (Measurement)	6	Scale rate and short answer
Part 4: MPM Usage (Analysis)	6	Scale rate
Part 5: Feedback	5	Short answer

3.5.5.5 Interview

Interviews are worthwhile because they allow researchers to uncover information that is probably inaccessible using techniques such as questionnaires and observations. An interview is a standard data-gathering method. The interview method involves questioning or discussing issues with people (Baxter et al. 2006).

Apart from a set of questionnaire questions, I conducted an unstructured interview with my participants during their user usability testing session. Discussions and questions were asked as I observed participants' interests and skills related to my research and the MOOC. Feedback was recorded and later to be analysed. Appendix H list questions asked during interview with participants.

3.6 Data Analysis

Data analysis methods are used to understand, summarise, illustrate and assess data gathered from the research study. Therefore, data analysis tools or techniques were carefully selected based on the research study to analyse data. I use quantitative and qualitative data analysis methods in this mixed-method research study to meet my research study requirements.

3.6.1 Hypothesis Testing

Hypothesis testing is a formal procedure for investigating ideas or concepts. It consists of any statistical method used to confirm a hypothesis or the relationship between two variables to a certain confidence level. Four hypothesis test steps in data-driven decision-making (Nile Singh. 2020):

i. Formulate a hypothesis.
ii. Find the right test for the hypothesis.
iii. Execute the test.
iv. Make a decision based on the result.

With the idea, "today, better than yesterday", I define MOOC courses and learner performance. Then, my hypothesise that performance can be monitored and measured using MOOC learning analytics. I also believe that monitoring and measuring MOOC courses or learner performance can be done at cross-platform capabilities using the semantic web approach.

A statistical test is used to determine whether or not a hypothesis is correct by telling us how likely it is that the result of a simulation or an experiment is due to chance alone (Stolar MH, 1980). The statistical test method used in this research study to support my hypothesis test is explained in the following subsection.

3.6.2 Statistical Test

Statistical test analysis is preferred for performance analysis research studies (Merry McDonald et al. 2004). Statistical test data analysis method was used to test the hypothesis during the design and development of my measurement algorithm. I used the difference of two means (paired) test method. This method was chosen considering the data used is interval data from MOOC learning analytics, where the sample is one sample with two measures. The purpose of the test is to test against a value. In my case, I am measuring the difference value of the current module with the previous module in the same data sample. I also used statistical test analysis to analyse data from my user usability activity. Details of the algorithm design are explained in Chapter 5 and user usability testing analysis will be explained in Chapter 7.

3.6.3 Ground Theory

Ground theory is a qualitative research method that enables us to derive new theories based on the iterative collection and analysis of real-world data. According to Flick, U. (2020), Ground theory coding can be applied to data analysis from interviews, focus groups, observations, newspapers or the internet.

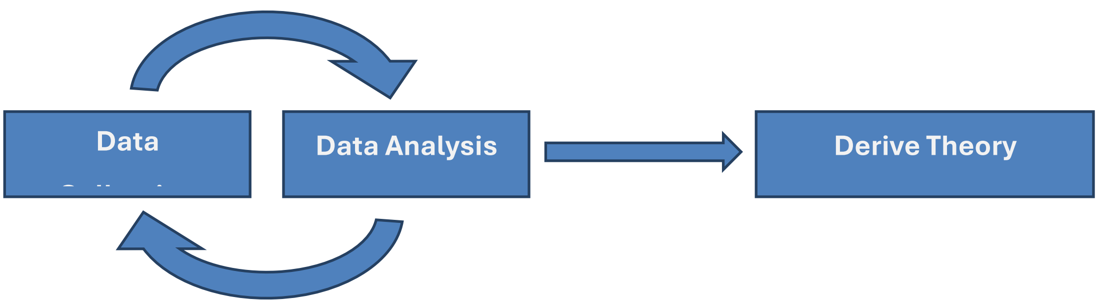


Figure 5: Ground Theory Process

I performed a content analysis on the collected data. Next, the process of interpretation begins with open coding, while, towards the end of the whole analytical process, selective coding comes more to the fore. Coding here represents the operations by which data are broken down, conceptualised and put back together in new ways (Flick, U. 2020). Coding includes constantly comparing phenomena, cases, and concepts and formulating questions about the text. Open coding aims at expressing data and phenomena in the form of concepts.

This study was limited to the scope of research and focused on learning analytics and the performance measurement algorithm. On the educational aspect and input, I did relay to others the previous study that already focuses on the educational and learning-specific area of research. Raw data and information collected from literature review activity and discussion with experts were analysed cyclically for Phase 1 to Phase 3 to drive a theory for the Consideration Factor Indicator used in the MPM Model. It helps us to develop my Consideration Factor Indicator. A set of indicators that are used to guide users based on the analysis made from my MPM algorithm to the areas where they should pay more attention or consider improving. The details of the Consideration Factor Indicator are explained in Section 5.4.3.

3.7 Data Validity and Reliability

Data validity serves the purpose of checking the data quality, the results and the researchers' interpretation of the data results (Creswell and Plano Clark., 2018). In this sub-section, I inform how data used in this research was collected, used, and stored. This study uses four data sources: literature review publications, MOOC platforms, researcher activity, and user usability testing participants. Data were categorised as primary and secondary data and explained in Subsection 3.7.1 and 3.7.2.

3.7.1 Primary Data

Primary data or primary resources is where the researcher gathers information and data directly from their recruited subjects. During different research phases in this study, research activities are conducted when I obtain valuable data from it. Research activities where I gather data are simulations, experiments, observation, and user usability testing.

Observation: I used observation in several phases, which are during the simulation, experiment, and user usability testing. All observations are recorded. This data is considered critical primary data, where I experience and collect the data from direct sources.

Simulation: My first primary data is the results from the simulation's activity. During the simulation activity, I used made-up MOOC learning analytic data. I simulate to test the algorithm's design. Simulation results are valuable data that are later used to justify the algorithm design and as a reference in designing my MPM Model.

Experiment: I used secondary MOOC learning analytics data from FutureLearn and OpenLearning MOOC. Results and findings from these experiments are considered my second primary data, which I used to justify the proposed MPM Model.

User Usability Testing: Finally, I obtain primary data from my user usability testing. During this testing, I invite a special group of users with MOOC experiences to try using my proposed MPM Model as a participant. At the end of each session, the participant is asked to complete the questionnaire form. We also had an interview during the testing session where all matters discussed related to the research study were recorded.

3.7.2 Secondary Data

Two main secondary data used in this study are data from the literature review and learning analytics data from MOOC platforms.

Literature review: In Phase 1 of this research study, I used the literature review method as my preliminary study to extract relevant information from other sources or previous studies. I initially studied four areas: linked data and semantic web, MOOC learning analytics, learning performances, and MOOC ontologies. In Phase 2, I conduct another secondary data study from journal data collection.

MOOC learning analytic data: In this study, my aim is to use the existing MOOC learning analytics data. Therefore, in Phase 2, I used secondary data, FutureLearn and OpenLearning datasets. This sample dataset gives me actual details on the data format made available by MOOC platforms and information on the data structure used. This data was used to establish the parameters for measurement and allowed me to compare datasets from two different MOOC platforms to create a uniform dataset.

This secondary data is also used as a sample during the user usability testing. To protect the respondents' confidentiality, the data made available are sometimes purposively altered. When data are available on a micro level, combining information from different sources may make it possible to identify individual respondents (Hox and Boeije., 2005). I used part of the data as a sample for my user usability testing, where personal linked data was removed and altered when appropriate before sample data was shared with participants.

3.8 Chapter Conclusion

This chapter provides details on how this research study will be conducted. Using a mixed-method research approach provides me with various methods for collecting and analysing data as I need to answer the research questions. The complexity of this study required the operational framework to be designed to derive from my research framework as a guideline for the research study activities. The research design is prepared with aims addressing the research questions and objectives. An appropriate data collection and data analysis method is used to ensure that research results are theoretically, technically and ethically acceptable in contributing to the body of knowledge of this study. In the next chapter, I present the activity of identifying parameters from existing MOOC learning analytics.

Chapter 4 Identifying Parameters from an Existing MOOC Learning Analytics

4.1 Introduction

In this chapter, I present essential research activities and findings fundamental to the MPM measurement algorithms, which identify parameters from MOOC learning analytics for measuring course and learner performance. I begin with data analysis on the MOOC learning analytics structure and follow with uniform dataset creation using a semantic approach. Next, I present the parameters for monitoring and measuring performance before ending this chapter with a conclusion.

4.2 Data Analysis: MOOCs Learning Analytics Structure

MOOC learning analytic data promises many benefits to explore. Unfortunately, the learning analytic data provided was in raw data form. Moreover, the kinds of relationships linking performance, learning and engagement lend themselves to different interpretations (Maria et al., 2020). These data are difficult to interpret. Several researchers developed MOOC dashboards to leverage the availability of learning analytic data from their MOOC platform providers. For example, (Ruth Cobos et al., 2016) developed a MOOC dashboard called Open-DLA for edX and Open edX platform, (Manuel., et al., 2016; Manuel and Adrian, 2017 and Manuel and Tang., 2017) developed the University of Southampton MOOC Observatory Dashboard for FutureLearn platform, (Chitsaz, Vigentini and Clayphan., 2016) developed a MOOC dashboard for FutureLearn platform, (Vigentini, Clayphan and Chitsaz., 2017a) developed a MOOC dashboard for UNSW MOOCs and (Vigentini., et al., 2017b) developed MOOC Dashboards for Coursera and FutureLearn.

Most of the dashboards were developed for monitoring their MOOCs that reside in one single MOOC, except (Vigentini., et al., 2017b), which developed their MOOC dashboards for two different MOOC platforms. Since many MOOC platforms exist and provide various benefits, having different approaches, it is common for universities to have their MOOCs on multiple platforms. These have added more complexity for course administrators in monitoring their MOOCs. Vigentini et al. (2017b) developed two different MOOC dashboards to solve their UNSW MOOCs.

Based on the preliminary study conducted, my data analysis will investigate data on course completion and assessment scores from two MOOC platforms to indicate performance.

FutureLearn provides a learning analytic dataset in CSV format. Previous studies (Manuel., et al., 2016; Manuel and Tang., 2017) reported that FutureLearn provides eight dataset files to their MOOCs course administrators. Recently, four additional new dataset files have been made available. This new addition is to fulfil requirements by previous research that highlighted the limitation of metadata available in the learning context, such as video interaction data, incomplete demographic information and how the platform tends to develop features to improve rapidly. Table 16 describes each dataset file with details about their purposes.

Table 16: FutureLearn Datasets

DATASET FILES	**DESCRIPTIONS**
Archetype Survey Responses*	Information about learners' responses to the archetype survey is provided at enrolment to the course.
Campaigns	Information about the referral used to advertise a course is stored in this file, following the number of enrolments and activity learners for each referral.
Comments	Information about the learner's contributions to the discussion section in each step is stored in this file. It includes the comment's text and the timestamp corresponding to when the comment was made. It also saves the number of likes associated with a comment.
Enrolments	This file provides basic information regarding the enrolled learners and staff. It also includes learners' demographic information derived from their responses to the more-about-you survey, such as gender, country age range, highest education level, employment status, and employment area.
Leaving Survey Responses*	This file holds information about responses from the learner who left the course. It stores the learner's timestamp when unenrolled from the course, the learner's reason for unenrolling, the timestamp's last completed step, the last completed step number, and the last completed week number.
Peer Review Assignments	This file provides information regarding peer-review assignments, including when the assignment was first viewed and submitted and the number of associated views.
Peer Review Reviews	This file provides information about the reviews on an assignment, including when the review was submitted, the reviewers' ID and feedback text on each assignment guideline.
Question Response	This file holds information about the quiz activity of earners. It stores learners' responses, correctness, and timestamps associated with answering a quiz.
Step Activity	This file stores information regarding step activity from learners in the course, e.g., when a step is first visited and the last time a step is marked as completed.

Team Members	Information about organisation staff, such as their IDs and names, is stored in this file.
Video Stats*	Information about learners' interaction with video content. It includes the video title, video duration, total views, total downloads, total caption view, total transcript view, total view in HD setting, total view at least five, ten, twenty-five, fifty, seventy-five, ninety-five and one hundred per cent of the video and device type percentage. It also saves the region view percentage.
Weekly Sentiment Survey Responses*	This file stores information regarding the learners' responses to weekly course summative surveys, e.g., the responded timestamp, week number, rating, and reason.

**New MOOC dataset files are made available by FutureLearn to the MOOC course administrator.*

Figure 6 shows the course sequence used in OpenLearning. This information helps us to understand how the learning analytic dataset was structured and what the data represents.

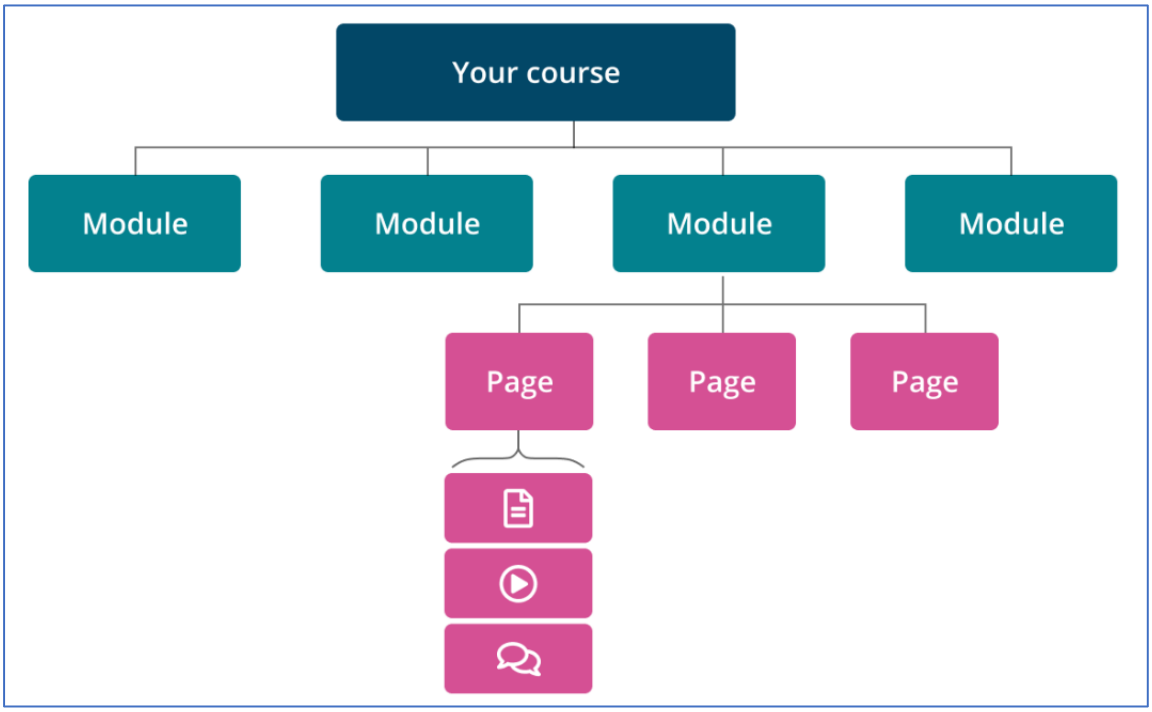


Figure 6: OpenLearning Course Sequencing Modules

OpenLearning provides learning analytic datasets in CSV and JSON format. Eight learning analytic datasets are made available for the MOOC course administrator. These datasets are categorised into three categories: Student Administration Data, Student Engagement Data and Other. Table 17 describes each file with details about its purposes.

Table 17: OpenLearning Datasets

DATASET FILE	CATEGORY	DESCRIPTIONS
Enrolments	Student Administration Data	Export a list of students who have enrolled in the course.
Payments	Student Administration Data	Export history of all payments made in the course. This record includes payment for enrollment and certification.
Posts	Student Engagement Data	Post widgets allow students to post their work to the platform. By default, when a learner makes a post, it is visible to other learners in a class. Export all student posts for a particular course page. Related media and file attachments can be exported with the data fields.
Completion Summary for Modules:	Student Engagement Data	Course module completion summaries as % of the total number of students who completed this item.
Completion Summary for Pages:	Student Engagement Data	Course page completion summaries as % of the total number of students who completed this item.
Completion Summary for Widgets:	Student Engagement Data	Course widgets completion summaries as % of the total number of students who completed this item.
Student Data	Student Engagement Data	Export student information such as profile name, course progress, and others.
Course pages	Other	Export all the course pages in HTML format. Use this option to move the course content onto another system or archive it. This action does not export student artefacts (e.g. shared posts, comments, galleries, or feeds), only static content.

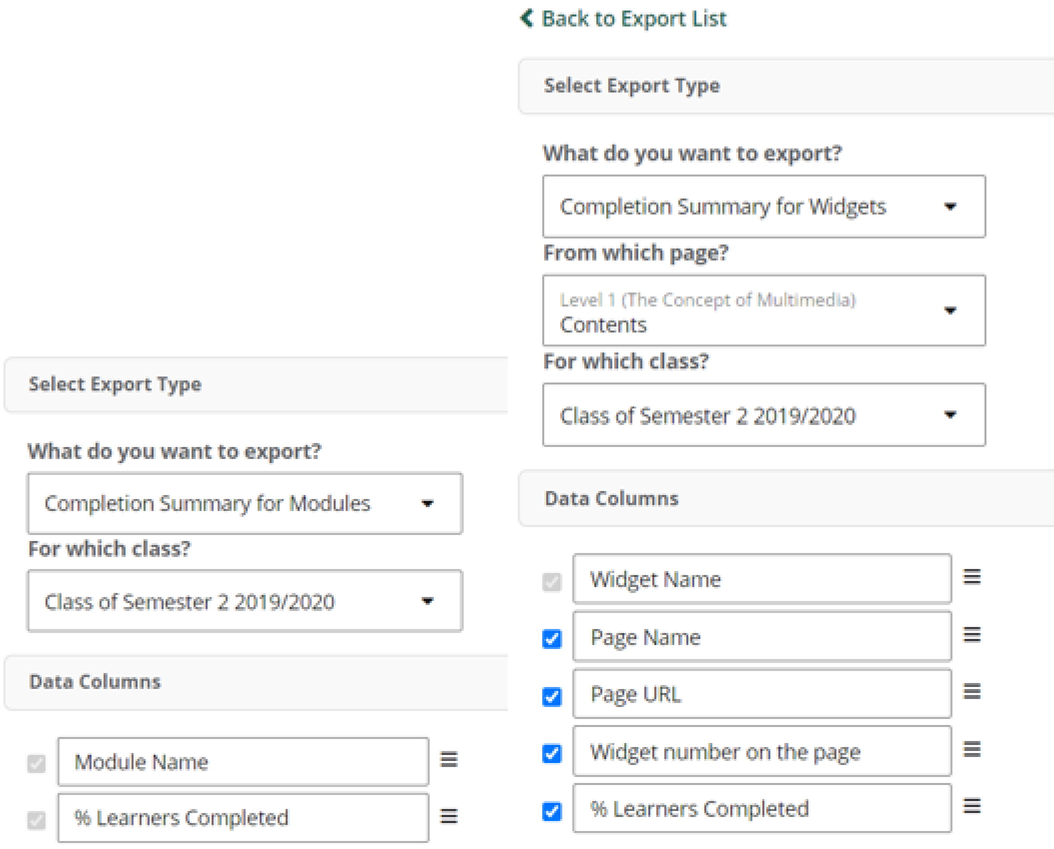


Figure 7: Settings for OpenLearning Learning Analytic Dataset Export

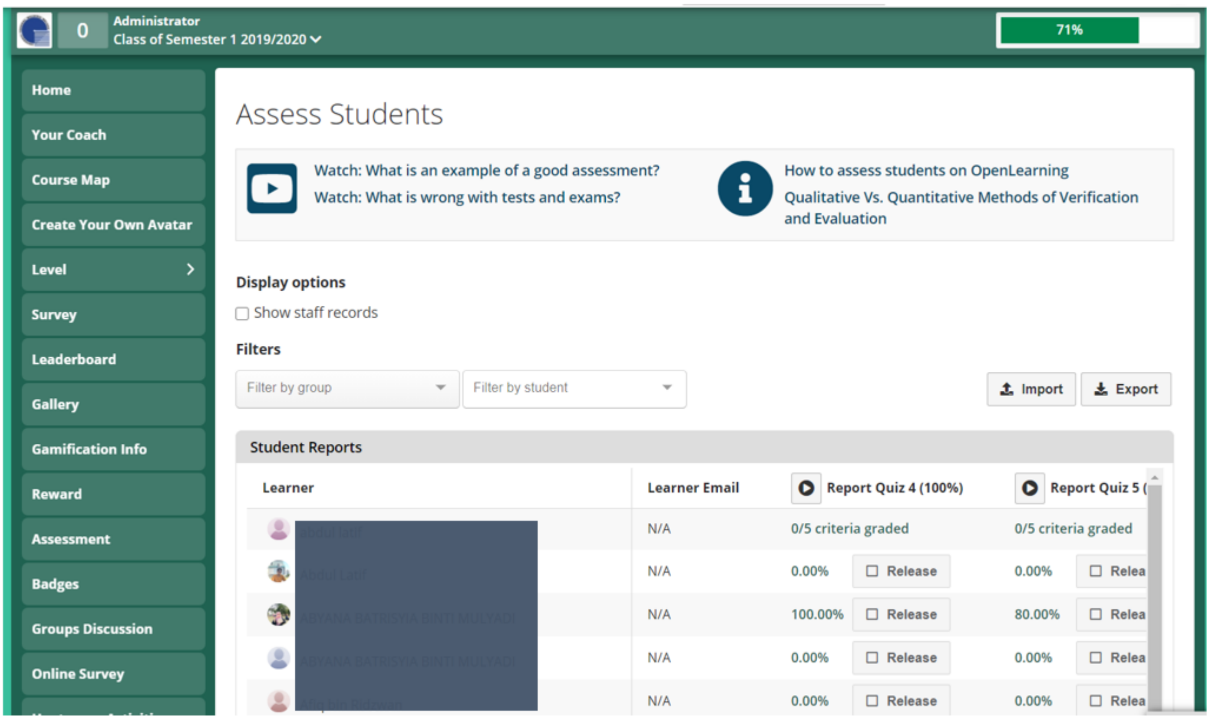


Figure 8: Assessment Data in OpenLearning

OpenLearning learning analytics data is measured and recorded based on the completion rates. The score for assessment is provided at another data source. My observations show that OpenLearning did not provide analytic data on learner interaction with video. The OpenLearning approach is for course administrators to create activities or assessments based on the video, which would require knowing the material presented in the video.

	A	B	C	D	E	F
1	Module	Page Title	Page Path	Page ID	Listed in Progress Bar	Completed (Yes/No)
2	Course Map	Syllabus	courses/m	59b8c19e1	Yes	No
3	Course Map	Course Map	courses/m	582d66b0	Yes	Yes
4	Level 1 (The Concept of Multimedia)	Lab Tutorial 1&2 (Photoshop)	courses/m	57d90255	Yes	No
5	Level 1 (The Concept of Multimedia)	My thought on 1st Topic	courses/m	57856efa0	Yes	No
6	Level 1 (The Concept of Multimedia)	Guess MyHomeTown	courses/m	57857c10	Yes	No
7	Level 1 (The Concept of Multimedia)	Notes OCW (The Concept of Multimedia)	courses/m	5b8f61fb0	Yes	No
8	Level 1 (The Concept of Multimedia)	Lab Activity 1&2 (Photoshop)	courses/m	57d902cc0	Yes	No
9	Level 1 (The Concept of Multimedia)	Contents	courses/m	5729566a	Yes	Yes
10	Level 1 (The Concept of Multimedia)	Video Chapter 1	courses/m	575780d0	Yes	No
11	Level 1 (The Concept of Multimedia)	Note Chapter 1	courses/m	5783a27f0	Yes	Yes
12	Level 1 (The Concept of Multimedia)	Learning in 21st Century	courses/m	57cbcb94	Yes	No
13	Level 2 (The Multimedia Technology)	Notes OCW (Multimedia Platform)	courses/m	5b8f62b4a	Yes	No
14	Level 2 (The Multimedia Technology)	Notes OCW (Multimedia Delivery System Storage)	courses/m	5b8f62250	Yes	No
15	Level 2 (The Multimedia Technology)	Quiz	courses/m	572ab3b4	Yes	No
16	Level 2 (The Multimedia Technology)	Notes OCW (Multimedia Hardware, PC, Software)	courses/m	5b8f5da2	Yes	No
17	Level 2 (The Multimedia Technology)	Activity1	courses/m	572ab1e6	Yes	No
18	Level 2 (The Multimedia Technology)	Contents	courses/m	57a17412	Yes	No
19	Level 2 (The Multimedia Technology)	GUESS IT RIGHT !	courses/m	572ab323	Yes	No
20	Level 2 (The Multimedia Technology)	Video Chapter 2	courses/m	57a16ef71	Yes	No
21	Level 2 (The Multimedia Technology)	Slide(MM Technology)	courses/m	5754706a	No	No
22	Level 2 (The Multimedia Technology)	VIDEO LECTURE	courses/m	57aad63c1	Yes	No

Figure 9: Example of Individual Student Page Completion Data

	A	B	C	D	E	F	G
1		Learner Name	Learner Email Address	OL Account ID			
2	Report Name				Report Quiz 4	Report Quiz 5	Evaluation Examination Report
3	(Report ID)				(5d9d4e3f2861e5cf76b2128f)	(5d9d4da3972759b4985e1a66)	(5e12e7577675714d10da930e)
4	Outcome Tag						
5	(Outcome ID)						
6	Criteria Name						
7	Assessment Options						
8	(Criteria ID)						
9		abd[redacted]	N/A	5d[redacted]c			
10		Abd[redacted]	N/A	5d[redacted]a	0	0	
11		ABY[redacted]	N/A	5d[redacted]9	0	0	
12		ABY[redacted]	N/A	5d[redacted]f	5	4	
13		Afiq[redacted]	N/A	5d[redacted]0	0	0	
14		Ahm[redacted]	N/A	5d[redacted]2			
15		Ahm[redacted]	N/A	5d[redacted]d0	5	3	
16		Ahm[redacted]	N/A	5d[redacted]d9	0	0	
17		Ain[redacted]	N/A	5d[redacted]d4	5	4	
18		Ainu[redacted]	N/A	5d[redacted]0	5	4	
19		Ainu[redacted]	N/A	5d[redacted]b	0	0	
20		Ainu[redacted]	N/A	5a[redacted]f			
21		Aish[redacted]	N/A	5d[redacted]a			
22		Aisy[redacted]	N/A	5d[redacted]b	0	0	
23		Aisy[redacted]	N/A	5d[redacted]0	5	4	
24		Alia[redacted]	N/A	5d[redacted]a	5	4	
25		Alif[redacted]	N/A	5d[redacted]d			
26		alis[redacted]	N/A	5d[redacted]3			
27		Alvi[redacted]	N/A	5d[redacted]8			
28		Alya[redacted]	N/A	5d[redacted]8			
29		AM[redacted]	N/A	5d[redacted]f			

exportAssessments-courses_multi

Figure 10: An Example of Student Assessment Dataset

Based on my observations and findings, the MOOC platform makes all datasets available to course admin, regardless of course structure design. Each course could have a different structure on how the course is designed and implemented by the course admin. The same course could have a different setting or design update between different semester or year offerings, depending on how course admin update or change their course design. No tools in the OpenLearning platform are made available to view the learning analytic data, and all data need to be generated and downloaded in CSV or JASON format for viewing or analysis. The course admin will do an analysis based on their understanding. In most cases, there is no prior training in analysing the available learning analytics data.

4.3 Uniform Dataset

The Semantic Web refers to a set of standards and technologies that are used to enable the machine-driven design and operation of a wide range of aspects of data management, from the description and organisation of collections of digital artefacts to the access to distributed digital repositories, as well as search, ranking, and recommendation (Simperl, Cuel and Stein., 2013).

Recall that my RQ1 in this study is: what are the parameters for measuring course and learner performance at the macro and micro level using learning analytics from cross-platform MOOC? To answer the stated research question, a uniform dataset will be created from two learning analytic dataset platforms, FutureLearn and OpenLearning.

This process involved several iterations in analysing and classifying the data in each dataset. The first iteration (Iteration 1) analyses the content in each dataset file to find a matching dataset for both platforms. The second iteration (Iteration 2) groups datasets from the two different MOOC platforms based on similarity. The third iteration (Iteration 3) is the process of analysing and comparing at the lowest granularity level, i.e. data level, by comparing data to data from each data in each group.

At any iteration, there is a possibility to go back to the previous iteration process based on findings in the current iteration process. There is also a possibility that the FutureLearn dataset has no matching data in the OpenLearning dataset. The overall analysis process will be ended when each data existing in each dataset for each group has been analysed and compared. Figure 11 shows the 3-iteration methodology used in this study to produce a uniform dataset from two different datasets.

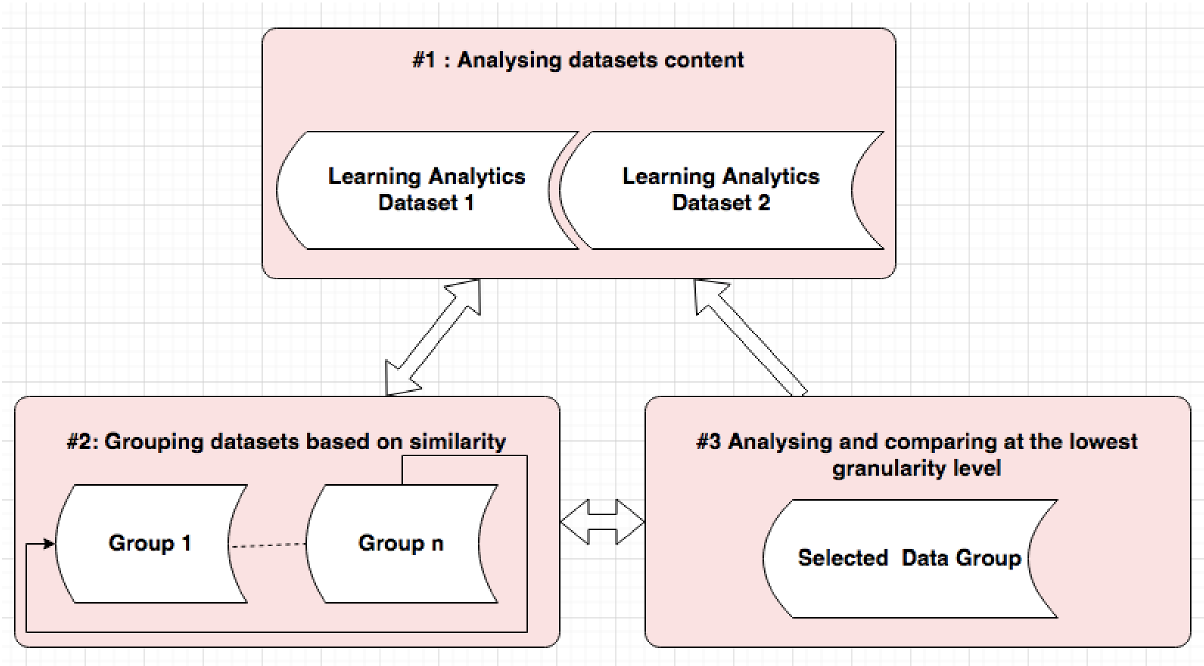


Figure 11: Creating a Uniform Dataset Methodology

Iteration 1: Finding A Matching Dataset

Finding matching datasets required a clear understanding of the dataset file's purposes and identifying the data stored in each file. The same dataset name could hold different information, especially if dataset sources are from different platforms. In this iteration process, I aim to identify the identical learning analytic data available in FutureLearn and OpenLearning datasets. Table 18 below shows the results of iteration 1. It shows the list of dataset files that contain data that can be matched.

Table 18: Results of Iteration 1

FutureLearn Dataset Files	**OpenLearning Dataset Files**
Archetype Survey Responses	Enrolments
Campaigns	Payments
Comments	Posts
Enrolments	Course completion summaries
Leaving Survey Responses	Completion Summary for Modules
Peer Review Assignments	Completion Summary for Pages
Peer Review Reviews	Completion Summary for Widgets
Question Response	Student Data
Step Activity	Course pages
Team Members	

Video Stats	
Weekly Sentiment Survey Responses	
Practicalities of working with these datasets	

Iteration 2: Grouping Dataset Based on Similarity

Based on the available datasets from both platforms, I then grouped the datasets based on their similarity. My first combination results in four groups of datasets, and the final combination datasets group is reduced into two, as shown in Table 19 and detailed in Figure 12 and Figure 13 below. Then, I study each dataset within these four groups to analyse its data detail.

Table 19: Results of Iteration 2: Dataset Groups

GROUP	FutureLearn Dataset	OpenLearning Dataset
1	Archetype Survey Responses Campaigns Enrolments Leaving Survey Responses Team Members	Enrolments Student Data Payments
2	Comments Peer Review Assignments Peer Review Reviews Question Response Step Activity Video Stats Weekly Sentiment Survey Responses	Posts Completion Summary for Modules Completion Summary for Pages Completion Summary for Widgets

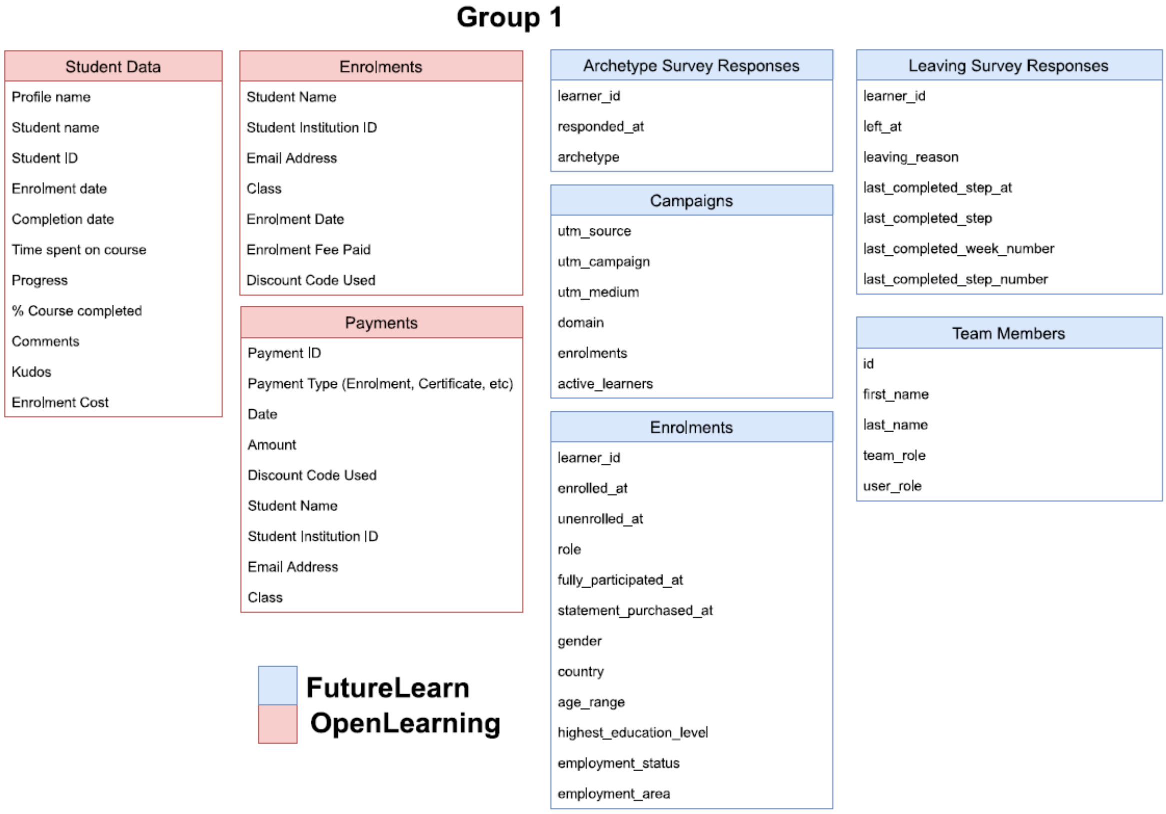


Figure 12: Detailed Dataset Data for Group 1

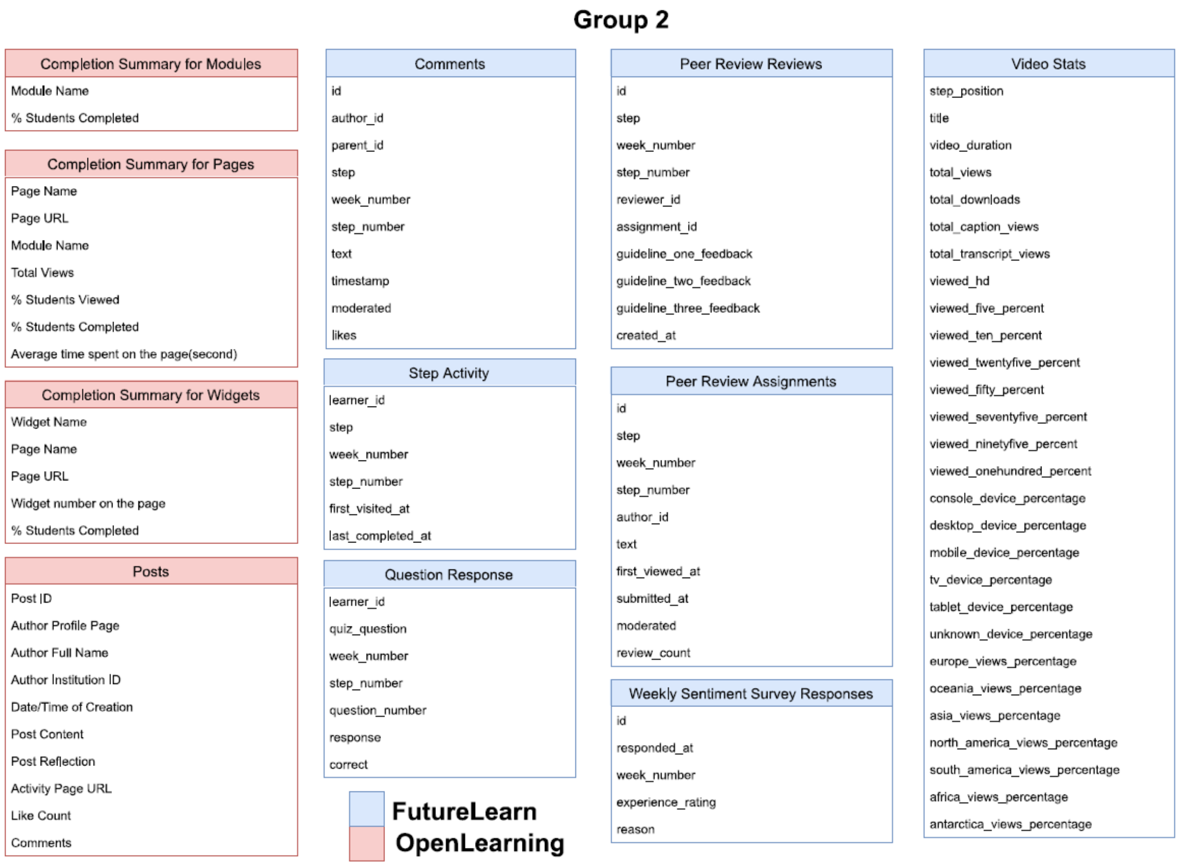


Figure 13: Detailed Dataset Data for Group 2

Iteration 3: Detailed Analysis of Group Datasets

Table 20: Matching Integrated Data Datasets for Each Group

FutureLearn		**OpenLearning**	
Group 1			
Dataset	Data	Data	**Dataset**
Enrolments	learner_id (string)	Student ID	**Student Data**
Enrolments	enrolled_at (timestamp)	Enrollment Date	**Student Data**
Enrolments	fully_participated_at (timestamp)	Completion date	**Student Data**
Enrolments	statement_purchased_at (timestamp)	Date	**Payment**
Group 2			
Dataset	Data	Data	**Dataset**
Step Activity	last_completed_at [timestamp]	% Student Completed	**Completion Summary of Modules**
Step Activity	last_completed_at [timestamp]	% Student Completed	**Completion Summary of Pages**
Step Activity	last_completed_at [timestamp]	% Student Completed	**Completion Summary of Widgets**
Video Stats	viewed_onehundred_percent [float]	% Student Completed	**Completion Summary of Widgets**
Step Activity	first_visited_at [timestamp]	Total View	**Completion Summary of Pages**
Step Activity	week_number [integer]	Module Name	**Completion Summary of Modules**
Step Activity	week_number [integer]	Page Name	**Completion Summary of Pages**
Step Activity	week_number [integer]	Widget Name	**Completion Summary of Widgets**
Peer Review Assignments	submitted_at [timestamp]	% Student Completed	**Completion Summary of Widgets**

4.4 Parameters for Monitoring and Measuring Performances

Next, I investigate data in each dataset by group section. Detailed data from the previous iteration is shown in Figure 12 and Figure 13 above. In this process, I faced two main challenges. The first challenge is to interpret what each actual data means accurately. In my case study, I use FutureLearn and OpenLearning datasets. FutureLearn provides proper documentation explaining each data, while OpenLearning provides general online information for each dataset they offer. There is no detailed explanation for each piece of information in the dataset.

The second challenge is to identify the identical match between two platform datasets. For example, FutureLearn uses full_participated_at with a timestamp data type, while OpenLearning uses Completion date with a timestamp data type. Another finding is that the same data could be found in a different dataset. For example, the Enrollment Date in OpenLearning can be found in the Student Data and Enrolments datasets. After conducting Iteration 3 activity, results of the matching data from these two MOOC platform datasets in Table 20 are used as guideline and consideration selection of parameters as show in Table 21.

Table 21: Selection Parameters from Matching Integrated Data Datasets.

Parameter	MOOC Platform	Data Sources	Description
Completion of Module	FutureLearn	Step Activity	Percentage of completion. Value in the percentage of students that completed the module. Each module will have only one value.
	OpenLearning	Completion Module	
Completion of Widget	FutureLearn	Step Activity, Video Stats	The average percentage of completion. The percentage value of the average completed widgets in a module. The number of widgets in each module is unknown and may vary in other modules. The average value will be calculated and converted as a percentage.
	OpenLearning	Completion Widget	
Assessments Score/marks	FutureLearn	Peer Review Assignments, Offline Assignments	The percentage value of assessment scores or marks students receives from assessments (assignments, quizzes, tests), either from MOOC platforms or offline data sources.
	OpenLearning	Completion Widget, Offline Assignments	

Based on the data analysis, the Completion Summary of Modules and Completion Summary of Widgets were identified to be helpful datasets. The percentage of modules completed, the number of widgets available, and the percentage of widgets completed were identified as suitable parameters for use.

For assessment data, I discovered an issue where there is not enough reliable data to be made available due to the differences in course design. This issue is also acknowledged by (Stephens-Martinez, Hearst and Fox., 2014), who describe quantitative data sources such as assignment grades as insufficient in evaluating MOOC performance. Assessments in MOOC courses depend on the course design by admin. There is no guaranteed availability of assessment data in each week or stage. There is a possibility that a course could be designed without any assessment of MOOC. A flexible approach is suggested and will be explained in the subsection 5.2.3.

4.5 Chapter Conclusion

This chapter presents findings from research activity in Phase 1 and Phase 2. It is also considered the breakthrough chapter for my research study as I successfully identified parameters that can be used for monitoring and measuring performances.

In this chapter, I have demonstrated and presented the process I undertake to understand the information represented by each dataset from two different sources. After completing three iteration activities, I finally completed the uniform dataset creation. The creation of uniform datasets based on the study of two different data sources also supports the epistemology stated in Chapter 3, which is:

> *I also believe that each MOOC platform has its unique style or structure of tracking and recording learning analytics. However, at some point, there are similarities in the data collected.*

In the following research phase, I will design and develop the measurement algorithm and analysis model based on the parameters identified. Details on the algorithm development, including simulations and experimental activity, are presented in the next chapter.

Chapter 5 Design and Development of The MPM Model

5.1 Introduction

This chapter presents research activity on the design and development of the MOOC Performance Measurement (MPM) Model. The two performance measurement algorithms were designed based on the measurement parameters identified from my previous dataset analysis activity and my conceptual logic. Once the algorithms are designed, I conduct a series of algorithm simulations using made-up data to test and evaluate the algorithm logic in various scenarios. Observation and findings from the simulation activities give insight into the required measurement metrics and analysis indicators. In the model development activity, I design indicators and metrics to support the use of the proposed measurement algorithm and complete the design of the MPM Model. Finally, findings from the design and simulation process were concluded at the end of this chapter.

5.2 Algorithms Design

As described in the previous chapter, an algorithm's main objective is to solve a specific problem and accomplish a specific task. It is also essential to determine the concept or approach of the algorithm before I design it. A conceptual framework helps us design measurement algorithms by overseeing the relationship between data and how it can be utilised in solving a specific problem.

In this sub-section, I describe the conceptual framework used, followed by pseudocode steps of input, process and output of the algorithm design. Flowcharts or pseudocode are two approaches that can be used to design an algorithm. Flowcharts provide more visualised detail, while pseudocode is more structured in details and steps. Regardless of the approach, it consists of three crucial components in algorithm design: clear input, logic process and output that address the specific problem or task.

5.2.1 Conceptual Framework

The task that I want to accomplish by using algorithms is measuring performance for MOOC courses or MOOC learners. Performance, as defined in this study, is the value of improvement or ability to maintain the highest score value throughout the course, either for the course performance or individual learner performance.

Previous studies discussed in Chapter 2 give me ideas for designing my course and student performance measurement algorithms. Chapter 4 presents identified parameters that meet the characteristic of cross-platform capabilities and with valuable data meaning it holds.

A conceptual framework is considered a vital novelty and innovation element of this research study, where I could apply new ideas and concepts to tackle the existing issues described in this research scope and questions. The data used is a crucial component that I am focusing on. It is also described as the measurement parameters or variables affecting performance that I monitor, measure, and analyse.

The conceptual framework illustrates the relationship between different variables. I select independent and dependent variables based on the stated research question. Next, I visualize the cause-and-effect relationship. Finally, I identified other influencing variables. The four steps used are:

Step 1: RQ1 wants to identify parameters that can be used to measure MOOC course and learner performance, which will also work in cross-platform MOOC scenarios. The independent variable reflects the expected cause, which I consider to be learner' module progression'. The dependent variable reflects the expected effect, which I consider a better 'module score'. By progressing throughout the MOOC module, learners will learn and do tasks or activities that eventually result in a good module score. Figure 14 below visualizes my cause-and-effect relationship.

Figure 14: Cause-and-effect Relationship

Step 2: Next, I identify other influencing variables. There are three standard variables: moderating, mediating, and control variables. Figure 15 illustrates a conceptual model with a moderating variable. Moderating variables alter the independent variable's effect on a dependent variable. I consider content design as the moderator variable. Considering that suitable content design is prepared for learners to participate and engage, it will affect how the learning activity progresses. Too many tasks or complicated activities within a module might deter learners' motivation to complete that specific module.

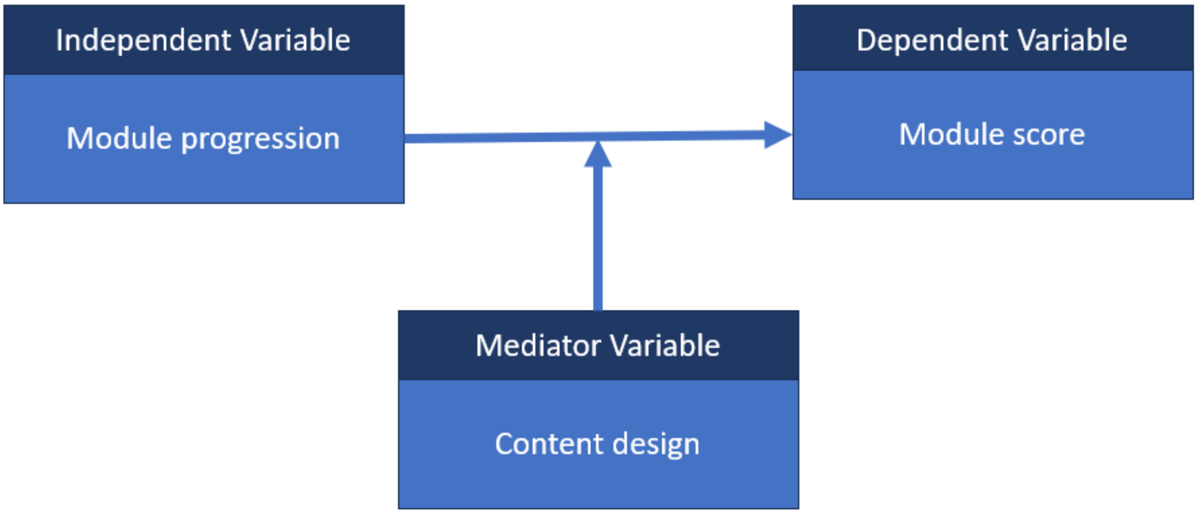


Figure 15: Moderating Variables

Step 3: Next, I expand the influencing variable by illustrating it using mediating variables. Mediating variables link the independent and dependent variables and give a better explanation of the relationship between them. I consider the percentage of completion and percentage of task or activity score as two mediator variables—the percentage of completion for course measurement and the percentage of task or activity score for learner measurement.

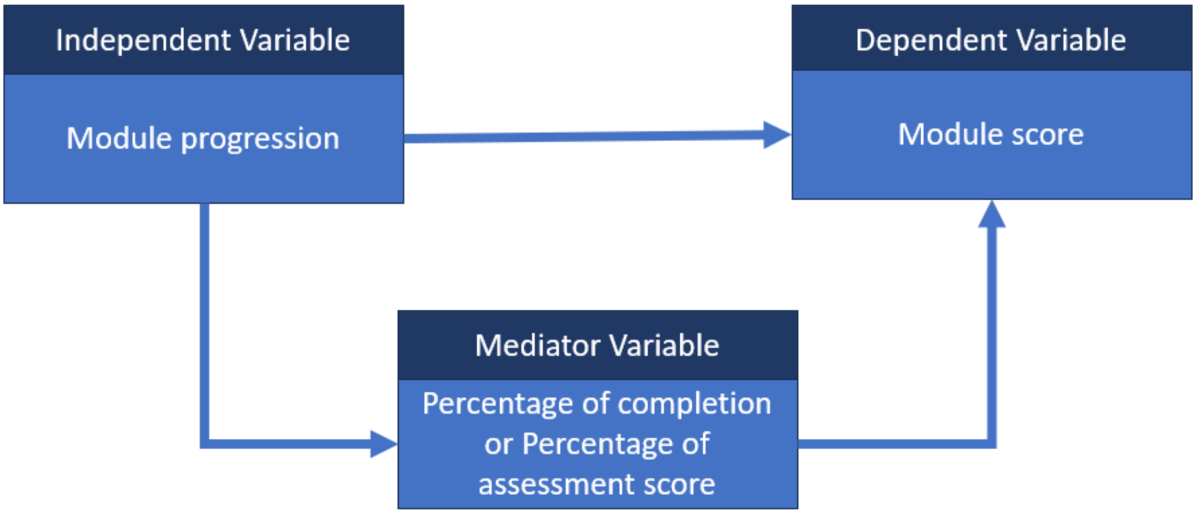


Figure 16: Expanded Influencing Variable

Based on the Figure 16 illustration, the mediator explains why progression in the learning module leads to a better score. The more learners progress, the higher the percentage of completion or assessment scores that can be collected, and the more scores are collected, the better the module score will be.

Step 4: Finally, in Figure 17, I consider the constant control variables that will not interfere with the results. Measuring control variables is beyond my research study scope and objectives, but it is crucial to have control variables identified and aware.

Different learning goals could affect score value on the completion of a module. However, my research scope excludes learner learning goals preference. I will only include learning analytics data if available.

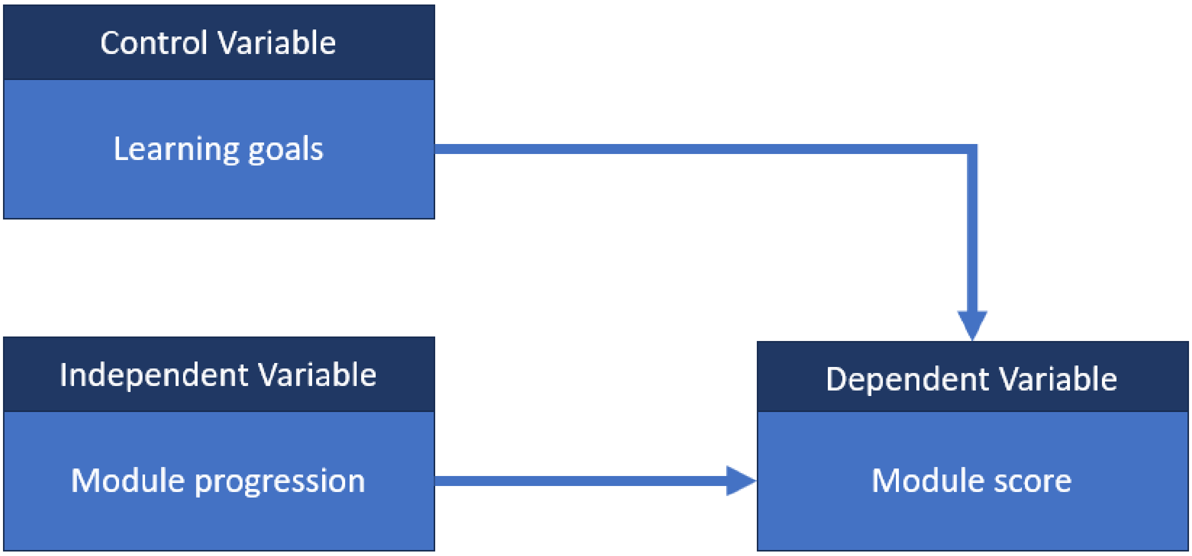


Figure 17: Control Variables

Inspired by a simple concept of "today better than yesterday" and referring to the variables in the conceptual framework, I am likely designing the algorithm and analysis approach with an adaptation of mixed data analysis methods. As described in the previous chapter, the five data analysis methods used are Descriptive Statistics, Multivariate Analysis, Time Series Analysis, Recurrent Neural Network, and Factor Analysis. Both course and learner performance algorithm design are explained in subsections 5.2.2 and 5.2.3, and the pseudocode approach used is explained in subsection 5.2.4.

5.2.2 Course Performance Algorithm

The Course Performance Algorithm is designed to measure the performance of a MOOC course, regardless of the learner's diversity, demography or MOOC platforms used. Individual learner achievement is not the main contribution used to measure course performance. A good course, with high scores, at the same time, can be poor in performance.

Figure 18 is an example of a scenario where two groups of learners enrolled on the same Course A. Assuming there is no change regarding the course content or structure, in general observation, I can agree that the 2021 group of learners achieved better scores compared to the 2022 group of learners. Although it shows that the 2021 group's achievement is a downtrend, they still score better than the 2022 group of learners at the end of the course. The 2022 group of learners, from a performance point of view, is the better group of learners as they show an uptrend score. If the trend is unchanged, Course A in 2022 can overtake Course A in 2021 score achievement.

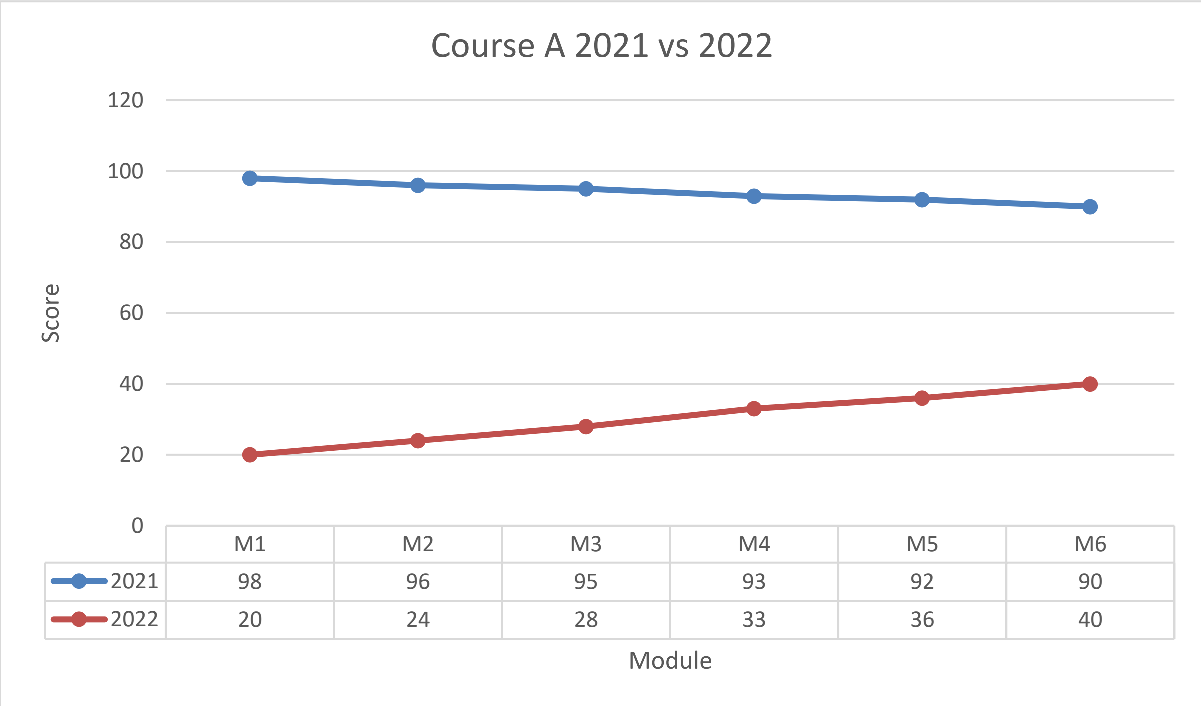


Figure 18: The Two Learners Group Scenario

Based on the example scenario and study presented in the previous chapter, two input data will be used as measurement parameters. Input data will be compared against previous input to measure the value of the difference. A positive value indicates an uptrend performance, while a negative value indicates a downtrend performance.

For the course performance algorithm, the two parameters as input data are the percentage of module completion and widget completion. A course consists of several modules, usually structured weekly.

A module contains several widgets that learners use as learning and activity content with the expectation of completing it. These two parameters are recorded in the percentage of completion by the MOOC platform. In a module, there could be more than one widget made available by the course admin. Therefore, I need to calculate the average percentage of widget completion as the value for my measurement.

When measuring using the algorithm, a default positive indicator is used for the first module measurement if any scores are recorded. A default negative indicator will be used if a 0 score is recorded on the first module. Next, a formula used to measure Module Difference Score (MDS) is shown in Table 22 below.

Table 22: Module and Widget Difference Score Formula

Module Difference Score = Module 2 Completion Module – Module 1 Completion Module $MDS = M_{[x]} - M_{[x-1]}$
Widget Difference Score = M2 Completion Widget – M1 Completion Widget $WDS = M_{[x]} - M_{[x-1]}$

For any positive MDS value, the result is considered increment and marked as Positive in Indicator 1 (I1). The exact process applies to calculate the widget difference score.

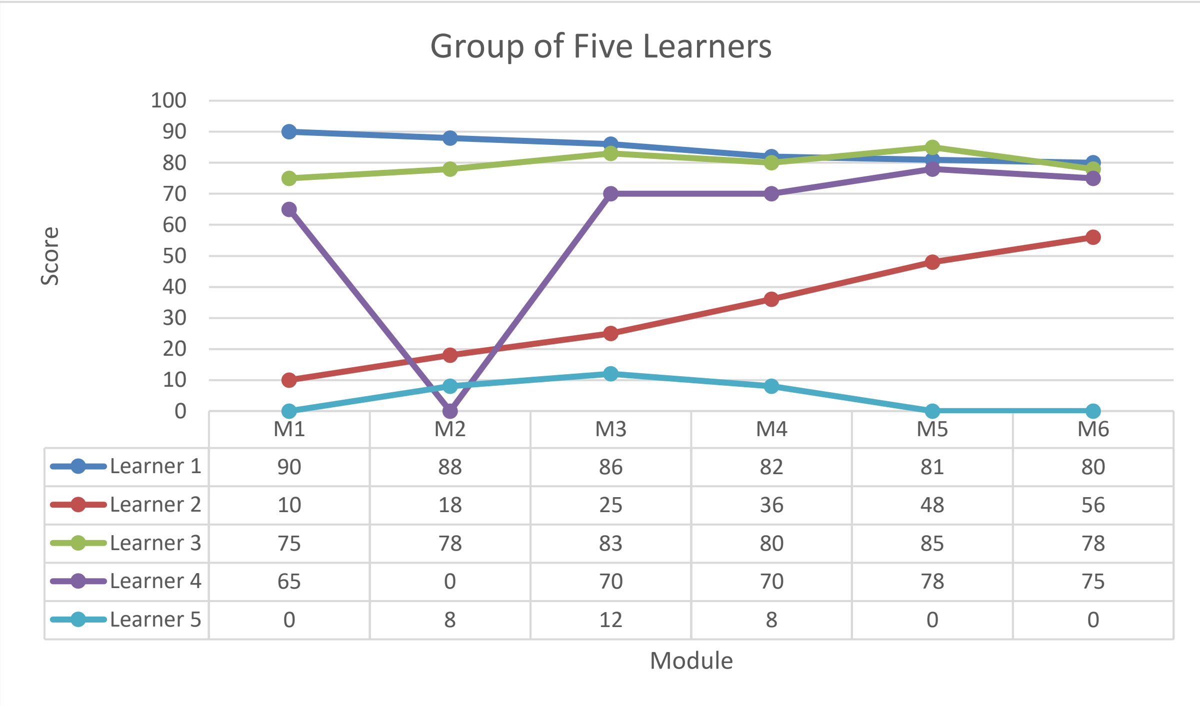
A question arises when the condition is unchanged between two consecutive data. In this situation, a second validation is performed to determine whether the unchanged data is 100%. If the unchanged data is 100%, this indicates the full mark and positive performance with no possibility for improvement. If the unchanged data is 99.99% or below, this indicates negative performance, with an improvement still possible. This setting was justified by the logic that the course or learner maintains the achievement at the entire state, and no more excellent score can be achieved.

5.2.3 Learner Performance Algorithm

The Learner Performance algorithm was designed to measure the performance of an individual MOOC course learner in a specific MOOC course, regardless of other learners' achievement or course performance. Course achievement is not the main contribution used to measure individual learner performance. A learner with high achievement scores could be poor in performance, and a low score in achievements could be good in performance.

Figure 19 below shows an example scenario group of five learners in the same MOOC course. Assuming each learner does not know or interact with the others, in general observation, I can agree that Learner 1 is the smartest, as Learner 1 scores were highest in every module except in M5.

Although it shows that Learner 1 consistently achieved a downtrend score, from a ranking, Learner 1 remains ranked one at the end of the course, closely followed by Learner 3 and Learner 4.



	M1	M2	M3	M4	M5	M6
Learner 1	90	88	86	82	81	80
Learner 2	10	18	25	36	48	56
Learner 3	75	78	83	80	85	78
Learner 4	65	0	70	70	78	75
Learner 5	0	8	12	8	0	0

Figure 19: Example Scenario of Learner Performance

Learner 2 and Learner 5 are poor compared to Learner 1, Learner 3 and Learner 4. However, from a performance point of view, Learner 2 is an excellent learner who demonstrates an example of a consistent uptrend in score achievement.

From the data visualisation observation, I can notice there are possibilities for a variety of line patents for every learner. Another observation is that if the trend is unchanged, Learner 2 can overtake Learner 1's, Learner 3's, and Learner 4's score achievement.

Based on the example scenario and study presented in the previous chapter, two input data will be used as measurement parameters. Identically to the Course Performance algorithm, I will compare current input data against previous input to measure the value of the differences. A positive value indicates an uptrend performance, while a negative value indicates a downtrend performance.

The input data parameters for the learner performance algorithm are the percentage of module completion and assessment scores or marks. The learner's completion percentage indicates that the learner is going through the learning content.

Similar to the usage of the average percentage of completion widget in course performance, in learner performance, I use average scores or marks received by students from assessments. The course admin provides no specific number of assessments in each module or week. Therefore, using the average score is suggested. I also suggest using the marks or score value, not the completion rate, for learner assessment parameters. Student Assessment parameter is set to be flexible where data sources can be either from MOOC platform or not. The course admin can obtain assessment scores from offline assessments to calculate the average score to be used.

Like the Course Performance Algorithm, a default positive indicator is used for the first module measurement if any scores are recorded. A default negative indicator will be used if a 0 score is recorded on the first module. Next, the formula used to measure Module Difference Score (MDS) is shown in Table 23 below.

Table 23: Module and Assessment Difference Score Formula

Module Difference Score = Module 2 Completion Module – Module 1 Completion Module $MDS = M_{[x]} - M_{[x-1]}$
Assessment Difference Score = M2 Assessment Score – M1 Assessment Score $ADS = M_{[x]} - M_{[x-1]}$

For any positive MDS value, the result is considered increment and marked as Positive in Indicator 1 (I1). The exact process applies to measuring assessment difference scores. The result from the assessment's difference score will be positive or negative in Indicator 2 (I2).

A question arises when the course provides no assessments. As a result, there is a possibility for a sequence of 0 scores and a negative indicator for I2. My model encourages at least a small activity or task in assessing the learner. Providing statistical or measured parameters to evaluate learners' learning is impossible without any assessment activity.

5.2.4 Pseudocode

A descriptive statistics data analysis method is used in preparing the dataset from the raw MOOC learning analytics data. This task involves summarising and calculating both parameters' mean as a percentage value. Generally, both course and learner algorithms will apply the same concept and calculation. The only differentiation between them is the input parameters used.

Input

Datasets containing learning analytic data extracted from MOOC platforms are considered raw datasets, which must be pre-processed before the datasets are suitable for analysis. This activity is also known as the data pre-processing activity. Data pre-processing is converting or preparing the raw data into a suitable form for my model. Recommendation dataset pre-processing task includes:

- Access the data: Ensure data is available and accessible. The dataset can be generated and downloaded directly from the MOOC platform in CSV or XLSX format.
- Cleanse the data: Also referred to as data cleaning, it is the process of fixing or removing incorrect, corrupted, incorrectly formatted, duplicate or incomplete data within a dataset.
- Format the data: Once the dataset has been cleaned, it must be formatted according to the MPM data model format.
- Combine the data: The MOOC platform records each piece of data individually. For example, multiple module data will be available in a single course, referring to each learner record or interaction. The user needs to merge and get the average data. This process will be explained in the next section.

Once datasets complete the pre-processing activity, they will be considered suitable for input data. Input data is the MOOC learning analytics data I will use as the measurement parameter. The main characteristic of a suitable parameter for my algorithm is that the data must be available in all MOOC platforms within the research scope. The justification for this characteristic is that I want the algorithm to be cross-platform compatible and not MOOC platform-dependent. I want the algorithm to be able to be used regardless of which MOOC platform.

As explained in the previous chapter, I apply the semantic web approach and study datasets from two MOOC platforms. As a result, I successfully created a uniform dataset and categories and described the data it represents. Table 24 is the list of data selected as suitable measurement parameters.

Table 24: Score Value Parameters

Algorithm	Parameter	Data Sources	Description
Course Performance	Completion of Module *(Input 1)*	MOOC Platform	Percentage of completion. Value in the percentage of students that completed the module. Each module will have only one value.
	Completion of Widget *(Input 2)*	MOOC Platform	The average percentage of completion. The percentage value of the average completed widgets in a module. The number of widgets in each module is unknown and may vary in other modules. The average value will be calculated and converted as a percentage.
Student Performance	Completion of Module *(Input 1)*	MOOC Platform	Percentage of completion. Value in the percentage of modules that individual students completed. Each module consists of Pages. The number of Pages in each module may vary in each Module. The average value will be calculated and converted as a percentage.
	Assessments Score/marks *(Input 2)*	MOOC Platform, other online platforms, offline assessments.	The percentage value of assessment scores or marks students receive from assessments (assignments, quizzes, tests), either from MOOC platforms or offline data sources.

For each set of measurements, two input data are required. Input 1 will be the Module Completion for Course and Student Performance measurements. Input 2 will be either the Completion of Widget for Course Performance or Assessments scores or marks for Student Performance measurement. All data is a percentage value; therefore, it is in floating point data type input.

Process

Once the user provides the required input data, the measurement process is started. With time series analysis concepts applied, current input data will be compared with previous input data to determine the different score values and indicate positive or negative performance for that module or week. Three main processes at this stage are calculating difference scores, determining positive and negative indicators and measuring the total performance score.

Calculate Difference Score

Difference1 = Input1[i] – Input1[i-1]

Difference2 = Input2[i] – Input2[i-1]

Determine Positive and Negative Indicators

Indicator1 == 1 if (Difference1 > 0), Or if (Difference1 = 0 && Input1[i] == 100), else 0.

Indicator2 == 1 if (Difference2 > 0), Or if (Difference2 = 0 && Input2[i] == 100), else 0.

Measure total Performance

(sum(Indicator1 + Indicator2)) / (len(Indicator1) + len(Indicator2)) * 100

A default value of 0 for Difference1 and Difference2 where Input1[i == 0] and Input2[I == 0] are the first calculations in sequence.

Output

The final output will be the Performance Score value measured in a percentage format. I also consider the Difference1 and Difference2 values as output to project the measurement chart for better-visualised analysis. Performance Score output is a percentage value that can be analysed and referred to in the proposed Performance Metric. Difference1 and Difference2 values are used to project the analysis chart, which analysis can be done by referring to the proposed Consideration Factor Indicators.

Pseudocode itself used the input-process-output (IPO) model approach. As a result, based on the input, process, and expected output described above, the generic MOOC performance algorithm designed was outlined in Pseudocode 1 shown in Table 25 below:

Table 25: Pseudocode 1

0. Start
1. User input Dataset1 consists of a sequence of Data1.
2. User input Dataset2 consists of a sequence of Data2
3. Calculate Difference1 as current Data1 minus previous Data1 in the sequence.
4. Calculate Difference2 as current Data2 minus previous Data2 in the sequence.
5. If Difference1 is greater than 0, set Indicator1 to 1.
6. If Difference1 equals 0 and current Data1 equals 100, set Indicator1 to 1.
7. If Difference1 equals 0 and current Data1 is less than 100, set Indicator1 to 0.
8. If Difference1 is less than 0, set Indicator1 to 0.
9. If Difference2 is greater than 0, set Indicator2 to 1.
10. If Difference2 equals 0 and current Data2 equals 100, set Indicator2 to 1.
11. If Difference2 equals 0 and current Data2 is less than 100, set Indicator2 to 0.
12. If Difference2 is less than 0, set Indicator2 to 0.
13. Calculate totalIndicator as Indicator1 plus Indicator2.
14. Calculate Performance as (totalIndicator divided by count number of Indicator1 and Indicator2) multiple by 100.
15. Print Performance as a percentage value.
16. End.

The Pseudocode 1 describes in a formula:

*Performance = ((sum (1 for i in Difference1 if i > 0 or (i == 0 and Data1[i] == 100) or (i == 0 and Data1[i] < 100)) + sum(1 for j in Difference2 if j > 0 or (j == 0 and Data2[j] == 100) or (j == 0 and Data2[j] < 100))) / (len(Indicator1) + len(Indicator2))) * 100*

Next, I implement the pseudocode as a working algorithm to validate the logic flow and calculation results. I conduct a series of simulations using made-up sample data to test various possible scenarios. The details will be explained in the next section.

5.3 Algorithm Simulations

To enhance the potential validity of the proposed MPM model, I used an algorithm simulation method that approximates and imitates the actual operations of a process. Combination stages of system dynamic and agent-based simulation modelling processes were used in algorithm simulation activities. Four steps applied are developing a conceptual design and proposing the MPM algorithm, elaborating equations based on sample data, performing statistical analysis and creating algorithm equation, validating the results against actual data, and finally performing experimental scenario, results analysis and interpretation.

Step 1: Develop a conceptual design and propose the MPM algorithm.

At the beginning of this research study, problem statements, research questions and objectives are determined. Systematic literature review activity performed. Based on the existing literature, I develop a conceptual design and propose a theoretical MPM algorithm to be tested.

Step 2: Elaborate equations based on sample data. Perform statistical analysis and create algorithm equations.

Statistical analysis of the proposed theoretical MPM algorithm using sample data was conducted. This process includes data cleaning, analysis, parameter identification, and uniform dataset creation. Then, MPM algorithm equations are developed based on the early conceptual design.

Step 3: Validate the results against actual data.

Next, results from the MPM model simulation are compared and validated against actual data. At this current research stage, I conducted simulations using data from OpenLearning. The result from this step was used for any necessary corrections and updates on the MPM algorithm. This is an integral part as validation of the proposed MPM algorithm is necessary for the next step activity.

Step 4: Perform experimental scenarios, result analysis and interpretation.

This final step in my research simulation involved sample data from MOOC platforms. This step gives us better consideration simulations on the overall process of using the MPM Model. Indicators and metrics are also tested as I stimulate the weekly module measurement.

In this part of my research study, I conduct a series of course and learner performance simulations using made-up MOOC learning analytic data based on the proposed MPM model.

Simulation conducted in this research study served four purposes: to make a proof and theory discovery, observe performance, understand the existing process, and address research questions. The simulation method can prove the existence of a potential solution to a problem. It can reveal phenomena that concentrate theoretical attention in turn. Another purpose of conducting simulation is to observe performance and provide a way to investigate the effectiveness of solutions. Simulation may be used with a correctly calibrated and validated model to execute activities, such as diagnosis or decision-making, within an organisation or system.

The simulation provides more general information about how complex systems work and how the proposed MPM model has been used. Researchers can gain deeper conceptual. Finally, simulation was used in this study to address the research questions and research objectives.

5.3.1 Course Performance Simulations

A series of course performance simulations were conducted using the proposed measurement algorithm on made-up data based on the measurement parameters. From the data analysis on MOOC learning analytics data, I identified the percentage completion module and percentage completion of the widget as two parameters for measuring course performances. The fundamental concept of the MPM algorithm is to identify any increasing or decreasing score value by comparing the score value from the current module with the previous module. This value difference determines whether there is any significant improvement or not. Frequent measurements are also suggested at the end of each module. This will provide the Course Performance Level (PL) for each module.

5.3.1.1 Simulation: Controlled Setting

In controlled setting simulations, I made up data of the percentage completion module and percentage completion of the widget in six possible simulation scenarios. Each scenario consists of a seventh module labelled M1 to M7. The module difference score (MDS) and widget difference score (WDS) are calculated, and the result was indicated by Indicator 1 (I1) and Indicator 2 (I2). Finally, I calculate the Performance Level (PL) as shown in Table 11 below.

Simulation Data: All simulation data is not real data but instead made up based on actual learning analytics data structure. Simulation data consist of six sets of controlled data representing various possible scenario.

Table 26: Controlled Simulation Data

	% Completion Module	% Completion of Widget	MDS	I1	WDS	I2	PL
Simulation 1							
M1	60	58	0	Positive	0	Positive	100%
M2	63	61	3	Positive	3	Positive	100%
M3	67	65	4	Positive	4	Positive	100%
M4	73	71	6	Positive	6	Positive	100%
M5	80	78	7	Positive	7	Positive	100%
M6	88	86	8	Positive	8	Positive	100%
M7	98	99	10	Positive	13	Positive	100%
Simulation 2							
M1	98	99	0	Positive	0	Positive	100%
M2	88	86	-10	Negative	-13	Negative	50%
M3	80	78	-8	Negative	-8	Negative	33%
M4	73	71	-7	Negative	-7	Negative	25%
M5	67	65	-6	Negative	-6	Negative	20%
M6	63	61	-4	Negative	-4	Negative	17%
M7	60	58	-3	Negative	-3	Negative	14%
Simulation 3							
M1	60	98	0	Positive	0	Positive	100%
M2	63	85	3	Positive	-13	Negative	75%
M3	67	75	4	Positive	-10	Negative	67%
M4	70	70	3	Positive	-5	Negative	63%
M5	75	67	5	Positive	-3	Negative	60%
M6	85	63	10	Positive	-4	Negative	58%

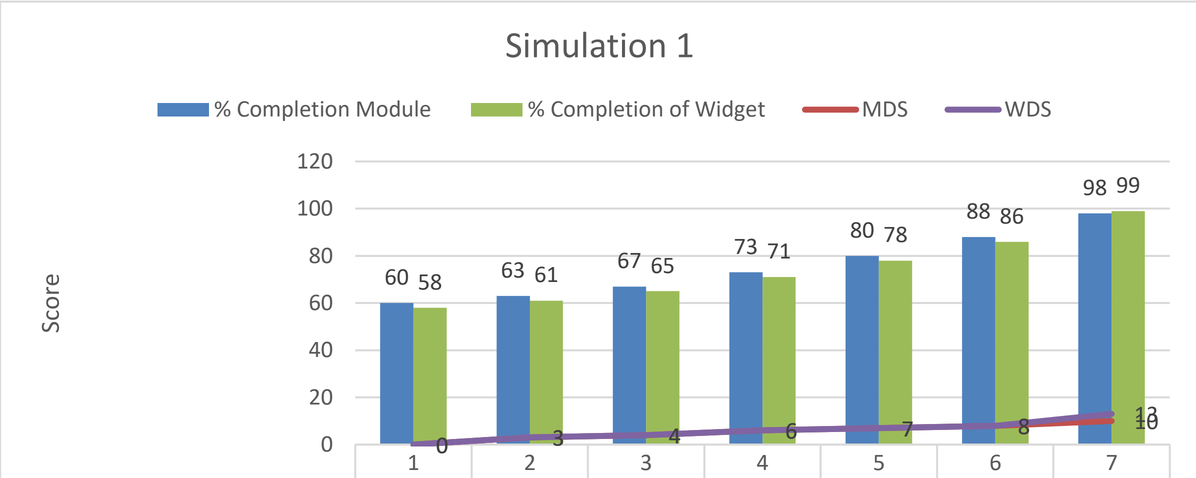
M7	98	60	13	Positive	-3	Negative	57%
Simulation 4							
M1	98	60	0	Positive	0	Positive	100%
M2	85	63	-13	Negative	3	Positive	75%
M3	75	67	-10	Negative	4	Positive	67%
M4	70	70	-5	Negative	3	Positive	63%
M5	67	75	-3	Negative	5	Positive	60%
M6	63	85	-4	Negative	10	Positive	58%
M7	60	98	-3	Negative	13	Positive	57%
Simulation 5							
M1	45	47	0	Positive	0	Positive	100%
M2	50	55	5	Positive	8	Positive	100%
M3	65	70	15	Positive	15	Positive	100%
M4	98	96	33	Positive	26	Positive	100%
M5	48	60	-50	Negative	-36	Negative	80%
M6	41	52	-7	Negative	-10	Negative	58%
M7	40	45	-1	Negative	-5	Negative	57%
Simulation 6							
M1	88	96	0	Positive	0	Positive	100%
M2	65	70	-23	Negative	-26	Negative	100%
M3	50	55	-15	Negative	-15	Negative	100%
M4	40	45	-10	Negative	-10	Negative	100%
M5	45	50	5	Positive	5	Positive	80%
M6	55	60	10	Positive	10	Positive	58%
M7	96	98	41	Positive	38	Positive	57%

**MDS (Module Difference Score), WDS (Widget Difference Score), PL(Performance Level), I1(Indicator 1), I2(Indicator 2)*

- **Simulation 1**: Gradually increment on both the % completion module and % completion of a widget. No unchanged score in a consequent week and no 100% score.
- **Simulation 2**: Gradually decrease on the % completion module and % completion of a widget—no unchanged score in a consequent week and no 0% score.
- **Simulation 3**: Gradually increment on % completion module but decrease on % completion of a widget—no unchanged score in a consequent week and no 0% or 100% score.
- **Simulation 4**: Gradually decreasing on % completion module but increment on % completion of a widget. No unchanged score in a consequent week and no 0% or 100% score.

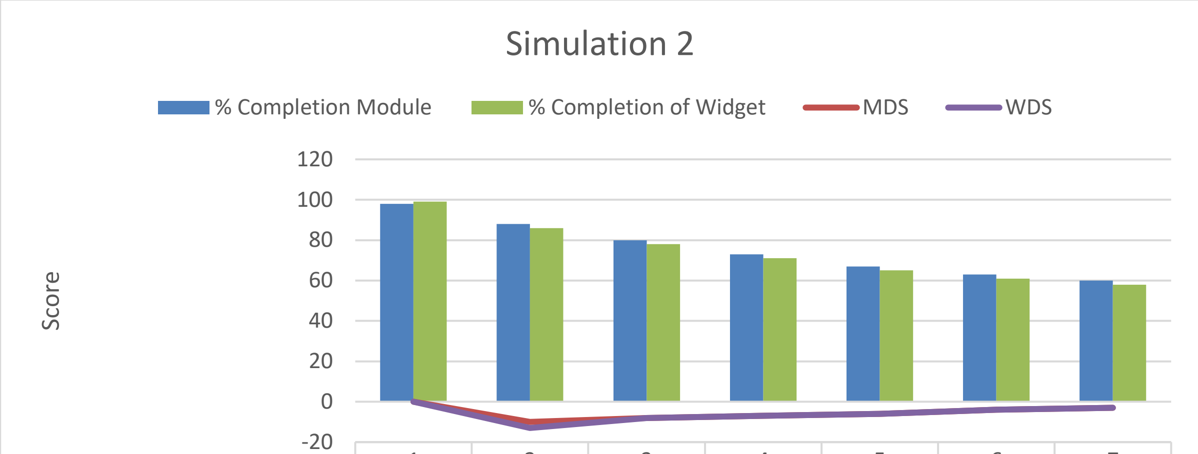
- **Simulation 5**: Gradually increment, then change the trend in the middle of the course.
- **Simulation 6**: Gradually decrease, then change the course's middle trend.

Graph projected: Output from the algorithm measurement is visualised into a time-series style graph. I used a combination of a line graph and a bar graph. The bar graph shows the actual score from the dataset, while the line graph shows data from algorithm calculations, representing the different scores. Figure 20 to Figure 25 show all six simulation graphs projected based on the algorithm measurement.



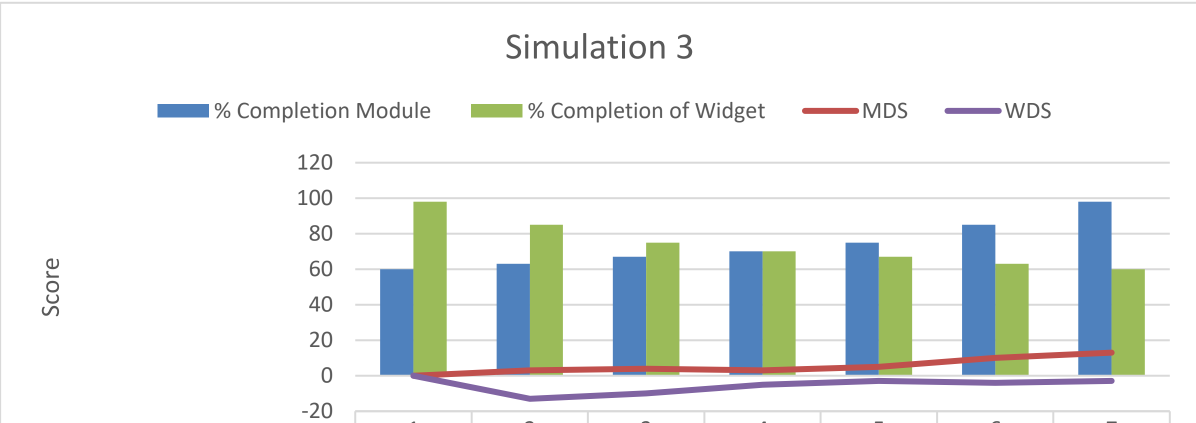
	1	2	3	4	5	6	7
% Completion Module	60	63	67	73	80	88	98
% Completion of Widget	58	61	65	71	78	86	99
MDS	0	3	4	6	7	8	10
WDS	0	3	4	6	7	8	13

Figure 20: Simulation 1 Performance Analysis



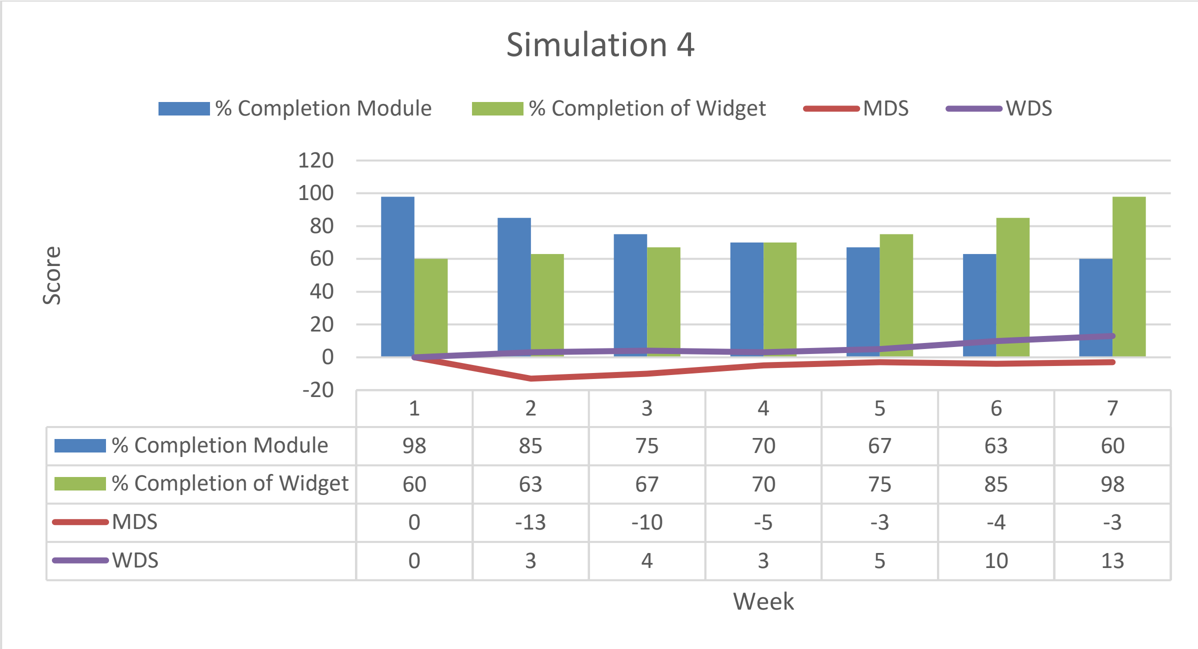
Week	1	2	3	4	5	6	7
% Completion Module	98	88	80	73	67	63	60
% Completion of Widget	99	86	78	71	65	61	58
MDS	0	-10	-8	-7	-6	-4	-3
WDS	0	-13	-8	-7	-6	-4	-3

Figure 21: Simulation 2 Performance Analysis



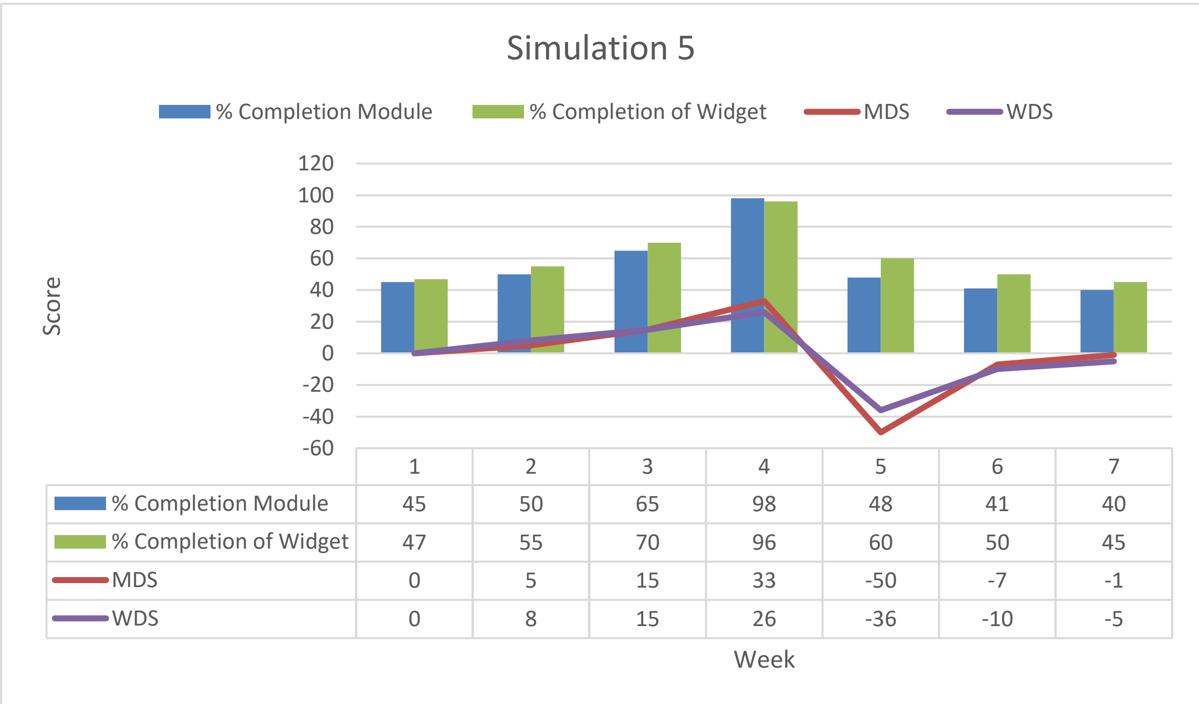
Week	1	2	3	4	5	6	7
% Completion Module	60	63	67	70	75	85	98
% Completion of Widget	98	85	75	70	67	63	60
MDS	0	3	4	3	5	10	13
WDS	0	-13	-10	-5	-3	-4	-3

Figure 22: Simulation 3 Performance Analysis



Week	1	2	3	4	5	6	7
% Completion Module	98	85	75	70	67	63	60
% Completion of Widget	60	63	67	70	75	85	98
MDS	0	-13	-10	-5	-3	-4	-3
WDS	0	3	4	3	5	10	13

Figure 23: Simulation 4 Performance Analysis



Week	1	2	3	4	5	6	7
% Completion Module	45	50	65	98	48	41	40
% Completion of Widget	47	55	70	96	60	50	45
MDS	0	5	15	33	-50	-7	-1
WDS	0	8	15	26	-36	-10	-5

Figure 24: Simulation 5 Performance Analysis

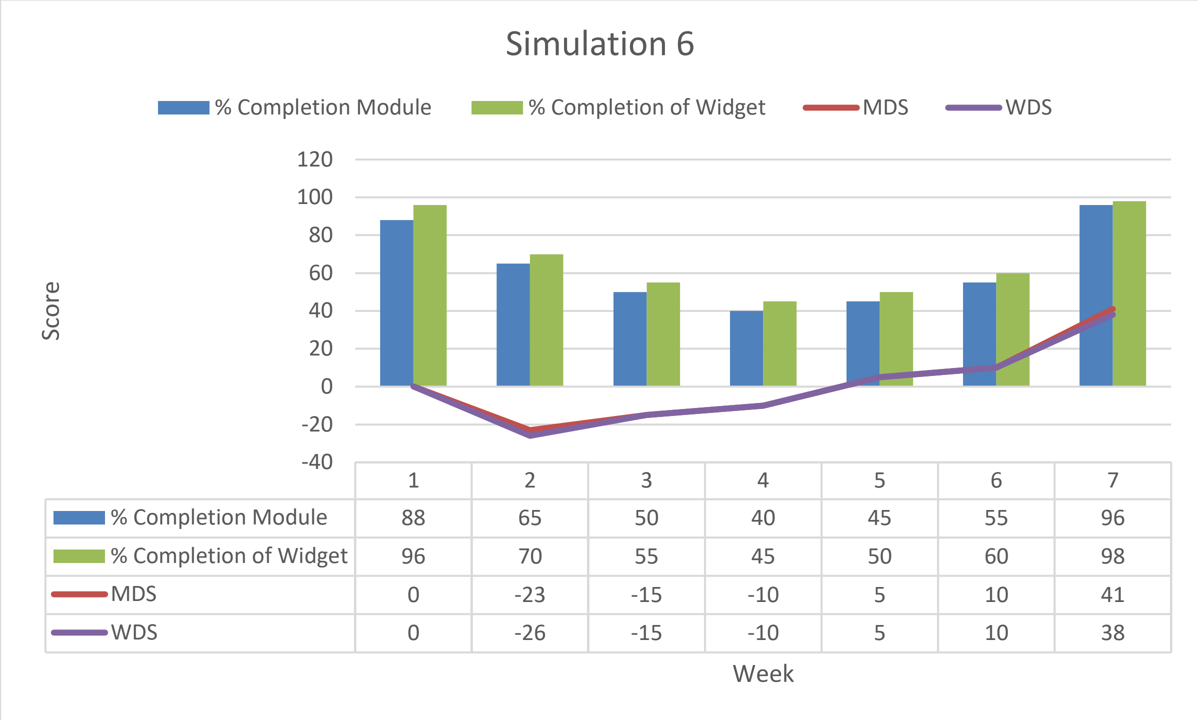


Figure 25: Simulation 6 Performance Analysis

Simulation Results: Table 27 below shows all simulation results, where I measured, compared, and observed the positive and negative scores in each simulation.

Table 27: Controlled Simulation Indicator Score Results

	I1	I2	PL
Simulation 1: Excellent Performance (100%)			
Positive	7	7	14
Negative	0	0	0
Simulation 2: Very Poor Performance (14.28%)			
Positive	1	1	2
Negative	6	6	12
Simulation 3: Good Performance (57.14%)			
Positive	7	1	8
Negative	0	6	6
Simulation 4: Good Performance (57.14%)			
Positive	1	7	8
Negative	6	0	6
Simulation 5: Good Performance (57.14%)			
Positive	4	4	8
Negative	3	3	6

Simulation 6: Good Performance (57.14)			
Positive	4	4	8
Negative	3	3	6

Results Observed: In each simulation, I observed the positive and negative indications calculated to determine the performance percentage value. I also provide the first diagnosis based on the simulation, which the course admin could do to improve the performance score.

- **Simulation 1** shows an Excellent Performance Level (PL) after a score of 14 Positive indicators and 0 Negative indicators. This result gives the course admin a better view of increasing scores at MDS and WDS.
- **Simulation 2** shows a Very Poor Performance Level (PL) after scoring 2 Positive and 12 Negative indicators. The course admin could better understand decreasing scores at MDS and WDS from this result. The PL score from M1 to M2 shows a drastic decrease.
- **Simulation 3** shows a Good Performance Level (PL) after scoring 8 Positive and 6 Negative indicators. From this result, the course admin should keep track of MDS and WDS for higher score changes. M5 and M7 scores on WDS are -3. Attention to encouraging improvement in these two modules could help get better PL. From the MDS and WDS, attention should be on the slightest positive or negative score. A more minor positive score shows an early sign of a weak performance. At the same time, a more minor negative score could be a potential for speed improvement.
- **Simulation 4** shows a Good Performance Level (57.14%) with eight positive and six negative indicators. Data and graph plotted show a significant uptrend on % Completion Widget but a downtrend direction on % Completion of Module, indicating mixed performances concerning module design. Based on the MDS, Modules 2 and 3 record higher downtrend scores (-13 and -10). Based on WDS data, Module 6 and Module 7 record the highest increasing performance (10 and 13). The course admin should strategise on how to improve overall module design and, at the same time, maintain overall widget completion.
- **Simulation 5** shows a Good Performance level (57.14%) with eight positive and six negative indicators. Data and graph plotted a significant uptrend for both % Completion of Module and % Completion Widget before a student drop-in M5. Both scores are still in a downtrend direction, but the difference score was minimised in each module. I can observe that the bar chart shows a downtrend from M4 to M7. The line chart shows a massive drop for M5 (-50 MDS and -36 WDS) and back to an uptrend for the remaining

module. Nevertheless, the difference score is still negative, which indicates underperforming. The difference score was reduced from M5 to M7.

- **Simulation 6** shows a Good Performance level (57.14%), like Simulation 5, with eight positive and six negative indicators. Data from learning analytics show a significant U-shape bar chart where it starts with a high score in M1 and keeps on a downtrend before turning to an uptrend starting from M5 to M7. From observation of the difference score, I can indicate a considerable drop only at M2 (-23 and -26) and the negative score was reduced until it turned positive in M5 to M7.

5.3.1.2 Simulation: Random Generated Setting

In random setting simulations, I used randomly generated data of the percentage completion module and percentage completion of the widget in five various simulations, representing the possibility of an unpredicted scenario. Each scenario consists of a seventh module labelled M1 to M7. I repeat the steps used in the previous controlled setting in calculating the Performance Level (PL), as shown in Table 28 below.

Simulation Data: All simulation data is not real data but instead made up based on actual learning analytics data structure. The simulation data consists of five random data sets, as shown in Table 28 below.

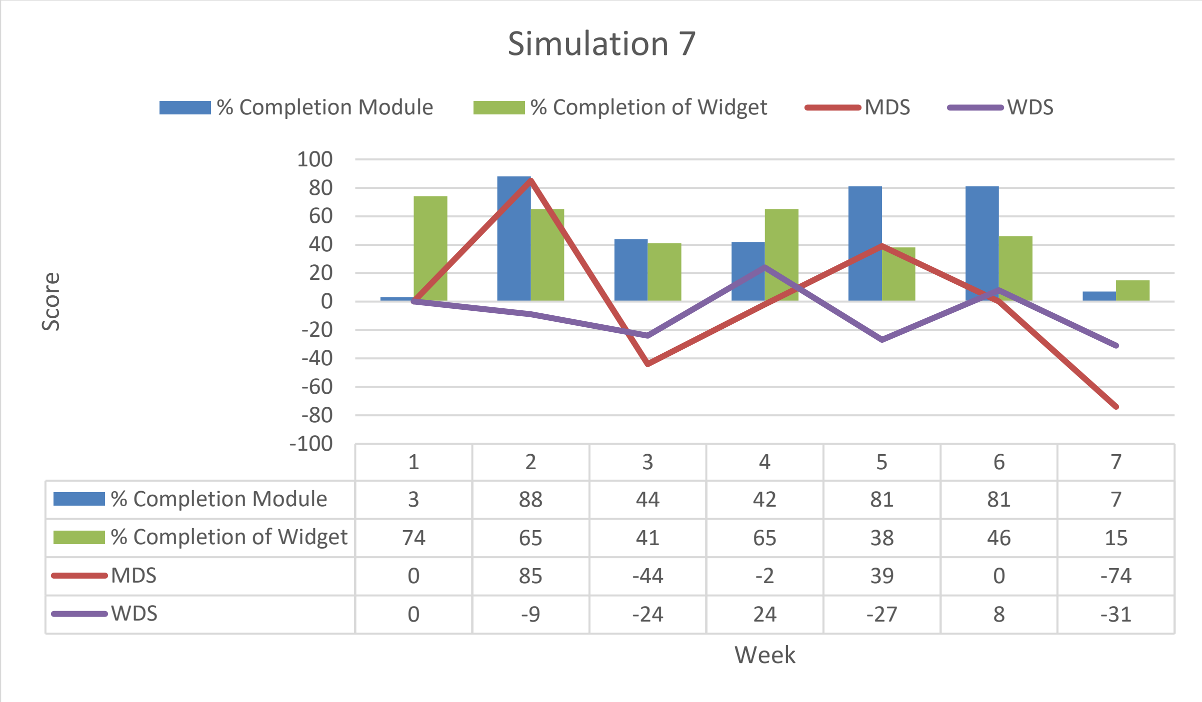
Table 28: Random Simulation Data

	% Completion Module	% Completion of Widget	MDS	I1	WDS	I2	PL
Simulation 7							
M1	3	74	0	Positive	0	Positive	100%
M2	88	65	85	Positive	-9	Negative	75%
M3	44	41	-44	Negative	-24	Negative	50%
M4	42	65	-2	Negative	24	Positive	50%
M5	81	38	39	Positive	-27	Negative	50%
M6	81	46	0	Positive	8	Positive	58%
M7	7	15	-74	Negative	-31	Negative	50%
Simulation 8							
M1	18	90	0	Positive	0	Positive	100%
M2	17	81	-1	Negative	-9	Negative	50%

M3	18	38	1	Positive	-43	Negative	50%
M4	69	65	51	Positive	27	Positive	63%
M5	99	71	30	Positive	6	Positive	70%
M6	24	14	-75	Negative	-57	Negative	58%
M7	62	78	38	Positive	64	Positive	64%
Simulation 9							
M1	40	67	0	Positive	0	Positive	100%
M2	97	6	57	Positive	-61	Negative	75%
M3	3	80	-94	Negative	74	Positive	50%
M4	59	4	56	Positive	-76	Negative	50%
M5	44	16	-15	Negative	12	Positive	50%
M6	74	86	30	Positive	70	Positive	58%
M7	31	83	-43	Negative	-3	Negative	50%
Simulation 10							
M1	81	83	0	Positive	0	Positive	100%
M2	78	94	-3	Negative	11	Positive	75%
M3	75	68	-3	Negative	-26	Negative	50%
M4	74	66	-1	Negative	-2	Negative	38%
M5	73	56	-1	Negative	-10	Negative	30%
M6	66	94	-7	Negative	38	Positive	33%
M7	40	80	-26	Negative	-14	Negative	29%
Simulation 11							
M1	5	10	0	Positive	0	Positive	100%
M2	88	90	83	Positive	80	Positive	100%
M3	88	10	0	Positive	-80	Negative	67%
M4	70	85	-18	Negative	75	Positive	63%
M5	2	5	-68	Negative	-80	Negative	50%
M6	92	100	90	Positive	95	Positive	58%
M7	10	100	-82	Negative	0	Positive	57%

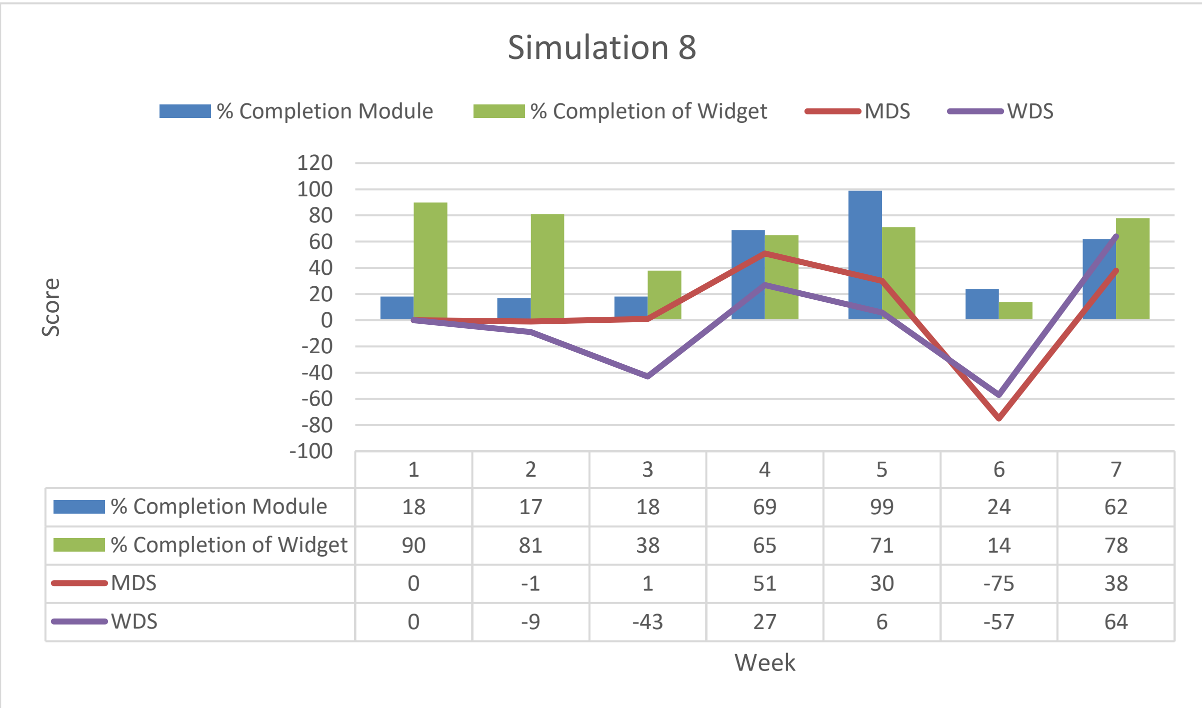
**MDS (Module Difference Score), WDS (Widget Difference Score), PL (Performance Level), I1 (Indicator 1), I2 (Indicator 2)*

Graph projected: Output from the algorithm measurement has again been visualised into a time-series style graph. The same combination of bar chart and line chart was used. Unlike the controlled simulation setting, where I can expect and observe the measurement graph pattern, the randomised simulation generates more challenging results as the patent is hardly noticed. All five simulation graphs are shown in Figure 26 to Figure 30 below.



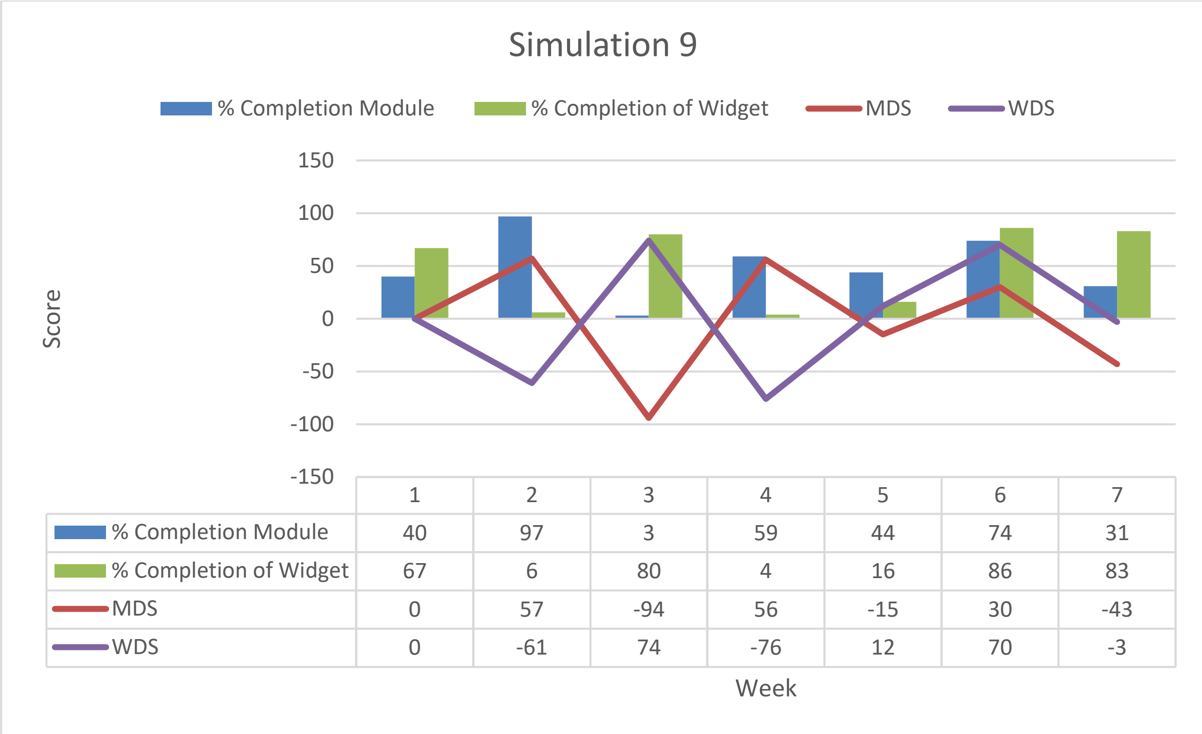
	1	2	3	4	5	6	7
% Completion Module	3	88	44	42	81	81	7
% Completion of Widget	74	65	41	65	38	46	15
MDS	0	85	-44	-2	39	0	-74
WDS	0	-9	-24	24	-27	8	-31

Figure 26: Simulation 7 Performance Analysis



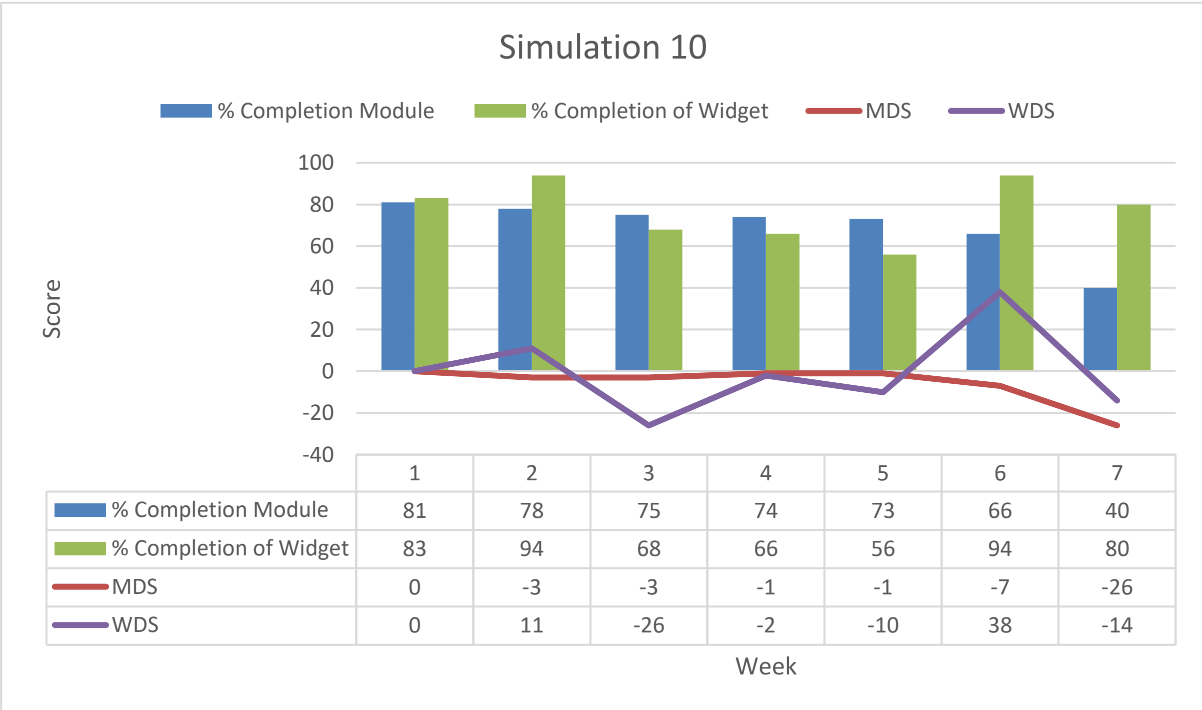
	1	2	3	4	5	6	7
% Completion Module	18	17	18	69	99	24	62
% Completion of Widget	90	81	38	65	71	14	78
MDS	0	-1	1	51	30	-75	38
WDS	0	-9	-43	27	6	-57	64

Figure 27: Simulation 8 Performance Analysis



	1	2	3	4	5	6	7
% Completion Module	40	97	3	59	44	74	31
% Completion of Widget	67	6	80	4	16	86	83
MDS	0	57	-94	56	-15	30	-43
WDS	0	-61	74	-76	12	70	-3

Figure 28: Simulation 9 Performance Analysis



	1	2	3	4	5	6	7
% Completion Module	81	78	75	74	73	66	40
% Completion of Widget	83	94	68	66	56	94	80
MDS	0	-3	-3	-1	-1	-7	-26
WDS	0	11	-26	-2	-10	38	-14

Figure 29: Simulation 10 Performance Analysis

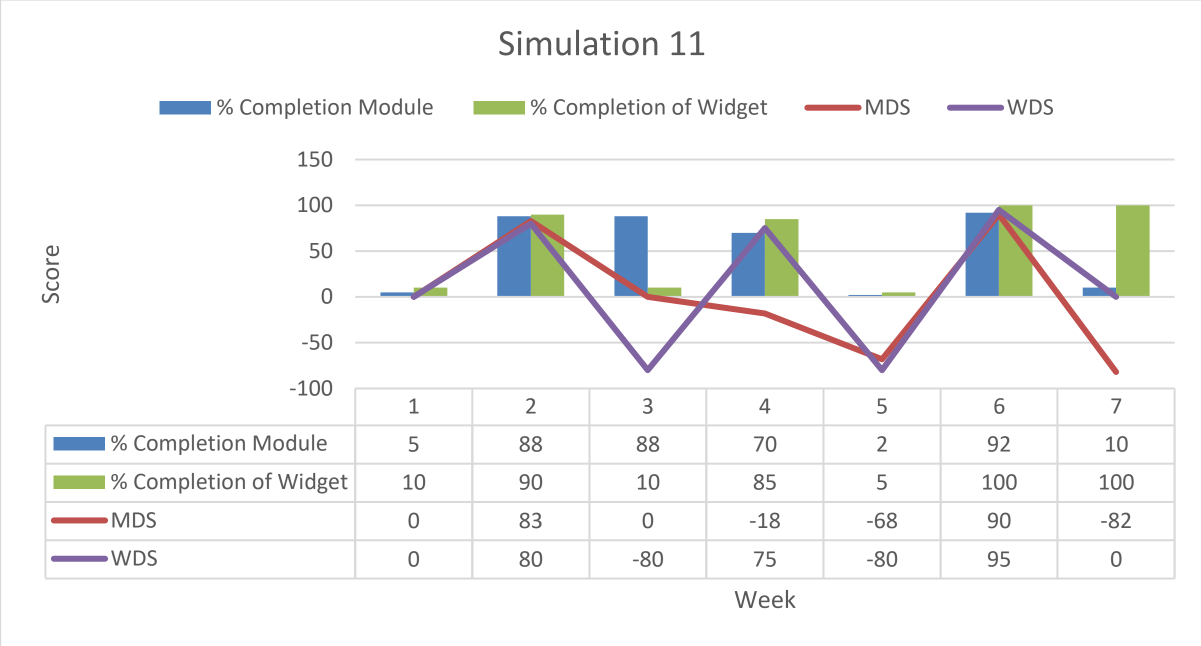


Figure 30: Simulation 11 Performance Analysis

Simulation Results: Table 29 below shows all simulation results, where I measure, compare, and observe the positive and negative scores in each simulation.

Table 29: Random Simulation Indicator Score Results

	I1	I2	PL
Simulation 7: Good Performance (50%)			
Positive	4	3	7
Negative	3	4	7
Simulation 8: Good Performance (64.28%)			
Positive	5	4	9
Negative	2	3	5
Simulation 9: Good Performance (57.14%)			
Positive	4	4	8
Negative	3	3	6
Simulation 10: Poor Performance (28.57%)			
Positive	1	3	4
Negative	6	4	10
Simulation 11: Good Performance (64.29%)			
Positive	4	5	9
Negative	3	2	5

Results Observed: In each simulation, I observed the positive and negative indications calculated to determine the performance percentage value. I also provide the first diagnosis based on the simulation, which the course admin could do to improve the performance score.

- **Simulation 7** shows mixed chart patents with up and down trends within seven modules. The final performance level is Good (50%). The most significant downtrend was recorded for module 7, followed by module 3. This indicates that future attention should be paid to modules 7 and 3 to reduce the negative scores. Minor action could also be considered for modules 2 and 4 as both record small negative scores (-9 for WDS in module 2 and -2 for MDS in module 4). The overall performance score can be improved to 64% if a positive score can be recorded in both module 2 and module 4, as stated.
- **Simulation 8** shows a good performance level (64.28%) with nine positive and five negative indicators. At the overall difference score, two modules show a massive drop in M3 (-43 WDS) and M6 (-75 MDS and -57 WDS). Slight differences in scores recorded for MDS in M2 (-1) and M3 (1) exist. Attention on widget completion in M3 and both module and widget completion in M6 could help improve course performance for this scenario. Both module and widget completion are also aligned with each other, indicating no abnormal scenario to be concerned about.
- **Simulation 9** shows a good performance (57.14%). Unlike previous simulations, Simulation 9 shows a different trend between module and widget completion in M2 to M4. For example, in M2, the MDS is positive (57), but the WDS is negative (-61). Followed by M3 with the MDS is negative (-94) and WDS is positive (74). In M4, the MDS is positive (56), while the WDS is negative (-76). The main concerns are module completion in M3 (-94) and M7 (-43). Regarding widget completion, M4 (-76) show the most significant drop, followed by M2 widget completion (-61). Course admin should look at various factors, from technical to instructional and content design.
- **Simulation 10** shows poor performance (28.57%). In general, the average score is 69% for the completion of the module and 77% for the completion of the widget, which is considered not a bad average score. However, due to the high number of negative scores (10) against positive scores (4) in performance measurement, this course generally is in a downtrend trajectory. The course admin should focus on modules with small difference scores to improve the performance.
- **Simulation 11** shows good performance (64.29%) with nine positive and five negative scores. Simulation 11 did share similar characteristics with Simulation 9, consisting of substantial score differences. The highest negative score was recorded for M3 (-80 WDS), M5 (-80 WDS), and M7 (-82 MDS). Worse scores are recorded in M5, with MDS (-

68) and WDS (-80) in negative scores. Although the drop is huge, on only a few occasions, I record a drop score, and in another module, the score shows a positive score, indicating an improvement.

5.3.2 Learner Performance Simulations

A series of learner performance simulations were conducted using the proposed measurement algorithm on made-up data as shown in Table 30. From the data analysis on MOOC learning analytics data, I identified the Page Completion score and calculated the percentage value. Then, I identified the assessment score and calculated the percentage value.

I simulate two learners in three different course assessment settings in the simulation activity. The assessment activity is simulated in M3, M6 and M7 in the first setting. The assessment is simulated in M5, M6 and M7 in the second setting. I simulated assessment activity in M1, M4, and M7 in the third setting.

The main objective of learner simulation is to test and observe any significant outcome concerning assignment settings. It was acknowledged that in each MOOC course, the number and frequency of assignments vary, highly depending on course admin preference settings by using the same data but in different scenarios, in which scenario one assignment was given at M3 and the remaining two assignments at the end of the course (M6 and M7). Scenario 2 is when an assignment was given sequentially to the last three modules (M5, M6, and M7). Finally, Scenario 3 is when an assignment is given evenly at the beginning of the course (M1), at the middle of the course duration (M4), and at the end of the course (M7).

Simulation Data: All simulation data is not real data but instead made up based on actual learning analytics data structure. I simulate two learners, with Learner 1 representing an overall increment in scores and Learner 2 representing an overall decrease in scores.

Table 30: Learners Simulation Data

	Module Completion							Assessment Score		
LEARNER	M1	M2	M3	M4	M5	M6	M7	A1	A2	A3
Learner 1 (score)	1/9	3/11	3/8	3/7	6/8	7/7	6/7	3/5	4/5	5/5

Learner 1 (percentage)	11.11 %	27.27 %	37.50 %	42.85 %	75 %	100 %	85.71 %	60%	80 %	100 %
Learner 2 (score)	8/9	11/11	6/8	4/7	4/8	7/7	1/7	5/5	4/5	3/5
Learner 2 (percentage)	88.88 %	100%	75%	57.14 %	50 %	100 %	14.28 %	100 %	80 %	60%

The same score data used for each learner is simulated in three different assessment settings, as shown in Table 31 below.

Table 31: Learner Simulation Performance Result

	% Completion Module	% Assessment Score	PDS	I1	ADS	I2	PL
Simulation Learner 1a							
M1	11.11	0	0	Positive	0	Negative	50%
M2	27.27	0	16.16	Positive	0	Negative	50%
M3	37.50	60	10.23	Positive	60	Positive	50%
M4	42.85	0	5.35	Positive	-60	Negative	63%
M5	75	0	32.15	Positive	0	Negative	60%
M6	100	80	25	Positive	80	Positive	67%
M7	85.71	100	-14.29	Negative	20	Positive	64%
Simulation Learner 1b							
M1	11.11	0	0	Negative	0	Negative	50%
M2	27.27	0	16.16	Positive	0	Negative	50%
M3	37.5	0	10.23	Positive	0	Negative	50%
M4	42.85	0	5.35	Positive	0	Negative	63%
M5	75	60	32.15	Positive	60	Positive	60%
M6	100	80	25	Positive	20	Positive	67%
M7	85.71	100	-14.29	Negative	20	Positive	64%
Simulation Learner 1c							
M1	11.11	60	0	Positive	0	Positive	100%
M2	27.27	0	16.16	Positive	-60	Negative	75%
M3	37.5	0	10.23	Positive	0	Negative	67%
M4	42.85	80	5.35	Positive	80	Positive	75%
M5	75	0	32.15	Positive	-80	Negative	70%
M6	100	0	25	Positive	0	Negative	67%
M7	85.71	100	-14.29	Negative	100	Positive	64%
Simulation Learner 2a							
M1	88.88	0	0	Positive	0	Negative	50%
M2	100	0	11.12	Positive	0	Negative	50%

M3	75	100	-25	Negative	100	Positive	50%
M4	57.14	0	-17.86	Negative	-100	Negative	38%
M5	50	0	-7.14	Negative	0	Negative	30%
M6	100	80	50	Positive	80	Positive	42%
M7	14.28	60	-85.72	Negative	-20	Negative	36%
Simulation Learner 2b							
M1	88.88	0	0	Positive	0	Negative	50%
M2	100	0	11.12	Positive	0	Negative	50%
M3	75	0	-25	Negative	0	Negative	33%
M4	57.14	0	-17.86	Negative	0	Negative	25%
M5	50	100	-7.14	Negative	100	Positive	30%
M6	100	80	50	Positive	-20	Negative	33%
M7	14.28	60	-85.72	Negative	-20	Negative	29%
Simulation Learner 2c							
M1	88.88	100	0	Positive	0	Positive	100%
M2	100	0	11.12	Positive	-100	Negative	75%
M3	75	0	-25	Negative	0	Negative	50%
M4	57.14	80	-17.86	Negative	80	Positive	50%
M5	50	0	-7.14	Negative	-80	Negative	40%
M6	100	0	50	Positive	0	Negative	42%
M7	14.28	60	-85.72	Negative	60	Positive	43%

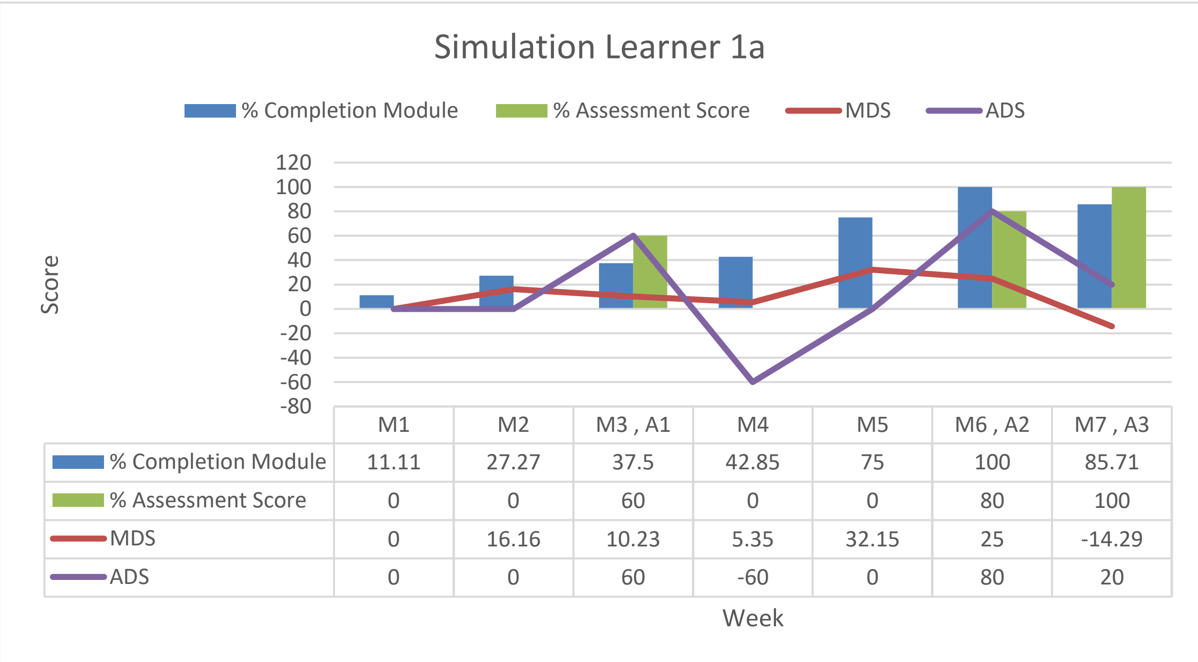
- **Simulation Learner 1a**: Gradually increment on the % completion module and % assessment score. Assessment is set in the middle of the course (M3) and the last two modules (M6 and M7).
- **Simulation Learner 1b**: Gradually increment on the % completion module and % assessment score. All assessments are set at the end of course modules (M5, M6, and M7).
- **Simulation Learner 1c**: Gradually increment on the % completion module and % assessment score. Assessment is set evenly at the beginning of the course (M1), at the middle of the course (M4) and the last module (M7).
- **Simulation Learner 2a**: Gradually decreasing on % completion module and % assessment score. Assessment is set in the middle of the course (M3) and the last two modules (M6 and M7).
- **Simulation Learner 2b**: Gradually decreasing on % completion module and % assessment score. All assessments are set at the end of course modules (M5, M6, and M7).

- **Simulation Learner 2c**: Gradually decreasing on % completion module and % assessment score. Assessment is set evenly at the beginning of the course (M1), at the middle of the course (M4) and the last module (M7).

5.3.2.1 Simulation: Learner 1

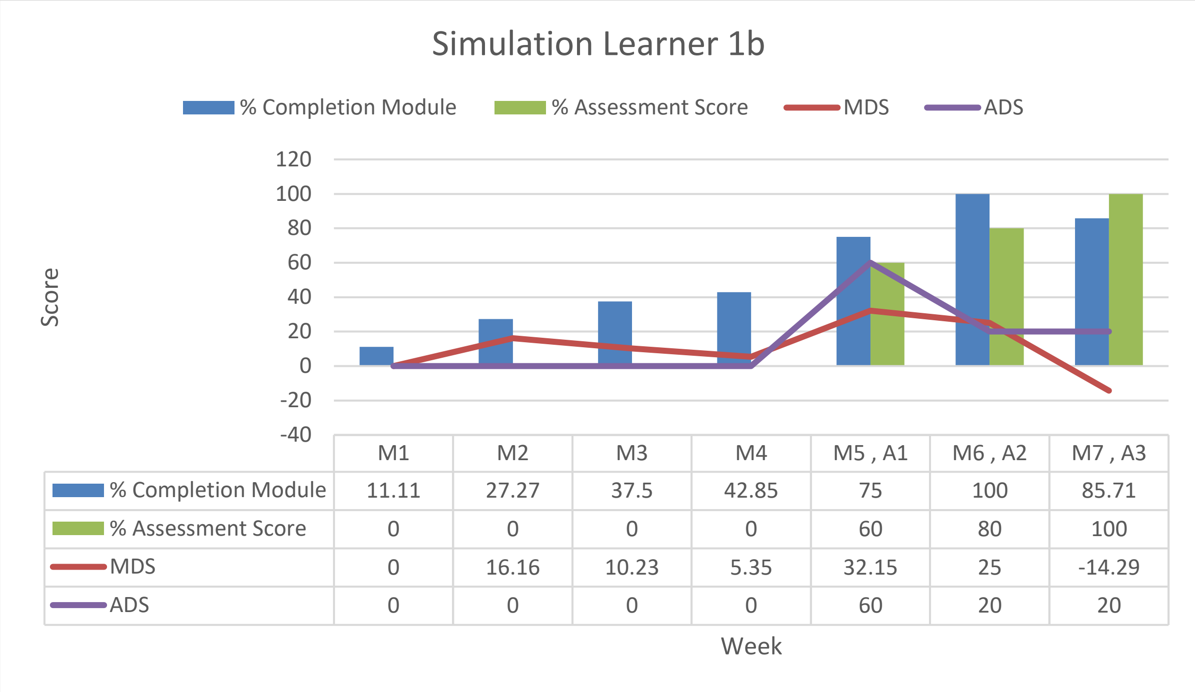
Learner 1, as described, is a learner with an overall increment score. Three simulations were conducted using the same data set to observe the assessment setting effect between them.

Graph projected: Output from the algorithm measurement is visualised into a time-series style graph. I used a combination of a line graph and a bar graph. The bar graph shows the actual score from the dataset, while the line graph shows data from algorithm calculations, representing the different scores. Figure 31 to Figure 33 show all three simulation graphs projected based on the algorithm measurement.



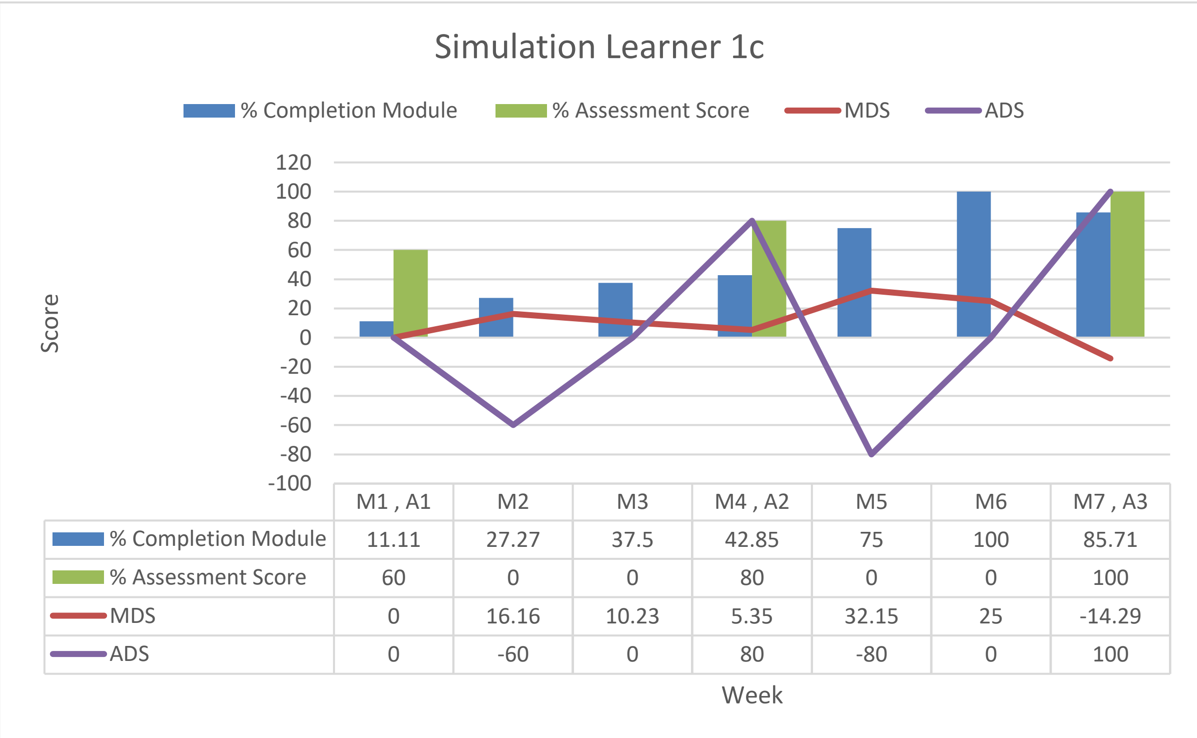
	M1	M2	M3 , A1	M4	M5	M6 , A2	M7 , A3
% Completion Module	11.11	27.27	37.5	42.85	75	100	85.71
% Assessment Score	0	0	60	0	0	80	100
MDS	0	16.16	10.23	5.35	32.15	25	-14.29
ADS	0	0	60	-60	0	80	20

Figure 31: Simulation Learner 1a Performance Analysis



	M1	M2	M3	M4	M5 , A1	M6 , A2	M7 , A3
% Completion Module	11.11	27.27	37.5	42.85	75	100	85.71
% Assessment Score	0	0	0	0	60	80	100
MDS	0	16.16	10.23	5.35	32.15	25	-14.29
ADS	0	0	0	0	60	20	20

Figure 32: Simulation Learner 1b Performance Analysis



	M1 , A1	M2	M3	M4 , A2	M5	M6	M7 , A3
% Completion Module	11.11	27.27	37.5	42.85	75	100	85.71
% Assessment Score	60	0	0	80	0	0	100
MDS	0	16.16	10.23	5.35	32.15	25	-14.29
ADS	0	-60	0	80	-80	0	100

Figure 33: Simulation Learner 1c Performance Analysis

Simulation Results: Table 32 below shows all simulation results for Learner 1, where I measured, compared, and observed the positive and negative scores in each simulation.

Table 32: Learner 1 Simulation Indicator Score Results

	I1	I2	PL
Simulation Learner 1a: Good Performance (64.28%)			
Positive	6	3	9
Negative	1	4	5
Simulation Learner 1b: Good Performance (64.28%)			
Positive	6	3	9
Negative	1	4	5
Simulation Learner 1c: Good Performance (64.28%)			
Positive	6	3	9
Negative	1	4	5

Results Observed: In each simulation, I observed the positive and negative indications calculated to determine the performance percentage value. A secondary observation is focused on the assessment setting affecting my algorithm measurement and analysis results. As a result, the bar chart shows identical patents for every simulation, with the only difference being on the assessment chart patent. When observing the line chart patent, it is significant to notice the different patents between them, although they are from the same data sample.

I also provide the first diagnosis based on the simulation, which the course admin could do to improve the performance score.

- **Simulation Learner 1a** shows mixed chart patents with up and down trends within seven modules. The final performance level is Good (64.28%). The most significant downtrend was recorded for module 4 results from assessment data. It is expected to be a downtrend in module 4 as the course admin provides no assessment to the learner. This indicates that a follow-up assessment activity or assessment in a sequence was recommended for a better assessment performance result. The M4 completion page deference score is also small, and attention should be paid to this module to ensure it does not go lower and produce a negative indication of performance.
- **Simulation Learner 1b** shows a final performance score similar to Learner 1a, with a good performance level (64.28%) from nine positive and five negative indicators. At the assessment deference score, there is no negative score, unlike Learner 1a. All three assessments were conducted sequentially in the last three modules, which showed a good effect. It is expected to be challenging to maintain a 100 per cent score, but attention can be put on M7 for page completion to reduce the negative scores or even achieving a 100 per cent score to match achievement on the previous module.

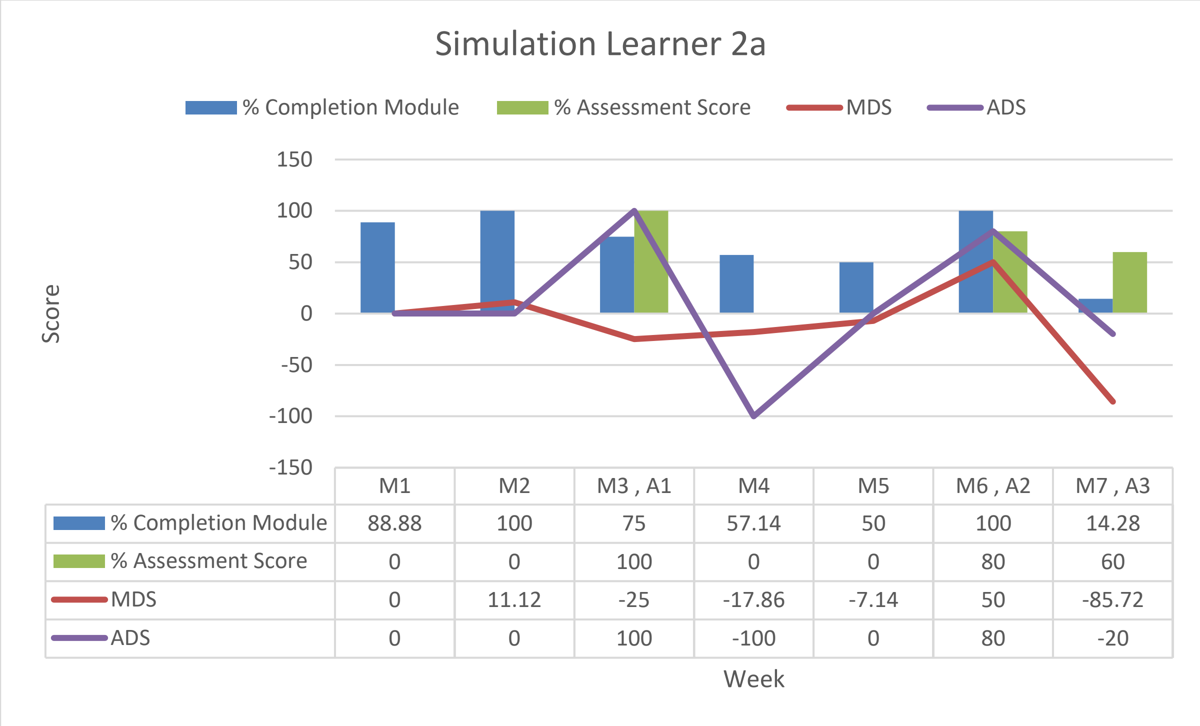
- **Simulation Learner 1c** show a similar good performance (64.28%). The Learner 1c simulation shows the worst assessment performance results with two negative scores, compared to Learner 1a (one negative score) and Learner 1b (no negative score). This result indicates planning assessment only at the beginning, middle and last, with few module gaps and a high risk of negative deference scores. Looking at the chart patent, it was visible up and down patent. For a better assessment strategy, the course admin should consider additional assessments to fill the gap or move the assessment sequent.

Interestingly, although all three simulations are from the same data sample and apply different assessment settings that significantly affect the assessment's different scores, the final performance score is the same for all of them, with the same positive and negative indications calculated.

5.3.2.2 Simulation: Learner 2

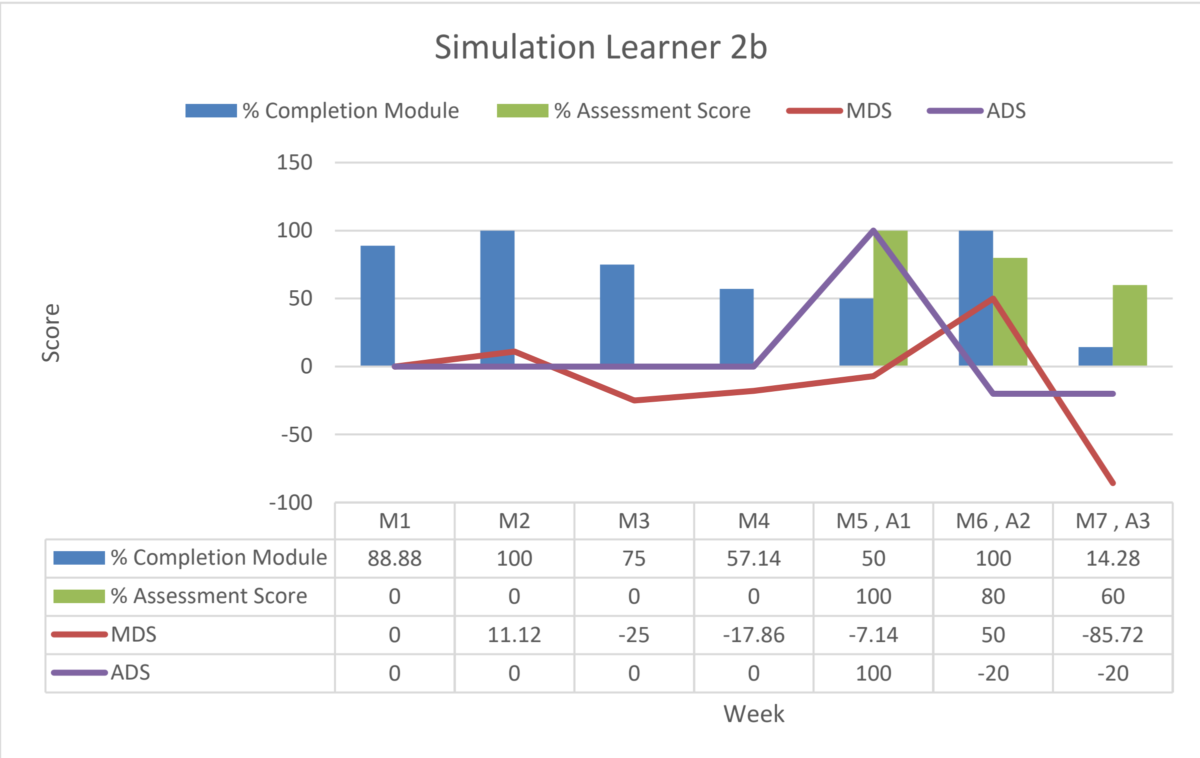
Learner 2, as described, is a learner with an overall decrement score. Three simulations were conducted using the same data set to observe the assessment's setting effect between them.

Graph projected: Output from the algorithm measurement is visualised into a time-series style graph. I used a combination of a line graph and a bar graph. The bar graph shows the actual score from the dataset, while the line graph shows data from algorithm calculations, representing the different scores. Figure 34 to Figure 36 show all three simulation graphs projected based on the algorithm measurement.



	M1	M2	M3 , A1	M4	M5	M6 , A2	M7 , A3
% Completion Module	88.88	100	75	57.14	50	100	14.28
% Assessment Score	0	0	100	0	0	80	60
MDS	0	11.12	-25	-17.86	-7.14	50	-85.72
ADS	0	0	100	-100	0	80	-20

Figure 34: Simulation Learner 2a Performance Analysis



	M1	M2	M3	M4	M5 , A1	M6 , A2	M7 , A3
% Completion Module	88.88	100	75	57.14	50	100	14.28
% Assessment Score	0	0	0	0	100	80	60
MDS	0	11.12	-25	-17.86	-7.14	50	-85.72
ADS	0	0	0	0	100	-20	-20

Figure 35: Simulation Learner 2b Performance Analysis

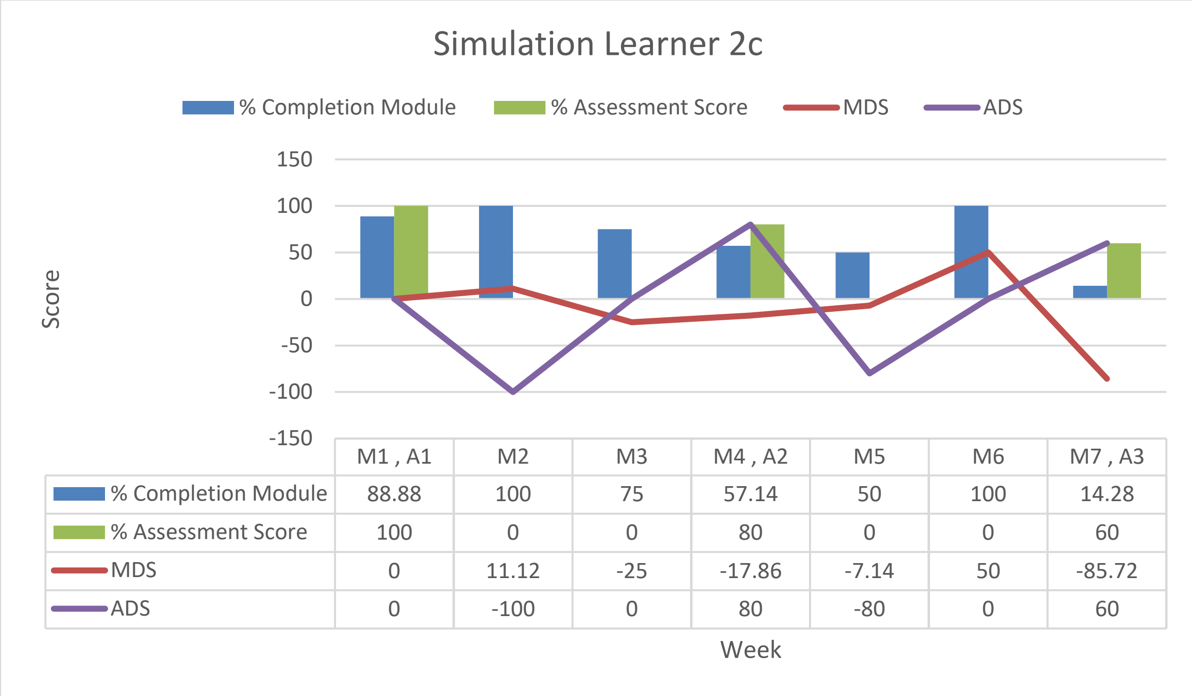


Figure 36: Simulation Learner 2c Performance Analysis

Simulation Results: Table 33 below shows all simulation results for Learner 2, where I measured, compared, and observed the positive and negative scores in each simulation.

Table 33: Learner 2 Simulation Indicator Score Results

	I1	I2	PL
Simulation Learner 2a: Poor Performance (35.71%)			
Positive	3	2	5
Negative	4	5	9
Simulation Learner 2b: Poor Performance (28.57%)			
Positive	3	1	4
Negative	4	6	10
Simulation Learner 2c: Poor Performance (42.86%)			
Positive	3	3	6
Negative	4	4	8

Results Observed: Similar to Learner 1 observation, I observed the positive and negative indications calculated to determine the performance percentage value for Learner 2. A secondary observation is focused on the assessment setting affecting my algorithm measurement and analysis results. The bar chart shows identical patents for every simulation, the only difference being the assessment chart patent. Differences in score patents represented by the line graph show significant differences between each simulation as expected, although they are from the same data sample.

Based on future observation, I provide the first diagnosis on the simulation for which course admin could do to improve the performance score for Learner 2.

- **Simulation Learner 2a** shows an analysis chart for the assessment set in M3 and the last two modules, M6 and M7. I noticed a significant uptrend in M3 as the first assessment was set and a huge drop due to no follow-up assessment. There is no assessment in M5, but the line patent shows an up-trend toward M6 for a positive second assessment. Focusing on the assessment settings, the course admin could introduce additional assessments or rearrange A1 to M1 or M5. The final performance level is Poor (35.71%). The M3 completion module difference score is considered minor, and attention should be paid to this module to make it positive.
- **Simulation Learner 2b** shows a worse final performance score than Learner 1a, although it is at the same poor performance level (28.57%). There are negative scores from M1 to M4 due to no assessment provided at the assessment deference score. A total score in M5 gives a positive indication, but the negative indication is recorded due to a downtrend for the remaining assessment. All three assessments were conducted sequentially in the last three modules, which showed a significantly bad effect. It is expected to be challenging to maintain a 100 percent score, but attention to the last assessment (M7) could be a reasonable effort for possible positive indications in ADS M7.
- **Simulation Learner 2c** show a similar poor performance but a better score (42.86%). Learner 1c simulation shows better assessment performance results with three positive scores, compared to Learner 1a (two positive scores) and Learner 1b (one positive score). This indicates that planning assessment in the first module is a good strategy to secure the first positive indication. Unfortunately, similar to Learner 1c, planning assessment only at the beginning, middle and last, with few module gaps, is most likely to risk negative deference scores. This was proven with a visible up-and-down chart patent for different scores. For a better assessment strategy, the course admin should consider additional assessments to fill the gap or move the assessment sequent.

5.3.3 Simulation Discussions

The main objective of algorithm simulation is to evaluate the algorithm's logic. Simulations also aim to observe algorithm bias and robustness against various possible data scenarios. Therefore, the discussion presented in this sub-section will be based on these three aspects.

In total, 17 simulations were conducted. 11 simulations on course performance and six on learner performance. Course simulation was conducted with two main settings, controlled and random data, while learner simulation was designed and conducted with three different assessment data settings.

Course Simulations

The performance measurement algorithm was designed based on the conceptual design proposed. Generally, there is no significant anomaly or error when various scenario data are tested. Current data is compared with previously available data using the time-series approach. If no previous data is available, usually at the first module, a default indication value is applied. Comparison value that determines positive or negative logic is demonstrated. If the data value was equal and resulted in a 0 difference score, algorithm rules were applied to determine whether 0 indicates positive or negative. Measurement logic works excellently for both controlled and random data categories.

Observing for possible algorithm bias, I rule out input data bias due to the nature of the data used, which must be cleaned and pre-processed before being used for performance measurement and analysis; therefore, there is no algorithm bias on missing data scenarios. Data can be 0, and as mentioned, algorithm logic and rules already consider a scenario when encountering 0 data for the first module or 0 data for the rest of the module that will determine positive or negative indication and avoid any error or indication bias.

The robustness level of the algorithm, as tested within the research scope, shows no errors or issues. As the scope of research covers datasets from two different MOOC platforms, I have identified datasets and data suitable for my algorithm. Therefore, regardless of which dataset platforms are sourced, the algorithm has no limitations and works as it should. The accepted data is set in percentage value ranges from 0 to 100.

I am satisfied with the course simulation results and confirm that the algorithm is accurate and error-free.

Figure 37: Course Simulations Performance Graph

Learner Simulations

Learner simulations are similar to previous course simulations from the algorithm logic point of view and as described by the conceptual design proposed. The only difference is the parameter used. The learner algorithm measures two input data, which are the percentage of module completion and the percentage of assessment scores. Assessment score data can be from MOOC learning analytics or in combination with offline data. For learner simulations, I was concerned with the assessment settings' deafferentation and how it affected my algorithm measurement if the same assessment was given in a different timeframe duration between modules. Table 34 show the performance score calculated for Learner 1, while Table 35 show the performance score calculated for Learner 2.

Learners 1a, 1b and 1c share the same score, but an assessment was given in different modules. Interestingly, I measured no significant differences between them and recorded 100% identical results at 64.28% good performance level, with nine positive and five negative indications.

Table 34: Learner 1 Simulation Performance Score

	I1	I2	PL
Simulation Learner 1a: Good Performance (64.28%)			
Positive	6	3	9
Negative	1	4	5
Simulation Learner 1b: Good Performance (64.28%)			
Positive	6	3	9
Negative	1	4	5
Simulation Learner 1c: Good Performance (64.28%)			
Positive	6	3	9
Negative	1	4	5

Learners 2a, 2b and 2c, on the other hand, although they share the same data between them, did not record the same performance level. These range from 28.57% to 42.86% of the same poor performance level measured.

Table 35: Learner 2 Simulation Performance Score

	I1	I2	PL
Simulation Learner 2a: Poor Performance (35.71%)			
Positive	3	2	5
Negative	4	5	9
Simulation Learner 2b: Poor Performance (28.57%)			
Positive	3	1	4
Negative	4	6	10
Simulation Learner 2c: Poor Performance (42.86%)			
Positive	3	3	6
Negative	4	4	8

Learner 1 data stimulates uptrend data, while learner 2 stimulates downtrend data. Algorithm logic is validated and indicates no significant effect if data was in an uptrend score. This means the performance measurement will show no significant difference if the learner performed well and got better scores, regardless of when or how much gap assessment was given. Unlike learners with a downtrend score, when an assessment was given as to how long the gap was, it would affect an acceptable range (below 10%). Providing assessment in the first module is recommended and will help to set the first assessment performance indication.

The trendline chart for ADS compares Learner 1a with Learner 2a (Figure 38), Learner 1b with Learner 2b (Figure 39), and Learner 1c with Learner 2c (Figure 40) show a similar patent. This indicates logic regardless of whether the learner is in an uptrend or downtrend score; performance was measured based on the current and previous scores. A good uptrend learner can show a downtrend performance patent, and a downtrend learner can show an uptrend performance patent. Simulations 1b and 2b clearly show this scenario when the assessment score for Learner 1a in M6 was slightly higher than M5, and M7 was slightly higher than M6. The ADS was 60, 20 and 20. Line patents show a trend followed by linear lines, indicating no changes in performance. For Learner 2b, the assessment score in M6 was slightly lower than M5, and M7 was slightly lower than M6. The ADS was 100, -20 and -20. The line patent shows an identical patent as Learner 1b when it shows an up trend followed by a linear line indicating no changes in performance. The only difference was that the linear liner for Learner 2b was under the 0 score value as it was measured as negative.

Figure 38: Learners Simulation a

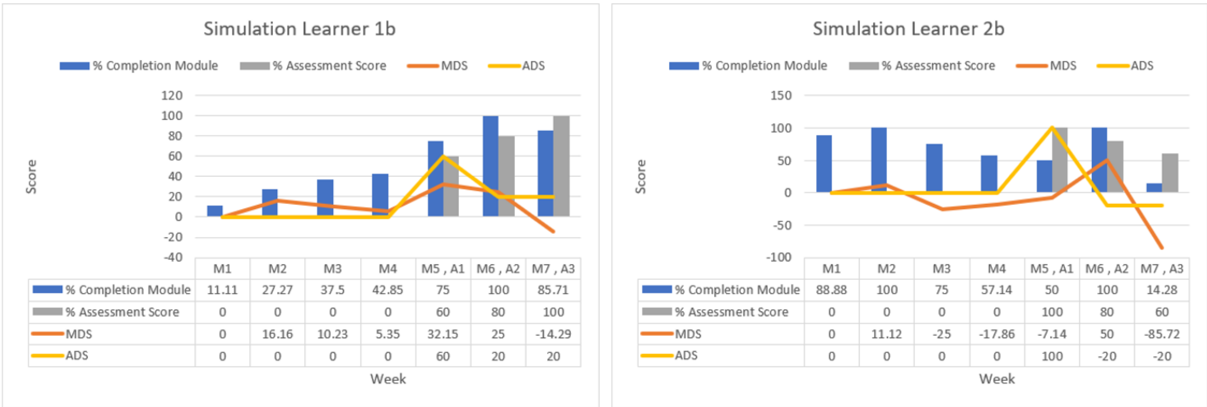


Figure 39: Learners Simulation b

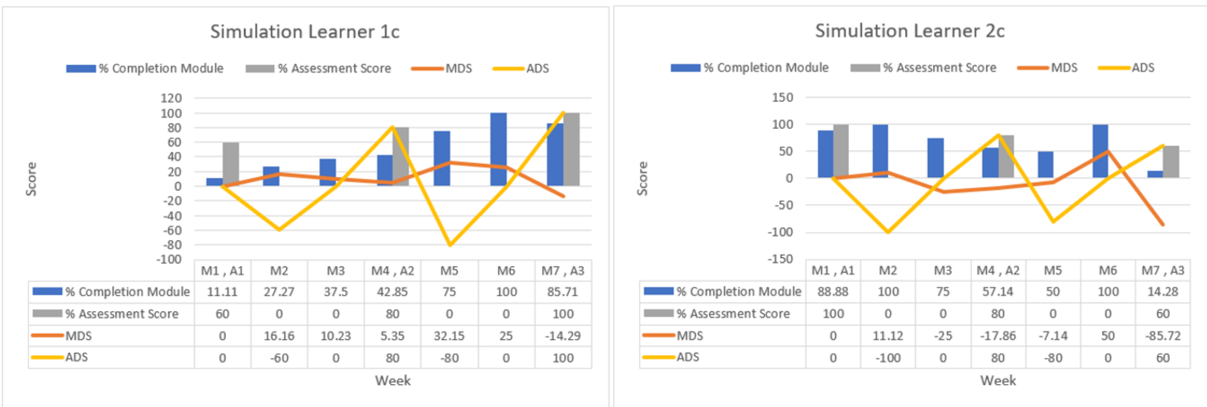


Figure 40: Learners Simulation c

Learner simulation shares the same data bias with course simulation; when I rule out input data bias due to the nature of data, it must be cleaned and pre-processed before being used for performance measurement and analysis; therefore, no algorithm bias on missing or repetition data scenarios is applied. Additionally, in learner simulation, I purposely introduce two different learner data with significant uptrend and downtrend sample data to test the learner algorithm in six simulation settings.

The robustness level of the algorithm, as tested within the research scope, shows no errors or issues. The logic concept I applied also indicates that the algorithm successfully measures and determines performance without significantly affecting the learner or data score level. This is to say that although the data or learner is a high scorer and the average score throughout the course is high, the algorithm can still measure any downtrend I measure as performance.

I am satisfied with the course simulation results and confirm that the algorithm is accurate and error-free. Based on the algorithm design and simulations conducted, my observation and consideration indicate the need for specific indicators and metrics for the MPM Model.

5.4 Indicator and Metrics Settings

The MPM Model is comprised of two primary elements: measurement algorithms and collections of indicators and metrics. This segment clarifies the Condition Indicator, Performance Metric, and Consideration Factor Indicator that together constitute the entire MPM Model. The variables observed in the simulations, including completion rates, learner performance trends, and algorithmic calculations, are crucial in guiding the development and integration of these elements within the MPM Model.

5.4.1 Condition Indicator

MPM Condition Indicator approach is based on the difference in scores measured. I propose Condition Indicator (Indicator 1 and Indicator 2) with four-set conditions. It will compare scores between two modules (current and previous) within the same dataset.

For example, for the first module, Table 37, M1 will apply a default setting where the difference score (MDS, WDS, or ADS) is 0. This is a logical approach, considering there is no previous module to compare. How do I determine either a Positive or Negative indication for M1? I will refer to the score value in the % Completion Module or % Completion of Widget or Assessment Score. If there is a score other than 0, a Positive indication is set for M1. A negative indication for the first module only happens if the score is 0, which indicates no completion from learners. The first module does not affect whether the score was high or low. A 0.1% score will also be considered a positive and good start for M1.

Table 36 will be used for the next module (M2 onwards). Any increasing difference score value indicates a positive, and any decreasing difference score value indicates a negative. When the current module has the same score as the previous module, 0 score differences will be recorded. In this scenario, the rule is set for the indicator to be Positive if the unchanged score value is 100% (full score). This rule was based on the logic that no higher score can be obtained, and the ability to maintain a score at the highest value reflects an excellent performance level. Unlikely for an unchanged score value that is not reaching 100%, there is a possibility to improve. Therefore, I conclude that it is a negative indicator.

Table 36: Condition Indicator

Differences Score Condition	Indicator
Any increasing score value	(+) positive
Any decreasing score value	(-) negative
Any unchanged score value if the value is 100% or full score	(+) positive
Any unchanged score value if the value is not 100% or not a full score	(-) negative

Table 37: Default Setting for First Module

Module	% Completion Module	% Completion of Widget	MDS	I1	WDS	I2
M1	83.87	**66.46**	0	Positive	0	Positive
M2	82.91	**82.28**	-0.96	Negative	15.82	Positive
M3	80.83	**79.87**	-2.08	Negative	-2.41	Negative

The methodology of the MPM Condition Indicator is based on analyzing the variations in scores obtained from two modules within a single dataset. By examining completion rates and assessment scores, a module is classified as either Positive or Negative. These factors, which are obtained from learner performance patterns and completion statistics, guide the Condition Indicator's algorithm and decision-making procedure, providing a standard evaluation of module performance through comparative analysis.

5.4.2 Performance Metric

Once I determine the positive and negative indicators using the proposed Condition Indicator, I am ready to measure the Performance Score (PS). Performance Score will be referred to the proposed Performance Metric for the final Performance Level. Table 38 below shows the proposed Performance Metric.

The default Performance metric was set in four levels: Excellent Performance, Good Performance, Poor Performance and Very Poor Performance. My observation found that it is subjective to determine the benchmark level as different institutions might have their standards. Therefore, changing the Current Performance Score benchmark according to macro-level requirements is possible, although not recommended. The same macro-user will get standard and justified monitoring and performance measurement data using the MPM Model regardless of which MOOC platforms are used.

Table 38: Performance Metric

Current Performance Score	Performance Level	Description
76% to 100%	Excellent Performance	More than 76% of the modules show positive indicators. Significant uptrend score.
51% to 75%	Good Performance	More than 50% of the modules show positive indicators.
26% to 50%	Poor Performance	Mostly negative indicator with an average close to an uptrend. Early improvement will promote better performance.
0% to 25%	Very Poor Performance	Most indicators were negative, and no more than 25% were positive. Significant downtrend score or zero scores recorded.

Table 39 shows example data of 5 modules. In M1, both MDS and WDS default values are set as 0 and are positive indications (I1 and I2). With two positive and 0 negative out of 2 measurements, the Performance Score is 100%, which is an excellent performance at the end of Module 1.

Then, at M 2, I have another 1 Positive indicator and 1 Negative indicator. Three positives and one negative will give a 75% total score at the end of M2 with Performance Level dropped to Good Performance.

Table 39: Positive Performance Measurement

Module	% Completion Module	% Completion of Widget	MDS	I1	WDS	I2	PS (%)	positive	negative	%
M1	83.87	**66.46**	0	Positive	0	Positive	100	2	0	100
M2	82.91	**82.28**	-0.96	Negative	15.82	Positive	75	3	1	75
M3	80.83	**79.87**	-2.08	Negative	-2.41	Negative	50	3	3	50
M4	79.55	**79.03**	-1.28	Negative	-0.84	Negative	38	3	5	38
M5	0.32	**52.96**	-79.23	Negative	-26.07	Negative	30	3	7	30

Next, in M3, I have another 2 Negative indicators. With three positives and three negatives, this will give a 50% total score, with the Performance Level dropped to Poor Performance. This measurement will be updated each time a new module is completed.

The Performance Metric in the MPM Model assesses course and learner performance quantitatively using predetermined parameters. Factors like completion rates and performance trends play a crucial role in determining the calculation methodology of the Performance Metric. Through the incorporation of these factors into the design of the metric, the MPM Model is able to specifically measure and evaluate performance levels, providing insightful information about how well the learning process works and identifying areas that need improvement.

5.4.3 Consideration Factor Indicator

As part of this research contribution, MPM helps users monitor and measure their MOOC performances based on the existing dataset. This gives another point of view on what the MOOC analytic data tries to inform. Considering the massive number of learners, I believe many possibilities could affect the course or learner's performance. Looking at the completion rates, according to (Tian-yi Liu and Xiu Li., 2017), even with a single rule, different researchers may hold respective ways of explanation and inference.

Course admin can never know all learners from different countries and social strata. Therefore, different types of learners and different levels of knowledge must be faced within the planning and designing phase (Scagnoli, N. I. 2012). Giving specific recommendations on what needs to be done to improve performance is not within the scope of this research study. A future detailed study, including other research areas, must be done to provide such recommendations. This may involve a study on learning style, instructional design or MOOC pedagogy. Instead, the MPM model introduced the Consideration Factors Indicator.

MPM measurement identifies the weakest point or in which module something needs to be done to improve. Based on Jo et al. (2014) and Scagnoli, N. I. (2012) research study, I designed the Consideration Factors Indicator (Table 40) with five areas where improvement actions are to be considered by either the course admin or learner. The five areas are Technical, Instruction, Content, Human and Environment.

Table 40: Consideration Factors Indicator

Area	Indication	Consideration Factor
Technical	• Zero score • Odd or significant changes in Indicator	• Did the MOOC platform have issues? • Does the user have internet connection/access issues? • Is there a bug or error on the platform? • Is the device use compatible? • Did learners have access to the platform? • Was the content (settings) available/accessible to the learner?
Instruction	• They are continuously decreasing or increasing. • A volatile indicator on both dataset scores.	• Has the course admin given explicit instruction? • Did a reminder be given to learners? • Did language use be understandable? • Is instruction confusing?
Content	• Low differences score • Low widget score	• Did content was new to learners? • What type of content was used? (Text, video, image, audio, activity?) • Did content was appropriate to learners? • Was the content relevant to the course?
Human	• Mixing trends (uptrend and downtrend) for both datasets	• Are there any security or health issues? • Did learners show any sign of protest/ejection?
Environment	• Significant decreasing or increasing score. • Significant decreasing or increasing scores in early module	• Has any event happened recently? (Holiday, and others.) • Is there any related promotion or marketing ongoing recently?

Technical: Technical issues affect the capabilities of the MOOC platform to record any analytic data, thus making it extremely difficult to indicate performances. Odd or significant changes in indicators could be affected by technical issues. As an online platform, teaching and learning on MOOCs requires a good internet connection and sufficient technical settings to ensure users can access and use it effectively. In most situations, a MOOC platform is hosted by a designated provider or learning institution with adequate IT supervision. In cases there are any technical issues at the platform end, the support team will give notification or take prompt action to resolve them. MOOC platforms could be offline until issues are fixed. As I observed from the UTeM case study, it will lead to an odd or significant change (very low or zero scores) to the module or widget completion rate. At the user end, weak or no internet connectivity or device compatibility are two possible reasons to consider. Learners must also ensure appropriate technical arrangements to access the learning tools, materials and activities. The course admin should consider getting feedback from learners on whether they are technically ready for MOOC learning, as (Gütl C. et al., 2014) discovered that 14.93% of learners indicated they were 'not technically prepared for MOOC courses.

Instruction: MOOCs have been criticised for poor instruction design, leading to dropout and low completion numbers issues (Fredricks, Blumenfeld and Paris., 2004). Continuously decreasing or volatile indicators on both dataset scores in the MPM model indicate possible issues in the instruction design area that are worth considering. The course admin could reflect on how explicitly the instruction was given to learners or if the instruction was confusing. As MOOC learners come from various backgrounds, is the instruction and language used understandable to general learners? A study by (Gütl C. et al., 2014) found that 6.72% of learners indicated that 'classes were poorly taught' and 3.73% said the course was poorly designed.

Content: A slight decrease or increase will generate a low difference score. The reasonable hypothesis from lower difference scores is that learners already get used to the course, thus retaining them to keep progressing. An update on content might give new motivation to learners. In this situation, the course admin should identify their learner's benchmark level and plan to increase the difficulty level, reduce it, or introduce a new content type. A study by (Gütl C. et al., 2014) found that 8.96% of learners stated the program was too difficult; in contrast, 10 (7.46%) emphasised that the 'program was not challenging'. This contrast feedback is expected, considering MOOC learners come from various backgrounds.

Human: The MPM model uses two data sets to measure course or learner performances. The algorithm will use data from the completion module and the completion widget for course performance. The algorithm will use data from the completion module and assessment scores for learner performance. There is a possibility that the learner could progress and complete the module but not complete the widget activities or assessments. This will give the mixing trend results. "Personal health problems" and "family problems" are two feedbacks given by learners as factors for not completing (Gütl C. et al., 2014). Whether to skip part of the learning activities or not is a decision solely made by the learner, and human factors are one of the areas course admins should consider inspecting.

Environment: The environment area for consideration factors is addressing the learner environment, not the platform. MOOCs are promoted as a learning platform that enables learners to use it at any time and their convenience. Therefore, the learner environment is also essential in determining performance. Significant increase or decrease relates to the sudden learner enrolment or course departure. These situations often happen in the early weeks of MOOC course offerings. Good marketing or advertising also affects the enrolment boom. Although most MOOC courses are free, many of today's platforms charge fees to enrol. Promotion where the first module is free and then the learner needs to enrol and pay for the future module is part of the MOOCs business model nowadays. A study by (Gütl C. et al., 2014) indicated that 7.46% raised 'financial difficulties as a reason for not completing MOOC courses. Another environmental factor to consider is if any events took place. Festive semester breaks and national holidays often put learners in holiday moods as well, and the tendency to pause learning on MOOCs is high.

These consideration factors could be observed easily in some courses where the course admin has experienced a previous group of students. Over time, and with more data, I believe the consideration factor indicator can be updated and improved for more accuracy with the MPM model results. This belief is also shared by (Tian-yi Liu and Xiu Li., 2017) as they mentioned, the approach to finding out the reason for low completion on MOOC could be improved by testing on larger scale dataset with more learner features, applying senior clustering and association rules mining algorithms with various arguments, and cooperating with other statistical or descriptive methods to find out reasons for low completion altogether. As for the MPM model consideration factor, future study is required, mainly based on the five areas.

The MPM model incorporates the Consideration Factors Indicator alongside the Condition Indicator and Performance Metric to pinpoint areas that need improvement in course delivery. The assessment criteria of the Consideration Factor Indicator are influenced by variables such as technical issues, content quality, and learner engagement. By integrating these variables into the design of the indicator, the MPM Model can provide practical suggestions to course administrators and learners, enabling them to make targeted improvements based on the analysis of crucial performance factors.

The MPM Model utilizes variables derived from simulations, such as completion rates, learner performance trends, and algorithmic calculations, to shape the Condition Indicator, Performance Metric, and Consideration Factor Indicator. Through the strategic incorporation of these variables into the design of essential components like metrics and indicators, the MPM Model is able to assess performance, offer practical insights, and foster ongoing enhancements in MOOC platforms.

5.5 Chapter Conclusion

The successful completion of the uniform dataset design activity marked a significant milestone in the Chapter Conclusion. This accomplishment yielded vital information and appropriate data parameters that were essential for commencing the algorithm design process. The Course Performance and Learner Performance algorithms were meticulously developed, drawing upon the conceptual framework and logic derived from the pseudocode. To ensure their effectiveness and resilience against potential biases and challenges, the algorithm designs underwent rigorous testing through a series of simulations encompassing various data scenarios.

Simulations hold great importance in research endeavours as they serve multiple purposes. Firstly, they validate the algorithm logic, ensuring its accuracy and reliability. Secondly, simulations aid in identifying biases that may be present within the algorithms. Lastly, they assess the algorithms' ability to withstand diverse case scenarios, thereby gauging their robustness. By focusing on performance measurement, these simulations provide valuable insights into the necessary components required to finalize the performance measurement model.

The meticulous design of measurement metrics and indicators played a pivotal role in completing the MPM Model. These metrics, such as the Condition Indicator, Performance Metric, and Consideration Factor Indicator, are instrumental in evaluating algorithm results and offering guidance for potential enhancements based on the analysis conducted.

The effective implementation of parameters in simulations has successfully achieved the goals and objectives of the algorithms. Performance evaluations were carried out and validated in various scenarios, showcasing the adaptability and precision of the algorithms. A crucial insight gained from the simulations was the vital role played by metrics and indicators in enhancing the

MPM model. These elements not only aid in result interpretation but also provide valuable insights for refining the algorithms and improving performance outcomes.

The successful development of the MPM model design represents a significant milestone in this research project. The model now includes two distinct performance measurement algorithms for courses and learners, supported by the Condition Indicator, Performance Metric, and Consideration Factor Indicator. Through rigorous testing in simulations using both generated and random sample data, the effectiveness and dependability of the algorithms were extensively assessed. The upcoming section will present a detailed analysis of the MPM model experiments, highlighting findings and outcomes obtained from real sample data collected from MOOC platforms.

The functionality of the algorithms in simulations has been validated through meticulous design and testing. This process has not only confirmed their effectiveness but has also emphasized the crucial role of metrics and indicators in improving the performance measurement model. The successful development of the MPM model represents a significant advancement in the understanding and evaluation of course and learner performance. By utilizing the knowledge gained from simulations and algorithm testing, this research study has established a strong foundation for further exploration and refinement of performance measurement methodologies within the context of MOOC platforms.

The variables examined in the simulations, such as completion rates, learner performance trends, and algorithmic calculations, have informed the creation of key metrics within the MPM model. For example, completion rates and performance trends have been translated into Performance Metrics, which provide a quantitative assessment of course and learner performance. On the other hand, factors that influence performance, such as technical issues or content quality, have been incorporated into the Consideration Factor Indicator. This indicator guides administrators in identifying areas that require improvement based on the analysis conducted. This strategic integration of variables into metrics and consideration factors enhances the MPM model's ability to offer comprehensive insights and actionable recommendations for optimizing performance outcomes in MOOC platforms.

Chapter 6 MPM Model Experiments

6.1 Introduction

The main goal of the experiments is to test the MPM Model, which consists of the indicator, metric, and algorithm for performance measurement. Every experiment activity uses sample data from the MOOC platforms OpenLearning and FutureLearn. I created a Microsoft Excel document that included the embedded MPM performance algorithms as a tool. In each experiment, I used the tool to compute learning analytic data, assess performance, show findings, and create charts with visual aids for analysis. I describe the results of my experiments in this chapter. Each experiment section includes an observation and discussion sub-section.

6.2 Course Performance Experiments

I extracted data from MOOC platforms for a total of fifteen MOOC courses. Ninety-five courses are included in the data, and each course has between one and eleven cohorts. Each course has between 75 and 4,927 students enrolled.

Table 41: List of MOOC Learning Analytics Data Sources

#	Course Name	Course Label	Number of Learner	Data Cohort	MOOC Platform
1	Multimedia Systems	A	1,589	11	OpenLearning
2	Programming Technique	B	696	6	OpenLearning
3	Critical and Creative Thinking	C	6,185	7	OpenLearning
4	Mechanical Vibration	D	622	14	OpenLearning
5	Motion Graphics	E	221	4	OpenLearning
6	Numerical Methods	F	460	5	OpenLearning
7	Malaysian University English Test Preparation	G	499	5	OpenLearning
8	Principles of Electrical and Electronic	H	403	6	OpenLearning
9	An Introduction to Database	I	1,881	7	OpenLearning
10	Pengurusan Tenaga Efisien	J	75	2	OpenLearning
11	Bahasa Jepun 1	K	597	9	OpenLearning
12	Mandarin 1	L	1,619	7	OpenLearning
13	Technology Entrepreneurship	M	4,611	7	OpenLearning

14	Information Technology Security	N	177	4	OpenLearning
15	Teaching Language in Primary School. Putting Research into Practice 2	O	4,927	1	FutureLearn

The decision to include only one FutureLearn course in the experiment activity was primarily driven by the limited availability of data samples from the platform. Challenges related to data accessibility, privacy constraints, and complexities in extracting data may have hindered researchers from including multiple courses in their analysis, resulting in the selection of a single course for examination. Despite the constrained data sample, focusing on one course enabled a more thorough and the potential uncovering valuable insights that may not have been as evident in a broader sample. Although the results may not be broadly applicable to all FutureLearn courses, the detailed examination of one course can provide targeted and context-specific recommendations for enhancing online learning experiences within that specific course framework. Moreover, the focused analysis on a single FutureLearn course allowed researchers to gain a comprehensive understanding of the unique factors influencing learner performance within that specific context. By closely examining one course, researchers could identify trends, challenges, and opportunities that are specific to that particular course and may have been overlooked in a broader analysis. Despite the constraints imposed by the limited data sample, the detailed exploration of one course can offer valuable insights into the effectiveness of instructional strategies, course design elements, and approaches to learner engagement within that specific course setting.

I begin each experiment for every MOOC course cohort by cleaning and pre-processing the data. Upon obtaining a comprehensive understanding of the learning analytics data made accessible in every course, I chose six cohorts for in-depth investigations, scrutiny, and evaluation. The filter selection was based on the availability of data, where it is reasonable to conduct follow-up studies on a course with a sufficient amount of data and cohorts for comparison.

Table 42 and Table 43 shows the data label and performance benchmark used for each course performance experiment.

Table 42: Data Table Label

Code	Label
MDS	Module Difference Score
WDS	Widget Difference Score
PI 1	Module Performance Indicator
PI 2	Widget Performance Indicator
PL	Performance Level

Table 43: Performance Metric

Percentage	Performance Indication
76% to 100%	Excellent Performance
51% to 75%	Good Performances
26% to 50%	Poor Performance
0% to 25%	Very Poor Performance

The MPM Course algorithm, which compares data from the current module with the previous module, calculates performance indication. Indications: any increase is regarded as positive, and any decrease is regarded as negative. Below are the subsections containing the results of experiments 1, 2, and 3 based on Course A and experiments 4, 5, and 6 based on Course L.

6.2.1 Experiment 1: Course A 2019-1

Course A, Sem 1 2019 cohort data is used in Experiment 1. Course Map (M1), Evaluation (M15), Related Sources (M16), and Sample Project (M17) by the course administrator are among the topics covered in its total of 17 modules, which are arranged as Level 1 (M2) to Level 13 (M14). Completed Widget and Completed Modules are the two datasets that were used. Next, Table 44 shows both data sets were used for measurement. The MDS and WDS are computed to find the I1, I2, and PL.

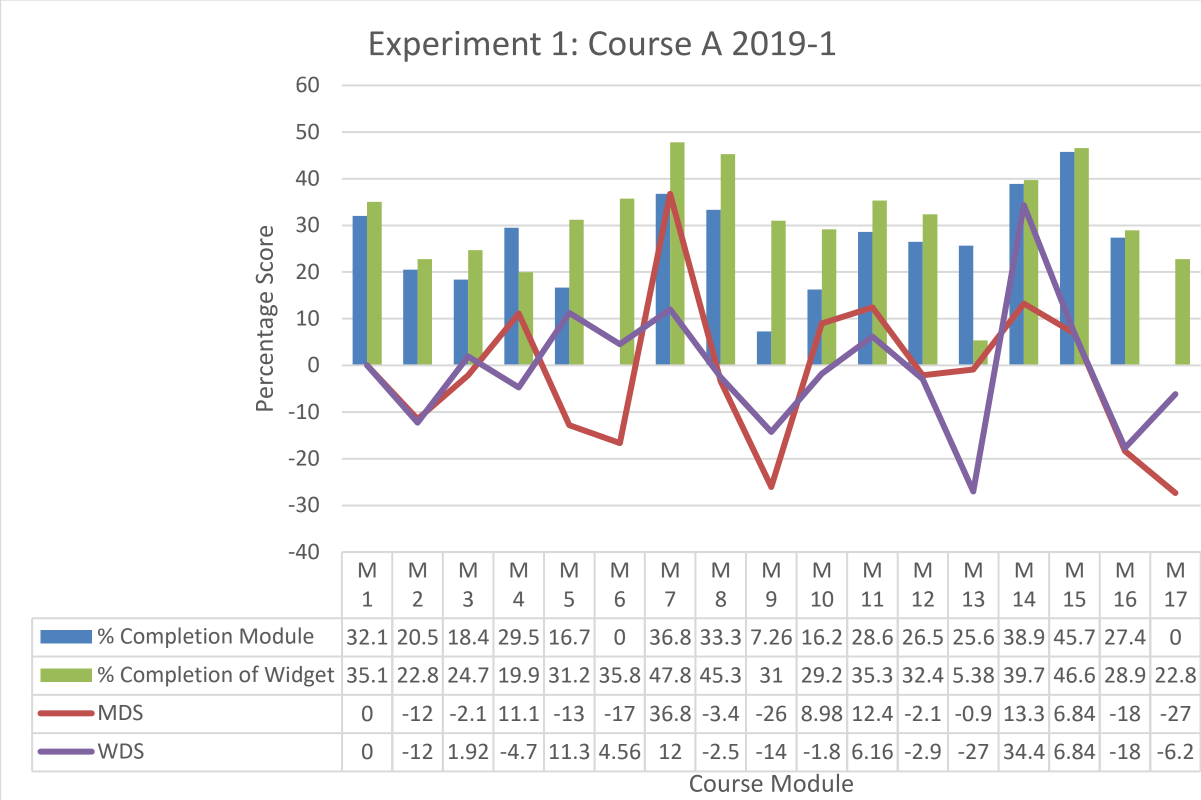
Table 44: Experiment 1 Data Table

	% Completion Module	% Completion of Widget	MDS	I1	WDS	I2	PL
M1	32.05	35.05	0	Positive	0	Positive	100%
M2	20.51	22.75	-11.54	Negative	-12.3	Negative	50%
M3	18.38	24.67	-2.13	Negative	1.92	Positive	50%
M4	29.49	19.93	11.11	Positive	-4.74	Negative	63%
M5	16.67	31.2	-12.82	Negative	11.27	Positive	50%
M6	0	35.76	-16.67	Negative	4.56	Positive	42%
M7	36.75	47.78	36.75	Positive	12.02	Positive	50%

M8	33.33	45.25	-3.42	Negative	-2.53	Negative	44%
M9	7.26	30.98	-26.07	Negative	-14.27	Negative	44%
M10	16.24	29.17	8.98	Positive	-1.81	Negative	50%
M11	28.63	35.33	12.39	Positive	6.16	Positive	50%
M12	26.5	32.4	-2.13	Negative	-2.93	Negative	46%
M13	25.64	5.38	-0.86	Negative	-27.02	Negative	42%
M14	38.89	**39.74**	13.25	Positive	34.36	Positive	65%
M15	45.73	**46.58**	6.84	Positive	6.84	Positive	57%
M16	27.35	**28.92**	-18.38	Negative	-17.66	Negative	53%
M17	0	**22.77**	-27.35	Negative	-6.15	Negative	53%

	I1	I2	PL
Positive	7	8	**15**
Negative	10	9	19
			44%
		Poor Performance	

There were a total of 15 positive performances and 19 negative performances, as determined by the course performance algorithm. The performance level in this experiment is 44%, considered a low-performance course. A bar and line graph is used to visualise data, as seen in the Figure 41 below.



	M 1	M 2	M 3	M 4	M 5	M 6	M 7	M 8	M 9	M 10	M 11	M 12	M 13	M 14	M 15	M 16	M 17
% Completion Module	32.1	20.5	18.4	29.5	16.7	0	36.8	33.3	7.26	16.2	28.6	26.5	25.6	38.9	45.7	27.4	0
% Completion of Widget	35.1	22.8	24.7	19.9	31.2	35.8	47.8	45.3	31	29.2	35.3	32.4	5.38	39.7	46.6	28.9	22.8
MDS	0	-12	-2.1	11.1	-13	-17	36.8	-3.4	-26	8.98	12.4	-2.1	-0.9	13.3	6.84	-18	-27
WDS	0	-12	1.92	-4.7	11.3	4.56	12	-2.5	-14	-1.8	6.16	-2.9	-27	34.4	6.84	-18	-6.2

Figure 41: Experiment 1 Data Visualization

Experiment 1 Observation: Based on the percentage of completion modules and completion widget, I can conclude Course A 2019-1 is a poor course where the average percentage completion module score is 23.73% and 31.39% completion widget score. This can be observed by referring to the bar chart plotted. This is also clearly visible on the graph, where scores are below the 50% line. As I look and analyse future details on each module and widget differences scores, I can start to see a negative performance indication.

A performance indicator is computed. A 44% Performance Level score is obtained from measuring 15 positive signs and 19 negative indications. Course A 2019-1 is regarded as a *poor performance* course following the performance metrics I established for this experiment.

Only 15 Course A 2019-1 components have increasing scores, indicating weak performance and low engagement among most learners.

6.2.2 Experiment 2: Course A 2019-2

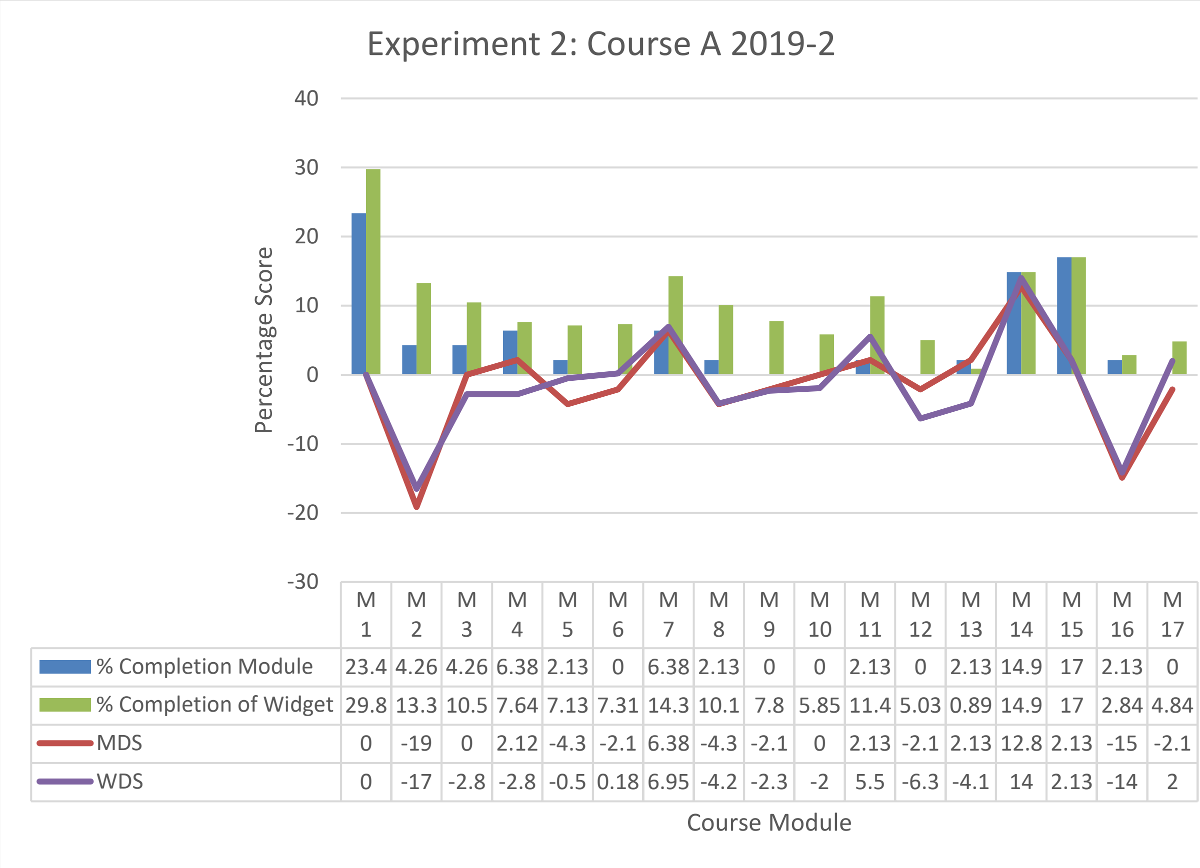
Data from the Course A, Sem 2 2019 cohort is used in Experiment 2. The course structure is in line with that of the course's prior cohort. Completion of Modules and Completion of Widget are the two datasets utilised, and the set consists of 17 modules in total. Following that, both data sets were used for measurement, as the Table 45 illustrates. The MDS and WDS are computed to find the I1, I2, and PL.

Table 45: Experiment 2 Data Table

	% Completion Module	% Completion of Widget	MDS	I1	WDS	I2	PL (%)
M1	23.4	29.79	0	Positive	0	Positive	100
M2	4.26	13.28	-19.14	Negative	-16.51	Negative	50
M3	4.26	10.46	0	Positive	-2.82	Negative	43
M4	6.38	7.64	2.12	Positive	-2.82	Negative	44
M5	2.13	7.13	-4.25	Negative	-0.51	Negative	36
M6	0	7.31	-2.13	Negative	0.18	Positive	36
M7	6.38	14.26	6.38	Positive	6.95	Positive	44
M8	2.13	10.11	-4.25	Negative	-4.15	Negative	39
M9	0	7.8	-2.13	Negative	-2.31	Negative	37
M10	0	5.85	0	Negative	-1.95	Negative	33
M11	2.13	11.35	2.13	Positive	5.5	Positive	36
M12	0	5.03	-2.13	Negative	-6.32	Negative	35
M13	2.13	0.89	2.13	Positive	-4.14	Negative	36
M14	14.89	14.89	12.76	Positive	14	Positive	40
M15	17.02	17.02	2.13	Positive	2.13	Positive	44
M16	2.13	2.84	-14.89	Negative	-14.18	Negative	41
M17	0	4.84	-2.13	Negative	2	Positive	42

	I1	I2	PL
Positive	8	7	**15**
Negative	9	10	19
			44%
		Poor Performance	

There were a total of 15 positive performances and 19 negative performances, as determined by the course performance algorithm. As a result, the course's performance level comes to 44%, which is considered low. As seen in Figure 42 below, a bar and line graph are used to display data.



	M 1	M 2	M 3	M 4	M 5	M 6	M 7	M 8	M 9	M 10	M 11	M 12	M 13	M 14	M 15	M 16	M 17
% Completion Module	23.4	4.26	4.26	6.38	2.13	0	6.38	2.13	0	0	2.13	0	2.13	14.9	17	2.13	0
% Completion of Widget	29.8	13.3	10.5	7.64	7.13	7.31	14.3	10.1	7.8	5.85	11.4	5.03	0.89	14.9	17	2.84	4.84
MDS	0	-19	0	2.12	-4.3	-2.1	6.38	-4.3	-2.1	0	2.13	-2.1	2.13	12.8	2.13	-15	-2.1
WDS	0	-17	-2.8	-2.8	-0.5	0.18	6.95	-4.2	-2.3	-2	5.5	-6.3	-4.1	14	2.13	-14	2

Figure 42: Experiment 2 Data Visualization

Experiment 2 Observation: Based on the percentage of completion module and completion widget, I can conclude Course A 2019-2 is a very poor course where the average percentage completion module score is 5.13% and 10.02% completion widget score. This can be observed by referring to the bar chart plotted, where scores are relatively below the 10% line. I can see a negative performance indication as I look at and analyse future details on each module and widget difference scores.

Performance indication is calculated with 15 positive and 19 negative indicators, resulting in a 44% Performance Level score. Regarding the performance metrics I set for this experiment, Course A 2019-2 is considered a *poor performance* course.

Course A 2019-2 is a *very poor* course where most learners are not engaged or complete the module and widget, and poor performance as only 15 components record increasing scores.

6.2.3 Experiment 3: Course A 2020-1

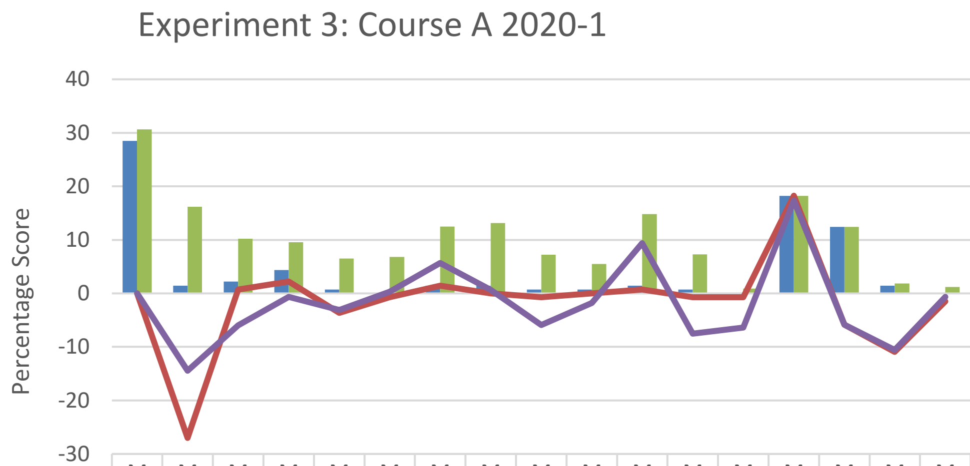
Data from the Course A, Sem 1 2020 cohort is used in Experiment 3. The course design is in line with that of the course's prior cohort. Completion of Modules and Completion of Widget are the two datasets utilised, and the set consists of 17 modules. Both data sets were measured and illustrates in Table 46 below. The I1, I2, and PL are calculated using MDS and WDS.

Table 46: Experiment 3 Data Table

Module	% Completion Module	% Completion of Widget	MDS	I1	WDS	I2	PL (%)
M1	28.47	30.66	0	Positive	0	Positive	100
M2	1.46	16.21	-27.01	Negative	-14.45	Negative	50
M3	2.19	10.22	0.73	Positive	-5.99	Negative	43
M4	4.38	9.58	2.19	Positive	-0.64	Negative	44
M5	0.73	6.5	-3.65	Negative	-3.08	Negative	36
M6	0	6.8	-0.73	Negative	0.3	Positive	36
M7	1.46	12.48	1.46	Positive	5.68	Positive	44
M8	1.46	13.14	0	Positive	0.66	Positive	45
M9	0.73	7.24	-0.73	Negative	-5.9	Negative	43
M10	0.73	5.48	0	Positive	-1.76	Negative	42
M11	1.46	14.84	0.73	Positive	9.36	Positive	43
M12	0.73	7.3	-0.73	Negative	-7.54	Negative	41
M13	0	0.91	-0.73	Negative	-6.39	Negative	40
M14	18.25	18.25	18.25	Positive	17.34	Positive	44
M15	12.41	12.41	-5.84	Negative	-5.84	Negative	44
M16	1.46	1.83	-10.95	Negative	-10.58	Negative	41
M17	0	1.19	-1.46	Negative	-0.64	Negative	40

	I1	I2	PL
Positive	8	6	**14**
Negative	9	11	20
			41%
		Poor Performance	

There were a total of 14 positive performances and 20 negative performances, as determined by the course performance algorithm. As a result, the course's performance level adds up to 41%, which is considered poor. A bar and line graph is used to visualise data, as seen in Figure 43 below.



	M 1	M 2	M 3	M 4	M 5	M 6	M 7	M 8	M 9	M 10	M 11	M 12	M 13	M 14	M 15	M 16	M 17
% Completion Module	28.5	1.46	2.19	4.38	0.73	0	1.46	1.46	0.73	0.73	1.46	0.73	0	18.3	12.4	1.46	0
% Completion of Widget	30.7	16.2	10.2	9.58	6.5	6.8	12.5	13.1	7.24	5.48	14.8	7.3	0.91	18.3	12.4	1.83	1.19
MDS	0	-27	0.73	2.19	-3.7	-0.7	1.46	0	-0.7	0	0.73	-0.7	-0.7	18.3	-5.8	-11	-1.5
WDS	0	-14	-6	-0.6	-3.1	0.3	5.68	0.66	-5.9	-1.8	9.36	-7.5	-6.4	17.3	-5.8	-11	-0.6

Figure 43: Experiment 3 Data Visualization

Experiment 3 Observation: Course A 2020-1 is a very poor course, with an average percentage completion module score of 4.46% and an average percentage completion widget of 10.30%. This conclusion is based on the percentages of completion modules and completion widgets. The plotted bar chart, where scores fall significantly below the 10% line, illustrates this. I can observe a negative performance indication as I examine and evaluate further information on every module and widget difference score.

Performance indication is calculated with 14 positive and 20 negative indicators measured, resulting in a 41% Performance Level score. Regarding the performance metrics I set for this experiment, Course A 2020-1 is considered a ***poor performance course***.

Course A 2020-1 is a ***very poor course*** where most learners are not engaged or complete the module and widget, and poor performance as only 14 components record increasing scores.

6.2.4 Experiment 4: Course L 2019-1

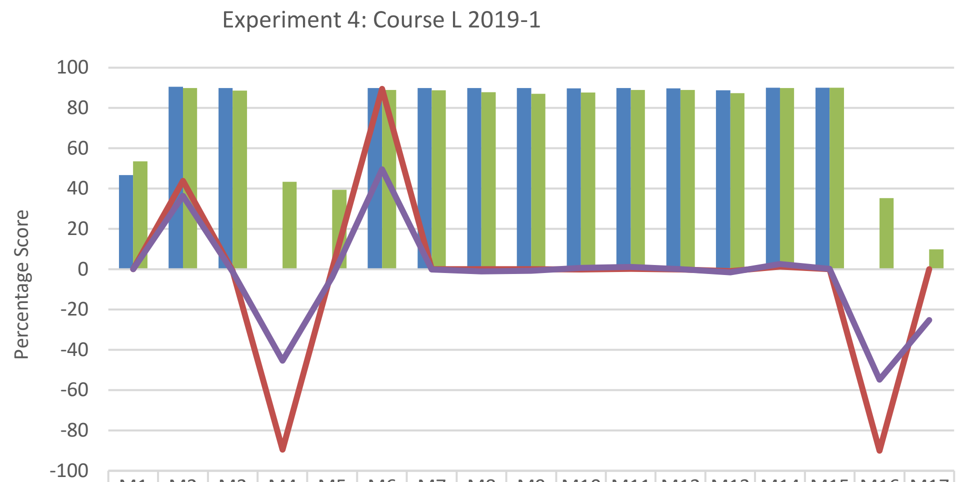
Data from Course L, Sem 1 2019 cohort is used in Experiment 4. It is divided into 17 modules, numbered M1 through M17. Completion of Modules and Completion of Widget are the two utilised datasets. Both data sets were measured, as illustrates in Table 47. The I1, I2, and PL are calculated using MDS and WDS.

Table 47: Experiment 4 Data Table

Module	% Completion Module	% Completion of Widget	MDS	I1	WDS	I2	PL (%)
M1	46.74	53.53	0	Positive	0	Positive	100
M2	90.58	89.85	43.84	Positive	36.32	Positive	100
M3	89.86	88.68	-0.72	Negative	-1.17	Negative	67
M4	0.36	43.33	-89.5	Negative	-45.35	Negative	50
M5	0.36	39.34	0	Negative	-3.99	Negative	40
M6	89.86	88.91	89.5	Positive	49.57	Positive	50
M7	89.86	88.79	0	Negative	-0.12	Negative	43
M8	89.86	87.79	0	Negative	-1	Negative	38
M9	89.86	87.04	0	Negative	-0.75	Negative	33
M10	89.67	87.75	-0.19	Negative	0.71	Positive	35
M11	89.86	88.89	0.19	Positive	1.14	Positive	41
M12	89.67	88.97	-0.19	Negative	0.08	Positive	42
M13	88.77	87.36	-0.9	Negative	-1.61	Negative	38
M14	90.04	89.92	1.27	Positive	2.56	Positive	43
M15	90.04	90.04	0	Negative	0.12	Positive	43
M16	0	35.24	-90.04	Negative	-54.8	Negative	41
M17	0	9.96	0	Negative	-25.28	Negative	38

	I1	I2	PL
Positive	5	8	**13**
Negative	12	9	21
			38%
		Poor Performance	

Calculated using the Course Performance Algorithm, a total of 13 positive performances and 21 negative performances were recorded. This sums the performance level to 38%, a poor performance course. Data is visualised using a bar and line graph, as shown in the Figure 44 below.



	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17
% Completion Module	46.74	90.58	89.86	0.36	0.36	89.86	89.86	89.86	89.86	89.67	89.86	89.67	88.77	90.04	90.04	0	0
% Completion of Widget	53.53	89.85	88.68	43.33	39.34	88.91	88.79	87.79	87.04	87.75	88.89	88.97	87.36	89.92	90.04	35.24	9.96
MDS	0	43.84	-0.72	-89.5	0	89.5	0	0	0	-0.19	0.19	-0.19	-0.9	1.27	0	-90	0
WDS	0	36.32	-1.17	-45.4	-3.99	49.57	-0.12	-1	-0.75	0.71	1.14	0.08	-1.61	2.56	0.12	-54.8	-25.3

Course Module

Figure 44: Experiment 4 Data Visualization

Experiment 4 Observation: Based on the percentage of completion modules and completion widget, I can conclude Course L 2019-1 is a good course where, in most modules, it records a high score (average 89.82% in 12 modules out of 19 modules). This is also clearly visible on the bar graph, where the score is at 80%-line areas. I can see a negative performance indication as I look at and analyse future details on each module.

Performance indication is calculated using the MPM Course algorithm, where data from the current module is compared with the previous module. Any increment is considered a positive indication, while any decrement is a negative indication. A total of 13 positive and 21 negative indications were measured, resulting in a 38% Performance Level score. Regarding the performance metrics I set for this experiment, Course L 2019-1 is considered a ***poor performance course***.

Course L 2019-1 is a ***good course*** where most learners engage and complete the widget and module, and it is poor in performance as only 13 components record increasing scores. The next chapter will present more discussion on how this can be improved.

6.2.5 Experiment 5: Course L 2019-2

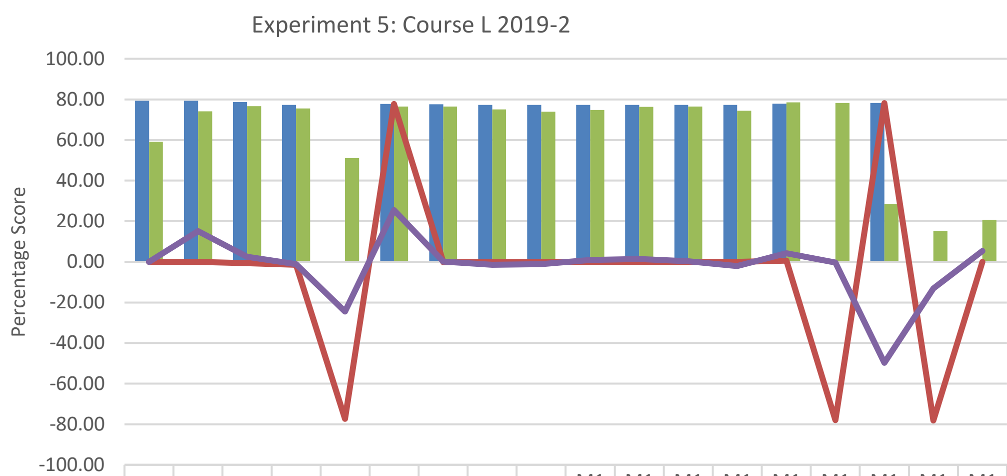
Experiment 5 uses data from Corse L's Sem 2 2019 cohort. The course structure had a minor update, with additional modules introduced and making 18 modules for the course, compared to the previous cohort of the same course. Consisting of updated 18 modules, two datasets used are Completion of Modules and Completion of Widget. Both data were then used for measurement, as shown in the Table 48 below. MDS and WDS are calculated to determine the I1, I2 and PL.

Table 48: Experiment 5 Data Table

Module	% Completion Module	% Completion of Widget	MDS	I1	WDS	I2	PL (%)
M1	79.36	59.12	0	Positive	0	Positive	100
M2	79.36	74.17	0	Negative	15.05	Positive	75
M3	78.76	76.7	-0.6	Negative	2.53	Positive	67
M4	77.35	75.52	-1.41	Negative	-1.18	Negative	50
M5	0	51.02	-77.35	Negative	-24.5	Negative	40
M6	77.76	76.49	77.76	Positive	25.47	Positive	50
M7	77.56	76.55	-0.2	Negative	0.06	Positive	50
M8	77.35	75.07	-0.21	Negative	-1.48	Negative	44
M9	77.35	73.94	0	Negative	-1.13	Negative	39
M10	77.35	74.81	0	Negative	0.87	Positive	40
M11	77.35	76.26	0	Negative	1.45	Positive	41
M12	77.35	76.47	0	Negative	0.21	Positive	42
M13	77.35	74.37	0	Negative	-2.1	Negative	38
M14	77.96	78.56	0.61	Positive	4.19	Positive	43
M15	0	78.16	-77.96	Negative	-0.4	Negative	40
M16	78.16	28.41	78.16	Positive	-49.75	Negative	41
M17	0	15.3	-78.16	Negative	-13.11	Negative	38
M18	0	20.65	0	Negative	5.35	Positive	39

	I1	I2	PL
Positive	4	10	**14**
Negative	14	8	22
			39%
		Poor Performance	

Calculated using the Course Performance Algorithm, a total of 14 positive performances and 22 negative performances were recorded. This sums the performance level to 39% as a poor performance course. Data is visualised using a bar and line graph, as shown in the Figure 45 below.



	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17	M18
% Completion Module	79.3	79.4	78.8	77.4	0	77.8	77.6	77.4	77.4	77.4	77.4	77.4	77.4	78	0	78.2	0	0
% Completion of Widget	59.1	74.2	76.7	75.5	51	76.5	76.6	75.1	73.9	74.8	76.3	76.5	74.4	78.6	78.2	28.4	15.3	20.7
MDS	0	0	-0.6	-1.4	-77	77.8	-0.2	-0.2	0	0	0	0	0	0.61	-78	78.2	-78	0
WDS	0	15.1	2.53	-1.2	-25	25.5	0.06	-1.5	-1.1	0.87	1.45	0.21	-2.1	4.19	-0.4	-50	-13	5.35

Course Module

Figure 45: Experiment 5 Data Visualization

Experiment 5 Observation: Based on the percentage of completion modules and completion widget, I can conclude Course L 2019-2 is a good course where, in most modules, it records a high score, averaging 71.29% in 14 modules out of 18 modules. This can be observed by referring to the bar chart plotted, visible on the graph where scores are close to the 80% score line. I can see a negative performance indication as I look at and analyse future details on each module.

Performance indication is calculated. A total of 14 positive and 22 negative indications were measured, resulting in a 39% Performance Level score. Regarding the performance metrics I set for this experiment, Course L 2019-2 is considered a ***poor performance course***.

Course L 2019-2 is a ***good course*** where most learners engage and complete the widget and module, but it is poor in performance as only 14 components record increasing scores and six components record unchanged scores (modules 2, 9, 10, 11, 12 and 13). The next chapter will present more discussion on how this can be improved.

6.2.6 Experiment 6: Course L 2020-1

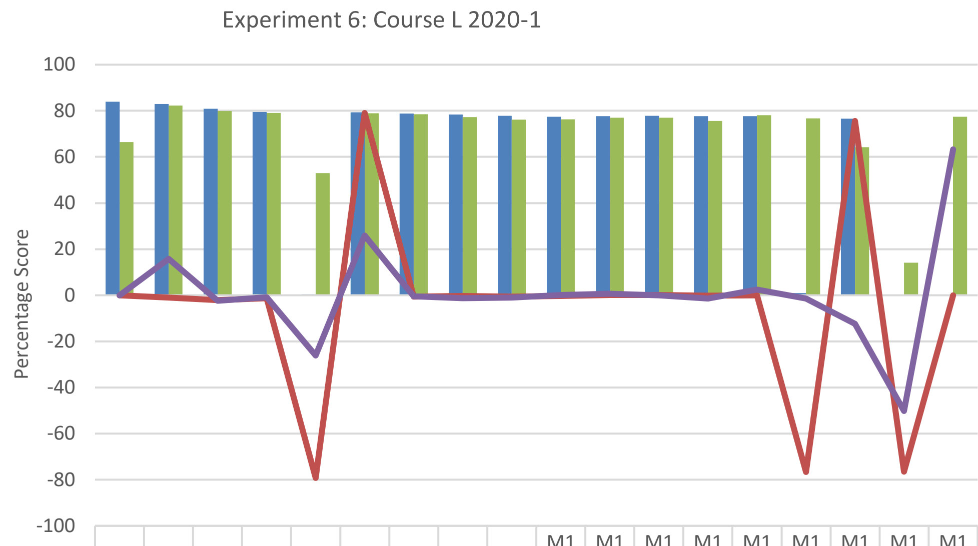
Experiment 6 is using data from Course L, Sem 1 2020 cohort. The course structure is consistent with the previous cohort of the same course. Consisting of 18 modules, two datasets used are Completion of Modules and Completion of Widget. Both data were then used for measurement, as shown in Table 49 below. MDS and WDS are calculated to determine the I1, I2 and PL.

Table 49: Experiment 6 Data Table

Module	% Completion Module	% Completion of Widget	MDS	I1	WDS	I2	PL (%)
M1	83.87	**66.46**	0	Positive	0	Positive	100
M2	82.91	**82.28**	-0.96	Negative	15.82	Positive	75
M3	80.83	**79.87**	-2.08	Negative	-2.41	Negative	50
M4	79.55	**79.03**	-1.28	Negative	-0.84	Negative	38
M5	0.32	**52.96**	-79.23	Negative	-26.07	Negative	30
M6	79.39	**78.9**	79.07	Positive	25.94	Positive	42
M7	78.75	**78.48**	-0.64	Negative	-0.42	Negative	36
M8	78.43	**77.23**	-0.32	Negative	-1.25	Negative	31
M9	77.8	**76.19**	-0.63	Negative	-1.04	Negative	28
M10	77.48	**76.35**	-0.32	Negative	0.16	Positive	30
M11	77.64	**77.05**	0.16	Positive	0.7	Positive	36
M12	77.8	**77.04**	0.16	Positive	-0.01	Negative	38
M13	77.64	**75.68**	-0.16	Negative	-1.36	Negative	35
M14	77.64	**78.13**	0	Negative	2.45	Positive	36
M15	0.96	**76.68**	-76.68	Negative	-1.45	Negative	33
M16	76.52	**64.3**	75.56	Positive	-12.38	Negative	34
M17	0	**14.11**	-76.52	Negative	-50.19	Negative	32
M18	0	**77.38**	0	Negative	63.27	Positive	33

	I1	I2	PL
Positive	5	7	**12**
Negative	13	11	24
			33%
		Poor Performance	

Calculated using the Course Performance Algorithm, a total of 12 positive performances and 24 negative performances were recorded. This sums the performance level to 33% as a poor performance course. Data is visualised using a bar and line graph, as shown in the Figure 46 below.



	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17	M18
% Completion Module	83.9	82.9	80.8	79.6	0.32	79.4	78.8	78.4	77.8	77.5	77.6	77.8	77.6	77.6	0.96	76.5	0	0
% Completion of Widget	66.5	82.3	79.9	79	53	78.9	78.5	77.2	76.2	76.4	77.1	77	75.7	78.1	76.7	64.3	14.1	77.4
MDS	0	-1	-2.1	-1.3	-79	79.1	-0.6	-0.3	-0.6	-0.3	0.16	0.16	-0.2	0	-77	75.6	-77	0
WDS	0	15.8	-2.4	-0.8	-26	25.9	-0.4	-1.3	-1	0.16	0.7	-0	-1.4	2.45	-1.4	-12	-50	63.3

Course Module

Figure 46: Experiment 6 Data Visualization

Experiment 6 Observation: Based on the percentage of completion modules and completion widget, I can conclude that Course L 2020-1 is a good course where the average percentage completion module score is 61.52% and 71.56% completion widget score. This can be observed by referring to the bar chart plotted. This is also clearly visible on the graph, where scores are closed below the 80% line. As I look and analyse future details on each module and widget differences scores, I can start to see a negative performance indication.

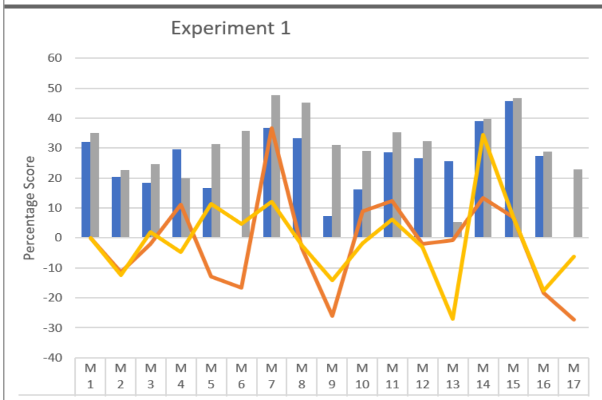
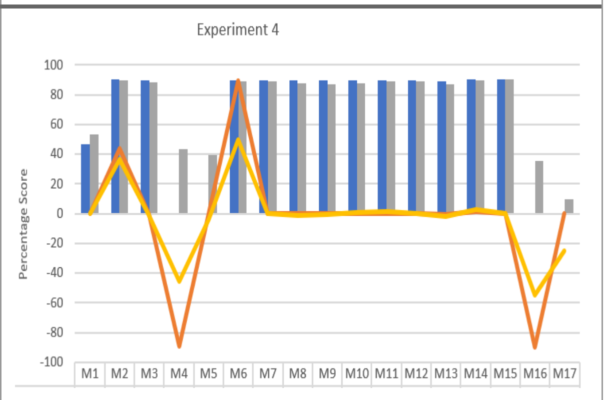
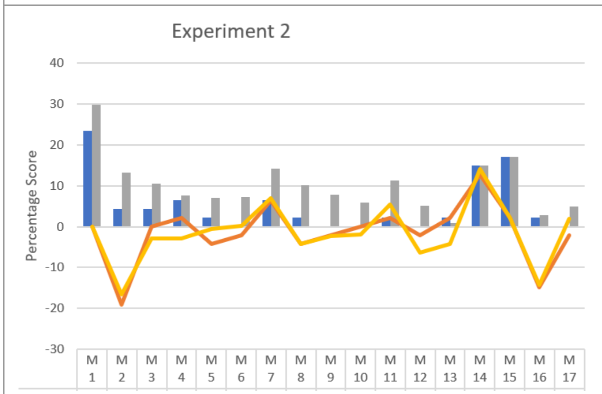
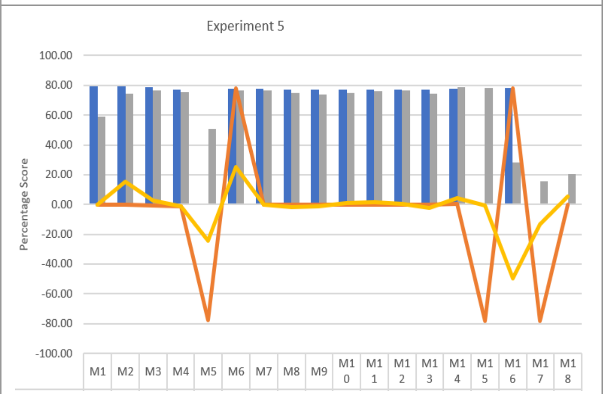
Performance indication is calculated. A total of 12 positive and 24 negative indications were measured, resulting in a 33% Performance Level score. Regarding the performance metrics I set for this experiment, Course L 2020-1 is considered a ***poor performance course***.

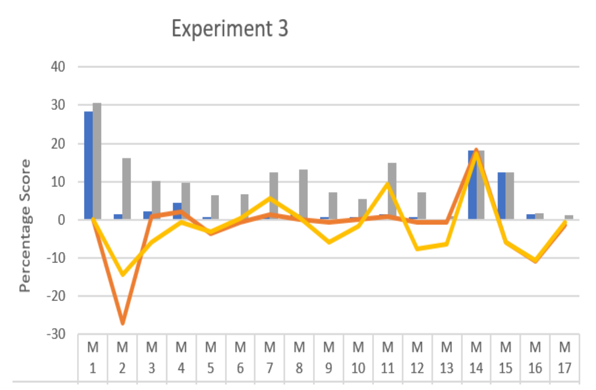
Course L 2020-1 is a ***good course*** where most learners engage and complete the widget and module, but it is poor in performance as most components record slightly decreasing scores. A total of 24 components record decreasing scores. The next chapter will present more discussion on how this can be improved.

6.2.7 Course Performance Experiment Discussions

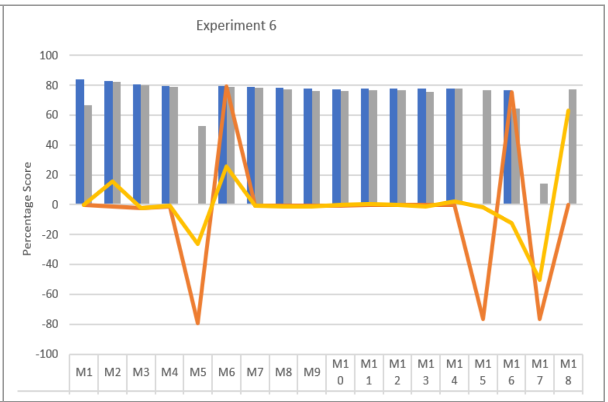
In this subsection, I address the findings from experiments 1 through 6 and the observations made in each experiment. By comparing each experiment to comprehend the learning analytic data and what steps can be taken to improve, the process of using the MPM model to perform course performance monitoring and measurement, analysis results, graph projection, and observation is the main topic of discussion.

Table 50: Course Performance Analysis Graph

Course A	Course L
	
Poor course and poor performance (44%)	Good course but poor performance (38%)
	
Very poor course and poor performance (44%)	Good course but poor performance (39%)



Very poor course and poor performance (41%)



Good course but poor performance (33%)

All six experiment graphs from two courses and three cohorts are displayed in Table 50 above. Remembering that benchmarking and performance metrics are adaptable and can be adjusted to meet user standards is critical. I employ the standard performance metric in this experiment, as indicated in the Table 51 below.

It is essential to recognize that the metrics in Table 51 are default and can be tailored to suit user benchmark systems. However, the data indicating a downward trend in scores is a significant factor contributing to the poor performance ratings observed across all courses in the experiments. Understanding the performance definition embedded in the MPM Model is crucial in interpreting these findings accurately.

Table 51: Default Performance Metric

Score	Performance Level
76% to 100%	Excellent Performance
51% to 75%	Good Performances
26% to 50%	Poor Performance
0% to 25%	Very Poor Performance

The first step in conducting measurement and analysis is dataset preparation. It is necessary to filter out the necessary data selection and clean up raw datasets directly downloaded from the MOOC platform. More focus and a fundamental grasp of the course structure were needed for this laborious procedure. The MOOC learning analytics data has been cleaned and is ready for use in the same way as in this research study; the data cleaning procedure is outside the scope of this study. Nonetheless, I believe support is required to guarantee that the dataset is appropriate for the MPM model and that the data-cleaning procedure can be carried out correctly.

Another crucial step that needs to be taken into consideration, in addition to data cleaning, is making sure the suitable dataset and data are used when transferring them into the MPM tool.

Based on the results of the six experiments, I can say that in all three cohorts, Course L had a higher completion score than Course A. Each course in Course A had a low completion score and was rated as poor or extremely poor. This is not the case for Course L, wherein all three cohorts received relatively high completion scores and were noted as good courses.

Significant similarities between the trend patents of various cohorts within the same course can also be observed. This phenomenon is the outcome of the course delivery method remaining largely unchanged.

6.3 Learner Performance Experiments

Table 52 shows the first parameter (Parameter 1) data of six learners chosen from my sample dataset for the learner performance experiments. Every student was chosen from the same MOOC course. There are seventeen modules available, but only three tests have been administered.

Table 52: Learners Module Completion Score

	Learner 1	Learner 2	Learner 3	Learner 4	Learner 5	Learner 6
M1	50.00	50.00	25.00	50.00	50.00	50.00
M2	83.33	83.33	41.67	83.33	83.33	83.33
M3	41.67	83.33	41.67	83.33	83.33	83.33
M4	40.00	80.00	40.00	80.00	80.00	80.00
M5	42.86	64.29	42.86	42.86	85.71	85.71
M6	45.45	68.18	45.45	45.45	90.91	90.91
M7	44.44	44.44	44.44	44.44	44.44	88.89
M8	44.44	44.44	44.44	44.44	44.44	44.44
M9	45.00	45.00	45.00	45.00	45.00	45.00
M10	45.45	45.45	45.45	45.45	45.45	45.45
M11	44.44	44.44	44.44	44.44	44.44	44.44
M12	45.00	45.00	45.00	45.00	45.00	45.00
M13	45.00	45.00	45.00	45.00	45.00	45.00

M14	50.00	100.00	50.00	50.00	100.00	66.67
M15	0.00	0.00	0.00	0.00	0.00	0.00
M16	50.00	50.00	50.00	50.00	50.00	50.00
M17	0.00	0.00	0.00	0.00	0.00	0.00

For the second parameter (Parameter 2), input data can be from MOOC analytic data or non-MOOC analytic data such as offline assignments or offline or other platform-based quizzes, exams or assignments. Unfortunately, assessment data available for this course is only from MOOC platform activities. Table 53 shows the Parameters 2 data used.

Table 53: Learners Assessment Percentage Score

	Learner 1	Learner 2	Learner 3	Learner 4	Learner 5	Learner 6
M1						
M2						
M3	17.00	21.00	75.00	6.00	29.00	74.00
M4						
M5						
M6						
M7						
M8	44.00	86.00	54.00	18.00	0.00	6.00
M9						
M10						
M11						
M12						
M13						
M14						
M15						
M16	31.00	94.00	82.00	2.00	87.00	58.00
M17						

Like Course Performance experiments, I run each experiment individually, starting with data cleaning and pre-processing for each MOOC learner. After getting a clear picture of the learning analytic data that was made available, I conducted individual experiments for each of the six learners for detailed experiment observation and analysis. The selection was random, from one same MOOC course.

For each learner performance experiment, data table label (Table 54) and performance benchmark (Table 55) are used as follows:

Table 54: Data Table Label

Code	Label
MDS	Module Difference Score
ADS	Assessment Difference Score
PI 1	Module Performance Indicator
PI 2	Assessment Performance Indicator
PL	Performance Level

Table 55: Performance Metric

Percentage	Performance Indication
76% to 100%	Excellent Performance
51% to 75%	Good Performances
26% to 50%	Poor Performance
0% to 25%	Very Poor Performance

Performance indication is calculated using the MPM learner algorithm, where data from the current module is compared with the previous module. Any increment is considered a positive indication, while any decrement is a negative indication. In subsection 6.3.1 to subsection 6.3.6, I present experiments 7, 8, 9, 10, 11 and 12 based on Course A.

6.3.1 Experiment 7: Learner 1

Experiment 7 uses random learner data from Course A. It consists of a total of 17 modules and three assessments. Two datasets used as Input 1 and Input 2 are Completion of Module and Assessment Score, with an option to add data from other sources for Input 2. Both data were then used for measurement, as shown in the Table 56 below. MDS and ADS are calculated to determine the I1, I2 and PL.

Table 56: Experiment 7 Data Table

MODULE	% Completion Module	% Assessment Score	MDS	I1	ADS	I2	% PL	+	-
M1	50.00	0.00	0.00	Positive	0.00	-	100%	1	0
M2	83.33	0.00	33.33	Positive	0.00	-	100%	2	0
M3	41.67	17.00	-41.67	Negative	17.00	Positive	75%	3	1
M4	40.00	0.00	-1.67	Negative	-17.00	-	60%	3	2
M5	42.86	0.00	2.86	Positive	0.00	-	67%	4	2
M6	45.45	0.00	2.60	Positive	0.00	-	71%	5	2

M7	44.44	0.00	-1.01	Negative	0.00	-	63%	5	3
M8	44.44	44.00	0.00	Negative	44.00	Positive	60%	6	4
M9	45.00	0.00	0.56	Positive	-44.00	-	70%	7	4
M10	45.45	0.00	0.45	Positive	0.00	-	67%	8	4
M11	44.44	0.00	-1.01	Negative	0.00	-	67%	8	5
M12	45.00	0.00	0.56	Positive	0.00	-	64%	9	5
M13	45.00	0.00	0.00	Negative	0.00	-	60%	9	6
M14	50.00	0.00	5.00	Positive	0.00	-	63%	10	6
M15	0.00	0.00	-50.00	Negative	0.00	-	59%	10	7
M16	50.00	31.00	50.00	Positive	31.00	Negative	58%	11	7
M17	0.00	0.00	-50.00	Negative	-31.00	-	55%	11	8
							I1	**I2**	**PL**
						Positive	9	2	**11**
						Negative	8	1	9
									55%
								Good Performance	

Calculated using the Learner Performance Algorithm, a total of 11 positive performances and 9 negative performances were recorded. This sums the performance level to 55% as a Good Performance learner. Data is visualised using a bar and line graph, as shown in Figure 47 below.

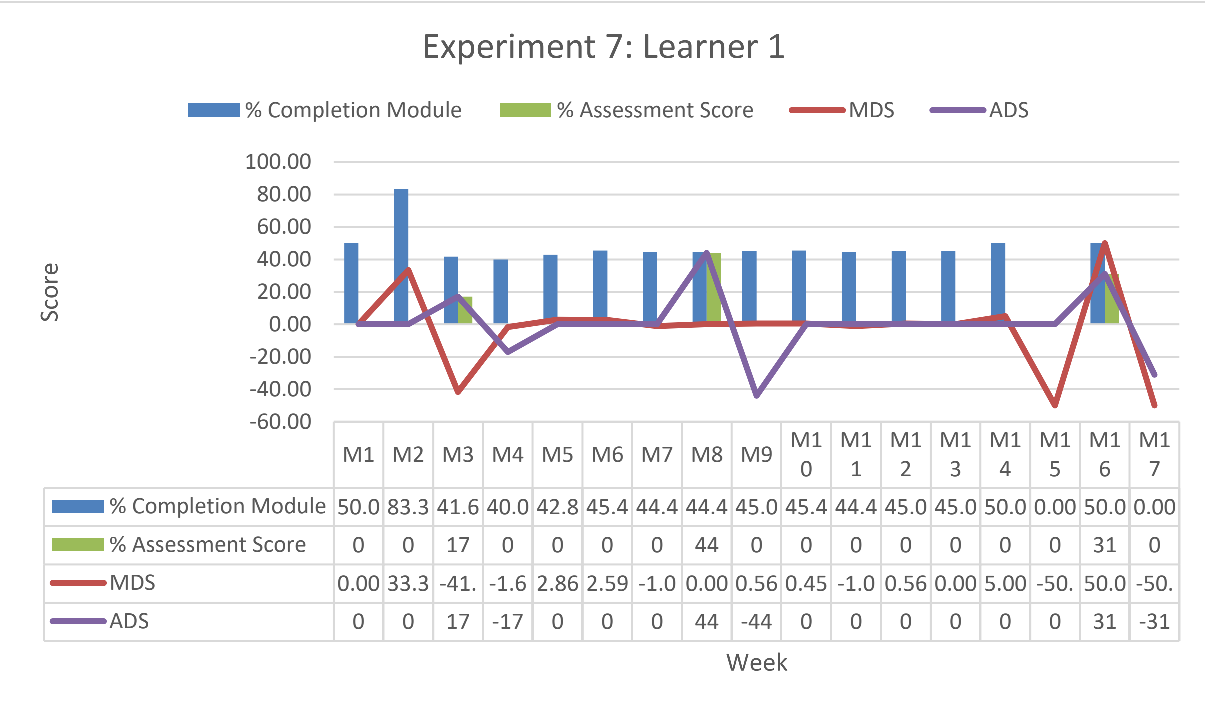


Figure 47: Experiment 7 Data Visualization

Experiment 7 Observation: Based on the percentage of completion module and assessment scores, I can conclude that Learner 1 is a poor achievement learner, where the average percentage completion module score is 42.18% and 30.66% assessment score. This can be observed by referring to the bar chart plotted. This is also clearly visible on the graph, where scores are closed at the 40% line. As I look and analyse future details on each module and assessment differences scores, I can start to see a negative performance indication.

Performance indication is calculated. A total of 11 positive and 9 negative indications were measured, resulting in a 55% Performance Level score. Referring to the performance metrics I set for this experiment, Learner 1 is considered a ***good-performance learner***, but as a ***poor in score achievement*** based on the average percentage of Input 1 and 2. Nine components recorded decreasing scores. The next chapter will present more discussion on how this can be improved.

6.3.2 Experiment 8: Learner 2

Experiment 8 uses random learner data from Course A. It consists of a total of 17 modules and three assessments. Two datasets used as Input 1 and Input 2 are Completion of Module and Assessment Score, with an option to add data from other sources for Input 2. Both data were then used for measurement, as shown in the Table 57 below. MDS and ADS are calculated to determine the I1, I2 and PL.

Table 57: Experiment 8 Data Table

MODULE	% Completion Module	% Assessment Score	MDS	I1	ADS	I2	% PL	+	-
M1	50.00	0.00	0.00	Positive	0.00	-	100%	1	0
M2	83.33	0.00	33.33	Positive	0.00	-	100%	2	0
M3	83.33	21.00	0.00	Negative	21.00	Positive	75%	3	1
M4	80.00	0.00	-3.33	Negative	-21.00	-	60%	3	2
M5	64.29	0.00	-15.71	Negative	0.00	-	50%	3	3
M6	68.18	0.00	3.90	Positive	0.00	-	57%	4	3
M7	44.44	0.00	-23.74	Negative	0.00	-	50%	4	4
M8	44.44	86.00	0.00	Negative	86.00	Positive	50%	5	5
M9	45.00	0.00	0.56	Positive	-86.00	-	60%	6	5
M10	45.45	0.00	0.45	Positive	0.00	-	58%	7	5
M11	44.44	0.00	-1.01	Negative	0.00	-	58%	7	6

M12	45.00	0.00	0.56	Positive	0.00	-	57%	8	6
M13	45.00	0.00	0.00	Negative	0.00	-	53%	8	7
M14	100.00	0.00	55.00	Positive	0.00	-	56%	9	7
M15	0.00	0.00	-100.00	Negative	0.00	-	53%	9	8
M16	50.00	94.00	50.00	Positive	94.00	Positive	58%	11	8
M17	0.00	0.00	-50.00	Negative	-94.00	-	55%	11	9
							I1	**I2**	**PL**
						Positive	8	3	**11**
						Negative	9	0	9
									55%
								Good Performance	

Calculated using the Learner Performance Algorithm, a total of 11 positive performances and 9 negative performances were recorded. This sums the performance level to 55% as a Good Performance learner. Data is visualised using a bar and line graph, as shown in the Figure 48 below.

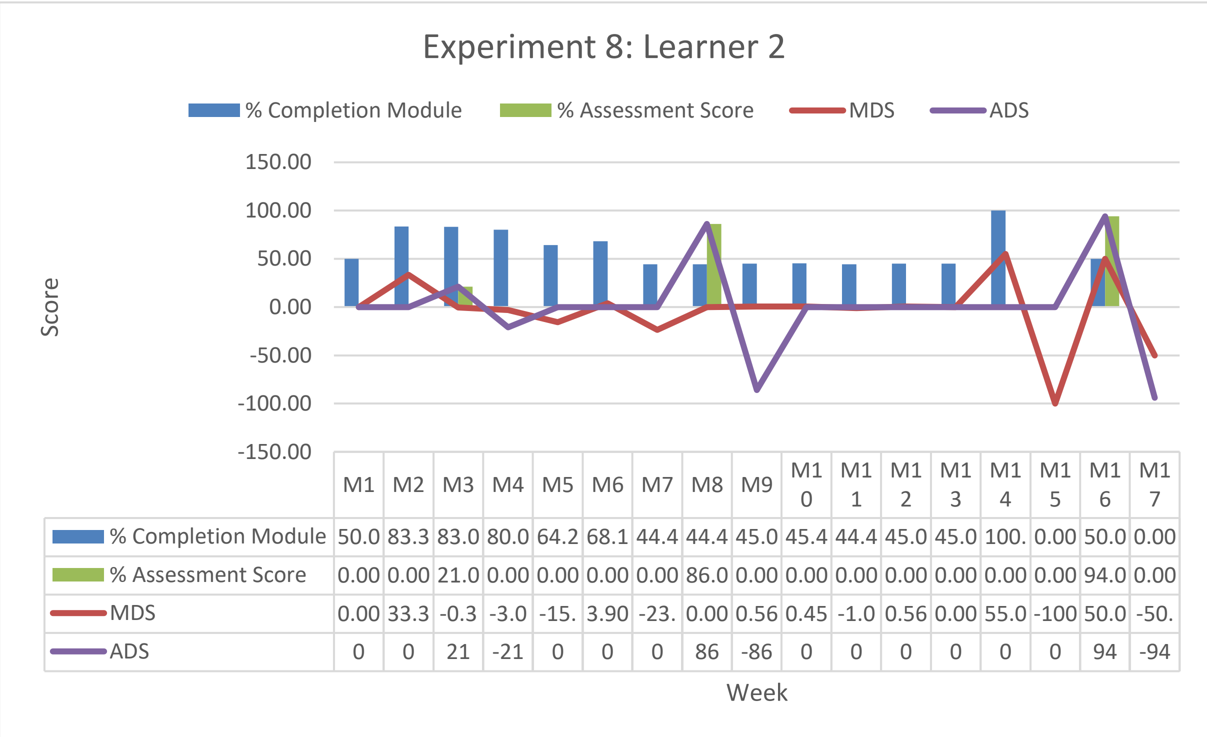


Figure 48: Experiment 8 Data Visualization

Experiment 8 Observation: Based on the percentage of completion module and assessment scores, I can conclude that Learner 2 is a good achievement learner, where the average percentage completion module score is 52.52% and 67% assessment score. This can be observed by referring to the bar chart plotted. This is also clearly visible on the graph, where scores are closed at the 50% line. As I look and analyse future details on each module and assessment differences scores, I can start to see a negative performance indication.

Performance indication is calculated. A total of 11 positive and 9 negative indications were measured, resulting in a 55% Performance Level score. Referring to the performance metrics I set for this experiment, Learner 2 is considered a ***good-performance learner*** and is ***good in score achievement*** based on the average percentage of Input 1 and Input 2. The next chapter will present more discussion on how this can be improved.

6.3.3 Experiment 9: Learner 3

Experiment 9 uses random learner data from Course A. It consists of a total of 17 modules and three assessments. Two datasets used as Input 1 and Input 2 are Completion of Module and Assessment Score, with an option to add data from other sources for Input 2. Both data were then used for measurement, as shown in the Table 58 below. MDS and ADS are calculated to determine the I1, I2 and PL.

Table 58: Experiment 9 Data Table

MODULE	% Completion Module	% Assessment Score	MDS	I1	ADS	I2	% PL	+	-
M1	25.00	0.00	0.00	Positive	0.00	-	100%	1	0
M2	41.67	0.00	16.67	Positive	0.00	-	100%	2	0
M3	41.67	75.00	0.00	Negative	75.00	Positive	75%	3	1
M4	40.00	0.00	-1.67	Negative	-75.00	-	60%	3	2
M5	42.86	0.00	2.86	Positive	0.00	-	67%	4	2
M6	45.45	0.00	2.60	Positive	0.00	-	71%	5	2
M7	44.44	0.00	-1.01	Negative	0.00	-	63%	5	3
M8	44.44	54.00	0.00	Negative	54.00	Negative	50%	5	5
M9	45.00	0.00	0.56	Positive	-54.00	-	55%	6	5
M10	45.45	0.00	0.45	Positive	0.00	-	58%	7	5
M11	44.44	0.00	-1.01	Negative	0.00	-	54%	7	6
M12	45.00	0.00	0.56	Positive	0.00	-	57%	8	6
M13	45.00	0.00	0.00	Negative	0.00	-	53%	8	7
M14	50.00	0.00	5.00	Positive	0.00		56%	9	7
M15	0.00	0.00	-50.00	Negative	0.00		53%	9	8
M16	50.00	82.00	50.00	Positive	82.00	Positive	58%	11	8

M17	0.00	0.00	-50.00	Negative	-82.00		55%	11	9
							I1	**I2**	**PL**
						Positive	9	2	**11**
						Negative	8	1	9
									55%
								Good Performance	

Calculated using the Learner Performance Algorithm, a total of 11 positive performances and 9 negative performances were recorded. This sums the performance level to 55% as a poor performance learner. Data is visualised using a bar and line graph, as shown in the Figure 49 below.

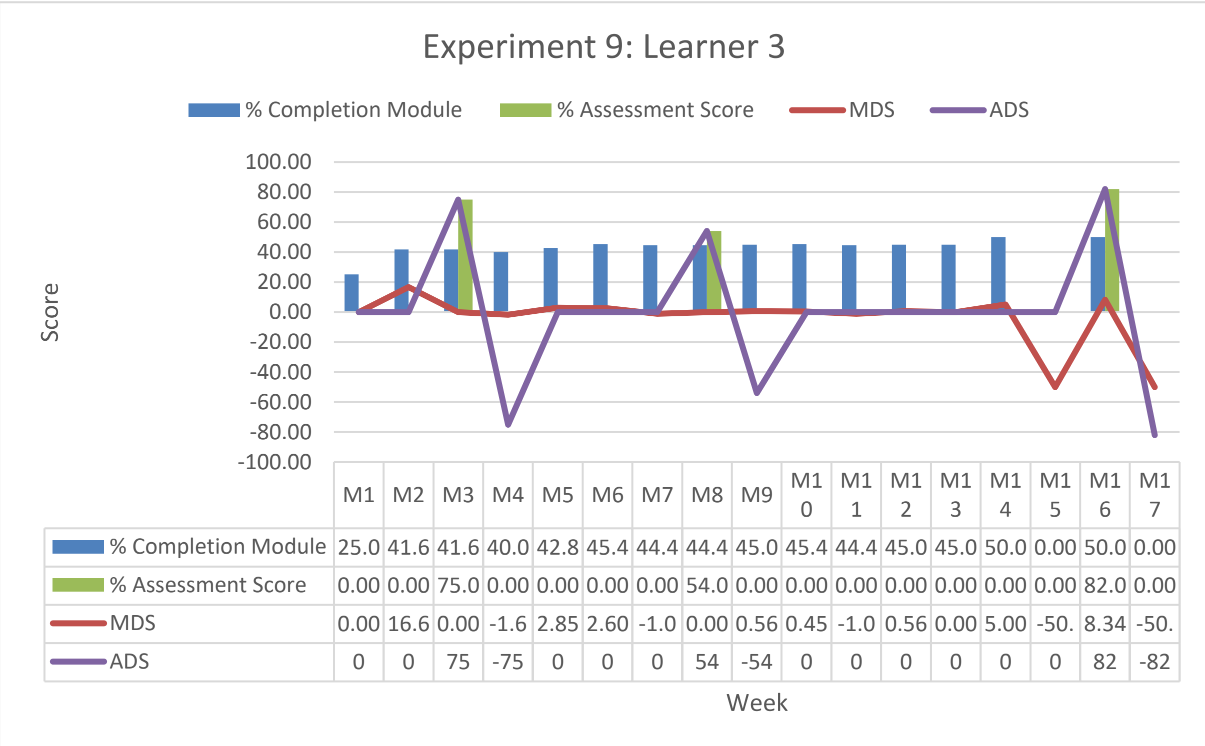


Figure 49: Experiment 9 Data Visualization

Experiment 9 Observation: Based on the percentage of completion module and assessment scores, I can conclude that Learner 3 is a poor achievement learner, where the average percentage completion module score is 38.26% and 70.33% assessment score. This can be observed by referring to the bar chart plotted. This is also clearly visible on the graph, where scores are closed to the 40% line.

Performance indication is calculated. A total of 11 positive and 9 negative indications were measured, resulting in a 55% Performance Level score. Referring to the performance metrics I set for this experiment, Learner 3 is considered a ***good-performance learner*** but ***poor in score achievement*** based on the average percentage of Input 1 and Input 2. Chapter 7 will present more discussion on how the performance can be improved.

6.3.4 Experiment 10: Learner 4

Experiment 10 uses random learner data from Course A. It consists of a total of 17 modules and three assessments. Two datasets used as Input 1 and Input 2 are Completion of Module and Assessment Score, with an option to add data from other sources for Input 2 (Assessment Score). Both data were then used for measurement, as shown in the Table 59 below. MDS and ADS are calculated to determine the I1, I2 and PL.

Table 59: Experiment 10 Data Table

MODULE	% Completion Module	% Assessment Score	MDS	I1	ADS	I2	% PL	+	-
M1	50.00	0.00	0.00	Positive	0.00	-	100%	1	0
M2	83.33	0.00	33.33	Positive	0.00	-	100%	2	0
M3	83.33	6.00	0.00	Negative	6.00	Positive	75%	3	1
M4	80.00	0.00	-3.33	Negative	-6.00	-	60%	3	2
M5	42.86	0.00	-37.14	Negative	0.00	-	50%	3	3
M6	45.45	0.00	2.60	Positive	0.00	-	57%	4	3
M7	44.44	0.00	-1.01	Negative	0.00	-	50%	4	4
M8	44.44	18.00	0.00	Negative	18.00	Positive	50%	5	5
M9	45.00	0.00	0.56	Positive	-18.00	-	55%	6	5
M10	45.45	0.00	0.45	Positive	0.00	-	58%	7	5
M11	44.44	0.00	-1.01	Negative	0.00	-	54%	7	6
M12	45.00	0.00	0.56	Positive	0.00	-	57%	8	6
M13	45.00	0.00	0.00	Negative	0.00	-	53%	8	7
M14	50.00	0.00	5.00	Positive	0.00	-	56%	9	7
M15	0.00	0.00	-50.00	Negative	0.00	-	53%	9	8
M16	50.00	2.00	50.00	Positive	2.00	Negative	53%	10	9
M17	0.00	0.00	-50.00	Negative	-2.00	-	50%	10	10
							I1	**I2**	**PL**
						Positive	8	2	**10**
						Negative	9	1	10
									50%

								Poor Performance

Calculated using the Learner Performance Algorithm, a total of 10 positive performances and 10 negative performances were recorded. This sums the performance level to 50% as a poor performance learner. Data is visualised using a bar and line graph, as shown in the Figure 50 below.

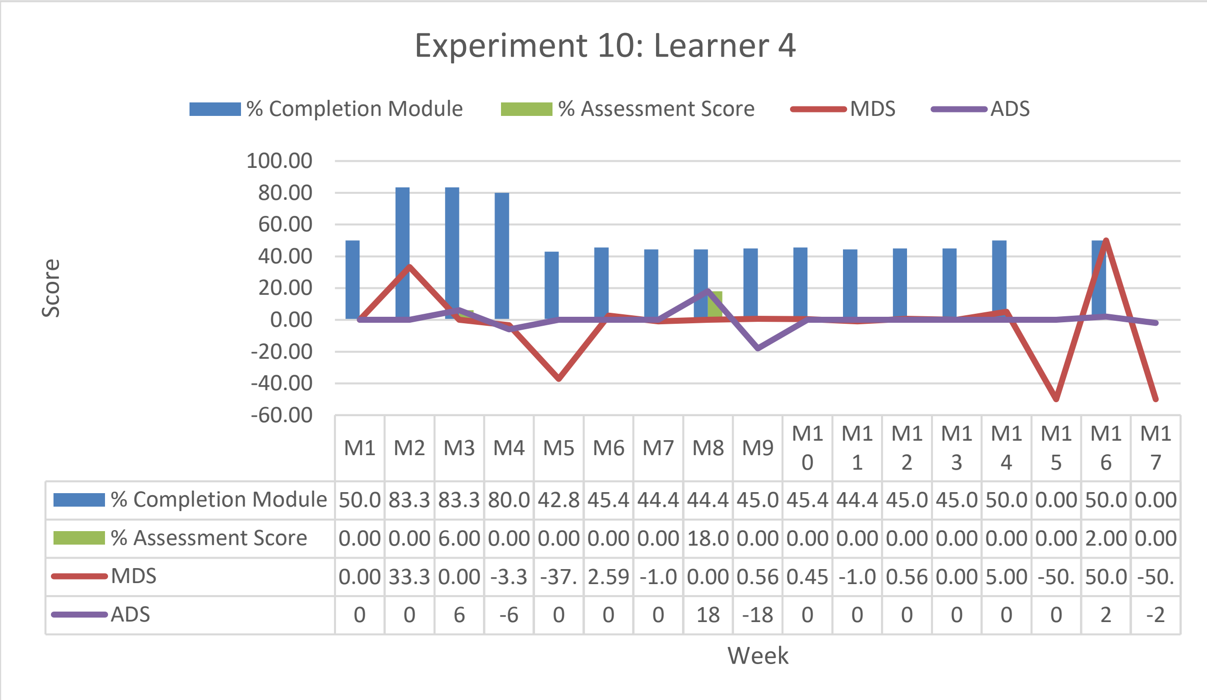


Figure 50: Experiment 10 Data Visualization

Experiment 10 Observation: Based on the percentage of completion module and assessment scores, I can conclude that Learner 4 is a poor achievement learner, where the average percentage completion module score is 46.98% and 8.66% assessment score. This can be observed by referring to the bar chart plotted. This is also clearly visible on the graph, where scores are closed at the 40% line. As I look and analyse future details on each module and assessment differences scores, I can start to see a negative performance indication.

Performance indication is calculated. A total of 10 positive and 10 negative indications were measured, resulting in a 50% Performance Level score. Referring to the performance metrics I set for this experiment, Learner 4 is considered a ***poor-performance learner***. Learner 4 is also considered as ***poor in score achievement*** based on the average percentage of Input 1 and Input 2.

6.3.5 Experiment 11: Learner 5

Experiment 11 uses random learner data from Course A. It consists of a total of 17 modules and three assessments. Two datasets used as Input 1 and Input 2 are Completion of Module and Assessment Score, with an option to add data from other sources for Input 2. Both data were then used for measurement, as shown in the Table 60 below. MDS and ADS are calculated to determine the I1, I2 and PL.

Table 60: Experiment 11 Data Table

MODULE	% Completion Module	% Assessment Score	MDS	I1	ADS	I2	% PL	+	-
M1	50.00	0.00	0.00	Positive	0.00	-	100%	1	0
M2	83.33	0.00	33.33	Positive	0.00	-	100%	2	0
M3	83.33	29.00	0.00	Negative	29.00	Positive	75%	3	1
M4	80.00	0.00	-3.33	Negative	-29.00	-	60%	3	2
M5	85.71	0.00	5.71	Positive	0.00	-	67%	4	2
M6	90.91	0.00	5.19	Positive	0.00	-	71%	5	2
M7	44.44	0.00	-46.46	Negative	0.00	-	63%	5	3
M8	44.44	0.00	0.00	Negative	0.00	Negative	50%	5	5
M9	45.00	0.00	0.56	Positive	0.00	-	55%	6	5
M10	45.45	0.00	0.45	Positive	0.00	-	58%	7	5
M11	44.44	0.00	-1.01	Negative	0.00	-	54%	7	6
M12	45.00	0.00	0.56	Positive	0.00	-	57%	8	6
M13	45.00	0.00	0.00	Negative	0.00	-	53%	8	7
M14	100.00	0.00	55.00	Positive	0.00	-	56%	9	7
M15	0.00	0.00	-100.00	Negative	0.00	-	53%	9	8
M16	50.00	87.00	50.00	Positive	87.00	Positive	58%	11	8
M17	0.00	0.00	-50.00	Negative	-87.00	-	55%	11	9
							I1	**I2**	**PL**
						Positive	9	2	**11**
						Negative	8	1	9
									55%
								Good Performance	

Calculated using the Learner Performance Algorithm, a total of 11 positive performances and 9 negative performances were recorded. This sums the performance level to 55% as a good performance learner. Data is visualised using a bar and line graph, as shown in the Figure 51 below.

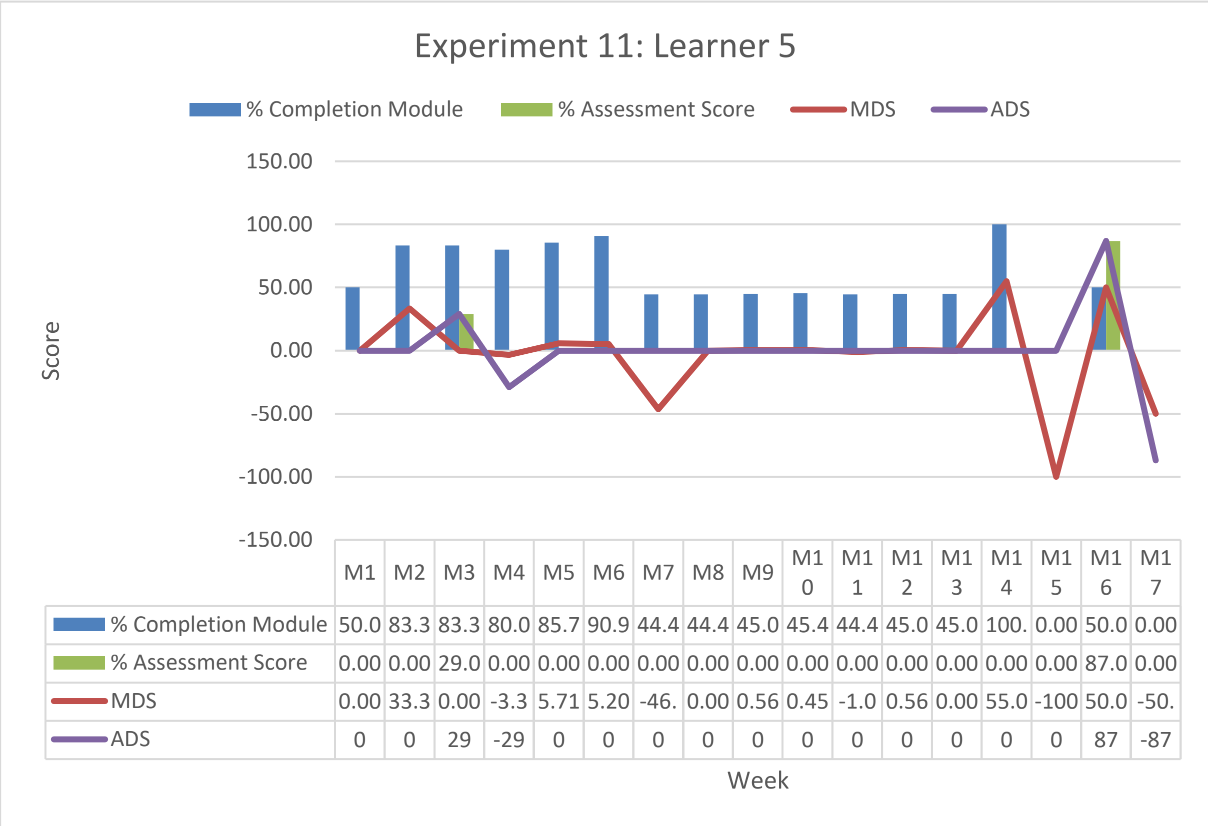


Figure 51: Experiment 11 Data Visualization

Experiment 11 Observation: Based on the percentage of completion module and assessment scores, I can conclude that Learner 5 is a poor achievement learner, where the average percentage completion module score is 55.12% and 38.66% assessment score. This can be observed by referring to the bar chart plotted. This is also clearly visible on the graph, where scores are closed at the 40% line.

Performance indication is calculated. A total of 11 positive and 9 negative indications were measured, resulting in a 55% Performance Level score. Referring to the performance metrics I set for this experiment, Learner 5 is considered a ***good-performance learner*** but is ***poor in score achievement*** based on the average percentage of Input 1 and 2. More discussion on how this can be improved is presented in Chapter 7.

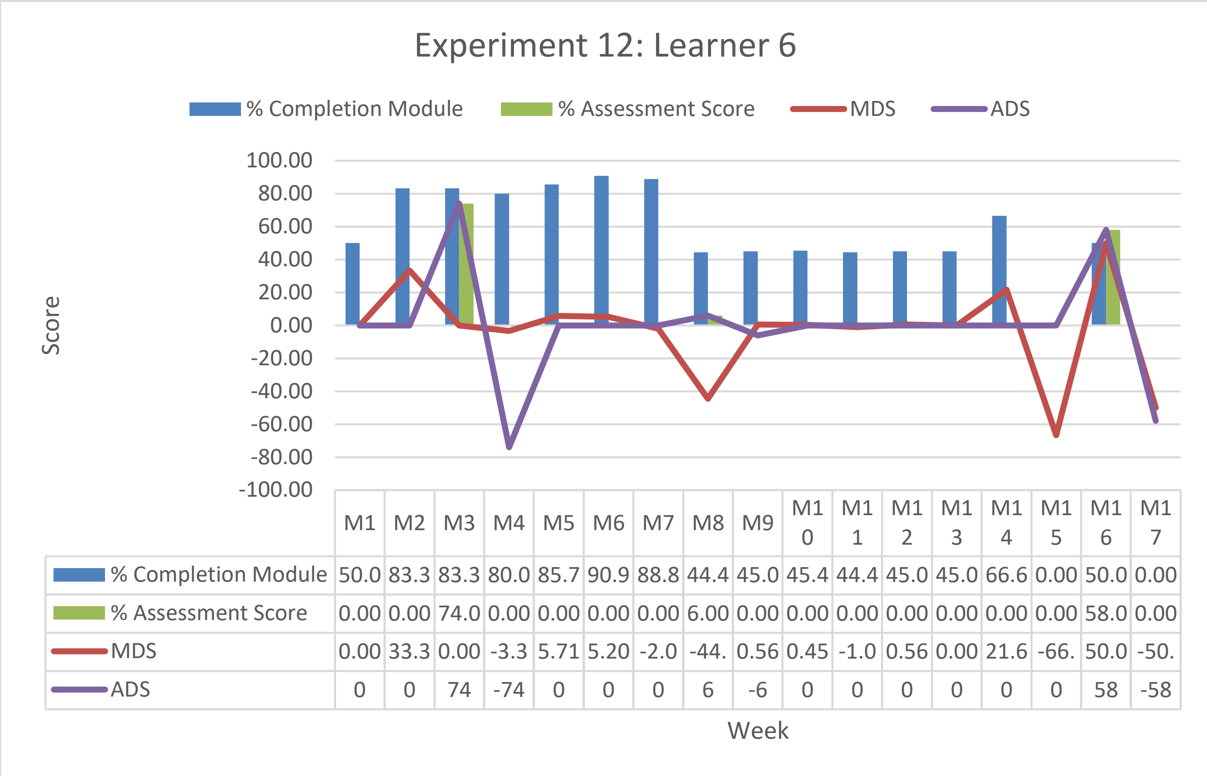
6.3.6 Experiment 12: Learner 6

Experiment 12 uses random learner data from Course A. It consists of a total of 17 modules and three assessments. Two datasets used as Input 1 and Input 2 are Completion of Module and Assessment Score, with an option to add data from other sources for Input 2. Both data were then used for measurement, as shown in the Table 61 below. MDS and ADS are calculated to determine the I1, I2 and PL.

Table 61: Experiment 12 Data Table

MODULE	% Completion Module	% Assessment Score	MDS	I1	ADS	I2	% PL	+	-
M1	50.00	0.00	0.00	Positive	0.00	-	100%	1	0
M2	83.33	0.00	33.33	Positive	0.00	-	100%	2	0
M3	83.33	74.00	0.00	Negative	74.00	Positive	75%	3	1
M4	80.00	0.00	-3.33	Negative	-74.00	-	60%	3	2
M5	85.71	0.00	5.71	Positive	0.00	-	67%	4	2
M6	90.91	0.00	5.19	Positive	0.00	-	71%	5	2
5	88.89	0.00	-2.02	Negative	0.00	-	63%	5	3
M8	44.44	6.00	-44.44	Negative	6.00	Negative	50%	5	5
M9	45.00	0.00	0.56	Positive	-6.00	-	55%	6	5
M10	45.45	0.00	0.45	Positive	0.00	-	58%	7	5
M11	44.44	0.00	-1.01	Negative	0.00	-	54%	7	6
M12	45.00	0.00	0.56	Positive	0.00	-	57%	8	6
M13	45.00	0.00	0.00	Negative	0.00	-	53%	8	7
M14	66.67	0.00	21.67	Positive	0.00	-	56%	9	7
M15	0.00	0.00	-66.67	Negative	0.00	-	53%	9	8
M16	50.00	58.00	50.00	Positive	58.00	Positive	58%	11	8
M17	0.00	0.00	-50.00	Negative	-58.00	-	55%	11	9
							I1	**I2**	**PL**
						Positive	9	2	**11**
						Negative	8	1	9
									55%
								Good Performance	

Calculated using the Learner Performance Algorithm, a total of 11 positive performances and 9 negative performances were recorded. This sums the performance level to 55% as a good performance learner. Data is visualised using a bar and line graph, as shown in the Figure 52 below.



	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17
% Completion Module	50.0	83.3	83.3	80.0	85.7	90.9	88.8	44.4	45.0	45.4	44.4	45.0	45.0	66.6	0.00	50.0	0.00
% Assessment Score	0.00	0.00	74.0	0.00	0.00	0.00	0.00	6.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	58.0	0.00
MDS	0.00	33.3	0.00	-3.3	5.71	5.20	-2.0	-44.	0.56	0.45	-1.0	0.56	0.00	21.6	-66.	50.0	-50.
ADS	0	0	74	-74	0	0	0	6	-6	0	0	0	0	0	0	58	-58

Figure 52: Experiment 12 Data Visualization

Experiment 12 Observation: Based on the percentage of completion module and assessment scores, I can conclude that Learner 6 is a good achievement learner, where the average percentage completion module score is 55.77% and 46% assessment score. This can be observed by referring to the bar chart plotted. This is also clearly visible on the graph, where scores are mixed between the 80% line and closed at the 40% line. As I look and analyse future details on each module and assessment differences scores, I can start to see a positive performance indication.

Performance indication is calculated. A total of 11 positive and 9 negative indications were measured, resulting in a 55% Performance Level score. Referring to the performance metrics I set for this experiment, Learner 6 is considered a ***good-performance learner***. Learner 6 is ***good in score achievement*** based on the average percentage of Input 1 and Input 2.

6.3.7 Learner Performance Experiment Discussions

Findings from experiment 7 to experiment 12 were discussed, focused on using the MPM model to perform learner performance monitoring and measurement, analysed the measurement results, observed the projected graph to understand the learning analytic data and looked at what option can be considered for improvement.

I used the default performance metric, as shown in the Table 62 below. It is essential to remember that the performance metric is flexible and can be changed or updated based on users' or organisation benchmarks or standards.

Table 62: Default Performance Metric

Score	Performance Level
76% to 100%	Excellent Performance
51% to 75%	Good Performances
26% to 50%	Poor Performance
0% to 25%	Very Poor Performance

The impact of missing assessments on performance evaluation is significant. When assessments are not provided for specific modules, adjustments in performance calculations are necessary. In cases where assessments are missing, no positive or negative scores are considered, affecting the overall performance measurement. To determine performance changes between assessments, the current assessment score is compared to the last available assessment data, irrespective of the gap between modules.

The approach taken to handle missing assessments acknowledges the challenge of incomplete data and its impact on performance evaluation. By adjusting performance calculations for missing assessments, the analysis becomes more accurate and reflective of actual performance. Comparing current assessment scores with the last available data ensures a consistent method of measuring performance changes, even in the absence of certain assessments. This approach maintains the integrity of performance evaluation despite missing assessment weeks, providing a more reliable basis for decision-making and improvement strategies.

Findings from Process of using the MPM model to perform learner performance monitoring and measurement in series of experiments:

Finding 1: The MPM model comprises of measurement algorithms, metrics, and indicators. Users could be confused about the process flow, especially first-time users without experience with MOOC learning analytics or data analysis tasks.

> *It is vital to clearly understand the process flow and steps needed when planning using the model.*

Finding 2: Learning analytics data from the MOOC platform is raw data. Some MOOC platforms combine all learner data into single datasets, while some other MOOC platforms provide the option to view learner data individually.

> *Learning analytics data must be cleaned before it can be used for performance measurement and analysis. I need to extract individual learner data from the MOOC platform that combines and cleans all learner data. I can proceed with data cleaning for MOOC platforms that provide learner data individually.*

Finding 3: The number of learners for each MOOC course varies. The minimum learner data for a MOOC course in my sample is 75 learners, and the max learner data is 6,185. The average learner within my study's 15 MOOC course data sample is 1,637. Identifying or extracting individual learner data from the MOOC platforms is challenging.

> *Identifying which learner to measure is subjective and depends on course admin requirements or needs. The possible situation: The course administrator has already noticed a specific learner worth measuring or who gets the administrator's attention. In these experiments, I randomly selected six learners from the same course to perform measurement and analysis.*

Finding 4: The data cleaning process could be complicated depending on the structure of the MOOC course. The amount of data that needs to be filtered and cleaned individually could demotivate course admin to implement learner performance measurement.

> *Indeed, the data cleaning process is challenging, especially for course admins with no previous experience in this task. MPM model currently does not include automation data cleaning features; therefore, users need to manually clean their data or apply any other data cleaning method or tools available. However, data-cleaning tasks can be much*

easier if the MOOC course is structured and organised well. For example, they are using proper numbering or labels to index each module.

Finding 5: Obtaining course or learner learning analytics data will be much more challenging and complex for some course administrators. The most observed reasons are data policy set by the university or faculty, unfamiliar with the learning analytic data features by MOOC platforms, or computer literacy issues.

Each MOOC platform has its navigation system to access the learning analytics data. Most of the navigation system is straightforward to understand. Course admins are expected to quickly understand and get used to the process of getting the learning analytic data after a few practices. Another option is for the course admin to ask for assistance from faculty or the university IT support team.

Process of analysing measurement results:

Once the dataset is cleaned and ready to be used, the user will copy the learning analytic data into the MPM Tool Excel document provided. Data were automatically calculated, and learner performance was measured. Results from the measurement are displayed in data table and chart data visualisation.

Finding 6: The provided tool was prepared within the limit of 52 data rows for learner performance measurement. Although the row number provided is generally able to cover all data within the duration of the course, there is a possibility that an extra row is required. This requirement depends on the MOOC course design and structure.

Based on the sample data used in the study, I observed that the provided data row can handle input from users. I also provide additional details on how to add extra data rows if needed. This includes the Excel function scrip used.

Finding 7: Calculation results are accurate based on the algorithm, and the calculation result is easy to review and understand.

I conduct manual calculations for each measurement calculated using the provided Excel tool to validate the results. Initially, there were some errors in the formula used, and I corrected it according to the MPM model.

Finding 8: Using a chart for data visualisation and combining line and bar charts provides better assistance in analysing the performance measurement results.

Data visualisation plays a vital role in analysing results from the performance measurement. For instance, the Meta Trader trading chart platform is one example of how good data visualisation and analytic data were used for the greater good. Data visualization effectively conveys information through graphical means (Omar Addam et al., 2016). Various charts, indicators, and patterns were observed and studied to gain insight and give users better information in making their decisions. Omar Addam et al. (2016), in their study related to knowledge discovery leading to informative decision-making, also suggest creating more visualization techniques to help interpret the results. In this study, I apply bar and line chart styles into one data visualisation chart for analysis. The chart will be automatically generated once data has been input and measured.

Finding 9: Metrics and indicators assist the analysis, especially the Consideration Factors Indicator.

Metrics and indicators assist users with data and result analysis. Metrics were used to determine positive and negative values, eventually calculated as the performance score. The Consideration Factor Indicator assist the user in analysing results from the generated chart based on five suggested areas. The indicator includes chart patent reference, which was one of the novelties of this research study.

Process of understanding learning analytics data by observing the analysis graph:

Once data has been input into the provided Excel tool for performance measurement, a graph is automatically generated based on the measurement results. Users have the option to analyse results from the data table or chart.

Finding 10: The graph was generated automatically based on the input data and calculations made by the measurement algorithms.

> *Although the graph was generated automatically, we manually checked to confirm the correct setting. During experiments, no error was found. From a series of experiments conducted, a minor adjustment was made to the graph style and design for better visualisation.*

Finding 11: A significant detail observed from the generated graph is that the line chart patent represents the difference score value versus the bar chart patent, which represents the actual data scores. Trend and patent can be observed.

> *My study found that generating a graph based on the actual data from MOOC learning analytics is a straightforward data visualisation approach. As I introduce the differences in score data, additional information can now be visualised and give better insight to course admin in analysing and interpreting the original data they had. Performance trends are now much visualised with the use of line charts.*

Process of identifying improvement options:

Finding 12: The graph patent was hard to read and understand initially. Fortunately, a Consideration Factor Indicator with a patent guide helps the user interpret the data.

> *Conducted simulation activities allow us to re-evaluate the MPM model and iteration improvement. Consideration Indicator Factor was designed and introduced based on literature review and research ground theory. Observation and previous experience also significantly influence the design of the indicators. The current indicator includes five areas to consider with multiple consideration suggestions. The consideration option will most likely be improved and updated occasionally. This flexibility, considering the nature of changes I encounter. In the future, more user input will help construct more accurate and robust consideration options.*

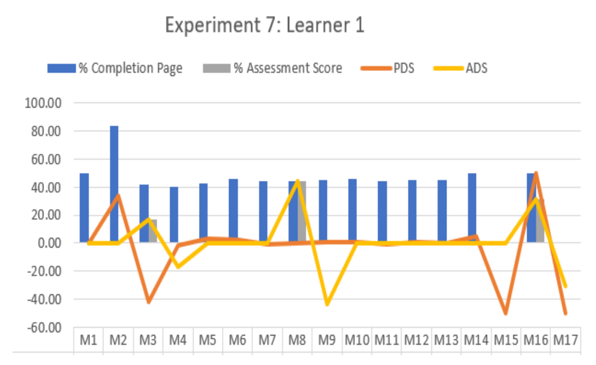
Findings 13: Although the five areas in the Consideration Factor Indicator proposed are well accepted and support previous studies, the Consideration Factor criteria linked with the indication could be expanded.

Technical, Instruction, Content, Human and Environment are five areas that, based on my observation and previous studies, show significant effects on learners' interaction with learning activities. I identified the Consideration Factor list based on the justified areas and from my observations and studies. The list is limited and also based on the most common indication. More factors can be considered. Future and regular studies to update and produce a much more accurate possibility list are suggested due to the new data that will be made available and the learning evolution process occurring over time.

Data Visualisation and Result Analysis:

The Table 63 below shows six experiment graphs generated from six learners in the same course based on performance measurement and observation.

Table 63: Learner Performance Experiments Analysis Graph

<table>
<tr>
<td>
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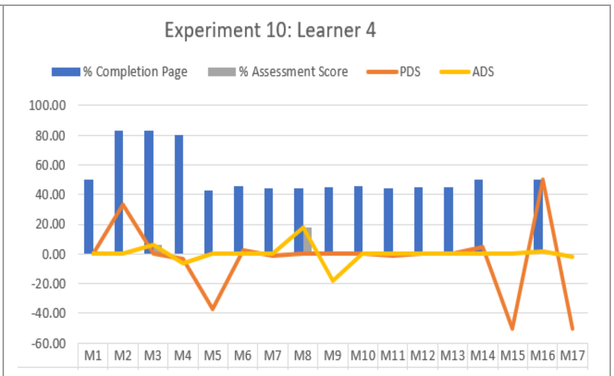
<td>
</td>
</tr>
<tr>
<td>Poor score and poor performance (38.24%)</td>
<td>Poor score and poor performance (35.29%)</td>
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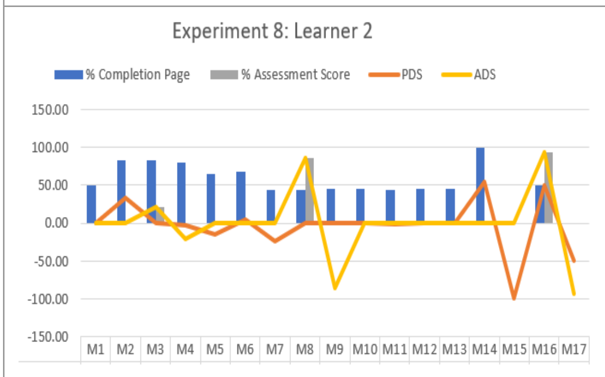
<td>
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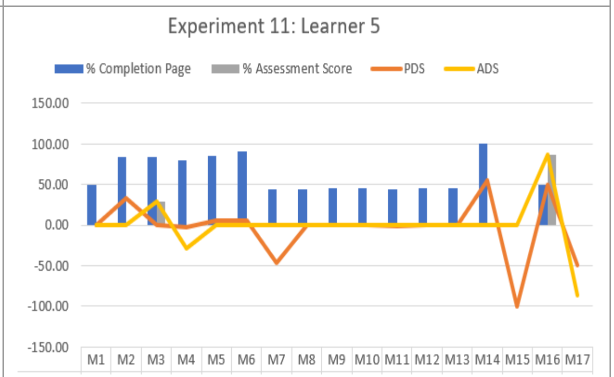
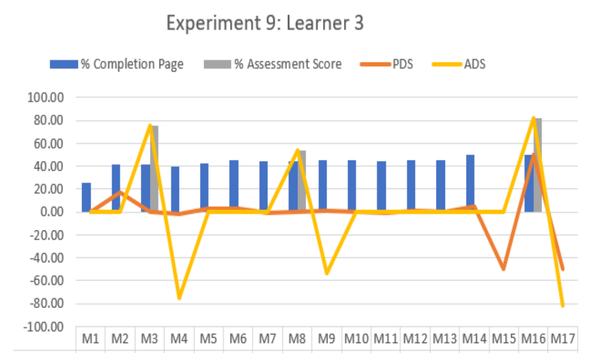
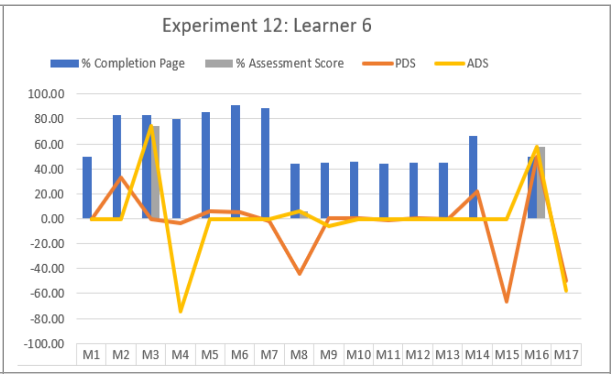
<td>
</td>
</tr>
<tr>
<td>Good score but poor performance (35.29%)</td>
<td>Poor score and poor performance (35.29%)</td>
</tr>
</table>



Poor score and poor performance (38.24%)



Poor score and poor performance (38.24%)

Finding 14: The bar chart used is the most commonly used approach to data visualisation and has been practised by most MOOC course admin that utilises the learning analytic data available. The chart was used for general or basic reporting purposes.

> *Using a bar chart to visualise data from MOOC learning analytics in this context resembles the typical approach. This approach looks familiar and easy to understand for users with experience analysing MOOC learning analytic data. For users with no experience analysing MOOC learning analytic data, this approach is still easy to understand as it represents data from MOOC learning analytics in each module.*

Finding 15: The line chart representing the difference score value is a data visualisation approach that has not been used or viewed before.

> *Data used to generate the line graph are from the differences in calculated score values. It gives a new point of view on how performance was visualised in the context of this research study and a significant novelty approach.*

Finding 16: The line chart provided a significantly different patent or trend than the bar chart.

> *The line chart highlights the difference in scores between the current and previous modules. Understandably, the line and bar chart were plotted based on different data, but they prove that I can have more information and points of view within the same data.*

Finding 17: Combination data visualisation of MOOC learning analytics data and the calculated differences scores helps users view and understand data from a new perspective. This gives users ideas to consider the best action to improve course or learner performance.

> *Using only the existing learning analytics data gives partial implicit information for analysis. By including the differences in score data, I provide additional explicit information for better performance monitoring and measuring. This combination gives the user an overview of the actual and trend scores between the current and previous modules for better analysis.*

Finding 18: Observing and comparing each graph generated in the experiments, I noticed that a high-score achiever learner could also show poor performance. Conversely, a low or average score achiever learner could achieve a better performance score if their data show incremental trends and an improvement score.

> *This observation was missed or hardly noticed in an analysis of the standard learning analytic data. As a result, course administrators tend to view high-achiever learners as good-performance learners. Using the MPM model, course admin can now identify learners' performance with no bias towards their score recorded by MOOC learning analytics.*

6.4 Chapter Conclusion

At the end of the experiments and based on the findings, I am satisfied with the outcome of this research activity to test and evaluate the use of the MPM algorithm for performance measurement using proposed metrics and indicators.

Using the MPM model, I have completed a series of experiments for both course and learner performance measurement. Experiments cover both FutureLearn and OpenLearning MOOC platforms. A total of six experiments on course performance involving two different MOOC courses were conducted to compare the measurement and analysis of the same MOOC course in three different cohorts. A total of six experiments on learner performance from the same course were conducted. The learner was randomly selected, and measurement results and analysis were compared.

Eighteen findings were recorded and discussed in both course and learner performance experiments. It is essential to highlight the difference between achievement and performance that was measured. A high-achievement course or learner could have high or low performances. The same condition applies to low-achievement courses or learners with either low or high performance.

Metrics and indicators demonstrate significant usability and are essential in measurement and analysis. I am satisfied with the algorithms, metrics, and indicators designed based on the observation and results.

Next, I plan a series of user usability tests on the proposed MPM Model with participants selected based on specific relevant criteria. In the next chapter, I presented details of the user usability testing.

Chapter 7 MPM Model User Usability Testing

7.1 Introduction

In this chapter, I will discuss the user usability testing conducted to evaluate the usability of the proposed MPM model for monitoring and measuring course or learner performance. The primary purpose of this testing activity was to address RQ3 and get feedback on the usability of the MPM model from a specific group of users.

The user usability testing was conducted in line with the methodology presented in the previous chapter. The chapter is organised into four subsections: an introduction, User usability testing resources and participants, user usability testing results, user usability testing observation and discussions, questionnaire results and feedback analysis, and chapter conclusion.

7.2 User Usability Testing Resources and Participants

Two critical components that must be prepared for user usability testing are resources and participants. Resources include sample datasets and tools to be used. Participant preparation refers to identifying and obtaining approval from suitable participants to participate in the study.

7.2.1 Resources

The study provided two types of resources to participants: sample datasets and an Excel-based tool. The datasets were prepared in two versions, raw and cleaned, in CSV format for each MOOC platform as shown in Appendix I. The raw datasets were downloaded from MOOC platforms and did not include personal or sensitive data. The cleaned version datasets had been pre-processed by removing data noise and sorting data according to the module sequence. The two versions of datasets were provided to give participants a clear idea of the preparation required before using the datasets from MOOC platforms for analysis.

In addition, an Excel-based tool was prepared for user usability testing purposes. The tool was embedded with the MPM model and included a user guide and instructions for each MOOC platform user for using the tool. Participants were required to input learning analytics data to calculate and measure performance using the tool. The tool also included a questionnaire form for participants to provide feedback. Microsoft Excel was chosen as the software for the tool due to its availability to the target participants.

7.2.2 Participants

My user usability testing research activity focuses on the usability of the MPM model involving volunteer participants of FutureLearn and OpenLearning MOOC course admin as participants. Initially, I identified a list of users as potential participants and contacted them for the invitation to participate.

However, it was challenging to get users involved due to various circumstances. Despite the challenges, I got seven participants, three from FutureLearn and four from OpenLearning as shown in Table 64, who met the requirements of having experience managing or delivering courses on MOOC platforms and allocating a minimum of one-hour session for the testing. The data collected from the participants were valuable and rich, regardless of the number of participants.

Table 64: List of User Usability Testing Participants

#	COUNTRY	MOOC PLATFORM	TESTING METHOD
1	Malaysia	OpenLearning	Online Teams
2	Malaysia	OpenLearning	Online Teams
3	United Kingdom	FutureLearn	Face to face
4	United Kingdom	FutureLearn	Online Teams
5	Malaysia	OpenLearning	Online Teams
6	Malaysia	OpenLearning	Online Teams
7	United Kingdom	FutureLearn	Face to face & Online Teams

7.3 User Usability Testing Results

I organized and presented the user usability testing results for each participant in this section, which included years of experience in using MOOC and MOOC platforms used by the participants. The result observed for each participant is the process and outcome of how usable the MPM model is for participants.

7.3.1 Participant 1

Participant 1 is a professor at a university in Malaysia that uses the OpenLearning MOOC platform. Participant 1 had more than two years of experience using and offering more than four MOOC courses. Having experience using Microsoft Excel and SPSS, Participant 1 demonstrated good adaptability in understanding and using the MPM tool provided.

During the testing session, participant 1 observed a demonstration and briefing on how the MPM model works using sample datasets before Participant 1 took time to explore using the same datasets. Later, Participant 1 practised and explored using their dataset on their own. Participant 1 shared results from their datasets and asked questions and four arguments related to the usage of the MPM model.

Below are two sample results from Participant 1 own datasets. Four arguments from Participant 1 based on the results are:

Argument 1: "*I am not agreeing with the Current Performance conclusion. How is it that MPM can then recognize the MOOC as having excellent performance? Are there any examples of MOOCs that can meet the Excellent Performance criteria?*"

Argument 2: "*The judgment for MOOC Performance shown in this graph, Very Poor Performance, is unfair. My justification is roughly speaking, I can see the average % of Completion Module = 72.38% and the average % of Completion Widget = 74.66%, which means the average MOOC Performance > 76% or can be counted as Excellent Performance.*"

Module	% Completion Module	% Completion of Widget	MDS	I1	WDS	I2	PS (%)	Positive Count	Negative Count	PS (%)
Lesson 1	82.91	77.95	0	Positive	0	Positive	100	2	0	100
Lesson 2	83.83	78.87	0.92	Positive	0.92	Positive	100	4	0	100
Lesson 3	84.55	79.58	0.72	Positive	0.71	Positive	100	6	0	100
Lesson 4	85.32	80.96	0.77	Positive	1.38	Positive	100	8	0	100
Lesson 5	86.39	81.71	1.07	Positive	0.75	Positive	100	10	0	100
Lesson 6	87.75	82.48	1.36	Positive	0.77	Positive	100	12	0	100
Lesson 7	88.43	83.74	0.68	Positive	1.26	Positive	100	14	0	100
Lesson 8	89.8	84.45	1.37	Positive	0.71	Positive	100	16	0	100
Lesson 9	90.48	85.94	0.68	Positive	1.49	Positive	100	18	0	100
Lesson 10	91.64	86.96	1.16	Positive	1.02	Positive	100	20	0	100
Lesson 11	92.8	87.94	1.16	Positive	0.98	Positive	100	22	0	100
Lesson 12	93.64	88.3	0.84	Positive	0.36	Positive	100	24	0	100

Figure 53: Participants 1 Data Entry 1

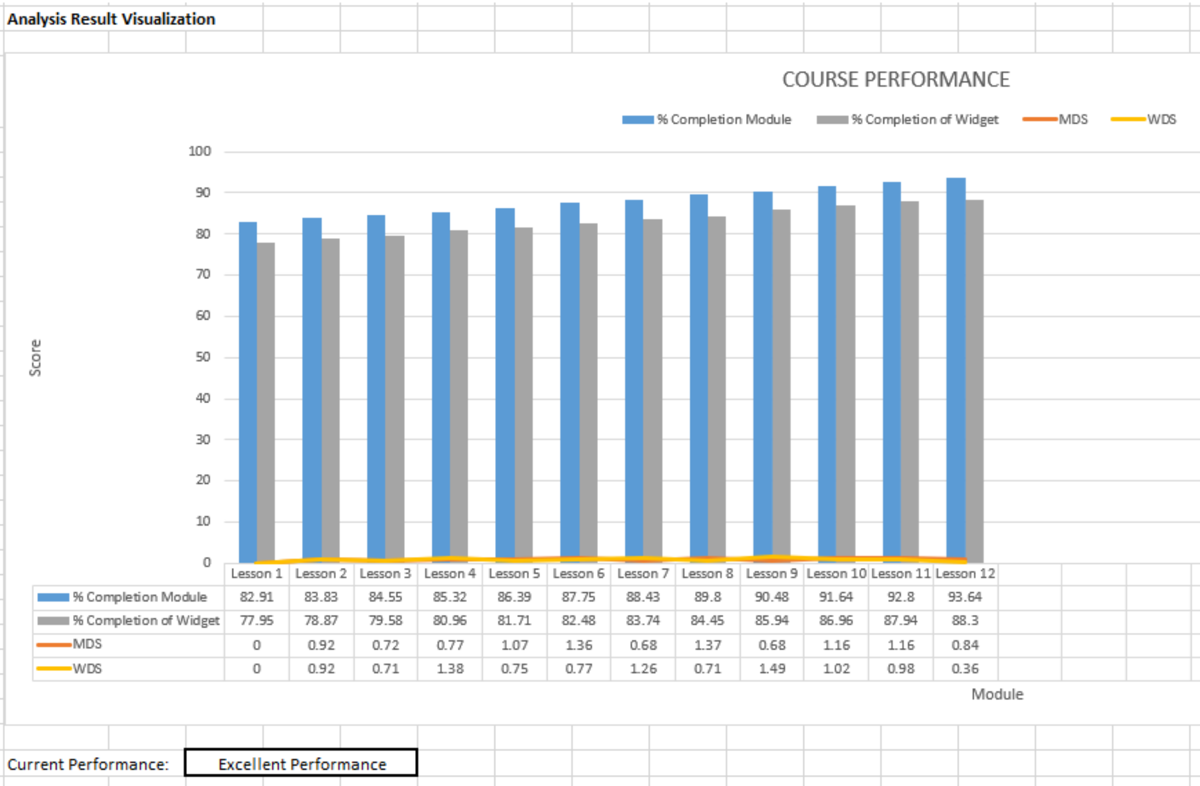
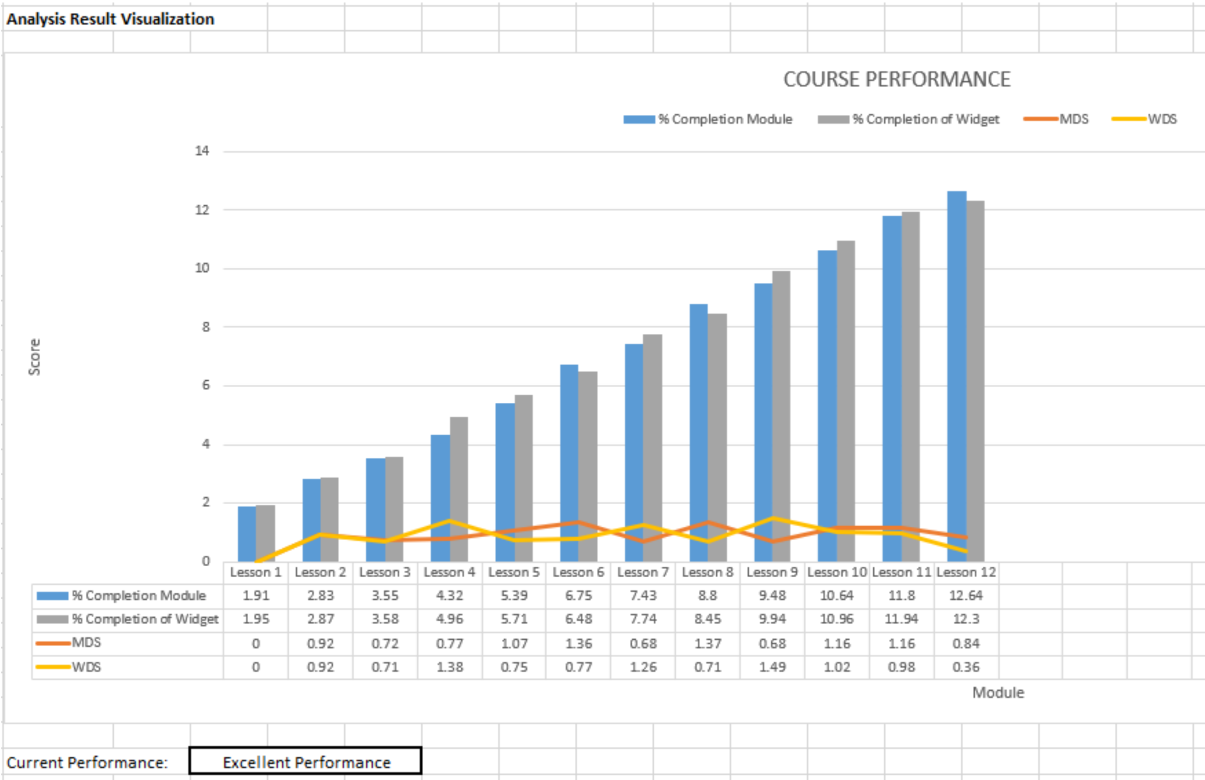


Figure 54: Participant 1 Analysis Result Visualization 1

Module	% Completion Module	% Completion of Widget	MDS	I1	WDS	I2	PS (%)		Positive Count	Negative Count	PS (%)
Lesson 1	1.91	1.95	0	Positive	0	Positive	100		2	0	100
Lesson 2	2.83	2.87	0.92	Positive	0.92	Positive	100		4	0	100
Lesson 3	3.55	3.58	0.72	Positive	0.71	Positive	100		6	0	100
Lesson 4	4.32	4.96	0.77	Positive	1.38	Positive	100		8	0	100
Lesson 5	5.39	5.71	1.07	Positive	0.75	Positive	100		10	0	100
Lesson 6	6.75	6.48	1.36	Positive	0.77	Positive	100		12	0	100
Lesson 7	7.43	7.74	0.68	Positive	1.26	Positive	100		14	0	100
Lesson 8	8.8	8.45	1.37	Positive	0.71	Positive	100		16	0	100
Lesson 9	9.48	9.94	0.68	Positive	1.49	Positive	100		18	0	100
Lesson 10	10.64	10.96	1.16	Positive	1.02	Positive	100		20	0	100
Lesson 11	11.8	11.94	1.16	Positive	0.98	Positive	100		22	0	100
Lesson 12	12.64	12.3	0.84	Positive	0.36	Positive	100		24	0	100

Figure 55: Participants 1 Data Entry 2



	Lesson 1	Lesson 2	Lesson 3	Lesson 4	Lesson 5	Lesson 6	Lesson 7	Lesson 8	Lesson 9	Lesson 10	Lesson 11	Lesson 12
% Completion Module	1.91	2.83	3.55	4.32	5.39	6.75	7.43	8.8	9.48	10.64	11.8	12.64
% Completion of Widget	1.95	2.87	3.58	4.96	5.71	6.48	7.74	8.45	9.94	10.96	11.94	12.3
MDS	0	0.92	0.72	0.77	1.07	1.36	0.68	1.37	0.68	1.16	1.16	0.84
WDS	0	0.92	0.71	1.38	0.75	0.77	1.26	0.71	1.49	1.02	0.98	0.36

Figure 56: Participants 1 Analysis Result Visualization 2

Argument 3: “*You can compare the results of MPM Measurement using the actual and simulated data I have attached. 1 - follow the measurements you explained yesterday and use the correct course data. 2 - I adjusted a little so that he stops at l28, and the current performance follows the figure at l28; it becomes Poor Performance. 3 - average completion of 80% and above and increase by 1% every week as you expected. Therefore, the final performance is Excellent Performance. 4 & 5 - low average completion (16 - 26%) & very low (7%) but a weekly increase of 1%.so final performance is Excellent Performance as well.*”

Argument 4: “*There are excellent, intermediate, and weak classes. However, the simulation data that I gave is not a weak class performance. On the contrary, it is an example of MOOC performance in a university, and there is no term excellent, intermediate, or weak class. Based on my experience as a MOOC administrator at a university, this performance usually depends on the university policy (mandatory or non-mandatory use of MOOCs), the lecturer's role as a facilitator (ensuring students use and motivate students with various learning strategies), ensuring interesting content & enable students to understand & master learning.*”

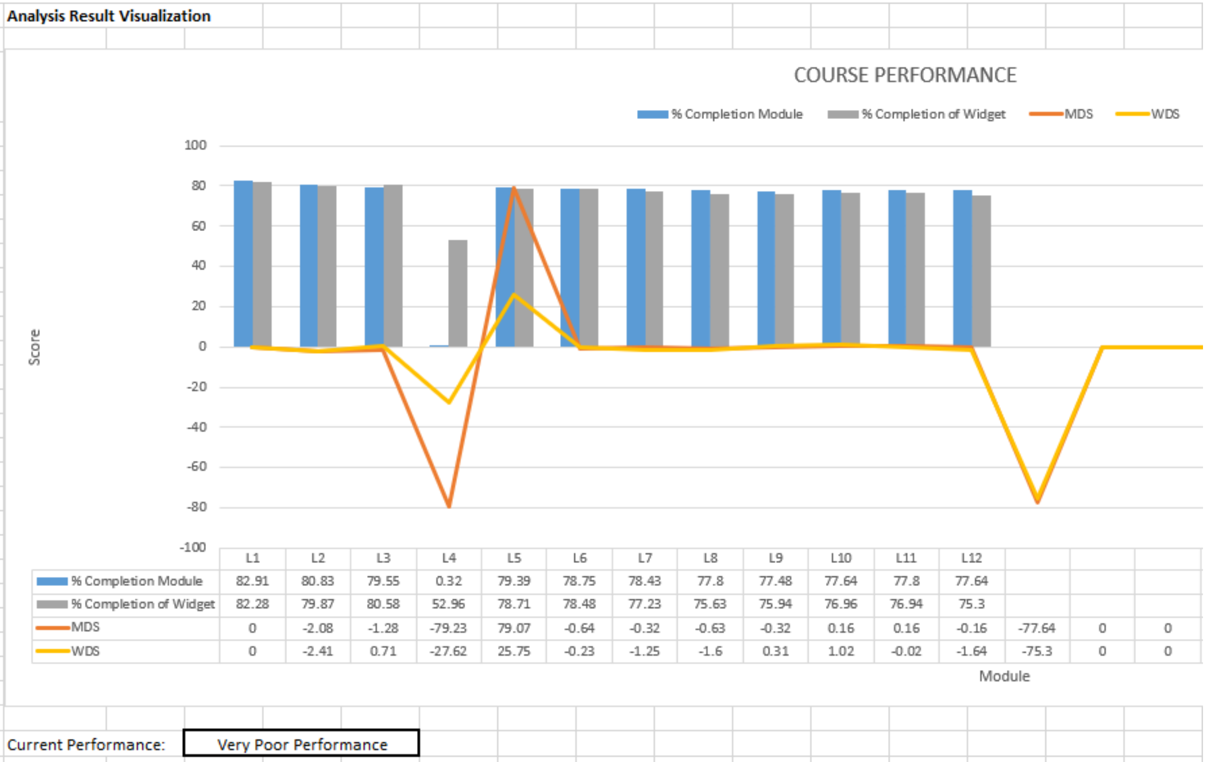
7.3.2 Participant 2

Participant 2 is a lecturer at a higher learning institution in Malaysia that uses the OpenLearning MOOC platform. Participant 2 had over two years of experience using and offering three MOOC courses. Having no experience using learning analytics for analysis, Participant 2 demonstrated interest and eagerness in understanding and using the MPM tool provided.

During the testing session, Participant 2 observed a demonstration and briefing on how the MPM model works using sample datasets before Participant 2 took time to explore using the same datasets. During the testing session, Participant 2 shared results from their analysis and interacted in a discussion-arguments related to the MPM model usage. Participant 2 also expressed a positive conclusion about the proposed MPM model as Participant 2 found the MPM model to demonstrate great usability for course admin.

Module	% Completion Module	% Completion of Widget	MDS	I1	WDS	I2	PS (%)	Positive Count	Negative Count	PS (%)	Module Name
L1	82.91	82.28	0	Positive	0	Positive	100	2	0	100	Lesson 1 : Chinese Phonetics Part 1
L2	80.83	79.87	-2.08	Negative	-2.41	Negative	50	2	2	50	Lesson 2: Chinese Phonetics Part 2
L3	79.55	80.58	-1.28	Negative	0.71	Positive	50	3	3	50	Lesson 3: Chinese Characters Part 1
L4	0.32	52.96	-79.23	Negative	-27.62	Negative	38	3	5	38	Lesson 4: Chinese Characters Part 2
L5	79.39	78.71	79.07	Positive	25.75	Positive	50	5	5	50	Lesson 5: Dialogue 1 - What Is Your Name?
L6	78.75	78.48	-0.64	Negative	-0.23	Negative	42	5	7	42	Lesson 6: Dialogue 2 - Greetings
L7	78.43	77.23	-0.32	Negative	-1.25	Negative	36	5	9	36	Lesson 7: Dialogue 3 - Etiquette Expressions
L8	77.8	75.63	-0.63	Negative	-1.6	Negative	31	5	11	31	Lesson 8: Dialogue 4 - My Family
L9	77.48	75.94	-0.32	Negative	0.31	Positive	33	6	12	33	Lesson 9: Dialogue 5 - My University
L10	77.64	76.96	0.16	Positive	1.02	Positive	40	8	12	40	Lesson 10: Dialogue 6 - Numerals
L11	77.8	76.94	0.16	Positive	-0.02	Negative	41	9	13	41	Lesson 11: Dialogue 7 - Dates and Festivals
L12	77.64	75.3	-0.16	Negative	-1.64	Negative	38	9	15	38	Lesson 12: Dialogue 8 - Invitation

Figure 57: Participant 2 Data Entry



	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12			
% Completion Module	82.91	80.83	79.55	0.32	79.39	78.75	78.43	77.8	77.48	77.64	77.8	77.64			
% Completion of Widget	82.28	79.87	80.58	52.96	78.71	78.48	77.23	75.63	75.94	76.96	76.94	75.3			
MDS	0	-2.08	-1.28	-79.23	79.07	-0.64	-0.32	-0.63	-0.32	0.16	0.16	-0.16	-77.64	0	0
WDS	0	-2.41	0.71	-27.62	25.75	-0.23	-1.25	-1.6	0.31	1.02	-0.02	-1.64	-75.3	0	0

Figure 58: Participant 2 Analysis Result Visualization

Argument 1: “*Does the MOOC platform also provide graph data visualisation? What is the difference with the graph generated using the MPM model if it does?*”

Argument 2: “*We experience diverse MOOC course learners' levels. As a result, there is a tendency to have a cohort group of learners that achieve high scores, and in other cohorts, we had a group of learners with very low scores. How does the MPM model measure performance in this situation?*”

Argument 3: “*Has this model been published or available openly to users?*”

7.3.3 Participant 3

Participant 3 is a Senior Teaching Fellow at a university in the United Kingdom that uses the FutureLearn MOOC platform. Participant 3 had over two years of experience using and offering three MOOC courses. Having experience looking at MOOC analytics data and being aware of the basic information from it, Participant 3 previous role was not involved deeply enough to make ongoing use of such statistics. Therefore, Participant 3 demonstrated a good understanding of using the MPM tool provided.

During the in-person testing session, Participant 3 observed a demonstration and briefing on how the MPM model works using sample datasets before Participant 3 took time to explore using the same datasets. Participant 3 shared results from their testing, asked questions and provided their feedback for discussion during the testing session based on experience related to the MPM model usage. Later, Participant 3 practised and explored using their dataset on their own. Participant 3 shared results from their datasets and asked questions and four arguments related to the usage of the MPM model. Below are sample results from Participant 3 own datasets.

Table 65: Participant 3 Data Entry

Steps/Learning Object	% Completion Module	% Completion of Widget	MDS	I1	WDS	I2	PS (%)		Positive Count	Negative Count	PS (%)
1.1	0.12	0.10	0	Positive	0	Positive	100		2	0	100
1.2	0.12	10.80	0.00	Negative	10.6959	Positive	75		3	1	75
1.3	0.11		0.00	Negative	-10.8	Negative	50		3	3	50
1.4	0.11		0.00	Negative	0.1323	Positive	50		4	4	50
1.5	0.10	0.13	-0.01	Negative	0	Negative	40		4	6	40
1.6	0.09		-0.01	Negative	-0.1323	Negative	33		4	8	33
1.7	0.09		0.00	Negative	0	Negative	29		4	10	29
1.8	0.09		0.00	Negative	0	Negative	25		4	12	25
1.9	0.08	0.09	-0.01	Negative	0.0936	Positive	28		5	13	28
1.10	0.08		0.00	Negative	-0.0936	Negative	25		5	15	25
1.11	0.07		0.00	Negative	0	Negative	23		5	17	23
1.12	0.07		0.00	Negative	0	Negative	21		5	19	21
1.13	0.07		0.00	Negative	0	Negative	19		5	21	19
1.14	0.07		0.00	Positive	0	Negative	21		6	22	21
1.15	0.06		0.00	Negative	0	Negative	20		6	24	20
1.16	0.07	7.16	0.00	Positive	7.16	Positive	25		8	24	25
1.17	0.07		0.00	Negative	-7.16	Negative	24		8	26	24
1.18	0.07		0.00	Negative	0	Negative	22		8	28	22
2.1	0.06	0.05	-0.01	Negative	0.0493	Positive	24		9	29	24
2.2	0.06		0.00	Positive	-0.0493	Negative	25		10	30	25
2.3	0.06		0.00	Negative	0	Negative	24		10	32	24
2.4	0.06		0.00	Negative	0	Negative	23		10	34	23
2.5	0.06		0.00	Negative	0	Negative	22		10	36	22

2.6	0.06		0.00	Negative	0	Negative	21		10	38	21
2.7	0.05	0.05	0.00	Negative	0.0489	Positive	22		11	39	22
2.8	0.05	0.05	0.00	Negative	-0.0018	Negative	21		11	41	21
2.9	0.05	0.05	0.00	Negative	-0.002	Negative	20		11	43	20
2.10	0.05		0.00	Negative	-0.0451	Negative	20		11	45	20
2.11	0.05		0.00	Negative	0	Negative	19		11	47	19
2.12	0.05		0.00	Negative	0	Negative	18		11	49	18
2.13	0.05		0.00	Positive	0	Negative	19		12	50	19
2.14	0.05		0.00	Negative	0	Negative	19		12	52	19
2.15	0.05	5.52	0.00	Positive	5.52	Positive	21		14	52	21
2.16	0.05		0.00	Positive	-5.52	Negative	22		15	53	22
2.17	0.05		0.00	Negative	0	Negative	21		15	55	21
3.1	0.05	0.04	0.00	Negative	0.0359	Positive	22		16	56	22
3.2	0.05		0.00	Positive	-0.0359	Negative	23		17	57	23
3.3	0.05	0.04	0.00	Negative	0.042	Positive	24		18	58	24
3.4	0.05		0.00	Negative	-0.042	Negative	23		18	60	23
3.5	0.05		0.00	Negative	0	Negative	23		18	62	23
3.6	0.05		0.00	Negative	0	Negative	22		18	64	22
3.7	0.05	0.04	0.00	Negative	0.0408	Positive	23		19	65	23
3.8	0.05	0.04	0.00	Negative	-0.0014	Negative	22		19	67	22
3.9	0.05		0.00	Negative	-0.0394	Negative	22		19	69	22
3.10	0.05		0.00	Negative	0	Negative	21		19	71	21
3.11	0.04		0.00	Negative	0	Negative	21		19	73	21
3.12	0.04		0.00	Negative	0	Negative	20		19	75	20
3.13	0.04		0.00	Negative	0	Negative	20		19	77	20
3.14	0.04	5.03	0.00	Negative	5.03	Positive	20		20	78	20
3.15	0.04		0.00	Positive	-5.03	Negative	21		21	79	21
3.16	0.04	0.03	0.00	Negative	0.0252	Positive	22		22	80	22
3.17	0.04		0.00	Negative	-0.0252	Negative	21		22	82	21

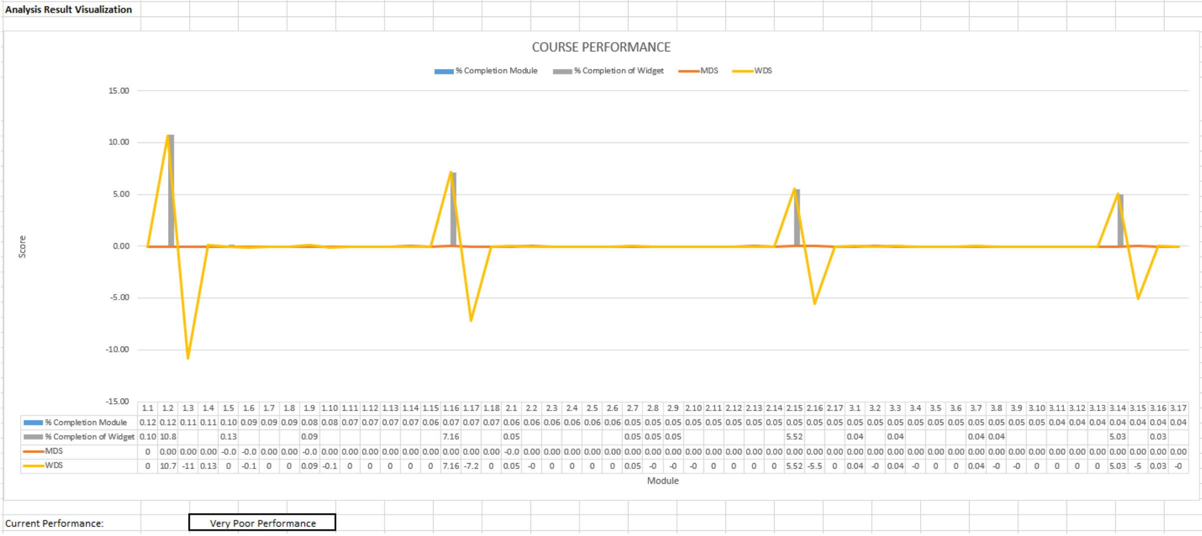


Figure 59: Participant 3 Analysis Result Visualization

Three arguments from Participant 3 based on the results are:

Argument 1: The pre-task, data cleaning and entry confusing and non-intuitive.

Argument 2: “*The graph currently includes "very poor performance" and indicates either technical problems, as it shows zero scores at many points or instructional problems, as the datasets are very volatile. However, this might be because I did not enter overall learner completion data, which would have given a fuller indication of participation above just videos and questions*.”

Argument 3: “*Is there a role for motivation in the 'instructional' element? Motivation is a key factor in learning, so might there be a prompt about motivation*.”

Participant 3 also expressed a positive conclusion towards the proposed MPM model as Participant 3 found the MPM model to be useful as an overall indicator of the course performance and each step or module. Two additional remarks from Participant 3 are:

Remark 1: Participant 3 skipped the Learner Performance testing due to time constraints to go through the pre-task data cleaning and transfer the raw learning analytics data.

Remark 2: However, Participant 3 thinks this tool could be very useful as a snapshot or diagnostic tool for evaluating a MOOC's design. Participant 3 liked the idea of having these different ways to get a holistic evaluation of a course.

7.3.4 Participant 4

Participant 4 is a professor at a university in the United Kingdom that uses the FutureLearn MOOC platform. Participant 4 had over two years of experience using and offering three MOOC courses. Having experience using Microsoft Excel and working with FutureLearn learning analytics data, Participant 4 demonstrated good adaptability in understanding and using the MPM tool provided.

During the testing session, participant 4 observed a demonstration and briefing on how the MPM model works using sample datasets before Participant 4 took time to explore using the same datasets. Later, Participant 4 practised being interested to know what the measurement and analysis graph looks like within different data scenarios. Participant 4 shared results from their data and asked questions and four arguments related to the usage of the MPM model.

COURSE PERFORMANCE

Steps/Learning Object	% Completion Module	% Completion of Widget	MDS	I1	WDS	I2	PS (%)		Positive Count	Negative Count	PS (%)
1.1	0.20	0.10	0	Positive	0	Positive	100		2	0	100
1.2	0.19	0.10	-0.01	Negative	0	Negative	50		2	2	50
1.3	0.19	0.09	0.00	Negative	-0.01	Negative	33		2	4	33
1.4	0.18	0.09	-0.01	Negative	0	Negative	25		2	6	25
1.5	0.18	0.08	0.00	Negative	-0.01	Negative	20		2	8	20
1.6	0.17	0.06	-0.01	Negative	-0.02	Negative	17		2	10	17
1.7	0.15	0.03	-0.02	Negative	-0.03	Negative	14		2	12	14
1.8	0.15	0.03	0.00	Negative	0	Negative	13		2	14	13
1.9	0.14	0.06	-0.01	Negative	0.03	Positive	17		3	15	17
1.10	0.15	0.06	0.01	Positive	0	Negative	20		4	16	20

Figure 60: Participant 4 Data Entry

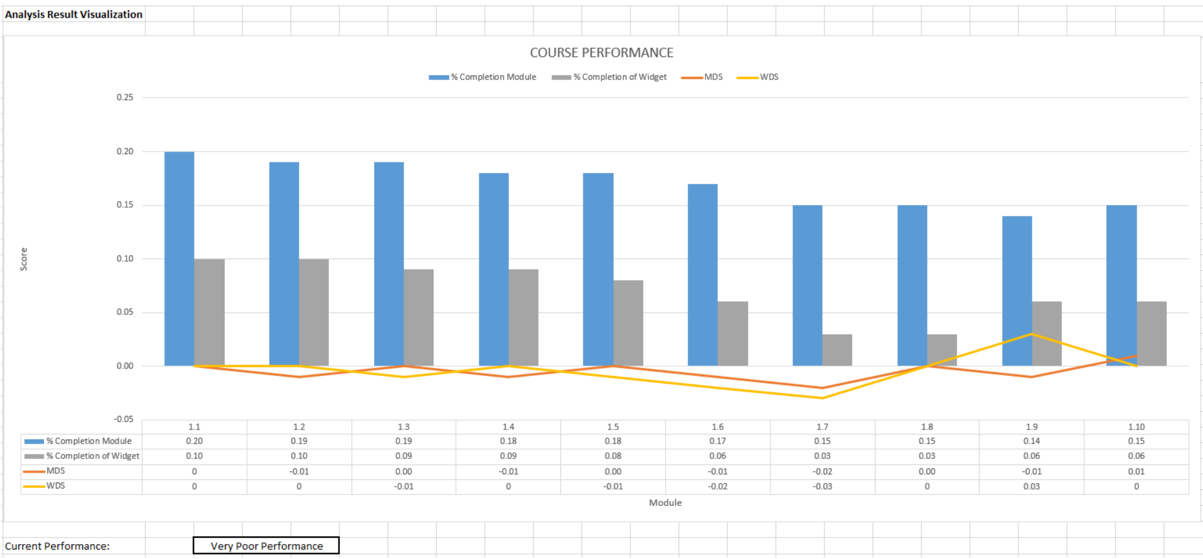


Figure 61Participant 4 Analysis Result Visualization

Above are sample results from Participant 4 own data testing. Four arguments from Participant 4 based on the results and testing session are:

Argument 1: "*With regards to the definition of performance used in this study. Researchers mix academic performance measurement and completion rate. I would argue that they were different. Researchers assume everybody needs to be engaged to succeed, but someone might follow.*"

Argument 2: "*Why do you discard the widget completion in learner performance measurement?*"

Argument 3: There are assumptions that student numbers and engagement would drop. Participant 4 is interested in seeing what different data would look like. Therefore, Participant 4 just put some sample data in scenarios when engagement increases.

Argument 4: "*To what extent is there noise? What is considered normal? We will not expect data to be flat, but what does normality look like? What the researcher did was problematic, spotting things.*"

7.3.5 Participant 5

Participant 5 is a lecturer at a higher learning institution in Malaysia that uses the OpenLearning MOOC platform. Participant 5 had over two years of experience using and offering one MOOC course since 2013. Having no experience using learning analytics for analysis, Participant 5 demonstrated interest in MOOC learning analytic data analysis and showed a good understanding of using the MPM model. Participant 5 also demonstrated a good understanding of using the provided tool.

During the testing session, Participant 5 observed a demonstration and briefing on how the MPM model works using sample datasets before Participant 5 took time to explore using the same datasets. Participant 5 shared their analysis results during the testing session and discussed the MPM model usage. Participant 5 expressed a positive conclusion about the proposed MPM model as Participant 5 found the MPM model to give valuable and useful insight to the MOOC course admin. Three arguments highlighted by Participant 5 are shown below.

COURSE PERFORMANCE													
Module	% Completion Module	% Completion of Widget	MDS	I1	WDS	I2	PS (%)		Positive Count	Negative Count	PS (%)		Module Name
Unit 0	87.79	42.59	0	Positive	0	Positive	100		2	0	100		Unit 0: Introduce Yourself
Unit 1	80.23	60.47	-7.56	Negative	17.88	Positive	75		3	1	75		Unit 1: Overview of Multimedia Technology
Unit 2	78.49	67.98	-1.74	Negative	7.51	Positive	67		4	2	67		Unit 2: Text
Unit 3	79.07	58.45	0.58	Positive	-9.53	Negative	63		5	3	63		Unit 3: Image
Unit 4	79.65	57.51	0.58	Positive	-0.94	Negative	60		6	4	60		Unit 4: Graphics
Unit 5	78.49	59.83	-1.16	Negative	2.32	Positive	58		7	5	58		Unit 5: Sound
Unit 6	78.49	70.38	0	Negative	10.55	Positive	57		8	6	57		Unit 6: Video
Unit 7	77.91	54.16	-0.58	Negative	-16.22	Negative	50		8	8	50		Unit 7: Animation
Unit 8	77.91	64.14	0	Negative	9.98	Positive	50		9	9	50		Unit 8: Making Multimedia
Unit 9	77.33	62.68	-0.58	Negative	-1.46	Negative	45		9	11	45		Unit 9: Planning and Costing Multimedia Product
Unit 10	77.33	64.44	0	Negative	1.76	Positive	45		10	12	45		Unit 10: Designing and Producing Multimedia Product
Unit 11	76.16	76.58	-1.17	Negative	12.14	Positive	46		11	13	46		Unit 11: Delivering Multimedia Product
Unit 12	76.16	59.24	0	Negative	-17.34	Negative	42		11	15	42		Unit 12: Professional Issues in Multimedia Development
Unit 13	76.16	67.7	0	Negative	8.46	Positive	43		12	16	43		Unit 13: Internet and Multimedia
Unit 14	76.16	59.24	0	Negative	-8.46	Negative	40		12	18	40		Unit 14: Mobile Multimedia

Figure 62: Participant 5 Data Entry

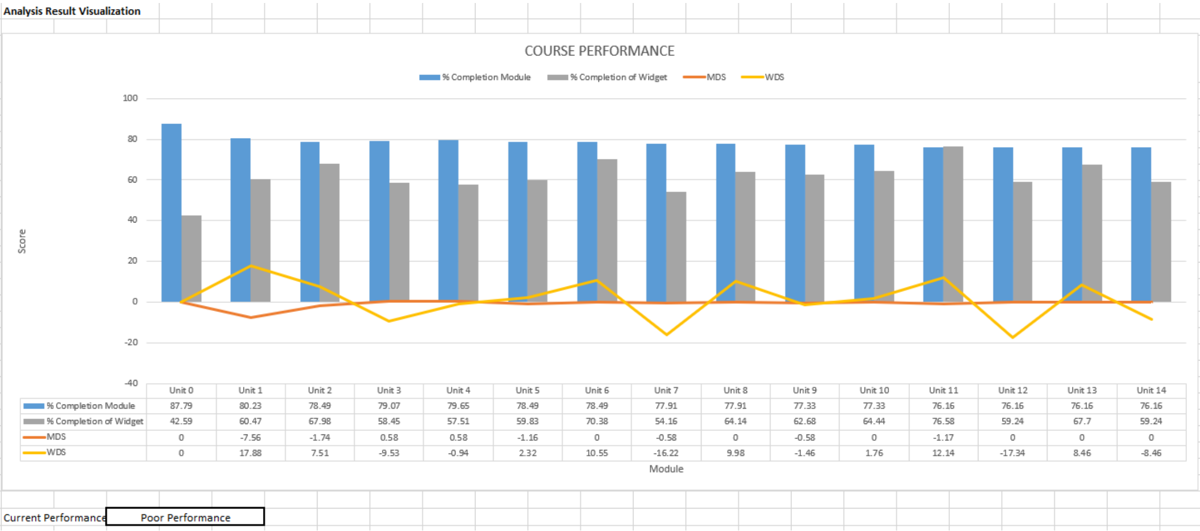


Figure 63: Participant 5 Analysis Result Visualization

Argument 1: “*We have MOOC data for a course from 2013 until 2023. We have never analysed the data. One of the reasons we are not considering analysing MOOC learning analytics data is that when most students do their MOOC and answers, we assume everything is in order, with no future analysis or inspection needed.*”

Argument 2: “*There is another internal learning tool where students answer questions or tasks; therefore, not all assessments or activities were done on the MOOC platform to avoid repetition.*”

Argument 3: “*There is a trend where Higher learning institution in Malaysia are changing their MOOC platform. Ministry policy might affect the platform used for public universities, while private universities control which MOOC platform to use or retain.*”

7.3.6 Participant 6

Participant 6 is a lecturer at a higher learning institution in Malaysia that uses the OpenLearning MOOC platform. Participant 6 had over two years of experience using and offering one MOOC course.

Having no experience using learning analytics for analysis, Participant 6 demonstrated a good understanding of the MPM model. Participant 6 also demonstrated a good understanding of using the provided tool, as Participant 6 is familiar with using Microsoft Excel software.

During the testing session, Participant 6 observed a demonstration and briefing on how the MPM model works using sample datasets before Participant 6 took time to explore using the same datasets. Participant 6 shared their analysis results during the testing session and discussed the MPM model usage. Participant 6 expressed a positive conclusion about the proposed MPM model as Participant 6 found it to be useful in learning analytics. Five arguments highlighted by Participant 6 are shown below.

Module	% Completion Module	% Completion of Widget	MDS	I1	WDS	I2	PS (%)
1	82.91	78	0	Positive	0	Positive	100
2	80.83	85	-2.08	Negative	7	Positive	75
3	79.55	85	-1.28	Negative	0	Negative	50
4	0.32	84	-79.23	Negative	-1	Negative	38
5	79.39	70	79.07	Positive	-14	Negative	40

Figure 64: Participant 6 Data Entry

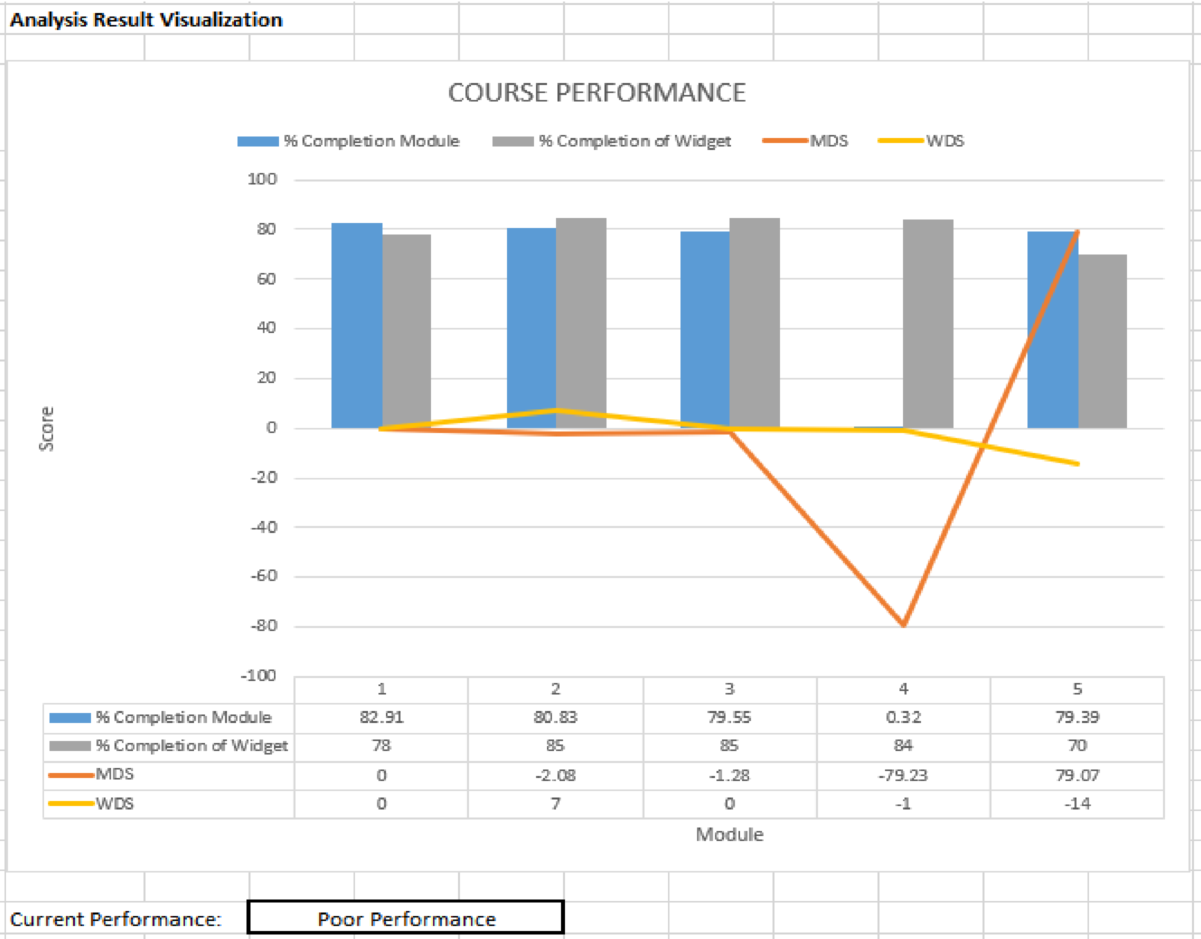


Figure 65: Participant 6 Analysis Result Visualization

Argument 1: "*Normally, when we mention performance, we evaluate learner assessment marks as good. Is this model more for the evaluation of assessment?*"

Argument 2: MOOC content is usually prepared in advance and ready to use. Therefore, this model can be considered as a learning analytics helper with no direct effect on current MOOC content.

Argument 3: Some students already know about the topic, and some may skip topics they consider known or have learned before.

Argument 4: "*We recently changed our MOOC platform, and some courses were upgraded to micro-credential. Will the model work on other MOOC platforms?*"

Argument 5: "*Can this model work with live or direct learning analytics data from MOOC platforms?*"

7.3.7 Participant 7

Participant 7 is a lecturer at a university in the United Kingdom that uses the FutureLearn MOOC platform. Participant 7 had more than two years of experience using and offering more than four MOOC courses. Familiar with FutureLearn learning analytics data structure and experienced in FutureLearn learning analytics data analysis via customised web-based dashboard, Participant 7 demonstrated good adaptability in understanding and using the MPM tool provided.

During the in-person testing session, participant 7 observed a demonstration and briefing on how the MPM model works using sample datasets before Participant 7 took time to explore using the same datasets in an online session via Teams.

Participant 7 emphasised the critical aspect of having a good application or platform for this model that will improve the user experience using the MPM model for its purpose. Participant 7 shared his experience and provided two arguments for discussion.

COURSE PERFORMANCE

Module	% Completion Module	% Completion of Widget	MDS	I1	WDS	I2	PS (%)
1	82.91	77.95	0	Positive	0	Positive	100
2	80.83	82	-2.08	Negative	4.05	Positive	75
3	79.55	78	-1.28	Negative	-4	Negative	50
4	0.32	88	-79.23	Negative	10	Positive	50
5	79.39	68	79.07	Positive	-20	Negative	50
6	78.75	59.52	-0.64	Negative	-8.48	Negative	42
7	78.43	53	-0.32	Negative	-6.52	Negative	36
8	77.8	78	-0.63	Negative	25	Positive	38
9	77.48	75	-0.32	Negative	-3	Negative	33
10	77.64	77	0.16	Positive	2	Positive	40
11	77.8	75.3	0.16	Positive	-1.7	Negative	41
12	77.64	70	-0.16	Negative	-5.3	Negative	38

Positive Count	Negative Count	PS (%)
2	0	100
3	1	75
3	3	50
4	4	50
5	5	50
5	7	42
5	9	36
6	10	38
6	12	33
8	12	40
9	13	41
9	15	38

Figure 66: Participant 7 Data Entry

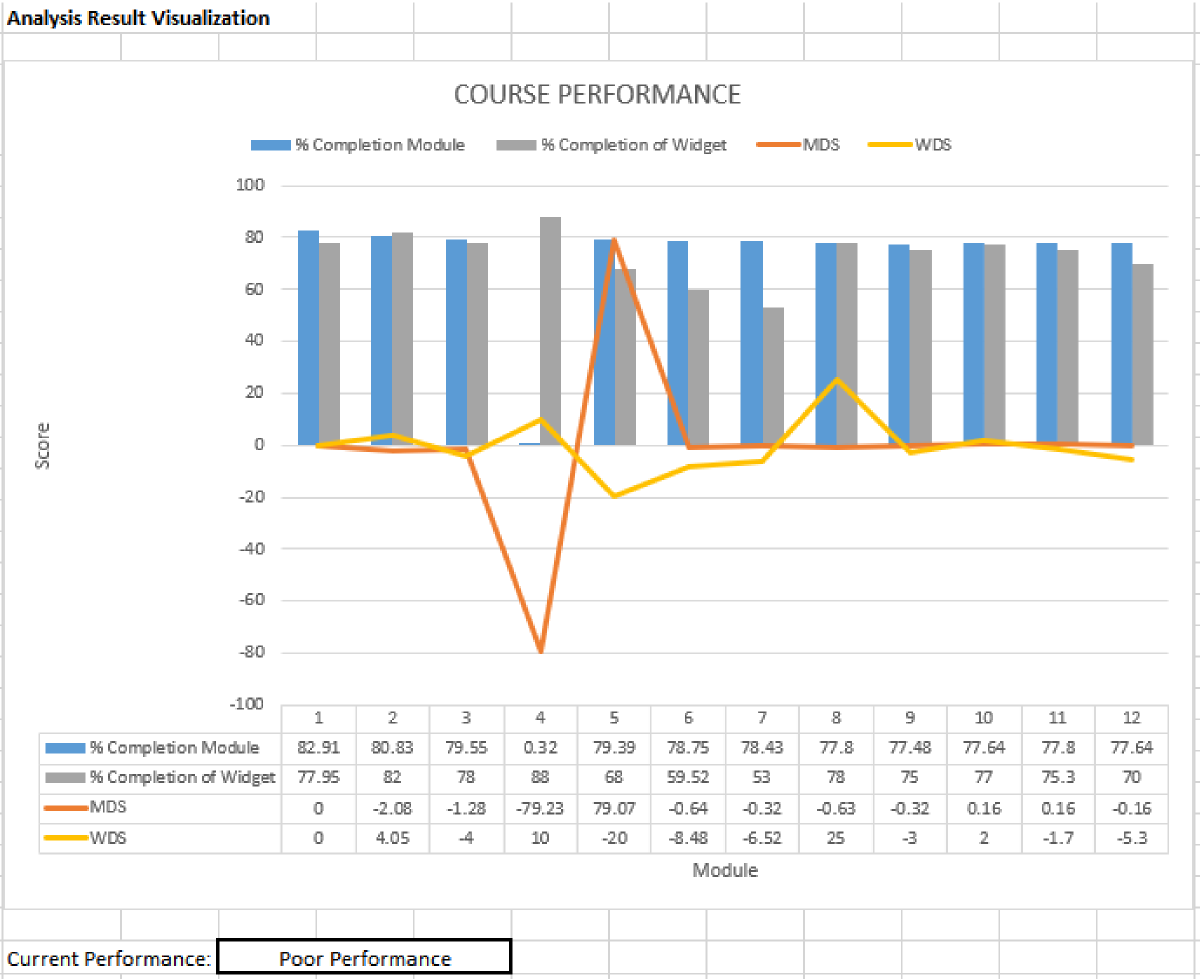


Figure 67: Participant 7 Analysis Result Visualization

Argument 1: It is not easy to compare results with the consideration factor indicator.

Argument 2: “*What user interface have you prepared for this model?*”

7.4 Questionnaire Results and Feedback Analysis

Each participant is required to answer questionnaire questions and provide feedback. The questionnaire form is included in the provided MPM tool document, with a total of 31 questions asked. Questions were structured into four parts: Demography, MPM Usage (Monitoring), MPM Usage (Measurement), MPM Usage (Analysis), and Feedback.

7.4.1 Part 1: Demography

Seven participants participated in this MPM Model user usability testing; 57% used the OpenLearning MOOC platform, while the remaining 43% used the FutureLearn MOOC platform. All participants have more than two years of experience using MOOC.

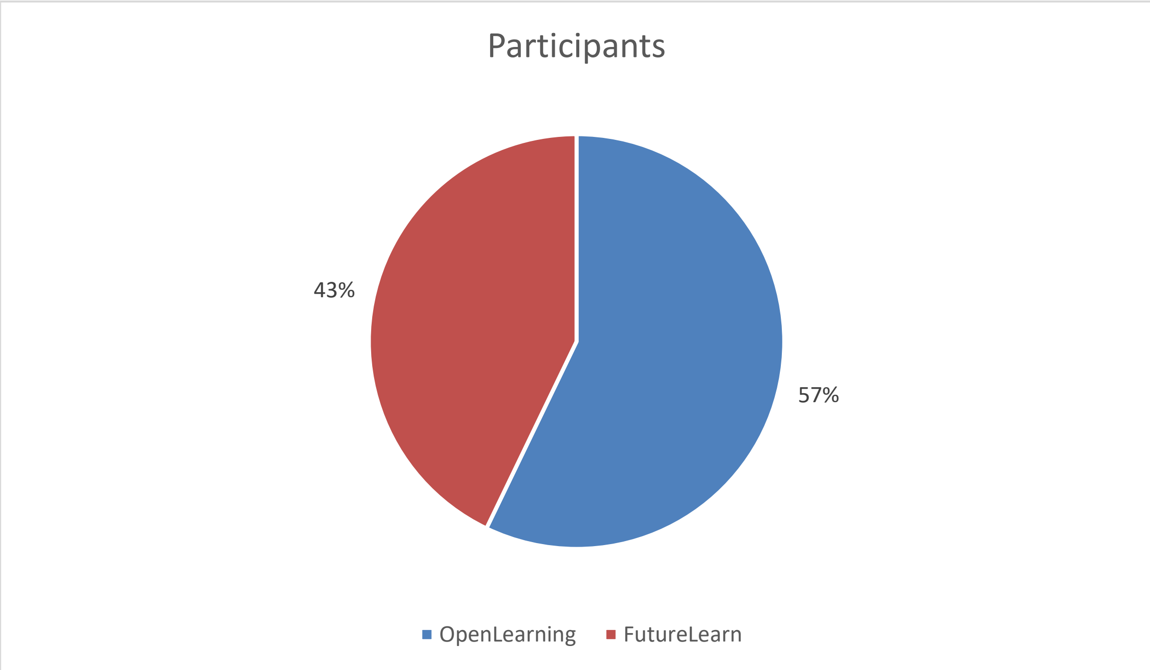


Figure 68: User Usability Testing Participant Demography

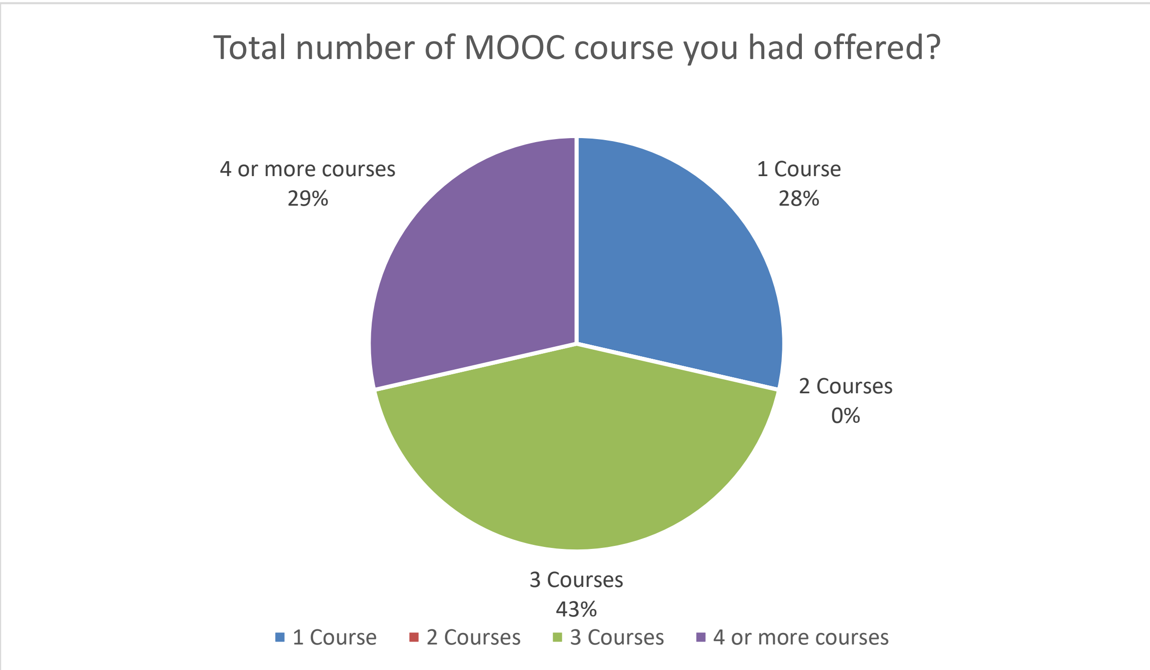


Figure 69: Participant MOOC Course Offering Experience

Participants are mixed in roles. Participants identified their roles as MOOC content developer (5 participants), course admin (2 participants), course moderator (2 participants), instructor (1 participant), tutor (1 participant), course lead (1 participant), and course designer (1 participant).

Six participants indicated their MOOC course was designed for Undergraduate learners, while one participant indicated their MOOC course was designed for open and mixed learners.

All participants are using the provided sample datasets. Later, one participant used their datasets to explore further how the MPM model works with different data sets, and the remaining used their made-up data sample.

7.4.2 MPM Usage (Monitoring)

In Part 2, I ask six questions about the MPM model's monitoring element. While 29% of participants responded neutral when asked if it would make their job easier to monitor course or learner performance using the MPM model, the remaining 71% responded satisfied and very satisfied. All participants find the MPM model helpful in monitoring tasks. 71% of participants indicated that using the MPM model would enhance their understanding of the learning analytics data recorded. When asked if learning to use the MPM model for monitoring using the provided tool would be easy, 29% responded unsatisfied, and only one participant indicated dissatisfaction when asked if the monitoring element of the MPM model was easy to understand. This unsatisfied response was expected due to the lack of automation and interactive features in the provided MPM tool, built using Microsoft Excel.

Table 66: MPM Usage (Monitoring) Respond

	Very Unsatisfied	Unsatisfied	Neutral	Satisfied	Very Satisfied	
	[-2]	**[-1]**	**[0]**	**[1]**	**[2]**	
Q9: Using MPM would make it easier to do my job as a MOOC course admin.			2	3	2	7/14
Q10: I would find MPM useful in my job				5	2	9/14
Q11: Using MPM would enhance my			2	3	2	7/14

understanding of the learning analytic data for the course I am offering						
Q12: Learning to use MPM from the provided tool would be easy for me		2	2	1	2	3/14
Q13: I would find MPM to be flexible to interact with			3	3	1	5/14
Q14: I would find MPM easy to use		1	1	3	2	6/14

In general, 69% of participants responded that they were satisfied and very satisfied with the monitoring element of the MPM model. 24% of participants indicated neutral, with only 7% responding unsatisfied.

7.4.3 MPM Usage (Measurement)

We ask four questions in Part 3, which focuses on the measurement element of the MPM model. All participants were satisfied with the performance measurement approach used in the MPM model, with 1 participant indicating very satisfied in Q17. However, in Q18, one participant responded with an unsatisfied experience with understanding the Condition Indicator used. The unsatisfied experience response was due to the argument that the parameter used for measurement feels like it combines engagement and assessment performance. When asked about changing the default performance metrics, 57% of participants indicated they would change based on their institution benchmark. As we described earlier, the performance metrics used in the testing session are default metrics with recommendations to change based on users' standards.

Table 67: MPM Usage (Measurement) Respond

	Very Unsatisfied	Unsatisfied	Neutral	Satisfied	Very Satisfied	
	[-2]	**[-1]**	**[0]**	**[1]**	**[2]**	
Q17: I would find the measurement approach used by the MPM Model				6	1	8/14

is acceptable in reflecting improvement or deterioration of performance.						
Q18: I would find the Condition Indicator used in this model easy to understand.		1	1	3	2	6/14
Q19: I would change the default Performance Metric proposed to follow my institution's standard.			3	2	2	6/14
Q20: It would be easy for me to become skilful at importing data into the MPM Model ready for performance measurement		1	1	3	2	6/14

Q20 asks if it would be easy for participants to become skilful at importing data into the MPM model for performance measurement; one participant responded unsatisfied, one participant responded neutral, and the remaining 71% responded satisfied and very satisfied.

In general, 75% of participants responded that they were satisfied and very satisfied with the measurement element of the MPM model. 18% of participants indicated neutral, with only 7% responding unsatisfied.

7.4.4 MPM Usage (Analysis)

Six questions related to the analysis element of the MPM model were asked. All participants responded with satisfaction and were very satisfied when asked whether using analysis based on the MPM model would enhance their effectiveness in improving the offered MOOC course. We recorded the same response with another two questions when asked if they found the analysis result from the MPM model useful in their job and if the Consideration Factor Indicator provided was helpful.

Table 68: MPM Usage (Analysis) Respond

	Very Unsatisfied	Unsatisfied	Neutral	Satisfied	Very Satisfied	
	[-2]	**[-1]**	**[0]**	**[1]**	**[2]**	
Q21: Using analysis based on the MPM Model would enhance my effectiveness in improving the offered MOOC course.				4	3	10/14
Q22: I would find analysis results from the MPM Model useful in my job.				5	2	9/14
Q23: Learning to compare analysis results with the provided indicator would be easy for me.		1	1	4	1	5/14
Q24: The analysis result was successfully generated with no error		1		2	4	9/14
Q25: The result gives insight into which module needs extra attention for improvement.			1	3	3	9/14
Q26: I would find the Consideration Factor Indicator provided is helpful				2	5	12/14

One participant indicated an unsatisfied response when asked if learning to compare analysis results with the provided indicator would be easy for them. 71% of participants responded satisfied and very satisfied for the same question. This response is partly affected by the fact that we are applying a manual analysis method, where participants need to observe the performance graph patent generated and refer it to the indicators. One participant was also unsatisfied when asked if the analysis result was successfully generated with no error. This response was later justified in the feedback section, where the participant could not provide the required data.

In general, 90% of participants responded that they were satisfied and very satisfied with the analysis element of the MPM model. 5% of participants indicated neutral, and another 5% responded unsatisfied.

7.4.5 Feedback Analysis

In Part 5 of the questionnaire, I ask four feedback questions (Q27 to Q31). Each question explicitly addresses the essential elements of the MPM model, which are monitoring (Q27), measuring (Q28), analysis (Q29), previous experience with MOOC learning analytics (Q30), and general improvement recommendations for the MPM Model (Q31). Below is feedback from all participants and my responses to it.

Q27: Monitoring performance is one of the MPM Model features. Please provide your feedback and related improvement recommendations based on recent monitoring performance experience using the MPM model.

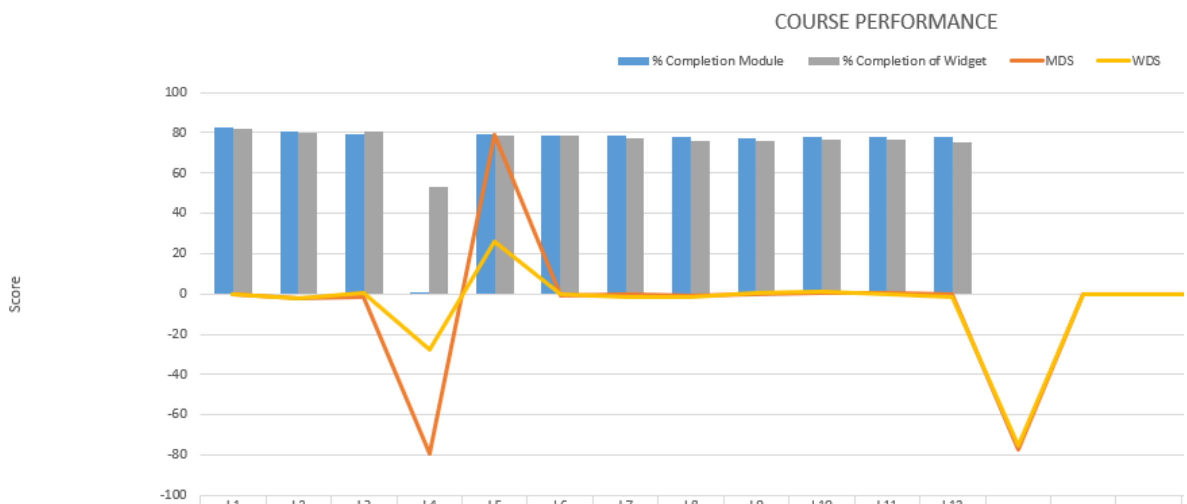
Table 69: Participants Q27 Feedback

Participant Feedback	Feedback Summary
P1: It is easy to monitor the course performance by using this MPM Model. I can easily identify which lesson has a lower performance. However, the chart should immediately stop when there is no more lesson after that. For example, stop charting after Lesson 12.	• **It is easy** to monitor course performance by using this MPM Model. • Can **quickly identify** which lesson has a lower performance. • **However**, the chart should immediately stop when there is no more lesson after that.
P2: The monitoring performance of this MPM Model is very good. It helps to identify course analysis that needs to be improved and is very useful for developers and researchers.	• The monitoring performance of this MPM Model is **very good**, • It **helps to identify** course analysis that needs to be improved, • And **very useful** for developers and researchers.
P3: I haven't worked with MOOCs recently, so I don't really know what monitoring dashboards or data is currently available. However, I feel like this snapshot of the performance of the MOOC would be useful as an overall indicator of the course performance and of each step or module.	• I have not worked with MOOC recently, so I **do not really know** what monitoring dashboards or data are **currently available.** • **However**, this snapshot of the performance of the MOOC would be **useful as an overall indicator** of the course performance of each step or module.

P4: It still feels like a relatively simple analysis (that is similar to what I would do by hand already). So, it is a useful analysis, but as it replicates what I would already be looking for, I would only find it useful for communication rather than analysis. It might be useful to flag where the peaks or troughs were outside of the standard statistical range - that might help to highlight which ones were worth looking at.	• It still feels like a relatively **simple analysis** (that is similar to what I would do by hand already) • It is a **useful analysis**, • However, as it **replicates** what I would **already be looking** for, I would only find it **useful for communication** rather than analysis. • It might be **useful to flag** where the peaks or troughs were outside of the standard statistical range, • That might **help to highlight** which ones were worth looking at
P5: Perhaps you may consider other factors, such as whether the students are being "forced" to complete the modules or not. The completion rates of MOOCs can be influenced by motivation from external factors like the instructor and whether students take MOOCs voluntarily or are required to complete them.	• **Consider other factors,** such as "being forced" to complete the modules. • Completion rates of MOOCs can be **influenced by external motivation**, • **Whether** students **voluntarily or are required** to complete them
P6: Monitoring helps to give a big view of students' learning behaviour.	• **It helps** view students **learning behaviour**.
P7: The adoption of this model highly depends on how engaged I can be. The current tool provides me with a very clear overview of how it could work in a real environment. For a wider adoption, I highly recommend a friendly UX that can engage a wider community of academics.	• **Adoption** of this model **highly depends** on how engaged the course can be. • The current tool **provides a very clear overview** of how it could work in a real environment. • **Highly recommend a friendly UX**.

In Q27, I asked for feedback on participants' experiences monitoring performance using the MPM model. All participants indicated that the monitoring experience was useful and helpful. Particularly in providing insight and flagging to which module required attention for improvement.

Participants also provided us with an improvement recommendation to consider. For example, the current tool was not responsive enough to the data input. As a result, the generated graph did not end, and a flat line was visualized. This recommendation will be considered for future work focusing on developing and delivering dynamic user experience tools, considering the MPM tool is not within the scope of my research study.



	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12			
% Completion Module	82.91	80.83	79.55	0.32	79.39	78.75	78.43	77.8	77.48	77.64	77.8	77.64			
% Completion of Widget	82.28	79.87	80.58	52.96	78.71	78.48	77.23	75.63	75.94	76.96	76.94	75.3			
MDS	0	-2.08	-1.28	-79.23	79.07	-0.64	-0.32	-0.63	-0.32	0.16	0.16	-0.16	-77.64	0	0
WDS	0	-2.41	0.71	-27.62	25.75	-0.23	-1.25	-1.6	0.31	1.02	-0.02	-1.64	-75.3	0	0

Figure 70: Visualization Improvement Recommendation

Another recommendation is to consider other factors, such as whether learners are being forced to complete their MOOC course module or not and learners' voluntary element. In the Consideration Factor Indicators, instruction, humans, and environment are three areas out of five that, at some level, cover the factor mentioned. For example, "Did a reminder be given to learners?", "Did learners show any sign of protest/ejection?" and "Is there any related promotion or marketing ongoing recently?" are three questions that relate to "being forced" or "whether learner voluntarily or required to complete them". In the previous chapter, I informed that the consideration factor indicators introduced and used in this study will most likely expand over time with more data, observation, and further study.

Q28: Measuring performance is another feature of the MPM Model. Design based on the fundamental concept where the latest score is better than the previous score; please provide your feedback and related improvement recommendations on recent experience measuring performance using the MPM model.

Table 70: Participants Q28 Feedback

Participant Feedback	Feedback Summary
P1: It is also easy to measure the course performance by using this MPM Model. I	• Using this MPM Model, it is also **easy to measure** the course performance.

can easily identify which lesson has the lowest performance score. However, the measurement should immediately stop when there is no more lesson after that. For example, it should stop measuring after Lesson 12.	• I can **easily identify which lesson** has the lowest performance score. • **However**, the measurement should immediately stop when there is no more lesson after that.
P2: Measuring the performance of the MPM model is very helpful for the developer to know the performance of the developed course is appropriate by measuring the performance of the students before and after the module is taken.	• Measuring the performance of the MPM model is **very helpful** for the developer, • To know if the performance of the developed course is **appropriate by measuring the students' performance before and after the module is taken**.
P3: Because my results were quite volatile and indicated poor performance of the MOOC, it's hard to say. Mostly, the score was zero, with a few peaks and dips. However, the example shown to me in the training was more informative, and I think it would be a useful way of getting an idea of performance measurement.	• **Because results** were quite **volatile** and • **Indicated** poor performance of the MOOC, it is **hard to say**. • **Mostly, the score was zero** within a few peaks and dips. • **However**, the example shown to me in the training was **more informative and** • I think would be a **useful way** of getting an idea of **performance measurement**.
P4: It feels like it combines engagement and performance (on assessment), which I would regard as two separate things. Knowing both how many people are attempting activities as well as the performance of those that do feel important. Performance is a neutral term; it is always measuring something against a metric, and the choice of metric matters. So, in this case, you are measuring performance against engagement metrics, so this is not measuring 'performance'; it is measuring 'engagement'.	• It **feels like it combines engagement and performance** (on assessment), which I would **regard as two separate things**. • **Knowing** how many people are attempting activities and the **performance of those who do feel important.** • **Performance is a neutral term**, • It always measures something against a metric, and **the choice of metric matters**. • In this case, **you are measuring performance against engagement metrics**, • So, **this is not measuring 'performance' but measuring 'engagement.'**
P5: Ensure that the measures used are relevant and aligned with the UNIMAS or KPT's agenda. It's important to choose the right metrics that will give a clear picture of progress towards achieving the goals.	• Ensure the **measurements are relevant and aligned with the university or ministry agenda**. • The **right Metric is important to indicate progress** towards **achieving the learning goals**.
P6: Measuring performance helps the student maintain their learning effort	• Measurement **helps** students **maintain learning efforts**.
P7: There was an improvement in the consideration factor table, one of the most useful tools of this model, in my opinion.	• **The consideration factor table is the most useful element**.

In Q28, I asked for feedback on participants' experiences measuring performance using the MPM model, in which I applied a concept comparing current and previous scores. I received mixed feedback, with most of it being positive. Participants responded that the measurement element was easy to use and understand and did provide helpful results. The consideration factor table is also mentioned as the most useful element.

However, I received some feedback on the definition of performance and how I implement my measurement within the proposed concept. Some participants argue about the definition of 'performance' and 'engagement' and the parameters used for measurement in my model. As mentioned in the previous chapter, a broad definition of performance can be used, depending on the context. This study defines performance as the ability to maintain the highest score, including constantly improving or maintaining the highest score possible. In my definition, performance is not limited to an assessment or activities marked or evaluated by the course.

In another argument, in my measurement algorithm, I am not measuring performance against engagement metrics; instead, I measure current data against the previous data of the same parameter. For example, in course performance, I measure the completion module against the completion module as Parameter 1 and the completion widget against the completion widget as Parameter 2, and in learner performance, I measure the completion module against the completion module as Parameter 1 and the assessment score against the assessment score as Parameter 2.

I can agree on defining the completion module and completion widget used as Parameter 1 and Parameter 2 in course performance measurement categorized as engagement data. This, considering course performance, is different from learner performance. Learner performances are more personal; I had assessment data to justify that. Course performance is a general measurement of the collective of learners in that course; how they interact with each module is what I consider best fit to measure the course performance. I consider this as course performance, as I measure the difference score of the current module with the previous module, which fits well with my performance definition and concept. I can agree that the calculated data for a single module is an engagement measurement, and when comparing these two engagement data, it creates the performance score for a MOOC course.

I include assessment data as Parameter 2 in learner performance measurement due to the personalised element that can be measured in each learner. I removed the widget completion data for learner performance measurement, considering the possible redundancy with the assessment data used.

I also agreed that the right metric is vital to indicate progress towards achieving the learning goal. It is critical to understand the meaning behind each analytic data inorder to identifying the suitable measurement parameters. I also limit the measurement parameters to two parameters to avoid and reduce data noise. Next, I design and use metrics and indicators to support my data measurement and analysis. As described in the previous chapter, the performance metric is flexible and can be changed based on user or university benchmarks or requirements. As I consider, a different user might have different standards or levels used.

One participant provided interesting feedback: measuring performance used in my model could help students maintain learning effort. This statement identically reflects the performance concept I applied. It also encourages learners to improve, a significant sign of performance constantly.

For example, a learner can be seen as engaging with the modules throughout the course. Scoring the same 90% completion module or widget does not reflect a good performance definition in my study. I can agree that this example learner is a high achiever or highly engaged learner but not a good performance learner. A similar condition with a poor achiever or poor engaged learner. If they, based on my measurement, can record an improvement difference score, it will indicate an improvement. A learner who starts a course with a 20% score and achieves 60% at the end is better in terms of performance than a learner who starts a course with a 90% score and achieves 88%.

Q29: Analysis performance is another feature of the MPM Model. It includes consideration factors and indicators that cover five areas (technical, instruction, content, human, and environmental). Please provide your feedback based on recent analysis experience using the MPM model.

Table 71: Participants Q29 Feedback

Participant Feedback	Feedback Summary
P1: Indicators and factors provided are helpful and useful for performance analysis. However, some of them are confusing. Further elaboration is recommended. Here is the list: **Technical - Did learners have access to the platforms? Instruction - The following consideration factor is confusing: Did**	• The indicators and factors provided are **helpful**. • And **useful for performance analysis**. • **However**, some of them are confusing. • **Further elaboration is recommended**. • **Technical** – did learners have access to the platforms? • **Instruction** – the following consideration factor is **confusing: Was explicit**

explicit instruction have been given by the course admin? Why course admin is referred here? Does the 'instruction' here mean instructions delivery by educators/instructors? **Instruction - The following Indication is confusing: Volatile indicator on both dataset scores. 'Both dataset scores' are referring to what? Why 'both'?** **Content - The following consideration factor is confusing: Is content new to learners? Do you mean 'content type used was new to the learners', since in learning, educators always present new learning content to the learners?** **Human - again, it's not clear why 'both datasets'?**	**instruction given by the course admin?** Why is course admin referred here? **Does the 'instruction' here mean instructions delivery by educators/instructors?** • **Instruction** – the following consideration factor is **confusing**: Volatile indicator on both dataset scores. **Are 'Both dataset scores' referring to what? Why 'both'?** • **Content** – The following consideration factor is **confusing**: Is content new to learners? **Do you mean the 'content type used was new to the learners' since educators always present new learning content to the learners in learning?** • **Human** – again, it is **not clear why 'both datasets.**
P2: Performance analysis The MPM Model provides a clear picture to developers for module improvement and the appropriateness of measuring performance and analysing student performance.	• Performance analysis of the MPM Model **provides a clear picture to developers for module improvement**. • And the **appropriateness** of measuring and analysing student performance.
P3: Yes - I think it's useful to break down performance into different categories. I've made some comments on the previous sheet about possible enhancements to the 'instruction' category. I suppose it's important to remember that MOOCs aren't really heavily reliant on 'instruction' as such but are also opportunities for independent learning and reflection (so Heutagogy, or self-determined learning, as much as pedagogy). This means that motivation will be a key factor - and it might be useful to have that as a consideration in the instruction element. Does the MOOC motivate the learners to complete a step/course and to persist? There might be a good prompt about motivation to add to the questions in the 'instruction' field. For example, ' Does the step make clear the benefit of learning this skill/content'? Not just a 'cold' description of what is coming but a reason for the participant to do it. Perhaps stated as a motivating learning outcome: 'This step will enable you to ...' **I suppose you could also ask about**	• Yes, I think it's **useful to break down** performance **into different categories**. • I've made some **comments on the previous** sheet about **possible enhancements to the 'instruction' category**, • I suppose it's **important** to remember that **MOOCs aren't heavily reliant on 'instruction' as such**, • But there are **also opportunities for independent learning and reflection** (so Heutagogy, or self-determined learning, as much as pedagogy). • This means that **motivation will be a key factor** – and it **might be useful to consider that in the instruction element**. • **Does the MOOC motivate** the learners to complete a step/course and to persist? • There might be a good **prompt about motivation** to add to the questions in the 'instruction' field. • For **example**, 'Does the step make clear the benefit of learning this skill/content.' Not just a 'could' description of what is coming but a reason for the participant to do it.

	• Perhaps stated as a **motivating learning outcome**: 'This step will enable you to...'
P4: This provides a useful framework for analysing changing engagement - and reminds one of both internal and external factors.	• This provides a **useful framework** for analysing changing engagement. • It reminds us of both **internal and external factors**.
P5: You may add these factors too: User-friendly platform, clear and engaging instruction and content, opportunities for interaction and feedback, and flexible scheduling options to accommodate learners' needs.	• **Considering** adding other factors: ○ **User-friendly platform**, ○ clear and engaging **instruction and content**, ○ opportunities for **interaction and feedback**, ○ **flexible scheduling options** accommodating learners.
P6: Analysis of performance gives an insight into which performance may relate	• Give an **insight into which performance relates**.
P7: Very useful!	• **Very useful**.

In Q29, I asked for feedback on participants' experiences on their analysis experience using the MPM model, which involves using the Consideration Factor Indicators that cover five areas: technical, instruction, content, human, and environmental.

In general, I received positive feedback, with some acknowledging that the analysis and indicator are helpful and provided insight into which performance relates. I also received arguments and multiple recommendations regarding the proposed Consideration Factor Indicator.

While participants found the indicator useful, some indications were confusing and required clarification. I agree with this suggestion and consider this to be something that will require further updates with a linguistic expert.

"Motivation" is also suggested to be included in the indicator. I agree that the motivation element significantly affects performance. From my study, I found that the proposed five-factor categories are the best fit to cover most factors. Alternatively, I embedded the motivation element into existing proposed areas. For example, in the environment area, I asked, "Has any related promotion or marketing recently?" In the human area, I asked, "Did learners show any sign of protest/ejection?". In the instruction area, I asked, "Was a reminder given to the learner?" All thesis factors, in some way, address the motivation element. As mentioned previously, the consideration factor is most likely to be updated and expanded in the future. I are also considering further updates to improve the consideration factor detail, avoiding confusion, and including more motivation-lead factors. I am not planning to introduce a new area. This suggestion will be considered for future work with a specific research scope.

Q30: As an experienced MOOC user, have you used and analysed MOOC learning analytics data, and if yes, what tools or method was used?

Table 72: Participants Q30 Feedback

Participant Feedback	Feedback Summary
P1: Normally, we just use Excel and SPSS only.	• Normally, we **just use Excel**. • And **SPSS only**
P2: Never used analysed MOOC learning and data analytics.	• **Never used** analysed MOOC learning. • And data analytics.
P3: Not a lot. We looked at user data such as the number of participants, completion rates of weeks/steps, views of videos, and the number of comments/replies in forums. **I wasn't involved deeply enough to make ongoing use of such statistics, but I'm aware of these basic things. As someone who researched a bit in learning technology in the past, I always saw Learning Analytics as something with potential, but I had/still have a lot of scepticism about whether it can provide really meaningful and useful data which we can use well within the constraints of respecting user privacy etc.** **See Q30 above.**	• **Not a lot**. • We looked at user data such as the **number of participants, completion rates of weeks/steps, views of videos, and number of comments/replies in forums**. • I wasn't involved deeply enough to make ongoing use of such statistics, • But I'm **aware of these basic** things. • As someone who researched a bit about learning technology in the past, I always saw **Learning Analytics as something with potential**, • But I had/still **have a lot of scepticism** about **whether it can provide really meaningful and useful data that we can use well**, • Within the **constraints of respecting user privacy,** etc.
P4: Yes, Excel. Metrics are typically about engagement and changes to engagement over time.	• Yes, **Excel**. • Metrics are typically about **engagement** and **changes to engagement over time**.
P5: Never before.	• **Never before**
P6: No.	• **No**
P7: Yes, I have used the dashboards provided in FutureLearn and a dashboard that I developed based on FutureLearn	• **Yes**. • Using **dashboards provided in FutureLearn**.

data. The methods consisted of simple statistical analysis, mostly regressions, and visualisation tools such as heat maps to spot attention points and shank diagrams to analyse learner journeys.	• Using **own dashboard developed based on FutureLearn**. • Using **simple statistical analysis methods**, mostly **regressions** • V**isualisation tools** include **heat maps to spot attention points** and **Sankey diagrams to analyse the learning journey**.

In Q30, I asked for feedback on participants' experiences using and analysing MOOC learning analytics data. I want to know if any other tools or methods have been used by participants before. Based on the feedback, 43% of participants never used MOOC learning analytics for analysis. Other than SPSS and its own dashboard, Excel is mentioned as the most used software to analyse MOOC learning analytics data.

The methods used range from regression analysis and heat map to spot attention points and engagement changes over time, which looks like a time-series analysis method. In my model, I used difference scores to spot attention points and consideration factor indicators to assist in analysing the data.

Only one participant indicated that they developed their dashboard based on existing MOOC platforms. Few will develop their own tool, as expertise and resources are required to develop tools that best suit user requirements.

I was intrigued by one participant's feedback, which informs that although they always saw learning analytics as something with potential, they still had a great deal of scepticism about whether MOOC learning analytics can provide meaningful and valuable data that I can use well. I share the same concerns at the beginning of my study. At some level, some additional analytical data might be helpful or essential to have but are not currently made available from the MOOC platforms. I acknowledge possible restrictions and limits on what data can be collected or made available. The ideas for additional new learning analytics data to be available will require more studies and collaboration with MOOC platform providers. However, the existing MOOC learning analytics data should be fully utilised. This studies found that existing data provided insightful information in a way that has not been utilised before. The existing learning analytics data could be manipulated for meaningful usage, improving course or learner performances and identifying points of interest within course duration using proper methods and strategy, *Q31: In general, after trying to use the MPM model to monitor and measure performance from MOOC learning analytics data, what improvement can you suggest to make the experience of using the MPM model easier?*

Table 73: Participants Q31 Feedback

Participant Feedback	Feedback Summary
P1: The conclusion on whether the current MOOC performance is Excellent/Good Performance/Poor Performance/Very Poor Performance may need to be revised to also consider the average percentage of all lessons before deciding on the overall level of the current MOOC performance. **In mathematics, 0 cannot be considered a negative or positive value. If a MOOC has WDS=0 or MDS=0, it is recommended to consider that the 0 value shows consistent performance.**	• **The conclusion** on whether the current MOOC performance is Excellent/Good Performance/Poor Performance/Very Poor Performance may need to be **revised to also consider an average percentage of all lessons before deciding** on the overall level of the current MOOC performance. • **In mathematics, 0 cannot be considered a negative or positive value.** • If a MOOC has WDS=0 or MDS=0, it is **recommended to consider that the 0 value** shows consistent performance.
P2: No improvements have been suggested so far for the MPM model.	• **No improvements** have been **suggested** so far for the MPM model.
P3: This tool seems to give a useful and valuable snapshot of a course, which could point the designer in the direction of needed improvements. The level of diagnosis of problems isn't very deep - which is fine, provided the effort to use/obtain the data is low. My experience of trying to transfer data between spreadsheets in this case wasn't good - it was confusing. I'm sure I could learn the process, but the steps and design of the spreadsheets need to lead the user more clearly through the steps required. Ideally, the computer would do all the transfers automatically and just show me the graph!	• **This tool** seems to give a **useful and valuable snapshot of a course**, • This **could point** the designer in the direction of **needed improvements**. • The **level of diagnosis** of problems **isn't very deep** – which is **fine,** provided the effort to use/obtain the data is low. • In this case, my experience of trying to transfer data between spreadsheets **wasn't good – it was confusing**. • I'm sure **I could learn the process**, but the steps and design of the spreadsheets need to lead the user more **clearly** through the steps required. • **Ideally**, the computer would do all the transfers **automatically** and just show me the graph!
P4: Easier import of data. Having to manipulate data is time-consuming. Also, there is guidance (mentioned above) about when changes were outside of the expected statistical range.	• **Easier import of data.** • Having to **manipulate data is time-consuming**. • Also, there is **guidance** (mentioned above) about when changes **exceed the expected statistical range**.
P5: Automate data collection: Use technology to automate the collection of	• **Automate data collection**.

data, which can help reduce errors and save time. This can also provide real-time data, allowing for more timely adjustments to the MOOC. Create a form the user just needs to upload their raw data, and the MPM tool will extract the CSV file automatically.	○ Help **reduce errors and save time**. ○ Provide **real-time data**, ○ Allowing for more **timely adjustments** to the MOOC ○ Form for a user to upload raw CSV dataset and **automate data cleaning and extraction**.
P6: Perhaps we can highlight the names of students who did not perform after learning a few topics.	• Perhaps **highlight** the names of students **who did not perform** after learning a few topics.
P7: The user experience is very important, as stated in Q27. Therefore, the main improvement would consist of developing a friendly front end.	• Improving user experience, as stated in Q27. • Considering developing a **user-friendly front-end dashboard**.

In Q31, I asked for feedback on participants' experience using the MPM model to monitor and measure performance from MOOC learning analytics data and what improvements they could suggest for a much easier user experience.

Based on the feedback, I received suggestions for improvement, primarily regarding a better data handling process, including automated data collection, cleaning, and import into the MPM tool, making data ready for performance monitoring, measuring, and analysis. A real-time data that could used for real-time performance monitoring and analysis is also suggested. All improvement suggestions are acknowledged and will be considered for future works research projects. I agreed a user-friendly tool or MPM dashboard would improve the usability of this MPM model. Developing tools for the MPM model is beyond my research scope. The current tool is a fundamental tool embedded with the MPM model for model usability testing and proof of concept purposes.

One participant also suggested improvement in the performance indicator conclusion. This suggestion was related to participant concern for a course, or learners were indicated as poor performance due to low positive indication detected, although recorded high scores in measured parameters. I have justified my algorithm and performance measurement concept in the previous section. It is possible for a high achiever course or learner to be considered as low performance. Regarding the zero value in my performance indicator setting, that suggested cannot be positive or negative and should be indicated neutral; I have my justification. Indicator 1 (I1) and Indicator 2 (I2) in the algorithm is a Boolean value, either True (Positive) or False (Negative). Although zero is an integer, it is neither positive nor negative. For that reason, mathematicians often test their theories and ideas using zero as a special case (Wilson, P.S, 2001).

Another suggestion is to highlight learners or modules that did not perform after a few weeks. Users must manually analyse and observe the measured data and compare the analysis chart with the consideration factor indicators. This is a good suggestion for future works, as it will improve the analysis user experience.

7.5 User Usability Testing Observation and Discussions

In previous sub-sections, I have discussed results and feedback from the user usability testing activities. The individual testing session was conducted online or in person. These testing sessions have allowed us to observe participants using the MPM model and experience how to measure course or learner performance.

Observation 1: Participants are not actively updating or developing MOOC content, as most of the content or courses have been developed and are in use. Only one participant indicates they are currently in a development mode due to the change of MOOC platform. However, their initial plan is to reuse the existing content from the previous MOOC platform into the new platform. The main reason why MOOC content is not actively updated or maintained is due to the resources, time, and expertise limitations. As a result, there is a tendency for a course to record identical scores and performance patterns within different cohorts of learners. Another significant reason why there is no effort for the content update is that the course admin did not notice which module they need to prioritise for improvement.

After experience using the MPM model, they can now pinpoint modules that might need updating to help improve course or learner performances.

Observation 2: Participants were observed putting effort into learning how to use the provided MPM tool and understanding how the MPM model works during their one-hour session. I observed that some participants struggled to get used to the process involved, especially when I demonstrated the data-cleaning process needed before data was suitable for the MPM model. It took a while, but in the end, participants showed confidence and understanding of how the model works with the provided tool. In terms of the model, it was easy to understand and implement. In terms of the tool used, it will require improvement in the future. I will discuss this matter in the next chapter.

Observation 3: Data cleaning is a crucial process for data analysis. Unfortunately, my study scope does not focus on the data cleaning task but on the MPM model that includes monitoring and measurement performance, metrics, and indicators for analysis. When I assumed users got their data clean and ready to be used with the MPM model, I observed that participants were reluctant to use their data due to the limited time and expertise for data cleaning.

Observation 4: Participants show great interest in the Consideration Factor Indicator used during the analysis process. When analysing MOOC learning analytics data, looking at the generated chart patent and comparing it to the indicator is a new approach for participants. It was later acknowledged that the indicator and approach are helpful and have the potential to be expanded.

Observation 5: During my observation and from discussion with participants, the performance concept applied in my measurement algorithm was proven to have valid logic and reflect the theory I embraced. Today is better than yesterday. A small increment is still considered performing, although the score is still low. There are arguments regarding the terms "performance" and "engagement" used in this research study. I had positive discussions with participants and justified the terminology argument based on the research definition and relevant previous studies.

Observation 6: I had two in-person user usability testing sessions, and the rest was conducted online via Microsoft Teams. During the in-person session, I was unable to have the session recorded. Nevertheless, the session delivered a better experience and promoted better discussion between the researcher and participants. Unlike online sessions, the session is recorded and can be reviewed later. The online session could only deliver the same experience as the in-person session if the internet connection and communication devices work excellently. I did encounter minor technical issues during the online testing sessions. These issues must be considered in the future to ensure user usability testing sessions and the testing objective can be conducted successfully.

7.6 Chapter Conclusion

A total of seven participants took part in my MPM Model user usability testing. Participants were asked to answer questionnaires and feedback questions after completing and experiencing how the MP Model works. Apart from demography, the questionnaire sections were categorised into monitoring, measurement, and analysis. For each question, the participants were asked to give their rating based on the questionnaire rating system used, shown below:

Table 74: Questionnaire Rating System

Very Unsatisfied	Unsatisfied	Neutral	Satisfied	Very Satisfied
-2	-1	0	1	2

Results from the rating were calculated and analysed.

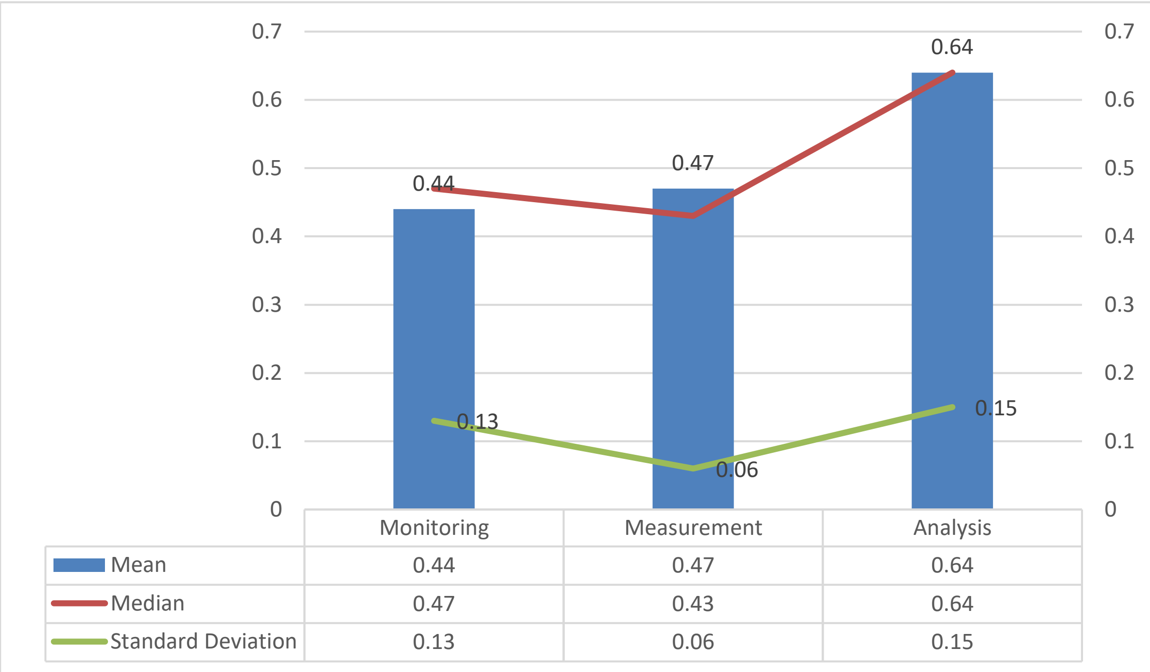


Figure 71: MPM Model Category Mean, Median and Standard Deviation Rating Score

In general, I can conclude that participants indicate satisfaction with the usability of the proposed MPM model. The analysis component, which includes the generated result in a time-series graph and the Consideration Factors Indicators, scored the highest rating. These positive results from user usability testing activities answered the RQ3 and confirmed my MPM model usability.

During the testing session, I received recommendations and suggestions for the MPM model and tool improvement, particularly concerning the tool for better user experiences. In the following research conclusion and future works chapter, I will discuss the consideration toward received feedback from participants, my plan for future works and the conclusion of this research study.

Chapter 8 Research Conclusion and Future Works

8.1 Introduction

This thesis attributes a research study started in January 2019, with initial research motivation and plan years prior. Facing challenges, including the unprecedented COVID-19 pandemic that is affecting all of us, the completion of this research is believed to give us a new perspective on how higher learning education should be prepared, monitored, and measured in the context of MOOC usage. In this concluding chapter, I highlight solutions to the research gap addressed and answer the research questions. Next, a discussion of the contributions of this research study is presented, followed by a set of recommendations for different stakeholders. Finally, I list future work suggestions to expand the significant impact on stakeholders.

8.2 Answer to the Research Questions

Despite the existing studies on MOOC learning analytics data usage, little is known about the data model for MOOC courses or learner performance monitoring and measurement that works and is tested within different MOOC platforms. In this sub-section, all three research questions will be answered. The research questions were the following:

- RQ 1: What parameters can be used for measuring course and learner performance at macro and micro levels using learning analytics that were MOOCs cross-platform friendly?
    - What MOOC learning analytics dataset was made available to macro and micro-level users?
    - What parameters are considered cross-platform compatible?
- RQ2 How can monitoring and measuring course and learner performance at the macro and micro level be done using MOOC learning analytics?
    - What tool can easily be used with MOOC learning analytics data?
    - What analysis method can be used?
    - What visualisation approach is suitable for illustrating analysis results from the performance measurement?
- RQ3 How do we evaluate the usability of the proposed MOOC Performance Measurement (MPM) model design?
    - How the algorithm usability aspect can be measured?

- Who could be suitable participants for the user usability testing?
- Is the model proposed proven to be usable for users?

Research plans and activities were designed and undertaken to find relevant answers to the stated research questions. This study was anchored to the computer science domain, specifically data science research areas, with learning analytics and education technology as the context of studies. Therefore, in answering the research question, prioritisation is first towards the data science perspective, followed by education and learning.

8.2.1 Question Block 1

Research question 1 questions what parameters can be used for measuring course and learner performance at macro and micro levels using existing MOOC learning analytics that were MOOC cross-platform friendly.

Answering this research question, I conducted an initial study and a series of literature studies on learning analytics in higher education, monitoring MOOCs using learning analytics, learning analytics from cross-platform MOOCs, data analysis with the semantic web, and measurement and analysis of learning performances. Two essential aspects were considered.

Firstly, the parameters chosen have the characteristics of generic learning analytic data that is potentially available in other MOOC platforms. A theoretical framework was developed spiral around the engagement, improvement, and performance in MOOC learning and the potential of cross-platform MOOC learning analytics data sources features. Guided by the research epistemological orientation and findings from my literature review and preliminary study, a study on different datasets was performed in Phase 2 of my research framework. FutureLearn and OpenLearning MOOC platforms were chosen, and datasets from both platforms were used to find similarities in information that can be used as measurement parameters. A uniform dataset is created after performing three iteration steps. As a result, I successfully match and find parameters from existing MOOC learning analytics for measuring course or learner performance.

Secondly, theoretically and practically, the parameters should be proven to reflect this study's course or learner performance definition. Two parameters were identified for measuring course performance: the percentage of module completion and widget completion. For measuring learner performance, two parameters were identified: the percentage of module completion and the percentage of assessment scores.

8.2.2 Question Block 2

Before I can start considering monitoring or measuring course and learner performance, it is essential to understand and define what is known as MOOC course and MOOC learner performance. From the theoretical framework and literature review study, I define MOOC performance as the value of improvement or the ability to maintain the highest score value throughout the learning course, either for the course performance or individual learner performance.

Next, I addressed how I can monitor and measure defined MOOC courses and MOOC learner performance questions. Based on the definition in the context of the research study and literature study on MOOC learning analytics topics, I studied learning analytics datasets from two different MOOC platforms. I successfully found suitable learning analytic data that can be used as the monitoring and measurement parameters for MOOC courses or MOOC learner performance. These parameters are available, and datasets can be downloaded directly from the MOOC platform in Microsoft Excel or CSV format. The raw datasets need to be cleaned and pre-processed. Finally, a ready-to-use dataset containing important learning analytics data is created as the uniform dataset.

Various existing tools can be used to analyse analytic data. Data analytic tools include Microsoft Power BI, Tableau, Python, R, Apache Spark, and even Microsoft Excel. My model and algorithms can be applied to almost any existing tools. In this research study, I used Microsoft Excel as an example tool, considering Microsoft Excel is generally well-known and used by most users. Although it is not my objective or scope of study to develop a tool, I prepare a Microsoft Excel file embedded with my MPM Model for the experiments and user usability testing activities.

As much as data visualisation can help users understand data better, it also can lead to more confusing situations if not used appropriately. My approach is to visualise data as simply and straightforwardly as possible by using line and bar graph data visualisation, customised for time series data analysis. The visualisation will include two input data and two different score data generated from algorithm calculation. By observing the line between the actual and the different scores, users can clearly understand the performance that their learning analytic data represent.

8.2.3 Question Block 3

Evaluating the usability of the MPM model will include evaluating the usability of the proposed measurement algorithms, metrics, and indicators. I performed two usability evaluation activities. The researcher did the first evaluation during the experimental phase. The second usability evaluation activity was done with actual end users as my user usability testing participants during the testing phase.

In the experimental phase, the researcher used sample data from MOOC platforms. Experiments were performed with different course datasets, where researchers encountered different scenarios. Overall, the experiment activities help the researcher to experience a complete process of how the proposed measurement algorithm works and performs. The experiment also helped the researcher improve the integration of the MPM model to Microsoft Excel as a prototype tool, which was later used in the user usability testing phase.

In the user usability testing phase, I conduct one-to-one sessions with participants. During each session, participants were briefly introduced to the research study background and demonstrated how the MPM model works using the provided tool and sample data. The participants were later given time to try by themselves, experiencing how to input data, observe the measurement and analyse results with provided metrics and indicators. Finally, participants were asked to complete and submit a questionnaire and feedback form. The user feedback consists of five parts.

- Part 1: Demography
- Part 2: MPM Usage (Monitoring)
- Part 3: MPM Usage (Measurement)
- Part 4: MPM Usage (Analysis)
- Part 5: Feedback

Suitable participants for the user usability testing are FutureLearn and OpenLearning MOOC course admin, designer, and users who could have access to the MOOC learning analytics data.

8.3 The Proposed MPM Model

A data model represents an information system that defines the structure and organisation of data, the relationship between data elements, and operations that can be performed on these data. The Massive Open Online Course Performances Measurement Model, also known as the MPM Model, is a learning analytics data model that uses the existing MOOC learning analytics data to monitor and measure course or learner performances. The proposed model was designed and developed based on two MOOC platforms, with cross-platform dependent capabilities. The model consists of four main elements: the performance measurement algorithms, condition indicators, performance metrics, and consideration factors indicators, used to analyse and interpret the learning analytics data.

8.3.1 Performance Measurement Algorithms

A performance measurement algorithm was designed after I successfully identified suitable parameters from existing MOOC learning analytics datasets. Two main challenges during this process were to identify robust parameters that were not MOOC platform-dependent and to design measurements for two different purposes: course performance and learner performance.

I apply the concept of being better than before as a justification for performance, and being the same or worse than before is considered not performing. With this theory set, I apply a time series analysis method and compare current data with previous data as my measurement approach.

8.3.1.1 Uniform Dataset

Parameters used for performance measurement are critical, primarily when I aim to develop a cross-platform measurement algorithm. To achieve this aim, I created a uniform dataset that involved a three-iteration process from datasets of two MOOC platforms. The uniform dataset created gives a clear view of the data available on each MOOC platform. Based on the uniform dataset and my previous studies, the parameters selected are completion of the module, completion of the widget and assessment score or marks.

8.3.1.2 Course Performance Measurement Algorithm

A course is a learning programme enrolled by multiple users as a group of learners. Due to the nature of MOOCs that encourage learners from various backgrounds to enrol, there is a high possibility for a course to have different levels of learners. Course performance measured using this algorithm is measuring the performance of the course, not the learners. Two parameters used are the module's completion and the widget's completion.

8.3.1.3 Learner Performance Measurement Algorithm

A learner is an individual user who enrolled on a specific MOOC course. The nature of MOOCs that promote self-paced learning, where the learner can do their learning at any time and anywhere, there is a tendency to have different learners with different learning styles, capabilities and motivations.

Learner performance measured using this algorithm measures the individual learner's performance, not the group of learners. Two parameters used are completion of the module and assessment score or marks.

8.3.2 Condition Indicator

A Condition Indicator was proposed as part of the MPM algorithm's component. The indicator sets the logical indication of performance based on the differences in the score measured. Designed based on the concept of performance used in this research study, "today better than yesterday", a positive indicator is given when the measurement shows increment value or static total 100% value. A negative indicator is given when measurement shows a decrement or static value below the 100% score. There are four conditional rules, set as shown below:

Table 75: Condition Indicator

Difference Score Condition	Indicator
Any increasing score value	(+) positive
Any decreasing score value	(-) negative
Any unchanged score value IF the value is 100% or full score	(+) positive
Any unchanged score value IF the value is not 100% or not a full score	(-) negative

No previous data is available for the first module measurement to measure the differences score. Therefore, a default value is set. A positive indicator is given if there is any score value recorded at the first module, and a negative score if the score value is zero.

8.3.3 Performance Metrics

The algorithm will produce a percentage score value based on the positive indicator calculated. Performance Metrics are proposed as the performance status benchmarking system. A default Performance Metrics consist of four performance levels, as shown in the table below. Performance metrics are flexible metrics that can be changed or updated according to the user's institution or organisation's standard. This metric should be set by the top-level stakeholder, for example, the university and used by all within their institution or organisation, for example, users at school or faculties.

Table 76: Performance Metric

Current Performance Score	Performance Level	Description
76% to 100%	Excellent Performance	More than 76% of the data show positive indications. Significant uptrend score.
51% to 75%	Good Performance	More than 50% of the data show positive indications.
26% to 50%	Poor Performance	Mostly negative indication with an average close to an uptrend. Early improvement will promote better performance.
0% to 25%	Very Poor Performance	Most indications were negative, and no more than 25% were positive. Significant downtrend score or zero scores recorded.

8.3.4 Consideration Factors Indicators

A Consideration Factor Indicator was designed and proposed as part of the MPM analysis component. The indicator consists of an area, indication and consideration factors. The area is categorised into five areas of interest: Technical, Instruction, Content, Human and Environment. For each area, indication rules are set to help users read and interpret measured performance results and charts. Users will observe the generated chart patent and result data and refer it to the Consideration Factor Indicator for suggestions of action that they can consider to improve the course or learner performance. The consideration factor provided will most likely be updated and improved over time. This scenario is highly possible when this model has been trained with more data and usage scenarios.

Table 77: Consideration Factors Indicators

Area	Indication	Consideration Factor
Technical	• Zero score • Odd or significant changes in indicator	• Did the MOOC platform have issues? • Does the user have internet connection/access issues? • Is there a bug or error on the platform? • Is the device use compatible? • Did learners have access to the platform? • Was the content (settings) made available/accessible to the learner?
Instruction	• They are continuously decreasing or increasing • A volatile indicator on both dataset scores	• Has the course admin given explicit instruction? • Did a reminder be given to learners? • Did language use to be understandable? • Is instruction confusing?
Content	• Low differences score • Low widget score	• Did content was new to learners? • What type of content was used? (text, video, image, audio, activity?) • Did content was appropriate to learners? • Was the content related or relevant to the course?
Human	• Mixing trends (uptrend and downtrend) for both datasets	• Are there any security or health issues? • Did learners show any sign of protest/ejection?
Environment	• Significant decreasing or increasing score • Significant decreasing or increasing scores in early module	• Has any event happened recently? (Holiday, etc.) • Is there any related promotion or marketing ongoing recently?

8.4 Contribution of This Thesis

This thesis has been the product of a series of studies that have constructed a model on how higher education institutions can benefit from using MOOC learning analytics data for course or learner performance monitoring and measuring. In this section, a breakdown of the contributions is presented.

8.4.1 Theoretical Contribution

Interpretation of Cross-Platform MOOC Learning Analytics: This study makes a substantial theoretical contribution by providing a novel interpretation of the datasets used in cross-platform MOOC learning analytics, which helps to identify parameters that are important for tracking learner and course performance. The study provides a unique perspective on how macro and micro-level users interact with MOOCs as educational tools by exploring the theory of MOOC courses and performance measurement. In addition to improving comprehension of MOOC data, this interpretation aids in the creation of efficient monitoring and measurement plans.

Research Framework and Methodology Integration: The study contributes to the research framework and methodology by integrating various methods and processes to address empirical challenges in MOOC learning analytics. By combining different approaches into a coherent narrative, the study provides a robust foundation for analyzing and interpreting data across different MOOC platforms. This methodological integration enhances the study's theoretical underpinnings and contributes to the advancement of research in MOOC learning analytics.

Efficiency of Data Model for Cross-Platform Analysis: An ontological approach was used in this study in the development of a data model that bridges the gap between diverse platforms and systems in learning analytics. By designing a uniform dataset and identifying measurement parameters across different MOOC platforms, the study enhances the efficiency and accuracy of data analysis. This theoretical advancement not only facilitates knowledge sharing and the development of new applications but also lays the groundwork for future research in AI and the evolution of learning analytics theories and techniques.

8.4.2 Practical Contributions

Policy Implementation for MOOC Learning Analytics: Drawing from the study's findings, practical contributions include the advocacy for policy development and guidelines within higher learning institutions to leverage MOOC learning analytics effectively. The study highlights the importance of aligning MOOC usage with national agendas and emphasizes the need for institutions to be learning analytics-ready by 2025. By advocating for the integration of MOOC learning analytics into educational policies, the study promotes data-driven decision-making and enhances learning outcomes at institutional levels.

MPM Model Implementation for Course Improvement: A key practical contribution of this study is the development and implementation of the MPM (MOOCs Performance Measurement) Model to monitor and measure course and learner performance systematically. By providing a standardized model that works across different MOOC platforms, institutions can now flexibly choose platforms for content delivery while using the same model for performance measurement and reporting. This practical solution empowers course administrators to make informed decisions for course improvement and enhances the overall quality of education delivery.

Metrics and Indicators for Effective Analysis: The study introduces metrics and indicators that significantly aid course administrators in analyzing learning analytics data and planning for future improvements. By incorporating technical, instructional, content, human, and environmental considerations into the Consideration Factors Indicator, the study provides a comprehensive framework for performance evaluation. The practical contribution extends to the development of user-tested metrics that enhance the usability and effectiveness of the MPM Model, enabling stakeholders to derive actionable insights from visualized results for continuous improvement in course delivery.

8.4.3 Ontological Contribution

Application of Ontology Approach in MOOC Learning Analytics: In this study, due to certain limitations, the focus is on applying an ontology approach to study learning analytics data from two distinct MOOC platforms rather than developing a complete ontology. By utilizing the ontology approach, the study successfully maps and harmonizes data from different platforms, despite variations in dataset structures. This methodological application enables the representation of key concepts and relationships specific to MOOC learning analytics, facilitating data integration and analysis.

Enhanced Data Integration through Ontology Methodology: Through the application of the ontology approach, the study advances data integration by harmonizing datasets from diverse MOOC platforms. Despite not developing a comprehensive ontology, the study effectively captures and represents data in a uniform dataset, promoting standardized performance measurement across platforms. This methodological innovation underscores the importance of leveraging ontology methodologies to bridge data disparities and enhance interoperability in MOOC learning analytics.

Facilitating Knowledge Sharing and Interoperability: By applying the ontology approach, this study contributes to promoting knowledge sharing and interoperability within the MOOC learning analytics domain. While not developing a full ontology, the study's methodology enables the exchange of insights and information between different platforms. This approach not only supports the development of new AI theories and techniques but also lays the groundwork for future research endeavors aimed at advancing the field of MOOC learning analytics through enhanced data representation and analysis.

8.4.4 Methodological Contribution

Research Framework Development: The research framework development in this study aims to fill the research gap in cross-platform MOOC learning analytics. To achieve this, a carefully designed research framework is created to align with the study's objectives and scope. By incorporating a semantic web approach and utilizing simulation and experiment methods, the framework establishes the foundation for constructing a data model that can effectively handle various MOOC platforms for performance measurement. This innovative methodology allows for the collection of comprehensive and significant data, while also ensuring uniformity in data representation across different platforms.

Iterative Data Model Development: The study employs a thorough three-iteration process to develop an iterative data model that overcomes platform-specific constraints, enabling the smooth integration of data from multiple MOOC platforms. This approach includes data analysis and classification from various platforms, algorithm design through simulations, and sample data experiments to enhance the data model. By following this iterative methodology, the model can easily adapt to new platforms while offering a comprehensive analysis of its strengths, weaknesses, and suggestions for implementation in different settings.

Enhanced Performance Measurement Strategies: The research presents an innovative method for measuring performance in MOOC settings through the utilization of semantic web techniques and the application of simulation and experimentation. Through the creation of a standardized data model for performance metrics across various platforms, educational institutions are equipped to make well-informed choices when selecting MOOC platforms and implementing strategies for course enhancement. This methodological advancement also includes the establishment of metrics and indicators that allow course administrators to efficiently analyze learning analytics data, promoting a data-driven approach to improving courses and reporting to stakeholders.

8.4.5 Mapping MOOC Data Models

The significance of Mapping MOOC Data Models in this research is crucial for addressing the complexities associated with integrating data models from various MOOC platforms. The process involves overcoming challenges related to aligning datasets with different structures and schemes across platforms. Through the proposal of a methodological approach, the research aims to create a standardized dataset capable of accommodating the unique characteristics of different MOOC platforms for efficient performance evaluation. This approach highlights the importance of capturing comprehensive and valuable data from multiple sources while ensuring consistency in data representation to guarantee accurate and reliable analysis.

By establishing a standardized dataset, I emphasize my dedication to improving the efficiency and accuracy of performance evaluation across a wide range of MOOC platforms. This also ensures data compatibility from different sources, thereby laying the groundwork for robust and insightful data analysis within the realm of learning analytics.

8.4.6 MPM Model Development

The study presents a significant contribution through the creation of the MPM (MOOCs Performance Measurement) Model. This model offers a systematic approach for monitoring and measuring the performance of both courses and learners across various MOOC platforms. Its key features, such as cross-platform compatibility and standardized performance analysis, make it a versatile and effective tool for assessing performance metrics.

By providing a standardized framework for performance analysis, the MPM Model empowers administrators to make data-driven decisions that improve course quality and reporting accuracy. The model's systematic nature ensures consistent tracking and assessment of course and learner performance, leading to a comprehensive understanding of educational outcomes. Its focus on compatibility across different MOOC platforms means that performance analysis remains reliable and consistent, making it applicable and beneficial for various educational institutions.

In addition to its central role in monitoring performance within the MOOC environment, the MPM Model emphasizes the importance of facilitating data-driven decision-making processes. This involves identifying areas for improvement and implementing targeted strategies to enhance the overall learning experience. My commitment to systematic monitoring and standardized analysis within the MPM Model demonstrates a dedication to promoting evidence-based practices in educational settings and advancing effective pedagogical approaches within the realm of Massive Open Online Courses (MOOCs).

8.4.7 Metrics Definition and Validation

The study emphasizes the importance of defining and validating key metrics and indicators for analyzing learning analytics data effectively. It provides a comprehensive framework for course administrators to evaluate performance metrics through the Consideration Factors Indicator, which encompasses technical, instructional, content, human, and environmental aspects. This approach ensures that administrators have a holistic understanding of the various factors influencing course and learner performance, enabling them to make informed decisions based on data-driven insights.

The study also highlights the significance of these metrics in enabling course administrators to analyze visualized results and effectively strategize for future improvements. By concentrating on key areas that impact learning outcomes, the Consideration Factors Indicator establishes a strong foundation for performance evaluation and enhancement.

Furthermore, the validation process of these metrics through user usability testing underscores the practical relevance and effectiveness of the Consideration Factors Indicator within the MPM model. Through engaging participants in usability testing, the study ensures that the metrics align with user needs and expectations, thereby enhancing the indicator's usability and applicability in real-world scenarios. The positive feedback received from participants regarding the indicator's essential role in the MPM model emphasizes its value in facilitating data-driven decision-making processes and promoting continuous improvement in MOOC course administration.

8.4.8 Standardized Presentation of MPM

The standardized presentation of the MPM Model in this study aims to establish a consistent and validated method for conveying performance measurement analysis to analysts. By emphasizing the importance of standardization, the study ensures effective communication of the MPM Model to analysts, enabling them to gain valuable insights into course and learner performance. This standardized approach simplifies the process of data-driven decision-making by providing analysts with a clear framework for accurately and efficiently interpreting and utilizing performance data.

Additionally, the study delves into the detailed process of presenting performance measurement analysis in a standardized and systematic manner. It highlights the structured approach adopted to effectively convey complex data insights. By outlining a methodical presentation format, the study aims to enhance analysts' ability to extract meaningful information from the MPM Model, empowering them to make informed decisions based on performance metrics. The study's commitment to ensuring stakeholders and decision-makers can easily comprehend and act upon the insights derived from the model is underscored by the emphasis on presenting MPM results in a clear and actionable format.

Furthermore, the study emphasizes the significance of presenting MPM results in a manner that is both easily understandable and actionable for stakeholders and decision-makers. By prioritizing clarity and relevance in the presentation of performance data, the study aims to bridge the gap between data analysis and decision-making processes. This facilitates more informed and strategic actions based on the insights provided by the MPM Model. The meticulous focus on standardized presentation enhances the model's utility and applicability in real-world scenarios, enabling stakeholders to effectively leverage performance data for continuous improvement and enhanced decision-making in the MOOC environment.

8.5 Recommendations

This thesis is the product of professional experience and research accumulated during almost five years of MOOC-related activities, as stated in many sections of this publication. My observations throughout this time have led us to draw conclusions that have allowed this study to formulate three sets of recommendations aimed at different stakeholder levels. This section will begin with recommendations for Universities and Educational Ministries, followed by recommendations to the MOOC platform providers and conclude with recommendations for Instructors and Course Administrators.

8.5.1 Recommendations to Higher Learning Institutions and Educational Ministry

It is recommended that learning analytics data be used by the Higher Learning Institution and Educational Ministry to establish a standard national MOOC performance monitoring and measuring system. Giving higher education institutions the freedom to select which MOOC platforms to utilise should align with the national objective. A policy on the usage of learning analytics should also be prepared to guarantee appropriate management of user access, privacy, security, and API integration. Lastly, more significant funding for data science and data model research projects is needed to enhance and broaden the scope of ongoing research projects. This investment will ensure learners and higher education institutions benefit from and find value in learning analytics data with high-quality MOOC courses.

8.5.2 Recommendations to MOOC Platform Providers

Five recommendations are proposed to MOOC platform providers to improve the effectiveness and usability of learning analytics. First, to ensure that shared data, such as progress reports, completion rates, and engagement metrics, is available to all learners and instructors. This data will allow a better understanding of the learning process and provide insights for improving course content delivery and learners' motivations. Secondly, provide a plugin or API for learning analytics data exchange that supports real-time external data analysis features. These features will enable third-party tools and applications to access and analyse data, allowing for greater flexibility and customisation in analysing learning data. The following recommendation is to develop partnerships or collaborations with higher learning institutions to promote more research and innovations on how MOOC learning analytics can be utilised. This will lead to the development new and improved methods for analysing and understanding learning data, ultimately leading to better learning outcomes. Next, it is recommended that MOOC platform providers offer users rich analytical features, including data filtration, cleaning, visualisation, and parameter modifications. These features will enable learners and instructors to analyse data in a more granular and detailed manner, allowing for more targeted insights and improvements. A final recommendation is to make learning analytics data much more accessible and useable by non-data science background course administrators. These changes can be achieved through user-friendly interfaces and dashboards that simplify data access and analysis.

8.5.3 Recommendations to Faculty and Course Admin

Faculty and Course Admin are important MOOC stakeholders ensuring the quality of MOOC courses created and offered to learners. Therefore, it is also essential to offer a range of services, support, and training to MOOC course instructors or admins on how learning analytics data can be used to improve their course or learner performances.

One of the primary contributions of the MPM Model is the establishment of a comprehensive, data-driven framework for analyzing MOOC learning analytics data. By harnessing the power of existing MOOC learning analytics, the MPM Model empowers administrators and course providers to assess the performance of MOOC courses and learners with unprecedented accuracy and precision.

The MPM Model, as designed and developed in my research, is specifically tailored to facilitate the interpretation of learning analytics data and support informed decision-making in the realm of MOOCs. The model incorporates several key components, including measurement algorithms, Condition Indicators, Performance Metrics, and Consideration Factors Indicators, that collectively contribute to the creation of actionable insights and recommendations.

To clarify the link between the MPM Model and the recommendations derived from it, the following sections detail how each component contributes to the transformation of raw data into meaningful, actionable insights.

Measurement Algorithms: The first element of the MPM Model, measurement algorithms, serves to standardize and quantify the various metrics that contribute to the overall performance assessment of MOOC courses and learners. This standardization ensures consistent and reliable evaluation, thus facilitating the accurate comparison of performance across different timeframes, platforms, and students.

Condition Indicator: The Condition Indicator is a critical component of the MPM Model, as it helps to pinpoint specific areas of concern or improvement within the MOOC system by indicating a positive or negative performance. By analyzing specific parameters, such as completion module, completion widget, and learning outcomes based on assignment or test marks, the Condition Indicator can provide administrators and course providers with an understanding of the aspects that require their attention and action.

Performance Metric: The Performance Metric evaluates the entire MOOC experience, combining multiple performance indicators to generate a comprehensive assessment of the course or learner's performance. By integrating these diverse metrics, the MPM Model ensures a holistic understanding of MOOC performance, facilitating the identification of areas for improvement and the formulation of targeted interventions. The Performance Metric is a flexible metric that can be changed based on each faculty or university standard.

Consideration Factors Indicator: The final component of the MPM Model, the Consideration Factors Indicator, plays a crucial role in deriving recommendations based on the analyzed data. By examining the impact of various factors, the MPM Model can provide insights into how these variables may influence MOOC performance. This understanding can, in turn, inform the design and implementation of targeted interventions and educational strategies aimed at enhancing the overall learning experience.

Additionally, regular and timely feedback approach should be provided to learners, and learning analytics data should be used to track learner progress and identify areas for improvement in course design and delivery. Course admin should be provided with guidelines on how a MOOC course is developed, managed, and assessed.

In summary, the MPM Model serves as a powerful tool for enabling data-driven decision-making in the realm of MOOCs. By leveraging the power of existing learning analytics data, the model provides administrators and course providers with the insights and recommendations necessary to optimize learning outcomes, improve educational experiences, and address the unique needs and challenges of the modern, digital learner.

8.6 Limitations

Like every research study, there are certain restrictions on this thesis. Chapter 3 contained an explanation of the methodological limitations. After having presented the MPM Model and its various components in the previous sections, this section delves into critical reflections on the proposed framework, acknowledging both its limitations and the wider applicability of the model. It is vital to comprehend its validity and pinpoint possible avenues for enhancement.

The MPM Model is designed specifically for MOOCs and has shown promise in facilitating a data-driven approach to course administration and design, as demonstrated by its initial application to the FutureLearn and OpenLearning platforms. By leveraging the power of learning analytics data, the model aims to empower educators and administrators in making informed decisions to improve the overall learning experience, enhance learner outcomes, and ensure the quality and relevance of MOOC courses.

Critical Reflection 1: Limitations of Metrics in the Face of Consideration Factors Indicators

While the MPM Model provides a structured approach to analyzing and interpreting learning analytics data, it is important to recognize the inherent limitations of metrics in fully capturing the complexity of the human learning experience. The model's ability to offer actionable recommendations is fundamentally dependent on the quality and completeness of the data it relies on. As a result, the presence of missing assessment data from MOOC platforms can introduce considerable uncertainty and bias into the analysis process, potentially impacting the accuracy and utility of the resulting recommendations.

To mitigate these challenges, the model incorporates the Consideration Factors Indicator, which seeks to supplement the objective metrics with valuable qualitative insights on how various contextual factors – nine areas are technical, instruction, content, human and environment – may be influencing the performance metrics. By acknowledging these limitations and incorporating richer, more nuanced data sources, the model can enhance its overall credibility and effectiveness.

Critical Reflection 2: Exclusivity to FutureLearn and OpenLearning Platforms

The initial research and development of the MPM Model were carried out with a focus on improving the quality and performance of MOOC courses on two specific platforms: FutureLearn and OpenLearning. While these platforms share many common characteristics and learning analytics capabilities, it is essential to acknowledge that the model's applicability and effectiveness may vary across different MOOC providers, platforms, and learning environments.

As such, the research team must continue to conduct rigorous testing and refinement of the MPM Model across a broader range of platforms and learning analytics systems, ensuring that its recommendations remain relevant, timely, and actionable for the diverse range of stakeholders involved in administering, designing, and delivering MOOC courses worldwide.

Critical Reflection 3: Acknowledgement of the Challenges of Missing Assessment Data from MOOC Platforms

The study acknowledges the challenges posed by missing assessment data from MOOC platforms, which can impact the accuracy and completeness of the analysis. The limitations in data access, particularly due to incomplete or missing data from learning analytics, highlight the need for a more robust data collection strategy. The Consideration Factors Indicators within the MPM Model framework may face constraints in providing a comprehensive assessment of MOOC platforms when crucial data points are unavailable.

To address the challenges of missing assessment data from MOOC platforms, consider implementing the following mitigation options:

- **Improved Course Design**: Enhance course structure design to ensure comprehensive tracking and recording of learning analytics data, reducing the likelihood of missing data due to poor design.
- **Increased User Participation**: Encourage more users to participate in user usability testing activities by extending testing durations, reaching out to a broader pool of potential participants, and ensuring diverse levels of expertise and experiences are covered.
- **Enhanced Communication**: Improve communication strategies, especially during challenging times like the COVID-19 pandemic, to facilitate better interaction and engagement with participants, potentially reducing limitations in data collection.

The study is subject to additional limitations that mainly stem from the researcher's positionality, variations in the research settings, the dynamic character of the subject matter and critical reflections. Three fundamental limitations will be looked at in this section: personal bias, diversity of contexts, and limited access to data.

8.6.1 Personal Bias

The research study's emphasis on the use of learning analytics in MOOCs meant that personal bias would inevitably be introduced as almost all the participants in the user usability testing and the researchers themselves were proponents of MOOCs. The selection criteria for the user usability testing participants inevitably involved having experiences taught either through

FutureLearn or OpenLearning MOOCs. As a result, the sample possessed inherent self-selection. While the discourses that highlight the concerns about MOOCs have been well treated, most of the conversations were predicated on the idea that MOOCs, especially MOOC learning analytics, were good for society and education.

8.6.2 Diversity of Contexts

Each participant in the user usability testing is an experienced MOOC user. That may be the only characteristic they had in common. Furthermore, because of the study's scope, every participant in the user usability testing was either a FutureLearn or OpenLearning MOOC platform user. As a result, this study might not represent the other MOOC platforms. On the other hand, there was much variation in the remaining areas. The pedagogical strategy employed, the quantity and frequency of courses given, and the participants' motivation on MOOC potential and limits are just a few of the many experiences participants have had.

One such ubiquitous contextual variation was the MOOC policies and procedures employed by the participants across various organisations. Diverse narratives on the participants' experiences with the function of MOOCs at their universities also emerged from this. Each participant's proficiency in data analysis varies significantly as a result. This variability was expected, but attaining a uniform learning analytics competence was hard. Some participants had never worked with learning analytics data before, and an expert used MOOC learning analytics data regularly for reporting. This diversity helps my study by providing comments and insights from various viewpoints.

8.6.3 Limited Access to Data and Sample Size

The research study may not have been able to capture data from all expected sources. Based on this study for future consideration, I would like to highlight two limitations of data access: incomplete or missing data from learning analytics due to poor course structure design and limited numbers of users participating in the user usability testing activity.

Learning analytics data was automatically tracked and recorded by the MOOC platform. However, in some possibilities, data might be missing due to foreseeing reasons such as technical and connectivity issues, poor course structure design, and poor instructional design. In this study, I have gathered learning analytics data from 95 MOOC courses involving 190 datasets. The OpenLearning platform contributes the most data compared with the FutureLearn platform.

Regarding the limited number of users participating in the user usability testing activity, effort has been put into extending the testing duration and reaching out to more potential participants. I also put in extra effort, ensuring the participants cover various levels of expertise and experiences. Two possible reasons for the difficulty gathering participants are that this study was undertaken during the peak of the COVID-19 pandemic. As a result, communication and interaction are limited to some extent, not to mention personal limitations in each potential participant I engaged. Secondly, due to the nature of the context of this study, which focuses on two specific MOOC platform users with experience developing or offering MOOC courses, only a few that I filter are suitable for invitation to take part with little positive response.

However, I have designed my research framework and method to ensure that the limited access to data does not significantly limit the validity and generalizability within the context of the study.

8.7 Future Works

As the demand for MOOCs continues to grow, there is a need for further research to explore the potential of MOOCs in various contexts, including enhancing learning outcomes using learning analytics data at cross-platform levels. This thesis aims to contribute to this research by exploring the potential of MOOCs in cross-platform data model study for improving user performance and learning outcomes. The thesis will also explore the potential of six future works.

8.7.1 Expanding MOOC Platform Compatibility

I recommend expanding the capabilities of MOOC platforms by testing the model on other platforms. The research study scope was set to two specific MOOC platforms, but the model has been successfully tested and demonstrated positive results meeting its objective and purpose. Therefore, it is ready to be tested on other platforms, increasing its capabilities. By expanding the model’s capabilities, we can reach a broader audience and improve the learning experience for learners on various MOOC platforms. Additionally, expanding the model’s capabilities could improve model analysis, discoveries, and insights into how analytic data can help MOOCs improve for better course and learner performance.

8.7.2 Develop Tool Based on the MPM Model

Develop an online or offline tool based on the MPM model incorporating user experience (UX) and user interface (UI) design considerations. The tool should be developed to improve the usability of the model and enable users to access and analyse the data quickly. The tool should be designed with a user-friendly interface to achieve this objective and provide users with real-time feedback on their progress. Additionally, the tool should incorporate data visualisation features that enable users to identify trends and patterns in the data quickly. Finally, the tool should be tested with a diverse group of users to ensure that it is accessible and easy to use for all users.

8.7.3 Automate the Data Entry Process

It is recommended that the possibility of automating the data entry process is explored to improve the efficiency and accuracy of the MPM model. This work can also be achieved by developing customised scripts or using existing programs to clean and pre-process the data before it is used with the MPM model. By automating the data entry process, researchers can save time and reduce the risk of human error, ultimately leading to more accurate and reliable results. In addition, automating the data entry process can also help to standardise the data preparation process, making it easier for users to replicate the analysis across different platforms and datasets. Further research should explore the feasibility of automating the data entry process and its potential benefits to the MPM model.

8.7.4 Apply Advanced AI and ML Capabilities on Result Analysis

I recommend that in future works, researchers should explore the application of advanced AI and ML capabilities in the Result Analysis process of the MPM model. One of the components in the MPM model that was found to be the most significant contribution to this model is the Consideration Factor Indicator. This indicator is used to identify possible reasons and potential solutions based on analysed data patterns. However, users must manually observe and compare analysed charts with the consideration factor indicator. To overcome this challenge, I propose to apply AI and ML capabilities for this task. This proposed solution can be achieved by developing an automated system to analyse the data patterns and identify the consideration factor indicator without human intervention. Additionally, I propose using Generative AI, which can improve the model's features in the analysis and reporting aspect. With these advancements, I can enhance the MPM model's Result Analysis process and provide users with more accurate and efficient results.

8.7.5 Get Involvement from MOOC Platform Providers

Based on the current research study and suggestions from faculty members, it is highly recommended to get involvement from MOOC platform providers in future works. Direct involvement from MOOC platform providers could lead to insight from a different point of view in the context of technicality and data analytics. It could improve the existing model and provide a more accurate student engagement and performance analysis. It could also lead to the development of new features and plugins that could enhance the learning experience for students enrolled in MOOCs. Overall, the involvement of MOOC platform providers in future works could greatly benefit the research community and provide a more comprehensive understanding of student engagement and performance in MOOCs.

8.7.6 Expanding Research Study with Bigger User Usability Participants Sample Size

It is recommended that future works on expanding this study should focus on increasing the sample size of user usability participants. The current study has successfully achieved its research objectives and addressed the research gap, but the small sample size limits the generalizability of the findings. Therefore, future studies should aim to recruit a more extensive and diverse sample of users to test the model's usability. Additionally, different study methods, such as surveys or interviews, could be explored to gather more comprehensive data on user usability. Overall, expanding this study with a larger and more diverse sample size and exploring different study methods will provide a more comprehensive understanding of user usability in the context of the MPM model.

8.8 Research Conclusion

In conclusion, this research study provides evidence that it is possible to have a cross-platform learning analytics data model that can be used for MOOC courses or learner performance monitoring, measurement, and analysis purposes.

My findings suggest that certain factors moderate the relationship between learning analytics data and MOOC platforms. Each MOOC platform has its scheme and structure for how learning analytics data will be tracked and recorded. Alternatively, the semantic web and ontology approach provided possible solutions to this issue, justified by the data mapping activity and creation of uniform dataset in this study. Within the context and the definition of performance of this study, the use of the time series analysis method is proven suitable. I also found that new metrics and indicators are needed to support the analysis and interpretation of MOOC learning analytics data.

The implications of my findings are significant for both theory and practice, and they highlight the importance of each stakeholder in improving MOOC course and learner performance using learning analytics data.

However, my study has some limitations that should be considered when interpreting the findings, and future research should address these limitations to further our understanding of the relationship between learning analytics data, MOOC platforms and learning context.

Appendix A Questionnaire Answer Participant 1

PART 1: Demography

This section required users to provide answers for questions 1 to question 8 that focuses on the user demography.

Question	Answer / Respond
Q1: Country of the Institution / university you are working now?	Answer Q1: ◉ Malaysia ○ United Kingdom ○ Other :
Q2: MOOC Platform used for this MOOC course?	Answer Q2: ○ FutureLearn ◉ OpenLearning
Q3: Years of experience in offering MOOC course?	Answer Q3: ○ 1st years offering MOOC course ○ 2nd years offering MOOC course ◉ More then 2 years
Q4: Total number of MOOC course you had offered?	Answer Q4: ○ 0 course ○ 1 course ○ 2 courses ○ 3 courses ◉ 4 or more courses
Q5: Your role in offered course? (Exp: Course Moderator, Course Admin, Content developer, ...)	Answer Q5: Content Developer
Q6: Provide the course name if you are using your own dataset. If you using a sample dataset, write "Sample course"	Answer Q6: Sample course
Q7: Learner level of the MOOC course	Answer Q7: ◉ Undergraduate ○ Postgraduate ○ Open Undergraduate ○ Open Postgraduate ○ Open and mix
Q8: Dataset used in this User Testing	Answer Q8: ◉ Using provided sample datasets ○ Using own datasets

PART 2: MPM Usage (Monitoring)

This section required users to provide answers for questions 9 to question 14 that focuses on the monitoring feature of the MPM Model. MPM Model is using available learning analytic data from MOOC platforms and external data (assignment) provided by the course admin.

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
Q9: Using MPM would make it easier to do my job as MOOC course admin.	○	○	○	○	◉
Q10: I would find MPM useful in my job.	○	○	○	○	◉
Q11: Using MPM would enhance my understanding on the learning analytic data toward course I am offering.	○	○	○	○	◉
Q12: Learning to use MPM from the provided tool would be easy for me.	○	○	○	○	◉
Q13: I would find MPM to be flexible to interact with.	○	○	○	○	◉
Q14: I would find MPM easy to use.	○	○	○	○	◉

PART 3: MPM Usage (Measurement)

This section required users to provide answers for questions 15 to question 20 that focuses on the measurement feature of the MPM Model. The measurement approach used is based on comparing data with the previous data and identifying the positive or negative indication.

Questions	Answer / Respond
Q15: MPM Model enable user to conduct two type of performance measurements. Course performance or student performance. Which type of measurement is used in this testing?	◉ Course Performance ○ Student Performance
Q16: Data used in the measurement involving how many students?	586 *Example: 127*

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
Q17: I would find the **measurement approach** used by MPM Model (measure current score vs previous score) is acceptable in reflecting improvement or deterioration of performance.	○	○	○	◉	○
Q18: I would find the **Condition Indicator** used in this model easy to understand.	○	○	○	○	◉
Q19: I would change the **default Performance Metric** proposed, to follow my institution standard.	○	○	○	○	◉
Q20: It would be easy for me to become skilful at **importing data into MPM Model** ready for performance measurement.	○	○	○	○	◉

PART 4: MPM Usage (Analysis)
This section required users to provide answers for questions 21 to question 26 that focuses on the analysis feature of the MPM Model. An analysis in the MPM Model enables a user to visualize the measurement result and refer it to the Consideration Factor Indicator.

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
Q21: Using analysis based on MPM Model would enhance my effectiveness in improving offered MOOC course.	○	○	○	○	◉
Q22: I would find analysis results from MPM Model useful in my job	○	○	○	◉	○
Q23: Learning to compare analysis result with provided indicator would be easy for me.	○	○	○	◉	○
Q24: Analysis result was successfully generated with no error	○	○	○	◉	○
Q25: Result give insight on which module need an extra attention for improvement.	○	○	○	○	◉
Q26: I would find the **Consideration Factor Indicator** provided is helpful	○	○	○	◉	○

PART 5: Feedback
This section required users to provide feedback and improvement recommendations on each specific MPM Model feature based on recent experience using it.

Question	Answer / Respond
Q27: Monitoring performance is one of the MPM Model features. Please provide your feedback and related improvement recommendation based on recent monitoring performances experience using the MPM model.	It is easy to monitor the course performance by using this MPM Model. I can easily identify which lesson has a lower performance. However, the chart should immediately stop when there is no more lesson after that. For example, stop charting after Lesson 12.
Q28: Measuring performance is another feature of the MPM Model. Design based on the fundamental concept where the latest score is better than the previous score, please provide your feedback and related improvement recommendation on recent experience measuring performance using the MPM model.	It is easy also to measure the course performance by using this MPM Model. I can easily identify which lesson has the lowest performance score. However, the measurement should immediately stop when there is no more lesson after that. For example, it should stop measuring after Lesson 12.
Q29: Analysis performance is another feature of the MPM Model. It includes consideration factors indicators that cover five areas (technical, instruction, content, human and environment). Please provide your feedback based on recent analysis experience using the MPM model.	Indicators and factors provided are helpful and useful for performance analysis. However, some of them are confusing. Further elaboration is recommended. Here are the list: Technical - Did learners have access to the platforms? Instruction - The following consideration factor is confusing: Did explicit instruction been given by the course admin? Why course admin is referred here? Are the 'instruction' here means instructions delivery by educators/instructors? Instruction - The following Indication is confusing: Volatile indicator on both dataset score. 'Both dataset scores' are referring to what? Why 'both'? Content - The following consideration factor is confusing: Is content was new to learners? Do you mean 'content type used was new to the learners', since in learning educators always present new learning content to the learners. Human - again not clear why 'both datasets'?
Q30: As an experience MOOC user, have you used and analysed MOOC learning analytics data, and if yes, what tools or method was used?	Normally, we just use Excel and SPSS only.
Q31: In general, after trying using the MPM model to monitor and measure performance from MOOC learning analytics data, what improvement can you suggest to make experience in using the MPM model more easy?	The conlusion on whether the current MOOC performance is Excellent/Good Performance/Poor Performance/Very Poor Performance may need to be revised to also consider average percentage of all lessons before deciding on the overall level of the current MOOC performance. In mathematics, 0 cannot be considered as negative or positive values. If a MOOC has WDS=0 or MDS=0, it is recommended to consider that the 0 value shows consistent performance.

Appendix B Questionnaire Answer Participant 2

PART 1: Demography

This section required users to provide answers for questions 1 to question 8 that focuses on the user demography.

Question	Answer / Respond
Q1: Country of the Institution / university you are working now?	Answer Q1: ◉ Malaysia ○ United Kingdom ○ Other :
Q2: MOOC Platform used for this MOOC course?	Answer Q2: ○ FutureLearn ◉ OpenLearning
Q3: Years of experience in offering MOOC course?	Answer Q3: ○ 1st years offering MOOC course ○ 2nd years offering MOOC course ◉ More then 2 years
Q4: Total number of MOOC course you had offered?	Answer Q4: ○ 0 course ○ 1 course ○ 2 courses ◉ 3 courses ○ 4 or more courses
Q5: Your role in offered course? (Exp: Course Moderator, Course Admin, Content developer, ...)	Answer Q5: Course Moderator, Course Admin & Content developer
Q6: Provide the course name if you are using your own dataset. If you using a sample dataset, write "Sample course"	Answer Q6: sampel data set
Q7: Learner level of the MOOC course	Answer Q7: ◉ Undergraduate ○ Postgraduate ○ Open Undergraduate ○ Open Postgraduate ○ Open and mix
Q8: Dataset used in this User Testing	Answer Q8: ◉ Using provided sample datasets ○ Using own datasets

PART 2: MPM Usage (Monitoring)

This section required users to provide answers for questions 9 to question 14 that focuses on the monitoring feature of the MPM Model. MPM Model is using available learning analytic data from MOOC platforms and external data (assignment) provided by the course admin.

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
Q9: Using MPM would make it easier to do my job as MOOC course admin.	○	○	○	○	◉
Q10: I would find MPM useful in my job.	○	○	○	○	◉
Q11: Using MPM would enhance my understanding on the learning analytic data toward course I am offering.	○	○	○	◉	○
Q12: Learning to use MPM from the provided tool would be easy for me.	○	○	○	○	◉
Q13: I would find MPM to be flexible to interact with.	○	○	○	◉	○
Q14: I would find MPM easy to use.	○	○	○	○	◉

PART 3: MPM Usage (Measurement)

This section required users to provide answers for questions 15 to question 20 that focuses on the measurement feature of the MPM Model. The measurement approach used is based on comparing data with the previous data and identifying the positive or negative indication.

Questions	Answer / Respond
Q15: MPM Model enable user to conduct two type of performance measurements. Course performance or student performance. Which type of measurement is used in this testing?	◉ Course Performance ○ Student Performance
Q16: Data used in the measurement involving how many students?	138 *Example: 127*

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
Q17: I would find the **measurement approach** used by MPM Model (measure current score vs previous score) is acceptable in reflecting improvement or deterioration of performance.	○	○	○	◉	○
Q18: I would find the **Condition Indicator** used in this model easy to understand.	○	○	○	◉	○
Q19: I would change the **default Performance Metric** proposed, to follow my institution standard.	○	○	○	◉	○
Q20: It would be easy for me to become skilful at **importing data into MPM Model** ready for performance measurement.	○	○	○	○	◉

PART 4: MPM Usage (Analysis)
This section required users to provide answers for questions 21 to question 26 that focuses on the analysis feature of the MPM Model. An analysis in the MPM Model enables a user to visualize the measurement result and refer it to the Consideration Factor Indicator.

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
Q21: Using analysis based on MPM Model would enhance my effectiveness in improving offered MOOC course.	○	○	○	○	◉
Q22: I would find analysis results from MPM Model useful in my job	○	○	○	○	◉
Q23: Learning to compare analysis result with provided indicator would be easy for me.	○	○	○	◉	○
Q24: Analysis result was successfully generated with no error	○	○	○	○	◉
Q25: Result give insight on which module need an extra attention for improvement.	○	○	○	○	◉
Q26: I would find the **Consideration Factor Indicator** provided is helpful	○	○	○	○	◉

PART 5: Feedback
This section required users to provide feedback and improvement recommendations on each specific MPM Model feature based on recent experience using it.

Question	Answer / Respond
Q27: Monitoring performance is one of the MPM Model features. Please provide your feedback and related improvement recommendation based on recent monitoring performances experience using the MPM model.	The monitoring performance of this MPM Model is very good and helps to identify courses analysis that needs to be improved and is very useful for developers and researchers.
Q28: Measuring performance is another feature of the MPM Model. Design based on the fundamental concept where the latest score is better than the previous score, please provide your feedback and related improvement recommendation on recent experience measuring performance using the MPM model.	Measuring the performance of the MPM model is very helpful for the developer to know the performance of the developed course is appropriate by measuring the performance of the students before and after the module is taken.
Q29: Analysis performance is another feature of the MPM Model. It includes consideration factors indicators that cover five areas (technical, instruction, content, human and environment). Please provide your feedback based on recent analysis experience using the MPM model.	Performance analysis the MPM Model provides a clear picture to developers for module improvement and the appropriateness of measuring performance and analyzing student performance.
Q30: As an experience MOOC user, have you used and analysed MOOC learning analytics data, and if yes, what tools or method was used?	Never used analyzed MOOC learning and data analytics.
Q31: In general, after trying using the MPM model to monitor and measure performance from MOOC learning analytics data, what improvement can you suggest to make experience in using the MPM model more easy?	No improvements have been suggested so far for the MPM model.

Appendix C Questionnaire Answer Participant 3

PART 1: Demography
This section required users to provide answers for questions 1 to question 8 that focuses on the user demography.

Question	Answer / Respond
Q1: Country of the Institution / university you are working now?	Answer Q1: ○ Malaysia ◉ United Kingdom ○ Other :
Q2: MOOC Platform used for this MOOC course?	Answer Q2: ◉ FutureLearn ○ OpenLearning
Q3: Years of experience in offering MOOC course?	Answer Q3: ○ 1st years offering MOOC course ○ 2nd years offering MOOC course ◉ More then 2 years
Q4: Total number of MOOC course you had offered?	Answer Q4: ○ 0 course ○ 1 course ○ 2 courses ◉ 3 courses ○ 4 or more courses
Q5: Your role in offered course? (Exp: Course Moderator, Course Admin, Content developer, ...)	Answer Q5: Some learning design work, plus as facilitator within some courses (monitoring discussions, creating summary/response videos) - this was back in 2015 or so!
Q6: Provide the course name if you are using your own dataset. If you using a sample dataset, write "Sample course"	Answer Q6: sample course
Q7: Learner level of the MOOC course	Answer Q7: ◉ Undergraduate ○ Postgraduate ○ Open Undergraduate ○ Open Postgraduate ◉ Open and mix
Q8: Dataset used in this User Testing	Answer Q8: ◉ Using provided sample datasets ○ Using own datasets

PART 2: MPM Usage (Monitoring)
This section required users to provide answers for questions 9 to question 14 that focuses on the monitoring feature of the MPM Model. MPM Model is using available learning analytic data from MOOC platforms and external data (assignment) provided by the course admin.

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
Q9: Using MPM would make it easier to do my job as MOOC course admin.	○	○	○	◉	○
Q10: I would find MPM useful in my job.	○	○	○	◉	○
Q11: Using MPM would enhance my understanding on the learning analytic data toward course I am offering.	○	○	○	◉	○
Q12: Learning to use MPM from the provided tool would be easy for me.	○	◉	○	○	○
Q13: I would find MPM to be flexible to interact with.	○	○	◉	○	○
Q14: I would find MPM easy to use.	○	◉	○	○	○

PART 3: MPM Usage (Measurement)
This section required users to provide answers for questions 15 to question 20 that focuses on the measurement feature of the MPM Model. The measurement approach used is based on comparing data with the previous data and identifying the positive or negative indication.

Questions	Answer / Respond
Q15: MPM Model enable user to conduct two type of performance measurements. Course performance or student performance. Which type of measurement is used in this testing?	◉ Course Performance ○ Student Performance
Q16: Data used in the measurement involving how many students?	4927 *Example: 127*

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
Q17: I would find the **measurement approach** used by MPM Model (measure current score vs previous score) is acceptable in reflecting improvement or deterioration of performance.	○	○	○	◉	○
Q18: I would find the **Condition Indicator** used in this model easy to understand.	○	○	○	◉	○
Q19: I would change the **default Performance Metric** proposed, to follow my institution standard.	○	○	◉	○	○
Q20: It would be easy for me to become skilful at **importing data into MPM Model** ready for performance measurement.	○	◉	○	○	○

PART 4: MPM Usage (Analysis)
This section required users to provide answers for questions 21 to question 26 that focuses on the analysis feature of the MPM Model. An analysis in the MPM Model enables a user to visualize the measurement result and refer it to the Consideration Factor Indicator.

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
Q21: Using analysis based on MPM Model would enhance my effectiveness in improving offered MOOC course.	○	○	○	◉	○
Q22: I would find analysis results from MPM Model useful in my job	○	○	○	◉	○
Q23: Learning to compare analysis result with provided indicator would be easy for me.	○	○	○	◉	○
Q24: Analysis result was successfully generated with no error	○	◉	○	○	○
Q25: Result give insight on which module need an extra attention for improvement.	○	○	○	◉	○
Q26: I would find the **Consideration Factor Indicator** provided is helpful	○	○	○	◉	○

PART 5: Feedback	
This section required users to provide feedback and improvement recommendations on each specific MPM Model feature based on recent experience using it.	
Question	**Answer / Respond**
Q27: Monitoring performance is one of the MPM Model features. Please provide your feedback and related improvement recommendation based on recent monitoring performances experience using the MPM model.	I haven't worked with MOOCs recently so don't really know what monitoring dashboards or data is currently available. However, I feel like this snapshot of the performance of the MOOC would be useful as an overall indicator of the course performance and of each step or module.
Q28: Measuring performance is another feature of the MPM Model. Design based on the fundamental concept where the latest score is better than the previous score, please provide your feedback and related improvement recommendation on recent experience measuring performance using the MPM model.	Because my results were quite volatile and indicated poor performance of the MOOC, it's hard to say. Mostly the score was zero with a few peaks and dips. However, the example showed to me in the training was more informative and I think would be a useful way of getting idea of performance measurement.
Q29: Analysis performance is another feature of the MPM Model. It includes consideration factors indicators that cover five areas (technical, instruction, content, human and environment). Please provide your feedback based on recent analysis experience using the MPM model.	Yes - i think it's useful to break down performance into different categories. I've made some comments on the previous sheet about possible enhancements to the 'instruction' category. I suppose it's important to remember that MOOCs aren't really heavily reliant on 'instruction' as such, but are also opportunities for independent learning and reflection (so heutagogy, or self-determined learning as much as pedagogy). This means that motivation will be a key factor - and it might be useful to have that as a consideration in the instruction element. Does the MOOC motivate the learners to complete a step/course and to persist? There might be a good prompt about motivation to add to the questions in the 'instruction' field. For example ' does the step make clear the benefit of learning this skill/content'? Not just a 'cold' description of what is coming, but a reason for the participant to do it. Perhaps stated as a motivating learning outcome: 'This step will enable you to ...' I suppose you could also ask about
Q30: As an experience MOOC user, have you used and analysed MOOC learning analytics data, and if yes, what tools or method was used?	Not a lot. We looked at user data such as number of participants, completion rates of weeks/steps, views of videos, number of comments/replies in forums. I wasn't involved deeply enough to make ongoing use of such statistics, but I'm aware of these basic things. As someone who researched a bit in learning technology in the past, I always saw Learning Analytics as something with potential, but I had/still have a lot of skepticism about whether it can provide really *meaningful* and *useful* data which we can use well, within the contraints of respecting user privacy etc. See Q30 above.
Q31: In general, after trying using the MPM model to monitor and measure performance from MOOC learning analytics data, what improvement can you suggest to make experience in using the MPM model more easy?	This tool seems to give a useful and valuable snapshot of a course which could point the designer in the direction of needed improvements. The level of diagnosis of problems isn't very deep - which is fine provided the effort to use / obtain the data is low. My experience of trying to transfer data between spreadsheets in this case wasn't good - it was confusing. I'm sure I could learn the process, but the steps and design of the spreadsheets needs to lead the user more clearly through the steps required. Ideally, the computer would do all the transfer automatically, and just show me the graph!

Appendix D Questionnaire Answer Participant 4

PART 1: Demography

This section required users to provide answers for questions 1 to question 8 that focuses on the user demography.

Question	Answer / Respond	
Q1: Country of the Institution / university you are working now?	Answer Q1: ○ Malaysia ◉ United Kingdom ○ Other :	
Q2: MOOC Platform used for this MOOC course?	Answer Q2: ◉ FutureLearn ○ OpenLearning	
Q3: Years of experience in offering MOOC course?	Answer Q3: ○ 1st years offering MOOC course ○ 2nd years offering MOOC course ◉ More then 2 years	
Q4: Total number of MOOC course you had offered?	Answer Q4: ○ 0 course ○ 1 course ○ 2 courses ◉ 3 courses ○ 4 or more courses	
Q5: Your role in offered course? (Exp: Course Moderator, Course Admin, Content developer, ...)	Answer Q5: Content Developer, Designer, and Tutor	
Q6: Provide the course name if you are using your own dataset. If you using a sample dataset, write "Sample course"	Answer Q6: Sample	
Q7: Learner level of the MOOC course	Answer Q7: ◉ Undergraduate ○ Postgraduate ○ Open Undergraduate ○ Open Postgraduate ◉ Open and mix	Open and Mix
Q8: Dataset used in this User Testing	Answer Q8: ◉ Using provided sample datasets ○ Using own datasets	

PART 2: MPM Usage (Monitoring)

This section required users to provide answers for questions 9 to question 14 that focuses on the monitoring feature of the MPM Model. MPM Model is using available learning analytic data from MOOC platforms and external data (assignment) provided by the course admin.

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
Q9: Using MPM would make it easier to do my job as MOOC course admin.	○	○	◉	○	○
Q10: I would find MPM useful in my job.	○	○	○	◉	○
Q11: Using MPM would enhance my understanding on the learning analytic data toward course I am offering.	○	○	◉	○	○
Q12: Learning to use MPM from the provided tool would be easy for me.	○	◉	○	○	○
Q13: I would find MPM to be flexible to interact with.	○	○	◉	○	○
Q14: I would find MPM easy to use.	○	○	○	◉	○

PART 3: MPM Usage (Measurement)

This section required users to provide answers for questions 15 to question 20 that focuses on the measurement feature of the MPM Model. The measurement approach used is based on comparing data with the previous data and identifying the positive or negative indication.

Questions	Answer / Respond		
Q15: MPM Model enable user to conduct two type of performance measurements. Course performance or student performance. Which type of measurement is used in this testing?	◉ Course Performance	○ Student Performance	Both
Q16: Data used in the measurement involving how many students?		*Example: 127*	

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied	
Q17: I would find the **measurement approach** used by MPM Model (measure current score vs previous score) is acceptable in reflecting improvement or deterioration of performance.	○	○	○	◉	○	
Q18: I would find the **Condition Indicator** used in this model easy to understand.	○	◉	○	○	○	
Q19: I would change the **default Performance Metric** proposed, to follow my institution standard.	○	○	◉	○	○	There was no standard
Q20: It would be easy for me to become skilful at **importing data into MPM Model** ready for performance measurement.	○	○	○	◉	○	

PART 4: MPM Usage (Analysis)

This section required users to provide answers for questions 21 to question 26 that focuses on the analysis feature of the MPM Model. An analysis in the MPM Model enables a user to visualize the measurement result and refer it to the Consideration Factor Indicator.

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied	
Q21: Using analysis based on MPM Model would enhance my effectiveness in improving offered MOOC course.	○	○	○	◉	○	
Q22: I would find analysis results from MPM Model useful in my job	○	○	○	◉	○	
Q23: Learning to compare analysis result with provided indicator would be easy for me.	○	○	○	◉	○	
Q24: Analysis result was successfully generated with no error	○	○	○	○	◉	
Q25: Result give insight on which module need an extra attention for improvement.	○	○	◉	○	○	fake data
Q26: I would find the **Consideration Factor Indicator** provided is helpful	○	○	○	○	◉	

PART 5: Feedback	
This section required users to provide feedback and improvement recommendations on each specific MPM Model feature based on recent experience using it.	

Question	Answer / Respond
Q27: Monitoring performance is one of the MPM Model features. Please provide your feedback and related improvement recommendation based on recent monitoring performances experience using the MPM model.	Still feels like a reletively simple analysis (that is similar to what I would do by hand already). So its a useful analysis, but as it replicates what I would already be looking for, I would only find it useful for communication rather than analysis. It might be useful to flag where the peaks or troughs were outsode of the standard statistical range - that might help to highlight which ones were worth looking at.
Q28: Measuring performance is another feature of the MPM Model. Design based on the fundamental concept where the latest score is better than the previous score, please provide your feedback and related improvement recommendation on recent experience measuring performance using the MPM model.	It feels like it combines engagement and performance (on assessment), which I would regard as two seperate things. Knowling both how many people are attempting activities as well as the performance of those that do feels important. Performance is a neutral term, it is always measureing something against a metric, and the choice of metric matters. So in this case you are measuring performance against engagement metrics, so this is not measuring 'perforamance' it is measuring 'engagement'.
Q29: Analysis performance is another feature of the MPM Model. It includes consideration factors indicators that cover five areas (technical, instruction, content, human and environment). Please provide your feedback based on recent analysis experience using the MPM model.	This provides a useful framework for analysing changing engagement - and reminds one of both internal and external factors.
Q30: As an experience MOOC user, have you used and analysed MOOC learning analytics data, and if yes, what tools or method was used?	Yes, Excel. Metrics typically about engagement, and changes to enaggement over time.
Q31: In general, after trying using the MPM model to monitor and measure performance from MOOC learning analytics data, what improvement can you suggest to make experience in using the MPM model more easy?	Easier import of data. Having to manipulate data is time consuming. Also the guidance (mentuoned above) about when changes were outside of the expected statistical range.

Appendix E Questionnaire Answer Participant 5

PART 1: Demography

This section required users to provide answers for questions 1 to question 8 that focuses on the user demography.

Question	Answer / Respond
Q1: Country of the Institution / university you are working now?	Answer Q1: ◉ Malaysia ○ United Kingdom ○ Other :
Q2: MOOC Platform used for this MOOC course?	Answer Q2: ○ FutureLearn ◉ OpenLearning
Q3: Years of experience in offering MOOC course?	Answer Q3: ○ 1st years offering MOOC course ○ 2nd years offering MOOC course ◉ More then 2 years
Q4: Total number of MOOC course you had offered?	Answer Q4: ○ 0 course ◉ 1 course ○ 2 courses ○ 3 courses ○ 4 or more courses
Q5: Your role in offered course? (Exp: Course Moderator, Course Admin, Content developer, ...)	Answer Q5: Couse admin, course instructor
Q6: Provide the course name if you are using your own dataset. If you using a sample dataset, write "Sample course"	Answer Q6: Multimedia Technology and Design
Q7: Learner level of the MOOC course	Answer Q7: ◉ Undergraduate ○ Postgraduate ○ Open Undergraduate ○ Open Postgraduate ○ Open and mix
Q8: Dataset used in this User Testing	Answer Q8: ○ Using provided sample datasets ◉ Using own datasets

PART 2: MPM Usage (Monitoring)

This section required users to provide answers for questions 9 to question 14 that focuses on the monitoring feature of the MPM Model. MPM Model is using available learning analytic data from MOOC platforms and external data (assignment) provided by the course admin.

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
Q9: Using MPM would make it easier to do my job as MOOC course admin.	○	○	○	◉	○
Q10: I would find MPM useful in my job.	○	○	○	◉	○
Q11: Using MPM would enhance my understanding on the learning analytic data toward course I am offering.	○	○	◉	○	○
Q12: Learning to use MPM from the provided tool would be easy for me.	○	○	◉	○	○
Q13: I would find MPM to be flexible to interact with.	○	○	○	◉	○
Q14: I would find MPM easy to use.	○	○	○	◉	○

PART 3: MPM Usage (Measurement)

This section required users to provide answers for questions 15 to question 20 that focuses on the measurement feature of the MPM Model. The measurement approach used is based on comparing data with the previous data and identifying the positive or negative indication.

Questions	Answer / Respond	
Q15: MPM Model enable user to conduct two type of performance measurements. Course performance or student performance. Which type of measurement is used in this testing?	◉ Course Performance	○ Student Performance
Q16: Data used in the measurement involving how many students?	179	*Example: 127*

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
Q17: I would find the **measurement approach** used by MPM Model (measure current score vs previous score) is acceptable in reflecting improvement or deterioration of performance.	○	○	○	◉	○
Q18: I would find the **Condition Indicator** used in this model easy to understand.	○	○	◉	○	○
Q19: I would change the **default Performance Metric** proposed, to follow my institution standard.	○	○	◉	○	○
Q20: It would be easy for me to become skilful at **importing data into MPM Model** ready for performance measurement.	○	○	○	◉	○

PART 4: MPM Usage (Analysis)

This section required users to provide answers for questions 21 to question 26 that focuses on the analysis feature of the MPM Model. An analysis in the MPM Model enables a user to visualize the measurement result and refer it to the Consideration Factor Indicator.

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
Q21: Using analysis based on MPM Model would enhance my effectiveness in improving offered MOOC course.	○	○	○	◉	○
Q22: I would find analysis results from MPM Model useful in my job	○	○	○	◉	○
Q23: Learning to compare analysis result with provided indicator would be easy for me.	○	○	◉	○	○
Q24: Analysis result was successfully generated with no error	○	○	○	◉	○
Q25: Result give insight on which module need an extra attention for improvement.	○	○	○	◉	○
Q26: I would find the **Consideration Factor Indicator** provided is helpful	○	○	○	○	◉

PART 5: Feedback	
This section required users to provide feedback and improvement recommendations on each specific MPM Model feature based on recent experience using it.	
Question	**Answer / Respond**
Q27: Monitoring performance is one of the MPM Model features. Please provide your feedback and related improvement recommendation based on recent monitoring performances experience using the MPM model.	Perhaps you may consider other factors such as whether the students are being "forced" to complete the modules or not. The completion rates of MOOCs can be influenced by motivation from external factors like the instructor, and whether students take MOOCs voluntarily or are required to complete them.
Q28: Measuring performance is another feature of the MPM Model. Design based on the fundamental concept where the latest score is better than the previous score, please provide your feedback and related improvement recommendation on recent experience measuring performance using the MPM model.	Ensure that the measures used are relevant and aligned with the UNIMAS or KPT's agenda. It's important to choose the right metrics that will give a clear picture of progress towards achieving the goals.
Q29: Analysis performance is another feature of the MPM Model. It includes consideration factors indicators that cover five areas (technical, instruction, content, human and environment). Please provide your feedback based on recent analysis experience using the MPM model.	You may add these factors too: User-friendly platform, clear and engaging instruction and content, opportunities for interaction and feedback, and flexible scheduling options to accommodate learners' needs.
Q30: As an experience MOOC user, have you used and analysed MOOC learning analytics data, and if yes, what tools or method was used?	Never before.
Q31: In general, after trying using the MPM model to monitor and measure performance from MOOC learning analytics data, what improvement can you suggest to make experience in using the MPM model more easy?	Automate data collection: Use technology to automate the collection of data, which can help reduce errors and save time. This can also provide real-time data, allowing for more timely adjustments to the MOOC. Create a form that user just need top upload their raw data and MPM tool will extract the CSV file automatically.

Appendix F Questionnaire Answer Participant 6

PART 1: Demography

This section required users to provide answers for questions 1 to question 8 that focuses on the user demography.

Question	Answer / Respond
Q1: Country of the Institution / university you are working now?	Answer Q1: ◉ Malaysia ○ United Kingdom ○ Other :
Q2: MOOC Platform used for this MOOC course?	Answer Q2: ○ FutureLearn ◉ OpenLearning
Q3: Years of experience in offering MOOC course?	Answer Q3: ○ 1st years offering MOOC course ○ 2nd years offering MOOC course ◉ More then 2 years
Q4: Total number of MOOC course you had offered?	Answer Q4: ○ 0 course ◉ 1 course ○ 2 courses ○ 3 courses ○ 4 or more courses
Q5: Your role in offered course? (Exp: Course Moderator, Course Admin, Content developer, ...)	Answer Q5: Content developer
Q6: Provide the course name if you are using your own dataset. If you using a sample dataset, write "Sample course"	Answer Q6: Introduction to Database
Q7: Learner level of the MOOC course	Answer Q7: ◉ Undergraduate ○ Postgraduate ○ Open Undergraduate ○ Open Postgraduate ○ Open and mix
Q8: Dataset used in this User Testing	Answer Q8: ◉ Using provided sample datasets ○ Using own datasets

PART 2: MPM Usage (Monitoring)

This section required users to provide answers for questions 9 to question 14 that focuses on the monitoring feature of the MPM Model. MPM Model is using available learning analytic data from MOOC platforms and external data (assignment) provided by the course admin.

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
Q9: Using MPM would make it easier to do my job as MOOC course admin.	○	○	◉	○	○
Q10: I would find MPM useful in my job.	○	○	○	◉	○
Q11: Using MPM would enhance my understanding on the learning analytic data toward course I am offering.	○	○	○	○	◉
Q12: Learning to use MPM from the provided tool would be easy for me.	○	○	○	◉	○
Q13: I would find MPM to be flexible to interact with.	○	○	◉	○	○
Q14: I would find MPM easy to use.	○	○	◉	○	○

PART 3: MPM Usage (Measurement)

This section required users to provide answers for questions 15 to question 20 that focuses on the measurement feature of the MPM Model. The measurement approach used is based on comparing data with the previous data and identifying the positive or negative indication.

Questions	Answer / Respond
Q15: MPM Model enable user to conduct two type of performance measurements. Course performance or student performance. Which type of measurement is used in this testing?	○ Course Performance ◉ Student Performance
Q16: Data used in the measurement involving how many students?	10 *Example: 127*

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
Q17: I would find the **measurement approach** used by MPM Model (measure current score vs previous score) is acceptable in reflecting improvement or deterioration of performance.	○	○	○	○	◉
Q18: I would find the **Condition Indicator** used in this model easy to understand.	○	○	○	○	◉
Q19: I would change the **default Performance Metric** proposed, to follow my institution standard.	○	○	○	○	◉
Q20: It would be easy for me to become skilful at **importing data into MPM Model** ready for performance measurement.	○	○	○	◉	○

PART 4: MPM Usage (Analysis)

This section required users to provide answers for questions 21 to question 26 that focuses on the analysis feature of the MPM Model. An analysis in the MPM Model enables a user to visualize the measurement result and refer it to the Consideration Factor Indicator.

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
Q21: Using analysis based on MPM Model would enhance my effectiveness in improving offered MOOC course.	○	○	○	○	◉
Q22: I would find analysis results from MPM Model useful in my job	○	○	○	○	◉
Q23: Learning to compare analysis result with provided indicator would be easy for me.	○	○	○	○	◉
Q24: Analysis result was successfully generated with no error	○	○	○	○	◉
Q25: Result give insight on which module need an extra attention for improvement.	○	○	○	○	◉
Q26: I would find the **Consideration Factor Indicator** provided is helpful	○	○	○	○	◉

PART 5: Feedback

This section required users to provide feedback and improvement recommendations on each specific MPM Model feature based on recent experience using it.

Question	Answer / Respond
Q27: Monitoring performance is one of the MPM Model features. Please provide your feedback and related improvement recommendation based on recent monitoring performances experience using the MPM model.	Monitoring helps to give a big view on students learning behaviour
Q28: Measuring performance is another feature of the MPM Model. Design based on the fundamental concept where the latest score is better than the previous score, please provide your feedback and related improvement recommendation on recent experience measuring performance using the MPM model.	Measuring performance help which student maintain their learning effort
Q29: Analysis performance is another feature of the MPM Model. It includes consideration factors indicators that cover five areas (technical, instruction, content, human and environment). Please provide your feedback based on recent analysis experience using the MPM model.	Analysis of performance gives an insight into which performance may related
Q30: As an experience MOOC user, have you used and analysed MOOC learning analytics data, and if yes, what tools or method was used?	No.
Q31: In general, after trying using the MPM model to monitor and measure performance from MOOC learning analytics data, what improvement can you suggest to make experience in using the MPM model more easy?	Perhaps, can highlight the names of students who did not perform after a few topics learned

Appendix G Questionnaire Answer Participant 7

PART 1: Demography
This section required users to provide answers for questions 1 to question 8 that focuses on the user demography.

Question	Answer / Respond
Q1: Country of the Institution / university you are working now?	Answer Q1: ○ Malaysia ◉ United Kingdom ○ Other :
Q2: MOOC Platform used for this MOOC course?	Answer Q2: ◉ FutureLearn ○ OpenLearning
Q3: Years of experience in offering MOOC course?	Answer Q3: ○ 1st years offering MOOC course ○ 2nd years offering MOOC course ◉ More then 2 years
Q4: Total number of MOOC course you had offered?	Answer Q4: ○ 0 course ○ 1 course ○ 2 courses ○ 3 courses ◉ 4 or more courses
Q5: Your role in offered course? (Exp: Course Moderator, Course Admin, Content developer, ...)	Answer Q5: Course lead
Q6: Provide the course name if you are using your own dataset. If you using a sample dataset, write "Sample course"	Answer Q6: Sample set
Q7: Learner level of the MOOC course	Answer Q7: ◉ Undergraduate ○ Postgraduate ○ Open Undergraduate ○ Open Postgraduate ◉ Open and mix
Q8: Dataset used in this User Testing	Answer Q8: ◉ Using provided sample datasets ○ Using own datasets

PART 2: MPM Usage (Monitoring)
This section required users to provide answers for questions 9 to question 14 that focuses on the monitoring feature of the MPM Model. MPM Model is using available learning analytic data from MOOC platforms and external data (assignment) provided by the course admin.

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
Q9: Using MPM would make it easier to do my job as MOOC course admin.	○	○	○	◉	○
Q10: I would find MPM useful in my job.	○	○	○	◉	○
Q11: Using MPM would enhance my understanding on the learning analytic data toward course I am offering.	○	○	○	◉	○
Q12: Learning to use MPM from the provided tool would be easy for me.	○	○	◉	○	○
Q13: I would find MPM to be flexible to interact with.	○	○	○	◉	○
Q14: I would find MPM easy to use.	○	○	○	◉	○

PART 3: MPM Usage (Measurement)
This section required users to provide answers for questions 15 to question 20 that focuses on the measurement feature of the MPM Model. The measurement approach used is based on comparing data with the previous data and identifying the positive or negative indication.

Questions	Answer / Respond
Q15: MPM Model enable user to conduct two type of performance measurements. Course performance or student performance. Which type of measurement is used in this testing?	◉ Course Performance ○ Student Performance
Q16: Data used in the measurement involving how many students?	1500 *Example: 127*

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
Q17: I would find the **measurement approach** used by MPM Model (measure current score vs previous score) is acceptable in reflecting improvement or deterioration of performance.	○	○	○	◉	○
Q18: I would find the **Condition Indicator** used in this model easy to understand.	○	○	○	◉	○
Q19: I would change the **default Performance Metric** proposed, to follow my institution standard.	○	○	○	◉	○
Q20: It would be easy for me to become skilful at **importing data into MPM Model** ready for performance measurement.	○	○	◉	○	○

PART 4: MPM Usage (Analysis)
This section required users to provide answers for questions 21 to question 26 that focuses on the analysis feature of the MPM Model. An analysis in the MPM Model enables a user to visualize the measurement result and refer it to the Consideration Factor Indicator.

Question	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
Q21: Using analysis based on MPM Model would enhance my effectiveness in improving offered MOOC course.	○	○	○	◉	○
Q22: I would find analysis results from MPM Model useful in my job	○	○	○	◉	○
Q23: Learning to compare analysis result with provided indicator would be easy for me.	○	◉	○	○	○
Q24: Analysis result was successfully generated with no error	○	○	○	○	◉
Q25: Result give insight on which module need an extra attention for improvement.	○	○	○	◉	○
Q26: I would find the **Consideration Factor Indicator** provided is helpful	○	○	○	○	◉

PART 5: Feedback

This section required users to provide feedback and improvement recommendations on each specific MPM Model feature based on recent experience using it.

Question	Answer / Respond
Q27: Monitoring performance is one of the MPM Model features. Please provide your feedback and related improvement recommendation based on recent monitoring performances experience using the MPM model.	The adoption of this model highly depends on how engaged I can be. The current tool provides me with a very clear overview of how it could work in a real environment. For a wider adoption, I highly recommend a friendly UX that can engage a wider community of academics.
Q28: Measuring performance is another feature of the MPM Model. Design based on the fundamental concept where the latest score is better than the previous score, please provide your feedback and related improvement recommendation on recent experience measuring performance using the MPM model.	There was an improvement in the consideration factor table, one of the most useful tools of these model in my opinion.
Q29: Analysis performance is another feature of the MPM Model. It includes consideration factors indicators that cover five areas (technical, instruction, content, human and environment). Please provide your feedback based on recent analysis experience using the MPM model.	Very useful!
Q30: As an experience MOOC user, have you used and analysed MOOC learning analytics data, and if yes, what tools or method was used?	Yes, I have used the dashboards provided in FutureLearn, and a dashboard that I developed based on FutureLearn data. The methods consisted of simple statistical analysis, mostly regressions, and visualistation tools such as heat maps to spot attention points and shank diagrams to analyse learner journeys.
Q31: In general, after trying using the MPM model to monitor and measure performance from MOOC learning analytics data, what improvement can you suggest to make experience in using the MPM model more easy?	The user experience is very important, as stated in Q27. Therefore, the main improvement would consist of developing a friendly front end.

Appendix H Interview Questions

Participant:	For data, I must use provided sample data?
Researcher:	For user usability testing, participant can use the provided sample data. If participant can get and have own data, we highly encourage participant to try using own data. Previously, we do have participant that use their own data and return 4 documents. One document using provided sample data and other three based on participant own data.
Participant:	Participant: Oh my,
Researcher:	But that is optional, for using own data or do multiple testing. Because some participants want to try this using their own data to get result based on their actual course data, and we can discuss the results in future.
Participant:	Yes, that true. Because as for now I am using MOOC course setup by another user.
Researcher:	Researcher: Are you one of the course admin or normal users?
Participant:	Participant: I was also one of the course admins for that MOOC course. I am keen to try your measurement model as it looks good. I am not sure; currently, they provide analytic tools in our MOOC platform. I reckon a graph was generated in the MOOC platform as well.
Researcher:	Researcher: In MOOC platform, they do display a graph, but a simple direct graph. For example, number of completion module, the MOOC platform display graph based on that score only, showing how much percentage it goes up. In our graph, we also display the difference score. Our measurement calculates the deference score. If MOOC platform, they did not provide difference score.
Participant:	Yes, that’s correct. MOOC platform only have and display graph based on the completion rate only. In my study, I also use the completion rate only, as that’s the only data available. I understand now, this is good and will be helpful for teaching and learning for lecturer. We can understand and know, where we are lacking or where the good engagement occurs.

Appendix I User Usability Testing Resource - Sample Datasets

Dataset Name	Platform Source	Dataset Version	Analysis Usage
sample-fl-1-enrolments	FutureLearn	Raw	Get total enrolment number.
sample-fl-1-step-activity	FutureLearn	Raw	Get completion module data.
sample-fl-1-question-response	FutureLearn	Raw	Get completion widget data.
sample-fl-1-video-stats	FutureLearn	Raw	Get completion widget data.
sample-ol-1-completion-summary-of-modules	OpenLearning	Raw	Get completion module data.
sample-ol-1-completion-summary-of-widgets	OpenLearning	Raw	Get completion widget data.
sample-ol-1-student1	OpenLearning	Raw	Get individual learner widget and assessment data.
sample-ol-1-student2	OpenLearning	Raw	Get individual learner widget and assessment data.
sample-ol-1-student3	OpenLearning	Raw	Get individual learner widget and assessment data.
sample-ol-1-student4	OpenLearning	Raw	Get individual learner widget and assessment data.
sample-ol-1-student5	OpenLearning	Raw	Get individual learner widget and assessment data.
sample-ol-1-student6	OpenLearning	Raw	Get individual learner widget and assessment data.
sample-ol-1-student7	OpenLearning	Raw	Get individual learner widget and assessment data.
sample-ol-1-student8	OpenLearning	Raw	Get individual learner widget and assessment data.

sample-ol-1-student9	OpenLearning	Raw	Get individual learner widget and assessment data.
sample-ol-1-student10	OpenLearning	Raw	Get individual learner widget and assessment data.
sample-ol-1-Competency-test	OpenLearning	Raw	Get learner's widgets and assessment data based on one sample course. Datasets may differ for other courses, but structure data is the same.
sample-ol-1-getting-start	OpenLearning	Raw	Get learner's widgets and assessment data based on one sample course. Datasets may differ for other courses, but structure data is the same.
sample-ol-1-Lesson-1-Chinese-Phonetics-Part-1	OpenLearning	Raw	Get learner's widgets and assessment data based on one sample course. Datasets may differ for other courses, but structure data is the same.
sample-ol-1-Lesson-2-Chinese-Phonetics-Part-2	OpenLearning	Raw	Get learner's widgets and assessment data based on one sample course. Datasets may differ for other courses, but structure data is the same.
sample-ol-1-Lesson-3-Chinese-Characters-Part-1	OpenLearning	Raw	Get learner's widgets and assessment data based on one sample course. Datasets may differ for other courses, but structure data is the same.
sample-ol-1-Lesson-4-Chinese-Characters-Part-2	OpenLearning	Raw	Get learner's widgets and assessment data based on one sample course. Datasets may differ for other courses, but structure data is the same.
sample-ol-1-Lesson-5-Dialogue-1-What-Is-Your-Name	OpenLearning	Raw	Get learner's widgets and assessment data based on one sample course. Datasets may differ for other courses, but structure data is the same.
sample-ol-1-Lesson-6-Dialogue-2-Greetings	OpenLearning	Raw	Get learner's widgets and assessment data based on one sample course.

			Datasets may differ for other courses, but structure data is the same.
sample-ol-1-Lesson-7-Dialogue-3-Etiquette-Expressions	OpenLearning	Raw	Get learner's widgets and assessment data based on one sample course. Datasets may differ for other courses, but structure data is the same.
sample-ol-1-Lesson-8-Dialogue-4-My-Family	OpenLearning	Raw	Get learner's widgets and assessment data based on one sample course. Datasets may differ for other courses, but structure data is the same.
sample-ol-1-Lesson-9-Dialogue-5-My-University	OpenLearning	Raw	Get learner's widgets and assessment data based on one sample course. Datasets may differ for other courses, but structure data is the same.
sample-ol-1-Lesson-10-Dialogue-6-Numerals	OpenLearning	Raw	Get learner's widgets and assessment data based on one sample course. Datasets may differ for other courses, but structure data is the same.
sample-ol-1-Lesson-11-Dialogue-7-Dates-and-Festivals	OpenLearning	Raw	Get learner's widgets and assessment data based on one sample course. Datasets may differ for other courses, but structure data is the same.
sample-ol-1-Lesson-12-Dialogue-8-Invitation	OpenLearning	Raw	Get learner's widgets and assessment data based on one sample course. Datasets may differ for other courses, but structure data is the same.
sample-ol-1-Pinyin-Exercises-Pinyin-Exercises	OpenLearning	Raw	Get learner's widgets and assessment data based on one sample course. Datasets may differ for other courses, but structure data is the same.
sample-ol-1-Survey-Survey-SEM-1-2019-2020	OpenLearning	Raw	Get learner's widgets and assessment data based on one sample course. Datasets may differ for other courses, but structure data is the same.

sample-ol-1-Tests-Tests	OpenLearning	Raw	Get learner's widgets and assessment data based on one sample course. Datasets may differ for other courses, but structure data is the same.

Glossary of Terms

#To create each entry:

1. Type the abbreviation/word
2. Press **Tab**
3. Provide your definition. The text will wrap around as you keep typing

The examples below are using the style ‘Definitions’#

[BBC .... A British public service broadcaster. Formerly known as the British Broadcasting Corporation. It strives to follow the directive of its founder, Lord Reith, to "inform, educate and entertain"

Word................................ Definition]

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