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ORIGINAL RESEARCH

Understanding Students' Behavior in Learning Management Systems Through Their Personality Traits

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Abstract
Personalizing educational experiences based on user behavior is a complex challenge, particularly given that learners' diverse backgrounds, learning experiences, and cognitive styles significantly influence their learning outcomes. Despite recent advancements, the relationship between students' personality traits and their behavior within learning environments remains insufficiently understood. To address this gap, we conducted a 15-week longitudinal study with 95 undergraduate Computer Science students, examining how engagement metrics and communication frequency within a learning management system relate to their Myers-Briggs Type Indicator dimensions i.e., extroversion/introversion, sensing/intuition, thinking/feeling, and judging/perceiving. Our findings indicate that (i) extroverted students demonstrated consistently higher engagement over multiple weeks; (ii) students with judging traits negatively related to the total activities performed and (iii) students with thinking traits are positively associated with overall activity levels.

Keywords Personality traits · Students' behavior · Learning traits · Learning management systems · Longitudinal study

1 Introduction

The growing reliance on technology in Computer Science Education has led to the widespread adoption of learning management systems (LMS) such as Moodle[1] (Mwatilifange & Mufeti, 2022), Blackboard[2] (Martin, 2024), and Canvas[3] (Oudat & Othman, 2024) to

[1] https://moodle.org/
[2] https://blackboard.com
[3] https://canvas.com

During the preparation of this work, the authors utilized generative artificial intelligence (i.e., Microsoft Copilot) to improve the grammatical quality of the text. After the utilization of this tool/service, the authors diligently reviewed and edited the content as necessary, assuming full responsibility for the publication's content. This article is an extension of the conference paper Alseitova et al. (2024).

Extended author information available on the last page of the article

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facilitate course delivery, assignments, and student interaction (Gamage et al., 2022; Bond et al., 2020; Crompton et al., 2020; Oliveira et al., 2021; Swerzenski, 2021; Mpungose & Khoza, 2022). In today's programming courses, these platforms play a critical role in tracking student engagement, personalize instruction, and fostering collaborative learning environments (Paiva et al., 2022; Messer et al., 2024; Nannim et al., 2025; Taylor et al., 2021; Raj & Renumol, 2022). In Computer Science Education contexts specifically, platforms such as HackerRank,[4] Codeforces[5] or LeetCode[6] generate granular data on problem-solving attempts, coding styles, and response times, offering potential for data-driven personalization (Oliveira et al., 2021; Li et al., 2022). Although LMS platforms offer benefits, students exhibit varying levels of participation and success depending on individual differences (Acar & Kayaoglu, 2020; Valtonen et al., 2022; Gamage et al., 2022). At the same time, these systems generate extensive activity log data, capturing behavioral data (e.g., frequency of accesses, submission timestamps, communication patterns) that can be harnessed to build predictive models of student behavior (Kadoić & Oreški, 2018; Li et al., 2023).

1.1 Problem

A key factor influencing student behavior in LMS-based Computer Science Education is personality (Weston et al., 2019; Rodrigues et al., 2022; Lunn et al., 2024). Prior research has explored how students' cognitive styles, problem-solving tendencies, and motivation affect their engagement with LMS features such as discussion forums, quizzes, and coding challenges (Oyibo et al., 2017; Bajaj & Sharma, 2018; Oliveira et al., 2020). One widely studied model for categorizing personality differences is the Myers-Briggs Type Indicator (MBTI) (Boghikian-Whitby & Mortagy, 2016). MBTI classifies individuals into four dimensions: Extroversion (E) vs. Introversion (I), Sensing (S) vs. Intuition (N), Thinking (T) vs. Feeling (F), and Judging (J) vs. Perceiving (P) (Myers, 1962; Briggs, 1976). However, while the MBTI has been applied to personalize education, improve team-based learning, and tailor feedback mechanisms, its relationship with the behavior of Computer Science students in LMS-based Computer Science Education remains unclear, making it difficult to design a user-centered LMS.

1.2 Review of Relevant Scholarship

Over recent years, various cognitive style models have emerged, with the Big Five personality framework (i.e., OCEAN model) being prominent for its robust psychometric properties and cross-cultural validity (Zuckerman et al., 1993; Qin et al., 2022). This model, which encompasses openness, conscientiousness, extraversion, agreeableness, and neuroticism, is widely applied in educational settings to study learners' motivation, persistence, and collaboration (Meyer et al., 2023). In Computer Science Education, it helps predict coding performance and tailor feedback (Ikizer et al., 2022; Li et al., 2023). However, the Big Five's focus on broad traits leads some educators to prefer the MBTI for its intuitive, typology-based approach, which aids in personalized learning and team dynamics (Myers,

[4] https://hackerrank.com

[5] https://codeforces.com

[6] https://leetcode.com

1962; Furnham, 2020a). The MBTI, rooted in Jung's Theory, identifies four preference pairs: Extraversion vs. Introversion, Sensing vs. Intuition, Thinking vs. Feeling, and Judging vs. Perceiving, strongly correlated with other personality tests (Schaubhut et al., 2009; Furnham, 2022).

Over the years, MBTI has been explored in health (Merlo et al., 2020), sports (David et al., 2019), and education (DeVries & Beck, 2020). Recent studies have analyzed and predicted the MBTI profiles of students in education, examining their impact on classroom behavior and learning outcomes (Amirhosseini & Kazemian, 2020; Murphy et al., 2020). Adewale et al. (2019) developed a personalized e-learning platform, adapting teaching methods to MBTI types, achieving a 78% first-attempt pass rate. Sari and Bashori (2020) found extroverted traits dominant among Yogyakarta's school principals. Kodweis et al. (2023) linked introverted, intuitive, and perceptive traits to higher Clance Imposter Phenomenon Scale scores among pharmacy students. Guven and Mustul (2023) noted that extroverts excelled in voice training, while introverts excelled in instrumental performance. Zhalgassova et al. (2023) created an MBTI-based recommendation system for extracurricular activities, showing improved performance over traditional models. While most MBTI research involves self-reported outcomes, fewer studies use LMS log data to link personality traits to usage patterns (Jelley, 2021; Kodweis et al., 2023).

Learning analytics suggest that platforms such as Moodle can provide objective engagement indicators, revealing the lower posting frequency of introverted students but higher reading behaviors, and the repeated quiz attempts of thinking-oriented students (Labanova et al., 2020; Gamage et al., 2022; Oliveira et al., 2020). However, systematic analyses of MBTI and LMS logs in Computer Science Education remain scarce, with previous research in educational psychology suggesting that personality traits can significantly shape learning behaviors, particularly in online and technology-mediated environments (Rivers, 2021; Wong & Hughes, 2023; Kara et al., 2024). Traits such as extraversion, judging, or thinking influence how students manage their time, interact with digital tools, and seek help (Lee & Wu, 2022; Wong & Hughes, 2023; Kara et al., 2024). In Computer Science Education, personality traits may influence distinct patterns of interaction within an LMS. Investigating these patterns can provide insights into how personality-related factors shape learning strategies and system engagement, particularly in programming education.

1.3 Hypothesis, Aims, and Objectives

Personalization has become a cornerstone of technology-enhanced learning, particularly in Computer Science Education, where diverse student backgrounds, prior programming experience, and cognitive styles influence learning outcomes (Ma et al., 2014; Huang et al., 2020; Shemshack & Spector, 2020; Li et al., 2023). Personality models have been explored to predict and understand how learners interact with online platforms (Oyibo et al., 2017; Shi et al., 2013). Different personality frameworks offer distinct theoretical and practical insights (Myers, 1962; Furnham, 2020a). Based on prior literature, we hypothesize that MBTI personality traits influence specific behavioral patterns in LMS-based programming education.

Specifically, this study investigates how Computer Science students' engagement within a Moodle-based LMS (*dependent variables*: LMS engagement metrics) varies based on their MBTI personality traits (*independent variables*: Extraversion *vs*. Introversion, Sensing *vs*. Intuition, Thinking *vs*. Feeling, Judging *vs*. Perceiving).

Extraversion is characterized by a preference for external stimulation, sociability, and assertiveness (Myers, 1962; Furnham, 2020a; Costa & McCrae, 2008b; Watson & Clark, 1997; Eysenck, 1967). While these traits often support active engagement, they can also lead extraverted students to prioritize social interactions or external stimulation over solitary academic tasks, potentially delaying their study behavior. Research on procrastination further suggests that extraverts may be more likely to mobilize effort under pressure, showing increased activity as deadlines approach (Steel, 2007). In the context of programming courses with evenly distributed workloads, this personality profile suggests that extraverted students might not only engage more actively but may also display distinct timing patterns in their engagement. Therefore, it is hypothesized that:

H1 (Extraversion–Introversion) *Extraverted students will reach their peak activity in the LMS during later weeks of the semester*

Students with an Intuition preference, who are inclined toward abstract ideas, conceptual frameworks, and theoretical principles, are expected to show greater engagement with the course's theoretical and content-focused materials in the LMS. In contrast, students with a Sensing preference, who rely more on concrete, factual, and directly applicable information, may engage less intensively with such theoretical resources (Felder & Silverman, 1988; Litzelman et al., 2006). Given that the LMS in this study primarily provided theoretical aspects of the course rather than hands-on programming tasks, it is reasonable to anticipate differences in engagement patterns between these two groups.

H2 (Sensing–Intuition) *Intuitive students will demonstrate higher levels of interaction with LMS activities.*

Judging types prefer structure, organization, planning, and closure (Myers, 1962; Furnham, 2020a; Costa & McCrae, 2008b). They tend to be decisive and like to have things settled. Perceiving types, on the other hand, are more flexible, adaptable, and curious, and prefer to keep their options open (Myers, 1962; Furnham, 2020a; Costa & McCrae, 2008b). Because Judging-oriented students are likely to approach coursework in a structured and efficient manner, they may require fewer interactions with the LMS to complete assigned tasks. In contrast, Perceiving-oriented students may engage in more frequent, exploratory use of the system. Based on this reasoning, we hypothesize that:

H3 (Judging–Perceiving *Judging-oriented students will perform fewer activities in the LMS compared to their peers.*

Thinking types tend to be logical, objective, and analytical, focusing on facts and principles (Myers, 1962; Furnham, 2020a; Costa & McCrae, 2008b). Feeling types prioritize values, empathy, and the impact of decisions on others (Myers, 1962; Furnham, 2020a; Costa & McCrae, 2008b). In a computer science-related course, problem-solving and coding activities often require logical reasoning, analytical skills, and a focus on objective solutions (Newell & Simon, 1972; Wing, 2006). Because these demands align closely with the strengths of Thinking-oriented students, they are expected to engage more actively with course tasks in the LMS. Therefore, we hypothesize:

H4 (Thinking–Feeling) *Thinking-oriented students will perform more activities in the LMS compared to their peers.*

These hypotheses directly address our primary research question: *How are MBTI personality types associated with student behavioral patterns in LMS?* To test these hypotheses, we conducted a longitudinal (15-week) study involving 95 undergraduate Computer Science students, utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM) for data analysis.

2 Methods

2.1 Inclusion and Exclusion

The selection criteria for participants in this study were defined to ensure the integrity and relevance of the collected data. Only undergraduate students enrolled in the Computer Science program who had actively participated throughout the entire 15-week course were included in the analysis. This requirement ensured that all participants had experienced the full scope of the course. Additionally, only students who had officially registered for the course and provided informed consent were considered, preventing the inclusion of informal attendees or auditors without formal enrollment.

No additional selection criteria were imposed regarding demographic characteristics, such as age, gender, sex, or cultural orientation, to maintain a diverse and representative sample. This approach allowed for a more inclusive analysis of the course's impact, avoiding biases that could arise from demographic restrictions. By not limiting participation based on these factors, the study ensured that findings could be generalized to a broader population of Computer Science students, thereby enhancing the external validity of the results.

2.2 Participant Characteristics

The study analyzed data from 95 undergraduate students enrolled in the Faculty of Computer Science and Engineering, of the SDU University, in Kazakhstan. The majority of participants (N = 75) were first-year students, while the remaining students were distributed among the second (N = nine), third (N = two), and fourth (N = nine) years of the program. The participants' ages ranged from 17 to 22 years, reflecting the typical age range of undergraduate students in the university, where the study was conducted. This distribution allowed for an examination of students at different stages of their academic journey, although the sample was predominantly composed of first-year students.

All participants were from Kazakhstan, ensuring a culturally and contextually relevant analysis of educational experiences within the country. Additional information on ethnicity or socioeconomic status was not collected, as these factors were not the focus of the study. For ethical reasons, no data regarding the sex of participants was collected. This decision was made to respect privacy concerns. Furthermore, the study did not assess participants' levels of academic achievement, as the primary objective was to analyze their experiences rather than performance outcomes.

2.3 Sampling Procedures

Participants in this study were undergraduate Computer Science students enrolled in a 15-week course during the Fall semester of 2021. A self-selection sampling approach was used, as participation was voluntary and contingent on students' willingness to provide MBTI data for analysis. Of the 787 students officially enrolled, 95 consented to participate by completing the MBTI assessment and allowing their LMS activity logs to be analyzed. No additional criteria were imposed to ensure a diverse and representative sample.

Data were collected through the university's Moodle system and a separate online platform for the MBTI assessment. The course followed a blended learning format, integrating online activities with in-person instruction. Participants engaged in various course activities, including mini-tests, weekly contests, quizzes, and projects, with their activity data automatically logged in Moodle. No financial compensation or incentives were provided, as participation was entirely voluntary. To uphold ethical standards, personally identifiable information was not collected, and all data were anonymized before analysis.

2.4 Sample Size, Power, and Precision

To ensure that the study had an adequate sample size for detecting statistical effects with sufficient precision, we employed an a priori sample size calculation. This approach determines the minimum number of participants required to conduct a robust analysis based on predefined statistical parameters (Cohen, 1988). Specifically, we used the Online Calculator for A-priori Sample Size Calculator for SEM developed by Soper (2023).

Following the recommendations of Cohen (1988) and Westland (2010), we set the parameters for sample size determination as follows: an anticipated effect size of 0.5, a statistical power level of 0.8, and a probability level of 0.05. Considering the structural model used in our study, which included eight latent variables and 22 observed variables, the calculator determined that a minimum of 44 participants was necessary to detect any effect. This calculation ensured that the study had sufficient power to avoid Type II errors while maintaining the feasibility of data collection. No interim analyses or stopping rules were applied, as the study aimed to include all eligible participants who met the inclusion criteria.

2.5 Measures and Covariates

The primary measures in this study included both dependent and independent variables, with data collected from students' activities in the LMS. The dependent variables were students' personality traits as assessed by the MBTI. To facilitate analysis, the MBTI dimensions were coded as follows: Extraversion (−1) and Introversion (1); Sensing (−1) and Intuition (1); Thinking (−1) and Feeling (1); and Judging (−1) and Perceiving (1). These categorical variables served as the primary outcome measures in examining the relationship between personality traits and students' engagement patterns in the online course environment.

The independent variables were derived from students' activity logs in Moodle LMS and reflected different aspects of their engagement throughout the 15-week course. The *Activity*

Out of the Course variable measured any activities performed outside the regular course period. The *Most Active Week* variable represented the week during which each student had the highest number of logged activities, while the *Most Active Day* variable identified the specific weekday with the highest recorded activity level for each student (coded as Monday = 1 to Sunday = 7). Additionally, *Total Activities Performed* quantified the overall number of activities completed throughout the entire course duration. These independent variables provided insight into students' participation patterns and how they varied based on different engagement metrics. Additional covariates were not included in the analysis, and all collected variables were reported in the study. The complete dataset is available in the appendix for further examination.

2.6 Data Collection

All participants were officially registered in the university's Moodle system, which served as the primary platform for course management and activity tracking. This platform facilitated data collection by monitoring students' interactions within the environment. As part of the experimental procedure, students were required to complete a psychological assessment using an online platform.[7] After obtaining their personality type results, participants manually selected and recorded their MBTI classifications within the university's Moodle system.

Log data from student interactions within the system was systematically collected and analyzed. The data extraction and analysis were conducted using Python, enabling automated processing of activity logs and personality classifications. This method ensured accurate and efficient handling of large datasets, facilitating the examination of patterns in student engagement and their relationship to personality traits.

2.7 Quality of Measurements

To enhance the quality of measurements in this study, several methodological strategies were implemented to ensure the reliability and accuracy of the collected data. First, students were required to register on the university's Moodle system, ensuring that only officially enrolled participants took part in the study. Additionally, students independently completed a psychological assessment to determine their personality type. Participants manually selected their MBTI classification within the system, ensuring direct control over their self-reported data.

To improve the reliability of data collection, multiple observations were conducted through log data tracking. The study systematically collected students' interaction logs from Moodle, capturing engagement patterns over time rather than relying on a single measurement. Using automated logging mechanisms, the study ensured that activity data were objectively recorded, reducing the risk of bias associated with self-reported measures. The combination of self-reported personality data and system-tracked activity logs enhanced the validity of the dataset by integrating multiple sources of information.

[7] https://16Personalities.com

2.8 Instrumentation

This study utilized a combination of validated and ad hoc instruments to ensure accurate data collection and analysis. Moodle served as a structured platform for tracking students' engagement and activities throughout the course. As a widely used educational technology, Moodle provides reliable data on student interactions. Additionally, HackerRank was used as a coding assessment tool, offering an objective measure of students' programming performance. As a platform commonly used in both educational and professional settings, HackerRank effectively evaluates coding skills.

For personality assessment, students completed the MBTI test through a widely recognized online platform that provides personality type classifications based on the MBTI framework. While the MBTI has been extensively used in research and practical applications, the online version used in this study was self-reported, which may introduce some variability in responses. Data processing was conducted using Python, specifically leveraging the SciPy library, which is widely recognized for its robust statistical computing capabilities. SmartPLS was used to perform SEM-based analyses.

This study employed the 16Personalities test to assess students' personality traits. Although the instrument reports results in the familiar MBTI format, it is grounded in the Big Five framework, providing both accessibility for students and educators and a stronger theoretical basis. While it is less extensively validated than traditional Big Five inventories, prior studies suggest it produces consistent and interpretable outcomes, making it appropriate for examining personality-related patterns in student engagement (Tobiaszewska et al., 2024; Scroccaro, 2024).

2.9 Masking

In this study, participants were partially aware of their assigned condition as they were required to register on the Moodle platform, complete a psychological assessment, and engage with the system. However, they were not explicitly informed about the study's specific hypotheses or the potential relationships between their personality type and learning behaviors. This approach was necessary to ensure natural engagement with the platform while minimizing demand characteristics that could influence their interactions. The administration of experimental manipulations and the assessment of the results were performed automatically, reducing potential researchers' biases.

Student activity data was collected through Moodle system logs, ensuring that researchers did not influence or interfere with participant behavior. Similarly, personality classification was self-reported, further eliminating researcher intervention in the categorization process. No formal masking procedures were implemented, as participants self-reported their MBTI classification, and their interactions were passively recorded through log data. However, since data processing was conducted using Python (SciPy), researchers who performed data analysis were blinded to individual identities, ensuring an unbiased evaluation of patterns and relationships.

2.10 Psychometrics

PLS-SEM provides a form of analysis that remains robust regardless of the data distribution, eliminating the need for normality tests (Hair Jr et al., 2021). Therefore, our psychometric analysis involved calculating the discriminant validity (i.e., to ensure that different measurements truly reflect separate concepts rather than being too closely related) of the variables. Table 1 presents the discriminant validity results for the scale used in our study.

Psychometric evidence from the original text provided by the 16Personalities test demonstrates acceptable reliability. Internal consistency values (Cronbach's alpha) range from 0.79 to 0.91 across the main scales, while test–retest reliability over a 5–7-month interval with a sample of nearly 2900 respondents shows correlations between 0.74 and 0.83. These findings indicate that the instrument provides stable and coherent measurements over time, making it suitable for use in this study.

2.11 Conditions and Design

In this study, conditions were naturally observed rather than experimentally manipulated. Students participated in a 15-week course that incorporated a structured curriculum consisting of Mini Tests, Weekly Contests, Quizzes, and Projects. These activities were designed to assess and enhance students' theoretical knowledge, problem-solving abilities, and practical application of course concepts. The course followed a flipped classroom approach, in which students engaged in video lectures before attending in-person sessions, fostering an interactive and discussion-based learning environment.

While students' engagement with course activities and their learning behaviors were systematically tracked through Moodle, no direct experimental interventions were applied to control their participation. Instead, data were passively collected from system logs to analyze natural variations in student behavior. By relying on naturally occurring behaviors and self-reported personality assessments, this study aimed to explore the relationships between student MBTI traits and learning engagement without imposing artificial constraints.

2.12 Data Diagnostics

The course was offered during the Fall 2021 semester, with a total enrollment of 787 students. A subset of 95 students voluntarily participated in the study by providing their MBTI

Table 1 Discriminant validity

	AOC	I-E	S-N	J-P	MAW	MAD	T-F
I-E	0.075						
S-N	0.014	0.007					
J-P	0.079	0.067	0.215				
MAW	0.107	0.214	0.069	0.179			
MAD	0.267	0.328	0.186	0.185	0.24		
T-F	0.152	0.157	0.366	0.248	0.119	0.231	
TAP	0.258	0.127	0.026	0.189	0.073	0.442	0.205

Key: I, introversion; E, extroversion; S, sensing; N, intuition; J, judging; P, perceiving; T, thinking; F, feeling; AOC, activity out of the course; TAP, total activities performed; MAW, most active week; MAD, most active day information for analysis. As a result, only data from consenting participants were included, with no exclusions based on performance or engagement levels after data collection. Regarding missing data, no imputation methods were required, as all collected data were complete and suitable for statistical analysis.

Students who consented to participate provided full datasets without gaps in their MBTI classification or activity logs, eliminating the need for data inference or missing value handling. This ensured that all analyses were performed on a fully observed dataset, minimizing the risk of bias introduced by data imputation techniques. Furthermore, no statistical outliers were removed from the dataset. The decision to retain all data points was made to preserve the ecological validity of the study and accurately reflect the students' learning behaviors in the real world.

2.13 Analytic Strategy

This study's analytic strategy for inferential statistics was based on PLS-SEM, a well-established approach for exploratory research and theory development (Henseler et al., 2009). PLS-SEM was selected for its ability to explain variance in dependent variables while accommodating unobservable constructs measured through indicator variables. Additionally, it provides robust model estimation even with relatively small sample sizes, making it particularly suitable for this study's dataset (Hair Jr et al., 2021). The primary hypotheses were tested by assessing the structural model's path coefficients and their significance using bootstrapping procedures, ensuring a rigorous statistical evaluation of the proposed relationships.

Since only "Most active day" was modeled as a latent variable, Composite Reliability (CR) and Average Variance Extracted (AVE) were not assessed. We calculated the Confidence Interval. Discriminant validity was assessed through the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio (Ab Hamid et al., 2017), ensuring that the constructs were empirically distinct. R^2 was used to determine the proportion of the variance in an endogenous variable that is explained by its predictors within the structural model. These additional analyses strengthened the validity of the findings by verifying measurement quality and the robustness of the relationships among constructs. No adjustments were made for experimental errors, as the study was primarily exploratory and aimed at the development of theories rather than the testing of confirmed hypotheses.

3 Results

3.1 Participant Flow

The study was conducted during the Fall semester of 2021, with 787 students enrolled in the course. Of these, 95 students actively participated throughout the 15-week duration and provided ethical consent for data usage. The study followed a three-step process: (1) all students were registered in the LMS, where they accessed course materials and engaged in activities; (2) study participants completed the MBTI assessment on a separate platform and self-reported their personality type; and (3) log data were extracted from Moodle and processed using Python. Data Collection Flow is provided in Fig. 1.

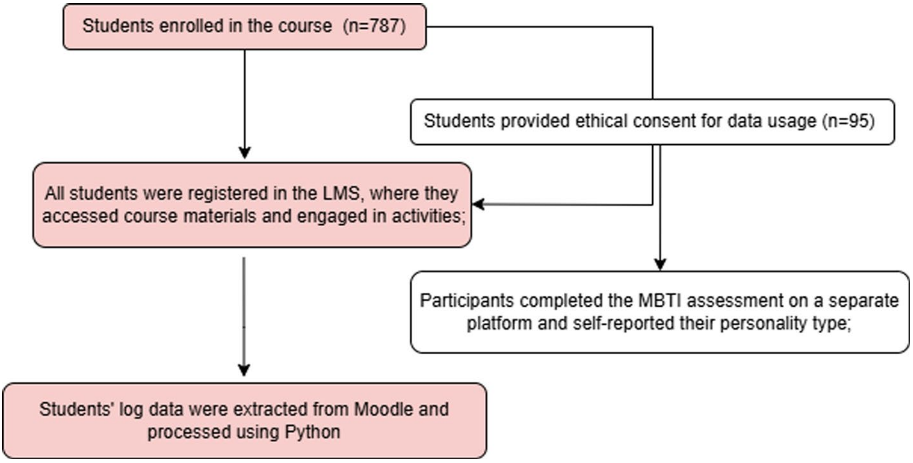

Fig. 1 Data collection flow

The final dataset included complete and usable data from all 95 participants, with no missing values. No post-data collection exclusions were made, and outliers were retained to ensure an accurate representation of the natural learning behaviors of the students. The dataset was then analyzed using PLS-SEM to explore hypotheses and examine the relationships between personality traits and student engagement patterns.

3.2 Recruitment

Participants were recruited from a 15-week Computer Science course, where they engaged in various learning activities, including mini-tests, weekly contests, quizzes, and projects. At the beginning of the course, students were introduced to the study and invited to participate. Students voluntarily provided their MBTI information and consented to the use of their data for analysis the following week after the invitation.

Data collection for this study took place during the Fall 2021 semester. Log data were continuously collected throughout the semester, tracking students' interactions within Moodle. Since this study focused on analyzing activity patterns within a single semester, no follow-up measures were implemented. The data collected captures the students' engagement and learning behaviors within a consistent 15-week time frame.

3.3 Statistics and Data Analysis

The analyses were based on PLS-SEM. Table 2 displays the correlational matrix and Table 3 presents the results of a statistical analysis measuring the goodness of fit of four different independent variables in predicting a dependent variable (i.e., indicating the proportion of variance in the dependent variable that can be explained by the independent variables), as represented by their respective R^2 values.

Table 2 reports the regression coefficients (β) describing the association between personality traits and learning activities. The β values indicate the direction and magnitude of these associations, with positive coefficients reflecting a direct relationship and negative coeffi-

Table 2 Correlational matrix

	β	SD	*P-values*	Bias	2.5%	97.5%
Extroversion → Activity out of the course	−0.038	0.116	0.743	0.003	−0.256	0.194
Extroversion → Most active week	0.225	0.109	**0.039**	0.002	0.009	0.429
Extroversion → Most activity day	−0.463	0.319	0.147	0.164	−0.680	0.325
Extroversion → Total activities performed	−0.070	0.112	0.532	−0.001	−0.288	0.155
Intuition → Activity out of the course	−0.062	0.112	0.580	−0.003	−0.282	0.168
Intuition → Most active week	0.143	0.113	0.204	−0.001	−0.091	0.358
Intuition → Most activity day	0.040	0.195	0.836	−0.009	−0.394	0.403
Intuition → Total activities performed	−0.078	0.106	0.461	−0.001	−0.282	0.137
Judging → Activity out of the course	−0.116	0.118	0.327	−0.008	−0.347	0.118
Judging → Most active week	−0.211	0.110	0.054	0.000	−0.413	0.015
Judging → Most activity day	0.097	0.228	0.671	−0.097	−0.334	0.479
Judging → Total activities performed	−0.248	0.104	**0.017**	0.000	−0.435	−0.025
Thinking → Activity out of the course	0.197	0.107	0.065	−0.001	−0.024	0.399
Thinking → Most active week	−0.088	0.115	0.446	−0.002	−0.311	0.135
Thinking → Most activity day	−0.087	0.264	0.741	0.088	−0.564	0.401
Thinking → Total activities performed	0.283	0.116	**0.015**	0.001	0.023	0.486

Key: β, Regression Coefficient; SD, standard deviation; CI, Confidence interval

Table 3 R^2 results

	R^2	Adjusted R^2
Activity out of the course	0.042	−0.001
Most active week	0.102	0.062
Most activity day	0.187	0.151
Total activities performed	0.113	0.074

cients reflecting an inverse relationship. The corresponding *p-values* denote the probability that the observed effects occurred by chance; smaller values provide stronger evidence of a statistically reliable association. In this table, coefficients with *p-values* below 0.05 are highlighted to indicate significance. The additional columns provide the standard deviation (SD), bias, and the 95% confidence intervals (2.5% and 97.5%), which together describe the variability and precision of the estimates.

Extroversion was positively associated with the most active week ($\beta = 0.225 \mid P = 0.039$), Judging negatively associated with total activities performed ($\beta = -0.248 \mid p = 0.017$), and Thinking positively associated with total activities ($\beta = 0.283 \mid p = 0.015$). These associations were small in terms of R^2, suggesting they explain only a small proportion of the variance in activity levels. Also, the confidence intervals can be considered high, indicating a possible high variation in the real value of β. Furthermore, extroverted participants participated in the course for a greater number of weeks, while judging and thinking participants performed more activities during the course.

4 Discussion

This study contributes to understanding how personality traits, as measured by the MBTI, influence student engagement and learning behaviors in an LMS. By analyzing LMS log data over a semester, we identified patterns in student activity that offer insight into their interactions with the course structure and assessment components. In this section, we interpret key findings concerning existing literature, highlighting both expected and unexpected results. We also examine the implications for designing gamified learning environments and consider potential limitations that may affect generalizability. Finally, we propose directions for future research to refine the understanding of student engagement and personalization strategies in online learning.

4.1 Support of Original Hypotheses

The hypothesis that extraverted students would demonstrate higher engagement during the week of peak LMS activity was supported. A more nuanced pattern was also observed: extraverts reached their highest activity later in the semester, despite the course workload being evenly distributed across weeks. This finding suggests that extraversion influences not only the intensity of engagement but also its temporal distribution. Extraverts, who are generally oriented toward external stimulation and social interaction (Eysenck, 1967; Watson & Clark, 1997), may initially allocate less attention to structured academic tasks, deferring concentrated effort until deadlines approach. Previous work on procrastination supports this interpretation, as extraverts are often found to mobilize energy effectively under time constraints (Steel, 2007). Thus, while extraversion is positively associated with overall activity, it may also shape distinctive patterns of pacing and timing in online learning contexts.

The hypothesis that Intuitive students would demonstrate higher levels of interaction with LMS activities was not supported. The analysis revealed no significant correlation between Sensing–Intuition preferences and engagement with course materials. This suggests that, despite theoretical expectations that Intuitive learners might be more inclined toward abstract, content-focused resources, such differences did not emerge in the context of this study. One possible explanation is that the LMS materials were used uniformly by students regardless of cognitive style.

The hypothesis that students with higher Judging scores would perform fewer total LMS activities was also supported. Judging-oriented individuals typically prefer planning, order, and closure, relying on efficient strategies to complete tasks (Costa & McCrae, 2008a; Furnham, 2020b; Myers, 1962). This tendency appears to translate into selective engagement with LMS materials, where fewer interactions may reflect a structured and purposeful approach rather than disengagement. By contrast, Perceiving types, who value flexibility and exploration, may generate higher activity counts as they browse, revisit, and adapt to materials dynamically. The present findings align with the expectation that Judging-oriented students focus on essential activities and reduce redundant or exploratory interactions, leading to lower but more concentrated LMS activity.

The hypothesis that higher Thinking scores would be positively associated with total LMS activities was confirmed. Thinking-oriented students prioritize logical reasoning and objective analysis in their decision-making (Costa & McCrae, 2008a; Furnham, 2020b; Myers, 1962). In the context of programming education, these traits align well with the cognitive demands of coding and problem-solving, which often require iterative exploration, hypothesis testing, and error correction (Newell & Simon, 1972; Wing, 2006). The elevated activity levels observed for Thinking types may thus reflect an engagement style characterized by systematic trial-and-error and sustained interaction with materials. This suggests that the Thinking dimension supports persistence and depth of engagement in tasks requiring structured reasoning.

The associations between personality traits and LMS activity, while consistent, were moderate in strength and may interact with additional variables such as prior knowledge, motivation, or external commitments. Moreover, reliance on self-reported personality assessments introduces potential measurement bias. These findings extend understanding of how personality traits shape online learning behavior, highlighting not only differences in overall activity levels but also in the style and timing of engagement. Future studies could integrate personality with motivational or behavioral indicators to develop predictive models of learner engagement and examine whether these relationships hold across diverse course structures and academic disciplines.

4.2 Similarity of Results

The results of our study indicated that extraverted participants reached their peak LMS activity in later weeks of the semester, suggesting an association between extraversion and the timing of engagement in online learning environments. This aligns with previous findings that extraverts, who are oriented toward social interaction and external stimulation (Furnham, 2022; Sari & Bashori, 2020; Schaubhut et al., 2009), may postpone peak academic effort until later stages of a course.

Students with higher judging orientations were associated with high activity levels during the course. This finding diverges from the assumption that Judging types, who prefer closure and structure, would engage in fewer activities once they had met basic requirements. One possible explanation is that the structured design of the course encouraged these students to remain consistently active, aligning with their preference for organized and clearly sequenced tasks (Kodweis et al., 2023; Guven & Mustul, 2023; Sardjono, 2023).

Students with higher thinking orientations demonstrated higher levels of activity throughout the course. This result is consistent with prior studies indicating that Thinking types are more inclined toward analytical and objective tasks, which likely translates into greater engagement in problem-solving and decision-making activities within the learning environment (Kodweis et al., 2023; Guven & Mustul, 2023; Sardjono, 2023). Their systematic approach to evaluating information may therefore explain their higher activity levels in our context.

Furthermore, our results indicate that while MBTI traits do show statistically significant correlations with engagement metrics, the effect sizes and R^2 values remain small. This highlights the multifaceted nature of online learning behaviors, wherein factors like motivation, prior programming experience, and time constraints can also play crucial roles (Kadoić & Oreški, 2018). MBTI preferences thus appear to be one piece of a complex puzzle, helping explain certain patterns of engagement, but far from serving as a singular predictor of student success.

Comparing these findings with the broader body of personality-driven educational research, we observe parallels with other MBTI-based studies that document heightened engagement among extraverts and more structured, methodical patterns among judging types (Sari & Bashori, 2020; Guven & Mustul, 2023). However, the positive relationship between thinking traits and higher total activities suggests these learners may actively seek multiple attempts or iterative feedback loops, corroborating the idea that thinking-oriented students are drawn to logical and systematic problem-solving tasks. These contextual subtleties underscore the importance of investigating MBTI dimensions in specific educational settings, such as an online programming course, rather than applying generic assumptions across different domains.

4.3 Interpretation

Nevertheless, it is critical to recognize the limitations of relying solely on MBTI. Beyond ongoing criticisms about its binary typology and psychometric validity (Gardner & Martinko, 1996; Coffield et al., 2004), our study did not account for factors like prior coding experience, scheduling constraints, or social support systems-all of which likely influence engagement metrics. Additionally, our single-institution sample limits external validity, particularly in cross-cultural contexts where norms surrounding communication and collaboration may differ.

Concerns have been raised about the scientific rigor of the MBTI due to its theoretical underpinnings (Gardner & Martinko, 1996; Coffield et al., 2004). However, in this study, we opted for the MBTI, given its extensive research base and practical applications in education and psychology. Nevertheless, to address these concerns, we employed a well-established MBTI questionnaire with strong psychometric properties. In our study, all participants were from the same country, the same university, and the same faculty. This restricts the generalizability of our findings to broader populations. Also, it might affect the behaviour of students within the LMS. The sample size, although sufficient for a case study, may not allow the generalization of results to other contexts. Also, the nature of the study can generate a series of biases related to student behavior while using the system.

In addition to these concerns, our use of a self-selected sample (students who voluntarily provided their MBTI data) could introduce selection bias: those with a strong interest or awareness of personality tests may differ systematically from students who opted out. Moreover, the study's focus on quantitative engagement metrics, such as overall activity logs, may miss qualitative nuances in how learners experience and interpret their coursework. Factors such as time management skills, group project dynamics, or instructor feedback may interact with MBTI traits in ways not captured by numeric LMS usage data. Additionally, the reliance on a single-semester snapshot limits our ability to observe how MBTI-related behaviors evolve across multiple courses or academic years. Future investigations could employ multi-semester or longitudinal designs to better capture long-term patterns and potential shifts in learner behavior.

One limitation of our study lies in its reliance on frequency-based metrics of LMS engagement, which, while informative, may not fully capture the quality or depth of students' learning interactions. For instance, two students may log similar activity counts, yet one may engage more meaningfully with learning materials or submit higher-quality assignments. Future work should explore richer indicators of engagement, such as forum content analysis, quiz performance, and time management patterns, to better understand how personality influences not just how often students engage, but how effectively they learn within LMS environments. Finally, the wide confidence intervals observed for certain path coefficients suggest potential threats to the study's validity arising from low statistical power, possibly due to limited sample size, measurement reliability or validity issues, or model misspecification. These factors contribute to a high degree of uncertainty regarding the true population parameters.

4.4 Generalizability

The generalizability of this study's findings is influenced by factors related to the target population, study setting, and measurement approach. The sample consisted exclusively of undergraduate Computer Science students from a single university in Kazakhstan, which limits the applicability of the results to students from other disciplines, institutions, or cultural contexts. Although no demographic restrictions were imposed beyond course enrollment and ethical consent, the voluntary nature of participation may have introduced selection bias, affecting the representativeness of the sample.

Ecological validity was strengthened by conducting the study in a real-world educational setting over a full academic semester, ensuring relevance to similar learning environments that use LMS platforms. However, reliance on MBTI as a personality measure presents limitations, given ongoing debates about its reliability and validity in predicting behavior. At the same time, participants manually selected their MBTI classification within the system, so that the researchers did not have access to the original MBTI result and could not guarantee the veracity of the data. Additionally, data collection was confined to the university's Moodle system, meaning students' engagement with external resources or alternative study methods was not captured, potentially influencing interpretations of learning behaviors.

Temporal validity is also a consideration, as the primary dataset was collected in Fall 2021. While this timeframe supports the stability of findings across cohorts, evolving educational technologies and instructional methods may impact their applicability to future student populations. Moreover, no statistical outliers were excluded to preserve real-world data integrity, which enhances authenticity but may also introduce variability from extreme cases. Future research should replicate these findings in diverse institutional settings, explore alternative personality frameworks, and incorporate additional behavioral data sources to improve external validity.

4.5 Implications

The present study's findings offer insights that future studies can leverage to enrich online learning environments, making them more effective and inclusive. The variations in student behavior linked to MBTI personality types emphasize the significance of incorporating personalized learning approaches into learning platforms. Thus, educators and instructional designers can enhance the educational experience by personalizing course content, assessments, and communication strategies to align with the cognitive preferences of diverse personality types.

While the current study focused on MBTI personality types, it is important for future research to explore additional user models influencing student behavior within LMS platforms. Factors like digital literacy levels and motivation are crucial in shaping how students interact with online resources. Integrating multiple user models can contribute to a more comprehensive understanding of the intricate interplay between individual characteristics and learning behavior.

The study serves as a valuable starting point for elucidating the relationship between MBTI personality types and Moodle LMS usage in this specific context. However, to ensure robust statistical significance and generalizable findings, future research should strive for larger and more diverse samples. Expanding the sample size can empower researchers to uncover subtle patterns and trends that might be overlooked in smaller cohorts.

Moreover, subsequent research could adopt *multi-method* or *mixed-method* designs (combining quantitative LMS data with qualitative insights) to provide a more holistic view of how MBTI traits shape-or are shaped by-pedagogical strategies, social interaction, and motivational factors. Investigating the longevity of MBTI-linked behaviors across multiple semesters or sequential courses would further clarify the stability of these patterns over time. Additionally, integrating other personality frameworks, alongside MBTI, could offer deeper insights into whether certain traits correlate more closely with specific engagement metrics in computing-related contexts. Finally, employing controlled experimental approaches-such as *adaptive courseware* tailored to different MBTI profiles-would help confirm causal relationships between personality-informed interventions and student performance outcomes.

Follow-up experiments could manipulate specific course features-for example, introducing adaptive interventions targeted at different MBTI types-to assess causal impacts on engagement and performance. Scaling this approach to larger samples or diverse universities would provide deeper insights into how personality-informed design might be generalized within Computer Science Education. Overall, while MBTI-based insights alone do not fully predict or determine student outcomes, they do offer actionable cues that instructors and instructional designers can use to refine course structures and personalize learning experiences. By considering personality factors in tandem with other learner characteristics, the field can make strides toward more dynamic, inclusive, and efficient online learning ecosystems in Computer Science Education. Understanding these behavioral differences may support the development of personalized LMS features or adaptive learning paths that align with students' personality-informed engagement preferences, ultimately improving retention and learning outcomes in Computer Science Education.

5 Concluding Remarks

Despite its recognized limitations, the MBTI remains widely used in practice to understand and model user behavior in educational systems. In this study, we examined the relationship between the MBTI profiles of the students and their interactions within an educational platform. Our findings indicate that distinct behavioral patterns may emerge based on MBTI profiles, highlighting opportunities for further exploration. Future research will aim to replicate this study with a larger sample and investigate relationships between user behavior and alternative user modeling approaches.

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Data Availability The study dataset can be accessed from this link: ?view_only=67304a1bc3a147b0a698b7fe5e4e5154.

Declarations

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References

Ab Hamid, M.R., Sami, W., & Sidek, M.M. (2017). Discriminant validity assessment: Use of Fornell & Larcker criterion versus htmt criterion. *Journal of physics: Conference series* (Vol. 890, p.012163).

Acar, A., & Kayaoglu, M. N. (2020). Moodle as a potential tool for language education under the shadow of covid-19. *Eurasian Journal of Educational Research, 90*, 67–82.

Adewale, O. S., Agbonifo, O. C., & Lauretta, O. (2019). Development of a Myers-Briggs type indicator based personalised e-learning system. *International Journal of Computer (IJC), 35*(1), 101–125.

Alseitova, A., Oliveira, W., Li, Z., Shi, L., & Hamari, J. (2024, July). The RelationshipBetween Students' Myers-Briggs Type Indicator and Their Behavior within Educational Systems.In 2024 IEEE International Conference on Advanced Learning Technologies IEEE.(ICALT) (pp. 3-7).

Amirhosseini, M. H., & Kazemian, H. (2020). Machine learning approach to personality type prediction based on the Myers-Briggs type indicator®. *Multimodal Technologies and Interaction, 4*(1), 9.

Bajaj, R., & Sharma, V. (2018). Smart education with artificial intelligence based determination of learning styles. *Procedia Computer Science, 132*, 834–842.

Boghikian-Whitby, S., & Mortagy, Y. (2016). Student preferences and performance in online and face-to-face classes using Myers-Briggs indicator: A longitudinal quasi-experimental study. *Issues in Informing Science and Information Technology, 13*, 89–109.

Bond, M., Buntins, K., Bedenlier, S., Zawacki-Richter, O., & Kerres, M. (2020). Mapping research in student engagement and educational technology in higher education: A systematic evidence map. *International Journal of Educational Technology in Higher Education, 17*(1), 1–30.

Briggs, K. C. (1976). *Myers-Briggs type indicator*. Consulting Psychologists Press.

Coffield, F., Moseley, D., Hall, E., Ecclestone, K., Coffield, F., Moseley, D., & Ecclestone, K. (2004). Learning styles and pedagogy in post-16 learning: A systematic and critical review. *Learning and Skills Research Council*.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Costa, P. T., & McCrae, R. R. (2008). *The five-factor model of personality*. Guilford Press.

Costa, P. T., & McCrae, R. R. (2008b). The revised neo personality inventory (neo-pi-r). *The SAGE Handbook of Personality Theory and Assessment, 2*(2), 179–198.

Crompton, H., Bernacki, M., & Greene, J. A. (2020). Psychological foundations of emerging technologies for teaching and learning in higher education. *Current Opinion in Psychology, 36*, 101–105.

David, S. L., McCuskey, K., Larson, M., & Hill, B. (2019). The relationship between athletic trainer personality and patient trust. *Athletic Training & Sports Health Care, 11*(3), 105–112.

DeVries, D., & Beck, T. (2020). Myers-Briggs type indicator profile of undergraduate therapeutic recreation students. *Therapeutic Recreation Journal, 54*(3), 243–258.

Eysenck, H. J. (1967). *The biological basis of personality*. Charles C. Thomas.

Felder, R. M., & Silverman, L. K. (1988). Learning and teaching styles in engineering education. *Engineering Education, 78*(7), 674–681.

Furnham, A. (2020a) Myers-Briggs type indicator (MBTI). *Encyclopedia of personality and individual differences*, 3059–3062.

Furnham, A. (2020). *Personality and individual differences*. Psychology Press.

Furnham, A. (2022). The big five facets and the mbti: The relationship between the 30 neo-pi (r) facets and the four myers-briggs type indicator (mbti) scores. *Psychology, 13*(10), 1504–1516.

Gamage, S. H., Ayres, J. R., & Behrend, M. B. (2022). A systematic review on trends in using moodle for teaching and learning. *International Journal of STEM Education, 9*(1), 1–24.

Gardner, W. L., & Martinko, M. J. (1996). Using the Myers-Briggs type indicator to study managers: A literature review and research agenda. *Journal of Management, 22*(1), 45–83.

Guven, D., & Mustul, O. (2023). Studies conducted using MBTI (Myers-Briggs type indicator) inventory in music education. *International Online Journal of Educational Sciences, 15*(5), 911–925.

Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (pls-sem)*. Sage publications.

Hair Jr, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M., Danks, N.P., Ray, S., & Sarstedt, M. (2021). An introduction to structural equation modeling. *Partial least squares structural equation modeling (PLS-SEM) using R: a workbook*, 1–29.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). *The use of partial least squares path modeling in international marketing*. New challenges to international marketing: Emerald Group Publishing Limited.

Huang, C. L., Luo, Y. F., Yang, S. C., Lu, C. M., & Chen, A.-S. (2020). Influence of students' learning style, sense of presence, and cognitive load on learning outcomes in an immersive virtual reality learning environment. *Journal of Educational Computing Research, 58*(3), 596–615.

Ikizer, G., Kowal, M., Aldemir, İD., Jeftić, A., Memisoglu-Sanli, A., Najmussaqib, A., & Chrona, S. (2022). Big five traits predict stress and loneliness during the covid-19 pandemic: Evidence for the role of neuroticism. *Personality and individual differences, 190*, Article 111531.

Jelley, R. B. (2021). Using personality feedback for work-related development and performance improvement: A rapid evidence assessment. *Canadian Journal of Behavioural Science/Revue canadienne des sciences du comportement, 53*(2), 175.

Kadoić, N., & Oreški, D. (2018). Analysis of student behavior and success based on logs in moodle. *2018 41st international convention on information and communication technology, electronics and microelectronics (mipro)* (pp. 0654–0659).

Kara, A., Ergulec, F., & Eren, E. (2024). The mediating role of self-regulated online learning behaviors: Exploring the impact of personality traits on student engagement. *Education and Information Technologies, 29*, 23517–23546.

Kodweis, K. R., Jasmin, H. M., Hall, E. A., & Havrda, D. E. (2023). Exploring the relationship between imposter phenomenon and Myers-Briggs personality types in pharmacy education. *American Journal of Pharmaceutical Education, 87*, Article 100076.

Labanova, O., Uukkivi, A., Safiulina, E., & Latõnina, M. (2020). Engaging engineering students in the educational process using moodle learning environment. *Developing technology mediation in learning environments* (pp. 239–263). IGI Global.

Lee, P.-J., & Wu, T.-Y. (2022). Mining relations between personality traits and learning styles. *Information Processing & Management, 59*(5), Article 103045.

Li, K.C., Wong, B.T., & Chan, H.T. (2023). Prediction of at-risk students using learning analytics: A literature review. *International conference on technology in education* (pp. 119–128).

Li, Z., Jacobsen, M., Shi, L., Zhou, Y., & Wang, J. (2023). Broader and deeper: a multi-features with latent relations Bert knowledge tracing model. *European conference on technology enhanced learning* (pp. 183–197).

Li, Z., Shi, L., Cristea, A., Zhou, Y., Xiao, C., & Pan, Z. (2022). Simstu-transformer: A transformer-based approach to simulating student behaviour. *International conference on artificial intelligence in education* (pp. 348–351).

Li, Z., Shi, L., Wang, J., Cristea, A. I., & Zhou, Y. (2023). Sim-Gail: A generative adversarial imitation learning approach of student modelling for intelligent tutoring systems. *Neural Computing and Applications, 35*(34), 24369–24388.

Litzelman, D. K., Stratos, G. A., Marriott, D. J., & Skeff, K. M. (2006). Personality preference influences medical student use of specific computer-aided instruction (CAI). *Medical Education, 40*(6), 582–589. https://doi.org/10.1111/j.1365-2929.2006.02407.x

Lunn, S. J., Zerbe, E., & Ross, M. (2024). You're hired! A phenomenographic study of undergraduate students' pathways to job attainment in computing. *ACM Transactions on Computing Education*. https://doi.org/10.1145/3636514

Ma, W. W., Sun, K., & Ma, J. (2014). The impacts of cognitive learning styles on the use of online learning and collaborative writing environments. *International Journal of Innovation and Learning, 16*(1), 97–111.

Martin, F. (2024). Blackboard as the learning management system of a computer literacy course. *MERLOT Journal of Online Learning and Teaching*.

Merlo, E. M., Sicari, F., Frisone, F., Alibrandi, A., & Settineri, S. (2020). Personality types and dreaming in future health professionals: Effect of age and gender. *International Journal of Dream Research, 13*, 160–172.

Messer, M., Brown, N. C. C., Kölling, M., & Shi, M. (2024). Automated grading and feedback tools for programming education: A systematic review. *ACM Transactions on Computing Education*. https://doi.org/10.1145/3636515

Meyer, J., Jansen, T., Hübner, N., & Lüdtke, O. (2023). Disentangling the association between the big five personality traits and student achievement: Meta-analytic evidence on the role of domain specificity and achievement measures. *Educational Psychology Review, 35*(1), 12.

Mpungose, C. B., & Khoza, S. B. (2022). Postgraduate students' experiences on the use of moodle and canvas learning management system. *Technology, Knowledge and Learning, 27*(1), 1–16.

Murphy, L., Eduljee, N. B., Croteau, K., & Parkman, S. (2020). Relationship between personality type and preferred teaching methods for undergraduate college students. *International Journal of Research in Education and Science, 6*(1), 100–109.

Mwatilifange, S.R., & Mufeti, T.K. (2022). Using moodle to teach computer literacy to first-time computer users: A unam case study. *Transforming Entrepreneurship Education*, 45–64.

Myers, I. B. (1962). *The Myers-Briggs type indicator: Manual*. Consulting Psychologists Press.

Nannim, F. A., Ibezim, N. E., Agbo, G. C., Mgboji, C., Ngwoke, S. O. R., & Mosia, M. (2025). Development of a project-based Arduino learning app: Fostering robotics programming competence among preservice teachers of computer and robotics education. *ACM Transactions on Computing Education*. https://doi.org/10.1145/3719016

Newell, A., & Simon, H. A. (1972). *Human problem solving*. Prentice-Hall.

Oliveira, G., Grenha Teixeira, J., Torres, A., & Morais, C. (2021). An exploratory study on the emergency remote education experience of higher education students and teachers during the covid-19 pandemic. *British Journal of Educational Technology, 52*(4), 1357–1376.

Oliveira, W., Toda, A., Toledo, P., Shi, L., Vassileva, J., Bittencourt, I.I., & Isotani, S. (2020). Does tailoring gamified educational systems matter? The impact on students' flow experience. *Proceedings of the 53rd Hawaii international conference on system sciences.*

Oudat, Q., & Othman, M. (2024). Embracing digital learning: Benefits and challenges of using canvas in education. *Journal of Nursing Education and Practice, 14*(10), 39.

Oyibo, K., Orji, R., & Vassileva, J. (2017). The influence of culture in the effect of age and gender on social influence in persuasive technology. *Adjunct publication of the 25th conference on user modeling, adaptation and personalization* (pp. 47–52).

Paiva, J. C., Leal, J. P., & Figueira, A. (2022). Automated assessment in computer science education: A state-of-the-art review. *ACM Transactions on Computing Education*. https://doi.org/10.1145/3513140

Qin, X., Liu, Z., Liu, Y., Liu, S., Yang, B., Yin, L., & Zheng, W. (2022). User ocean personality model construction method using a bp neural network. *Electronics, 11*(19), 3022.

Raj, N. S., & Renumol, V. (2022). A systematic literature review on adaptive content recommenders in personalized learning environments from 2015 to 2020. *Journal of Computers in Education, 9*(1), 113–148.

Rivers, D. J. (2021). The role of personality traits and online academic self-efficacy in acceptance, actual use and achievement in Moodle. *Education and Information Technologies, 26*(4), 4353–4378.

Rodrigues, L., Pereira, F., Toda, A., Palomino, P., Oliveira, W., Pessoa, M., & Isotani, S. (2022). Are they learning or playing? Moderator conditions of gamification's success in programming classrooms. *ACM Transactions on Computing Education*. https://doi.org/10.1145/3485732

Sardjono, O. (2023). Learning outcomes based on Myers-Briggs type indicator (MBTI) personality from accounting department students Sam Ratulangi university. *Accountability, 12*(1), 11–20.
Sari, E. Y. D., & Bashori, K. (2020). Predicting managerial styles: Is the Myers-Briggs type indicator still useful? *Journal of Education and Learning (EduLearn), 14*(4), 617–622.
Sari, I., & Bashori, I. (2020). Predicting managerial styles: Is the Myers-Briggs type indicator still useful. *Journal of Education and Learning (EduLearn)* , https://doi.org/10.11591/edulearn.v14i4.14582 (Based on MBTI study in Yogyakarta school principals (39 participants))
Schaubhut, N.A., Herk, N.A., & Thompson, R.C. (2009). Mbti® form m manual supplement. *Retrieved May, 15*, 2010,
Scroccaro, A. (2024). Social entrepreneurship and sustainability. a curricular challenge-based course at the university of Trento. *Edulearn24 proceedings* (pp. 3313–3317).
Shemshack, A., & Spector, J. M. (2020). A systematic literature review of personalized learning terms. *Smart Learning Environments, 7*(1), 33.
Shi, L., I. Cristea, A., Awan, M.S., Stewart, C., & Hendrix, M. (2013). Towards understanding learning behavior patterns in social adaptive personalized e-learning systems. *The 19th Americas conference on information systems (AMCIS)* (pp. 1–10).
Soper, D. (2023). *A-priori sample size calculator for structural equation models [software]*. https://www.danielsoper.com/statcalc (Accessed: 2023-04-05)
Steel, P. (2007). The nature of procrastination: A meta-analytic and theoretical review of quintessential self-regulatory failure. *Psychological Bulletin, 133*(1), 65–94. https://doi.org/10.1037/0033-2909.133.1.65
Swerzenski, J. (2021). Critically analyzing the online classroom: Blackboard, Moodle, canvas, and the pedagogy they produce. *Journal of Communication Pedagogy, 4*, 51–69.
Taylor, D.L., Yeung, M., & Bashet, A. (2021). Personalized and adaptive learning. *Innovative learning environments in STEM higher education: Opportunities, Challenges, and Looking Forward*, 17–34.
Tobiaszewska, M., Koweszko, T., Jurek, J., Mikołap, K., Gierus, J., Mikulski, J., et al. (2024). Personality types of medical students in terms of their choice of medical specialty: Cross-sectional study. *Interactive Journal of Medical Research, 13*(1), Article e60223.
Valtonen, T., López-Pernas, S., Saqr, M., Vartiainen, H., Sointu, E. T., & Tedre, M. (2022). The nature and building blocks of educational technology research. *Computers in Human Behavior, 128*, Article 107123.
Watson, D., & Clark, L. A. (1997). Extraversion and its positive emotional core. In R. Hogan, J. Johnson, & S. Briggs (Eds.), *Handbook of personality psychology* (pp. 767–793). Academic Press.
Westland, J. C. (2010). Lower bounds on sample size in structural equation modeling. *Electronic Commerce Research and Applications, 9*(6), 476–487.
Weston, T. J., Dubow, W. M., & Kaminsky, A. (2019). Predicting women's persistence in computer science- and technology-related majors from high school to college. *ACM Transactions on Computing Education*. https://doi.org/10.1145/3343195
Wing, J. M. (2006). Computational thinking. *Communications of the ACM, 49*(3), 33–35.
Wong, J. T., & Hughes, B. S. (2023). Leveraging learning experience design: digital media approaches to influence motivational traits that support student learning behaviors in undergraduate online courses. *Journal of Computing in Higher Education, 35*(3), 595–632.
Zhalgassova, Z., Shaikym, A., Sadyk, U., Kutzhan, A., Amirkumar, M., & Assangali, B. (2023). Mbti-based recommendation system for extracurricular activities for high school students. *2023 17th international conference on electronics computer and computation (ICECCO)* (pp. 1–4).
Zuckerman, M., Kuhlman, D. M., Joireman, J., Teta, P., & Kraft, M. (1993). A comparison of three structural models for personality: The big three, the big five, and the alternative five. *Journal of Personality and Social Psychology, 65*(4), 757.

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