The Relationship Between Students' Myers-Briggs Type Indicator and Their Behavior within Educational Systems

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***Abstract*—Leveraging user behavior has become an increasingly valuable resource for modeling and personalizing systems based on the unique characteristics of each user. While recent studies have recently been conducted along these lines, there is still a lack of understanding of the relationship between students' Myers-Briggs Type Indicators and their behavior within educational systems. Facing this problem, we conducted a long-term study (15 weeks) with 96 students, analyzing how their engagement metrics and communication frequency in a Moodle Learning Management System are related to their Myers-Briggs personality types (*i.e.*, extroversion/introversion, sensing/intuition, thinking/feeling, and judging/perceiving). The primary findings indicate that *i)* participants identified as extroverted demonstrated heightened activity levels throughout more weeks of the course, and *ii)* participants characterized by judging and thinking traits engaged in a greater number of activities over the course duration. The results contribute to the field of educational technologies by providing valuable insights into the relationships between different characteristics associated with the Myers-Briggs Type Indicator and students' behavior when using an educational system.**

***Index Terms*—Students' behavior, learning management systems, Myers Briggs Test Indicator, Moodle, long-term study**

I. Introduction

The integration of educational technology tools has become integral to contemporary education, as evidenced by numerous studies [1]–[3]. Over the past few years, a diverse array of educational technologies, including Learning Management Systems (LMS), educational games, and virtual reality systems, has emerged [4]. The impact of these technologies on education varies, with positive outcomes such as heightened engagement, improved performance, and increased satisfaction noted in some cases [5], [6]. Conversely, negative experiences, such as demotivation and frustration, have been reported in other instances [7]. To improve the quality of these educational technologies, recent studies are increasingly invested in understanding students' behavior [8]–[10], as a pivotal for tailoring designs and resources to suit the individual needs of each user [11]–[13].

At the same time, the data obtained from LMS concerning students' behavior can provide us with important information about real student engagement [14]. The general differences in user profiles investigated include learning styles [15], gamer type [16], demographic information [17] and personality type [18]. Consequently, the identification and modeling of personality in e-learning emerge as critical issues in education, given that multiple studies affirm the facilitative role of understanding personality in the learning process [19].

In response to this pressing issue, we conducted a long-term data-driven study (data collected during 15 weeks) involving 96 participants, to understand the relationship between students' personality types as determined by the Myers-Briggs Type Indicator (MBTI) and their behavior within a LMS. We aimed to answer the research question: **what is the relationship between students' MBTI types (*i.e.*, extroversion/introversion, sensing/intuition, thinking/feeling, and judging/perceiving) and their behavior within an educational system?** To answer the research question, we modeled this relationship using partial least squares structural equation modeling (PLS-SEM).

The main results indicate that *i)* individuals identified as extroverted exhibit heightened activity levels throughout the week, *ii)* those with judging traits tend to engage in fewer activities, and *iii)* thinkers demonstrate a propensity for in-

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The authors utilized generative artificial intelligence (*i.e.*, Microsoft Copilot) to improve the grammatical quality of the text.

creased activity participation. This study makes a significant contribution to the field of learning technologies by establishing a model that delineates the relationship between students' MBTI types and their behavior within an educational system.

II. Background and Related Work

The MBTI, proposed by Myers and McCaulley [20], as "four personal preferences affect how people behave in all situations" [21] is one of two well-established personality tests at the facet level, exhibiting a strong correlation with other tests such as the Big Five, CPI 260, Birkman Method, and Strong Interest Inventory [22], [23].

MBTI is rooted in Jung's Theory, which identifies four pairs of opposing preferences: Extraversion (E) versus Introversion (I), reflecting how an individual directs attention and derives energy; Sensing (S) versus Intuition (N), illustrating how a person processes information; Thinking (T) versus Feeling (F), outlining the decision-making approach; and Judging (J) versus Perceiving (P), indicating how one interacts with the outer world [23].

Over the years, MTBI has been investigated in different areas such as health [24], sports [25], and education [26]. In the education realm, recent research endeavors have focused on analyzing, modeling, and predicting the MBTI profile of students, exploring how these profiles affect their classroom behavior and learning outcomes [27], [28].

Adewale *et al*. [29] created a personalized e-learning platform that adapts teaching methods to students' MBTI types. Post-assessment data showed a 78% first-attempt pass rate, with the remainder passing on the second try [29]. Sari and Bashori [30] analyzed the personalities of Yogyakarta's school principals using MSDT for management styles and MBTI for personality, involving 39 principals. Findings highlighted a dominance of Extroverted over Introverted traits among them [30].

Kodweis *et al*. [31] investigated the correlation between MBTI personality traits and Clance Imposter Phenomenon Scale (CIPS) scores among pharmacy students through a retrospective study. Results indicated that students with introverted, intuitive, and perceptive traits had higher CIPS scores [31]. In the same year, Guven and Mustul [32] explored the impact of student-centered learning and MBTI on music education. Extroverted students thrived in voice training, while introverted students excelled in instrumental performance [32].

Zhalgassova *et al.* [33] developed a new MBTI-based recommendation system for high school students' extracurricular activities, leveraging feature engineering and machine learning for personalized suggestions. This system, tested against traditional models using precision, recall, and F1-score metrics, demonstrated enhanced performance, showcasing its capability to offer tailored activity options [33].

The aforementioned studies collectively underscore a growing recognition of the significant role that the MBTI plays in the educational context. Despite the increasing interest, there remains a paucity of research specifically addressing the application of MBTI within educational systems. This gap highlights the need for further exploration and development in this area. As far as we know, we are the pioneers in investigating the relationship between students' MBTI types and their behavior within an educational system.

III. Study Design

In this section, we present the study's design.

A. Materials and method

Students' behavior data was collected from a Moodle LMS, where the students participated in a freshmen course entitled "Fundamentals of Programming" within the Engineering faculty at SDU University, Kazakhstan. The course was provided during the Fall semester of 2021, catering to a total of 787 students. A subset of 95 students actively participated in the study, voluntarily providing their MBTI information for subsequent analysis.

The course, spanning 15 weeks, consisted of four main types of activities: *1)* Mini Tests - to test the theoretical knowledge of students; *2)* Weekly contests - to improve problem-solving skills of students; *3)* Quizzes - to examine students theoretical and practical knowledge; and *4)* Projects - to demonstrate students comprehension of the concepts covered in class by applying them to real-world systems. Additionally, the course follows a flipped classroom approach, wherein video lectures are provided before in-person sessions to facilitate comprehensive discussions and lectures on the topic. The HackerRank website[1] served as the platform for both weekly contests and quizzes, offering competitive programming challenges. In these activities, students write solutions to designated problems, and their submissions are scored based on the accuracy of the output. To assess students' practical and theoretical knowledge, the enterprise-level tool, HackerRank for Work, is employed. An illustrative example of the system is presented in Figure 1.

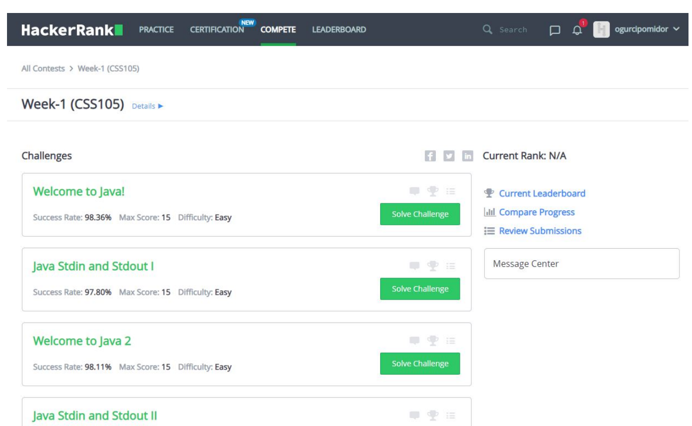

Fig. 1. The screenshot from the contest on the Hackerrank website

The study was organized in three different steps: *i)* MBTI identification, *ii)* course participation, and *iii)* data analysis. The *first step* of the study involves investigating the MBTI

1 www.hackerrank.com

types of students. Participants were instructed to learn their MBTI type through a validated questionnaire[2]. The website uses NERIS Type Explorer® assessment to discern users' personalities. The website uses extra letters A - Assertive and T - Turbulent type factors added to MBTI type as an identity aspect showing how confident the user is in his/her abilities and decisions. Since four type factors were the essentials of MBTI the last factor was not used. The *second step* involved student participation in the course, where students were invited to participate in the previously described course. The *third step* involved the organization, treatment, and analysis of data obtained during the course.

B. Participants and data analysis

Initially, to guarantee a sample size that allows for the accurate detection of effects, we employed the *a-priori* sample size calculation method (*i.e.*, a method for determining the minimum required sample size to perform some type of analysis) [34]. We used the Online Calculator for A-priori Sample Size Calculator for SEM proposed by Soper [35]. Due to the absence, to the best of our knowledge, of comparable experiments, we aimed to detect a range of effect sizes spanning from low to large. Thus, to set the correct number of participants for the study, following the recommendations of Cohen [34] and Westland [36] we used the following parameters: anticipated effect size: 0.5; desired statistical power level: 0.8; and probability level: 0.05. Based on our study, we have eight latent variables and 22 observed variables. The result indicated a minimum sample size of 44 participants to detect effects.

We used data obtained from 96 undergraduate students, comprising 75 students from the 1st course, 9 from the 2nd course, 2 from the 3rd course, and 9 from the 4th course within the Computer Science and Engineering Faulty. The participants' age range averaged between 17 and 22 years. The dependent variables (*i.e.*, students' MBTI) were coded as Extraversion (-1) Introversion (1); Sensing (-1) Intuition (1); Thinking (-1) Feeling (1); and Judging (-1) Perceiving (1). The following data (independent variables) were collected from Moodle LMS as Total Activity Log Files (the complete dataset is available as an appendix):

- **Activity out of the course**: Any activity done by the student in the course, carried out outside the regular course period (independent variable).
- **Most active week**: The number of students' activities during the course was divided by weeks according to week dates in the Fall 2021 semester. The most active week number represents the week number with the highest number of activities (considering the 15 weeks of the course).
- **Most active day**: Most active day was obtained by detecting the biggest number of activities done by a student in each week (considering the weekdays Monday as 1 and Sunday as 7).

[2]www.16personalities.com

- **Total activities performed**: Number of activities carried out throughout the course.

The data analysis was carried out using PLS-SEM, which in the realm of exploratory research stands as a well-established approach for theory development [37]. This class of SEM elucidates the variance in dependent variables by accommodating unobservable variables measured indirectly through indicator variables. Furthermore, PLS-SEM provides robust model estimation, even when dealing with relatively smaller sample sizes [38].

IV. Results

PLS-SEM provides a form of analysis that remains robust regardless of the data distribution, eliminating the need for normality tests [39]. Therefore, our initial focus involved calculating the discriminant validity (*i.e.*, to ensure that different measurements truly reflect separate concepts rather than being too closely related) of the scale. Table I presents the discriminant validity results for the scale used in our study.

TABLE I
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

Next, Table II displays the path model and Table III 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 II
CORRELATIONAL MATRIX

					CI	
	β	**SD**	***P-values***	**Bias**	**2.50%**	**97.50%**
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	-0.68	0.325
Extroversion → Total activities performaned	-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 performaned	-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 performaned	-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 performaned	0.283	0.116	**0.015**	0.001	0.023	0.486

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

Extroversion was positively associated with the most active week (β = 0.225 | P = 0.039), Judging negatively associated with total activities performed (β = -0.248 | p = 0.017), and Thinking positively associated with total activities (β=

TABLE III
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

0.283 | 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. In summary, personality traits showed weak but significant relationships with course activity levels.

A. Discussion

In this study, aiming to advance toward personalized education, we analyzed the relationship between students' MBTI and their behavior in an educational system. Firstly, the observation that extroverted participants exhibited heightened activity over more weeks suggests a compelling link between extraversion and sustained engagement in online learning environments. This finding aligns with the notion that extroverts, who thrive on social interactions [22], [23], [30], may find the collaborative and communicative features of the Moodle platform conducive to their learning preferences.

Our findings surpass those of comparable recent studies [31], [32], [40], revealing that participants with judging and thinking orientations exhibited greater activity levels during the course (see Table II). This observation prompts questions regarding the decision-making processes and task-oriented behaviors of individuals within an academic context. It can imply that students with judging and thinking orientations may be drawn to structured learning environments (similar to our case), engaging in a higher number of analytical and objective learning activities.

Identifying the relationships between personality and engagement patterns guides the development of personalized and adaptive learning experiences. For instance, understanding extroverted learners' preferences suggests incorporating collaborative and interactive elements into course design. Similarly, acknowledging judging and thinking participants' engagement emphasizes the importance of creating structured and goal-oriented tasks that cater to their decision-making and analytical preferences.

B. Threats to validity and limitations

Our study has some limitations that should be considered in interpreting the result. Concerns have been raised about the scientific rigor of the MBTI due to its theoretical underpinnings [41], [42]. 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. Another limitation is the study's homogeneity, as all participants were from the same country, same university, and same faculty. This restricts the generalizability of our findings to broader populations. Also, it might affect the behaviour of students within the Learning Management System. The sample size, although sufficient for a case study, may not allow the generalization of results to other contexts. Finally, the nature of the study can generate a series of biases related to student behavior while using the system.

C. Recommendations for future studies

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. **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.

V. Concluding Remarks

Despite the acknowledged limitations of the MBTI, it remains extensively employed in practice for understanding and modeling user behavior within educational systems. For this reason, in this particular case study, we investigated the relationship between students' MBTI profiles and their behavior within an educational system. Our findings suggest that distinct behaviors may manifest among students based on their MBTI profiles, prompting avenues for further investigation. In future work, we aim to replicate the study with a more expansive sample size and explore relationships between user behavior and other types of user models.

Appendix

The study dataset can be accessed from this link: https://osf.io/t7y5a/.

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