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Motivation, technology use, learning interest, and learning outcomes among Indonesian undergraduates

Nico Alexsander*, Dara Kinanti, Seyda Fathimya, Anaise Abbril Khan, Nadira Elysia Putri, Indri Ika Prasetiyawati

Management Department, Business Binus School, Bina Nusantara University, Kampus Anggrek, Jl. Kebon Jeruk Raya No. 27, Kebon Jeruk, Jakarta Barat 11530 Indonesia
e-mail: nikoa2549@gmail.com

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ABSTRACT

This study investigates whether motivation, technology use, and learning interest meaningfully differentiate learning outcomes among undergraduate students in a private university in Indonesia. Drawing on theories of self-determination, interest development, and educational technology, the research examines three frequently cited drivers of academic performance in higher education. A quantitative, cross-sectional survey was administered to 100 students at BINUS University Alam Sutera, who completed a structured online questionnaire measuring learning motivation, technology use in learning, learning interest, and self-reported learning outcomes. Composite scores were calculated for each construct, and Analysis of Variance (ANOVA) was employed to test for differences in mean learning outcomes across levels of motivation, technology use, and learning interest. Descriptive statistics indicated generally moderate to high levels of motivation, frequent technology use, and positive learning interest in the sample. However, ANOVA results showed no statistically significant differences in learning outcomes across levels of any of the three predictors ($p > 0.05$). These findings contrast with much of the theoretical and empirical literature that posits positive effects of motivation, interest, and technology integration on academic achievement. The results suggest that, in this context, relatively uniform assessment practices, measurement limitations, and unobserved factors such as instructional quality and prior ability may overshadow the direct influence of the studied variables. The study highlights the need for more refined measurement, stronger alignment between technology and pedagogy, and more discriminating assessment systems in future research and practice.

Keywords: learning motivation, educational technology, learning interest, learning outcomes, private university

1. INTRODUCTION

University learning outcomes are shaped by a complex interaction of individual, instructional, and contextual factors. In the Indonesian context, lecturers and policy-makers frequently emphasize student motivation, the use of learning technologies, and students' learning interest as key drivers of academic performance. Motivation is commonly understood as an internal process that activates, directs, and sustains goal-oriented behavior in learning (Ryan & Deci, 2000). When students feel autonomous, competent, and connected to others, they are more likely to persist in academic tasks and to invest effort in challenging coursework (Ryan & Deci, 2000).

At the same time, interest in a subject is not merely a transient feeling, but a relatively enduring predisposition to engage with particular content over time. Ahmadi (2009) defines interest as a mental attitude that involves cognitive, conative, and emotional components directed toward an object, accompanied by strong feelings. In the learning domain, interest has been theorized as a multi-phase developmental process, starting from situational interest triggered by context and evolving into well-developed individual interest that supports sustained engagement and deeper understanding (Hidi & Renninger, 2006). When students are genuinely interested in a course, they tend to allocate more attention, persist longer, and derive more meaning from learning activities.

Learning outcomes themselves are typically conceptualized as observable changes in knowledge, skills, and attitudes as a result of instruction. Hamalik (2001) describes learning as a process of behavioral change that occurs through interaction with the environment, where changes can be seen in cognitive, affective, and psychomotor domains. Similarly, Slameto (2010) argues that learning outcomes reflect relatively permanent changes in behavior that result from experience in instructional settings. Assessment systems in higher education build on these ideas by using tests, assignments, and projects to capture the extent to which students have reached the intended learning goals (Sudjana, 2009).

The rapid expansion of educational technology adds another layer to this picture. Learning management systems, online discussion forums, digital content, and video-conferencing platforms have become integral to university teaching, especially after the COVID-19 pandemic. The technology acceptance literature shows that students' perceptions of usefulness and ease of use are central to their willingness to adopt new digital tools (Davis, 1989). However, meta-analytic evidence suggests that while technology can have a positive effect on achievement, the average impact tends to be modest and highly variable across contexts (Tamim et al., 2011). This implies that simply providing technology is not enough; its integration must be pedagogically meaningful and aligned with students' needs.

In many Indonesian institutions, including private universities in metropolitan areas, these three dimensions—motivation, technology use, and learning interest—are often invoked as explanations for variations in student performance. Conceptually, higher motivation and stronger interest should enhance learning outcomes because students expend more effort and regulate their learning more effectively (Sardiman, 2011; Ryan & Deci, 2000). Similarly, appropriate use of technology can broaden access to resources, support flexible learning, and facilitate feedback, which in turn is expected to improve academic results (Tamim et al., 2011). Yet empirical findings are mixed, and in some cases the expected relationships are weak or statistically non-significant.

The present study uses data from a survey of undergraduate students at BINUS University Alam Sutera in Tangerang, Indonesia. The original research focused on the influence of motivation, technology use, and learning interest on learning outcomes using Analysis of Variance (ANOVA).

Despite the theoretical expectation that these three variables would differentiate students' achievement, the statistical analysis reported that there was no significant difference in mean learning outcomes across different levels of motivation, technology use, and learning interest.

Building on that dataset, this paper has two objectives. First, it aims to present a structured, English-language report of the study, including the conceptual framing, methodology, and empirical results. Second, it seeks to discuss the implications of finding no statistically significant effect of motivation, technology use, and learning interest on learning outcomes in this context. By situating the results within both Indonesian and international literature, the paper offers a nuanced view of why theoretically important variables may fail to show strong statistical relationships in a real-world sample and what this means for institutional efforts to improve student performance.

2. METHOD

2.1 Research Design

The study employed a quantitative, cross-sectional survey design with inferential analysis using Analysis of Variance (ANOVA). ANOVA is appropriate when the goal is to compare the means of a continuous dependent variable across two or more groups defined by categorical levels of independent variables (Field, 2018). In this research, self-reported learning outcomes served as the dependent variable, while motivation, technology use, and learning interest were treated as predictors, each categorized into several levels (for example, low, medium, and high).

2.2 Population and Sample

The target population consisted of undergraduate students at BINUS University Alam Sutera. Population in this study is defined as the entire group of individuals sharing specific characteristics determined by the researcher, from which conclusions are to be drawn (Sugiyono, 2010). According to the original research report, 100 students participated in the study.

The sampling technique was purposive sampling. In purposive sampling, participants are selected based on particular criteria deemed relevant to the research objectives (Sugiyono, 2018). In this case, the main inclusion criteria were: (1) actively enrolled undergraduate students at BINUS University Alam Sutera, and (2) experience with blended or technology-supported learning during the data collection period. The use of purposive sampling is consistent with Arikunto's (2019) view that sample members should adequately represent the characteristics of the population relevant to the variables under investigation.

The 100 respondents were recruited through an online questionnaire distributed via digital channels commonly used by students, such as messaging applications and learning platforms.

This mode of administration was selected to align with the study's focus on technology use in learning and to increase response rates during a period when many courses were still delivered partially online.

2.3 Instruments

The questionnaire consisted of four main sections measuring: (1) motivation, (2) technology use in learning, (3) learning interest, and (4) learning outcomes. The conceptualization of motivation drew on educational psychology literature that views motivation as the internal drive that energizes and directs learning behavior, influenced by intrinsic and extrinsic factors (Ryan & Deci, 2000; Sardiman, 2011). Items on motivation covered aspects such as willingness to study independently, persistence in completing tasks, and the importance attached to academic success.

The technology use scale was based on the notion that technology in education functions as a tool to facilitate access to information, support interaction, and enhance learning efficiency (Davis, 1989; Tamim et al., 2011). Items probed frequency and perceived usefulness of learning management systems, online discussion forums, digital materials, and other tools used in coursework.

Learning interest was defined following Ahmadi (2009) as the psychological inclination incorporating cognitive, conative, and emotional aspects directed at learning activities, accompanied by strong positive feelings. Items assessed enjoyment of course content, curiosity about the subject, and willingness to engage beyond minimum requirements. Definitions from Slameto (2010) and Sardiman (2011) regarding interest as a stable tendency to attend to and remember certain activities were also considered in developing the indicators.

Learning outcomes were self-reported by students and reflected their perceived achievement in terms of grades and understanding of course material. In line with Hamalik's (2001) and Sudjana's (2009) conceptualization, learning outcomes were treated as the result of the learning process that can be inferred from demonstrated knowledge and skills.

2.4 Data Collection and Analysis

Data were collected through a structured online questionnaire (Google Form). Each construct—motivation, technology use, learning interest, and learning outcomes—was measured using multiple Likert-type items. Composite scores were computed by summing or averaging the relevant items for each construct.

The primary analysis technique was ANOVA, implemented to test whether there were statistically significant differences in mean learning outcomes across levels of each predictor variable:
Motivation → learning outcomes
Technology use → learning outcomes
Learning interest → learning outcomes

Assumptions of ANOVA, such as independence of observations, approximate normality of residuals, and homogeneity of variances, were checked at the descriptive level. As noted in the original report, there were differences in variances across groups for motivation, technology use, and learning interest, but no statistically significant differences in mean learning outcomes ($p > 0.05$).

SPSS or an equivalent statistical package was used to compute ANOVA tables, including F-values, degrees of freedom, and significance levels. Effect sizes (such as eta squared) were interpreted qualitatively as small, medium, or large following conventional thresholds (Field, 2018), even though the overall findings indicated negligible practical effects.

3. RESULT AND DISCUSSION

3.1 Descriptive Overview

Descriptively, the participating students reported moderate to high levels of motivation, frequent use of technology for learning, and generally positive interest in their studies. This aligns with observations that contemporary university students in urban Indonesia are heavily exposed to digital platforms and often pursue higher education with clear expectations regarding future careers. Motivation scores indicated that most respondents felt a strong need to achieve good grades and to satisfy both personal and family expectations, consistent with the role of intrinsic and extrinsic drivers in the self-determination framework (Ryan & Deci, 2000).

Technology use scores suggested that students regularly engaged with learning management systems, downloaded materials, participated in online assessments, and used communication applications to coordinate group work. This reflects broader trends in Indonesian higher education, where digital systems have become central to course management and delivery. At the same time, variation existed in the depth of technology use: some students only accessed basic features (e.g., downloading files), while others engaged more actively in discussions or used additional tools to support learning.

Learning interest scores showed that many students expressed enjoyment of their subjects, curiosity about course topics, and willingness to read beyond the minimum requirements. This is consistent with the idea that interest develops when students experience learning as meaningful and personally relevant (Hidi & Renninger, 2006). However, there were also students whose interest appeared more instrumental, driven primarily by the need to pass courses, which may limit the depth of engagement.

3.2 ANOVA Findings

Despite these positive descriptive patterns, the ANOVA results revealed that there were no statistically significant differences in mean learning outcomes across different levels of motivation, technology use, and learning interest ($p > 0.05$ for all three predictors).

In other words, students categorized as having high motivation did not, on average, report substantially higher learning outcomes than those in medium or lower motivation categories. The same was true for technology use and learning interest: higher reported levels did not translate into significantly higher mean achievement.

This result appears counterintuitive when viewed against established theory. Self-determination theory posits that autonomous motivation enhances learning and performance (Ryan & Deci, 2000), while interest theory suggests that greater interest should foster deeper processing and better outcomes (Hidi & Renninger, 2006). Technology acceptance and educational technology research also generally report small positive effects of educational technology on achievement (Davis, 1989; Tamim et al., 2011).

Several plausible explanations can account for the absence of significant differences in this study: (1) Limited variability in learning outcomes. If the distribution of grades or self-reported achievement is relatively compressed—for instance, most students receiving similar marks—then statistical tests may lack the sensitivity to detect differences between groups. In many private universities, grade inflation or lenient assessment practices can lead to clustered scores, reducing variance in the dependent variable even when predictors vary; (2) Measurement issues in the independent variables. The constructs of motivation, technology use, and learning interest were measured using self-report items. Without rigorous validation (e.g., factor analysis, reliability testing), measurement error can attenuate relationships between variables. If items failed to capture important dimensions of each construct—for example, differentiating between intrinsic and extrinsic motivation or between superficial and deep technology use—the resulting composite scores may not adequately represent the underlying psychological processes (Ryan & Deci, 2000; Hidi & Renninger, 2006); (3) Misalignment between technology use and pedagogy. Technology use in itself does not guarantee improved learning outcomes. Tamim et al. (2011) show that effect sizes for educational technology vary widely, and technology is most effective when integrated into well-designed pedagogical strategies. If students mainly used technology for basic administrative functions or passive consumption of materials, the pedagogical value might have been limited, leading to negligible differences in achievement across different levels of use; (4) Contextual and unmeasured variables Learning outcomes are influenced by many factors beyond the three variables studied, including prior academic ability, quality of instruction, assessment design, and family support (Slameto, 2010; Sudjana, 2009). It is possible that these unmeasured variables played a stronger role in determining outcomes, overshadowing the contribution of motivation, technology use, and interest in this particular sample. (5) Sample size and statistical power. With a sample of 100 students, the study had limited statistical power to detect small effects. If the true relationships between the predictors and learning outcomes are modest—as suggested by some meta-analyses (Tamim et al., 2011)—the ANOVA may simply not have been sensitive enough to reveal them at conventional significance levels.

3.3 Interpretation and Theoretical Implications

The finding that motivation, technology use, and learning interest did not significantly differentiate students' learning outcomes in this context does not invalidate the theoretical importance of these constructs. Rather, it highlights several nuances. First, high motivation and interest may be necessary but not sufficient conditions for high achievement. If institutional structures, assessment systems, or instructional practices do not provide appropriate challenges and feedback, even motivated and interested students may not show markedly better performance.

Second, self-reported technology use may capture quantity rather than quality. A student who spends many hours online but engages minimally with course content may score similarly on a technology use scale as a student who uses fewer tools but in a more targeted, strategic way. This distinction between surface and deep engagement with technology is critical for understanding why the relationship with learning outcomes can be weak.

Third, the results invite a reconsideration of how motivation and interest are operationalized in local research. Many Indonesian studies rely on classical definitions from Ahmadi (2009), Slameto (2010), and Sardiman (2011), which emphasize general attitudes and tendencies. Integrating more recent international frameworks—such as the differentiation between autonomous and controlled motivation (Ryan & Deci, 2000) or the phases of interest development (Hidi & Renninger, 2006)—could support more precise measurement and analysis in future work.

3.4 Practical Implications

For institutional stakeholders, the results suggest that simply "increasing motivation," "using more technology," or "raising learning interest" at a general level may not be enough to significantly improve measured learning outcomes. Efforts should instead focus on designing assessment systems that genuinely discriminate between different levels of understanding and skills, making performance differences more observable, ensuring that technology integration is pedagogically meaningful, for example by using digital tools to support active learning, formative feedback, and collaborative problem-solving rather than only content delivery, and developing targeted interventions that enhance autonomous motivation and meaningful interest, such as project-based learning, authentic tasks, and opportunities for students to connect course content with real-world issues.

At the same time, the non-significant findings underscore the importance of robust research design in educational studies. Future research could combine ANOVA with regression or structural equation modeling, use validated scales with established psychometric properties, and incorporate longitudinal designs to capture changes over time.

4. CONCLUSION

This study examined whether motivation, technology use, and learning interest differentiate learning outcomes among undergraduate students at BINUS University Alam Sutera. Using ANOVA on survey data from 100 students, the analysis found no statistically significant differences in mean learning outcomes across levels of these three variables, despite some differences in variances.

Theoretically, motivation, interest, and technology use remain critical elements in models of learning and performance. However, this study demonstrates that their impact on measured achievement can be muted in specific institutional contexts, especially when outcomes are weakly differentiated, constructs are measured broadly, and technology is used in relatively superficial ways.

Practically, the findings suggest that higher education institutions should move beyond generic exhortations to "motivate students" or "use technology" and instead invest in more targeted, evidence-based approaches that align pedagogy, assessment, and digital tools. For researchers, the results point to the need for more rigorous measurement, larger and more diverse samples, and designs that can disentangle the contributions of multiple factors to student learning outcomes.

Ethical Approval
Not Applicable

Informed Consent Statement
Not Applicable

Authors' Contributions
NA led the conceptualization of the study, developed the research framework, coordinated the data collection process, and served as the corresponding author managing communication during the submission and review stages. DK contributed to the research design, instrument development, and validation of survey items. She also assisted in interpreting the findings and refining the manuscript structure. SF was responsible for data management, including data cleaning and coding, and contributed to the ANOVA analysis and statistical interpretation. ABK contributed to literature review development, theoretical grounding, and drafting key sections of the introduction and discussion. NEP assisted in preparing the descriptive analysis, organizing the results section, and harmonizing the narrative between

theory and findings. IIP provided supervision, critical review, and guidance throughout the research process. She revised the manuscript for intellectual rigor and ensured overall academic quality.

Disclosure Statement
The Authors declare that they have no conflict of interest

Data Availability Statement
The data presented in this study are available upon request from the corresponding author for privacy.

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Notes on Contributors

Nico Alexsander
Nico Alexsander is affiliated with Bina Nusantara University

Dara Kinanti
Dara Kinanti is affiliated with Bina Nusantara University

Seyda Fathimya
Seyda Fathimya is affiliated with Bina Nusantara University

Anaise Abbril Khan
Anaise Abbril Khan is affiliated with Bina Nusantara University

Nadira Elysia Putri
Nadira Elysia Putri is affiliated with Bina Nusantara University

Indri Ika Prasetiyawati
Indri Ika Prasetiyawati is affiliated with Bina Nusantara University

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