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**Research Article**

# Determinants of student engagement and behavioral intention towards mobile learning platforms

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**ABSTRACT**

This study explores the factors influencing student engagement and behavioral intention towards mobile learning platforms, with a focus on widely used platforms in Indonesia, such as Ruangguru, Zenius, and Quipper. A total of 375 questionnaires were distributed, out of which 363 were deemed valid and used for analysis. The research employed structural equation modeling with partial least squares to analyze the data, aiming to uncover the key determinants driving the adoption of mobile learning. The findings highlight the significant impact of perceived usefulness (PU) on students' attitudes toward mobile learning, emphasizing the crucial role of perceived utility in shaping positive attitudes. However, the study also reveals that the direct influence of PU on behavioral intention towards mobile learning is minimal, suggesting that attitude toward mobile learning plays a critical mediating role in this relationship. Additionally, the study demonstrates that perceived entertainment and facilitating conditions have substantial effects on shaping attitudes and behavioral intentions, underscoring the importance of enjoyment and support systems in fostering student engagement. The structural model developed in this research offers strong explanatory power, providing a comprehensive understanding of the factors that contribute to the success of mobile learning platforms. The insights gained from this study offer valuable guidance for educators and developers seeking to enhance mobile learning experiences and improve educational outcomes through targeted interventions that address these key determinants.

**Keywords:** mobile learning platforms, student engagement, behavioral intention, structural equation modeling, educational technology

## INTRODUCTION

The rapid advancement of technology over the past few decades has profoundly impacted various sectors, including education. One of the most transformative developments in this domain has been the rise of mobile learning platforms. These platforms have revolutionized the traditional learning environment by leveraging widespread access to mobile devices such as smartphones and tablets, offering unprecedented flexibility and accessibility in delivering educational content. Unlike conventional classroom settings, mobile learning allows students to access learning materials anytime and anywhere, effectively accommodating diverse learning needs and schedules. This flexibility is particularly advantageous in today's fast-paced world, where balancing education with other responsibilities has become increasingly challenging. The significance of mobile learning platforms has been further highlighted during the COVID-19 pandemic, which necessitated a sudden shift from traditional face-to-face learning to online modes (Zainuddin et al., 2022). These platforms, underpinned by mobile technologies, provide learning environments that transcend physical boundaries, offering accessible and flexible options for students (Bukharaev & Altaher, 2017). The integration of mobile technologies in education has the potential to reshape the delivery of higher education fundamentally (Biswas et al., 2020; Sukmana & Kim, 2024). By harnessing wireless communication, internet connectivity, and mobile computing technologies, mobile learning delivers educational software services that are not constrained by time or location, thus motivating learners and enhancing their educational outcomes (Shi et al., 2017). For example, mobile applications in specific educational contexts, such as Quran education, have demonstrated their potential to engage students and improve learning experiences (Hakimi, 2024). Mobile learning has emerged as a vital tool in modern education systems, offering new opportunities for interactive and engaging learning experiences (Stymne, 2020).

The growing emphasis on personalized learning experiences has significantly influenced integrating mobile learning into educational practices. Mobile learning platforms offer various interactive tools–quizzes, videos, and discussion forums–catering to individual learning styles and preferences. This personalized approach enriches the learning experience and fosters greater student engagement and motivation. Consequently, educational institutions and instructors have increasingly adopted mobile learning as a supplementary tool to traditional teaching methods, recognizing its potential to enhance student outcomes and bridge the gap between formal and informal learning environments. Mobile learning, often referred to as "M-learning," involves the use of personal mobile devices like smartphones and tablets to access educational content through mobile apps, online resources, and social media (Almogren & Aljammaz, 2022). This method offers unparalleled flexibility, allowing students to engage with learning materials anytime and anywhere. Such accessibility makes mobile learning a powerful tool for extending educational opportunities beyond the constraints of the traditional classroom. In formal education settings, the integration of mobile learning within the curriculum necessitates the development of specific, tailored educational apps that support teachers in their daily instructional tasks across all academic levels (Paule-Ruiz et al., 2016). The growing integration of mobile technologies into educational systems has emerged as one of the most significant advancements in the learning and teaching process (Althunibat et al., 2021).

The increasing popularity of mobile learning platforms, particularly in areas like Android-based mobile learning for graphic design, presents unique opportunities for student engagement in self-directed learning. This approach has been shown to enhance learning outcomes and boost student motivation (Department of Technology and Vocational Education, Universitas Negeri Yogyakarta, Sleman, Indonesia & Hakiki, 2024; Putawa & Sugianto, 2024). As mobile learning applications continue to grow in demand and popularity, they have become a common feature in modern educational systems, particularly with the widespread implementation of mobile learning projects (Almaiah et al., 2019). Furthermore, the use of mobile technology in universities and higher education institutions offers significant benefits, including flexibility in learning, the ability to extend learning beyond the physical classroom (a practice that became crucial during the pandemic), and the support of personalized learning experiences (Nikolopoulou et al., 2023). These benefits underscore the transformative potential of mobile learning in shaping the future of education. Despite the rapid adoption of mobile learning platforms, a critical need remains to understand the factors influencing students' decisions to engage with these technologies. While mobile learning offered numerous benefits, including flexibility and personalized learning experiences, the actual usage rates among students varied widely. This discrepancy underscored the importance of identifying and analyzing the determinants that shaped students' attitudes and intentions toward mobile learning. Previous studies had explored individual factors, such as perceived usefulness (PU) and perceived ease of use (PEU), which were central to the technology acceptance model (TAM). However, these studies often examined these variables in isolation, without considering the complex interplay between different factors that collectively influenced behavioral intentions.

Recent studies have increasingly focused on understanding technology adoption frameworks and user behavior in various digital contexts. For example, the adoption of metaverse platforms has been analyzed using structural equation modeling, highlighting the mediating effects of switching costs on behavioral intention (El Emary, 2024). Similarly, machine learning models have been employed to predict consumer perceptions of metaverse shopping, providing insights into factors influencing technology acceptance (Lenus, 2024). In the Indonesian context, blockchain adoption in supply chain management has been explored, emphasizing the significance of localized factors in technology implementation (Pratama & Prastyo, 2024).

Furthermore, trust has been identified as a critical mediator between electronic word-of-mouth and security on cryptocurrency purchase decisions, demonstrating its importance in digital decision-making (Irfan, 2024). Additionally, user satisfaction and continuous usage intentions for digital banking platforms in Indonesia have been studied using structural equation modeling, revealing parallels with mobile learning adoption (Pratama, 2024). Predictive modeling techniques, such as support vector machines, have also been utilized in digital marketing to analyze user interactions, offering methodological insights relevant to this study (Sangsawang, 2024). Broader reviews have discussed the role of data science and artificial intelligence in shaping modern industries within Society 5.0, providing a contextual backdrop for the integration of mobile technologies (Hartatik et al., 2024). Lastly, sentiment analysis of Indonesian healthcare reviews has demonstrated the applicability of advanced analytical methods, such as ensemble learning, in evaluating user attitudes and behaviors (Setiawan et al., 2024).

To comprehensively understand the factors influencing students' engagement with mobile learning, it is essential to consider a range of variables. These include the impact of mobile learning technologies on student engagement and learning outcomes, as well as the specific influence of mobile applications on student engagement in subjects like information and communication technology and computer science (Anuyahong, 2023; Hegarty & Thompson, 2019; Ibrahim, 2024). Additionally, the role of teachers in fostering student engagement using smartphones for vocational assessment is critical. Technical factors, such as the availability and quality of mobile devices, play a significant role in the adoption of mobile learning, as do pedagogical factors like effective instructional design and social factors such as student motivation and interaction (Alanazi et al., 2024; Wahyuningsih & Chen, 2024). Understanding students' perceptions, attitudes, and skills regarding the use of mobile devices, along with factors like usability, interactivity, and curriculum integration, are also key to enhancing student engagement with mobile learning (Alshammari et al., 2018; Wirawan, 2024). Furthermore, emotional engagement and the role of instructors in using mobile learning applications can significantly influence student engagement and learning development in mobile learning environments (Min, 2024; Tam et al., 2024; Wu et al., 2023).

This study aimed to address this gap by developing a comprehensive model that integrated multiple variables known to affect mobile learning adoption. In addition to PU and PEU, the study included perceived entertainment (ENT) as a significant factor, acknowledging that the enjoyment derived from using mobile learning platforms could also drive student engagement. Furthermore, the study incorporated attitude toward mobile learning (ATML) as a mediating variable, which linked students' perceptions to their behavioral intentions. Self-efficacy (SE) and facilitating conditions (FC) were also examined to understand their roles in shaping students' ease of use and overall intention to adopt mobile learning. This integrated approach provided a more holistic understanding of the factors that influenced mobile learning adoption, offering valuable insights for educators, policymakers, and developers seeking to enhance the effectiveness and reach of mobile learning platforms. The body of research on mobile learning adoption had largely focused on examining individual factors, such as PU and PEU, as determinants of students' acceptance and continued use of mobile learning platforms. While these studies provided valuable insights into the role of these variables, they often approached them in isolation, without considering the complex interrelationships that might exist among multiple factors. This approach resulted in a fragmented understanding of how different influences combined to shape students' attitudes and behavioral intentions toward mobile learning. Moreover, the existing literature primarily relied on traditional models, such as the TAM, which, although useful, did not capture the full range of variables that could affect mobile learning adoption in contemporary educational contexts. In addition to this gap in the integration of variables, more empirical evidence needs to be explored to explore how these factors interacted to influence behavioral intention toward mobile learning (BITML). Specifically, few studies have investigated the mediating role of ATML in this process or how variables like ENT, SE, and FC might interplay with PU and PEU to affect students' behavioral intentions. This limited understanding posed challenges for educators and policymakers seeking to enhance mobile learning adoption, as the strategies informed by existing research might not fully address the factors that drive students' intentions. Thus, there was a clear need for a more comprehensive, integrated model to provide a deeper understanding of the factors influencing BITML, incorporating a broader set of variables and exploring their interrelationships in greater detail.

The primary objective of this research was to develop and validate an integrated model that provided a comprehensive understanding of the factors influencing BITML. Recognizing the limitations of previous studies that focused on individual variables in isolation, this study examined how multiple key factors shaped students' intentions to adopt and use mobile learning platforms. The research aimed to bridge the gap in the existing literature by integrating various constructs from established models, such as the TAM, with additional variables that were increasingly relevant in the context of mobile learning. Specifically, the study examined the relationships between PU, PEU, and ENT with ATML as a mediating factor. The research also explored SE and FC's influence on PEU and BITML. By constructing this integrated model, the study intended to offer a more nuanced understanding of the determinants of mobile learning adoption, providing insights that could inform the development of more effective educational technologies and strategies to enhance student engagement and learning outcomes. Using structural equation modeling (SEM) as the analytical method allowed for a robust examination of the complex relationships among these variables, ensuring that the model was empirically validated and theoretically grounded. The study was designed to address research questions exploring the complex relationships among key variables influencing students' BITML. The first research question focused on understanding the effects of SE and FC on PEU. These variables were selected based on their established significance in technology adoption models. The hypotheses associated with this research question were, as follows:

**H1:** It was hypothesized that SE would positively influence PEU, implying that students who were confident in their abilities to use mobile learning platforms would find these platforms easier to use (Kumar et al., 2020).

**H2:** It was hypothesized that FC would positively affect PEU, indicating that better access to resources and support would make mobile learning platforms easier to use (Ebadi & Raygan, 2023).

The second research question examined the direct impact of FC on BITML. Given the importance of FC in technology adoption, this study sought to confirm whether access to resources and support directly led to an increased intention to use mobile learning platforms. The corresponding hypothesis for this question was:

**H3:** It was hypothesized that FC would positively influence BITML, suggesting that when students had sufficient resources and support, they would be more inclined to use mobile learning platforms (Hunde et al., 2023).

The third research question focused on the role of ENT in influencing ATML. The study aimed to determine how the entertainment value of mobile learning platforms shaped students' attitudes, recognizing that a positive attitude is a critical precursor to behavioral intention. The hypothesis associated with this research question was:

**H4:** The study posited that ENT would have a positive effect on ATML, reflecting the idea that the enjoyment derived from using mobile learning platforms would enhance students' attitudes (Hameed et al., 2024).

The fourth research question explored the impact of PEU on ATML and BITML. The study aimed to analyze how the ease of use of mobile learning platforms influenced both students' attitudes toward these platforms and their intention to use them. The hypotheses related to this question were:

**H5:** It was hypothesized that PEU would positively influence ATML, based on the assumption that students who found mobile learning platforms easy to use would develop more positive attitudes toward them (Kampa, 2023).

**H6:** It was also hypothesized that PEU would positively influence BITML, suggesting that students who found mobile learning platforms easy to use would be more likely to intend to use them (Kampa, 2023).

The fifth research question examined the direct and indirect effects of PU on ATML and BITML. The study aimed to determine whether students' perceptions of the usefulness of mobile learning platforms influenced their attitudes and behavioral intentions. The hypotheses associated with this research question were:

**H7:** It was hypothesized that PU would positively influence ATML, suggesting that students who found mobile learning beneficial would have a more favorable attitude toward its use (Kampa, 2023).

**H8:** It was also hypothesized that PU would directly influence BITML, reflecting the belief that the more useful students found mobile learning, the more likely they were to intend to use it (Kampa, 2023).

Finally, the study investigated the relationship between ATML and BITML. Given the central role of attitude in behavioral intention models, this study sought to confirm whether a positive ATML would directly lead to an increased intention to use such platforms. The corresponding hypothesis for this question was:

**H9:** It was hypothesized that ATML would positively influence BITML, indicating that students with a favorable ATML would be more likely to intend to use it in the future (Hameed et al., 2024).

These research questions and hypotheses formed the foundation of the study, guiding the development of the integrated model and the subsequent analysis of the relationships between these key variables.

## LITERATURE REVIEW

### Understanding the Value of Mobile Learning

PU has been established as a fundamental construct in the TAM, which refers to the degree to which an individual believes that using a particular system will enhance their performance. In mobile learning, PU is defined as the extent to which students perceive that using mobile learning platforms will improve their academic performance, increase learning efficiency, and contribute positively to their educational experience. This construct is particularly relevant in educational settings, where the perceived practical benefits of technology can significantly influence students' willingness to adopt and continue using new learning tools. Extensive research has consistently demonstrated the critical role of PU in shaping students' ATML and their BITML. For instance, Kampa (2023) found that PU is a significant predictor of ATML, suggesting that the more students recognize the usefulness of mobile learning, the more favorable their attitudes become. Moreover, several empirical studies have directly linked PU to BITML, indicating that students who perceive high usefulness in mobile learning are more likely to express a strong intention to adopt and continue using these platforms. This relationship highlights the importance of PU in the initial acceptance and the sustained use of mobile learning technologies.

The influence of PU extends across various contexts within mobile learning. Kumar et al. (2020) emphasized the impact of mobile learning SE on PU, which, in turn, affects subjective norms, attitudes, and behavioral intentions. Feng (2023) similarly highlighted that PU significantly impacts the behavioral intention to use mobile learning platforms, reinforcing the construct's central role in technology adoption. Additionally, Aljaaidi et al. (2020) found positive associations between PU, PEU, ATML, and BITML, further solidifying the interconnectedness of these variables. Moreover, Guo et al. (2020) explored how students' perceptions of PU and PEU influence their BITML, finding that both constructs are pivotal in the decision-making process. Al-Rahmi et al. (2021) further emphasized that student satisfaction with PU, PEU, ATML, and BITML is essential for achieving educational sustainability through mobile learning. Xu et al. (2022) demonstrated that PU and ATML significantly affect medical students' intention to continue using mobile health applications, underscoring the universal applicability of these constructs across different learning domains. These findings consistently support the notion that PU is a critical determinant in influencing ATML and BITML. Understanding and enhancing PU can thus lead to more effective strategies for promoting the adoption and continued use of mobile learning platforms, ultimately contributing to improved educational outcomes.

### The Importance of Usability in Learning Technologies

PEU was a central construct in the TAM and referred to the degree to which a user believed that using a particular system would be free of effort. In mobile learning, PEU was defined as the extent to which students found mobile learning platforms easy to use, navigate, and integrate into their daily routines. The significance of PEU in technology adoption lies in its potential to lower barriers to entry for users, thereby increasing the likelihood that they would accept and continue to use the technology. A system perceived as easy to use requires less mental and physical effort, which enhances user satisfaction and reduces resistance to adoption. Empirical evidence consistently linked PEU with ATML and BITML. Studies demonstrated that when students found mobile learning platforms easy to use, they were more likely to develop positive attitudes toward these platforms, which played a crucial role in their overall acceptance and continued use of the technology. For example, research conducted by Kampa (2023) showed that PEU was a significant predictor of ATML, indicating that the ease students could use mobile learning platforms directly influenced their attitudes toward them. Furthermore, PEU's influence extended beyond attitude formation, directly impacting BITML. Students who perceived mobile learning platforms as user-friendly were more likely to intend to use these platforms regularly, as the perceived ease reduced the cognitive and time investment required. This relationship underscored PEU's critical role in shaping ATML and driving BITML, making it a key variable in understanding mobile learning technologies' adoption and sustained use.

Further supporting the significance of PEU, Kumar et al. (2020) emphasized the impact of mobile learning SE on PEU, PU, subjective norms, ATML, and BITML. This underscores the interconnectedness of PEU with other important factors in technology adoption. Additionally, Huang and Li (2022) pointed out that PEU directly affects learners' interactive attitudes and mediates the relationship between PEU and ATML, highlighting the broader influence of ease of use on engagement in educational technologies. Aljaaidi et al. (2020) found positive associations between PEU, PU, attitudes, and behavioral intentions towards using a university mobile application. Similarly, Zhou et al. (2021) highlighted the significant positive impact of PEU on PU, usage attitudes, and intentions to use mobile learning technologies. These findings consistently underscored the importance of PEU as a determinant of users' attitudes and intentions in mobile learning contexts. Moreover, Naveed et al. (2020) demonstrated that PEU was significantly associated with mobile learning acceptance, alongside PU, ATML, and FC. This indicated that PEU was a critical factor influencing users' acceptance of mobile learning technologies. Additionally, Wang (2017) explored these relationships within a mobile learning environment for Japanese language learning, further reinforcing that PEU is a vital predictor of ATML and BITML. Collectively, these studies highlight the pivotal role of PEU in the context of mobile learning. Understanding and enhancing PEU can lead to more effective strategies for promoting the adoption and sustained use of mobile learning platforms, ultimately contributing to better learning outcomes.

## The Impact of Enjoyment on Learning Engagement

ENT refers to how users find an activity enjoyable and engaging. In mobile learning, ENT was defined as the degree to which students perceived mobile learning platforms as fun. This construct was particularly significant in voluntary learning environments, where learners could choose when and how they engaged with educational content. Unlike mandatory learning settings, where students might participate out of necessity rather than interest, voluntary environments require platforms to be effective and enjoyable to sustain long-term engagement. ENT played a critical role in these settings by enhancing learners' intrinsic motivation and encouraging them to invest more time and effort into learning. Several studies demonstrated the substantial impact of ENT on ATML and BITML. Research indicated that when students found mobile learning entertaining, they were more likely to develop positive attitudes toward using these platforms. For instance, Hameed et al. (2024) found that ENT significantly influenced ATML, suggesting that the enjoyment and pleasure derived from mobile learning platforms contributed to a more favorable evaluation of the technology. Additionally, ENT directly impacted BITML, as students who perceived mobile learning as entertaining were more likely to express a strong intention to use these platforms regularly. This relationship underscored the importance of incorporating entertainment elements into mobile learning platforms to enhance student attitudes and behavioral intentions, ultimately supporting mobile learning technologies' sustained adoption and use.

The role of ENT extended beyond just influencing attitudes; it also had a broader impact on various aspects of technology adoption. For example, Hameed et al. (2024) highlighted that ENT and factors like informativeness, trust, and value directly impacted ATML, influencing behavioral intentions. Similarly, Ghyas and Kondo (2016) identified ENT as a key determinant for the intention to use mobile entertainment services, with a strong direct effect on attitudes and an indirect effect on behavioral intention. These findings were further supported by Hameed and Qayyum (2018), who demonstrated that ATML mediated the relationship between entertainment, informativeness, irritation, and behavioral intention, reinforcing the critical role of entertainment in the adoption of mobile learning. Moreover, research has consistently shown that the adoption of mobile technologies was influenced by a combination of factors, including PU, ease of use, entertainment value, and attitudes, all of which contributed to behavioral intentions (Hamid et al., 2016; Murnawan et al., 2024). Jiang et al. (2015) also found that ENT significantly affected attitudes toward use, leading to a stronger behavioral intention to adopt mobile games. Additionally, Küçük et al. (2020) identified attitudes as a crucial factor influencing the behavioral intention to use mobile learning technologies, further highlighting the interconnectedness of these constructs. In related contexts, such as mobile advertising, Martínez-Ruiz et al. (2017) demonstrated that ENT and information, credibility, and irritation influenced attitudes toward mobile advertising, which subsequently affected behavioral intentions. This pattern was similarly observed in mobile learning for sustainability, where factors like PU, ease of use, enjoyment, attitude toward use, and behavioral intention were found to impact students' satisfaction and actual use of mobile learning (Al-Rahmi et al., 2021). Collectively, these studies emphasized the significance of ENT as a critical determinant in shaping attitudes and behavioral intentions in mobile learning. By enhancing the entertainment value of mobile learning platforms, educators and developers can increase student engagement and promote the sustained use of these technologies, leading to improved educational outcomes.

## Attitude Toward Mobile Learning

ATML refers to an individual's overall positive or negative evaluation of using mobile learning platforms. In technology adoption, attitude was a critical determinant of whether an individual would accept and continue to use a new technology. ATML encompassed students' feelings about the usefulness, ease of use, and enjoyment of mobile learning. This construct was particularly important because it directly influenced BITML, the primary outcome of interest in many technology acceptance studies. ATML also played a significant mediating variable, linking key antecedents such as PU, PEU, and ENT to BITML. When students had a positive ATML, it often served as a bridge between these antecedents and their behavioral intentions. For instance, even if a student found a mobile learning platform useful and easy, their intention to continue using it largely depends on their attitude. This mediating role of ATML was well-supported in the literature, as studies consistently showed that a positive ATML significantly increased the likelihood that students would intend to use these platforms in the future. Research has extensively documented the connection between ATML and BITML. Numerous studies confirmed that ATML was one of the strongest predictors of BITML, highlighting its central role in the technology adoption process. For instance, Hameed et al. (2024, p. 202) demonstrated that students with a favorable ATML were significantly more likely to intend to use these platforms consistently strongly. This finding was consistent across various educational contexts and technologies, reinforcing the importance of fostering positive attitudes toward mobile learning to encourage sustained use. The strong relationship between ATML and BITML underscored the need for educational institutions to focus not only on the functional aspects of mobile learning platforms but also on strategies that enhance students' overall attitudes toward these technologies.

Attitude was crucial in influencing BITML across various studies. Hameed and Qayyum (2018) found a positive and significant relationship between ATML and behavioral intention, emphasizing the importance of attitude in shaping students' intentions to adopt mobile learning technologies. Similarly, Pramana (2018) identified that students' attitudes, subjective norms, and behavioral control significantly influenced their intention to adopt mobile learning. Isaías et al. (2017) further emphasized that a positive ATML led directly to the intention to use such technologies, highlighting the direct pathway from attitude to behavioral intention. Moreover, Kumar et al. (2020) underscored the role of mobile learning SE in influencing PEU and PU and subjective norms, ATML and BITML. This interconnectedness suggested that improving students' SE could enhance their attitudes and, consequently, their intention to adopt mobile learning platforms. Al-Rahmi et al. (2021) also noted a positive effect of PEU on students' intention to use mobile learning, mediated through their attitudes. Additionally, Wang (2022) found that individuals' attitudes toward mobile learning, alongside perceived behavioral control, subjective norms, and compatibility, significantly influenced their adoption intention. Collectively, these studies highlighted the centrality of ATML in the adoption process of mobile learning technologies. A positive attitude directly influenced students' intentions and mediated the effects of other key factors, underscoring its pivotal role in the successful implementation and sustained use of mobile learning platforms.

## Behavioral Intention Toward Mobile Learning

BITML was defined as the degree to which students intended to use mobile learning platforms in the future. Within the context of TAMs, BITML served as the primary outcome variable, representing the ultimate behavioral response the model aimed to predict. The significance of BITML lies in its ability to forecast actual usage behaviors; a strong intention to use mobile learning often translated into sustained engagement with the technology. Therefore, understanding the factors that influenced BITML was crucial for educators and developers seeking to enhance the adoption and effective use of mobile learning platforms. Numerous studies demonstrated how key variables such as PU, PEU, FC, and ATML predicted BITML. PU consistently showed a strong positive impact on BITML, as students who believed that mobile learning would enhance their academic performance were more likely to intend to use these platforms regularly. Similarly, PEU played a significant role in shaping BITML, with research indicating that students who found mobile learning platforms easy to navigate and use were more inclined to adopt them in the long term.

FC also emerged as a critical predictor of BITML. Studies suggested that when students had access to necessary resources, such as reliable internet connections and technical support, they were more likely to intend to use mobile learning strongly. Finally, ATML was identified as one of the strongest predictors of BITML. Research consistently showed that a positive ATML mediated the effects of PU and PEU on BITML and directly influenced students' intentions to continue using these platforms. These findings highlighted the importance of creating supportive learning environments and fostering positive attitudes toward mobile learning to encourage widespread adoption and sustained use. BITML was influenced by various factors, as highlighted in the literature. Studies consistently showed that PU and PEU played crucial roles in shaping individuals' attitudes and intentions toward mobile learning (Handayati & Trisnawati, 2023; Huang & Li, 2022; Viriyasuebphong et al., 2021; Widiar et al., 2023). PU referred to the degree to which a person believed that using a particular system would enhance their performance, while PEU related to the extent to which a person believed that using the system would be free of effort (Aggarwal, 2019). These two factors were identified as significant determinants that could directly or indirectly affect behavioral intention.

Moreover, FC was recognized as a key factor influencing BITML (Açıkgül & Şad, 2021; Guo et al., 2020; Yadulla et al., 2024). FC encompassed external factors that might affect a system's ease of use, such as technical support, infrastructure, and resources. Studies showed that FC had a direct, significant effect on behavioral intention, indicating its importance in shaping individuals' decisions to engage with mobile learning platforms. Additionally, factors such as attitude towards use, social influence, SE, and personal innovativeness were identified as influencing behavioral intention in mobile learning (Berlilana & Mu'amar, 2024; Guo et al., 2020; Poong et al., 2016). Attitude towards use reflected an individual's overall evaluation or favorability towards using a system, while social influence pertained to the impact of social factors on an individual's decision-making process. SE refers to an individual's belief in their ability to successfully use a system, while personal innovativeness is related to the willingness to try out new technologies. These factors collectively shaped individuals' intentions to engage with mobile learning. Collectively, these findings reinforced the importance of understanding the multifaceted factors that influence BITML. By identifying and enhancing these key determinants, educators and technology developers can more effectively promote the adoption and sustained use of mobile learning platforms, leading to improved educational outcomes.

## The Role of Self-Efficacy in Learning Technology Adoption

SE was defined as an individual's belief in their ability to execute the actions required to achieve specific goals successfully. From Bandura's social cognitive theory, SE was considered a critical determinant of human behavior across various domains, including education and technology adoption. Within mobile learning, SE refers to students' confidence in their ability to use mobile learning platforms effectively. This construct was particularly relevant in educational settings where technology could pose challenges to students who might feel uncertain about their technical skills. SE influenced not only the initial decision to engage with mobile learning but also the extent to which students were willing to persevere in the face of difficulties. Previous research consistently highlighted the significant effect of SE on PEU. Studies indicated that students with high levels of SE were more likely to perceive mobile learning platforms as easy to use. This was because students who believed in their technical abilities were more likely to approach mobile learning with a positive mindset, capable of overcoming any challenges. For instance, Kumar et al. (2020) found that SE was a strong predictor of PEU, demonstrating that students with higher SE were more likely to see mobile learning tools as straightforward and manageable. This relationship underscored the importance of enhancing students' SE to improve their experiences with mobile learning platforms, ultimately leading to greater adoption and sustained use of these technologies.

The role of SE in influencing PEU has been widely recognized across various technological contexts. Widayati et al. (2023) emphasized that SE is a fundamental determinant of PEU, anchoring initial perceptions that can be adjusted based on user experience. This notion was further supported by Ozturk (2016), who demonstrated that SE significantly influences both PU and PEU. Suryawirawan (2021) also found a positive significant impact of SE on PEU, reinforcing the close relationship between these constructs. Additional studies have confirmed the substantial influence of SE on PEU. For example, Islam et al. (2015) reported that SE has a strong and positive direct influence on PEU, further solidifying the connection between these variables. Habibi et al. (2022) also noted that SE significantly influences PEU and PU, aligning with the broader understanding that SE is critical in shaping users' perceptions of technology. The literature further suggests that SE is closely linked to PEU in various contexts. Rosman et al. (2022) highlighted a positive and significant relationship between SE and PU and ease of use. Similarly, Jou et al. (2022) indicated that computer SE directly influences PEU, affecting PU and attitudes toward technology adoption. Collectively, these findings highlight the critical role of SE in technology adoption. By enhancing SE, educators and technology developers can help improve students' perceptions of ease of use, increasing the likelihood of sustained engagement with mobile learning platforms.

### Facilitating Conditions and Their Role in Learning Adoption

FC refers to the resources, infrastructure, and support systems that enable individuals to use a particular technology effectively. In mobile learning, FC encompassed the availability of necessary technological tools (such as smartphones or tablets), reliable internet connectivity, access to technical support, and a conducive learning environment. These conditions were critical in ensuring students could easily engage with mobile learning platforms without facing significant barriers. The relevance of FC in supporting technology use was well-established, as it directly influenced how users perceived the ease of using a given technology, particularly in educational settings where access to resources could vary widely. Empirical studies consistently demonstrated the impact of FC on PEU and BITML. Research indicated that when students had access to robust FC, they were more likely to perceive mobile learning platforms as easy to use. For instance, Ebadi and Raygan (2023) found that reliable internet and technical support significantly enhanced students' PEU, as these conditions reduced the cognitive load and frustration associated with using new technology. Furthermore, FC also had a direct influence on BITML. Studies showed that students who experienced strong FC were more likely to develop a positive intention to use mobile learning platforms consistently. Hunde et al. (2023) highlighted that the availability of necessary resources not only made the technology more accessible but also increased students' confidence in their ability to use it effectively, thereby strengthening their behavioral intention to adopt mobile learning as a regular part of their educational experience. These findings underscored the importance of investing in and maintaining robust FC to promote the successful adoption and sustained use of mobile learning technologies.

FC was crucial in influencing attitudes and BITML. Various studies emphasized the significance of FC, along with factors like social influence, performance expectancy, and effort expectancy, in shaping individuals' attitudes and intentions to use mobile learning resources (Botero et al., 2022; Handayani, 2023; Kumar et al., 2020; Pramana, 2018). These FCs, which included technical support, resource availability, and infrastructure, consistently emerged as key determinants of BITML (Hoang et al., 2021; Julita, 2023; Talan, 2024). Moreover, FC was shown to positively impact the adoption of various technologies, including mobile learning systems (Huang, 2015; Rahman et al., 2020; Rudhumbu, 2022). The unified theory of acceptance and use of technology (UTAUT) is frequently featured in studies to understand the factors influencing BITML. This theory included constructs such as performance expectancy, effort expectancy, social influence, and FC, all of which played critical roles in shaping attitudes and intentions toward technology use (Botero et al., 2022; Handayani, 2023; Kumar et al., 2020; Pramana, 2018). Additionally, some studies extended the UTAUT model to include other factors such as SE, satisfaction, and hedonic motivation, further illustrating the multifaceted influences on

BITML (Issaramanoros et al., 2018; Izkair & Lakulu, 2021; Kumar et al., 2020). Furthermore, research suggested that FC not only directly impacted behavioral intentions but also mediated the relationship between other factors, such as attitude and intention toward mobile learning (Hameed & Qayyum, 2018; Hameed et al., 2024). Studies also indicated that FC could enhance the learning environment and promote positive ATML, ultimately influencing individuals' intentions to engage with such platforms (Hananto & Srinivasan, 2024; Hoang et al., 2021; Wu & Ho, 2021).

# METHOD

## Research Design and Data Collection

This study adopted a quantitative research design, which was particularly well-suited for examining the relationships between multiple variables within a SEM framework. The quantitative approach was chosen because it allows for a statistical understanding of the factors influencing BITML. This method enabled the researchers to quantitatively assess the strength and significance of the hypothesized paths in the proposed model, providing a robust means to understand the complex interactions between variables such as PU, PEU, and ATML.

The sampling method employed in this study was purposive sampling, targeting students who were actively engaged in mobile learning. Initially, 375 questionnaires were distributed, of which 363 were deemed valid after a validation process. The validation step involved the key question, "Has the user ever used mobile learning?" Out of the 375 respondents, 363 confirmed that they had experience with mobile learning platforms, while the remaining respondents did not, and were therefore excluded from the analysis. The final sample size of 363 respondents was determined based on established guidelines for SEM, ensuring adequate power to detect significant effects within the model. This sample size was sufficient to accurately estimate the relationships between variables and ensure the generalizability of the findings, balancing statistical power with the practical constraints of data collection.

The research focused on users of popular mobile learning platforms widely used in Indonesia, such as Ruangguru, Zenius, and Quipper. These platforms were selected due to their significant presence and widespread adoption among students in Indonesia, making them representative of the broader mobile learning user population in the country. Data was collected from users who actively engaged with these platforms, providing valuable insights into their experiences and perceptions regarding mobile learning. The data collection process was conducted through an online survey using Google Forms, distributed between April and May 2024. The use of an online survey allowed for efficient data collection across a broad geographic area, ensuring diverse participation. Respondents completed a structured questionnaire that included demographic questions and items measuring the key constructs of the study. The two-month data collection period provided sufficient time to gather a representative sample, ensuring that the responses accurately reflected the target population. Google Forms facilitated the systematic organization and retrieval of data, which was then prepared for analysis within the SEM framework. This methodological approach provided a rigorous foundation for examining the factors influencing BITML, leveraging the strengths of quantitative analysis to draw meaningful conclusions from the data.

## Research Model and Hypothesis Development

The research model was grounded in well-established theoretical frameworks, primarily drawing from the TAM and UTAUT. These models provided a robust foundation for understanding how various factors influence the acceptance and use of technology, specifically within mobile learning. The constructs such as PU, PEU, and ATML were integral to these models and had been widely validated in prior research. The current study extended these theories by integrating additional constructs, including ENT, SE, and FC, to develop a more comprehensive understanding of the factors that drive BITML. The hypotheses were carefully developed based on the integrated model, which sought to explore these constructs' direct and indirect effects on BITML. For instance, **H1** hypothesized that SE would positively influence PEU, grounded in the idea that students confident in their technical abilities would find mobile learning platforms easier to use. **H2** and **H3** posited that FC would directly impact PEU and BITML, reflecting the importance of accessible resources and support

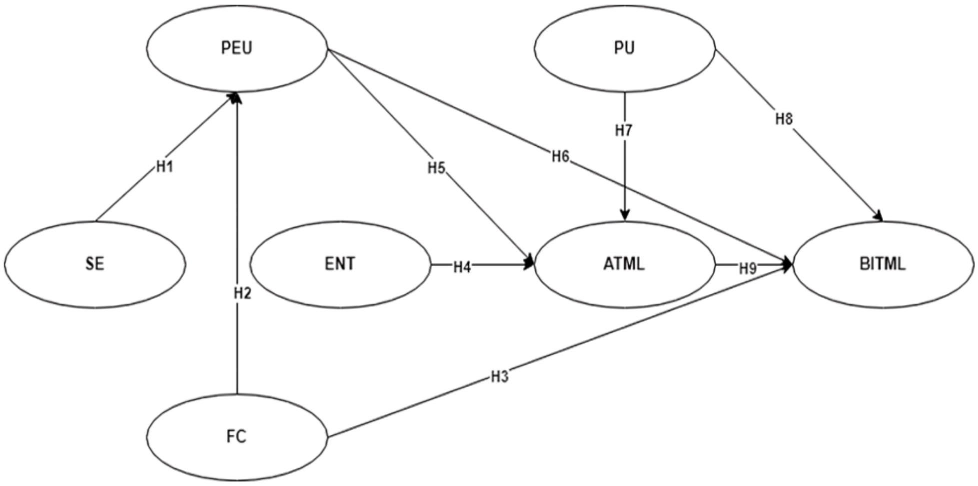


**Figure 1.** Research framework diagram (Source: Authors' own elaboration)

in facilitating the use and adoption of mobile learning technologies. These hypotheses acknowledged the significant role of external factors in easing the adoption process and promoting sustained usage.

Further, **H4** focused on the impact of ENT on ATML, suggesting that the enjoyment derived from mobile learning platforms would enhance students' attitudes toward these technologies. **H5** and **H6** examined PEU's influence on ATML and BITML, underpinned by the notion that easier-to-use technologies reduce cognitive load, thereby fostering more positive attitudes and intentions to use the platforms. The study also hypothesized that PU would directly and indirectly affect BITML. **H7** suggested that PU would positively influence ATML, as students who perceive mobile learning as beneficial to their educational goals will likely develop favorable attitudes toward its use. **H8**, on the other hand, posited a direct relationship between PU and BITML, indicating that the perceived utility of mobile learning could independently drive students' intentions to adopt these platforms. Finally, **H9** hypothesized that ATML would serve as a mediating variable, bridging the influence of PU, PEU, and ENT on BITML. This hypothesis was rooted in the extensive literature suggesting that attitudes are critical predictors of behavioral intentions, particularly in the context of technology adoption. At the conclusion of this section, the research framework diagram, shown in **Figure 1**, is presented to visually represent these hypothesized relationships. This diagram serves as a comprehensive overview of the research model, illustrating the expected pathways between the constructs and highlighting the integrated nature of the study's approach to understanding BITML. The framework provided a clear and structured guide for the subsequent data analysis, ensuring that each hypothesis was systematically tested within the SEM-PLS framework.

## Measurement Instruments

The measurement instruments employed in this study were meticulously developed or adapted from well-established sources to ensure reliability and validity for each construct. The process began with an extensive literature review, focusing on identifying existing scales previously validated in similar contexts. Where necessary, these scales were tailored to fit the specific focus on mobile learning within this research. PU and PEU were measured using items derived from Davis's (1989) TAM. The PU items assessed the extent to which students believed that using mobile learning platforms would enhance their academic performance, while the PEU items evaluated how easy students found it to use these platforms, particularly in terms of navigation and integration into their learning routines. ENT was measured using a scale adapted from Hameed et al. (2024). This construct focused on the degree of enjoyment and engagement students experienced while using mobile learning platforms, particularly in voluntary learning environments where the user's choice and enjoyment are critical for sustained engagement. SE was assessed using items based on Park et al. (2012). These items gauged students' confidence in their ability to effectively navigate and utilize mobile learning platforms, reflecting their perceived competence in using technology in an educational context. FC, which included the availability of necessary resources, infrastructure, and support systems, was measured using a scale adapted from Ebadi and Raygan (2023).

**Table 1.** Item questionnaire

| Item | Questionnaire |
|---|---|
| PU (Davis, 1989) | |
| PU1 | Mobile learning helps me to learn more efficiently. |
| PU2 | Mobile learning improves my academic performance. |
| PU3 | Mobile learning makes my learning more effective. |
| PU4 | Overall, mobile learning is beneficial for my learning. |
| PEU (Davis, 1989) | |
| PEU1 | Learning to use mobile learning is easy for me. |
| PEU2 | It is easy to get materials from mobile learning. |
| PEU3 | The process of using mobile learning is clear and understandable. |
| PEU4 | I find mobile learning easy to use. |
| ENT (Hameed et al., 2024) | |
| ENT1 | Mobile learning is entertaining to me. |
| ENT2 | Mobile learning is fun to use. |
| ENT3 | I feel excited while using mobile learning. |
| ENT4 | I enjoy using mobile learning. |
| SE (Park et al., 2012) | |
| SE1 | I have the necessary skills for mobile learning. |
| SE2 | I am a skillful user of mobile learning on mobile devices. |
| SE3 | I have confidence in using computers and mobile devices for mobile learning. |
| SE4 | I understand computer and mobile device terms well for mobile learning. |
| FC (Ebadi & Raygan, 2023) | |
| FC1 | I can easily access mobile-based technological devices (e.g., smartphones or tablets). |
| FC2 | I can have an internet connection on a smartphone or tablet regularly and easily. |
| FC3 | I have access to useful apps for mobile learning on smartphones or tablets. |
| FC4 | I am provided with enough support if I face issues with a smartphone or tablet. |
| ATML (Hameed et al., 2024) | |
| ATML1 | Using mobile learning is a good idea. |
| ATML2 | Using mobile learning for learning purposes is a wise idea. |
| ATML3 | Using mobile learning is a pleasant experience. |
| ATML4 | It is desirable to use mobile learning. |
| BITML (Hameed et al., 2024) | |
| BITML1 | I am likely to use mobile learning in the future. |
| BITML2 | I intend to use mobile learning for learning purposes. |
| BITML3 | I intend to use mobile learning frequently for learning purposes. |
| BITML4 | I would consider using mobile learning for learning purposes. |

ATML and BITML were measured using scales adapted from Hameed et al. (2024). ATML assessed students' overall positive or negative evaluation of mobile learning platforms, encompassing cognitive and affective components. BITML, on the other hand, measured the degree to which students intended to continue using mobile learning platforms in the future. These measurement instruments underwent rigorous testing for internal consistency and reliability through pilot studies before being employed in the main data collection process. The specific items used for each of these constructs are presented in **Table 1**: Questionnaire items, which provides a comprehensive overview of the survey items organized by construct. This careful selection and adaptation of measurement instruments ensured that the data collected was robust and suitable for subsequent SEM-PLS analysis, providing a strong foundation for the study's findings.

## Data Analysis

The data analysis in this study was conducted using SmartPLS, a powerful tool for partial least squares SEM. The process began with data preparation, where the collected survey responses were cleaned and screened for any missing or inconsistent entries. Once the dataset was finalized, it was imported into SmartPLS for further analysis. The analysis proceeded in two main stages: evaluation of the measurement model and evaluation of the structural model. The first stage involved assessing the measurement model to ensure that the constructs were reliably and validly measured. This was done by evaluating both reliability and validity metrics. Reliability was assessed using Cronbach's alpha and composite reliability, with thresholds of 0.70 or higher indicating acceptable internal consistency. Validity was examined through two main types: convergent validity and discriminant validity. Convergent validity was evaluated by checking the average variance extracted (AVE) for each construct, with values above 0.50 indicating that the construct explained

**Table 2.** Demographic data

| Demographic characteristic | Category | Frequency | Percentage (%) |
|---|---|---|---|
| Gender | Male | 182 | 50.14 |
| | Female | 181 | 49.86 |
| Education | High school | 85 | 23.42 |
| | Bachelor | 130 | 35.81 |
| | Master | 148 | 40.77 |
| Age | 18–24 | 111 | 30.58 |
| | 25–34 | 147 | 40.50 |
| | 35–44 | 62 | 17.08 |
| | 45+ | 43 | 11.85 |
| Smartphone usage for learning purposes (daily) | 1–2 hours | 109 | 30.03 |
| | 2–4 hours | 110 | 30.30 |
| | Less than 1 hour | 80 | 22.04 |
| | More than 4 hours | 64 | 17.63 |
| Smartphone usage for learning purposes (weekly) | 1 day | 60 | 16.53 |
| | 2–3 days | 109 | 30.03 |
| | 4–5 days | 116 | 31.96 |
| | 6–7 days | 78 | 21.49 |

more than half of the variance of its indicators. Discriminant validity was assessed using the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio, ensuring that each construct was distinct from the others in the model.

Following the validation of the measurement model, the analysis moved to the structural model evaluation. This stage involved assessing the relationships between the constructs as hypothesized in the research model. Path coefficients ($\beta$s) were calculated to determine the strength and direction of these relationships. Hypothesis testing was then conducted by examining the significance of the $\beta$, with bootstrapping procedures employed to generate t-statistics and p-values. A path was considered significant if the p-value was less than 0.05. Additionally, the model's overall fit was assessed using the standardized root mean square residual, with values below 0.08 indicating a good fit. The structural model's evaluation also included assessing the model's predictive accuracy through R-squared ($R^2$) values for each endogenous construct. These values indicated the proportion of variance in the dependent variables that the independent variables could explain. In this study, $R^2$ values were used to gauge the model's explanatory power, with higher values indicating greater predictive accuracy. The combined assessment of $\beta$, hypothesis testing results, and model fit indices provided a comprehensive evaluation of the structural model, ensuring that the relationships between the variables were robust and meaningful. This rigorous approach to data analysis ensured that the study's findings were based on a solid empirical foundation, providing valuable insights into the factors influencing BITML.

# RESULT & DISCUSSION

## Descriptive Statistics

The sample's demographic characteristics provided a comprehensive overview of the participants involved in the study, as shown in **Table 2**. **Table 2** provides a detailed breakdown of the demographic characteristics of the respondents, including gender, education level, age, hours spent on smartphones for learning, and the frequency of mobile learning platform usage. **Table 2** is a foundational reference for understanding the context in which the study's findings were derived, ensuring that the analysis was grounded in a well-characterized sample.

The sample consisted of 363 respondents, with a nearly even gender distribution. Specifically, 181 (49.86%) were female, while 182 (50.14%) were male. This balanced representation ensured that the study's findings were not biased toward one gender, allowing for more generalizable conclusions regarding the factors influencing BITML. Most respondents held advanced degrees in education. A total of 148 (40.77%) had obtained a master's degree, while 130 respondents (35.81%) held a bachelor's degree. The remaining 85 respondents (23.42%) had completed high school as their highest level of education. The distribution of education levels suggested that the sample was relatively well-educated, which could affect their familiarity

**Table 3.** Inner VIF results

| Path | VIF value |
|---|---|
| SE → PEU | 2.326 |
| FC → PEU | 2.326 |
| FC → BITML | 3.105 |
| ENT → ATML | 3.367 |
| PEU → ATML | 2.618 |
| PEU → BITML | 4.027 |
| PU → ATML | 4.003 |
| PU → BITML | 7.173 |
| ATML → BITML | 7.900 |

and comfort with mobile learning technologies. The age distribution of the respondents indicated a concentration in the younger and middle-aged demographics. The largest age group was 25–34 years old, comprising 147 respondents (40.50%), followed by the 18–24 age group, with 111 respondents (30.58%). The 35–44 age group accounted for 62 respondents (17.08%), while those aged 45 and above were the smallest group, with 43 respondents (11.85%). This age distribution highlighted that most respondents were likely to be in their careers' early or mid-stages, potentially influencing their engagement with mobile learning as a means of professional development or continued education.

Regarding smartphone usage for learning purposes, respondents varied in the amount of time they spent daily on mobile learning. A significant portion of the sample, 110 respondents (30.30%), reported spending 2–4 hours daily on their smartphones for learning. A similar percentage, 109 respondents (30.03%), used their smartphones for 1–2 hours daily. Meanwhile, 80 respondents (22.04%) spent less than 1 hour per day, and 64 respondents (17.63%) reported spending more than 4 hours on smartphone-based learning activities. These figures suggested that a considerable portion of the respondents were actively using mobile learning platforms, with a significant number dedicating multiple hours each day to these activities. Finally, the frequency of mobile learning platform usage varied among the respondents. A total of 116 respondents (31.96%) used mobile learning platforms 4–5 days per week, indicating a regular and consistent engagement with these technologies. Another 109 respondents (30.03%) reported using mobile learning platforms 2–3 days per week, while 78 respondents (21.49%) used them 6–7 days per week, reflecting a high commitment to mobile learning. The remaining 60 respondents (16.53%) engaged with mobile learning platforms only 1 day per week. This variation in usage frequency provided insights into the different levels of engagement and dependence on mobile learning across the sample.

The variance inflation factor (VIF) analysis was conducted as part of the preliminary evaluation of the measurement model to assess the presence of multicollinearity among the independent variables. Multicollinearity occurs when independent variables in a regression model are highly correlated, which can distort the regression coefficients' estimates and affect the results' reliability. VIF values greater than 10 typically indicate significant multicollinearity issues, while values below this threshold suggest that multicollinearity is not a concern.

The results of the VIF analysis, as presented in **Table 3**, indicated that all the VIF values were below the critical threshold of 10, suggesting that multicollinearity was not an issue in this study. The highest VIF value was observed for the path from ATML to BITML, with a VIF of 7.900, which, although substantial, was still within acceptable limits. This finding suggested that ATML, while highly correlated with BITML, did not excessively inflate the variance of the regression coefficients in the model. Other notable VIF values included 7.173 for the path from PU to BITML and 4.027 for the path from PEU to BITML, indicating moderate correlations between these variables and BITML. The VIF values for the paths from FC to BITML (3.105) and from ENT to ATML (3.367) further supported the absence of severe multicollinearity in the model. The remaining VIF values for the paths from FC to PEU (2.326), SE to PEU (2.326), PEU to ATML (2.618), and PU to ATML (4.003) were all well below the threshold, reinforcing the robustness of the model's estimates.

## Measurement Model Evaluation

The measurement model was evaluated to ensure the reliability and validity of the constructs used in this study. Reliability was assessed through Cronbach's alpha and composite reliability, shown in **Table 4**. While

**Table 4.** Reliability analysis and convergent validity

| Construct | Item | Factor loading | Cronbach's alpha | Composite reliability | AVE |
|---|---|---|---|---|---|
| ATML | ATML1 | 0.651 | 0.645 | 0.789 | 0.484 |
| | ATML2 | 0.69 | | | |
| | ATML3 | 0.686 | | | |
| | ATML4 | 0.751 | | | |
| BITML | BITML1 | 0.492 | 0.331 | 0.663 | 0.336 |
| | BITML2 | 0.494 | | | |
| | BITML3 | 0.57 | | | |
| | BITML4 | 0.729 | | | |
| ENT | ENT1 | 0.699 | 0.643 | 0.788 | 0.482 |
| | ENT2 | 0.712 | | | |
| | ENT3 | 0.645 | | | |
| | ENT4 | 0.718 | | | |
| FC | FC1 | 0.767 | 0.651 | 0.791 | 0.487 |
| | FC2 | 0.689 | | | |
| | FC3 | 0.621 | | | |
| | FC4 | 0.707 | | | |
| PEU | PEU1 | 0.579 | 0.382 | 0.68 | 0.349 |
| | PEU2 | 0.521 | | | |
| | PEU3 | 0.573 | | | |
| | PEU4 | 0.678 | | | |
| PU | PU1 | 0.739 | 0.721 | 0.826 | 0.544 |
| | PU2 | 0.707 | | | |
| | PU3 | 0.729 | | | |
| | PU4 | 0.773 | | | |
| SE | SE1 | 0.721 | 0.637 | 0.785 | 0.478 |
| | SE2 | 0.642 | | | |
| | SE3 | 0.632 | | | |
| | SE4 | 0.763 | | | |

**Table 5.** Discriminant validity

| | ATML | BITML | ENT | FC | PEU | PU | SE |
|---|---|---|---|---|---|---|---|
| ATML | 0.695 | | | | | | |
| BITML | 0.826 | 0.579 | | | | | |
| ENT | 0.897 | 0.725 | 0.694 | | | | |
| FC | 0.719 | 0.738 | 0.635 | 0.698 | | | |
| PEU | 0.841 | 0.778 | 0.722 | 0.742 | 0.59 | | |
| PU | 0.904 | 0.786 | 0.829 | 0.788 | 0.773 | 0.737 | |
| SE | 0.814 | 0.684 | 0.742 | 0.755 | 0.732 | 0.834 | 0.692 |

most constructs demonstrated acceptable internal consistency, with Cronbach's alpha values within reasonable ranges, a few constructs, such as BITML and PEU, exhibited lower Cronbach's alpha values. These findings suggest a degree of variation within the items of these constructs, which, while slightly below conventional thresholds, still provided meaningful insights into the constructs measured. Composite reliability values, on the other hand, ranged from 0.663 to 0.826, indicating that most of the constructs were measured with a good level of reliability.

Convergent validity was evaluated using each construct's AVE. The results showed that PU exceeded the commonly accepted AVE threshold of 0.50, reflecting strong convergent validity for this construct. Although a few other constructs, such as ATML and ENT, had AVE values slightly below the 0.50 threshold, they were nonetheless close to this benchmark, suggesting that these constructs captured a substantial portion of the variance of their indicators. The overall trend indicated that the constructs were generally well-defined and provided a reliable basis for further analysis.

Discriminant validity, shown in **Table 5**, was assessed using the Fornell-Larcker criterion, which confirmed that the constructs were distinct in most cases. The square root of the AVE for each construct generally exceeded the correlations with other constructs, affirming their discriminant validity. However, while some correlations were relatively high, the distinctiveness of each construct was maintained overall.

**Table 6.** Inner model results (summary)

| Hypothesis | Path | Coefficient | t-statistics | p-values | Supported |
|---|---|---|---|---|---|
| H1 | SE → PEU | 0.400 | 7.245 | 0.000 | Yes |
| H2 | FC → PEU | 0.440 | 7.601 | 0.000 | Yes |
| H3 | FC → BITML | 0.245 | 4.082 | 0.000 | Yes |
| H4 | ENT → ATML | 0.401 | 13.075 | 0.000 | Yes |
| H5 | PEU → ATML | 0.272 | 9.120 | 0.000 | Yes |
| H6 | PEU → BITML | 0.172 | 2.500 | 0.013 | Yes |
| H7 | PU → ATML | 0.362 | 10.859 | 0.000 | Yes |
| H8 | PU → BITML | 0.020 | 0.241 | 0.810 | No |
| H9 | ATML → BITML | 0.486 | 5.461 | 0.000 | Yes |

## Structural Model Evaluation

The evaluation of the structural model focused on examining the $\beta$s and their significance levels for each of the hypothesized relationships within the proposed framework. These $\beta$s provided insights into the strength and direction of the relationships between the variables. The analysis revealed that several paths were statistically significant, indicating meaningful relationships between the constructs. The relationship between ATML and BITML was particularly strong, with a $\beta$ of 0.486. This suggests that a positive attitude towards mobile learning significantly increased students' intention to use mobile learning platforms. Similarly, the path from ENT to ATML had a coefficient of 0.401, indicating that students who found mobile learning enjoyable were more likely to develop a favorable attitude towards it. Additionally, FC showed a moderate positive effect on both BITML (0.245) and PEU (0.440), highlighting the importance of supportive environments and resources in enhancing both the ease of use and the intention to use mobile learning.

Other notable paths included the influence of PEU on ATML (0.272) and BITML (0.172), as well as the impact of PU on ATML (0.362). Interestingly, the direct effect of PU on BITML was minimal (0.020), suggesting that while PU contributed to shaping attitudes towards mobile learning, its direct impact on behavioral intention was less pronounced. The relationship between SE and PEU was also significant, with a $\beta$ of 0.400, indicating that students' confidence in their ability to use mobile learning platforms positively influenced their PEU. The $R^2$ values provided further insights into the model's explanatory power. The $R^2$ value for ATML was 0.916, indicating that the independent variables in the model explained approximately 91.6% of the variance in students' ATML. For BITML, the $R^2$ value was 0.732, suggesting that the model accounted for 73.2% of the variance in behavioral intention. The $R^2$ value for PEU was 0.619, demonstrating that the model explained 61.9% of the variance in PEU. These high $R^2$ values indicated the model had strong explanatory power, effectively capturing the key factors influencing ATML and BITML. These findings supported the structural model's overall fit, as the $\beta$s and $R^2$ values suggested that the model was both statistically significant and practically meaningful.

## Hypothesis Testing Results

The hypothesis testing results provided critical insights into the relationships between the variables within the structural model. These results were evaluated based on the $\beta$, t-statistics, and p-values, all of which are summarized in **Table 6**.

**H1** examined the impact of SE on PEU and was strongly supported with a $\beta$ of 0.400, a t-statistic of 7.245, and a p-value of 0.000. This confirmed that students' confidence in their ability to use mobile learning platforms positively influenced their perception of ease of use. **H2** and **H3** explored the role of FC, showing significant effects on both PEU ($\beta$ = 0.440, t-statistic = 7.601, p-value = 0.000) and BITML ($\beta$ = 0.245, t-statistic = 4.082, p-value = 0.000). These results suggested that the availability of supportive resources and infrastructure significantly enhanced students' perception of the ease of use of these platforms and their intention to use mobile learning. **H4** focused on the influence of ENT on ATML, which was strongly supported with a $\beta$ of 0.401, a t-statistic of 13.075, and a p-value of 0.000. This demonstrated that students who found mobile learning enjoyable were more inclined to develop positive attitudes toward it.

**H5** and **H6** examined the impact of PEU on ATML and BITML, respectively. The relationship between PEU and ATML was significant ($\beta$ = 0.272, t-statistic = 9.120, p-value = 0.000), reinforcing the importance of user-friendly platforms in shaping positive attitudes. However, the direct impact of PEU on BITML, while significant,

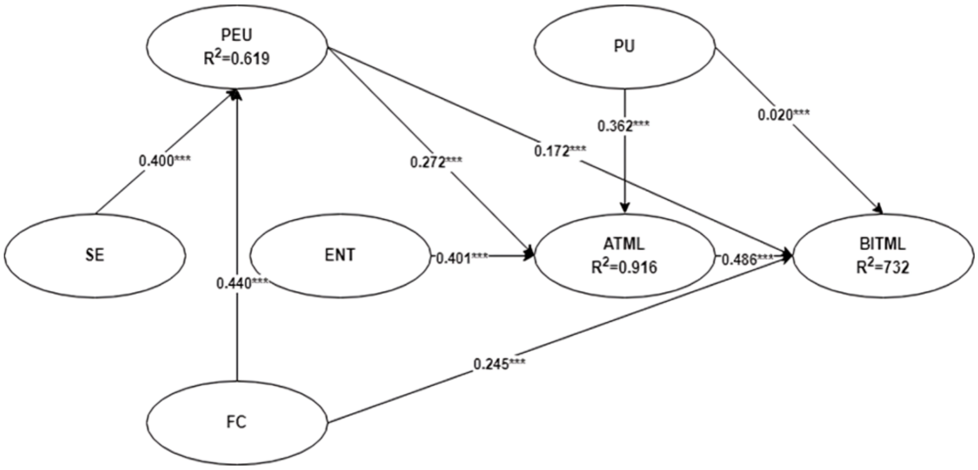


**Figure 2.** Inner model result framework (Source: Authors' own elaboration)

**Table 7.** Mediation testing results

| Construct | Construct relationship | t-value of path coefficient | Sobel test |
|---|---|---|---|
| PU → ATML → BITML | PU → ATML | 0.362 | 4.25 |
| | ATML → BITML | 0.486 | |
| ENT → ATML → BITML | ENT → ATML | 0.401 | 4.66 |
| | ATML → BITML | 0.486 | |
| PEU → ATML → BITML | PEU → ATML | 0.272 | 3.27 |
| | ATML → BITML | 0.486 | |

was less pronounced ($\beta$ = 0.172, t-statistic = 2.500, p-value = 0.013), suggesting that ease of use plays a role in shaping behavioral intentions, albeit to a lesser extent. **H7** and **H8** explored the influence of PU on ATML and BITML. PU had a significant effect on ATML ($\beta$ = 0.362, t-statistic = 10.859, p-value = 0.000), indicating that students who found mobile learning useful were more likely to develop positive attitudes toward it. However, the direct path from PU to BITML was not significant ($\beta$ = 0.020, t-statistic = 0.241, p-value = 0.810), suggesting that while PU contributed to shaping attitudes, its direct impact on BITML was minimal. Finally, **H9** evaluated the impact of ATML on BITML, which was strongly supported with a $\beta$ of 0.486, a t-statistic of 5.461, and a p-value of 0.000. This indicated a highly significant positive effect, confirming that students with a favorable ATML were more likely to intend to use these platforms. The inner model results highlighted the key drivers of BITML, emphasizing the significant roles of attitude, entertainment, FC, and ease of use. The final structural model, including all significant paths, is visually represented in the inner model results framework figure, which illustrates the strength and direction of each relationship within the model, shown in **Figure 2**.

## Testing for Mediating Effects

The mediating effects of ATML between the independent variables (PU, ENT, and PEU) and BITML were tested using the Sobel test, shown in **Table 7**. This test was conducted to assess the significance of the indirect effects of these independent variables on BITML through ATML.

The Sobel test results indicated that ATML significantly mediated the relationships between the independent variables and BITML. Specifically, the mediation effect in the path from PU through ATML to BITML yielded a significant Sobel Z-value of 4.25, suggesting that the indirect effect of PU on BITML via ATML was significant. Similarly, the mediation effect from ENT through ATML to BITML was also significant, with a Sobel Z-value of 4.66, highlighting the important role of ENT in shaping students' BITML through their ATML. Finally, the path from PEU through ATML to BITML showed a significant Sobel Z-value of 3.27, further reinforcing the mediating role of ATML in this relationship. These findings underscored the critical function of ATML as a mediator that channels the effects of key independent variables on BITML, emphasizing the importance of fostering positive ATML to enhance students' BITML.

## Interpretation of Findings

The results of this study indicated that PU had a strong impact on ATML, reaffirming the critical role that perceived utility plays in the adoption of mobile learning platforms. This finding aligns with the TAM, which posits that the more users perceive technology as useful, the more likely they are to develop a positive attitude toward its use. The positive relationship between PU and ATML in this study corroborates existing research, particularly the work of Kampa (2023), which emphasized the importance of PU in shaping users' attitudes in educational technology adoption. Furthermore, the analysis revealed that while PU had a significant direct effect on ATML, its direct impact on BITML was relatively weaker. Instead, the effect of PU on BITML was more pronounced when mediated by ATML. This suggests that students' behavioral intentions to use mobile learning platforms were not only influenced by the perceived benefits of the technology but were more strongly driven by their overall attitude toward using it. The stronger mediated effect highlights the importance of fostering positive attitudes to fully translate PU into sustained behavioral intentions. This finding is consistent with prior studies in technology acceptance, including the work of Davis (1989) on PU in TAM, Venkatesh and Davis (2000) on technology adoption in various contexts, and Venkatesh et al. (2003), who examined the impact of perceived utility across different technological environments.

The study found that PEU significantly impacted ATML, underscoring the importance of ease of use in shaping students' attitudes toward mobile learning platforms. This finding is consistent with the TAM, which posits that technologies perceived as easy to use are more likely to be embraced by users. The positive relationship between PEU and ATML suggests that when students find mobile learning platforms easy to navigate and integrate into their learning routines, they are more likely to develop favorable attitudes toward these platforms. However, the impact of PEU on BITML was found to be less pronounced than anticipated. While PEU did have a direct effect on BITML, its influence was weaker compared to other factors, such as PU and ATML. This outcome may be attributed to the growing familiarity of students with mobile applications, which has diminished the relative importance of ease of use as a determining factor in their intention to adopt and continue using mobile learning platforms. As students become more accustomed to using various digital tools, they may prioritize other aspects, such as content quality and engagement, over ease of use, leading to a lower-than-expected impact of PEU on their behavioral intentions.

The study highlighted ENT's significant role in influencing ATML and BITML. The findings indicated that when students found mobile learning platforms entertaining, they were more likely to develop positive attitudes toward these platforms, which in turn strengthened their intention to use them regularly. The entertainment value of mobile learning platforms played a crucial role in enhancing student engagement, making the learning process more enjoyable and intrinsically motivating. This relationship underscores the importance of designing educational technologies that are functional and enjoyable to use, as this can significantly drive adoption and sustained use. These results align with the findings of Hameed et al. (2024), who emphasized that entertainment value is a key factor in promoting user engagement and fostering positive behavioral intentions in voluntary learning environments. The study's results also resonate with other research highlighting the role of engagement and intrinsic motivation in educational settings. In environments where learning is not mandatory, a platform's ability to capture and retain students' interest through entertainment can be a decisive factor in its success. This underscores the need for educators and developers to prioritize entertainment elements in mobile learning platforms to maximize their impact on student learning outcomes and behavioral intentions.

The findings of this study underscored the strong impact of FC on PEU and BITML. The presence of robust FC, such as reliable internet access, availability of mobile devices, and adequate technical support, significantly enhanced students' perception of the ease of using mobile learning platforms. This, in turn, positively influenced their intention to adopt and consistently use these platforms. The study's results suggest that when students have access to necessary resources and a supportive infrastructure, their overall experience with mobile learning technologies becomes more seamless, reducing barriers to adoption and increasing their likelihood of sustained use. These findings align with the broader literature emphasizing the importance of infrastructure, resources, and support systems in technology adoption, as evidenced by studies like Ebadi and Raygan (2023) and Hunde et al. (2023). Previous studies have highlighted that strong FC are essential in lowering the cognitive and logistical barriers associated with using new technologies. This study's results further support the notion that educational institutions must invest in and enhance their supporting infrastructure to ensure that students can fully benefit from mobile learning platforms. By providing the necessary resources and support, institutions can improve the ease of use of these technologies and foster a more favorable environment for students' continued engagement and learning.

This study made significant contributions to the theoretical understanding of mobile learning adoption by confirming the roles of several key constructs within the context of SEM. One of the primary contributions was validating the mediating role of ATML between independent variables such as PU, PEU, and ENT and the dependent variable, BITML. The findings reinforced that students' attitudes play a crucial intermediary role in translating perceptions of usefulness, ease of use, and entertainment into actionable intentions to use mobile learning platforms. This underscores the importance of focusing on the technical attributes of mobile learning technologies and strategies that positively influence students' attitudes. Additionally, the study's results suggested a potential need to re-evaluate the role of PEU, especially in contexts where users are already familiar with technology. While PEU significantly influenced ATML, its direct impact on BITML was less pronounced than anticipated. This might indicate that in environments where students are already accustomed to digital platforms, the PEU may be less critical in determining their BITML. This finding encourages a re-examination of existing theoretical models to account for the evolving technological proficiency of users, suggesting that other factors, such as engagement or perceived value, might become more relevant in predicting technology adoption as user familiarity increases.

The findings of this study offered valuable insights for educators and developers seeking to enhance the effectiveness of mobile learning platforms. Based on the strong influence of PU and ENT on ATML and BITML, it was recommended that mobile learning platforms prioritize integrating features that maximize utility and entertainment. Educators and developers could achieve this by incorporating interactive and engaging content that meets educational objectives and sustains students' interest and enjoyment. Additionally, the platform should be designed to demonstrate the tangible benefits of its use, such as improving academic performance and learning efficiency, which could enhance students' perceptions of its usefulness. Moreover, FC's significant role highlighted the importance of ensuring that the necessary infrastructure and support systems are in place to facilitate the seamless adoption of mobile learning. Educational institutions and platform developers should focus on providing reliable access to technological resources, such as smartphones, tablets, and stable internet connections, as well as offering technical support to resolve any issues that students may encounter. This could reduce potential barriers to technology adoption and improve students' overall experience with mobile learning platforms.

Creating positive attitudes toward mobile learning emerged as a crucial driver of its adoption. Therefore, it was essential for educators and developers to focus on strategies that foster favorable attitudes among students. This could involve providing training sessions that build confidence in using mobile learning tools, promoting success stories that showcase the benefits of mobile learning, and actively seeking and responding to student feedback to improve the platform's design and functionality continuously. By emphasizing the development of positive attitudes, educators, and developers could significantly boost students' willingness to engage with and adopt mobile learning technologies in the long term. The findings of this study were largely consistent with existing research in technology adoption and mobile learning. For example, the significant impact of PU on ATML aligned with previous studies, such as those by Kampa (2023), which also emphasized the role of perceived utility in shaping user attitudes. Similarly, the influence of ENT on ATML and BITML echoed the findings of Hameed et al. (2024), who highlighted the importance of entertainment value in engaging users and driving their behavioral intentions. However, this study also observed some nuances that differed slightly from earlier research. The relatively weaker direct effect of PEU on BITML, compared to its impact on ATML, suggested that in contexts where users are already familiar with mobile technologies, ease of use might be less critical in determining their intention to continue using the platforms. This finding suggested a potential shift in the importance of PEU in more technologically literate populations, a factor that may warrant further investigation in future studies.

## Limitations of the Study

Despite the valuable insights gained from this research, several limitations should be acknowledged. One significant area for improvement was the reliance on self-reported data, which could introduce bias due to social desirability or inaccurate self-assessment. Using a cross-sectional survey design also limited the ability to establish causality between the variables, as the data only provided a snapshot of respondents' perceptions at a single point in time. Additionally, while adequate for SEM-PLS analysis, the sample size was relatively modest and may only partially represent the broader population of mobile learning users. The study was also conducted within a specific geographical and cultural context, which could affect the generalizability of the findings to other regions or educational systems. These constraints should be considered when interpreting the results, and future research should address these limitations by employing longitudinal designs, larger sample sizes, and more diverse populations to validate and extend the findings of this study.

## CONCLUSION

This study provided significant insights into the factors influencing BITML through developing and testing an integrated model using SEM. The findings revealed that PU, PEU, ENT, and FC were critical determinants of ATML, which played a pivotal role in shaping BITML. While PU and ENT exhibited strong direct effects on ATML, PEU's influence was more nuanced, showing a stronger impact through ATML than directly on BITML. FC enhanced PEU and directly influenced BITML, underscoring the importance of supportive infrastructure in mobile learning adoption. This research contributed to the theoretical understanding of mobile learning adoption by confirming the mediating role of ATML between key independent variables (PU, PEU, ENT, and FC) and BITML. The study extended existing models by integrating multiple constructs, offering a more comprehensive view of how different factors influence mobile learning adoption. The findings highlighted the critical role of entertainment value and FC in enhancing user attitudes and behavioral intentions, providing new insights into the motivational aspects of mobile learning.

The practical implications of this study were significant for educators, policymakers, and developers of mobile learning platforms. For educators, the findings suggested that enhancing mobile learning tools' PU and entertainment value could lead to more positive attitudes and higher adoption rates among students. Policymakers were encouraged to invest in and promote the necessary infrastructure, such as reliable internet access and technical support, to reduce barriers to mobile learning adoption. Developers should focus on creating engaging, easy-to-use platforms that meet educational needs and offer an enjoyable user experience, thereby fostering sustained usage. Despite the contributions of this study, several limitations were noted. The reliance on self-reported data could introduce bias, and the cross-sectional design limited the ability to infer causality. While adequate for SEM analysis, the sample size was relatively modest and may only partially represent the broader population of mobile learners. Additionally, the study's focus on a specific geographical region may limit the generalizability of the findings. Future research should address these limitations by employing longitudinal designs, expanding the sample size, and including more diverse populations to validate and extend the current findings. Investigating additional variables, such as social influence or personal innovation, could also provide a richer understanding of mobile learning adoption.

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**Ethics declaration:** The authors affirmed that this study was conducted under the affiliation of Bina Bangsa University and Amikom Purwokerto University. The study was carried out in accordance with the highest ethical standards, ensuring the integrity and reliability of the research process. Prior to data collection, the study received ethical approval from the Ethical Committee of Bina Bangsa University and Amikom Purwokerto University. Participants were fully informed about the purpose, scope, and nature of the study, and their voluntary informed consent was obtained before participation. The research adhered strictly to standards of data privacy and confidentiality, ensuring that all personal information provided by the participants was anonymized and used exclusively for academic purposes. As part of the ethical procedures, the study complied with institutional guidelines and followed internationally recognized principles to safeguard participant welfare and ensure their rights were respected throughout the research process. This declaration underscores the authors' commitment to conducting ethical and responsible research while maintaining transparency and accountability in all aspects of the study.

**Declaration of interest:** The authors declare no competing interest.

**Data availability:** Data generated or analyzed during this study are available from the authors on request.

## REFERENCES

Açıkgül, K., & Şad, S. N. (2021). High school students' acceptance and use of mobile technology in learning mathematics. *Education and Information Technologies, 26*(4), 4181–4201. https://doi.org/10.1007/s10639-021-10466-7

Aggarwal, D. (2019). Mobile technology adoption by Indian consumers. *International Journal of Recent Technology and Engineering, 8*(2S6), 892–899. https://doi.org/10.35940/ijrte.B1166.0782S619

Alanazi, A., Elias, N. F. B., Mohamed, H. B., & Sahari, N. (2024). The critical success factors influencing the use of mobile learning and its perceived impacts in students' education: A systematic literature review. *KSII Transactions on Internet and Information Systems, 18*(3), 610–632. https://doi.org/10.3837/tiis.2024.03.005

Aljaaidi, K. S., Bagais, O. A., & Sharma, R. B. (2020). Factors influencing usage of university mobile application among university students. *Journal of Asian Finance Economics and Business, 7*(10), 1129–1136. https://doi.org/10.13106/jafeb.2020.vol7.no10.1129

Almaiah, M. A., Alamri, M. M., & Al-Rahmi, W. M. (2019). Applying the UTAUT model to explain the students' acceptance of mobile learning system in higher education. *IEEE Access, 7*, 174673–174686. https://doi.org/10.1109/access.2019.2957206

Almogren, A. S., & Aljammaz, N. A. (2022). The integrated social cognitive theory with the TAM model: The impact of M-learning in King Saud University art education. *Frontiers in Psychology, 13*. https://doi.org/10.3389/fpsyg.2022.1050532

Al-Rahmi, A. M., Al-Rahmi, W. M., Alturki, U., Aldraiweesh, A., Almutairy, S., & Al-Adwan, A. S. (2021). Exploring the factors affecting mobile learning for sustainability in higher education. *Sustainability, 13*(14), Article 7893. https://doi.org/10.3390/su13147893

Alshammari, R., Parkes, M., & Adlington, R. (2018). Factors influencing Saudi Arabian preparatory year students' skills and attitudes in the use of mobile devices in learning English as a foreign language. *International Journal of Research Studies in Educational Technology, 7*(1). https://doi.org/10.5861/ijrset.2018.3002

Althunibat, A., Almaiah, M. A., & Altarawneh, F. (2021). Examining the factors influencing the mobile learning applications usage in higher education during the COVID-19 pandemic. *Electronics, 10*(21), Article 2676. https://doi.org/10.3390/electronics10212676

Anuyahong, B. (2023). Exploring the effectiveness of mobile learning technologies in enhancing student engagement and learning outcomes. *International Journal of Emerging Technologies in Learning, 18*(18), 50–63. https://doi.org/10.3991/ijet.v18i18.40445

Berlilana, & Mu'amar, A. (2024). Economic decentralization through blockchain opportunities challenges and new business models. *Journal of Current Research in Blockchain, 1*(2), 112–123. https://doi.org/10.47738/jcrb.v1i2.14

Biswas, B. B., Roy, S. C., & Roy, F. (2020). Students perception of mobile learning during COVID-19 in Bangladesh: University student perspective. *Aquademia, 4*(2), Article ep20023. https://doi.org/10.29333/aquademia/8443

Botero, G. G., Nguyet, D. A., Botero, J. G., Zhu, C., & Questier, F. (2022). Acceptance and use of mobile-assisted language learning by higher education language teachers. *Lenguaje, 50*(1), 66–92. https://doi.org/10.25100/lenguaje.v50i1.11006

Bukharaev, N., & Altaher, A. W. (2017). Mobile learning education has become more accessible. *American Journal of Computer Science and Information Technology, 5*(2). https://doi.org/10.21767/2349-3917.100005

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Department of Technology and Vocational Education, Universitas Negeri Yogyakarta, Sleman, Indonesia, & Hakiki, M. (2024). Effectiveness of Android-based mobile learning in graphic design course for digital learning: The development research study. *International Journal of Information and Education Technology, 14*(4), 602–611. https://doi.org/10.18178/ijiet.2024.14.4.2083

Ebadi, S., & Raygan, A. (2023). Investigating the facilitating conditions, perceived ease of use and usefulness of mobile-assisted language learning. *Smart Learning Environments, 10*(1), Article 30. https://doi.org/10.1186/s40561-023-00250-0

El Emary, I. M. M. (2024). Assessing the adoption of Metaverse platforms: A structural equation modeling approach with mediating effects of switching costs. *International Journal Research on Metaverese*, *1*(3), 236–263.

Feng, L. (2023). Factors influencing undergraduate students' intention to use online education platforms. *The Euraseans Journal on Global Socio-Economic Dynamics, 6(43)*, 239–250. https://doi.org/10.35678/2539-5645.6(43).2023.239-250

Ghyas, Q. M., & Kondo, F. N. (2016). Behavioural intention to use mobile entertainment services among Bangladeshi students. *International Journal of E-Services and Mobile Applications, 8*(2), 38–53. https://doi.org/10.4018/ijesma.2016040103

Guo, J., Huang, F., Yong-qiang, L., & Shao-mei, C. (2020). Students perceptions of using mobile technologies in informal English learning during the COVID-19 epidemic: A study in Chinese rural secondary schools. *Journal of Pedagogical Research, 4*(4), 475–483. https://doi.org/10.33902/jpr.2020063786

Habibi, A., Riady, Y., Alqahtani, T. M., Muhaimin, M., Albelbisi, N. A., Jaya, A., & Yaqin, L. N. (2022). Drivers affecting Indonesian pre-service teachers' intention to use M-learning: Structural equation modeling at three universities. *E-Learning and Digital Media, 20*(6), 519–538. https://doi.org/10.1177/20427530221118775

Hakimi, M. (2024). The impact of mobile applications on Quran education: A survey of student performance and satisfaction. *Journal of Digital Learning and Distance Education, 2*(8), 722–736. https://doi.org/10.56778/jdlde.v2i8.220

Hameed, F., & Qayyum, A. (2018). Determinants of behavioral intention towards mobile learning in Pakistan: Mediating role of attitude. *Business & Economic Review, 10*(1), 33–62. https://doi.org/10.22547/ber/10.1.2

Hameed, F., Qayyum, A., & Khan, F. A. (2024). A new trend of learning and teaching: Behavioral intention towards mobile learning. *Journal of Computers in Education, 11*, 149–180. https://doi.org/10.1007/s40692-022-00252-w

Hamid, N. A. A., Ang, S. H., Abdullah, N. H., Ngadiman, Y., & Ahmad, M. F. (2016). The adoption of 4G mobile network services in Klang Valley. In *Proceedings of 2016 6th International Workshop on Computer Science and Engineering* (pp. 272–279). https://doi.org/10.18178/wcse.2016.06.042

Hananto, A. R., & Srinivasan, B. (2024). Comparative analysis of ensemble learning techniques for purchase prediction in digital promotion through social network advertising. *Journal of Digital Market and Digital Currency, 1*(2). https://doi.org/10.47738/jdmdc.v1i2.7

Handayani, W. P. P. (2023). The UTAUT implementation model in defining the behavioral intention of mobile banking users. *Jurnal Manajemen Bisnis, 14*(2), 361–377. https://doi.org/10.18196/mb.v14i2.18649

Handayati, P., & Trisnawati, N. (2023). The intention to use mobile payment during the COVID-19 pandemic: The mediating role of attitude. *Jurnal Pendidikan Ekonomi & Bisnis, 11*(1), 42–50. https://doi.org/10.21009/jpeb.011.1.4

Hartatik, Isnanto, R. R., & Warsito, B. (2024). Applied data science and artificial intelligence for tourism and hospitality industry in society 5.0: A review. *Journal of Applied Data Sciences*, *5*(4), 1566–1578. https://doi.org/10.47738/jads.v5i4.300

Hegarty, B., & Thompson, M. (2019). A teacher's influence on student engagement: Using smartphones for creating vocational assessment ePortfolios. *Journal of Information Technology Education Research, 18*, 113–159. https://doi.org/10.28945/4244

Hoang, Q., Pham, T., Dang, Q., & Nguyễn, T. (2021). Factors influencing Vietnamese teenagers' intention to use mobile devices for English language learning. In *Proceedings of the 18th International Conference of the Asia Association of Computer-Assisted Language Learning* (pp. 230–245). Atlantis Press. https://doi.org/10.2991/assehr.k.211224.023

Huang, J., & Li, H. (2022). Influencing factors of mobile learning interactive behavior: Moderated mediating effect. *International Journal of Information and Education Technology, 12*(8), 772–777. https://doi.org/10.18178/ijiet.2022.12.8.1683

Huang, Y.-M. (2015). Exploring the factors that affect the intention to use collaborative technologies: The differing perspectives of sequential/global learners. *Australasian Journal of Educational Technology, 31*(3). https://doi.org/10.14742/ajet.1868

Hunde, M. K., Demsash, A. W., & Walle, A. D. (2023). Behavioral intention to use e-learning and its associated factors among health science students in Mettu University, southwest Ethiopia: Using modified UTAUT model. *Informatics in Medicine Unlocked, 36*, Article 101154. https://doi.org/10.1016/j.imu.2022.101154

Ibrahim, U. (2024). Assessing the impact of mobile applications on student engagement in ICT and computer science education. *International Journal of Applied Educational Research, 2*(1), 51–62. https://doi.org/10.59890/ijaer.v2i1.1457

Irfan, M. (2024). The role of trust in mediating the impact of electronic word of mouth and security on cryptocurrency purchase decisions. *Journal of Current Research in Blockchain*, *1*(3), 242–266.

Isaías, P., Reis, F. F. D., Coutinho, C. P., & Lencastre, J. A. (2017). Empathic technologies for distance/mobile learning. *Interactive Technology and Smart Education, 14*(2), 159–180. https://doi.org/10.1108/itse-02-2017-0014

Islam, A. Y. M. A., Leng, C. H., & Singh, D. (2015). Efficacy of the technology satisfaction model (TSM). *International Journal of Technology and Human Interaction, 11*(2), 45–60. https://doi.org/10.4018/ijthi.2015040103

Issaramanoros, E., Khlaisang, J., & Pugsee, P. (2018). Auto mechanic students' perceptions and readiness toward mobile learning in Thailand. *International Journal of Interactive Mobile Technologies, 12*(5), Article 28. https://doi.org/10.3991/ijim.v12i5.8906

Izkair, A. S., & Lakulu, M. M. (2021). Experience moderator effect on the variables that influence intention to use mobile learning. *Bulletin of Electrical Engineering and Informatics, 10*(5), 2875–2883. https://doi.org/10.11591/eei.v10i5.3109

Jiang, G., Peng, L., & Liu, R. (2015). Mobile game adoption in China: The role of TAM and perceived entertainment, cost, similarity and brand trust. *International Journal of Hybrid Information Technology, 8*(4), 213–232. https://doi.org/10.14257/ijhit.2015.8.4.24

Jou, Y., Mariñas, K. A., Saflor, C. S., & Young, M. N. (2022). Investigating accessibility of social security system (SSS) mobile application: A structural equation modeling approach. *Sustainability, 14*(13), Article 7939. https://doi.org/10.3390/su14137939

Julita, Z. (2023). Factor analysis of Sharia mobile banking using the UTAUT2 model in millennial generations. *International Journal of Scientific Research and Management, 11*(09), 5152–5163. https://doi.org/10.18535/ijsrm/v11i09.em11

Kampa, R. K. (2023). Combining technology readiness and acceptance model for investigating the acceptance of m-learning in higher education in India. *Asian Association of Open Universities Journal, 18*(2), 105–120. https://doi.org/10.1108/AAOUJ-10-2022-0149

Küçük, S., Onlu, O. B., & Kapakin, S. (2020). A model for medical students' behavioral intention to use mobile learning. *Journal of Medical Education and Curricular Development, 7*. https://doi.org/10.1177/2382120520973222

Kumar, J. A., Bervell, B., Annamalai, N., & Osman, S. (2020). Behavioral intention to use mobile learning: Evaluating the role of self-efficacy, subjective norm, and WhatsApp use habit. *IEEE Access, 8*, 208058–208074. https://doi.org/10.1109/ACCESS.2020.3037925

Lenus, L. (2024). Predicting consumer perceptions of Metaverse shopping through insights from machine learning models. *International Journal Research on Metaverese*, 1(3), 199–211.

Martínez-Ruiz, M. P., Izquierdo-Yusta, A., Pascual, C. O., & Lara, E. M. R. (2017). Do affective variables make a difference in consumers behavior toward mobile advertising? *Frontiers in Psychology, 7*. https://doi.org/10.3389/fpsyg.2016.02018

Min, L. (2024). Instructors' usage of mobile learning applications in classroom and its impact on the learners' performance. *World Journal of Educational Research, 11*(1), Article 48. https://doi.org/10.22158/wjer.v11n1p48

Murnawan, M., Lestari, S., Samihardjo, R., & Dewi, D. A. (2024). Sustainable educational data mining studies: Identifying key factors and techniques for predicting student academic performance. *Journal of Applied Data Sciences, 5*(3). https://doi.org/10.47738/jads.v5i3.347

Naveed, Q. N., Alam, M. M., & Tairan, N. (2020). Structural equation modeling for mobile learning acceptance by university students: An empirical study. *Sustainability, 12*(20), Article 8618. https://doi.org/10.3390/su12208618

Nikolopoulou, K., Saltas, V., & Tsiantos, V. (2023). Postgraduate students' perspectives on mobile technology benefits and learning possibilities: Insights from Greek students. *Trends in Higher Education, 2*(1), 140–151. https://doi.org/10.3390/higheredu2010009

Ozturk, A. B. (2016). Customer acceptance of cashless payment systems in the hospitality industry. *International Journal of Contemporary Hospitality Management, 28*(4), 801–817. https://doi.org/10.1108/ijchm-02-2015-0073

Park, S. Y., Nam, M.-W., & Cha, S.-B. (2012). University students' behavioral intention to use mobile learning: Evaluating the technology acceptance model. *British Journal of Educational Technology, 43*(4), 592–605. https://doi.org/10.1111/j.1467-8535.2011.01229.x

Paule-Ruiz, Mp., Álvarez-García, V. M., Pérez, J. M. E., Álvarez-Sierra, M., & Trespalacios-Menéndez, F. (2016). Music learning in preschool with mobile devices. *Behaviour and Information Technology, 36*(1), 95–111. https://doi.org/10.1080/0144929x.2016.1198421

Poong, Y. S., Yamaguchi, S., & Takada, J. (2016). Investigating the drivers of mobile learning acceptance among young adults in the world heritage town of Luang Prabang, Laos. *Information Development, 33*(1), 57–71. https://doi.org/10.1177/0266666916638136

Pramana, E. (2018). Determinants of the adoption of mobile learning systems among university students in Indonesia. *Journal of Information Technology Education Research, 17*, 365–398. https://doi.org/10.28945/4119

Pratama, S. F. (2024). Analyzing the determinants of user satisfaction and continuous usage intention for digital banking platform in Indonesia: A structural equation modeling approach. *Journal of Digital Market and Digital Currency*, *1*(3), 267–285. https://doi.org/10.47738/jdmdc.v1i3.21

Pratama, S. F., & Prastyo, P. A. (2024). Evaluating blockchain adoption in Indonesia's supply chain management sector. *Journal of Current Research in Blockchain*, *1*(3), 190–213.

Putawa, R. A., & Sugianto, D. (2024). Exploring user experience and immersion levels in virtual reality: A comprehensive analysis of factors and trends. *International Journal Research on Metaverse, 1*(1), 20–39. https://doi.org/10.47738/ijrm.v1i1.3

Rahman, S. M. M., Mia, M. S., Ahmed, F., Thongrak, S., & Kiatpathomchai, S. (2020). Assessing students' satisfaction in public universities in Bangladesh: An empirical study. *Journal of Asian Finance Economics and Business, 7*(8), 323–332. https://doi.org/10.13106/jafeb.2020.vol7.no8.323

Rosman, M. R. M., Aziz, M. A. A., Osman, M. A. F., & Razlan, N. M. (2022). Self-efficacy and user behavioral intention to use online consultation management system. *International Journal of Evaluation and Research in Education, 11*(3), Article 1240. https://doi.org/10.11591/ijere.v11i3.22875

Rudhumbu, N. (2022). Applying the UTAUT2 to predict the acceptance of blended learning by university students. *Asian Association of Open Universities Journal, 17*(1), 15–36. https://doi.org/10.1108/aaouj-08-2021-0084

Sangsawang, T. (2024). Predicting ad click-through rates in digital marketing with support vector machines. *Journal of Digital Market and Digital Currency*, *1*(3), 225–246. https://doi.org/10.47738/jdmdc.v1i3.20

Setiawan, E. I., Tjendika, P., Santoso, J., Ferdinandus, F. X., Gunawan, & Fujisawa, K. (2024). Aspect-based sentiment analysis of healthcare reviews from Indonesian hospitals based on weighted average ensemble. *Journal of Applied Data Sciences*, *5*(4), 1579–1596. https://doi.org/10.47738/jads.v5i4.328

Shi, Y., Shu-Qin, C., & Wang, H. (2017). Mobile multimedia classroom construction for rhythmic gymnastics based on APT teaching model. *International Journal of Emerging Technologies in Learning, 12*(07), Article 79. https://doi.org/10.3991/ijet.v12i07.7216

Stymne, J. (2020). Mobile learning in outdoor settings: A systematic review. In *Proceedings of the 16th International Conference Mobile Learning* (pp. 63–70). IADIS. https://doi.org/10.33965/ml2020_202004l008

Sukmana, H. T., & Kim, J. I. (2024). Exploring the impact of virtual reality experiences on tourist behavior and perceptions. *International Journal Research on Metaverse, 1*(2), 94–112. https://doi.org/10.47738/ijrm.v1i2.8

Suryawirawan, O. A. (2021). The effect of college students' technology acceptance on e-commerce adoption. *Bisma: Bisnis dan Manajemen, 14*(1), 46–62. https://doi.org/10.26740/bisma.v14n1.p46-62

Talan, T. (2024). Digital natives' mobile learning adoption in terms of UTAUT-2 model: A structural equation model. *Innoeduca: International Journal of Technology and Educational Innovation, 10*(1), 100–123. https://doi.org/10.24310/ijtei.101.2024.17440

Tam, N. T., Truc, N. M. T., & Thanh, H. L. T. (2024). Applying quantitative and data analysis using structural equation modeling for accessing factors influencing employee loyalty. *Journal of Applied Data Sciences, 5*(1), 1–15. https://doi.org/10.47738/jads.v5i1.151

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Viriyasuebphong, P., Sophea, D., & Sungsuwan, T. (2021). Factors influencing students' behavioral intention on using mobile learning (M-learning) in tourism and hospitality major in Phnom Penh, Cambodia. *Current Applied Science and Technology, 22*(2). https://doi.org/10.55003/cast.2022.02.22.010

Wahyuningsih, T., & Chen, S. C. (2024). Analyzing sentiment trends and patterns in bitcoin-related tweets using TF-IDF vectorization and k-means clustering. *Journal of Current Research in Blockchain, 1*(1), 48–69. https://doi.org/10.47738/jcrb.v1i1.11

Wang, C. C. (2017). A near field communication-enabled e-learning environment for context-aware mobile Japanese conversation learning. *International Journal of Applied Systemic Studies, 7*(1/2/3), Article 41. https://doi.org/10.1504/ijass.2017.088900

Wang, Z. (2022). Higher education management and student achievement assessment method based on clustering algorithm. *Computational Intelligence and Neuroscience*. https://doi.org/10.1155/2022/4703975

Widayati, T., Sulistiyani, S., Nurchayati, N., & Suprapti, S. (2023). Antecedents of user attitude towards e-commerce and future purchase intention. *International Journal of Data and Network Science, 7*(1), 505–512. https://doi.org/10.5267/j.ijdns.2022.8.007

Widiar, G., Yuniarinto, A., & Yulianti, I. (2023). Perceived ease of use's effects on behavioral intention mediated by perceived usefulness and trust. *Interdisciplinary Social Studies, 2*(4), 1829–1844. https://doi.org/10.55324/iss.v2i4.397

Wirawan, G. (2024). Exploring students' perceptions of mobile game-based social studies learning model. *Yupa Historical Studies Journal, 6*(2), 181–187. https://doi.org/10.30872/yupa.v6i2.3379

Wu, C.-G., & Ho, J. (2021). The influences of technological characteristics and user beliefs on customers' perceptions of live chat usage in mobile banking. *The International Journal of Bank Marketing, 40*(1), 68–86. https://doi.org/10.1108/ijbm-09-2020-0465

Wu, S.-J., Chang, T.-C., Lee, Z.-H., Liu, F.-L., & Xu, Y.-Y. (2023). Constructing a student engagement and learning development model in mobile learning by SEM. In *Proceedings of the International Conferences on E-Society 2023 and Mobile Learning 2023* (pp. 259–266). https://doi.org/10.33965/ES_ML2023_202302L032

Xu, Q., Hou, X., Ting-chao, X., & Zhao, W. (2022). Factors affecting medical students' continuance intention to use mobile health applications. *Journal of Multidisciplinary Healthcare, 15*, 471–484. https://doi.org/10.2147/jmdh.s327347

Yadulla, A. R., Nadella, G. S., Maturi, M. H., & Gonaygunta, H. (2024). Evaluating behavioral intention and financial stability in cryptocurrency exchange app: Analyzing system quality, perceived trust, and digital currency. *Journal of Digital Market and Digital Currency, 1*(2), 103–124. https://doi.org/10.47738/jdmdc.v1i2.12

Zainuddin, N. F. F. B., Bakar, Z. B. A., Mohammad, N. M. B., & Mohamed, R. B. (2022). The effect of the aesthetically mobile interfaces on students' learning experience for primary education. *International Journal of Advanced Computer Science and Applications, 13*(10). https://doi.org/10.14569/ijacsa.2022.0131028

Zhou, H., Liu, J., & Cui, X. (2021). Research on influencing factors of adoption behavior of mobile readers based on meta-analysis. *Mathematical Problems in Engineering*. https://doi.org/10.1155/2021/5082594