

PAPER

Understanding AI and Mobile Learning Adoption in Malaysian Universities: A UTAUT-Based Model

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Baghdad, Iraqmodi@meta.upsi.edu.my**ABSTRACT**

This study explores the key determinants influencing the intention to adopt artificial intelligence (AI) applications and mobile learning in Higher Education Institutions (HEIs) in Malaysia. As AI technologies and mobile learning increasingly transform the higher education landscape, it is crucial to understand the specific factors driving their adoption. The research identifies five critical determinants—social influence (SI), effort expectancy (EE), hedonic motivations (HM), performance expectancy (PE), and consumer trust (TR)—that significantly impact the intention to use AI-powered mobile learning solutions. Through a survey of 263 undergraduate and postgraduate students from Malaysian universities, the study develops an adapted model to assess these adoption factors, contributing unique insights into the integration of AI and mobile learning within the Malaysian higher education context. This model provides actionable recommendations for university administrators, educators, and mobile learning developers, offering practical guidance on promoting the adoption of these technologies to enhance student engagement and learning outcomes. By focusing on real-world application, this study not only bridges theoretical research with practical implementation but also offers valuable lessons for similar educational contexts globally, particularly in emerging markets.

KEYWORDS

mobile learning (M-learning), artificial intelligence (AI) applications, unified theory of acceptance and use of technology (UTAUT), higher education institutions (HEI), Malaysia, factors

1 INTRODUCTION

Mobile learning, as defined by scholars such as [1], [2], [3], [4], and [5], involves the use of various mobile devices, including smartphones, personal digital assistants, tablet PCs, laptops, and portable computers. Today's technological innovations and breakthroughs have a significant impact on people's daily lives [6]. Since mobile technology has demonstrated its efficacy in the teaching and learning process, it has become a crucial component of education [7]. In the educational landscape,

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emerging technologies have been reshaping traditional teaching and learning methods. According to [8], the artificial intelligence (AI) market within the U.S. education sector was projected to experience a substantial 48% growth between 2018 and 2022. With the rapid advancement of AI technology, its applications in education have expanded, showing promising potential to deliver personalized learning experiences, facilitate dynamic assessments, and foster meaningful interactions in online, mobile, or blended learning environments.

Mobile learning's potential is not only transformative for content delivery but also instrumental in the personalization of learning experiences, empowering learners to engage at their own pace and in ways that suit their individual preferences. These advancements in technology have the capacity to transcend traditional classroom boundaries, making education more accessible and tailored to diverse needs.

Malaysia's higher education system adopts a number of innovative teaching strategies, reflecting this worldwide trend [9]. Moreover, scholars such as [10] have proposed more radical ideas, such as replacing certain teaching roles with AI-powered robots, particularly to address the teacher shortage issues faced in the U.S. education system. The expanding applications of AI in Education (AIEd) underscore the need for interdisciplinary approaches, yet much of the AI research remains concentrated within STEM fields, as noted by [11]. Recent literature reviews, including those by [12] and [11], highlight the lack of educational perspectives in AIEd research. This emphasizes the importance of incorporating insights from educational disciplines to ensure that AI technologies are effectively leveraged to meet the diverse needs and challenges within educational settings.

Recent studies have further emphasized the potential of AI to transform mobile learning environments. AI's technological promise has been enthusiastically welcomed by the education sector, which recognizes its potential to transform learning through virtual and mobile platforms. AIEd has gained recognition within formal school curricula, increasingly viewed as a critical domain of knowledge for students' future success. The evolution of AI learning has progressed from its early stages of computer automation with abstract concepts to the contemporary era of machine learning, employing intelligent algorithms, rules, and reasoning.

For instance, Batista et al. [13] explored the role of generative AI in enhancing teaching techniques and improving student engagement, highlighting its relevance for higher education institutions (HEI). Similarly, Lakulu et al. [14] examined the applications of AI in mobile learning, particularly for supporting indigenous communities in Malaysia, and proposed a taxonomy of AI techniques in education. This taxonomy categorizes AI technologies, including machine learning, deep learning, and chatbots, which have been widely applied to personalize learning experiences, leading to increased retention rates and improved academic outcomes.

Additionally, recent research has investigated various characteristics that impact students' intent to use AI apps in educational settings. Lavidas et al. [15] highlighted the significance of students' attitudes and perceptions of AI technology, identifying key factors influencing Humanities and Social Science students' intentions to use AI for academic purposes. Their findings underscore the influence of these attitudes on the adoption of AI in learning environments, which is crucial for understanding how AI is integrated into mobile learning contexts.

These advancements underscore the growing importance of integrating AI technologies into mobile learning systems. Furthermore, studies such as those by Ahmed et al. [16] and Johnson et al. [17] have focused on addressing challenges related to user acceptance and the ethical considerations of AI in education, offering valuable frameworks for successful implementation.

Artificial intelligence's technological promise has been enthusiastically welcomed by the education sector, which recognizes its potential to transform learning through virtual and mobile platforms [18]. AI education has gained recognition within formal school curricula, increasingly viewed as a critical domain of knowledge for students' future success. The evolution of AI learning has progressed from its early stages of computer automation with abstract concepts [19] to the contemporary era of machine learning, employing intelligent algorithms, rules, and reasoning [20]. This includes advancements such as AI conversational agents [21], reflecting the dynamic landscape of AI education and its relevance in preparing students for the complexities of the digital age.

Recognizing the need to integrate AI education into school curricula, educators have launched various initiatives to keep pace with the rapid advancements in the field. These initiatives include the development of national AI-related curricula for K-12 students [22], efforts to democratize AI education [23], and the provision of free tools such as Learning ML to support AI instruction [24]. Accessible tools and resources, alongside fundamental cognitive development, relevant AI evaluations, and considerations of AI ethics and literacy, are embedded within diverse AI hands-on projects and artifacts [25][20]. Rather than merely being end-users of AI applications, students are increasingly empowered to become AI thinkers, creators, and innovators across various contexts [20]. This shift in approach aims to equip students with the necessary skills and mindset to navigate the evolving landscape of AI technology and contribute meaningfully to its development and application.

While existing research on AI applications and mobile learning in higher education has predominantly focused on Western contexts, it is crucial to evaluate how these findings apply to the Malaysian context. Malaysia's unique educational landscape, characterized by a wide range of socioeconomic conditions, varying levels of digital literacy, and regional disparities in technological access, requires a personalized approach to understanding AI and mobile learning adoption. Recent developments indicate that Malaysia is accelerating its digital transformation in education, with government-led initiatives such as the DELIMa platform demonstrating a strong commitment to enhancing digital literacy and integrating technology into teaching and learning environments [26]. This study acknowledges the value of Western research in providing a theoretical foundation but emphasizes the importance of contextualizing these findings within Malaysia's educational setting. It aims to provide valuable insights that can better inform the implementation and adoption of AI-powered mobile learning tools in Malaysian universities and higher education institutions.

To improve the understanding of AI applications in mobile learning within Malaysian higher education, recent studies on global trends and their local applicability should be considered. For example, Batista, Mesquita, and Carnaz [27] emphasize the growing significance of generative AI in higher education, focusing on its role in enhancing teaching techniques and student engagement. This is particularly relevant for Malaysian HEIs, where AI can serve as an effective tool to address challenges related to student-centered learning and individualized support. Dufresne and Lucas [28] also explore AI's ability to personalize learning experiences, which could have significant implications for mobile learning applications in Malaysia. Both studies highlight the potential of AI technology to improve learning environments, and their findings offer useful insights into how AI applications in mobile learning can be effectively adapted to meet the specific demands of Malaysian universities.

The integration of AI into educational settings has been transformative, influencing how students engage in creative and academic activities. A study by Alfarsi et al. [29] highlights how AI-enhanced learning experiences improve student engagement in media content creation (MCC). AI-driven tools play a significant role in fostering creativity and enhancing learning outcomes, as shown by the positive impact of linking AI application factors to content creation. Li [30] proposes an adaptive recommendation system for teaching content, addressing the need for more personalized learning through mobile interaction technology. This multi-dimensional dynamic system takes into account both location and temporal factors, offering a more effective approach for higher education. Similarly, Zhao and Zhao [31] explore the impact of interactive mobile learning on improving university students' English-speaking proficiency. Their study emphasizes the importance of leveraging mobile learning to enhance speaking skills, revealing the effectiveness of interactive mobile learning frameworks. Additionally, Lu et al. [32] investigate how blending mobile devices and virtual reality (VR) can enhance learning motivation. Their findings suggest that the immersive experience provided by VR, combined with the convenience of mobile devices, can significantly boost students' learning engagement and motivation. Zhao [33] further examines the role of collaborative virtual learning environments (VLE) in education, proposing a structure for designing digital educational materials. The study emphasizes the potential of virtual environments to facilitate cooperative learning, especially in online and remote learning contexts.

2 AIEd TECHNOLOGY APPLICATIONS AND EDUCATIONAL BENEFITS

AI technology indeed opens up virtually limitless possibilities for education. In the investigation of 40 articles, a diverse range of AI applications in education was explored, encompassing various types of learning technology. These include:

1. Chatbots: AI-powered conversational agents designed to interact with students and provide assistance or guidance.
2. Expert systems: AI systems that emulate the decision-making capabilities of human experts in specific domains.
3. Intelligent tutors or agents: AI-driven systems that offer personalized instruction and support to learners.
4. Machine learning: Utilization of algorithms and statistical models to enable computers to learn from and make predictions based on data.
5. Personalized learning systems or environments (PLS/E): Platforms and systems tailored to individual learner needs and preferences.

These diverse AI applications offer innovative ways to enhance teaching and learning experiences, cater to individual learner needs, and optimize educational outcomes.

2.1 Chatbot

The study conducted by [34] stands out as the only study dedicated solely to chatbots in education among the reviewed articles. This study, which involved a twelve-week experiment with 122 students in foreign language classes, aimed to

assess the impact of chatbot partners compared to human partners on students' course interest.

Surprisingly, the study's findings revealed that students' interests decreased after just one week of interacting with chatbots. Additionally, the structural equation modeling (SEM) analysis indicated that while task interest predicted future course interest in the human partner conditions, this relationship was not observed under chatbot partner conditions.

Although the researchers attributed the decline in interest to a novelty effect, these results underscore the importance of conducting further empirical studies to thoroughly examine the effects of chatbots in educational settings. This study highlights the need for more comprehensive research to elucidate the potential benefits and drawbacks of integrating chatbots into educational contexts and their impact on learning outcomes.

2.2 Expert system

The research in AIEd suggests that dynamic and holistic expert systems can significantly contribute to pedagogical planning and fully harness the potential of learning management systems (LMS) for teaching and learning purposes [35]. For instance, Dias and colleagues conducted a study involving 1037 students and 75 professors across multiple courses in an academic year to examine the quality of interactions in a blended learning environment facilitated by an LMS. The findings demonstrated that the structural characteristics of an expert system can effectively model how users interact with the LMS, thereby enhancing teaching and learning experiences [35].

In a more recent study, [36] investigated the effects of a fuzzy expert system on elementary students' math learning outcomes in Taiwan. The study revealed that students in the experimental group, which utilized the expert system, exhibited better mathematics learning achievement compared to those in the control groups. Furthermore, the adaptive learning model, incorporating affective and cognitive performance analysis, was found to be effective in reducing math anxiety among fifth graders in Taiwan [36].

These studies highlight the potential of expert systems and adaptive learning models powered by AI to enhance teaching and learning experiences, improve learning outcomes, and mitigate challenges such as math anxiety. They underscore the significance of leveraging AI technologies to create personalized and effective learning environments tailored to the needs and abilities of individual learners.

2.3 Intelligent tutors or agents

Intelligent tutors or agents play a crucial role in providing customized, timely, and appropriate materials, guidance, and feedback to learners. While they hold great potential, research has revealed mixed implications regarding their effects on learning. For instance, several studies have investigated the impact of teachable agents (TA). [37], [38] found that TA promoted learning among elementary students across different grades. Additionally, [39] observed that TA prepared students for learning new science content from their regular lessons, even when they were not actively using the AI software.

In a recent study conducted in Sweden by [40], preschoolers' understanding of a TA-based math game was examined based on their gaze behaviors. The study's findings suggested that young children perceived the TA as an independent entity, indicating promising potential for TA in facilitating metacognitive scaffolding.

Furthermore, [38] investigated the effects of metacognitive scaffolding by teaching a TA on 7th and 8th graders' learning outcomes. The researchers observed that students' problem-solving abilities increased with the three TA interventions, although there was no significant difference among the three different conditions.

These studies underscore the importance of further research to better understand the effectiveness and nuances of intelligent tutors or agents in educational contexts, as well as their potential to support learners' cognitive and metacognitive processes.

2.4 Machine learning

Although machine learning has widespread applications, only a limited number of research studies analyzed in this review met the criteria for comprehensive analysis. However, the research that did qualify showcased the effectiveness of this important AI technology in various educational contexts.

For instance, [41] demonstrated that machine learning was effective in assessing changes in learning styles among English as a Second Language (ESL)/English as a Foreign Language (EFL) students across multiple grades.

Similarly, [42] utilized machine learning algorithms to predict undergraduate students' attitudes toward the educational applications of cloud-based mobile computing services based on their information management behaviors. The machine learning algorithms achieved an impressive accuracy rate of 74%.

These studies highlight the potential of machine learning in education, showcasing its ability to analyze learning styles, predict attitudes, and provide valuable insights into students' behaviors and preferences.

2.5 Personalized learning systems or environments

Personalized learning systems or environments have proven to be effective in facilitating interactions and enhancing e-learning experiences. The study by [43] found that PLS systems helped learners achieve desirable learning outcomes and improved their overall learning experiences. Similarly, [44] discovered that personalized mobile learning, incorporating AI and augmented reality (AR), not only enhanced learning experiences but also improved learning outcomes in open computer education.

Moreover, in Hong Kong, [45] investigated an AI-enhanced e-learning system called SmartTutor, involving over 1300 participants. The study revealed that customized learning materials and resources provided by SmartTutor were well-received by both students and faculty, and they were deemed helpful in the teaching/learning process.

Additionally, a study conducted by [46] with high school students in the USA found that connecting mathematics to students' personal interests outside of school

could significantly increase learning within an intelligent tutoring system. This highlights the potential of highly customized personalization in promoting learning and ultimately fostering student success.

Furthermore, in tandem with the rise of VR technologies, research has begun to explore the potential benefits of visualizations and VLE with AI in education. This suggests an exciting avenue for leveraging AI-enhanced visualizations and VLE to further enhance teaching and learning experiences in diverse educational settings.

3 REVIEW OF THE UTAUT MODEL IN MOBILE LEARNING ACCEPTANCE

[47] discussed the development of various models aimed at understanding individuals' intentions and acceptance of modern innovations in information systems worldwide. [48] specifically attempted to identify the factors influencing individuals' acceptance of new data innovations.

The technology acceptance model (TAM), introduced by [49], stands as one of the most widely utilized models in the domain of technology adoption. TAM aims to provide a theoretical framework to elucidate the influence of external factors such as training, computer self-efficacy, and objective system design features on individuals' attitudes toward system use, internal beliefs, behavioral intentions, and actual system usage.

The Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by [50], integrates components from various innovation acceptance models, making it one of the most comprehensive frameworks for studying technology adoption. The selection of UTAUT for this study is driven by its ability to provide a holistic understanding of user behavioral intention and technology usage through its four constructs: 1) Performance Expectancy (PE), 2) Effort Expectancy (EE), 3) Social Influence (SI), and 4) Facilitating Conditions (FC) [51].

This framework is particularly well-suited to the context of AI-powered mobile learning in Malaysian HEIs because it effectively accounts for individual and contextual determinants of adoption. Furthermore, the UTAUT model has demonstrated high predictive capability in studies involving emerging technologies, offering a reliable foundation for analyzing adoption factors.

Building upon the UTAUT model, this study incorporates additional constructs such as hedonic motivation (HM) and consumer trust (TR), which are particularly relevant to AI and mobile learning. These additions enhance the model's applicability to the unique dynamics of the Malaysian higher education landscape. By adopting UTAUT and these complementary constructs, the research facilitates an in-depth understanding of the key determinants influencing technology adoption, offering actionable insights for academia, developers, and policymakers.

4 ARTICLES SCREENING

The article selection procedure was systematic, commencing with a comprehensive search of four main databases, which yielded 338 articles. After removing duplicates and filtering based on titles, abstracts, and full texts, 50 papers were left for further investigation (see Figure 1).

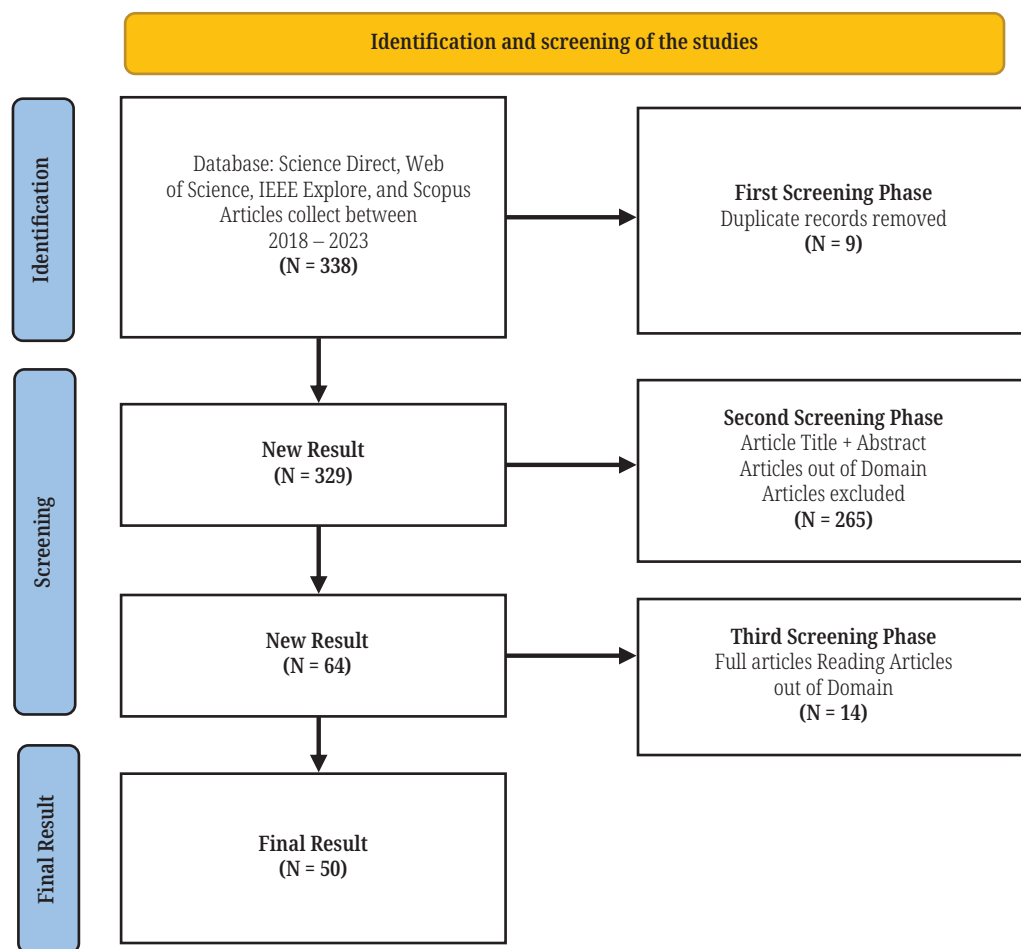


Fig. 1. Articles screening

5 RESEARCH HYPOTHESES

This study has proposed six factors that affect the intention to utilize AI applications and mobile learning within Malaysian universities and higher education.

5.1 Social influence

[52] Define SI as an individual’s perception of the extent to which important others believe they should or should not engage in a particular behavior [53]. In the context of modern innovation and its social impact, this concept can be understood as the degree to which an individual perceives that the adoption of a modern innovation is contingent upon the endorsement of significant others [50].

Research suggests that factors such as gender, experience, and age can moderate the influence of social factors on a learner’s behavioral intention to use mobile learning [50]. This underscores the importance of considering individual differences and contextual factors when examining the role of SI in technology adoption and usage.

Individuals within a community often exhibit a degree of influence on one another’s behavior, particularly when they share similar social status or perceive certain behaviors as necessary. This phenomenon, described as SI, plays a crucial role in shaping the perceptions and decisions of potential adopters. Especially in the early

stages of innovation diffusion, where uncertainty is high, prospective users tend to seek validation from other social actors by observing positive outcomes of adoption. This process can be conceptualized as “influence to accept information from another as evidence about reality” [54]. In essence, individuals rely on the experiences and decisions of others as a form of evidence to inform their own perceptions and actions regarding innovation adoption.

Indeed, Lao culture is deeply rooted in collectivism, as highlighted by [55]. According to [56], cultures characterized by high levels of collectivism emphasize the importance of adapting to the skills and virtues necessary to be accepted as a valued member of the group. Given this cultural context, it is reasonable to expect that SI plays a significant role in shaping the diffusion of mobile learning resources within Lao society. Individuals are likely to be influenced by the attitudes, behaviors, and opinions of their social groups when making decisions regarding the adoption and utilization of mobile learning technologies. This underscores the importance of considering sociocultural factors when designing and implementing mobile learning initiatives in Lao communities.

Research by [57] suggests that SI is closely linked to individuals' perceptions of their own image. People often conform to social norms to maintain a positive self-image. However, other studies, such as those by [50], indicate that SI may not directly impact behavioral intention to use innovation in voluntary settings.

In compulsory environments, such as corporate settings where individuals are required to use certain systems, SI may play a more direct role. However, in voluntary settings such as mobile learning for raising awareness of world heritage preservation, individuals are not obligated to use the systems. In such cases, SI may indirectly affect behavioral intention by influencing the perceived usefulness of an innovation.

Therefore, while SI may not directly drive behavioral intention in voluntary settings, it can still have an impact on individuals' perceptions of the usefulness of the innovation, which in turn influences their behavioral intentions.

In intentional settings, individuals often lean on the assumptions and desires of other users when considering the adoption of an innovation. These assumptions and desires stemming from the social environment significantly shape how an individual assimilates the innovation. Internalization, as described by [58], involves the gradual transfer of behavior regulation from external sources to become internalized within the individual.

In this context, SI plays a crucial role in shaping perceptions about the innovation. Research by [59] suggests that SI can indeed impact individuals' perceptions of the innovation by shaping their assumptions and desires based on the behaviors and attitudes of others within their social environment. As individuals observe their peers endorsing and utilizing the innovation, they may internalize these norms and beliefs, leading to changes in their own perceptions and attitudes towards the innovation. Thus, SI exerts a significant effect on how individuals perceive and ultimately adopt innovations within intentional settings.

H1: Social influence has a positive effect on behavioral intention to use mobile learning and AI applications.

5.2 Effort expectancy

Effort expectancy refers to the perceived level of ease associated with using a system [48], encompassing aspects such as ease of use and self-efficacy. For individuals to fully embrace a mobile learning framework, it must align with their needs

and values. Previous research, such as that by [60], has highlighted the significant impact of perceived ease of use on behavioral intention to use. Nowadays, it is clear that technology is easy to use because it makes daily tasks easier, especially in the educational sector [61].

[62] have emphasized the importance of EE in the acquisition of information technology, indicating the level of confidence individuals have in mastering an innovation [63]. In essence, the perceived ease of use and the level of certainty in one's ability to navigate and utilize the system play crucial roles in determining individuals' acceptance and adoption of mobile learning technologies.

Effort expectancy, or perceived ease of use, particularly in the context of mobile technology, refers to the extent to which a user perceives that a modern innovation will be easy to use [51]. [51] defined EE as the perceived level of ease that individuals believe they will experience when using an application system. This concept is reflected in previous models through components such as ease of use (IDT), perceived ease of use (TAM/TAM2), and complexity.

Indeed, the ease of use of a planned data framework is considered one of the key components of accepting data innovation [64]. Research suggests that individuals' willingness to use a system may vary significantly based on factors such as age, experience, and gender. These factors can influence individuals' perceptions of how easy or difficult it will be to use a particular technology, ultimately shaping their behavioral intentions towards its adoption.

Researchers have indeed supported the notion that factors related to EE play significant roles in determining the intention of female users, particularly those who are more experienced and have limited prior exposure to the system. Studies by [58] and [51] have highlighted the importance of EE in shaping the intentions of female users towards technology adoption.

Specifically, [58] found that EE was a significant determinant of intention among female users, especially those with greater levels of experience. Similarly, [51] suggested that individuals' acceptance of a mobile learning system is heavily influenced by their perceptions of its ease of use, as outlined in the UTAUT. [48] also emphasized the expectation that users' acceptance of a mobile learning system would depend on its perceived ease of use, further reinforcing the importance of EE in technology adoption processes.

H2: Effort expectancy has a positive effect on behavioral intention to use mobile learning and AI applications.

5.3 Price-value

Price-value, as defined by [65], represents an individual's cognitive assessment of the balance between the perceived benefits of using an application and the monetary costs associated with its usage. These benefits may include factors such as convenience, quality, comfort, and ubiquity. On the other hand, the costs considered in this trade-off include monetary expenses, usage fees (if applicable), and the perceived or actual risks of privacy loss associated with using the application or system [66].

It is worth noting that in various contexts, researchers have employed different terms or concepts interchangeably with price-value. For instance, in studies related to mobile commerce, perceived value may be used instead of price value [67]. Similarly, in the context of social network sites, privacy concerns may be considered as part of the overall perceived value rather than being explicitly labeled as

price-value [66]. These variations reflect the multidimensional nature of individuals' assessments when making decisions about the adoption and use of technology.

H3: Price-value has a positive effect on behavioral intention to use mobile learning and AI applications.

5.4 Hedonic motivation

Motivation, as defined by [68], refers to the tendency and intention that propel an individual's behavior toward the attainment of goals. In the context of information systems and applications, various features are often integrated to enhance consumer engagement, adoption, and usage and can be broadly categorized into two domains.

The first domain encompasses productivity-oriented features that offer utilitarian or instrumental value to consumers and users. These features, as elucidated by [69], typically foster extrinsic motivation, which is driven by rewards or external benefits. One prominent example of a construct that stimulates extrinsic motivation among users is perceived usefulness, also known as PE. This construct reflects users' beliefs about the extent to which a system or application can help them achieve specific tasks or goals efficiently.

The second category encompasses pleasure-oriented features that deliver hedonic or self-fulfilling value to consumers and users of systems and applications. According to [69], hedonic features are closely linked to family, home, and leisure activities, targeting pleasure, happiness, and the fun aspect of using information systems.

These hedonic features are integrated into applications with the underlying goal of encouraging sustained or continuous usage. They promote intrinsic motivation, which is driven by internal satisfaction rather than external rewards. Examples of constructs that drive intrinsic motivation include hedonic expectancy, perceived enjoyment, flow experience, and perceived playfulness.

[70] define HM as the "fun or pleasure derived from using a technology or system," emphasizing its importance in determining consumer technology acceptance and sustained use. Previous research demonstrated significant correlations between hedonic value and user behaviors in contexts such as mobile internet usage [71] and mobile social network games. Enjoyment has been identified as a factor in VR tourism [72]. These findings underscore the significance of pleasure-oriented features in driving user engagement and adoption of technology.

H4: Hedonic motivation has a positive effect on behavioral intention to use mobile learning and AI applications.

5.5 Performance expectancy

Performance expectancy refers to the extent to which an individual believes that using a system will help them achieve success in their tasks or goals [51]. In the context of mobile learning, PE suggests that individuals will perceive the usefulness of mobile learning because it provides them with the opportunity to access information quickly and conveniently anytime and anywhere.

Further studies are needed to fully understand the impact of PE on mobile learning. However, applying PE to a mobile learning context implies that learners will find mobile learning beneficial because it allows them to learn conveniently. They can

access learning materials on the go, which enhances their learning flexibility and efficiency [48] [63] [73].

[51] defined PE as the extent to which an individual believes that using a system will enable them to derive benefits from performing their tasks or achieving their goals. Additionally, their research indicated that PE is the strongest predictor of intention to use mobile learning. This suggests that individuals' perceptions of the usefulness and effectiveness of mobile learning significantly influence their intention to utilize it.

H5: Performance expectancy has a positive effect on behavioral intention to use mobile learning and AI applications.

5.6 Consumer trust

Consumer trust, as defined by [74], refers to the willingness of an individual to rely on an exchange partner in whom they have confidence. It is a fundamental concept in consumer-business relationships, playing a crucial role in fostering commitment and building strong, long-term connections between consumers and businesses. Trust in a technology, system, or brand is widely recognized as a cornerstone of effective working relationships, influencing consumer behaviors such as adoption and use.

The establishment of TR is essential for developing and maintaining consumer satisfaction, loyalty, and a sustainable competitive advantage. Research by [75] highlights the significant impact of TR on various aspects of business performance, including increased revenue. Therefore, businesses strive to cultivate trust among their consumers as it lays the foundation for enduring relationships and positive outcomes.

Trust in a consumer context reflects the confidence and security of the end user in their expectations of the other party in the relationship [76]. Users anticipate a high level of competence from e-service providers in task performance, adherence to service promises, and goodwill toward user benefits [77]. Research has consistently shown that trust is a strong predictor of behavioral intention in e-commerce contexts [78]. As indicated by [79], TR in a technological system can have a positive and direct impact on behavioral intention because users anticipate deriving benefits from the use of this technology. Therefore, based on this understanding, the following hypothesis can be formulated:

H6: Consumer trust has a positive effect on behavioral intention to use mobile learning and AI applications.

5.7 Behavioral intention to use

Behavioral intention to use (BIU) is defined as the user's willingness to use an information system, and it is considered a direct determinant of actual use [80].

As mentioned by [81], intention is a crucial variable recognized in previous studies based on the TAM. Intention refers to the likelihood that a person will use an information system. It plays a pivotal role in the actual adoption and use of a modern innovation [49]. In essence, individuals' intentions to use a technology strongly influence their subsequent behavior regarding its adoption and utilization.

Indeed, intention to use can be considered a form of behavior within the acceptance domain, as suggested by researchers such as [82]. In studies focusing on e-learning or mobile learning contexts, researchers have investigated the contextual relationship between intention to use and actual use [83] [84] [82].

[82] highlighted that intention to use positively influences actual use. Therefore, in the context of the research being discussed, it can be inferred that there exists a positive relationship between intention to use and actual use. This suggests that individuals who express a strong intention to use a particular technology or system are more likely to engage in its actual use.

The independent variable of intention to use has been a cornerstone in previous studies exploring the acceptance of information and communication technology [50] [51]. In the context of mobile learning, previous research has consistently found a positive relationship between intention to use and actual use [85] [81].

Given this background, intention to use can be viewed as the likelihood or possibility that a learner will engage with mobile learning in the future. Therefore, this construct has been adopted for the present study to signify learners' intentions to utilize mobile learning [86]. In essence, intention to use serves as a crucial predictor of individuals' willingness to adopt and engage with mobile learning technologies.

6 CONCEPTUAL MODEL OF AI APPLICATIONS AND MOBILE LEARNING

This study aims to explore the key factors influencing the intention to use mobile learning in HEI. The study proposes six factors that affect this intention: "Social Influence," "Effort Expectancy," "Price Value," "Hedonic Motivation," "Performance Expectancy," and "Consumer Trust." The conceptual model, as shown in Figure 2, illustrates how these factors interact to influence the intention to use mobile learning in HEI. Understanding these factors can provide valuable insights into promoting the adoption of mobile learning technologies in higher education institutions.

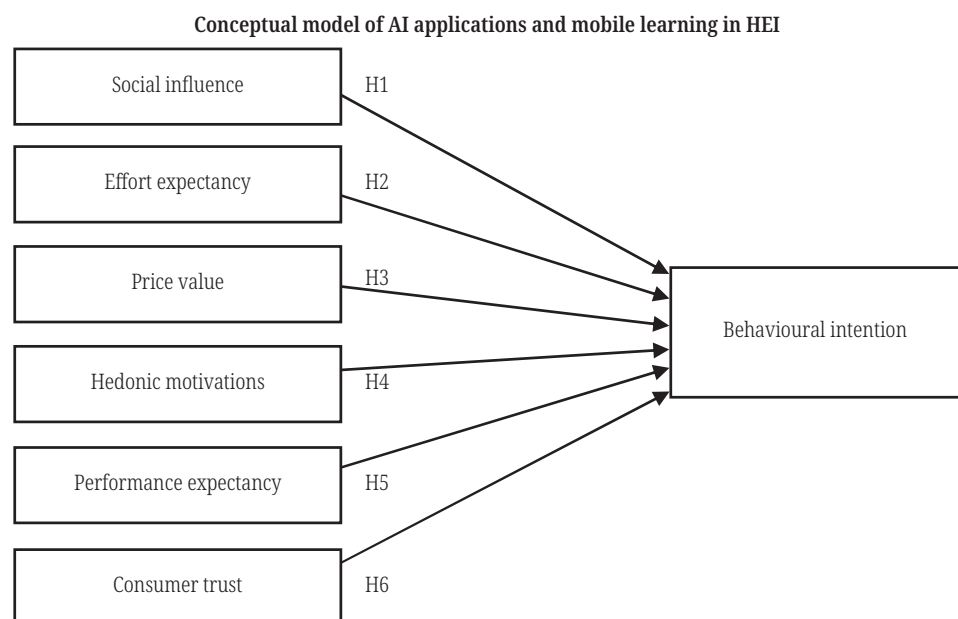


Fig. 2. Conceptual model of AI applications and mobile learning in HEI

7 SURVEY QUESTIONNAIRE ITEMS

This survey consists of six independent variables, which are 1) SI, 2) EE, 3) price value, 4) HM, 5) PE, and 6) TR. This study has one dependent variable.

7.1 Social influence

SI1: People who I care about think I should use AI applications.
 SI2: People who influence my behaviors think that I should use AI applications.
 SI3: People whose opinion I value believe that I should use AI apps.

7.2 Effort expectancy

EE1: I find it easy to learn to use AI tools.
 EE2: My interaction with AI tools is clear.
 EE3: I find it easy to use AI.
 EE4: I believe that learning to use an AI application is easy for me.

7.3 Price value

PV1: AI applications are reasonably priced.
 PV2: AI applications are worth what they cost.
 PV3: At the current price, AI gives good value.

7.4 Hedonic motivation

HM1: Using AI applications is fun.
 HM2: I enjoy using AI applications.
 HM3: Using AI applications is very entertaining.

7.5 Performance expectancy

PE1: I believe that AI is useful for me in my day-to-day life.
 PE2: I believe that AI will help me achieve things that are important to me.
 PE3: I believe that AI helps me carry out my tasks quickly.
 PE4: I believe that AI improves my performance.

7.6 Consumer trust

TR1: AI can be trusted.
 TR2: AI does what it promises.
 TR3: AI is concerned with satisfying the user.

7.7 Behavioral intention

BI1: I intend to use AI applications soon.
 BI2: I will always try to use AI applications in my daily life.
 BI3: I plan to use AI applications frequently.

8 DATA ANALYSIS

Clearly, a well-structured plan for analyzing the data collected from the survey was essential. In this study, SPSS software was used for various analyses, including descriptive statistics to summarize the data, frequencies to understand the distribution of categorical variables, and means to examine the central tendency of continuous variables. Checking for missing values, outliers, normality, multicollinearity, and non-response bias were essential steps to ensure the quality and reliability of the data analysis. Addressing these issues helped the researchers make valid interpretations and draw accurate conclusions from the data. Once these preliminary checks were completed, the main analysis was conducted to identify the factors influencing mobile learning in HEI. This process involved relevant techniques such as regression analysis to assess the relationships between predictor variables (e.g., SI and EE) and the outcome variable (intention to use mobile learning). Overall, the approach was deemed thorough and systematic, aligning well with best practices in research methodology.

8.1 Ethical considerations

In accordance with ethical research norms, all survey data were anonymized to preserve participant confidentiality. Only the research team had secure access to the encrypted platforms where the responses were kept. Survey questions were carefully crafted to steer clear of leading prompts in order to reduce potential biases, and the sample was chosen to represent a wide range of demographics. Furthermore, all participants gave their informed consent following thorough explanations of the study's goals, data use, and confidentiality protocols.

Some participants voiced worries during the data collection process concerning the usage of their data, especially when it came to AI-related subjects. The research team responded to these worries by reiterating the safeguards in place to secure data and elucidating the study's non-invasive nature in follow-up correspondence. Additionally, by presenting simplified explanations and the chance to ask questions during the consent procedure, issues with participants' comprehension of technical terms were resolved.

8.2 Data examination

Examining the data for missing values, outliers, normality, multicollinearity, and non-response bias was a crucial step to ensure the quality and reliability of the analysis. The following aspects were examined in this study:

- **Missing values:** Any missing values in the dataset were examined thoroughly, as they could affect the accuracy and reliability of the analysis.
- **Outliers:** Outliers are data points that significantly deviate from the rest of the data. These data points could distort statistical analyses and lead to inaccurate conclusions. Detecting outliers was performed through visual inspection, such as box plots or histograms, as well as statistical methods such as z-scores or Tukey's method.
- **Normality:** Assessing the normality of the data was important for determining the appropriateness of parametric statistical tests. Checking normality was carried

out using graphical methods such as histograms or quantile-quantile plots, as well as statistical tests such as the Shapiro-Wilk test.

- **Multicollinearity:** Multicollinearity occurs when independent variables in a regression model are highly correlated with each other. This can inflate standard errors and lead to unstable estimates. Detecting multicollinearity was conducted using correlation matrices or variance inflation factors (VIFs).

8.3 Missing values

The data examination carried out showed there were no missing values in our dataset. This could be attributed to all questions being marked as “required” in the online questionnaire, prompting respondents to provide responses to all items before submitting their feedback. This led to a complete dataset consisting of 263 responses.

8.4 Outliers

Boxplots were used to identify outliers in the dataset, which could potentially skew the results. Seven outliers were removed, resulting in a dataset consisting of 256 complete and usable responses. Such steps to clean the data helped enhance the validity and accuracy of the subsequent analyses.

8.5 Normality

The normality of the data was checked by assessing the skewness and kurtosis, as well as examining the histograms. The skewness and kurtosis values should ideally be within the acceptable range of ± 2 . The normality test showed the skewness values ranged from -0.027 to -0.663 , and the kurtosis values ranged from -0.780 to 1.606 for all the constructs, as summarized in Table 1. Additionally, the histograms showed the data followed a bell-shaped curve, further establishing its normality.

Table 1. Results of normality analysis

#	Variables	Skewness < ± 2	Kurtosis < ± 2
1.	Social influence	-.258	.980
2.	Effort expectancy	.111	-.780
3.	Price value	-.422	1.065
4.	Hedonic motivations	-.663	1.588
5.	Performance expectancy	-.027	1.606
6.	Consumer trust	-.070	.813

8.6 Reliability

The results of the reliability analysis showed a Cronbach’s alpha value of 0.91, indicating a high level of internal consistency among the items in the questionnaire. This suggested that the items in the survey were reliably measuring the same underlying construct. With a Cronbach’s alpha exceeding the commonly accepted threshold of 0.7 for reliability, the questionnaire demonstrated strong internal consistency.

8.7 Respondents' demographic profiles

Table 2 summarizes the demographic profiles of the respondents in terms of gender, age, education, and experience. The respondents were almost equally divided between males (50.6%) and females (49.4%), with a slight majority being male. The vast majority of respondents (92.4%) were young adults aged between 19 and 26 years. Only a small proportion were older, with 1.5% aged 27–34 years, 3.8% aged 35–42 years, 1.5% aged 43–50 years, and 0.8% over 50 years old.

Table 2. Respondents' demographic profiles

Variable	Label	Frequency	Percent
Gender	Male	133	50.6%
	Female	130	49.4%
Age	19–26 years	243	92.4%
	27–34 years	4	1.5%
	35–42 years	10	3.8%
	43–50 years	4	1.5%
	More than 50 years	2	0.8%
Education	Bachelor	243	92.4%
	Master	6	2.3%
	PhD	14	5.3%
Experience	0–3 years	70	26.6%
	4–7 years	102	38.8%
	8–11 years	50	19.0%
	12–15 years	19	7.2%
	More than 15 years	22	8.4%

9 HYPOTHESIS TESTING AND SHOWING THE RESULT

The validity of each hypothesis was determined by examining the associated p-value from the hypothesis tests. Following the guidelines suggested by [87] [88], a p-value less than 0.05 was considered statistically significant, indicating support for the corresponding hypothesis. Table 3 summarizes the results of hypothesis testing for the six hypotheses investigated in this study.

Table 3. Example table

H	DV	Path	IV	T	Sig./P	Label
H1	BI	<---	SI	-4.147	.000	Supported
H2	BI	<---	EE	3.943	.000	Supported
H3	BI	<---	PV	-1.654	.099	Rejected
H4	BI	<---	HM	3.552	.000	Supported
H5	BI	<---	PE	-2.655	.008	Supported
H6	BI	<---	TR	7.018	.000	Supported

Note: BI: Behavior intention to use, SI: social influence, EE: effort expectancy, PV: price value, HM: Hedonic motivations, PE: performance expectancy, TR: consumer trust.

10 DISCUSSION

The study's findings provide valuable insights into the factors influencing behavioral intention to use mobile learning in HEIs in Malaysia. By identifying "Social Influence," "Effort Expectancy," "Hedonic Motivations," "Performance Expectancy," and "Consumer Trust" as significant factors affecting behavioral intention, the research offers targeted guidance for educators, policymakers, and technology developers in the Malaysian HEI context. Notably, the inclusion of "Price Value" as a significant factor underscores the unique considerations and priorities of users in Malaysia regarding mobile learning adoption. This insight can inform the development of strategies and interventions aimed at promoting the uptake of mobile learning initiatives, highlighting the importance of emphasizing influential factors such as SI and PE alongside the consideration of price value.

By focusing on the factors that have the most substantial impact on behavioral intention, the study contributes to a more nuanced understanding of the dynamics shaping mobile learning adoption in Malaysian HEIs. This understanding can, in turn, inform the design of tailored interventions and policies aimed at fostering greater acceptance and utilization of mobile learning technologies among students and educators in Malaysia.

The research findings highlight the strong attitudes of students towards the adoption of AI applications and mobile learning in HEIs. The readiness expressed by students to embrace these technologies underscores their recognition of the potential benefits they could derive from enhancing their learning experiences. The conducive conditions for mobile learning identified in the study further support the willingness of students to adopt these innovations if introduced in universities.

The utilization of the UTAUT model in this study has proven effective in elucidating the factors influencing students' acceptance of AI applications and mobile learning. By leveraging UTAUT's comprehensive framework—incorporating PE, EE, SI, and Facilitating Conditions (FC)—this study has provided valuable insights into the determinants shaping students' perceptions and intentions toward these technologies in the context of higher education institutions.

In contrast to conventional approaches such as the TAM, which mostly concentrate on perceived utility and usability, UTAUT enables a more thorough analysis of social and environmental factors that are crucial in institutional contexts. The Theory of Planned Behavior (TPB) also places emphasis on attitudes and perceived behavioral control, but it does not specifically address technology-specific elements such as enabling situations and EE. Given that the adoption of AI-powered mobile learning is contingent upon peer influence and institutional support in addition to individual perceptions, UTAUT offered a more appropriate theoretical framework.

With a substantial sample size of 263 participants, the study captured a diverse range of perspectives from prospective mobile users, contributing to a comprehensive understanding of the factors driving the acceptance of AI applications and mobile learning in HEIs. Furthermore, the integration of HM and TR as additional constructs enhanced the model's applicability, reflecting the engagement-driven nature of AI-powered mobile learning.

The effectiveness of the suggested model in illuminating the elements of learners' acceptance highlights the applicability and resilience of UTAUT in evaluating the adoption of technology in classrooms. With actionable insights to improve the integration of AI-driven mobile learning solutions in higher education, these findings support the model's predictive ability and practical implications for educators, legislators, and tech developers.

Overall, the research findings underscore the importance of considering students' attitudes and perceptions when implementing AI applications and mobile learning initiatives in HEIs. By aligning technology adoption strategies with students' preferences and needs, institutions can effectively leverage these innovations to enhance teaching and learning outcomes in higher education.

While the findings of this study are particularly relevant to the context of Malaysian HEI, they offer important insights that can be applied to other developing nations. However, the unique challenges in these regions—such as limited digital infrastructure, low levels of digital literacy, and varying cultural attitudes towards technology—require careful consideration when applying these findings. Many developing countries face significant barriers to the adoption of AI-powered mobile learning, including inadequate internet access and affordability of devices.

Nevertheless, opportunities abound in these regions as mobile connectivity improves and affordable smartphones become more accessible. By tailoring AI-powered learning solutions to local needs—such as incorporating local languages, cultural context, and accessible technology—these solutions can be adapted to enhance user trust and engagement. Moreover, international collaborations between educational institutions, governments, and technology developers can play a key role in overcoming these barriers and fostering the adoption of mobile learning technologies.

Therefore, while this study primarily focuses on Malaysia, its findings contribute to the broader discourse on mobile learning adoption in developing countries. Future research and implementation efforts should aim to address the specific challenges faced by these regions, ensuring that the potential of AI and mobile learning is fully realized globally, especially in emerging economies where such innovations could have transformative effects on education.

11 HYPOTHESES TESTING

The study's hypothesis comprises six specific propositions. A hypothesis is deemed to be supported or accepted when the calculated P-value, also referred to as the level of significance, falls below the threshold of 0.05, in accordance with the guidelines put forth by [87] [88].

11.1 Social influence and behavioral intention to use

The analysis and findings regarding the first hypothesis provide strong support for the significant and positive effect of SI on the behavioral intention to use mobile learning and AI applications. This aligns with prior research in the same field, which has consistently highlighted the influential role of social factors in shaping individuals' intentions to adopt new technologies.

By referencing previous studies such as [89] and [90], the findings reinforce the importance of SI as a direct determinant of users' behavioral intentions toward modern innovations. Furthermore, the results of the study conducted by [86] emphasize the significance of SI within the realm of mobile learning, thereby offering additional substantiation for the research outcomes.

Moreover, the role of SI in mitigating uncertainty during the early stages of innovation adoption adds depth to the interpretation of the results. By highlighting the tendency of individuals to seek positive evidence from social actors, the study

provides valuable insights into the mechanisms through which SI influences the intention to use mobile learning.

Overall, the analysis adeptly connects the study's results with the body of existing literature, thereby offering a thorough comprehension of how SI influences behavioral intentions towards mobile learning and AI applications. This insightful interpretation fortifies the importance of the research outcomes and imparts valuable perspectives to the domain of technology adoption in education.

11.2 Effort expectancy and behavioral intention to use

The results of the second hypothesis show that EE has a significant and positive effect on the behavioral intention to use mobile learning and AI applications. Effectively, the implications of these findings underscore their importance in understanding users' attitudes and intentions toward technology adoption. They suggest that an increase in EE leads to a corresponding increase in behavioral intention. Such revelations provide valuable insights into the factors that drive users' willingness to engage with mobile learning and AI applications.

Additionally, the validity of the findings is strengthened when referencing it with the existing literature, which has consistently highlighted the significance of EE in technology acceptance. Therefore, such references can help contextualize the findings within a broader theoretical framework, demonstrating their consistency with established knowledge in the field.

Overall, the analysis effectively highlights the significance of the second hypothesis and its implications for understanding users' behavioral intentions in the context of mobile learning and AI applications.

Moreover, the citation of specific studies [91] [92] [62] [51] [73] adds credibility to the argument and demonstrates the breadth of evidence supporting the relationship between EE and user intention. Additionally, highlighting [73] the finding that EE was the strongest predictor of behavioral intention underscores the importance of EE in shaping users' perceptions and attitudes towards mobile learning.

Clearly, these findings have several implications that underscore the importance of understanding users' attitudes and intentions toward technology adoption, which offers practical insights for mobile learning design. By emphasizing the importance of providing user-friendly and easy-to-use mobile learning applications, attention is drawn to the need for designers to prioritize usability and accessibility. Overall, the integration of previous research enriches the analysis, strengthens the validity of this study's findings, and contributes to a deeper understanding of the factors influencing user intention in the context of mobile learning by contextualizing the results within existing literature and drawing practical implications.

11.3 Price value and behavioral intention to use

The testing of the price-value (PV) hypothesis, H3, reveals no significant effect on behavioral intention to use mobile learning and AI applications among respondents. With a PV exceeding 0.05, the study's results provide evidence to reject H3. The absence of PV as a significant factor influencing behavioral intention in this study offers valuable insights for result interpretation. By examining the participants' perspective, primarily users of the systems or university students, the stakeholders gain a crucial understanding of their decision-making process.

The astute observation that participants might not prioritize price value, perceiving it as the responsibility of practitioners or universities, is particularly noteworthy.

This suggests that users may place greater emphasis on other factors, such as perceived usefulness or ease of use, when evaluating their intention to adopt AI applications or mobile learning technologies. Furthermore, this finding underscores the importance of considering the broader context in which these technologies are implemented and the various factors that shape users' perceptions and behaviors.

The insignificance of PV in this study contrasts with previous research by [67], [65], and [66], which found it crucial for technology acceptance. This discrepancy highlights the variability in findings across different contexts and populations, particularly in educational settings where students may perceive cost as an institutional responsibility.

This study's results suggest that in the context of mobile learning and AI applications in education, other factors such as perceived usefulness or ease of use may take precedence over PV. This contrast emphasizes the context-dependent nature of technology adoption factors and underscores the need for nuanced, domain-specific approaches when studying technology acceptance, contributing valuable insights to the field and demonstrating the complexity of user behavior in educational technology adoption.

11.4 Hedonic motivation and behavioral intention to use

The testing of the fourth hypothesis, H4, reveals HM has a significant effect on behavioral intention to use mobile learning and AI applications among respondents. The significant impact of HM in driving intention to use such applications aligns with previous research that has highlighted the importance of hedonic aspects, such as enjoyment and pleasure, in technology acceptance and adoption [71] [70] [72]. These findings suggest that users may be motivated to engage with mobile learning and AI applications not only for instrumental or utilitarian purposes but also for the enjoyment and satisfaction derived from using these technologies. This understanding emphasizes the multifaceted nature of user motivation and underscores the importance of considering both practical and emotional factors in the design and implementation of educational technology solutions.

The contextualization of the findings within existing literature on HM and technology acceptance provides valuable support for the significance of these results. By referencing prior studies that have explored the relationship between HM and behavioral intention to use technology, this study strengthens its theoretical foundation and demonstrates the consistency of its findings with established knowledge in the field.

The reference to studies in various domains, such as touristic geolocation, mobile commerce, and omnichannel commerce, underscores the broad applicability of HM across different contexts of technology adoption. This breadth of evidence suggests that the role of enjoyment and pleasure in shaping users' behavioral intentions is not limited to specific technological domains but holds relevance across diverse areas of application.

Furthermore, by citing specific authors and studies that have contributed to understanding the influence of HM on technology adoption, the researchers provide a robust theoretical framework for interpreting the findings. This demonstrates engagement with existing scholarship and strengthens the credibility of this study within the broader academic discourse.

Overall, the integration of prior research on HM enriches the interpretation of the results and enhances the theoretical significance of this study in elucidating the factors driving intention to use mobile learning and AI applications in HEI. This comprehensive approach not only validates the findings but also positions the research within a wider context of technology acceptance studies, highlighting its contribution to the field.

11.5 Performance expectancy and behavioral intention to use

The support for the fifth hypothesis, H5, which posits that PE positively influences behavioral intention to use mobile learning and AI applications, aligns with previous research in this field. PE, referring to the perceived utility or effectiveness of technology in facilitating task accomplishment, has consistently emerged as a significant predictor of users' intention to adopt new technologies.

These findings corroborate prior studies that have highlighted the importance of PE in shaping users' behavioral intentions. By demonstrating its significant effect on the intention to use mobile learning and AI applications, this study contributes valuable insights to the existing body of literature on technology acceptance.

Moreover, this study provides a unique perspective on mobile learning adoption in Malaysia, offering evidence that PE plays a crucial role in influencing users' intentions in this specific setting. This contextualization adds depth to our understanding of technology adoption processes in diverse cultural and educational environments, enhancing the global applicability of technology acceptance models.

The support for this hypothesis underscores the significance of PE as a key determinant of behavioral intention to use mobile learning and AI applications. This finding aligns with prior studies [48] [91] [63] [51] [73], reinforcing the established understanding of PE as a critical factor influencing learners' behavioral intentions in mobile learning acquisition.

Further exploring this concept, [93] emphasizes the quality enhancement of learner interaction facilitated by mobile learning, as well as the convenience it offers in accessing information and improving learning outcomes. These aspects align with the notion that mobile devices serve as effective tools for accessing educational resources swiftly and flexibly, regardless of time and location. Similarly, the studies by [68] and [78] corroborate the idea that PE plays a pivotal role in shaping users' perceptions of mobile learning. The convenience and efficiency afforded by mobile devices for learning purposes contribute to users' belief in the usefulness and effectiveness of mobile learning platforms, thereby influencing their behavioral intentions to engage with such technologies.

The consistency of this study's results with previous research not only validates the significance of PE but also reinforces the theoretical foundations of TAM in the context of mobile learning adoption. This alignment adds robustness to our study's conclusions and contributes to the broader understanding of factors influencing technology adoption in educational settings. The emphasis on PE as the most significant predictor of learners' intentions highlights its pivotal role in shaping users' perceptions and attitudes toward mobile learning. This study confirms that learners' beliefs about the utility and effectiveness of mobile learning in facilitating their academic pursuits strongly influence their willingness to adopt and engage with such technologies.

Furthermore, the findings suggest that learners who perceive higher expected performance from mobile learning are more likely to accept and embrace these technologies compared to those with lower expectations. Importantly, these findings carry significant implications for practical implementations in education. They suggest that emphasizing the utility and effectiveness of mobile learning and AI applications could be a powerful strategy for promoting their adoption and successful integration into educational practices. By addressing learners' expectations and perceptions regarding the efficacy of these platforms in enhancing their educational experiences, institutions can potentially increase acceptance and engagement with these technologies.

11.6 Consumer trust and behavioral intention to use

The testing of the sixth hypothesis, H6, reveals TR has a positive and significant effect on behavioral intention to use mobile learning and AI applications. This particular finding is consistent with previous research demonstrating the importance of trust in shaping users' intentions to adopt and use various technologies [75]. TR, as a key determinant of technology adoption, influences individuals' perceptions of the reliability, security, and credibility of the technology or platform [69].

These results align well with existing research highlighting the significant relationship between trust and various behavioral outcomes in technology adoption contexts. Previous studies have demonstrated direct and positive relationships between trust and behavioral intention [94] [79], as well as between trust and attitude [95]. These findings underscore the crucial role of trust in shaping users' perceptions and intentions regarding technology adoption and usage.

By confirming the significant effect of TR on behavioral intention to use mobile learning, the study emphasizes the importance of fostering trust in educational technology environments. Students' trust in the reliability and security of mobile learning platforms can enhance their willingness to engage with these technologies, ultimately leading to increased adoption and usage.

Moreover, the findings highlight the need for educational institutions and technology providers to prioritize measures aimed at building and maintaining trust among users. This may include transparent communication about data privacy and security measures, providing reliable technical support, and ensuring the integrity of the learning platform.

The identification of TR as a key variable influencing behavioral intention to use AI applications and mobile learning adds further support to the importance of trust in the context of educational technology. The trust users have in the reliability, security, and credibility of AI applications and mobile learning platforms significantly influences their willingness to engage with these technologies.

Overall, this study contributes valuable insights into the factors influencing the acceptance and adoption of mobile learning and AI applications in educational contexts. It emphasizes the pivotal role of TR in shaping users' behavioral intentions and highlights the need for trust-building strategies. These insights can guide educational institutions and technology providers in implementing measures to foster a positive user experience and facilitate the successful implementation and utilization of AI applications and mobile learning platforms in educational environments.

12 FINAL MODEL OF AI APPLICATIONS AND MOBILE LEARNING IN HEI

This study has successfully refined the model based on the analysis findings, creating a more focused and accurate representation of the factors influencing intention to use mobile learning. The removal of price value from the final model due to its insignificant effect on intention to use ensures that the model includes only the most relevant and impactful factors.

The resulting streamlined model consists of five key components, namely 1) SI, 2) EE, 3) HM, 4) PE, and 5) TR (see Figure 3). This refined model provides a clearer understanding of the primary drivers behind users' intentions to engage with mobile learning and AI applications in higher education settings. By focusing on these significant factors, the model serves as a valuable tool for various stakeholders in the educational technology ecosystem.

Educators, policymakers, and technology developers can leverage this model to enhance the adoption and effectiveness of mobile learning initiatives. Specifically, it offers insights into the aspects that should be prioritized and optimized to promote user engagement and acceptance of these technologies.

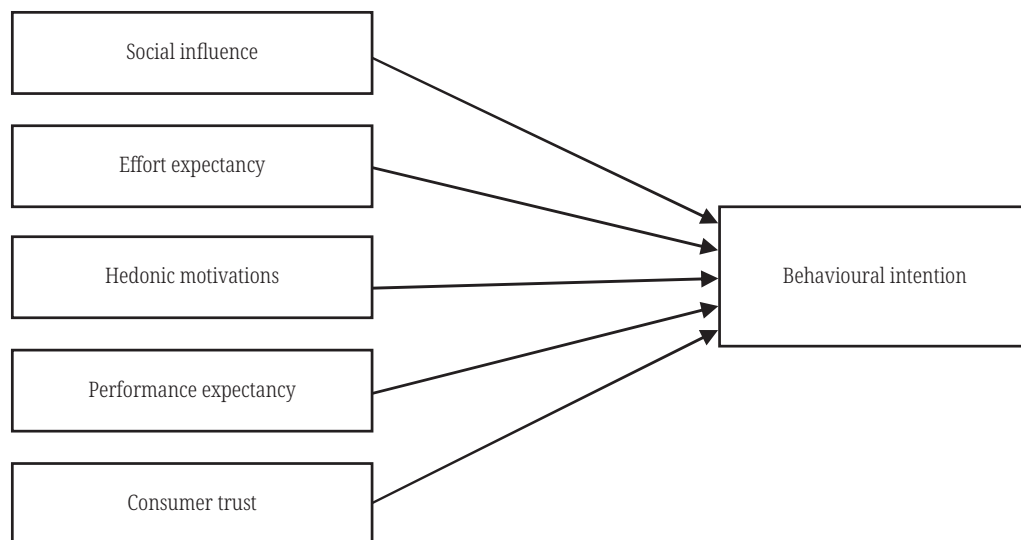


Fig. 3. Final model of AI and mobile learning applications in HEI

13 PRACTICAL IMPLICATIONS

The findings of this study have significant practical implications for HEIs, technology providers, and policymakers in Malaysia and similar developing contexts. By identifying SI, EE, HM, PE, and TR as key factors influencing the adoption of AI applications and mobile learning, this study provides actionable insights for stakeholders aiming to promote these technologies effectively.

13.1 For higher education institutions

Universities can leverage these findings to design targeted strategies that enhance user acceptance of AI and mobile learning platforms. For example, integrating features that emphasize ease of use and align with students' expectations of performance can boost adoption rates. Additionally, fostering trust in AI applications through transparent communication about data security and ethical AI usage will likely encourage wider acceptance among students and faculty.

13.2 For technology providers

Developers of AI-driven educational tools should consider embedding features that cater to user motivations, such as gamification elements to enhance engagement (HM) or personalized learning pathways to address PE. These considerations can make the tools more appealing and effective in addressing the unique needs of Malaysian higher education institutions.

13.3 For policymakers

Policymakers can use these findings to formulate supportive frameworks that encourage the integration of AI in education. For instance, subsidizing AI-driven tools for creating awareness campaigns about their benefits could accelerate their adoption in underserved regions.

These insights not only highlight the applicability of AI and mobile learning in Malaysia but also offer transferable lessons for other developing nations facing similar challenges in digital literacy and technological infrastructure. By bridging the gap between theoretical models and practical applications, this study contributes to the broader discourse on educational innovation and technology-driven learning advancements.

14 CONCLUSION

This study addresses a significant gap in the literature by investigating factors influencing the behavioral intention to use AI applications and mobile learning in HEI in Malaysia. Through a quantitative approach involving a survey method with 263 participants from Malaysian universities, the researchers empirically tested a proposed theoretical model examining various factors. This study identifies SI, EE, HM, PE, and TR as significant predictors of behavioral intention to use AI applications and mobile learning. This comprehensive model provides valuable insights into user behavior in educational technology adoption.

The study underscores the multifaceted nature of technology adoption decisions in higher education, emphasizing the need for educational institutions to consider various factors when implementing and promoting these technologies. Interestingly, our findings reveal that price value has an insignificant effect on behavioral intention, suggesting that other factors play a more significant role in influencing users' decisions to adopt these technologies in the higher education context.

The growing importance of AI applications and mobile learning in HEI worldwide, particularly in Malaysia, underscores the relevance and timeliness of this study. As AI applications continue to advance and integrate into various aspects of society, including education, understanding their impact on teaching and learning is crucial for educators, administrators, and policymakers.

In recent years, AI applications have emerged as powerful tools for enhancing educational experiences, offering personalized learning opportunities, automating administrative tasks, and facilitating data-driven decision-making. Similarly, mobile learning has gained traction as a convenient and flexible approach to education, allowing learners to access educational resources anytime, anywhere, using their mobile devices.

This study offers practical implications for educational institutions and technology providers seeking to promote the use of AI applications and mobile learning platforms among students and faculty in Malaysia. Key recommendations for stakeholders include:

1. **For Educators and Administrators:** Develop targeted training programs that improve digital literacy and raise awareness about AI and mobile learning tools to foster greater acceptance and usage among students.
2. **For Policymakers:** Formulate policies that incentivize the integration of AI and mobile learning technologies in educational systems, ensuring equitable access to these technologies across diverse regions and socioeconomic groups.
3. **For Technology Developers:** Design AI-powered mobile learning tools that are user-friendly, culturally relevant, and accessible to students with varying levels

of digital competence. These tools should emphasize personalization and address the specific needs of Malaysian learners.

While the findings are specific to Malaysia, they resonate with broader contexts, particularly in other developing nations facing similar challenges in digital literacy, socioeconomic diversity, and technology access. This global relevance highlights the potential applicability of the study's insights to inform strategies for AI and mobile learning adoption in diverse educational settings worldwide.

By implementing strategies to address the identified factors, educational institutions can create more conducive environments for the adoption and utilization of AI applications and mobile learning platforms. This study contributes to the ongoing dialogue on educational innovation and technology adoption, providing insights for stakeholders seeking to leverage these technologies to improve educational experiences and outcomes in Malaysia and beyond.

This study recognizes some limitations. While the sample size of 263 people from several universities increases data diversity, the schools included are quite small, limiting the findings' generalizability. A broader sample from a greater number of universities would provide a more complete picture. Furthermore, the analysis relied heavily on information from four databases: Science Direct, Web of Science, IEEE, and Scopus, which may have excluded significant papers published in other languages or indexed in lesser-known databases. Another drawback is that students' knowledge of AI applications and mobile learning may vary, influencing their usefulness in educational contexts. Additionally, the reliance on the UTAUT framework, while robust, excluded alternative frameworks that may offer complementary insights into technology adoption. Future studies could address these limitations, increasing the robustness and application of the findings.

Future research should explore the long-term effects of mobile learning and AI adoption on educational outcomes, focusing on tracking academic performance and retention rates. Additionally, cross-cultural comparisons could help to further understand the nuances of AI and mobile learning adoption in diverse global contexts. Collaboration between international research networks and educational institutions can foster a deeper understanding of how technology can be harnessed to improve global education outcomes, particularly in emerging economies where educational innovation has the potential to drive substantial societal change.

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