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Key factors influencing digital learning adoption among cambodian university students: An integrated theoretical approach

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ABSTRACT

This study investigates the factors influencing the adoption of digital learning platforms among university students in Cambodia, integrating multiple theoretical frameworks: the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Self-Determination Theory (SDT). Conducting a cross-sectional survey with 369 students from various institutions, this study employed partial least squares structural equation modelling (PLS-SEM) to analyze the data. The findings revealed significant connections among motivational factors, perceived ease of use, usefulness, and subsequent adoption behaviours. This study contributes significantly to the global discourse on digital education, particularly from the perspective of a developing country, at a pivotal point in its educational evolution in the digital age. This highlights the importance of enhancing intrinsic and extrinsic motivations among students to improve the adoption and effective use of digital learning resources, offering practical recommendations for educational stakeholders in Cambodia and similar contexts.

1. Introduction

Rapid technological advancement has instigated profound transformations across multiple sectors, with education in developing countries experiencing particularly notable shifts. Digital learning platforms have become pivotal to educational reforms as tools for technological integration and catalysts for broader sociocultural and pedagogical changes. Cambodia is a compelling case study that offers unique insights into adapting educational practices within specific socioeconomic and cultural frameworks. This study explores Cambodia's progression toward digital educational engagement by focusing on the complex interplay of attitudes, motivations, and sociocultural dynamics that drive this transformation. The existing literature predominantly focuses on developed countries, often overlooking the unique challenges and opportunities in developing contexts like Cambodia. Traditional models, such as TAM and the Unified Theory of Acceptance and Use of Technology (UTAUT), emphasize usability and utility but often fall short in culturally diverse educational settings where motivational factors play a significant role. There is a need for a more nuanced understanding that integrates these traditional models with motivational theories to better capture the factors influencing technology adoption in such contexts. Current studies broadly examine digital learning adoption in developed countries, leaving a gap in understanding how these processes unfold in developing nations with different socioeconomic and cultural dynamics (Han & Shin, 2016; Tarhini et al., 2015). Traditional acceptance models like TAM and UTAUT do not fully incorporate motivational aspects, which are crucial for understanding technology adoption in educational settings. Integrating these models with Self-Determination Theory (SDT) is necessary to capture intrinsic and extrinsic motivational factors (Deci & Ryan, 2000; Ryan & Deci, 2000). Also, existing studies often lack the contextual specificity needed to address countries like Cambodia's unique cultural and technological environments. This research examines Cambodian students' attitudes toward digital learning platforms and assesses how they influence their adoption while also evaluating the mediating effects of personal motivation on the Technology Acceptance Model (TAM).

Additionally, the study aims to refine conventional technology acceptance models better to capture the nuances of the Cambodian educational context, addressing both the practicalities of technology use and the integration of motivational aspects essential for a holistic understanding of technology adoption. The selection of Cambodia as a focus of this study is motivated by its rich cultural heritage and intricate

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historical context, which provides a fascinating backdrop for examining the impact of digital education. Recent studies have enhanced traditional models by incorporating Self-Determination Theory (SDT) elements to better understand motivational influences on technology acceptance in higher education contexts (Alowayr & Al-Azawei, 2021; Sophea et al., 2021). This study examined the factors influencing the adoption of digital learning platforms in Cambodia, mainly focusing on the perceived ease of use, usefulness, and the role of social and motivational influences. The objectives of this study are to analyze Cambodian students' attitudes towards digital learning platforms, assess the impact of personal motivation on the Technology Acceptance Model (TAM) in the Cambodian context, refine existing technology acceptance models by incorporating motivational aspects to better understand technology adoption in culturally diverse educational settings, and provide actionable recommendations for educators, policymakers, and technologists to enhance the adoption and effective use of digital learning technologies in developing countries. The key research question guiding this study is: What are the attitudes of Cambodian students towards digital learning platforms, and how do personal motivations influence their adoption? This central question, along with others, aims to investigate how these factors collectively shape students' attitudes and behaviors towards digital learning technologies in the Cambodian educational landscape, providing insights that can inform educational strategies and technology implementation in similar developing contexts. This study contributes to the global discourse on digital education by offering a culturally sensitive understanding of technology adoption. It highlights the transformative potential of digital platforms in shaping the future of education in Cambodia, providing insights that could inform similar initiatives in other developing contexts. The findings are expected to benefit educators, policymakers, and technologists by presenting actionable recommendations for enhancing the adoption and effective use of digital learning technologies in culturally diverse settings.

1.1. Adopting digital learning platforms in Cambodia

Adopting digital learning platforms in Cambodia's educational framework presents a significant area for scholarly investigation, mainly when analyzed through technology adoption models, such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), alongside motivational theories, such as Self-Determination Theory (SDT). These platforms have become crucial in enhancing educational delivery in universities across developing countries and creating unique and effective learning environments. Recent studies have provided a broader perspective on the critical factors influencing the adoption of digital learning platforms. For instance, integrating digital libraries in higher education institutions has seen substantial support from the Ministry of Education, Youth, and Sports in Cambodia, promoting scholarly journals as a step toward digital transformation in the educational sector (Chealy et al., 2022). Additionally, the rapid adoption of digital tools in higher education, driven by the COVID-19 pandemic, offers a unique opportunity to enhance Cambodia's educational framework (Heng & Doeur, 2022). Performance expectancy, effort expectancy, and social influence are pivotal in adopting digital platforms, as detailed in recent extensions of the UTAUT model, which now includes variables such as online course design and perceived system quality (Zhu et al., 2023). These models help understand technological acceptance in diverse educational settings, further affirmed by Bajunaied et al. (2023), who highlighted the importance of adapting these models to specific educational technologies and cultural contexts. On the motivational front, SDT focuses on autonomy, competence, and relatedness, emphasizing intrinsic motivation as essential for the successful adoption and sustained use of educational technologies (Ryan & Deci, 2000, 2017). This theory is crucial for understanding the motivational underpinnings that drive educators and students to engage with digital platforms, thus enhancing their learning experiences. However, challenges such as limited Internet connectivity, outdated teaching methodologies, and a lack of practical exposure are significant barriers that need to be addressed (Zhu et al., 2023). These issues underscore the necessity for continued research to develop comprehensive frameworks that effectively integrate the technological, pedagogical, and motivational dimensions to overcome these barriers. In addition, the educational impact of digital tools extends beyond simple adoption. For instance, the potential for digital solutions in traditional farming in Cambodia suggests a broader application of educational technologies, which can lead to substantial improvements in various sectors (Chin et al., 2021). This indicates the versatility and expansive potential of digital learning platforms, not only in urban settings but also in rural areas where traditional practices prevail.

1.2. Theoretical foundations

This research explores the adoption of digital learning platforms in Cambodia through a refined theoretical lens, focusing on the tailored integration of motivational and acceptance models. The study employs the Technology Acceptance Model (TAM) introduced by Davis (1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003) while incorporating motivational insights from Self-Determination Theory (SDT) by Deci and Ryan (1985, 2000). This combination was selected to address the intrinsic and extrinsic motivations influencing students' acceptance and usage of technology alongside traditional usability factors. The integrated framework in this study adopts a holistic approach by combining the focus of TAM on usability (ease of use and usefulness), the broader contextual factors from UTAUT (social influence and facilitating conditions), and the motivational insights from SDT (intrinsic and extrinsic motivations). This comprehensive framework examines the functional aspects of technology adoption and delves into the psychological and contextual factors that influence user behavior. Furthermore, integrating these theories allows for the model to be adapted to the Cambodian context, addressing both the technological and cultural specificities of this environment. This contextual adaptation ensures that the findings are relevant and actionable for stakeholders in Cambodian education.

The TAM is foundational in explaining how perceptions of ease of use and usefulness directly influence user acceptance and subsequent technology usage (Davis, 1989). UTAUT extends this model by integrating additional elements, such as social influence and facilitating conditions, enhancing its applicability across different demographic and cultural contexts (Venkatesh et al., 2003). Both models have been robustly validated, including in diverse cultural settings similar to Cambodia, underscoring their relevance in this study (Venkatesh & Davis, 2000; Wong et al., 2012). To enrich understanding of the motivational dimensions of technology adoption, SDT is integrated, distinguishing between intrinsic motivations (driven by personal interest and satisfaction) and extrinsic motivations (influenced by external rewards or pressures). SDT has been shown to complement TAM and UTAUT effectively by providing deeper insights into the psychological factors that can facilitate or hinder technology adoption (Deci & Ryan, 2000; Ryan & Deci, 2000). The relevance of SDT is particularly significant in educational settings, where motivation plays a crucial role in adopting and effectively using learning technologies (Ahmad et al., 2020; He & Li, 2023). Therefore, the inclusion of SDT addresses a critical aspect of technology adoption, as purely functional models, such as TAM and UTAUT, may overlook the role of student motivation. This is especially pertinent in the Cambodian context, where educational technology is a tool for enhancing learning efficiency and a potential motivator for student engagement and participation. Research in similar contexts has highlighted the importance of aligning technology with students' motivational and functional needs to ensure higher acceptance rates (Al-Nuaimi & Al-Emran, 2021; Granić & Marangunić, 2019). By harmonizing these theories, the framework investigates how perceived ease of use and usefulness impact technology adoption and how motivational factors shape students' attitudes toward digital learning platforms in Cambodia. This integrated approach provides a more holistic view of the factors driving technology adoption in education. It offers valuable insights for stakeholders in Cambodian education and beyond. This framework (Fig. 1) focuses on well-established, contextually adapted theories, ensuring that the study remains grounded in relevant academic discourse while providing actionable findings tailored to the unique technological and cultural landscape of Cambodia.

1.3. Hypothesis construction

Research has revealed a dichotomy in perceptions of online learning. On one hand, challenges are prominent; Adnan and Anwar (2020) identified digital accessibility issues and a lack of conventional social interaction as significant barriers. Similarly, Serhan (2020) and Hussein et al. (2020) reported increased student anxiety and perceived misinformation about online education. Unger and Meiran (2020) further articulated concerns about perceived reduced educational quality and efficiency within online platforms. Conversely, positive attitudes towards specific facets of online learning have emerged. Unger and Meiran (2020) reported positive student receptivity to Google Classroom, underscoring its innovative potential. Zhu et al. (2020) and Olum et al. (2020) highlighted enthusiasm for collaborative and social media-based learning, respectively, indicating the versatility of online educational engagement. Albashtawi and Al Bataineh (2020) suggested that while personal challenges may hinder initial engagement, the qualitative aspects of online learning experiences can significantly enhance future receptivity.

Jena (2020) emphasizes the importance of educator support and empathy in fostering positive online learning attitudes, highlighting the pivotal role of pedagogical relationships in digital contexts. Furthermore, Yue et al. (2021) and Jogezai et al. (2021) explored the positive implications of integrating advanced technologies, such as chatbots, and a balanced approach to online and traditional teaching methods, illustrating the potential for technological innovation to improve attitudes towards online learning platforms.

Moreover, various studies have consistently found that the perceived ease of use of digital learning platforms significantly influences students' attitudes toward using these platforms. Al-Dokhny et al. (2021) and Osman et al. (2016) found that perceived ease of use and usefulness strongly influenced students' intentions to use these platforms. Additionally, PEU and other factors significantly affect students' attitudes and intentions to use online learning platforms (Almusheifri, 2020; Singh & Tewari, 2021; Wei et al., 2019). Gogo and Fomsi (2023) highlighted the importance of training and support to enhance the ease of use of these platforms. Finally, Sayaf et al. (2022) and Bhattarai and Maharjan (2020) found that factors such as computer self-efficacy, social influence, and perceived enjoyment also play significant roles in influencing the perceived ease of use and usefulness of digital learning platforms. Based on these studies, this study posits that.

H1. Perceived ease of use of digital learning platforms significantly influences students' attitudes towards using these platforms.

Furthermore, social influence, accessibility, computer self-efficacy, infrastructure, and enjoyment have been found to affect the perceived ease of use and usefulness of digital learning systems (Bhattarai and Maharjan (2020). These factors, along with perceived usefulness, ease of use, and learning environment, also influence student satisfaction with e-learning platforms (Azmi et al., 2018; Wei et al., 2019). However, the actual experiences of students with digital technology may not always align with their potential benefits, suggesting the need for a nuanced understanding of the role of digital technologies in education (Henderson et al., 2017). Thus, this study suggests that.

H2. Perceived usefulness of digital learning platforms significantly influences students' attitudes toward using these platforms.

Baghlani and Tabbaa (2014) asserted that perceived usefulness, self-efficacy, and privacy concerns influence students' attitudes. Aifan (2015) identified perceived ease of use, perceived usefulness, subjective norms, experience with specific tools, and age as the significant determinants. Social media platforms also positively affect educational achievement through interactions between students and lecturers (Alhussain, 2020). Students' perceptions of social media's usefulness and ease of use are two critical factors influencing their use of social media as learning tools (Mahlambi et al., 2018, pp. 1–5; Wei et al., 2019). Kaur et al. (2012, pp. 1–5) also asserted that students use Facebook to access resources and stay connected with their teachers and peers. Sánchez et al. (2014) argued that students use Facebook to share ideas and collaborate. Datt et al. (2021) found YouTube to be a highly accessible and reliable media platform for students. Therefore, this study

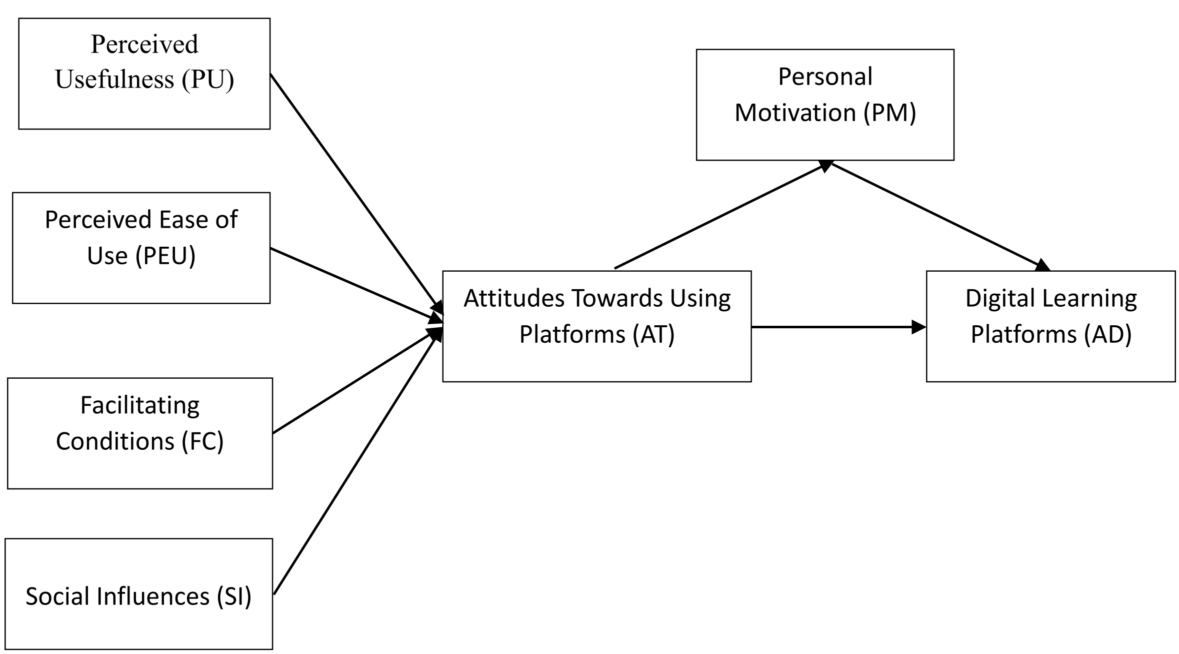

Fig. 1. Model for analyzing the use of online platforms.

posits that.

H3. Social influence significantly influences students' attitudes toward using these platforms.

Furthermore, facilitating conditions, such as the availability of resources and institutional support, significantly influence students' attitudes toward using online learning platforms (Al-Dokhny et al., 2021; Almaiah et al., 2022; Arias Barragan et al., 2015; Li, 2022; Maheshwari, 2021; Wut et al., 2022). These conditions can include information, social influence, technology infrastructure (Almaiah et al., 2022; Wut et al., 2022), and perceived ease of use, usefulness, and enjoyment (Al-Dokhny et al., 2021; Arias Barragan et al., 2015; Presley & Presley, 2009). Integrating these factors can enhance students' intention to use online learning platforms (Li, 2022; Maheshwari, 2021). Based on these studies, this study suggests that.

H4. Facilitating conditions significantly influence students' attitudes toward using these platforms.

Moreover, various studies have highlighted the significant impact of attitude on adopting digital learning platforms. For example, Singh and Tewari (2021) and Sayaf et al. (2022) found that perceived usefulness, ease of use, and social and peer influence play crucial roles in shaping attitudes towards online learning. Espejo et al. (2022) and Almaiah et al. (2022) further emphasized the importance of interactivity, cost-benefit ratio, system quality, service quality, and content quality in influencing attitudes. In addition, technology readiness and customer perception have been identified as crucial factors in shaping attitudes (Kaushik & Agrawal, 2021; Wei et al., 2019). Finally, various factors influence attitudes toward web-based and digital learning systems, including system quality, top management support, and information communication technology infrastructure (Kashada et al., 2018; Motaghian et al., 2013). Therefore, this study posits that.

H5. Attitudes toward using these platforms significantly impact the adoption of digital learning platforms.

Several studies have examined the impact of attitudes towards digital platforms on motivation. For example, Król and Zdonek (2021) found that, while social media use can have some motivational impact, many users are passive and infrequent in their activities. Löcker et al. (2020) highlighted the importance of intrinsic motivational factors in using online communities in business contexts, with intangible factors such as social and organizational aspects playing a significant role. Additionally, various studies have examined the impact of personal motivations on the use of social media, with Habes (2019) emphasizing the importance of sociability and usability and Gonzalez et al. (2020) focusing on the impact of prior experience and health conditions on the use of social media. Thus, understanding the motivations for their use has become increasingly important as many businesses and not-for-profit organizations have begun to use social media platforms as part of their daily business processes (Hallikainen, 2015).

In addition, apathetic motivation appears distinct and can coexist at times (Hansen & Levin, 2016). According to Hakami et al. (2017), the motivational factors that drive individuals to use MOOCs as learners are essential for successful MOOC environments. Finally, Al-Menayes (2015) asserted that social media users are motivated by entertainment, information-seeking, personal utility, and convenience. These arguments suggest that.

H6. Attitudes toward using these platforms significantly impact personal motivation.

According to Chen et al. (2002), personal motivation significantly affects adopting learning platforms. Thus, user attitudes and motivations are essential for successfully using these platforms (Faustmann et al., 2019). Mohamad et al. (2015) and Sabani et al. (2023, pp. 282–287) further identified specific factors influencing motivation, such as knowledge, perceptions, and performance expectancy. Shih (2008) and Sharma and Srivastava (2019) provide a cognitive perspective focusing on efficacy control and expectations and highlighting value beliefs, social influence, and perceived ease of use. Therefore, it is evident that cognitive factors are vital for motivating individuals to engage in online learning. Hakami et al. (2017) and Tarhini et al. (2017) expanded this discussion by identifying the influence of social, educational, and personal factors. When utilizing specific digital learning tools, they emphasized the importance of performance expectancy, social influence, habit, hedonic motivation, self-efficacy, and trust. These studies agree that multiple factors influence digital learning tools and must be understood to maximize their effectiveness. Thus, this study posits that.

H7. Personal motivation significantly impacts the adoption of digital learning platforms.

Furthermore, some studies have revealed that attitude significantly mediates the impact of perceived usefulness, ease of use, and social influence on the intention to adopt online learning (e.g., Ferrer et al., 2020; Singh & Tewari, 2021). Ortega et al. (2011) and Saadé et al. (2008) further emphasized the role of social and intrinsic motivators in influencing attitudes and usage behaviour. However, Espejo et al. (2022) found that perceived usefulness and ease of use do not always positively influence attitudes, suggesting further investigation. According to Van Acker et al. (2013), persuasive communication focusing on positive outcomes and skill-based training are appropriate interventions to promote positive attitudes toward digital learning materials and improve self-efficacy in using digital learning platforms (Shih, 2008). Faustmann et al. (2019) underscored the need to understand the motivation of both learners and teachers to use digital learning platforms successfully. Hence, this study suggests that.

H8. Personal motivation mediates the relationship between attitudes towards using these platforms and adopting digital learning platforms.

2. Methodology

This study employed a methodologically robust approach incorporating structured data collection through quantitative methods to investigate the relationships between the proposed theoretical frameworks. Standardized survey tools were used to obtain reliable and consistent data. The choice of Partial Least Squares-Structural Equation Modeling (PLS-SEM) for data analysis was pivotal because of its ability to handle complex constructs and its efficacy in non-parametric data analysis, which is ideal for predictive objectives and exploring variable interrelations, in contrast to the theory-confirming focus typical of Covariance-based SEM (CB-SEM) (Hair Jr et al., 2014). PLS-SEM is particularly noted for its flexibility in modelling intricate relationships without strict requirements on measurement scales, distributional assumptions, sample size, or residuals, making it suitable for formative measurement models and handling complex constructs under less stringent conditions (Henseler et al., 2009; Ringle et al., 2015). The primary rationale for selecting PLS-SEM lies in its suitability for theory development and prediction studies. Unlike CB-SEM, which is better suited for theory testing and requires large sample sizes and normally distributed data, PLS-SEM can efficiently work with smaller and non-normally distributed data samples. This capability is particularly relevant to this study, which involves complex models with multiple indicators and constructs. In addition, PLS-SEM is advantageous when dealing with formative constructs, which are critical in our theoretical framework. It allows for including reflective and formative measurement models, providing a more comprehensive analysis of the relationships between constructs. The predictive accuracy and exploratory nature of PLS-SEM make it an optimal choice for our study's objectives, which focus on understanding and predicting the interactions among various factors. The robustness and adaptability of PLS-SEM were crucial factors in its selection for this study, which focused on building rather than merely testing the theories. However, it is crucial to consider the limitations of PLS-SEM in interpreting these findings. The lower parameter consistency compared to CB-SEM suggests that while the predictive models are robust, they may not be as precise as those generated by CB-SEM with larger samples. SmartPLS 4 for PLS-SEM analysis facilitated a detailed examination of the research hypotheses, providing a nuanced understanding of the interactions among the study variables. This thorough analysis not only tested the hypotheses but also provided significant insights into the dynamics of the variables, thereby substantially enriching the understanding of the processes governing the theoretical framework.

2.1. Participants and sampling

The participants in this study were drawn from Cambodian higher education institutions, specifically selected for their engagement with digital learning platforms. The students from these institutions provided an ideal demographic for examining patterns of technology adoption and attitudes toward digital learning tools. A total of 400 students were surveyed using Structural Equation Modeling (SEM), aligning with sample size guidelines recommended by Hair et al. (2021), who suggest a range of 200–400 participants for practical SEM analysis. This sample size was adequate for robust SEM analysis, ensuring practical, efficient survey distribution and data collection. To achieve a diverse demographic representation, the sampling strategy employed snowball sampling initiated through digital channels, leveraging the interconnectedness of students via social media and online academic forums. This approach facilitated access to a broad cross-section of the student body, ensuring that the sample was adequate in size and, diverse and representative of various demographic segments within the higher education landscape in Cambodia.

2.2. Instruments and materials

The scale items were revised and tailored from existing research to suit the specific needs of the Cambodian context and the objectives of this research. This adaptation, grounded in our target population's socioeconomic realities, may influence our variance's comparability, which is explained with broader literature benchmarks. Precisely, to measure Perceived Usefulness (PU) and Perceived Ease of Use (PEU), a set of four items for each was derived from the foundational works of Davis (1989), Shaw (2014), and Venkatesh et al. (2012), with these adaptations corroborated by multiple studies (e.g., Ly et al., 2023; Ly & Ly, 2022, 2023). In addition, a three-item scale for Social Influences (SI) was refined based on Osswald et al. (2012) and Zhang et al. (2020). Similarly, the four-item scale for Facilitating Conditions (FC) and Attitudes Towards Using Platforms (AT), comprising three items, was adapted from Venkatesh et al. (2003). The Personal Motivation (PM) scale, encompassing six items, was developed by integrating concepts from established studies (e.g., Ajzen, 1991; Bandura, 1977; Elliot & McGregor, 2001; Ryan & Deci, 2000; Wigfield & Eccles, 2000). Finally, a three-item scale for the Adoption of Digital Learning Platforms (AD) was adapted from Ajzen (1991). All items on the survey were assessed using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). In addition, Confirmatory Factor Analysis (CFA) was used to validate the measuring instrument and determine how the observed variables related to the latent constructs and their relevance to the application of the instrument (Byrne, 2010).

3. Findings

The sample size for this study consisted of 369 completed questionnaires from students at Cambodian higher education institutions out of 400 distributed. The high response rate can be attributed to the concise survey design, which took approximately 10 min to complete. The sample demographics showed a predominantly young population, with 48.0% aged 18–35 and 47.7% aged 36–52, reflecting the typical age range of higher education students. A small percentage (4.3%) were aged 53–64, indicating lower participation from older students. Gender representation was nearly equal, with a slight male majority of 51.8%. Most participants were pursuing undergraduate (46.9%) and master's degrees (46.1%), while a smaller fraction (7.0%) held doctorate degrees. This diverse and academically oriented sample provides a solid foundation for examining digital learning platform implementation in Cambodian tertiary education.

To minimize confounding effects, control variables such as age, gender, and educational level were included. Age was controlled to account for differences in technology adoption and usage behavior across various age groups. Gender was controlled to address potential differences in access to and attitudes towards digital learning platforms, as previous studies have indicated gender-based differences in technology usage. Educational level was controlled to consider the variance in digital literacy and academic demands at different stages of higher education. These control variables were selected based on theoretical and empirical evidence to ensure that these external factors did not influence the observed relationships between the independent and dependent variables. This provided a more accurate analysis of the factors influencing digital learning platform adoption in Cambodian higher education.

3.1. Model assessment

In analyzing the measurement model, it is crucial to focus on three key aspects: internal consistency and discriminant and convergent validity (Hair et al., 2011, 2016; Henseler et al., 2009). A primary method for ensuring validity involves selecting indicators with outer loading values ≥ 0.70, as Hair et al. (2016) recommended. To assess internal consistency and composite reliability (CR), this study employed Cronbach's alpha coefficients, all of which surpassed the 0.70 benchmark, a standard set by Fornell and Larcker (1981). This high level of Cronbach's alpha across all constructs indicates robust convergent validity. This is corroborated by the Average Variance Extracted (AVE) surpassing the 0.50 threshold. Detailed results, including loadings, Cronbach's alpha, CR, and AVE, are presented in Table 1.

This study employed a two-pronged approach to evaluate discriminant validity. The first method involved comparing the square root of the AVE against the correlations among the items. According to Fornell and Larcker (1981), for adequate discriminant validity, the square root of the AVE should be larger than the inter-construct correlations.

This criterion was met, as indicated in Table 2, where the square root of the AVE for each construct was higher than the correlations between constructs. The second method utilized was the heterotrait-monotrait ratio of correlations (HTMT). The use of the HTMT to establish discriminant validity in a higher education context has been confirmed in various studies (e.g., Bervell et al., 2021; Mohd Dzin & Lay, 2021). As Henseler et al. (2015) suggested, an HTMT value below 0.90 indicates acceptable discriminant validity. The results in Table 2 confirm that all constructs meet this criterion, thereby establishing discriminant validity.

3.2. Structural model

Before delving into the findings of the structural model, it is essential to establish the validity and reliability of the construct. The Variance Inflation Factor (VIF) was calculated using PLS-SEM to address the potential multicollinearity issues. According to Hair et al. (2011), VIF values within the acceptable range should fall between 0.20 and 5.0. In this study, the VIF values varied from 1.40 to 3.40, indicating the absence of multicollinearity. Additionally, the study assessed Common Method Bias (CMB) using Harman's single-factor test, a method discussed by Fuller et al. (2016) and Podsakoff et al. (2003). This test involved unrotated factor analysis, which showed that only 27.73% of the variance could be attributed to a single factor. This result suggests that CMB was not a significant issue in this study. Furthermore, the study observed that each construct's VIF was below 5.0, reaffirming the lack of multicollinearity, as noted by O'brien (2007).

Table 1
Factor loadings, reliability, and validity.

Constructs	Loadings
Adoption of Digital Learning Platforms (AD) (Cronbach's Alpha = 0.808, CR = 0.887, AVE = 0.723)	
AD1-I regularly use digital learning platforms for my learning activities	0.861
AD2-I integrate digital learning platforms into my daily study routine	0.869
AD3-I intend to continue using digital learning platforms in my future courses	0.820
Perceived Usefulness (PU) (Cronbach's Alpha = 0.850, CR = 0.898, AVE = 0.688)	
PU1-Using digital learning platforms enhances my learning effectiveness	0.779
PU2–I find digital learning platforms useful in my academic work	0.903
PU3-Digital learning platforms improve the quality of my work	0.878
PU4–I think digital learning platforms make learning more efficient	0.748
Perceived Ease of Use (PEU) (Cronbach's Alpha = 0.849, CR = 0.897, AVE = 0.685)	
PEU1-I find digital learning platforms easy to navigate	0.784
PEU2-Learning how to use digital learning platforms is easy for me	0.771
PEU3-Interacting with digital learning platforms is clear and understandable	0.878
PEU4-I find it easy to learn new features on digital learning platforms	0.872
Social Influences (SI) (Cronbach's Alpha = 0.774, CR = 0.867, AVE = 0.686)	
SI1-The use of digital learning platforms is common among my academic circle	0.836
SI2-My friends and family would encourage me to use digital learning platforms	0.798
SI3–I feel pressured to use digital learning platforms because my peers do	0.849
Facilitating Conditions (FC) (Cronbach's Alpha = 0.873, CR = 0.912, AVE = 0.721)	
FC1–I have access to the necessary resources to use digital learning platforms effectively	0.865
FC2-My institution provides adequate support for using digital learning platforms	0.853
FC3-The infrastructure of my institution supports the use of digital learning platforms	0.871
FC4-Technical support is readily available for digital learning platforms	0.806
Attitudes Towards Using Platforms (AT) (Cronbach's Alpha = 0.775, CR = 0.869, AVE = 0.689)	
AT1-I feel comfortable using digital technologies for learning	0.854
AT2-I believe that digital technologies make learning more interesting	0.801
AT3-I am satisfied with the features and resources available on digital learning platforms	0.835
Personal Motivation (PM) (Cronbach's Alpha = 0.868, CR = 0.900, AVE = 0.601)	
PM1-It is inherently enjoyable and satisfying for me to use digital learning platforms	0.740
PM2-I use digital learning platforms because I need to achieve good grades	0.781
PM3-My main goal in using digital learning platforms is to learn new skills	0.737
PM4-I am confident in my ability to use digital learning platforms effectively	0.753
PM5-I value the knowledge I gain from using digital learning platforms	0.828
PM6-I feel in control of my learning when I use digital learning platforms	0.809

Table 2
Discriminant validity-Fornell & Larcker criterion.

	AD	AT	FC	PEU	PM	PU	SI
AD	0.850						
AT	0.383	0.830					
FC	0.523	0.343	0.849				
PEU	0.270	0.263	0.273	0.828			
PM	0.589	0.379	0.299	0.434	0.775		
PU	0.221	0.261	0.284	0.177	0.342	0.829	
SI	0.493	0.272	0.262	0.159	0.580	0.258	0.828
HTMT							
AD	–						
AT	0.479						
FC	0.617	0.400					
PEU	0.320	0.306	0.311				
PM	0.687	0.452	0.332	0.505			
PU	0.256	0.302	0.318	0.192	0.393		
SI	0.633	0.346	0.320	0.201	0.694	0.324	–

The quality of the model was then evaluated to predict the endogenous constructs. This evaluation encompassed several measures, including the coefficient of determination (R^2), Stone-Giesser test (Q^2), path coefficients (β), and significance of paths. Falk and Miller (1992) suggested that for a model to be considered adequate, the R^2 value for each latent dependent variable should be at least 0.1. In this study, the R^2 values for PM, AT, and AD were 0.144, 0.194, and 0.376, respectively, indicating that the model explained 14.4%, 19.4%, and 37.6% of the variance in these constructs (Fig. 2). While the R^2 values for PM and AT are modest compared to established benchmarks, these findings need to be interpreted within the context of digital learning platform adoption in Cambodia.

Moreover, Q^2 values assess the predictive relevance of endogenous constructs. As a result, Q^2 values of 0.080, 0.118, and 0.265 for PM, AT, and AD, respectively, suggest that the model has predictive relevance for each construct (see Table 3). In the model analysis, f^2 values range from 0.019 to 0.368, reflecting variable impact strengths (Table 3). PU, PEU, and SI exhibit small effect sizes on AT, indicating limited impacts. Conversely, FC demonstrates a moderate effect, while AT significantly influences PM and AD, with PM showing the most substantial effect on AD. This underscores Perceived Mobility as a critical factor for adoption strategies.

Another important aspect of model assessment in PLS-SEM is the standardized root mean square residual (SRMR), which helps to prevent model misspecification. SRMR represents the standardized difference between observed and predicted correlations (Hu & Bentler, 1999; Kenny, 2020). Although PLS-SEM has no established threshold for SRMR, it is commonly accepted that an SRMR value below 0.10 indicates an acceptable model fit (Hu & Bentler, 1998; Kara et al., 2022; Worthington & Whittaker, 2006). The SRMR in this study was 0.07, indicating adequate model fit. Additionally, the normed fit index (NFI) was evaluated. The NFI, also known as the Bentler-Bonett normed fit index (Moss, 2009), is an incremental fit measure. It calculates the Chi-square value of the proposed model and relates it to a meaningful standard (Bentler & Bonett, 1980). This index ranges between 0 and 1, with higher values signifying a superior fit (Lohmöller, 2013). The NFI value for this model is 0.70, indicating a 70% improvement in fit relative to the null or independence model. The third fit value indicates the exact model fit, assessing the statistical inference (bootstrap-based) on the dissimilarity between the empirical covariance matrix and the covariance matrix anticipated by the composite factor model. A good fit is achieved when the difference between the correlation matrix inferred by the model and the empirical correlation matrix is not statistically significant ($p > .05$) (Ramayah et al., 2017). This study determined that the discrepancy value for the unweighted least squares (d_ULS) was 0.802, and for the geodesic distance (d_G) was 0.396. It was established that the exact fit criteria exceeded the threshold of 0.05, a deviation higher than the original values (Dijkstra & Henseler, 2015). Thus, this model's fit is considered satisfactory, and there are no concerns to raise.

A hypothesis testing process was conducted to determine the significance of the correlations within the model (Fig. 3). As shown in Table 3, all path coefficients were statistically significant and supported. Initially, H1 proposed that perceived ease of use (PEU) significantly influences attitude (AT), was supported with a path coefficient of $\beta = 0.154$, $t = 2.749$, $p = 0.006$, an effect size of $f^2 = 0.027$, and a 95% confidence interval [0.049, 0.264]. This small effect size suggests a modest but significant impact of PEU on AT. H2, which suggested that perceived usefulness (PU) significantly affects attitude (AT), was also supported with $\beta = 0.131$, $t = 2.202$, $p = 0.028$, $f^2 = 0.019$, and a 95% confidence interval [0.028, 0.259]. This small effect size indicates a modest, practical impact of PU on AT. The hypothesis H3, that social influence (SI) has a significant and positive effect on attitude (AT), was supported with $\beta = 0.155$, $t = 3.029$, $p = 0.002$, $f^2 = 0.027$, and a 95% confidence interval [0.056, 0.255]. This small effect size suggests a modest but significant practical impact of SI on AT. H4 proposed that facilitating conditions (FC) are significantly and positively related to

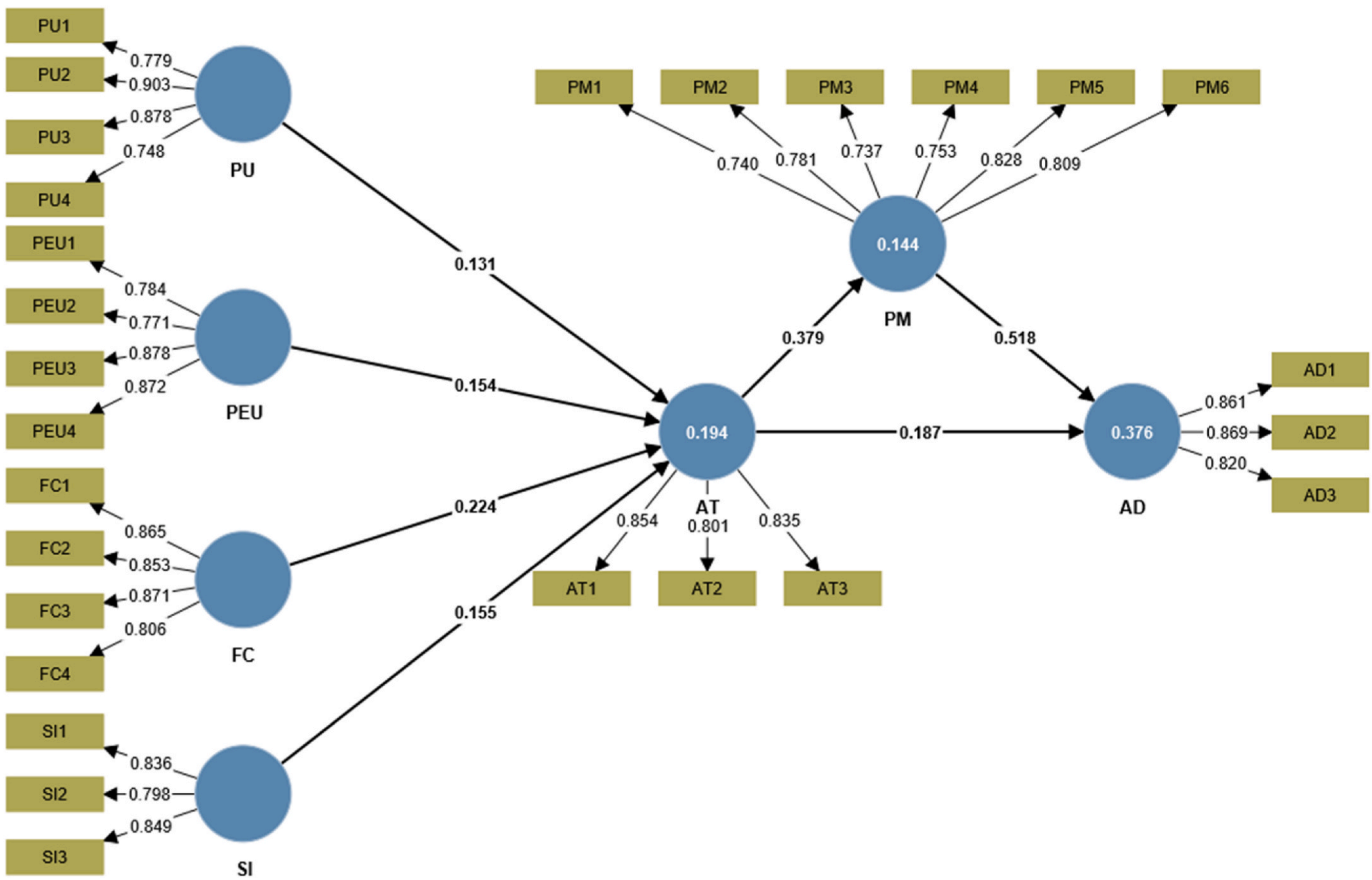

Fig. 2. PLS algorithm results.

Table 3
Hypotheses testing.

	Path coefficient	t-value	p-value	f-square	CI[2.5%–97.5%]	Decision
H1: PEU - > AT	0.154	2.749	0.006	0.027	0.049–0.264	Supported
H2: PU - > AT	0.131	2.202	0.028	0.019	0.028–0.259	Supported
H3: SI - > AT	0.155	3.029	0.002	0.027	0.056–0.255	Supported
H4: FC - > AT	0.224	2.992	0.003	0.052	0.084–0.374	Supported
H5: AT - > AD	0.187	3.385	0.001	0.048	0.078–0.294	Supported
H6: AT - > PM	0.379	5.888	0.000	0.168	0.248–0.502	Supported
H7: PM - > AD	0.518	8.515	0.000	0.368	0.393–0.631	Supported

	R^2	Q^2
PM	0.144	0.080
AT	0.194	0.118
AD	0.376	0.265

attitude (AT). This hypothesis was supported with $\beta = 0.224$, $t = 2.992$, $p = 0.003$, $f^2 = 0.052$, and a 95% confidence interval [0.084, 0.374]. The moderate effect size of 0.052 indicates a noticeable practical impact of FC on AT. H5, which suggested that attitude (AT) towards using the platform positively predicts adoption (AD), was supported with $\beta = 0.187$, $t = 3.385$, $p = 0.001$, $f^2 = 0.048$, and a 95% confidence interval [0.078, 0.294]. This moderate effect size indicates a noticeable practical impact of AT on AD. H6, which proposed that attitude (AT) positively influences perceived motivation (PM) to use these platforms, was supported with $\beta = 0.379$, $t = 5.888$, $p < 0.001$, $f^2 = 0.168$, and a 95% confidence interval [0.248, 0.502]. The large effect size of 0.168 suggests a substantial practical impact of AT on PM. Finally, H7 proposed that perceived motivation (PM) strongly predicts the adoption of digital learning platforms (AD). This hypothesis was supported with $\beta = 0.518$, $t = 8.515$, $p < 0.001$, $f^2 = 0.368$, and a 95% confidence interval [0.393, 0.631]. The effect size of 0.368 indicates a robust significance, suggesting that PM substantially impacts AD.

To evaluate the mediating effects within the model, bootstrap analysis using SmartPLS4 was implemented. This method aligns with the procedural guidelines established by Zhao et al. (2010), in which the product of paths a*b (representing the indirect effect) is calculated before the assessment of mediation within the Partial Least Squares (PLS) framework. Additionally, the magnitude of the mediating effect was determined. Consistent with the recommendations of Hair et al. (2016) and Zhao et al. (2010), this analysis used bootstrapping with 5000 subsamples. Table 4 presents the mediation analysis that explored the role of personal motivation (PM) in the relationship between attitudes toward digital learning platforms (AT) and the adoption of digital learning platforms (AD). The total effect of AT on AD was significant ($\beta = 0.383$, $t = 5.445$), indicating a strong relationship between these variables.

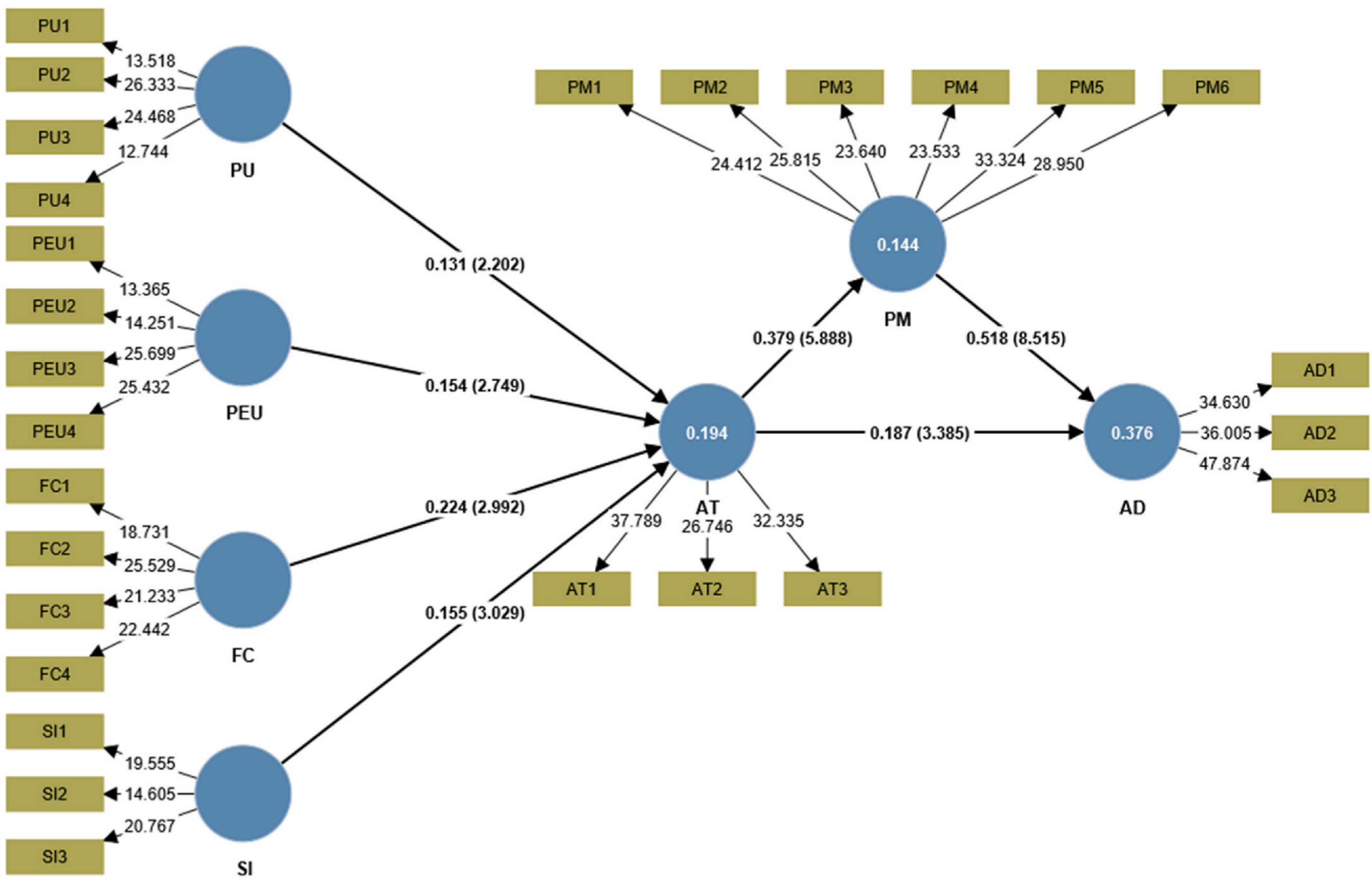

Fig. 3. PLS model analysis.

Table 4
Mediation analysis.

	Total effects			Direct effects		
	β	t-value	CI[2.5%–97.5%]	β	t-value	CI[2.5%–97.5%]
AT - > AD	0.383	5.445	0.239–0.514	0.187	3.385	0.078–0.294
Indirect effects						
Hypotheses	β	t-value	p-value	f-square	CI[2.5%–97.5%]	
H8: AT - > PM - > AD	0.196	4.371	0.000	0.360	0.113–0.287	

However, when examining the direct effect of AT on AD, with the mediator PM included in the model, this relationship remained significant but at a reduced level ($\beta = 0.187$, $t = 3.385$), suggesting that PM accounts for some of the influence of AT on AD. Hypothesis 8 posits that PM mediates the relationship between AT and AD. The indirect effect of AT on AD through PM was significant ($\beta = 0.196$, $t = 4.371$, $p < .001$), with a 95% bootstrap confidence interval ranging from 0.113 to 0.287, not containing zero. This indicated that PM is a significant mediator of the AT-to-AD pathway. The findings support the mediating role of PM, suggesting that while attitudes toward using digital learning platforms directly influence their adoption, they also exert an indirect influence through personal motivation. This finding implies that interventions to enhance the adoption of digital learning platforms should consider strategies that directly influence attitudes and foster personal motivations.

The f^2 value of 0.360 is considered large (Aiken et al., 1991), suggesting that PM strongly mediates AT and AD. The confidence interval for the indirect effect further confirms its robustness. Moreover, the strength of the mediating effect of PM, as determined using the Variance Accounted For (VAF) method, was 0.51, indicating that PM played a significant, though partial, mediating role. This confirms the importance of PM as a mediator in the model.

4. Discussion

The integration of the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Self-Determination Theory (SDT) into the Cambodian higher education system provides a comprehensive framework for understanding the various factors that influence digital learning adoption. Focusing on these well-established models, this study captures a broad range of determinants, from ease of use to intrinsic motivation, and demonstrates the intricate interplay between technological perceptions and motivational factors in this educational context. First, it revealed that PEU substantially influences students' attitudes towards digital platforms. This study aligns with the TAM and UTAUT, underscoring the importance of ease of use in technology adoption. Al-Dokhny et al. (2021) and Zhou et al. (2022) studies also emphasize the significance of straightforward digital interactions on user perceptions and their willingness to engage with technology. Given the ongoing digital transformation of Cambodia's educational system, ease of use is crucial in this context. These platforms must be functional and user-friendly to ensure widespread acceptance and integration of digital learning technologies. Accessible training and support resources can help address the challenges associated with adopting new technologies, as Gogo and Fomsi (2023) suggested. Comprehensive training programs are critical in Cambodia, where resources are limited, and educators may adapt to digital modalities. Educational institutions can foster inclusive and effective learning environments by implementing user-friendly digital learning platforms and comprehensive support systems. This approach aligns with international technology adoption theories. It addresses the specific needs of the Cambodian educational system, paving the way for a more digitized and efficient future in education.

Similarly, the perceived usefulness of digital learning platforms has been shown to significantly affect students' attitudes towards using them. In Cambodia, where the education sector actively integrates advanced technological tools, the efficiency and engagement of these tools in delivering educational content are crucial. The perceived usefulness of digital platforms is emphasized, as they must demonstrate their contribution to better learning environments and outcomes to be embraced by students. Azmi et al. (2018) and Wei et al. (2019) highlighted practical advantages, such as access to information, personalized learning, and interactive experiences, as crucial factors shaping positive student attitudes. In addition, social influence and computer self-efficacy play a role in the Cambodian educational system, with peers and instructors influencing the perceived utility of digital platforms. Enhancing computer self-efficacy can further strengthen the perceived usefulness of these platforms. The study also addresses potential gaps between the expected and actual benefits of digital tools, as highlighted by Henderson et al. (2017), and reaffirms that perceived usefulness remains a robust predictor of positive attitudes towards digital learning platforms in Cambodia. Policymakers and educators in Cambodia need to continue developing and implementing digital education strategies that focus on enhancing perceived usefulness, fostering a more receptive and enthusiastic adoption of digital learning platforms, and ultimately enriching students' educational experiences.

Furthermore, the utilization of digital learning platforms in Cambodia is significantly influenced by social factors, which provides valuable insights into how technologies are perceived and integrated into the educational system. This aligns with the findings of Kar et al. (2021) and Salhab and Daher (2023), who emphasize the importance of social influence in shaping technological behaviours. In Cambodia, where educational reform and digital transformation are ongoing, the perception of digital tools among peer groups can significantly accelerate or hinder their adoption. Therefore, it is crucial to leverage the collective dynamics to enhance the deployment and effective use of digital learning platforms by initiating targeted awareness and orientation programs that address the specific needs and expectations of the educational community. By fostering a supportive community around digital learning, educational policymakers and technology implementers can promote the adoption of digital learning technologies. This can be achieved by creating opportunities for students to experience digital platforms in group settings, sharing the success stories of peer groups benefiting from such technologies, and facilitating discussions that allow learners to express and address their concerns and expectations regarding digital education. By understanding and leveraging these social dynamics, Cambodia can improve its adoption rates of digital learning technologies and transform its educational landscape into a more adaptive, inclusive, and forward-looking approach.

Facilitating conditions such as technology infrastructure, substantial institutional support, and ample resources are critical factors in fostering positive student attitudes toward digital learning platforms. These elements are vital for the success of technology adoption and enhancement of user experience quality. Cambodia's evolving educational landscape uses digital technologies to address historical obstacles and disparities. Reliable technology infrastructure, such as extensive high-speed Internet access, contemporary computer labs, and mobile devices, facilitates seamless access to digital content and interactive learning experiences vital for student engagement and satisfaction. The commitment of educational leaders to invest in and advocate digital technologies is crucial, especially in Cambodia, where numerous schools and universities are still in the early stages of digital integration. Adequate resources, including training for students and educators and ongoing support for troubleshooting technical issues, are equally important. Enhancing digital literacy skills through targeted training programs is critical for maximizing digital platform use, particularly for students from rural or underprivileged backgrounds who require equal access to digital learning opportunities. Almaiah et al. (2022) and Li (2022) underscore the importance of supportive conditions in promoting technology adoption. These studies show that a conducive environment is critical in enhancing the user experience and satisfaction. To achieve the desired outcomes in Cambodia's ongoing educational reforms, building a robust technological infrastructure, offering solid institutional support, and ensuring ample resource availability are crucial. This will enable the country to realize the full potential of digital learning platforms, leading to improved educational results.

This study highlights the importance of cultivating favourable attitudes towards digital learning platforms in line with the TAM and UTAUT theoretical frameworks, as well as the integration of SDT, which emphasizes the significance of intrinsic and extrinsic motivational factors in promoting student engagement with these technologies (Chiu, 2022). Integrating digital technology into the Cambodian educational sector is vital for modernizing its curriculum and pedagogical methods. To ensure successful implementation, it is crucial to cultivate positive attitudes towards these platforms. The content and interface's quality, relevance, and user-friendliness can significantly impact students' willingness to use these platforms regularly and enhance their learning experiences and outcomes. In the Cambodian context, motivational factors, such as autonomy, competence, and relatedness, can be particularly effective. For example, platforms enabling customization and personalization support autonomy, whereas forums and chat features facilitating interaction with peers and instructors can enhance relatedness. Positive initial experiences with digital learning platforms are crucial, especially in Cambodia, where many students have limited exposure to advanced educational technologies. Therefore, it is critical to prioritize the system stability, intuitive design, and comprehensive support structures. Enhancing system quality to ensure reliability and improving content quality to engage pedagogically sound is essential. When students perceive digital tools as beneficial and supportive of their educational aspirations, their motivation to engage in these technologies increases. Focusing on developing and promoting high-quality digital learning environments that support motivational needs and foster positive attitudes is pivotal in the Cambodian educational reform agenda. This strategic focus will facilitate the adoption of these technologies across more educational institutions and enhance the overall educational landscape by making learning more accessible, interactive, and practical.

5. Conclusion

This study emphasizes the critical role of integrating established models, such as TAM, UTAUT, and SDT, in understanding the multifaceted influences on digital learning adoption within Cambodian higher education. This highlights how technological ease of use and perceived usefulness significantly impact students' attitudes toward digital platforms, stressing the importance of user-friendly and effective educational technologies. The findings also highlight the role of social influences and intrinsic motivational factors in shaping students' engagement and acceptance of these technologies, particularly in a transitioning educational context such as Cambodia.

This research makes substantial theoretical advancements in educational technology and adoption models by effectively incorporating TAM, UTAUT, and SDT into Cambodian higher education. Through this integration, this study deepens our understanding of the complex interplay between ease of use, perceived usefulness, and motivational factors. This synthesis offers a more refined perspective on how various elements interact to influence technology adoption in unique socioeconomic and cultural settings. The findings contribute to expanding the application of these theories beyond conventional Western contexts, offering a broader global perspective on educational technology adoption. This adaptation can guide future research to explore similar integrations in other developing countries, thereby enhancing the generalizability and applicability of adoption models across diverse educational environments.

Practically, this study highlights the necessity of creating user-friendly digital learning platforms that are easily accessible and appealing to Cambodian students. Given the crucial role of ease of use and perceived usefulness in shaping students' attitudes toward technology, educational leaders and policymakers should concentrate on these aspects to enhance the effectiveness of digital learning tools. This implies that extensive training programs for students and educators are crucial, particularly in regions with varying levels of digital literacy. Such training can facilitate smoother transitions to digital modalities, ensuring that all users are competent and self-assured to utilize new technologies. Furthermore, the study emphasizes the importance of leveraging social influence to accelerate the adoption of digital tools. Institutions can enhance the perceived value and acceptance of these technologies by involving peer groups and instructors to promote and demonstrate the advantages of digital learning. This social approach can be particularly effective in cultures that value communal learning and collective advancement.

Additionally, the study recommends substantial institutional support and resource allocation to develop a strong technological infrastructure. This includes providing dependable Internet access, modern computing facilities, and ongoing technical support to address challenges that may arise during the implementation phase. By addressing these practical considerations, Cambodia can establish an educational environment that fosters current digital transformation and prepares its institutions and learners for future advancements in educational technology. Adopting a proactive stance will ultimately help Cambodia achieve improved educational outcomes and offer students a more comprehensive and practical learning experience throughout the country. These practical implications underscore the importance of a holistic approach that considers both technical and motivational factors in promoting digital learning.

Future research should explore how digital learning adoption models, integrating TAM, UTAUT, and SDT, can be adapted and applied in other developing countries with diverse cultural and socioeconomic contexts. This cross-cultural comparison would help in understanding the generalizability and applicability of these models across different educational environments. Additionally, conducting longitudinal studies to track the long-term impact of digital learning platforms on educational outcomes in Cambodia would provide deeper insights into the sustained effectiveness of these technologies and the evolution of students' attitudes and motivations over time. It is also essential to investigate how emerging technologies, such as artificial intelligence and virtual reality, can be integrated with digital learning platforms to further enhance the learning experience and outcomes for students in developing countries. Moreover, exploring the role of government policies and infrastructure development in supporting the adoption of digital learning technologies is crucial. This includes examining the impact of initiatives aimed at improving internet access, providing modern computing facilities, and offering ongoing technical support. Future research should also focus on developing and testing specific interventions designed to boost intrinsic and extrinsic motivation among students to adopt digital learning tools. Understanding the effectiveness of these interventions can inform strategies to enhance technology adoption in educational settings. Additionally, evaluating the effectiveness of various teacher training programs to improve digital literacy and competency among educators is essential. This research can help identify the best practices for training educators to use digital learning platforms effectively and integrate them into their teaching methodologies.

Limitations

The present study had several limitations that require consideration. First, the use of snowball sampling may introduce potential biases, as it can lead to a non-representative sample that might not capture the full diversity of the student population. Additionally, the cross-sectional design of this study offers only a snapshot in time, limiting the ability to infer causality or observe changes over time. The results are highly contextual, which might limit their generalizability to various cultural or educational settings in which technological and educational dynamics differ. The reliance on established theoretical models, predominantly developed through Western research, may not fully capture the unique socioeconomic and cultural dynamics in developing countries such as Cambodia.

Additionally, the predominantly quantitative approach might not capture nuanced individual experiences and attitudes toward digital learning, thereby missing deeper qualitative insights. The rapidly changing nature of digital learning technologies poses a challenge, as this study may not account for the evolving nature of digital platforms, potentially making the findings less relevant over time. Another concern is sample diversity; if the sample does not represent the broader student population, particularly those from rural or underrepresented areas, the results may not reflect the broader national context. The practical implementation of the study's recommendations could face challenges, such as resource limitations, infrastructural constraints, and varying digital literacy levels, which could hinder the effectiveness of adopting digital learning platforms. Finally, the validity of the measures used to assess ease of use, perceived usefulness, and motivational factors could be compromised by how well respondents understand and interpret survey questions, affecting the reliability of the findings.

These limitations emphasize the need for ongoing research that embraces a wider variety of educational settings, includes both qualitative and quantitative methods, and adapts to the rapid technological advances that influence the effectiveness and acceptance of educational technology.

CRediT authorship contribution statement

Bora Ly: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Bunhorn Doeur:** Writing – review & editing, Writing – original draft, Conceptualization. **Son nat:** Writing – review & editing, Writing – original draft, Validation, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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