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# Students' adoption towards behavioral intention of digital learning platform

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## Abstract

The purpose of this research was to investigate students' behavioral intentions toward a digital learning platform. In the framework of Thai education, an empirical study evaluated and applied the adoption model. The recommended research model was tested using structural equation modeling with a sample of 1406 students from every part of Thailand. According to the findings, the best facilitator for students' recognition of using digital learning platforms is attitude (ATT), followed by internal factors such as perceived usefulness (PU) and perceived ease of use (PEU). Furthermore, technology self-efficacy (TSE), subjective norms (SN), and facilitating conditions (FC) are peripheral factors that enhance comprehension of a digital learning platform's approval. These results are consistent with past research, with the exception that PU is the only factor that has a negative influence on behavioral intention. Consequently, this study will be useful to academics and researchers by bridging a research gap in the literature review whilst also demonstrating the practical application of an impactful digital learning platform relating to academic accomplishment.

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**Keywords** Behavioral intention · Attitude · Digital learning platform

## 1 Introduction

Digital learning is concerned with the use of information and communication technology for academic achievement (Elkaseh et al., 2015). Using a platform as a learning environment that includes a curriculum, supporting tools, and services, digital learning is possible (Songkram & Chootongchai, 2022). It saves time and money on teaching and allows learners to utilize learning resources at any time and from any location. A digital learning platform also includes features like learning through modeling (animation and games), online tutorials, and live classes (Paechter et al., 2010). Since the global coronavirus pandemic (COVID-19) has seriously compromised conventional face-to-face instruction, institutions of higher learning are increasingly open to adopting digital learning platforms (Sobaih et al., 2022) In many nations, including the United States, academic institutions provide 90% of their students with digital learning platforms, with admissions at 47.84%. Further, digital learning platforms are used by 95% of all higher education institutions in the United Kingdom (Holsapple & Lee-Post, 2006; McGill & Klobas, 2009). Furthermore, the COVID-19 pandemic compelled colleges and universities in the US to relocate courses online, as evidenced by the soaring yellow line in the graph, which demonstrates that almost all undergraduate and graduate courses had transitioned online. Nothing in higher education history has prepared our institutions of higher learning to respond with such an inexplicable pace. Similar efforts have transpired in Europe and Asia. According to Covid-19, online learning will account for approximately 20–25% of all course admissions over the next ten years, while hybrid learning, defined as incorporated campus-based teaching and digital learning, will account for approximately 70–80% of all course admissions (Tony Bates, 2020) (Fig. 1).

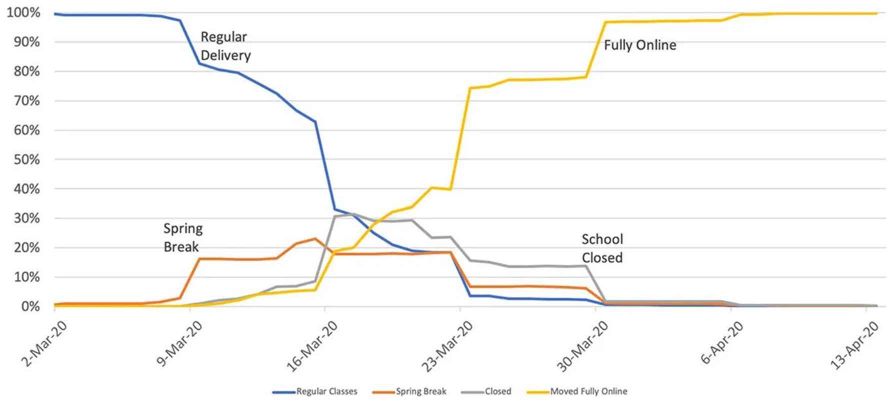



**Fig. 1** Proportion of institutions in the US transitioning to 100% online rather than conventional face-to-face courses through the COVID-19 pandemic (Tony Bates, 2020)

The current study discovered that, prior to the Covid-19 pandemic, the majority of junior high (31.07%) and senior high (23.16%) instructors had not yet hosted online learning. Educators used online learning in the classroom. During the Covid-19 pandemic, junior high school teachers (42.37%) and senior high school teachers (54.80%) were compelled to adopt online learning (Ambawati et al., 2021).

During COVID-19, social isolation made students less active and made them procrastinate more and feel worse about themselves. In a recent study in normal methods of online learning, students said that they get a lot of emails every day and have a lot of assignments and requirements to meet, which makes day-to-day life very stressful (Quillen, 2020). Several studies have proven that student satisfaction with the learning process has significant relationship with the learning outcome, therefore the consequences of online learning might affect the students' academic development and accomplishment. The results of these studies have indicated that the sudden shift to online learning instruction and learning methods have rendered the students dissatisfied with their learning experience. This is because many students lack vital incentives for their progression in their education or career (Fawaz & Samaha, 2021).

Thailand's Ministry of Education (MOE) hopes to inspire students of all levels to use digital learning platforms. As a result, the Ministry of Education (MOE) intends to develop a new digital learning platform for public and private schools to undertake online learning for primary and secondary school students. To help ensure that academic performance is achieved, national digital learning platforms must be developed. Thailand's national digital learning platform is a learning management system that contains a range of electronic educational features that facilitate teaching and learning processes and lead to the success of curricula as well as decision-making for academic objectives. Also, the core functionalities of academic accomplishment contain content management, assessment and testing, communication and collaboration, announcements, reports generation and help system.

These functions can be handled by blockchain technology that provide decentralized content production with collaboration by relevant persons. The learning process is controlled by smart contracts that verify completion of learning assessment. Finally, learning outcomes will be reported as transactions in a digital ledger to track student's performance. Moreover, it promotes the development of skills, values, and knowledge to allow learners to meet current and future digital criteria. Because the majority of previous research was undertaken at higher education levels, it is unclear whether these variables pertain to lower levels of education (Bakarman & Almezeini, 2021). To fill this gap in research, the present study conducted an empirical study with learners in primary and secondary education as participants to investigate students' adoption model toward the behavioral intention of digital learning platforms in Thailand.

The goal of this research is to emphasize the adoption model based on students' perceptions and the functionalities of the digital learning platform based on academic success. As a result, the present study used the adoption model to analyze the factors that affect students' integration of digital learning platforms in education, as well as the characteristics of digital learning platforms concerning academic accomplishment. The rest of the paper is organized as follows.

Section 2 outlines the objectives of the study. The research contributions are presented in Section 3, while the literature review is conveyed in Section 4. Section 5 discusses the methodology, and Section 6 confers the results. The discussion is presented in Section 7. Section 8 reviews the practical implications, and Section 9 discusses the conclusions.

## 2 Objective of the study

The purpose of this research was to investigate the implementation framework of digital learning platforms from the perspective of students in Thailand as well as to recommend the functional implications of digital learning for academic performance in school settings.

## 3 Research contributions

This article's contribution stems from the notion that it offers a complete view of the acceptance model in digital learning platforms, as well as mediators. The information in this paper comes from students' perspectives at various schools throughout Thailand. This indicates that the model is not specific to a particular school, sector, or region, but rather is reflective of all major Thai schools. To examine the key determinants in developing a proper digital learning platform in Thailand, a comprehensive acceptance model was created. To enhance the model, it integrates ideas and components from the Technology Acceptance Model (TAM) and adoption theory in the field of digital learning and explores the mediating function.

The Thai government has established an initiative to support the national digital learning platform, and many researchers are working to entice a diverse range of digital learning development. Nevertheless, learners' perceptions of the digital learning platform show a lack of consistency in terms of academic performance. As a result, continuing to investigate the acceptance model is critical for developing and improving the implementation level of digital learning platforms. The purpose of this paper was to investigate students' perspectives of digital learning according to their experiences in terms of academic participation and digital readiness within the context of a digital learning setting for academic performance. The results of this work will have ramifications for how to improve students' beneficial acceptance of digital learning platforms. Furthermore, the results can guide academics toward the development of a digital learning platform in the Thailand perspective.

## 4 Literature review

Theoretical concepts of technology adoption predominate in published literature. The goal of these concepts is to construct a route to technology adoption based on external factors in order to comprehend how people's intentions to use new technology change (Van Biljon & Kotzé, 2007). The most prevalent theory to arise is the Technology Acceptance Model (TAM). The Unified Theory of Acceptance and Use of Technology (UTAUT), Theory of Reasoned Action (TRA), and Theory of Planned Behavior (TPB) were among the other theories utilized (Hakami et al., 2017; Kaushik & Verma, 2019). Table 1 lists the most prominent and commonly utilized theories of technology adoption, as well as the connections built into the theories to research the usage of digital learning models.

For some time, researchers have used Davis's (1989a, b) Technology Acceptance Model (TAM) to help clarify and anticipate human willingness to adopt new technology, which is useful for studying distance learning (Valenzuela et al., 2009). In TAM, perceived usefulness (PU) and perceived ease of use (PEU), which are both facilitated by attitude (ATT), are the two primary indicators of behavioral intention (BI). This study then goes on to configure the model by including two external predictors of BI, i.e., subjective norms (SN) and facilitating conditions (FC). Moreover, technology self-efficacy (TSE) is a significant factor in students' adoption of innovative educational technology in the context of the national curriculum, as noted by Park et al. (2012). Lastly, we suggested a framework for predicting student integration of digital learning models. The primary correlations between the original TAM and external factors are displayed in Fig. 2.

### 4.1 Digital learning platform

A digital learning platform is a shared-use system aimed at institutions of higher learning to develop an education model that includes digital technologies as a prerequisite (Matsunaga, 2018). Numerous institutions are now actively planning educational reform by implementing such a digital learning platform (Zhou et al., 2020). Teamwork between fellow users involved in reciprocal teaching and learning, rather than teacher-centered instruction from educators to students, is pivotal to educational reform. Because such collaboration lays the groundwork for knowledge management, a digital learning platform can also be referred to as a platform that can integrate knowledge for education (Habib et al., 2021).

### 4.2 Behavioral intention

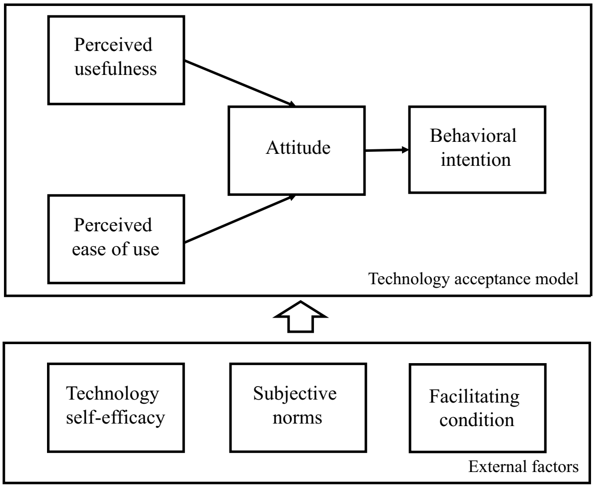
Individual motivation to use a piece of technology is involved (Turner et al., 2010). It is believed that behavioral intention to use technology influences the decision on whether or not to use it (Rizun & Strzelecki, 2020). The motivation of students to use technology impacts their educational objectives in an online classroom setting (Lee, 2010). Numerous researchers have discovered that behavioral intention has a considerable impact on actual system use, as discussed by Ain et al. (2016). In this research, "intention to use digital learning platform" was posited as a component and defined as the likelihood that an individual would use a digital learning platform. Individual behavioral intentions are pertinent in the overall implementation of technology (Davis, 1989a, b).

**Table 1** Concepts of technology implementation and their connection to digital learning platforms

| Essential concepts and authors | Construct correlation with a digital learning platform | Explanation | Literature of the constructs concerning digital learning models |
|---|---|---|---|
| TAM (Davis, 1986) and ETAM (Maillet et al., 2015) | PU (+), PEU (+), ATT (+) TSE (+) and BI (+) | Technology Acceptance Model (TAM) depicts motivational factors that influence a user's stance. These can be classified as either adverse or advantageous to the system. TAM extension (ETAM) is a complement of factors to the TAM model to enhance evidential support. | Scherer et al. (2020), Al-Azawei et al. (2017), Chang et al. (2017), Abdullah and Ward (2016), Weng et al. (2015), Agudo-Peregrina et al. (2014), Šumak et al. (2011) |
| UTAUT (Venkatesh et al., 2003; Venkatesh et al., 2012) | SN (+), FC (+) and BI (+) | The Unified Theory of Acceptance and Use of Technology (UTAUT) was created by combining various acceptance theories and models. | KSA (2017) Tarhini et al. (2017) and Dečman (2015) |
| TRA (Fishbein & Ajzen, 1977) | ATT (+), SN (+) and BI (+) | The Theory of Reasoned Action (TRA) identifies determinants that affect and explain human behavior in the context of examining participants' IT usage patterns. | El Alfy et al. (2017) and Lai et al. (2012) |
| TPB (Ajzen, 1991) | ATT (+), SN (+) and BI (+) | The Theory of Planned Behavior (TPB) is a continuation of the TRA model that includes a component for perceived behavioral control. | Hopkins et al. (2017), Chu and Chen (2016), Teo et al. (2016) and Zhou (2016) |

*BI* behavioral intention, *ATT* attitude, *PU* perceived usefulness, *PEU* perceived ease of use, *TSE* Technology self-efficacy, *SN* subjective norms, *FC* facilitating condition. (+) denotes a positive correlation between the constructs of technology acceptance theories and the digital learning platform, while (−) specifies a negative correlation between the constructs of technology acceptance theories and the digital learning platform

**Fig. 2** Research model




### 4.3 Attitude

Attitude is an aspect of psychology concerned with subjective assessment, perspective, and behavior patterns (Nisa & Solekah, 2022). Individual viewpoints influence the personal evaluation of technology usage (D. Y. Lee & Lehto, 2013) and how a stimulus is addressed. Attitudes are influenced by various stimulus factors, including perceived usefulness, perceived ease of use, technology self-efficacy, subjective norms, and facilitating conditions. The link between attitude and behavioral intention can be supported by a variety of theoretical background analyses. Those with positive attitudes are more likely to embrace a new learning system than those with negative attitudes. In the case of digital learning platforms, learners will likely have a positive attitude after completing a course, resulting in a continued willingness to use digital learning platforms (Ilyas & Zaman, 2020; Kintu et al., 2017).

### 4.4 Perceived usefulness

One widely held belief is that technology improves work performance (Scherer et al., 2019). The extent to which an individual considers that using a particular technology will improve personal job performance is identified as perceived usefulness (Davis, 1989a, b). People often use or avoid an application depending on how much they presume it will improve their work performance. This implies a positive or negative attitude toward perceived usefulness. Perceived usefulness is another important factor that has an instantaneous impact on students' behavioral intention, which influences users' commitment to use an innovation (Keikhosrokiani, 2020b; Venkatesh & Morris, 2000). Perceived usefulness is the degree to which a user thinks that using a system will improve work performance, as suggested by Davis (1989a, b).

### 4.5 Perceived ease of use

It is sometimes assumed that no effort will be necessary (Scherer et al., 2019). The extent to which a person thinks that using the system will be easy is characterized by perceived ease of use (Davis, 1989a, b). Moreover, perceived ease of use impacts behavior intentions implicitly through attitude, whereas perceived usefulness affects behavioral intention to use explicitly (Alfadda & Mahdi, 2021; Liu et al., 2009). Because it improves usability and thus performance, perceived ease of use has a direct impact on learners' perceptions, as revealed by Šumak et al. (2011). Further, numerous studies have also revealed a correlation between perceived ease of use, perceived usefulness attitude, and behavioral intention (Davis, 1989a, b; Davis et al., 1989).

### 4.6 Technology self-efficacy

This concerns having confidence in personal capabilities to organize and execute or achieve better performance by utilizing the system (Holden & Rada, 2011). Technology Self-Efficacy was deemed to be the most commonly utilized external factor in the TAM model, as revealed by Abdullah et al. (Abdullah & Ward, 2016; Keikhosrokiani, 2020a). According to Safie and Aljunid (2013), digital learning lowered learning time by 40–60% when likened to classroom-based teaching. As a result, technological self-efficacy is a stronger antecedent of intent to use digital learning platforms (Dünnebeil et al., 2012). Furthermore, technology self-efficacy is thought to have a positive impact, particularly on perceived ease of use in an e-learning setting (Abdullah et al., 2016; Chang et al., 2017).

### 4.7 Subjective norms

Family and friends use social pressure, also known as social influence, to persuade others to perform or act in a certain way (Agudo-Peregrina et al., 2014). Subjective norms are thought to be one of the most important predictors of behavioral intention. These include how the notions of related groups or individuals, such as family, friends, and peers, influence how we act (Ajzen, 1991; Fishbein & Ajzen, 2011; Malhotra & Galletta, 1999). As noted by Grandon et al. (2005), the subjective norm was a noteworthy factor in determining students' behavioral intention to use. According to Park's (2009) findings, the subjective norm has a direct effect on behavioral intention but also an indirect effect facilitated by perceived usefulness and attitude. According to those investigations, the subjective norm is a major determinant of perceived ease of use and a marginal predictor of student adoption of e-portfolio (Abdullah et al., 2016).

### 4.8 Facilitating condition

It is assumed that sufficient infrastructure exists to support the use of the technology. Knowledge, management, organization, and technical assistance are examples of infrastructure (Nikou & Economides, 2017). Resource availability has also been revealed to be a facilitating condition in the implementation of digital learning platforms (Cilliers & Flowerday, 2010), and has been acknowledged as a significant indicator in the context of acknowledging and applying innovation (Baptista & Oliveira, 2015; Venkatesh et al., 2003). Facilitating conditions have a significant positive influence on perceived ease of use as an operational development of a system, which results in increased behavioral intention towards digital learning platforms (Khrais & Alghamdi, 2021). A facilitating condition is an external control determinant relevant to the topic of facilitating resources (Taylor & Todd, 1995). Learners can complete their tasks and feel optimistic about digital learning platforms when adequate resources are available.

# 5 Methodology

## 5.1 Research design

A single-use, survey-form, correlational design was employed based on Venkatesh et al.'s original modeling of technology acceptance (2003). Per the original TAM model, our theorized impacting independent factors were "perceived usefulness," "perceived ease of use," and "attitude," with "behavioral intention (of use)" as the dependent factor. According to the original model, "technology self-efficacy," "subjective norms," and "facilitating condition" were deemed external factors in the connections between all guiding factors and "behavioral intention".

## 5.2 Collection of data and contributors

Data were gathered through the use of a questionnaire. The researcher used a multistage sampling design to survey K-12 learners from all geographic areas across Thailand. The first stage of sampling comprised a purposive sample of 12 provinces drawn from four regions in Thailand. The second stage of the sampling procedure included the choice of 5 schools (primary and secondary schools) from each province, while the final stage involved a random sample of ten students from each school. The total number of participating students was 1406. Most respondents (93.45%, $N=1314$) ranged in age from 13 to 18. Among them, 96.46% ($N=1356$) were in secondary school, and 3.56% ($N=50$) were in primary school.

## 5.3 Procedure

Quantitative methods were employed (Creswell & Creswell, 2017). To investigate the factors influencing student perceptions of digital learning platforms adoption in Thailand, a quantitative survey was used. By choosing systematic reviews on the implementation of digital learning platforms as learning resources, a literature review was carried out to investigate the adoption factors associated with digital learning platforms. A survey questionnaire comprising 28 questions about the perceived acceptability level of the acceptance model was then developed. A seven-point Likert scale was used to rate the questionnaire items, with 1 meaning strongly disagree and 7 meaning strongly agree concerning (1) behavioral intention, (2) attitude, (3) perceived usefulness, (4) perceived ease of use, (5) technology self-efficacy, (6) subjective norms, and (7) facilitating condition. To evaluate the framework for the contextual factors, structural equation modeling (SEM) analysis was performed using LISREL v8.80. Lastly, a strategy for implementing digital learning platforms was generated and introduced.

## 6 Results

### 6.1 Measurement model

The developed framework was measured using convergent and discriminant validity in the research. The goal of these tests was to evaluate the appropriateness of the model's concepts.

### 6.2 Convergent validity

Fornell and Larcker (1981) proposed three measures for assessing convergent validity, including Cronbach's Alpha (α), composite reliability (CR), and average variance extraction (AVE).

A reliability test evaluates the degree of consistency between several weights of a factor and should be performed prior to evaluating its validity (Hair et al., 2018). In this research, Cronbach's alpha (α) was used to evaluate internal consistency among the constructs that indicated construct reliability. Cronbach's Alpha has four different score levels: (a) high reliability (0.70–0.90), (b) moderate reliability (0.50–0.70), and (d) low reliability (0.90 and above) (0.50 and less) (Hinton et al., 2014). All Cronbach's alpha (α) values between 0.743 and 0.892 indicated high construct reliability, as shown in Table 2.

Table 2 shows that the composite reliability (CR) ranged from 0.684 to 0.876, indicating higher item reliability. Fornell and Larcker (1981) assert that the average variance extraction (AVE) for each construct should be greater than 0.5, but 0.4 is reasonable if the composite reliability (CR) is greater than 0.6. The construct's

**Table 2** Construct reliability and validity

| Construct | Intervals for factor loadings | Cronbach's Alpha (α) | CR | AVE |
|---|---|---|---|---|
| BI | 0.779–0.827 | 0.881 | 0.876 | 0.638 |
| ATT | −0.111 – 0.835 | 0.756 | 0.725 | 0.492 |
| PU | 0.734–0.794 | 0.892 | 0.868 | 0.586 |
| PEU | −0.162 – 0.839 | 0.743 | 0.684 | 0.460 |
| TSE | 0.785–0.870 | 0.873 | 0.873 | 0.697 |
| SN | 0.759–0.799 | 0.881 | 0.859 | 0.605 |
| FC | 0.650–0.841 | 0.867 | 0.851 | 0.590 |

convergent validity is also sufficient. As a result, data in Table 2 show that the average variation gained from each individual construct met the level of acceptance, meaning that the convergent validity of this research is acceptable.

In the process of getting a lot of people involved in schools, this means to collect several viewpoints on the adoption of digital learning platform. The reliability and validity of the process and the results achieved must also be analyzed. For this purpose, several criteria should be considered. By complying with these criteria, it is to ensure that the research methodology was prepared in a logical manner in which all components have a structured relationship with one another. This case showed the Construct reliability that all unique of Cronbach's Alpha (α) value went beyond 0.7 and composite reliability (CR) value went beyond 0.6. Also, all the AVE values analyzed convergent validity went beyond the proposed value of 0.40. Therefore, this technique confirmed the investigation to be effective and the expected results to be realized.

### 6.3 Discriminant validity

Discriminant validity is typically assessed using squared correlations between two separate weights in either construct, which should be less than the variance shared by the construct's measures (Fornell & Larcker, 1981). The findings of the discriminant validity test are shown in Table 3. The total variance revealed by any two separate constructs was less than the variance derived by either construct. The constructs of this model have satisfactory discriminant validity as a result.

### 6.4 Structural model

The study developed a structural model to examine the connections between the factors. Attitude (ATT) is a critical moderator in predicting behavioral intention (BI), as shown in Fig. 3. The role of attitude (ATT) prescribes a high level of predictive power in behavioral intention (BI) for learners' implementation of digital learning models. Furthermore, the existing structural model assumes that if learners have technology self-efficacy (TSE) and a positive attitude (ATT) in the digital learning

**Table 3** Correlation and discriminant validity

| | PU | PEU | ATT | BI | TSE | SN | FC |
|---|---|---|---|---|---|---|---|
| PU | **0.766** | | | | | | |
| PEU | 0.679** | **0.678** | | | | | |
| ATT | 0.695** | 0.629** | **0.701** | | | | |
| BI | 0.702** | 0.620** | 0.747** | **0.799** | | | |
| TSE | 0.580** | 0.580** | 0.545** | 0.689** | **0.835** | | |
| SN | 0.622** | 0.512** | 0.589** | 0.746** | 0.686** | **0.779** | |
| FC | 0.518** | 0.416** | 0.416** | 0.540** | 0.511** | 0.524** | **0.768** |

**$p < 0.0$

Diagonal elements in bold are square roots of the AVE values

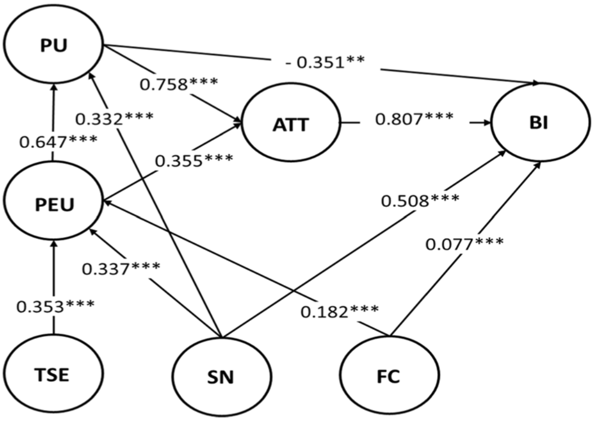



**Fig. 3** Structural model **$p<0.01$. ***$p<0.001$

platform, perceived usefulness (PU) and perceived ease of use (PEU) could facilitate the influence of behavioral intention (BI).

To corroborate the factor structure, Structural Equation Modeling (SEM) with the maximum-likelihood estimation approach was carried out using LISREL (linear structural relation program). To compare the tested model and the independent model with the saturated model ($\chi^2$ /df), comparative fit indexes (CFI), the goodness of fit index (GFI), adjusted goodness of fit index (AGFI) and root mean square error of approximation (RMSEA), good model fit was assessed using Chi-square statistics. A good-fitting model is indicated by $\chi^2$ /df values less than 3.00, CFI values greater than or equal to 0.95, GFI values greater than or equal to 0.95, AFGI values greater than or equal to 0.90, and RMSEA values less than or equal to 0.05, as suggested by Hair et al. (2014) as well as Jöreskog and Sörbom (1996). Table 4 shows the results of fit indexes. Signifying good fit to the observed data, the model of study demonstrated acceptable values ($\chi^2$ /df = 2.173, CFI = 0.997, GFI = 0.972, AGFI = 0.956, RMSEA = 0.029).

The structural model was adequate for explaining students' behavioral intentions toward digital learning models, as corroborated by the SEM data.

**Table 4** Fit indexes of the structural model

| Fit indexes | Level of acceptable fit | Model | Result |
|---|---|---|---|
| $\chi^2$ /df | < 3.00 | 2.173 | Pass |
| CFI | ≥ 0.95 | 0.997 | Pass |
| GFI | ≥ 0.95 | 0.972 | Pass |
| AGFI | ≥ 0.90 | 0.956 | Pass |
| RMSEA | < 0.05 | 0.029 | Pass |

### 6.5 Mediating influence

One potential mediator attitude (ATT) among the seven factors included in the proposed research model is depicted in Fig. 2. The path analysis of the mediation effect is derived in Table 5. According to the table, there are 15 indirect effects. Mediating effects were deemed to be insignificant for predicting positive behavioral intentions (BI) between students in the context of instituting a digital learning platform in 10 cases. However, 5 indirect effects were revealed to be negative. Unless the correlation passes through attitude (ATT), perceived usefulness (PU) alone cannot facilitate a positive relationship with behavioral intention (BI) in all cases. They facilitate for all external factors such as technology self-efficacy (TSE), subjective norms (SN), and facilitating (FC) factors in the residual circumstances for perceived usefulness (PU) and perceived ease of use (PEU). Substantial mediating effects were revealed for all external factors (TSE, SN, FC) when these two mediators were aligned with attitude (ATT). This result is consistent with previous research on estimating teachers' behavioral intentions to use digital learning models (Songkram & Osuwan, 2022). As a result, the main impact on behavioral intention (BI) to use digital learning platforms was revealed to be attitude (ATT). Furthermore, perceived usefulness (PU) and perceived ease of use (PEU) serve as mediators of external factors (TSE, SN, and FC) that influence students' attitudes toward new digital learning.

**Table 5** Impacts of mediation

| Path analysis | Direct effect | Indirect effect (Total effect) | t-statistic | P Value | Decision |
|---|---|---|---|---|---|
| ATT➔ BI | 0.807 | | 7.138 | 0.01 | Sig. (Accepted |
| PU ➔ BI | −0.351 | | −2.948 | 0.01 | Sig. (Accepted) |
| SN ➔ BI | 0.508 | | 12.609 | 0.01 | Sig. (Accepted) |
| FC ➔BI | 0.077 | | 3.342 | 0.01 | Sig. (Accepted) |
| PU ➔ ATT ➔ BI | | 0.611 | | 0.001 | Sig. (Accepted) |
| PEU ➔ PU ➔ BI | | −0.227 | | 0.001 | Sig. (Accepted) |
| PEU ➔ PU ➔ ATT ➔ BI | | 0.396 | | 0.001 | Sig. (Accepted) |
| PEU ➔ ATT ➔ BI | | 0.286 | | 0.001 | Sig. (Accepted) |
| TSE ➔ PEU ➔ ATT ➔ BI | | 0.101 | | 0.001 | Sig. (Accepted) |
| TSE ➔ PEU ➔ PU ➔ BI | | −0.080 | | 0.001 | Sig. (Accepted) |
| TSE ➔ PEU ➔ PU ➔ ATT ➔ BI | | 0.140 | | 0.001 | Sig. (Accepted) |
| SN ➔ PU ➔ BI | | −0.117 | | 0.001 | Sig. (Accepted) |
| SN ➔ PU ➔ ATT ➔ BI | | 0.203 | | 0.001 | Sig. (Accepted) |
| SN ➔ PEU➔ATT➔ BI | | 0.096 | | 0.001 | Sig. (Accepted) |
| SN ➔ PEU ➔ PU ➔ BI | | −0.076 | | 0.001 | Sig. (Accepted) |
| SN ➔ PEU ➔ PU ➔ ATT ➔ BI | | 0.133 | | 0.001 | Sig. (Accepted) |
| FC ➔ PEU ➔ ATT ➔ BI | | 0.052 | | 0.001 | Sig. (Accepted) |
| FC ➔ PEU ➔ PU ➔ BI | | −0.041 | | 0.001 | Sig. (Accepted) |
| FC ➔ PEU ➔ PU ➔ ATT ➔ BI | | 0.072 | | 0.001 | Sig. (Accepted) |

## 7 Discussion

The results of structural equation modeling (SEM) review reveals that nearly all adoption-related characteristics are considerably and progressively correlated with students' behavioral intention to utilize digital learning models at their institutions. A major predictor of the acceptance of using a digital learning platform, however, has been identified. The main conclusions are discussed in this section, along with advice for policymakers on how to encourage better student usage of digital learning models.

First, attitude (ATT) is the most important factor in determining behavioral intention (BI). The results of this study confirmed that ATT is a significant predictor of behavioral intention (BI). This is in line with the findings of earlier studies (Mailizar et al., 2021; Stockless, 2018). Students are more likely to adopt digital learning platforms when they believe such platforms improve their learning effectively and simple to use. They are likely to have positive opinion with creating strong influential to behavioral intention. Therefore, perceived usefulness (PU) and perceived ease of use (PEU) had indirect effects on behavioral intention (BI). However, the findings found that despite students see the value of digital learning platform, they may not desire to accept it. The sudden shift to exclusive online learning methods of instruction have caused anxiety and depression in a large number of students due to the stressful load of work required. This result can be explained that attitude (ATT) has a significant influence toward to behavioral intention (BI) of digital learning platform (Tondeur et al., 2017). Although digital learning platforms may be beneficial and schools give enough support, students may still be hesitant to utilize them if they do not have a positive attitude. Students that are more positive views of ICT and innovation are more likely to embrace online learning activities (Drossel et al., 2017; Yaoran Li et al., 2019a).

Second, the results demonstrated that every external factors (TSE, SN, and FC) influenced on perceived ease of use (PEU). In addition, technology self-efficacy (TSE) was identified as the most important factor on perceived ease of use (PEU). This is in line with findings from former investigation (Gurer, 2021; Siyam, 2019). This showed that students may have thought they had different skills when it came to using digital learning platforms. The high level of technology self-efficacy (TSE) may have contributed positively to the perception of digital learning platform usability. Therefore, this aspect plays a significant influence in the adoption of new classroom technologies (Al-Awidi & Alghazo, 2012). Similarly, subjective norms (SN) is a significant predictor of perceived ease of use (PEU). This is the same finding with Gurer (2021) and Milutinović (2022) because of social influence. Also, facilitating conditions (FC) had a good effect on perceived ease of use (PEU) which is consistent with previous researches (Al-Gahtani, 2016; Eksail & Afari, 2020). Therefore, students will likely have a good attitude toward new technology if the school creates a supportive atmosphere since they will be less worried about technical concerns (Li et al., 2019b).

Third, perceived usefulness (PU) has a negative impact on students' BI, but somehow has a favorable impact on students' ATT, which then has a positive impact on students' BI. The model demonstrates that the most important mediator of BI among students is attitude (ATT). For students, the online experience was novel and extremely challenging overall. In a typical face-to-face learning environment, students are accustomed to seeing their teachers and interacting with their peers. Online learning approaches have forced students to sit in front of their mobile phones, tablets, or laptops for long periods, which causes them to become distracted and troubled. It may produce unpleasant experiences if they do not have a positive attitude toward online learning to manage their studies and interact with their teachers and peers.

Fourth, despite the fact that many schools incorporated technology into their educational systems as a result of COVID-19, they were unable to adapt their teaching methods to better accommodate online instruction (Hodges et al., 2020). Conceivably, the digital learning platform's perceived ease of use (PEU) falls short of users' expectations. If so, it will be obvious that even though students were positively influenced by technology self-efficacy (TSE), subjective norms (SN), and facilitating conditions (FC), the negative experiences students had with digital learning platforms would cause them to dislike those platforms that are not user-friendly. Hence, it is important to pay attention to how PU, PEU, and ATT are related. The findings demonstrate that PEU and PU's beneficial effects can have a significant impact on ATT and cause students to have a behavioral intention (BI) to use digital learning models. Providing digital learning technologies as simple as possible for students to perceive usability (PU) and have a positive attitude (ATT) should be a priority for educators and policymakers. Additionally, we discovered that the primary cause of PEU is TSE. Consequently, the educator is crucial to students' TSE. This indicates that learners receive proper instruction on how to use digital learning models successfully to guarantee their effectiveness and ease of use. Nevertheless, if a student encounters a problem while using the system, they are more likely to turn to SN (their peers and parents) rather than FC (the IT/ technical support), since the latter may take longer to respond due to the burden from the COVID-19 pandemic and the transition of teaching and learning to digital learning approaches (Shyr & Chen, 2018).

## 8 Practical implication

According to the current models for digital learning models, all units with themes and lessons must be created by individual schools, which also supplies content development. In this work, a theoretical framework for using blockchain technology in decentralized content production is proposed. Online learning currently offers more content than previously possible, but the caliber of that content varies greatly at the topic and lesson levels, which results in unequal knowledge transmission. Blockchain-based decentralized learning models produce modular knowledge chunks made up of lessons that can be added to the core module or topic. The creator is closely interwoven with a permissioned blockchain that has reviewer nodes.

Figure 4 shows a theoretical model in which a creator develops a content module with modules, topics, and lessons in accordance with the specifications. These are

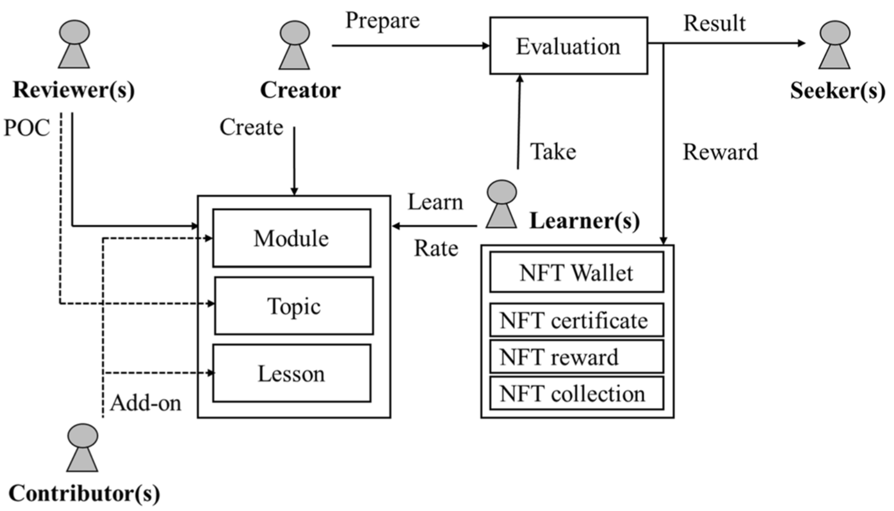



**Fig. 4** Framework for decentralized content generation in a digital learning platform built on blockchain

often created by a single author (teacher), who is followed by the reviewer serving as a moderator (POC: proof of concept) (teaching committee), which can then subsequently be uploaded on a digital learning portal. Under the POC approval of the teaching committee, contributors (researchers, specialists, or experts) may submit any modifications to boost the value. This architecture makes the assumption that the author will cover every subject and lesson. The first developer of new material, the best creator based on learner ratings, the most reviewers to POC, the most contributors to content add-on, and the strongest learner are just a few examples of the various methods to earn credit (coin) from the site. Smart contracts in the digital learning framework will automatically verify completion of the learning modules after students finish the module/topic/lesson, submit their ratings, and pass assessments. Depending on their performance, the learner will obtain NFT (NFT certificate, NFT reward and NFT collection). The learner's NFT wallet has the ability to display all NFT. Additionally, outcomes will be documented as transactions in a digital ledger in order to monitor learners' abilities and track their success by way of performance reports.

The best creators for designing the themes and lessons can be recruited by incorporating blockchain technology into the digital learning platform. Other authors are welcome to add their own subjects and lessons after teaching committee approval. The evaluation results are available to the seekers so they can assess the learners' progression. To choose the ideal learner for the module, these searchers may be headhunters, HR organizations, training firms, or specialists among creators, contributors, or approvers in the class of nodes.

Protection of personal security information is crucial in the educational sector, it should be a special concern about how digital learning platform deals with this issue. Some contribution (e.g. (Kheshaifaty & Gutub, 2020, 2021)) proposed captcha and hash functions for secure online authentication. Captcha was used to distinguish between human and robot. Hash functions were used in cryptology as a method to protect the authenticity of information. Kheshaifaty and Gutub (2020) reported that the effectiveness of the integration between captcha and crypto hash algorithms is roughly 30% better than that of the older methods. Therefore, the personal security issue is solved by providing strong security features to safely access a system. To enhance student's trust for online evaluation, the mechanism of steganography technique (Almutairi et al., 2019; Sahu & Gutub, 2022) is also required to authenticate identity when student take exams. The process start from schools uploads image steganography of student id card with hiding a private key to the document wallet. Students need to use the said image and text password to identify and authenticate the examinee in order decrease plagiarism and cheating in online exams. Also, student can use image steganography to recall the text password. The solution as shown in Fig. 5 can be secured and trusted as more protection by hash functions to protect users 'password, captcha to detect non-human users and reliance by steganography technique which is better identity than others. The system also includes a chatbot as community question-answering for sending messages. Students' attendance at lectures, grades, financial records, course information, and contact information will be provided. With this application, a school may give facilities for students and parents to check academic records in a way that is simple, inexpensive, quick, and accessible at any time.

A digital learning platform powered by blockchain can aid in academic success. The suggested platform offers a simple approach to monitor students' long-term skill improvement, which is tracked via a dashboard and documented in a digital ledger. A dashboard is accessible by aspirants (headhunters, HR in firms, or training companies), who can provide potential learners advice for career development in the form of interactive assessments of the abilities needed to do each role model's work. A checklist of skills with links to online learning resources (Kadenze, Udemy, Class Central, Skillshare) is available for developing each talent. Students can purchase lessons given inside the enroll ecosystem of partnering online education

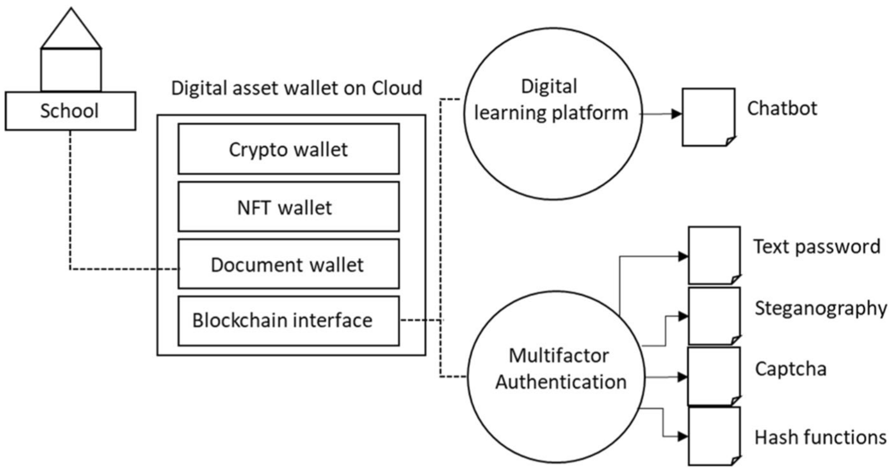



**Fig. 5** Authentication for digital learning platform built on blockchain

organizations using coins they acquired or online payments to access the best role models through webinars. Additionally, authors, reviewers, and contributors can use coins or online payments for business growth in online resources or trade their coins for other cryptocurrencies. These enable the planned digital learning platform to provide incentives to all stakeholders and provide positive reinforcement for efficient learning to enable academic success through a process of "learn-earn-return".

## 9 Conclusion

The goal of this study was to pinpoint what influences students' willingness to use a digital learning environment. Learners from a variety of Thai schools were given questionnaires as part of a quantitative approach. Our research showed that students frequently chose digital learning platforms and took into account the benefits of their ATT, which was promoted by PU and PEU. As predictors of behavioral intentions, attitudes about the adoption of digital learning platforms (B = 0.807) and subjective norms (B = 0.508) were shown to be statistically significant. The majority of noteworthy findings indicate that attitudes are absolutely crucial. Students may not use digital learning platforms if they maintain unfavorable attitudes about new technology usage even though they perceive the usefulness and ease of using technology or obtaining sufficient facilitating support. The user experience of the digital learning platforms needs to be given more consideration by policymakers. It could be a good idea to offer digital learning models so that students can take advantage of effective learning activities that are as simple to use as possible. As a result, PE and PEU are crucial components of their ATT to promote their BI of a digital learning platform. Findings also point to an external component, TES, as being necessary for students to properly benefit from digital learning. FC includes the infrastructure, tools, and resources that enable it, whereas SN includes how students can interact with each other.

The aims of the study were achieved by evaluating existing school requirements. Presently, Covid19 has had an impact on education around the world, and this will help us understand the factors in the practicability and accomplishment of adopting a digital learning platform as a reaction to school closures. The present situation is an excellent opportunity to investigate the advantages of digital learning platforms and identify benefits as well as sensitive areas in order to ensure maximum preparedness and the ability to cope with any future crisis. As a result, Thailand's educators should focus on designing, initiating, and integrating digital learning models while overcoming acceptance impediments. Plans should be developed specifically to handle worst-case scenarios in a way that ensures adaptability, cost effectiveness, and consistency. Considering that generational commonalities across nations appear to be stronger than commonalities across generations as a result of globalization, similar findings in terms of students' acceptance of online learning platforms as a form of distance learning in different parts of the world would not be remarkable in the midst of the recent pandemic. Through this session, we highlight the various findings. However, we neglected certain aspects that may have been a valid part of students' BI. Personal security and trust could be interested factors to identify student's adoption toward digital learning platform usage for future research.

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**Data availability** The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

## Declarations

**Conflict of interest** None.

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