Investigating Students' Behavioral Intentions towards a Smart Learning Platform Based on Machine Learning: A User Acceptance and Experience Perspective

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***Abstract*—This study investigated students' behavioral intentions toward a smart learning platform. In order to evaluate and implement the adoption model within the context of Thai education, an empirical study was conducted. On a sample of 1,250 pupils from throughout Thailand, an analysis technique known as structural equation modeling was used to evaluate the proposed research model. Results from the study showed that the adoption of smart learning platforms by students was most significantly impacted by attitudes towards using them. This was followed by internal variables, namely the Perceived Ease of Use (PEU) and Perceived Usefulness (PU) of the platforms. In addition, Accessibility (AC), Personalization (PL), and Perceived System Quality (PSQ) are peripheral factors that increase understanding of smart learning platform adoption. The findings of this study align with other research, with the exception that only AC had a detrimental impact on PEU. Therefore, this study will provide valuable insights for scholars and researchers by filling a knowledge gap in the existing literature and demonstrating the concrete use of a proficient smart learning platform in the realm of academic success.**

***Keywords*—behavioral intention, technology acceptance model, smart learning environment**

I. Introduction

In this age of technological advancement, the transformation of knowledge in the digital world is occurring rapidly. Educational institutions, teachers, and students must adapt to a new world of learning. Teachers need to adapt the teaching process, techniques, and new teaching methods and use modern technology as a tool to enhance learners' learning [1]. Instructional activities must be developed and an easily accessible learning environment must be provided to meet the differences of each learner through a smart learning environment, which should enable learners to learn and perform activities anytime and anywhere using technology and digital tools. Highlights of a smart learning environment It is an environment that provides an important personalized learning experience and manages learning appropriately. It encourages learners to have positive interactions and guides them towards their learning goals [2]. In addition, a smart learning environment is a supportive learning environment that uses intelligent technology. It indicates the learner's learning behavior, adapts to the right place and time as needed, and can provide appropriate support such as advice and feedback [3]. Therefore, the developed smart learning platform uses machine learning to classify students into different levels according to their innovative thinking abilities. This can be done by analyzing student data, such as their results on self-assessments. Once students have been classified, smart learning platforms can be assigned to learning activities that are appropriate for their level of ability. In addition to using machine learning to classify students, smart learning platforms design teaching using design thinking and project-based learning to help students improve their innovative thinking skills and enhance teaching and learning through technology. This includes processes and approaches used to improve teaching and learning to create a better learning experience for learners [4]. Smart learning can promote personalized learning. It can be accessed anytime, anywhere, and understood by different learners [5]. Accordingly, for the smart learning platform to be widely and successfully adopted in vocational education, it is obligatory to pinpoint the key factors that drive the adoption of the smart learning platform in vocational education from the students' standpoint.

In Thailand, vocational education has designed instruction with project-based learning but has not yet implemented a smart learning platform. To address this research gap, an empirical study was conducted to investigate the adoption models of vocational students in terms of their usage intentions when implementing a smart learning platform. The main objective of this study is to identify the key factors that influence vocational students' behavioral intentions when using smart learning platforms. Theoretical foundations and the proposed research model are presented in the next section. Then, the formulation of the research hypotheses is presented. Then, the results are presented, followed by a discussion of the main findings. Finally, the implications and conclusions of the study are presented.

II. Literature Review

Smart Learning Environments (SLEs) are multifaceted and can be used to achieve a variety of learning outcomes [6]. Basically defined as learning environments supported by innovative technologies, SLEs are able to adapt to students' needs through their learning behaviors at the appropriate time and place. Expanding upon this, SLEs can provide appropriate support to students in the form of guidance, feedback, tips, and general help [7]. Additionally, the impact and acceptance of precision instruction in an AI-enhanced learning environment have been key issues addressed in past

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studies. Numerous studies point to accessibility, personalization, and system quality of smart learning environments as ways to improve learning quality [8, 9]. The research includes an examination of SLE acceptance using the Technology Acceptance Model (TAM) framework [10]. Also, additional variables were added to expand TAM and form the theoretical framework of the study.

The TAM [10] and the Theory of Planned Behavior (TPB) [11] form the basis for the research paradigm used in this paper. Both the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) show how important it is to combine theories from psychology and Information Systems (IS) to better understand how people plan to use technology. The omission of external factors influencing Perceived Usefulness (PU) and Perceived Ease of Use (PEU) in TAM has prompted researchers from various fields [12, 13] to highlight the importance of PU and PEU as influential factors in shaping individuals' attitudes towards technology use and their intention to use it. The Theory of Planned Activity (TPB) is a very influential and well-studied psychological theory that says that attitude, subjective norm, and perceived behavioral control have a direct effect on the intention to do a certain activity, which is called behavioral intention (BI) to use. Based on the aforementioned theoretical frameworks, the researcher has identified and chosen relevant variables that are suitable and connected to the aforementioned theoretical framework, the objective of the study, and the research context. The researchers chose the relevant variables based on their alignment with the theoretical framework, study objectives, and research situation. The study incorporated many technical aspects, Including Accessibility (AC), Personalization (PL), and Perceived System Quality (PSQ), as these elements are hypothesized to have an impact on individuals' Perceptions of Usefulness (PU) and Perceived Ease of Use (PEU).

A. Smart Learning Platform Based on Machine Learning

Smart learning requires a basic foundation as a conceptual framework connected to smart education. According to Zhu *et al.* [14], smart learning consists of three primary elements: the smart learner, smart pedagogy, and the smart learning environment. Designing a smart learning environment requires advanced smart technologies that can be used to develop a smart learning environment. For example, artificial intelligence and the Internet of Things (IoT) can be combined to create an environment to make smart decisions in smart education systems. In addition, mobile and cloud computing can provide learning processes anywhere, anytime, and in response to increasing usage [15]. A smart learning platform is a software solution that uses Artificial Intelligence (AI) and other advanced technologies. To personalize and optimize the learning experience for each student. It uses advanced technology such as Artificial Intelligence (AI), machine learning, data analysis, and automation to improve the learning experience. These platforms are made to offer students and learners of all ages efficient, flexible, and personalized learning experiences.

B. Technology Acceptance Model (TAM)

Research in recent years have studied factors influencing technology acceptance; one major and widely researched theory is the information technology acceptance theory [16]. Also known as the Technology Acceptance Model (TAM), the model has two predictive factors: Perceived Usefulness (PU) and Perceived Ease of Use (PEU). According to the model, causal connections are drawn and depicted among PU, PEU, Attitudes toward Usage (ATU) and Behavioral Intentions (BI) in using technology. As described by Davis [10] himself, the concept of PU refers to an individual's belief that their performance would be enhanced through the use of technology. PEU, on the other hand, can be described as one's capacity to utilize technology effortlessly. PU is directly affected by PEU, and both PU and PEU influence the attitudes of individuals collectively. PU and ATU are also factors that can have a direct effect on BI [10]. The TAM has also been extended in some cases and subsequently studied for the prediction of certain outcomes. Considering all of the above points, the TAM was, hence, deemed suitable as a baseline model in this study. However, though the TAM's predictive power has improved across countries, the model has also been criticized for being parsimonious in the sense that it often lacked specifications of extended variables by which PU and PEU could be influenced [12]. Therefore, the theoretical framework of the study was adjusted and extended variables were included to expand the TAM. Based on this TAM, the following hypotheses were proposed for this study:

H1: PEU has a positive impact on the PU of a smart learning platform.

H2: PU has a positive impact on the ATU of a smart learning platform.

H3: PEU has a positive impact on the ATU of a smart learning platform.

H4: PU has a positive impact on the BI of a smart learning platform.

H5: ATU has a positive impact on the BI of a smart learning platform.

C. Accessibility (AC)

Within the context of this study, Accessibility (AC) can be described as the extent to which tools that are available on the platform can be accessed easily and utilized by users to retrieve necessary information [17]. Previous research by Sánchez and Hueros [18] suggests a proposition positing a positive correlation between the level of platform accessibility in digital learning and students' perception of its ease of use. Attis [19] further supports this notion by asserting that the accessibility of a platform serves as a prominent indicator of the perceived ease of use of a website. Additionally, the study by Salloum *et al.* [20] highlighted the effect of accessibility on the perceived usability of a digital learning platform. Also, research from the past has shown over and over again how important accessibility is for a digital learning platform's Perceived Ease of Use (PEU) [21] and Perceived Usefulness (PU) [22]. Therefore, the following hypotheses were proposed for this study:

H6: AC has a positive impact on the PU of a smart learning platform.

H7: AC has a positive impact on the PEU of a smart learning platform.

D. Personalization (PL)

Personalization (PL) refers to how learners learn for themselves by having access to different knowledge through different learning channels. The information is shared with others, and one's own learning progress is reviewed [23–25]. The study investigating users' intentions to continue using online learning applications found that PL positively influences PEU [26]. Furthermore, Venkatesh and Bala [13] investigated individual variations in computer self-efficacy, computer anxiety, enjoyment of computer play, and perceptions of external control. The study indicates that the utilization of online learning tools leads to variations among individuals in factors such as anxiety levels, perceived external control, self-efficacy in utilizing technological devices, and enjoyment derived from using such devices. This variable has the potential to significantly impact individuals' perceptions of usability and their inclination to engage in a certain behavior. Therefore, the following hypotheses were proposed for this study:

H8: PL has a positive impact on the PEU of a smart learning platform.

E. Perceived System Quality (PSQ)

Perceived system quality is how we evaluate the performance and functioning of an information system [27]. Simply put, it is concerned with the qualities or characteristics that an information system provides. These qualities include, for example, the speed of response, reliability, ease of use, flexibility, and accessibility of the system. These are some of the measures we use to evaluate system quality. Previous research has found a positive relationship between a system's perceived functionality (system quality) and perceived ease of use (perceived usability) [28, 29]. On the other hand, a high-quality system that can collect and analyze data and make predictions can also help students improve their innovative thinking skills. Imagine a learning system that adapts to a student's abilities and provides immediate feedback in the right way. Such a system can significantly improve student engagement when using a smart learning platform. Therefore, the following hypotheses were proposed for this study:

H9: PSQ has a positive impact on the PEU of a smart learning platform.

A comprehensive research model (see Fig. 1) was developed in an investigation of students' behavioral intentions toward a smart learning platform that considered key variables and relationships, which provide information about the factors that influence students' behavioral intentions when using innovative educational technology.

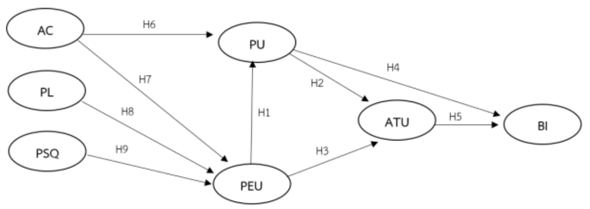


Fig. 1. Research model.

Note: BI: Behavioral intention to use, ATU: Attitude towards use, PU: Perceived usefulness, PEU: Perceived ease of use, AC: Accessibility, PL: Personalization, PSQ: Perceived system quality

III. MATERIALS AND METHODS

A. Participants

Research participants were vocational students (N = 1,250). The determination of the sample size was based on the idea of Hair *et al*. [30], who proposed a minimum criterion for sample size in data analysis with the program LISREL, using a sample size of 10–20 times the number of questions for confirmatory factor analysis. This research has 30 questions, so a sample size of 600 participants is required, but the response rate of the research questionnaire is at a good level of 75% [31]. The researcher therefore adjusts the sample size to 1,250 people to compensate for the incomplete responses to the questionnaire. The study adhered to ethical protocols, which encompassed obtaining informed permission from participants who willingly chose to partake in the research, granting them the freedom to withdraw from the study at their discretion, and ensuring the preservation of anonymity and confidentiality of their personal data. The act of participation was not obligatory, and there was no provision for additional credit or payment. The data was gathered from vocational training institutes located in Thailand. The samples were a stratified random sample divided into five regions: 1) north, 2) northeast, 3) eastern, 4) central, and 5) south.

In this study, 1,250 vocational students from 25 institutions in Thailand participated. Of them, 53.52% were women, and 46.48% were men. Their ages ranged from 18 to 21 years, with a mean age of 18.86 years (SD = 0.85). Of the participants, 48.30% reported owning a desktop computer, and 51.70% reported not owning one. 97% reported owning a cell phone or tablet, and 3% reported not owning one. Regarding the use of these technologies, 63% of respondents reported having access to the Internet, while 37% did not.

B. Instrument and Procedure

To investigate Thai vocational students' behavioral intentions in using a smart learning platform, a multiple-item questionnaire was developed by the researchers consisting of two parts. Part 1 of the questionnaire deals with eliciting the students' demographic information, including details of their age, gender and respective ownership of a desktop computer, smartphone or tablet; while Part 2 is comprised of items that draw out students' responses to the seven variables included in this study's research model. The seven variables are: PU (5 items), PEU (5 items), ATU (4 items), BI (3 items), AC (4 items), PL (4 items), and PSQ (5 items). All seven items were adopted from various reliable sources that have been considered sufficiently valid (see Appendix). All of these items were also measured using a 7-point Likert scale, with 1 indicating the notion of "strongly disagree" and 7 representing the notion of "strongly agree". With the assistance of coordinators, the data were collected at each institution where it took no more than 10 minutes for the students to complete the paper-based questionnaire. Before collecting the data at each institution, the students were also briefed on the goal of this study and their right to withdraw from the data collection process at any point or time without needing to provide a reason or justification.

C. Data Analysis

For this study, there are multiple procedures involved in the data analysis. Firstly, the descriptive statistics for the students' demographic profiles were calculated and tested for univariate normality. Secondly, the SEM approach (with tests of the measurement model and structural model) was used to analyze students' responses to the items by which the seven variables were measured. The LISREL 8.80 software was then employed to conduct a Confirmatory Factor Analysis (CFA) with a maximum likelihood estimation. Evaluating the factor loadings of the indicators associated with the suggested variables was also one of the research aims. Lastly, Composite Reliability (CR) and Average Variance Extracted (AVE) are reportedly used to ascertain construct reliability and validity, respectively. Thus, tests of the structural model were adhered to test the hypotheses of this research.

IV. Result and Discussion

A. Descriptive Statistics

Table 1 shows the descriptive statistics for the seven constructs calculated in terms of means, standard deviations, skewness, and kurtosis. It was found that all item means were greater than 5.00 (range: 5.24–5.32), while standard deviations ranged from 1.13 to 1.18, indicating that the data were highly variable. Accessibility has the most respondents, a mean of 5.32 and a standard deviation of 1.18, a skewness value of −0.190, which means it is skewed to the left, indicating that most respondents have an opinion about the accessibility of the Smart Learning Platform, and a kurtosis of −0.908 means that there are fewer outliers than in a normal distribution. Thus, skewness and kurtosis varied from −0.190 to −0.089 and from −0.908 to −0.834, respectively, and the skewness and kurtosis values were all below the threshold of ±2 [32]. This results in a univariate normal distribution.

Table 1. Descriptive statistics of constructs

Constructs	Number of items	Mean	Standard deviation	Skewness	Kurtosis
Behavioral Intention to Use	3	5.24	1.17	−0.089	−0.899
Attitude towards Using	4	5.27	1.15	−0.122	−0.873
Perceived Usefulness	5	5.26	1.15	−0.136	−0.834
Perceived Ease of Use	5	5.27	1.16	−0.125	−0.862
Accessibility	4	5.32	1.18	−0.190	−0.908
Personalization	4	5.30	1.14	−0.156	−0.867
Perceived System Quality	5	5.26	1.13	−0.106	−0.875

B. Preliminary Data Analysis

Multicollinearity and Common Method Bias (CMB) were examined before starting data analysis. To assess the presence of multicollinearity, the Variance Inflation Factor (VIF) was used. It is required that any VIF value be less than 3.0 [33]. The range of VIFs from 2.008 to 2.440 (see Table 2) confirmed that multicollinearity was not present. Subsequently, the presence of CMB was investigated using Harman's single factor. The results showed that the total variation was 46.527% when all the readings in the data set were loaded simultaneously. This value is below the threshold of 50%, which means that no CMB was detected [34].

Table 2. Multi-collinearity assessment

Construct	BI	PEU	PU
AC	-	-	2.206
PL	-	-	2.312
PSQ	-	-	2.331
PU	2.440	2.037	-
PEU	2.373	2.037	2.008
ATU	2.265	-	-

C. Testing the Measurement Model

CFA was used to conduct an assessment of the convergent validity, reliability, and discriminant validity of the measurement scales. Then, using Composite Reliability (CR) and Cronbach's alpha, the reliability of the scales was evaluated. The estimates for CR and Cronbach's alpha were above the recommended threshold of 0.7 [35] for all constructs, which marks good reliability in them. Generally, when the CR values exceed 0.90, it indicates a strong internal consistency in the model. Since the lowest CR value is 0.91 from the study, the model can be said to hold an internal consistency that is satisfactory. Convergent validity is usually achieved when the factor loadings of the items reach a value of 0.70 [36]. In this study, the strong convergent validity is shown evident by factor loadings that ranged from 0.77 to 0.92 [37]. Test results for reliability and validity vis-à-vis factor loadings are shown in Table 3 below. To assess the discriminant validity, the AVE values of each component was compared with the correlation value for each column or row. Because the square root of the AVE values surpassed the correlations between the constructs, this tells us that discriminant validity was achieved. Table 4 below further illustrates the correlation matrix and the results of the discriminant assessment.

Table 3. Internal and convergent validity assessment

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	AVE
Behavioral Intention to use (BI)	BI1	0.87	0.91	0.91	0.77
	BI2	0.89			
	BI3	0.88			
Attitude Towards Use (ATU)	ATU1	0.87	0.92	0.92	0.75
	ATU2	0.88			
	ATU3	0.85			
	ATU4	0.86			
Perceived Usefulness (PU)	PU1	0.88	0.96	0.95	0.81
	PU2	0.91			
	PU3	0.90			
	PU4	0.92			
	PU5	0.90			
Perceived Ease of Use (PEU)	PEU1	0.82	0.92	0.92	0.69
	PEU2	0.88			
	PEU3	0.87			
	PEU4	0.82			
	PEU5	0.77			
Accessibility (AC)	AC1	0.88	0.92	0.91	0.73
	AC2	0.88			
	AC3	0.82			
	AC4	0.83			
Personalization (PL)	PL1	0.83	0.92	0.92	0.74
	PL2	0.84			
	PL3	0.87			
	PL4	0.89			
Perceived System Quality (PSQ)	PSQ1	0.84	0.93	0.93	0.74
	PSQ2	0.84			
	PSQ3	0.89			
	PSQ4	0.90			
	PSQ5	0.82			

Note: SE, Standardized Estimates; CR, Composite Reliability; AVE, Average Variance Extracted.

Table 4. Correlation matrix and discriminant assessment

Constructs	BI	ATU	PU	PEU	AC	PL	PSQ
BI	**0.877**						
ATU	0.697	**0.866**					
PU	0.886	0.697	**0.900**				
PEU	0.666	0.686	0.713	**0.831**			
AC	0.679	0.607	0.703	0.724	**0.854**		
PL	0.641	0.708	0.669	0.727	0.648	**0.860**	
PSQ	0.742	0.648	0.768	0.737	0.802	0.652	**0.860**

D. Test of the Structural Model

ATU significantly influenced students' Behavioral Intention (BI) to use and accounted for 81% of the variance. ATU was also significantly linked to PU and PEU where these two factors accounted for 86.2% of the variance. PU, a vital determinant in the TAM, was found to be highly associated with PEU and AC, accounting for 85.4% of the variance; while PEU was significantly influenced by AC, PL, and PSQ, accounting for 84.8% of the variance in total. Validating the component structure is an important process and to do so, a SEM analysis would need to be conducted in conjunction with the maximum likelihood estimation method and employing LISREL as the linear structural relations software. To evaluate the adequacy of the tested and independent models against the saturated model, various fit indices were applied, not excluding the chi-square to degrees of freedom ratio (χ^2/df), Comparative Fit Indexes (CFI), Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), and Root Mean Square Error of Approximation (RMSEA). In this evaluation, the chi-square was used as a measurement of excellent model fit. According to Hair *et al.* [38] and his findings, a well-fitting model is characterized by χ^2/df values below 3.00, CFI values equal to or beyond 0.95, AFGI values equal to or above 0.90, and RMSEA values below or equal to 0.05. All of these fit indices can be found in Table 5 below. The model in this study bore acceptable values, thus indicating a good model fit according to the observed data (χ^2/df = 2.30, CFI = 1.00, GFI = 0.96, AGFI = 0.95, RMSEA = 0.032, and SRMR = 0.012).

Table 5. Fit indexes of the structural model

Fit indexes	Level of acceptable fit	Model	Result
χ^2/df	< 3.00	2.30	Pass
CFI	≥ 0.95	1.00	Pass
GFI	≥ 0.95	0.96	Pass
AGFI	≥ 0.90	0.95	Pass
RMSEA	< 0.05	0.32	Pass

The suitability of the structural model in elucidating students' behavioral intention to utilize smart learning environment models was validated by the analysis of data using Structural Equation Modeling (SEM) to examine the connections between the factors, as shown in Fig. 2.

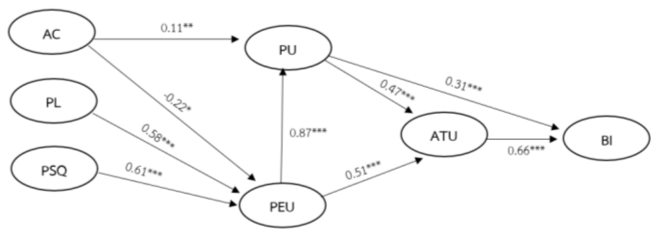


Fig. 2. The result of Hypothesis H1–H9 testing.

In addition, the results of hypothesis testing in a study that focused on students' behavioral intentions toward a smart learning platform that represent a relationship between different factors, and the path coefficients indicate the strength and direction of the relationships. All hypotheses are accepted, meaning that the observed data support the proposed relationships. Perceived Ease of Use (PEU) strongly influences Perceived Usefulness (PU). PEU and PU are both influencing factors for Attitude towards Use (ATU). Positive attitudes have a significant influence on the Behavioral Intention (BI) to use. Accessibility (AC) has a positive effect on PU but a negative effect on PEU, and Perceived System Quality (PSQ) contributes significantly to PEU. The summarized results of the hypothesis test are shown in Table 6.

Table 6. Results of hypotheses

Hypotheses	Relationship	Path coefficients	Results
H1	PEU → PU	0.87***	Accepted
H2	PU → ATU	0.47***	Accepted
H3	PEU → ATU	0.51***	Accepted
H4	PU → BI	0.31***	Accepted
H5	ATU → BI	0.66***	Accepted
H6	AC → PU	0.11**	Accepted
H7	AC → PEU	−0.22*	Accepted
H8	PL → PEU	0.58***	Accepted
H9	PSQ → PEU	0.61***	Accepted

Note: SE, Standardized Estimates; CR, Composite Reliability; AVE, Average Variance Extracted.
*p<0.05, **p<0.01; ***p<0.001.

E. Discussion

By extending the TAM as a baseline model, the purpose of this study was to examine factors that influenced vocational students' intentions in using a smart learning platform. The results from using the SEM indicated a strong and positive association between several adoption-related factors and students' intents to utilize smart learning platforms inside their educational institutions. However, a noteworthy determinant of the acceptance of smart learning platform use was revealed. This section presents a comprehensive analysis of the primary findings, accompanied by recommendations for policymakers to enhance student engagement using smart learning environment models.

The primary determinant of the intention to use smart learning platforms is the individual's Attitude toward their Usage (ATU). The results of this study strongly suggest that ATU is a significant factor in predicting individuals' Behavioral Intention (BI) to use these platforms. In previous studies, Sungkur and Maharaj [8] have also uncovered similar findings. This suggests that students are more likely to adopt smart learning platforms into their learning experience when the platforms are regarded as educationally beneficial and user-friendly. Therefore, the PU and PEU of these platforms indirectly impact individuals' behavioral intentions to use them as well. One intriguing observation of the results is that, even when the potential usefulness of smart learning platforms is realized, students may still be hesitant to adopt them. As demonstrated by the work of Tondeur *et al.* [39], this phenomenon can be attributed to the significant effect that ATU has on BI. Despite the potential advantages that come with smart learning environments and the assistance offered by educational institutions, students may still show a reluctance to adopt these platforms if they already possess a negative disposition towards them. The role of cultivating a positive, nurturing attitude among students when engaging with smart learning tools has never been more important.

On another note, the findings of this study also revealed that external factors, namely, PSQ, PL and AC, also play significant roles in influencing the PEU of smart learning platforms. Most notably, PSQ emerged from the results as the most defining factor affecting PEU. As mentioned in the study by Calisir *et al*. [40], this encompasses a myriad of characteristics such as reliability, security, convenient access and user interface design, all of which are echoed in a similar study by Zhou *et al*. [41] as well. This indicates that a user-friendly design at the core of the learning platform is paramount to fostering comfort and ease among users, which would lead to them having increased interactions with the platform. Moreover, Personalization (PL) also plays a significant role in predicting PEU, corroborating the findings of Ji *et al*. [26] that self-efficacy influences this relationship. Likewise, Accessibility (AC) was found to influence PEU, consistent with earlier research by Baleghi-Zadeh *et al*. [22] and Bhattarai and Maharjan [42]. The results of this study suggest that there is a higher likelihood for students to demonstrate a favorable disposition towards novel technologies when the system is readily available and user-friendly.

Thirdly, Perceived Usefulness (PU) exerts a positive influence on the Behavioral Intention to use (BI), with its effect mediated by the Attitude toward Use (ATU). The model underscores that the most critical mediator for students' behavioral intentions is their attitude toward using the smart learning platform, particularly one that caters to their individual differences and offers easy access. Additionally, the flexibility of using technology for learning and participation from any location further contributes to their positive attitude.

Fourthly, despite the integration of technology into educational systems by many institutions, smart learning platforms still lack adequate support for personalized learning experiences [2]. In addition, it may be seen that the Perceived Ease of Use (PEU) of these systems fails to align with the expectations of users. As a result, negative experiences with non-user-friendly smart learning platforms may lead students to reject similar platforms, even when factors like Accessibility (AC), Personalization (PL), and Perceived System Quality (PSQ) are considered. Therefore, this study highlights the need of comprehending the interconnectedness of Perceived Usefulness (PU), Perceived Ease of Use (PEU), and Attitude toward Use (ATU). The potential benefits of PEU and PU can have a substantial impact on the adoption of advanced technology use and shape students' behavioral intentions to utilize smart learning environment platforms.

F. Practical Implication

Results from the analysis conclude that AC, PL and PSQ indeed play significant roles in influencing students' intentions to interact with smart learning environments. Learning should be easily accessible anytime and anywhere. The acquisition of knowledge can occur through either synchronous or asynchronous methods, both of which are essential components within a smart learning environment. The provision of customized smart learning environments provides learners with customized learning resources, learning routes, and learning partners that cater to their individual requirements. Personalization plays a crucial role in enhancing the quality and self-motivation of student learning [43, 44]. With the development of smart technologies, there are tools to analyze data. Learning adaptation according to the learner's ability level and providing assessments and immediate feedback are features of perceived system quality in smart learning environments. Educators must employ information technology and effectively incorporate pertinent technological features into their instructional approaches in order to provide a smart learning environment.

Fig. 3 demonstrates the suggested constituents of a smart learning environment, encompassing accessibility, personalization, data analytics, adaptability, assessment, and feedback as the fundamental elements that enable the implementation of smart learning environments for students. Data analytics is about collecting, analyzing, and predicting innovative thinking skills. In addition, analysis results are presented in the form of data visualization, and a systematic learning progress report is generated. Adaptation is a learning system or environment that adapts to the learner's capabilities and designs the learning experience accordingly. Evaluation and feedback are the evaluation of learning and the provision of feedback in an appropriate and constructive manner. They also support learning outcomes and improve learning activities to be more effective.

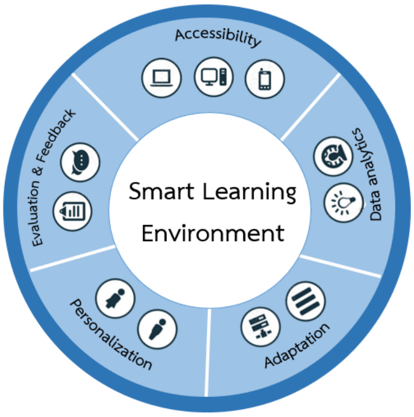


Fig. 3. Components of smart learning environments.

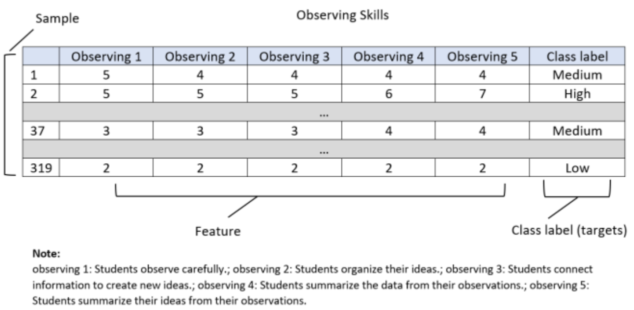
One suggestion is that the Smart Learning Environment Model be integrated with the Design of Teaching and Learning to create a smart learning environment that not only supports a variety of devices but, above all else, is easily accessible by learners and teachers, anywhere and at any time. After enrollment, learners self-assess their innovative thinking skills, consisting of five aspects: 1) Observing is a skill that pays attention to details; 2) Questioning is the ability to ask questions to expand knowledge by seeking answers and thinking analytically to create a body of knowledge; 3) Experimentation is the ability to identify problems, hypothesize, plan, and select appropriate methods to find answers or solutions; 4) The idea is that networking is a skill that creates collaboration in sharing knowledge to create and develop new knowledge; and 5) Association is a cognitive process that involves connecting pre-existing knowledge with novel information in order to problem-solve and generate innovative ideas. Then, data analytics collects the data, analyzes it, and predicts the innovative thinking ability by creating a supervised machine learning model that requires different datasets, consisting of a dataset and a result set that contains the information needed for training.

The steps for creating a machine learning model of supervised learning include: 1) Get Data is a collection of data from a sample group of 1,259 vocational students who answered the questionnaire on innovative thinking ability, and the evaluation form is a 7-step assessment scale (Likert scale); 2) Data cleaning and preparation is the process of preparing data for analysis by checking for missing data and dealing with outliers, thus resulting in a dataset used for training of 1,250 rows; 3) Training data is the dataset used to train an algorithm or model so it can accurately predict outcomes using 70% of the dataset of 1,250 rows used for building the model, as shown in Fig. 4. Validation data is used to assess and inform the choice of algorithm and parameters for the model being built. The researcher chose the K-Nearest Neighbors algorithm because it has the highest accuracy, as shown in Table 7; 4) Test dataset is a data set used to provide an unbiased evaluation of a final model fit on the training data set using 30% of the dataset of 1,250 rows for test.

Table 7. Testing the efficiency of the algorithm

Skills	Algorithm		Precision	Recall	F1-score	Accuracy
Observing skills	K-Nearest Neighbors	High	0.99	0.98	0.98	0.98
		Medium	0.97	0.98	0.98	
		Low	1.00	1.00	1.00	
	Decision Tree	High	0.96	0.98	0.97	0.96
		Medium	0.98	0.93	0.95	
		Low	0.82	1.00	0.90	
	Multi-layer Perceptron	High	0.96	0.99	0.98	0.96
		Medium	0.96	0.95	0.96	
		Low	1.00	0.56	0.71	
Questioning skills	K-Nearest Neighbors	High	1.00	0.98	0.99	0.98
		Medium	0.96	0.99	0.98	
		Low	1.00	0.83	0.91	
	Decision Tree	High	0.99	0.98	0.98	0.97
		Medium	0.97	0.95	0.96	
		Low	0.63	1.00	0.77	
	Multi-layer Perceptron	High	1.00	0.99	1.00	0.98
		Medium	0.97	1.00	0.98	
		Low	1.00	0.67	0.80	
Experimenting skills	K-Nearest Neighbors	High	0.98	0.99	0.99	0.98
		Medium	0.98	0.98	0.98	
		Low	1.00	0.91	0.95	
	Decision Tree	High	0.95	0.99	0.97	0.96
		Medium	0.98	0.92	0.95	
		Low	0.91	0.91	0.91	
	Multi-layer Perceptron	High	0.99	0.99	0.99	0.96
		Medium	0.93	0.98	0.96	
		Low	1.00	0.09	0.17	
Idea networking skills	K-Nearest Neighbors	High	0.99	0.98	0.99	0.97
		Medium	0.97	0.98	0.97	
		Low	0.80	1.00	0.89	
	Decision Tree	High	0.96	0.96	0.96	0.94
		Medium	0.94	0.91	0.93	
		Low	0.54	0.88	0.67	
	Multi-layer Perceptron	High	0.97	0.99	0.98	0.97
		Medium	0.98	0.95	0.97	
		Low	1.00	0.75	0.86	
Associating skills	K-Nearest Neighbors	High	0.89	0.87	0.88	0.85
		Medium	0.81	0.83	0.82	
		Low	0.57	0.50	0.53	
	Decision Tree	High	0.85	0.86	0.86	0.81
		Medium	0.78	0.77	0.78	
		Low	0.50	0.50	0.50	
	Multi-layer Perceptron	High	0.89	0.90	0.91	0.86
		Medium	0.84	0.84	0.84	
		Low	0.60	0.38	0.46	

The first one, the dataset of observing skills, consists of the following features: 1) students observe carefully; 2) students organize ideas; 3) students connect information to create new ideas; 4) students summarize the data from their observations; and 5) students summarize their ideas from their observations. The second one, the dataset of questioning skills, consists of the following features: 1) students ask thought-provoking questions; 2) students ask questions to encourage analytical thinking; 3) students ask questions to expand their thinking; 4) students ask questions to find out the nature of the problem; 5) students ask questions to empower or inspire. Third, the dataset of experimenting skills consists of the following features: 1) students identify problems; 2) students make assumptions; 3) students plan to search for answers; 4) students decide on effective methods; and 5) students summarize the results of finding the answer. Fourth, the dataset of ideas for networking skills consists of the following features: 1) students build cooperation power; 2) students communicate two-way; 3) students collect ideas and create new approaches; 4) students build relationships by having freedom of thought; and 5) students create collaborative teams. Fifth, the dataset of associating skills consists of the following features: 1) students can connect old and new information; 2) students explain new discoveries; 3) students quickly find solutions to problems using new methods; 4) students can apply new knowledge to solve problems; and 5) students bring their skills in questioning, observing, experimenting, and networking. Let's connect to create new things. As for the classification results, they are divided into high, medium, and low.



	Observing 1	Observing 2	Observing 3	Observing 4	Observing 5	Class label
1	5	4	4	4	4	Medium
2	5	5	5	6	7	High
...						
37	3	3	3	4	4	Medium
...						
319	2	2	2	2	2	Low

Fig. 4. Example: The dataset of observing skills.

The resulting dataset divides learners into three groups: high-ability learners, medium-ability learners, and low-ability learners. Learning uses algorithms to create a training model that learns the patterns in the data. Once the model is trained, it is evaluated to determine its correctness or accuracy in classification for learner information segmentation, as shown in Fig. 5.

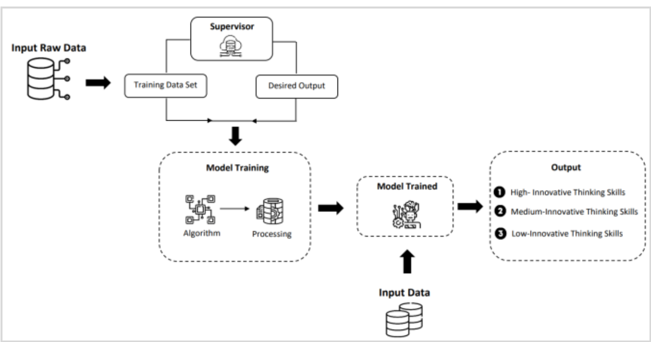


Fig. 5. Machine learning modeling.

Following this, the aforementioned findings were utilized in the development of an adaptive approach to learning management. To cater to the diverse abilities of learners, learning activities of varying levels of complexity are devised with the aim of promoting engagement in individualized learning tasks. The inherent characteristic of adaptive learning activities is their diverse range, all of which aim to achieve identical learning results. Highly proficient individuals employ learning activities of considerable complexity. Simpler learning exercises are employed for those with lower levels of expertise. The evaluation of learning is contingent upon real-world circumstances and is subject to variation dependent on the aptitude of the learners being evaluated. Additionally, feedback is provided to the learners on the assessment of their learning, as seen in Fig. 6.

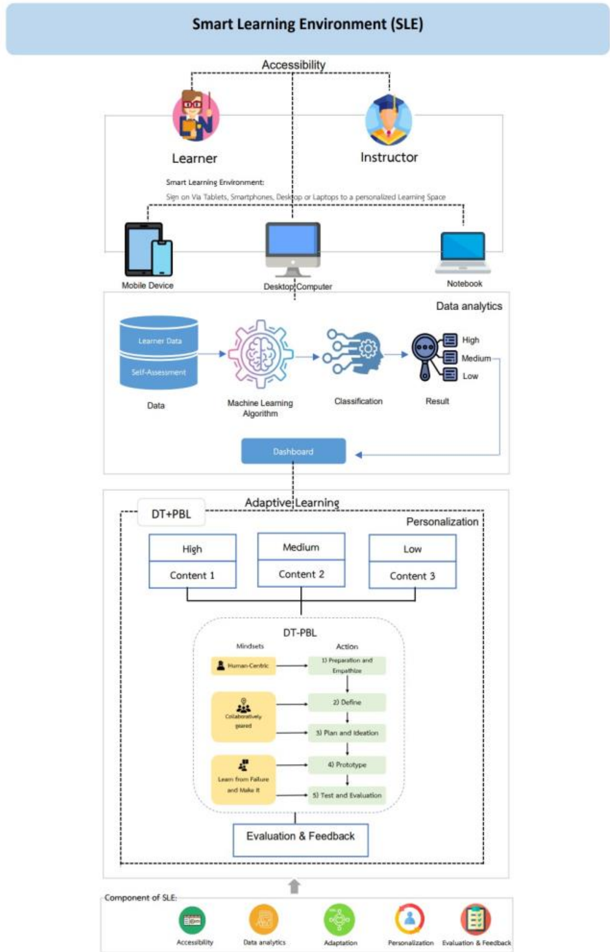


Fig. 6. Framework for smart learning environment based on machine learning.

The design of the learning process is based on design thinking and project-based learning for learning and activities over a 9-week period (Table 8). During the time students are learning and doing activities, data is collected and learning tracks are recorded, consisting of organizing learning activities in 5 steps: 1) Preparation and empathy are the steps that provide basic knowledge for conducting the project and prepare students to open their minds to stimulate innovative thinking skills in students and gain a deeper understanding of the target audience through an interview; 2) Define is clearly specifying the problem that needs to be solved by designing learning activities for students to collaborate and brainstorm in groups, ask questions to gain knowledge and understanding, and ask questions to get answers to the group's needs. The goal of the learning activities is to promote questioning skills and the networking of ideas; 3) Planning and ideation involve brainstorming and proposing solutions. The learning activities promote the ability to build a mental network and connect ideas; 4) A prototype is a model for solving problems by taking the best idea selected and turning it into a prototype. Learning activities promote the ability to experiment, build networks of thought, and connect ideas; and 5) Test and evaluation are the final steps in which the prototype is tested and the created prototype is evaluated to see whether it can really solve the users' problems or not. The learning activities encourage questioning, observation, building networks of thinking, and linking ideas.

Table 8. Learning activities on a smart learning platform with design thinking and project-based learning

Step	Learning objectives	Learner role	Media in (SLEs)
Preparation and empathize	1. Set a problem based on the situation. 2. Hypothesize the problem of interest.	1. Together, study and understand sustainable development through the SDGs by reflecting on a smart learning platform. 2. Observe and analyze community issues through understanding the community context and considering the strengths and weaknesses of the community in which one lives. 3. Gather into groups and brainstorm together on issues of common interest.	1.Personalization - Video - Academic Resource - Skill-training exercises 2. Collaboration - collaborative platform - Activity Sheet 1: Set the problem.
Define	3. Design and use data collection processes efficiently. 4. Study and research from a variety of learning sources on the chosen topic.	1. Interview the target group. 2. Tell the story of the interview and write down the problems of the target group. 3. Ask questions to capture the desired points of the audience, analyze the group's prior knowledge, identify new knowledge they need to study and learn more about, and explore the real issues of the selected topics. 4. Determine search sources and search methods that focus on working together to brainstorm and solve problems. 5. Formulate the problem together in the form of "How might we?"	1.Personalization - Video - Academic Resource - Skill-training exercises 2. Collaboration - collaborative platform - Activity Sheet 2: Interviewing the target group - Activity Sheet 3: Problem framing
Plan and Ideation	5. To search for information and be able to verify the reliability of the source of information.	Analyze and summarize important information from research to create a plan to solve problems, such as writing scripts, creating storyboards or mock-ups, etc.	1.Personalization - Video - Academic Resource - Skill-training exercises 2. Collaboration - collaborative platform - Activity Sheet 4: Brainstorming
Prototype	6. Synthesize knowledge and develop work.	1. Complete the solution according to the instructions. 2. Practice and edit according to the script, storyboard, or mockup.	1.Personalization - Video - Academic Resource - Skill-training exercises 2. Collaboration - collaborative platform - Activity Sheet 5: Prototyping
Test and Evaluation	7. Present ideas for solving problems systematically with newly discovered knowledge.	1. explain the prototype to the target group. 2. Present the prototype to the target audience and listen to their feedback.	1.Personalization - Video - Academic Resource - Skill-training exercises 2. Collaboration - collaborative platform - Activity Sheet 6: Prototype Test Record Form

V. Conclusion

The study investigates factors affecting students' adoption of smart learning environments in vocational training institutes across Thailand. It found that students actively choose to use smart learning platforms and are aware of the benefits of their PU and PEU in assistive technology use. The study identified two significant indicators of behavioral intent to use smart learning platforms: attitude toward adopting and perceived usefulness. Attitude plays a crucial role, as negative attitudes may hinder students' utilization of these platforms. Policymakers should focus on user experience and consider factors like accessibility, personalization, and system quality. Thai educators should prioritize the development, implementation, and incorporation of smart learning models while addressing adoption obstacles.

Appendix: Questionnaire on Students' Behavioral Intentions When Using Smart Learning Environment

A. Perceived Usefulness (PU) (Adapted from Davis [10])

PU1. The implementation of a smart learning environment is expected to enhance the process of learning for individuals.

PU2. The implementation of a smart learning environment has the potential to enhance my learning efficiency.

PU3. In a smart learning environment that is flexible and can be adapted to my abilities.

PU4. In a smart learning environment, I receive learning materials tailored to my application needs.

PU5. A smart learning environment suitable for learners with different learning styles.

B. Perceived Ease of Use (PEU) (Adapted from Davis [10])

PEU1. I have a clear and understanding engagement with the intelligent learning environment. I like utilizing a technologically advanced educational setting.

PEU2. In a smart learning environment, it can be controlled without much effort.

PEU3. I have easy access to a clever learning environment that allows me to accomplish my goals.

PEU4. I perceive a smart learning environment as being user-friendly.

PEU5. In a smart learning environment, I can use as many devices as I want.

C. Attitude towards Use (ATU) (Adapted from Davis [10])

ATU1. In a smart learning environment, learning is more interesting.

ATU2. Learning in a smart learning environment is fun.

ATU3. I find the utilization of a smart learning environment to be favorable.

ATU4. A smart learning environment provides a motivating and engaging learning experience.

D. Accessibility (AC) (Adapted from Agbo [24]; Spector [45]; Li et al. [35])

AC1. A smart learning environment supports learning anytime, anywhere.

AC2. A smart learning environment supports the use of multiple devices.

AC3. A smart learning environment authenticates before use.

AC4. A smart learning environment is easily accessible and straightforward.

E. Personalization (PL) (Adapted from Wang et al. [23]; Agbo [24]; Gambo and Shakir [25])

PL1. A smart learning environment promotes my learning abilities.

PL2. A smart learning environment provides multiple learning channels for me (e.g., learn from online sources, learn in action, and learn with peers).

PL3. A smart learning environment encourages me to collaborate with others.

PL4. A smart learning environment can share information and resources with others when working together.

F. Perceived System Quality (PSQ) (Adapted from Wang et al. [23]; Agbo [24]; Li et al. [46])

PSQ1. In a smart learning environment, it can analyze data to predict my ability to develop innovative thinking skills.

PSQ2. In a smart learning environment, it can collect information systematically.

PSQ3. In a smart learning environment, it is flexible and tailored to my abilities.

PSQ4. In a smart learning environment, it can report my learning progress.

PSQ5. In a smart learning environment, it is capable of assessing and providing appropriate creative feedback.

G. Behavioral Intention (BI) (Adapted from Davis [10])

BI1. In the future, I plan to pursue my education in a smart learning environment.

BI2. In the future, I anticipate learning in a smart learning environment.

BI3. In the future, I intend to learn in a smart learning environment.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Peeraya Sukkeewan: Design, conceptualization, deep analysis, writing and reviewing, supervision. Noawanit Songkram: Data acquisition, conceptualization, analysis and interpretation of data, writing, edition, and final approval. Jaitip Nasongkhla: Conceptualization, design, analysis, writing. All authors had approved the final version.

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