Research Article

COVID-19 in Emerging Countries and Students’ Intention to Use Cloud Classroom: Evidence from Thailand

Singha Chaveesuk and Wornchanok Chaiyasoonthorn

KMITL Business School, Bangkok, Thailand

Correspondence should be addressed to Wornchanok Chaiyasoonthorn; wornchanok.ch@kmitl.ac.th

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In many emerging markets, collectivist culture promotes interpersonal relationships which entail sharing both work and personal lives with one another. Nevertheless, the ubiquity of the World Wide Web has provided massive opportunities to teachers and learners around the globe to share knowledge anytime anywhere via online education. It is against this background that this study explores the perceptions of IT students in adopting virtual learning system in higher education institutes in an emerging country context under the COVID-19. We extended Davis’s (1989) Technology Acceptance Model (TAM) and evaluated students’ intention to use cloud classroom. Data were obtained from the five universities IT students in Bangkok, Thailand. Using partial least square structure equation modeling (PLS-SEM), the data of 373 IT students were analyzed. The findings of the research show that all hypotheses were supported, except one that was related to the positive impact of perceived usefulness on students’ intention to use cloud classroom. The extended TAM model explains 51.6% variance to explain students’ intention to use cloud classroom. The result of this study has useful implications for educationists and strategists related to the effectiveness and usability of cloud classroom in higher education institutions.

1. Introduction

The development of the World Wide Web has accelerated the pace of Internet activities. Through Internet activities, more and more people are connecting on the Internet [1]. The universality of the Internet has changed the traditional way of learning [2]. People from different backgrounds and education interact with one another because of shared goals [3]. Kaufmann and Buckner [4] stated that online learning provides opportunities for the advancement of online courses. Harrison et al. [5] emphasized the importance of online learning programs around the world. Technological competencies and instructional design are the crucial elements of online education [6]; therefore, future training programs should give ample focus to these areas [7, 8] and understand the needs and characteristics of the people involved in online learning [9, 10].

However, for training programs on online learning to be effective, the role of a teacher in traditional classroom learning is authoritative. The teacher determines the content of the course and delivers face-to-face lectures [11–13]. The classroom environment is centered on the discussion between teacher and students [3]. However, trends are changing towards technology-based learning methods where teachers use information technology to deliver the lectures [14]. Online courses are being offered to assist the students and improve their learning [15]. Online education is the subset of distance education where teachers adopt a variety of technological applications including web-based learning, digital collaboration, computer-based learning, and virtual classrooms [16]. It is a form of well-structured courses with content for “just-in-time” access to materials and learning [17]. The willingness of higher education institutions to avail themselves the opportunity of cloud classroom continues to grow with the access to high numbers of students [18, 19]. Consequently, universities at a point in time may ask the faculty members to consider online teaching partially or fully [20]. Jaschik et al. [21]
conducted a survey on faculty attitude towards technology which revealed that only twenty percent (20%) of faculty members used technology to record class lectures. In context of digital startups, Chaiyasoonthorn [22] and Benchhra et al. [23] also indicated attitude is the main determinant which affects behavioral intention among undergraduate students. To promote e-learning methodology in higher education institutions, universities must adopt advanced information and communication technologies [24]. Al-Tahitah et al. [25] urged the importance of using social media platforms as a medium of learning during COVID-19 pandemic. They posited that social media technology has a vital and effective role for students learning during emergency situation like COVID-19 outbreak. Therefore, the significant role of cloud classroom cannot be ignored during COVID-19 pandemic. For example, AlAjmi et al. [26] stressed on the role of higher education institution to transform face-to-face education to online learning. In relation to this, Prasetyo et al. [27] indicated that online learning is a viable solution that accelerates the face of students learning. Past studies have focused on the usage of latest technology to facilitate students learning [26, 28–30]. The literature remains scarce regarding the use of cloud classroom during COVID-19 pandemic. Therefore, this study focuses on importance dimensions of using cloud classroom and its effectiveness on students’ intention to use. The use of cloud computing technology is the most viable option due to its low cost [31]. It promotes e-learning which promotes knowledge sharing, scalability, and reusability of available learning materials around the globe [32–34]. Undoubtedly, cloud computing is one of the solutions to solving the problems of e-learning. But the applicability of advanced technology is difficult due to its complex migration process [24, 35]. Many factors influence willingness to adopt advanced technology such as the use of the system and facilitating conditions [36]. Therefore, it is essential to understand the factors affecting cloud classroom in higher education institutions (HEI). The understanding of respondents’ inclination towards the usage of cloud classroom is imperative in the higher education context, as it will improve future learning methodologies in HEIs.

This study explores the perceptions of IT students in adopting virtual learning system in higher education institutes in an emerging country context under the COVID-19. In the context of cloud classroom, facilitating conditions, ease of use, and usefulness are essential [2]. Facilitating conditions help to overcome the perceived barriers during the task [36, 37]. Individual confidence regarding the use of advanced technology represents computer self-efficacy [38]. Fathema et al. [39] extended technology acceptance model (TAM) to examine faculty use of learning management systems (LMSs). They incorporated facilitating conditions and perceived self-efficacy into the extended TAM model. Likewise, many scholars used the technology acceptance model (TAM) to examine students’ willingness to advance technology for learning [40–43]. Many studies have used integrated IS theories and TAM to understand individual behavioral intention towards technology adoption [44, 45]. However, a comprehensive integrated framework based on the TAM model for students cloud classroom has yet to be studied. Based on acceptance of information technology literature, we included three additional constructs: facilitating conditions and computer self-efficacy into the technology acceptance model (TAM) to predict students’ intention to use cloud classroom in HEIs. Hence, the outcomes of this study provide an understanding regarding students’ acceptance of cloud classroom in HEIs.

The first section of this study discussed the importance of cloud classroom in the contemporary world. The second section presented the theoretical framework adopted in this study and the literature of the constructs. In the third section, the methodology adopted in this study was explained. The fourth section elaborated the findings of the study. Finally, we discussed the conclusion and discussions, policy implications, limitations, and future research directions.

2. Theoretical Framework and Hypotheses Development

2.1. Theoretical Framework: An Extended Technology Acceptance Model. Several studies have attempted to develop theoretical models for predicting people’s acceptance of a particular product and technology. One of them is the technology acceptance model (TAM), introduced by Davis et al. [46] and designed to understand people’s tendency towards the adoption of technological products [47, 48]. TAM was originally derived from the theory of reasoned action (TRA) [49, 50], which is widely famous in the domain of social psychology. The TAM was developed in the information management system to assess people’s intention to adopt and use new technology or media. The original model of TAM was developed to explain users’ behavioral intention to use information management systems through perceived usefulness and perceived ease of use [51]. Later, Venkatesh and Davis [52] extended the original version of TAM by adding many important constructs, such as image, job relevance, subjective norms, experience, and voluntariness, and named it TAM 2. Eight years later, Venkatesh and Bala [53] proposed another extended model named TAM 3 in which experience was used as a moderator defining the relationships among the constructs. For the last three decades, TAM 1, TAM 2, and TAM 3 and its extended versions have been widely used by researchers around the globe to explain behavioral intention. Based on the technology acceptance model, we propose a conceptual model (Figure 1) that can predict students’ intention to use cloud classroom in higher education.

2.2. Perceived Usefulness. In the TAM model, perceived usefulness refers to an individual’s believes that using a specific system will accelerate his or her performance [54]. In the TAM model, perceived usefulness is related to task performance, effectiveness, and productivity [51]. It is a major belief construct leading to behavioral intention for the use of specific technology [55–58]. In the context of the World Wide Web, Moon and Kim [58] confirmed the effectiveness of perceived usefulness on the intention to use
2.3. Perceived Ease of Use. Researchers have recognized the significance of perceived ease of use in the technology acceptance model [51, 64, 65]. Perceived ease of use has the same meaning as the complexity variable in [66] diffusion of innovation theory. Davis and Venkatesh [67] give high value to perceive ease of use because many technology-oriented products were rejected based on users’ poor performance due to the poor interface of the systems. Prior researches have shown that site designs include updated information, simple checkout procedures, good layout, transparent navigational structures, effective search engines, and user-friendly interfaces which were important aspects of online shopping [68]. In the context of online learning, Liu et al. [3] explained the significant influence of perceived ease of use to use the online learning community. Saade et al. [63] posited that perceived ease of use develops a favorable perception of students towards the use of learning tools. Past studies found the important role of perceived ease of use on the usefulness of technologies that eventually leads towards the adoption of technology [46, 69, 70]. Based on the past studies, it can be assumed that teachers’ perceived ease of technology use will have a positive effect on the perceived usefulness and adoption of online technology in higher education. Hence, we hypothesized that

H2: perceived ease of use has a positive impact on student’s intention to use the cloud classroom

2.4. Facilitating Conditions (FC). Ngai et al. [40] define facilitating conditions as "perceived enablers or barriers” that affect an individual’s perception of ease or difficulty during the performance of an activity. Facilitating conditions are persons’ control beliefs regarding the availability of resources that serve to facilitate the use of a technology [53]. In the context of online teaching, facilitating conditions refer to the availability of hardware, software, technical help, training to faculty, and availability of Internet infrastructure [14]. Prior studies have indicated that facilitating conditions are crucial that influence the use of technology [37, 71–73]. Researchers revealed that facilitating conditions have a significant positive influence on intention to use technology [37, 74]. The use of technology requires professional development, instructional guidance, and careful management of teaching processes such as course management [14, 75]. Adequate technology supports, access to mentors, and a conducive environment enable students to migrate smoothly to this new form of learning and become familiar easily to use them. The successful transition from traditional to technology-based learning requires a change in the pedagogy and acceptance of new skills to deliver online lectures [14, 72, 76–78]. Based on past studies’ evidence related to the effectiveness of facilitating conditions on intention to use technology, we hypothesized that

H3: facilitating conditions have a positive impact on perceived usefulness
H4: facilitating conditions have a positive impact on perceived ease of use

2.5. Computer Self-Efficacy (CSE). Computer self-efficacy refers to an individual ability to use the computer and perform a task [79]. Deimann and Keller [80] argued that computer self-efficacy accelerates an individual performance of using computer-based technology. A study by Lieu et al. [79] on simulation-based learning depicts the influence of computer self-efficacy on task performance. In the context of education, studies revealed the effect of computer self-efficacy on technology acceptance for teaching purposes [81–83]. Computer self-efficacy activates intrinsic motivation for cloud classroom [44, 81, 84]. In the context of current research, computer self-efficacy refers to students’ ability and confidence level of using cloud classroom. Based on the above studies, we assume that students’ computer self-efficacy serves as an internal motivator that leads to intention to use cloud classroom. Hence, we hypothesized that

H5: computer self-efficacy has a positive impact on perceived usefulness
H6: computer self-efficacy has a positive impact on perceived ease of use

2.6. Perceived Usefulness and Perceived Ease of Use as a Mediator. Davis [51] posited that both perceived usefulness (PU) and perceived ease of use (PEOU) are the potential mediators of behavioral intention. Davis et al. [64] found the indirect effect PU and PEOU on intention to use technology.
Many researchers have proved that PU and PEOU fully mediate the relationship between external variables and usage intention [52]. In addition, Santhanamery and Ramayah [85] found that PU mediated the relationship between system support and continuance usage intention. Maheshwari [86] studied students’ online learning intention and found indirect effect of external factors on online learners’ intention. Chen and Aklikokou [87] proved that PU and PEOU mediated the relationships between external factors and e-government adoption. Furthermore, the study of Susanto and Aljoza [88] revealed that direct effect of facilitating conditions was insignificant on acceptance of e-government services, suggested the possibility of indirect effects. Based on this discussion, we have assumed that PU and PEOU will mediate the relationship between facilitating conditions and computer self-efficacy on intention to use cloud classroom. Hence, we hypothesized that

H7: PU will mediate the positive relationships between facilitating conditions and intention to use cloud classroom  

H8: PU will mediate the positive relationships between computer self-efficacy and intention to use cloud classroom  

H9: PEOU will mediate the positive relationships between facilitating conditions and intention to use cloud classroom  

H10: PEOU will mediate the positive relationships between computer self-efficacy and intention to use cloud classroom

3. Methodology

3.1. Sampling. The participants of this study are the students from five Bangkok universities. A purposive sampling technique was employed for the collection of students’ data. The questionnaire in Table 1 was distributed to past IT students and current ones. The preference for IT students was because they have a better understanding of cloud classroom technology than non-IT students. Participants were informed about the purposive of the study, and we ensured that their demographic details will be kept confidential and will be used for research purposive. The sample size for this study was determined by following the guidelines of researchers [89, 90]. They suggested a ratio of 5 to 10 responses per item. Given the total number of 23 items, a sample size of 230 was appropriate. However, we decided to collect a larger sample to increase data reliability. A total of 700 questionnaires were distributed to the participants of the study. A total of 392 questionnaires were received from the participants of the study with a response rate of 56%. The final analysis was performed on 373 useable data after discarding the incomplete questionnaires and performing a data screening test (outliers’ identification).

3.2. Instrument. A pilot test of the questionnaire was conducted on 65 IT students studying at different universitiess in Bangkok, Thailand. Necessary changes related to the language of constructs have been incorporated after consultation with three academic experts and one IT expert. The first part of the questionnaire deals with the demographics of students. The second part of the questionnaire deals with constructs’ items. We have employed a five-point Likert scale ranging from (1) strongly disagree to (5) strongly agree. Hung et al. [91] and Liu et al.’s [3] scales have been adapted for the measurement of students’ intention to use the cloud classroom. Liu et al.’s [3] scales have been adapted for the measurement of perceived ease of use and perceived usefulness. The items for the measurement of facilitating condition were adapted from Fathema et al. [39] and Hung et al.’s [91] study. Ismail et al.’s [92] four items scale was used for the measurement of computer self-efficacy. Before formally analyzing the data, it was tested for data bias. We have used Harman single factor test to assess the common method bias. The results of principle axis revealed that a single factor explained less than 50% of the variance in the data which represents that common method bias is not a potential for the collected data.

3.3. Students’ Profile. The demographic profile of the participants is shown in Table 2. Out of 373 participants, 207 (55.5%) were and 166 (44.5%) were females. The majority of the participants 246 (66%) belonged to the age group between 21 and 25. Third-year students were 182 (48.8%) which constitutes the highest percentage. Artificial intelligence was the major of most of the students 108 (29%).

4. Data Analysis, Findings, and Discussion

4.1. The Measurement Model. This study has employed partial least square structural equation modeling (PLS-SEM). Partial least square has many advantages such as avoidance of inadmissible solutions and factor indeterminacy, applicability to the theory development, and suitability for prediction [93]. This study has employed a two-step analytical method; first, we analyzed the measurement model and then tested the structural model. The items of the constructs are shown in measurement model, Table 3 and Figure 2. Composite reliability (CR) values more than 0.70 and average variance extracted (AVE) values above 0.50 are considered acceptable for convergent validity [94–96]. The values of composite reliability (CR) and average variance extracted (AVE) of this study are greater than the recommended threshold values of 0.70 and 0.50, respectively, thus confirming data robustness. Table 3 showing the values of all constructs composite reliability (CR) ranges from 0.868 to 0.951, and the values of average variance extracted (AVE) ranges from 0.622 to 0.831. Fornell and Larcker [97] criterion was used for the measurement of discriminant validity. The discriminant validity of the constructs was assessed by comparing the square root of average variances extracted with constructs correlations shown in Table 4. The square root of each construct of AVE is greater than the corresponding highest correlation confirming discriminant validity [98].
Table 1: Questionnaire.

|                  | Strongly disagree | Disagree | Neither agree nor disagree | Agree | Strongly agree |
|------------------|-------------------|----------|---------------------------|-------|----------------|
| FC1              |                   |          |                           |       |                |
| FC2              |                   |          |                           |       |                |
| FC3              |                   |          |                           |       |                |
| FC4              |                   |          |                           |       |                |
| CSE1             |                   |          |                           |       |                |
| CSE2             |                   |          |                           |       |                |
| CSE3             |                   |          |                           |       |                |
| CSE4             |                   |          |                           |       |                |
| PEO1             |                   |          |                           |       |                |
| PEO2             |                   |          |                           |       |                |
| PEO3             |                   |          |                           |       |                |
| PEO4             |                   |          |                           |       |                |
| PU1              |                   |          |                           |       |                |
| PU2              |                   |          |                           |       |                |
| PU3              |                   |          |                           |       |                |
| PU4              |                   |          |                           |       |                |
| INT1             |                   |          |                           |       |                |
| INT2             |                   |          |                           |       |                |
| INT3             |                   |          |                           |       |                |
| INT4             |                   |          |                           |       |                |

Note: encircle the best response like this: 5

Teacher's gender: (1) male; (2) female. Age: (1) 16 to 25 years; (2) 21 to 25 years; (3) 26 to 30 years; (4) 31 to 35 years. Year of study: (1) 1st year; (2) 2nd year; (3) 3rd year; (4) 4th year. IT specialization: (1) computational geometry and applications; (2) information and communication technology; (3) information management; (4) artificial intelligence; (5) computer networks; (6) embedded system design.
4.2. *The Structural Model.* The structural equation model (Figure 3) includes assessing the significance of path coefficients, analysis of the coefficient of determination ($R^2$), and predictive relevance ($Q^2$) value. Bootstrapping procedure, employing 2000 resampling, was used for the analysis of path coefficients. Path coefficient value ranges between $-1$ and $+1$. The estimated path closer to $+1$ indicates a strong positive relationship while the value closer to $-1$ indicates a negative relationship between the constructs. The value of $R^2$ was computed for the endogenous variables (cloud classroom intention) to measure the variances explained in the structural model. The model depicts 51.6% of the variance explained in faculty intention to adopt technology for online teaching (see Table 5). Besides the value of $R^2$, we have computed Stone Geisser’s $Q^2$ value as a criterion for the predictive relevance. The value ($Q^2$) above 0 indicates that exogenous variables possess predictive relevance [99]. The result of this study shows that $Q^2$ is 38.6% which is above 0 which indicates moderate to high predictive relevance (see Table 5).

The results of the structural model are shown in Table 5. The acceptance and rejection of theoretical relationships are

### Table 2: Demographic of respondents.

| Gender    | Frequency | Percentage |
|-----------|-----------|------------|
| Male      | 207       | 55.5       |
| Female    | 166       | 44.5       |
| Age       |           |            |
| 16–20     | 64        | 17.2       |
| 21–25     | 246       | 66         |
| 26–30     | 56        | 15         |
| 31–35     | 07        | 1.9        |
| Year of study |     |            |
| 1st year  | 09        | 2.4        |
| 2nd year  | 57        | 15.3       |
| 3rd year  | 182       | 48.8       |
| 4th year  | 125       | 33.5       |
| IT specialization | | |
| CGA    | 57        | 15.3       |
| ICT    | 93        | 24.9       |
| IM     | 97        | 26         |
| IA     | 108       | 29         |
| CN     | 16        | 4.3        |
| ESD    | 02        | 0.5        |

Note: CGA = computational geometry and applications; ICT = information and communication technology; IM = information management; IA = artificial intelligence; CN = computer networks; ESD = embedded system design.

### Table 3: Measurement model.

| Constructs                     | Items | Standardized factor loading | Cronbach’s (d) | Composite reliability (CR) | Average variance extracted (AVE) |
|-------------------------------|-------|-----------------------------|----------------|----------------------------|---------------------------------|
| Intention                     | INT1  | 0.885                       | 0.895          | 0.924                      | 0.761                           |
|                               | INT2  | 0.908                       |                |                            |                                 |
|                               | INT3  | 0.823                       |                |                            |                                 |
|                               | INT4  | 0.870                       |                |                            |                                 |
| Facilitating conditions       | FC1   | 0.887                       | 0.919          | 0.943                      | 0.804                           |
|                               | FC2   | 0.901                       |                |                            |                                 |
|                               | FC3   | 0.892                       |                |                            |                                 |
|                               | FC4   | 0.904                       |                |                            |                                 |
| Perceived usefulness          | PU1   | 0.754                       | 0.797          | 0.868                      | 0.622                           |
|                               | PU2   | 0.746                       |                |                            |                                 |
|                               | PU3   | 0.740                       |                |                            |                                 |
|                               | PU4   | 0.810                       |                |                            |                                 |
| Perceived ease of use         | PEO1  | 0.944                       | 0.931          | 0.951                      | 0.831                           |
|                               | PEO2  | 0.942                       |                |                            |                                 |
|                               | PEO3  | 0.826                       |                |                            |                                 |
|                               | PEO4  | 0.929                       |                |                            |                                 |
| Computer self-efficacy        | CSE1  | 0.929                       | 0.919          | 0.943                      | 0.805                           |
|                               | CSE2  | 0.874                       |                |                            |                                 |
|                               | CSE3  | 0.871                       |                |                            |                                 |
|                               | CSE4  | 0.914                       |                |                            |                                 |

Note: INT = intention to adopt; FC = facilitating conditions; PU = perceived usefulness; PEO = perceived ease of use; CSE = computer self-efficacy.
based on the path coefficients and significance values. The results of direct relationships show all hypotheses were accepted. H1 proposed the positive impact of perceived usefulness on students’ intention to use cloud classroom system which was supported ($\beta = 0.455$, $p \leq 0.001$). H2 proposed the positive impact of perceived ease of online teaching on students’ intention to use cloud classroom system which was supported ($\beta = 0.366$, $p \leq 0.001$). H3 proposed positive impact of facilitating conditions on perceived usefulness which was supported ($\beta = 0.504$, $p \leq 0.001$). H4 proposed positive impact of facilitating conditions on perceived ease of use which was supported ($\beta = 0.392$, $p \leq 0.001$). H5 proposed positive impact of computer self-efficacy on perceived usefulness which was supported ($\beta = 0.353$, $p \leq 0.006$). H6 proposed positive impact of computer self-efficacy on perceived ease of use which was supported ($\beta = 0.264$, $p \leq 0.006$). These findings are consistent with previous studies [39, 52, 84, 91, 100, 101].

We have followed Preacher and Hayes [102] method for mediation analysis. A 2000 bootstrapping resampling has been used to test the mediation analysis. The values of t-statistics and p values have been assessed for indirect (mediation) analysis. $T$ value is greater than 1.96 and $p \leq 0.005$ corresponds to acceptance of hypotheses. In addition, the mediation was confirmed through absence of “0” value in between confidence interval [102].

The results of mediation analysis presented at Table 6 depict that perceived usefulness mediates the relationships between both facilitation conditions and intention to use cloud classroom ($\beta = 0.229$, $t = 7.276$, $p \leq 0.001$) and computer self-efficacy and intention to use cloud classroom ($\beta = 0.161$, $t = 5.388$, $p \leq 0.001$). Perceived ease of use also mediates the relationships between both facilitation conditions and intention to use cloud classroom ($\beta = 0.143$, $t = 5.114$, $p \leq 0.001$) and computer self-efficacy and intention to use cloud classroom ($\beta = 0.097$, $t = 3.842$, $p \leq 0.001$).

All our hypotheses have been accepted and the mediation analysis showed significance. The COVID-19 might have a positive influence on participants of virtual classes given that the social distance requirements need to be maintained to avoid public health crisis. This is a huge shift in an emerging market context where collectivist cultures value person-to-person contacts and sharing.

4.3. Discussion. The research on cloud classrooms is getting momentum due to the outbreak of COVID-19 pandemic. Cloud classrooms are considered the viable medium for the
dissemination of knowledge [32]. In the emerging countries like Thailand, the importance of cloud classrooms cannot be ignored as it contributes to the development of knowledge. Therefore, the current study presented a novel framework that assesses the impact of factors affecting students’ intention to use cloud classrooms as a medium of instruction. The findings of the study revealed the effectiveness of the proposed model that explained more than 51.6% of the variance. The findings of the current study are consistent with previous research where researchers highlighted the importance of perceived usefulness and perceived ease of use of technology in the adoption of technology [27, 36]. The results depict that Thailand IT students considered the cloud classrooms are effective tools that would help students in learning. Further, the result of the study indicated the importance of computer self-efficacy affecting the perceived usefulness of the technology which is consistent with Wang et al. [81] and Valencia-Vallejo et al.’s [82] studies. These findings indicate that students feel that they are competent to operate the computer-based technology for learning purpose. Finally, the results revealed that facilitating condition is a vital factor that affects students’ intention to use cloud classrooms for their studies. These findings are consistent with previous researchers where they argued on the importance of facilitating conditions [37, 71, 74]. Our findings imply that students need adequate facilities to

Figure 3: Structural equation model.

Table 5: Hypotheses assessment summary.

| Hypotheses       | Beta   | SE    | p values ≤0.001 | t values | Decision  | $R^2$ | $Q^2$ |
|------------------|--------|-------|-----------------|----------|-----------|-------|-------|
| PU->INT          | 0.455  | 0.457 | 0.000           | 9.669    | Supported | 0.516 | 0.386 |
| PEOU->INT        | 0.366  | 0.365 | 0.000           | 7.437    | Supported |       |       |
| FC->PU           | 0.504  | 0.504 | 0.000           | 11.724   | Supported |       |       |
| FC->PEOU         | 0.392  | 0.393 | 0.000           | 7.667    | Supported |       |       |
| CSE->PU          | 0.353  | 0.355 | 0.006           | 7.258    | Supported |       |       |
| CSE->PEOU        | 0.264  | 0.264 | 0.000           | 4.858    | Supported |       |       |

Note: the relationships are significant at $p < 0.05^*$.

Table 6: Result of mediation analysis.

| Hypotheses       | Path coefficient | C.I           | p values ≤0.001 | t values | Decision  |
|------------------|------------------|---------------|-----------------|----------|-----------|
| CSE -- PU -- INT | 0.161            | 0.109, 0.212  | 0.000           | 5.388    | Mediation |
| CSE -- PEOU -- INT | 0.097          | 0.050, 0.149  | 0.000           | 3.842    | Mediation |
| FC -- PU -- INT  | 0.299            | 0.170, 0.295  | 0.000           | 7.276    | Mediation |
| FC -- PEOU -- INT | 0.143           | 0.091, 0.200  | 0.000           | 5.114    | Mediation |

Note: $p < 0.05$. 

In the emerging countries like NZ and Zealand, the importance of cloud classrooms cannot be ignored as it contributes to the development of knowledge 

Figure 3: Structural equation model.
participate to the cloud classrooms and the higher education institutions in Thailand are providing those facilities to continue the classes.

5. Conclusion

5.1. Conclusive Remarks. The progression of e-learning has extended the methods of teaching and learning at all levels of education. Scholars have studied many theoretical frameworks to analyze and understand teachers' and students' tendency towards cloud classroom. This study attempted to extend technology acceptance model (TAM) to predict students' intention to use cloud classroom systems. The extended TAM model included three usability constructs such as computer self-efficacy and facilitating conditions that have a significant role in attracting students for the use of cloud classroom. The findings of the study are encouraging and confirm the effectiveness of TAM in the context of cloud classroom system that matches with previous studies [40, 42, 103, 104]. This study covers a new dimension that focuses on computer self-efficacy on students' intention to use cloud classroom system. The findings of the current study depict that perceived ease of use, facilitating conditions, and computer self-efficacy have significance in the context of cloud classroom amongst university students. All constructs account 51.6% of the variance in the theoretical model, suggesting the effectiveness of the theoretical model in the context of cloud classroom. Among all studied factors, perceived ease of use has the greatest impact on students' cloud classroom system. Furthermore, the positive impact of facilitating conditions such as professional development and training related to the use of cloud classroom help and motivate students to learn new skills [14, 75, 105]. The results of mediation analysis depict that PU and PEOU mediated the relationships between two determinants (facilitating conditions and computer self-efficacy) and intention to use cloud classroom. These findings match with the previous researchers' findings where they found PU and PEOU have mediated effects on intention [52, 64, 85, 87, 88].

5.2. Policy Implications. To understand university students' intention to use cloud classroom in higher education institutions, this study highlights the importance of the TAM model and added three additional constructs that are crucial in students' learning systems. Additional constructs that help students to use cloud classroom include facilitating conditions and computer self-efficacy. The findings of the study offer guidance to educationists related to students' use of cloud classroom. First, the educationists and university leaders need to ensure that they have arranged the required facilities and materials that help to promote online teaching. Facilitating conditions vary from the availability of hardware to the availability of technical staff that supports the smooth running of the system [81, 92]. Last but not least, the components of the technology acceptance model: perceived ease of use has a significant impact on student's intention to use cloud classroom in higher education institutions. As posited by previous researchers that perceived ease of use internally motivated to perform the task effectively [39], therefore, educationists need to pay attention on attractive and communication friendly interface design. This would help the students to focus on learning and receive maximum content for educational purposes. Poor user-interface designs often create disturbance between the parties involved in the communication. However, this study fails to provide support regarding the effectiveness of perceived usefulness on students' intention to use cloud classroom in higher education institutions. Past studies in the context of students' intention to use cloud classroom applications and YouTube for procedural learning reported the same results [81, 106]. This finding suggests that IT students do not exert cognitive efforts on the cloud classroom system.

5.3. Limitation and Future Research Directions. This study has some limitations. The first limitation is related to the methodology of the study. Data of the students have been collected from only five universities of Bangkok. Future researchers can collect data through an online survey technique to include sample sizes from other regions of Thailand. This study has only considered IT students' intention to use cloud classroom in higher education institutes with higher homogeneity, therefore generalization cannot be done to all levels in Thailand. Future studies can be conducted by included students of other faculties who have used cloud classroom in higher education. Third, this study has adopted a self-reported approach and included subjective measures to answer the questionnaires.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] A. Szymkowiak, B. Melović, M. Dabić, K. Jeganathan, and G. S. Kundi, “Information technology and Gen Z: the role of teachers, the internet, and technology in the education of young people,” Technology in Society, vol. 65, Article ID 101565, 2021.
[2] Q. Alajmi, L. A. Al-Nuaimy, G. J. A. Jose, M. Mastan, and M. A. Al-Sharafi, "Cloud computing services and its effect on tertiary education: using google classroom," in Proceedings of the 2019 7th International Conference on ICT & Accessibility (ICTA), pp. 1–3, Hammamet, Tunisia, 2019, December.
[3] I.-F. Liu, M. C. Chen, Y. S. Sun, D. Wible, and C.-H. Kuo, “Extending the TAM model to explore the factors that affect intention to use an online learning community,” Computers & Education, vol. 54, no. 2, pp. 600–610, 2010.
[4] R. Kaufmann and M. M. Buckner, “Revisiting “power in the classroom”: exploring online learning and motivation to study course content,” Interactive Learning Environments, vol. 27, no. 3, pp. 402–409, 2019.

[5] R. A. Harrison, A. Harrison, C. Robinson, and B. Rawlings, “The experience of international postgraduate students on a distance-learning programme,” Distance Education, vol. 39, no. 4, pp. 480–494, 2018.

[6] X. Hong, M. Zhang, and Q. Liu, “Preschool teachers’ technology acceptance during the COVID-19: an adapted technology acceptance model,” Frontiers in Psychology, vol. 12, 2021.

[7] M. Dunn and M. Rice, “Community, towards dialogue: a self-study of online teacher preparation for special education,” Studying Teacher Education, vol. 15, no. 2, pp. 160–178, 2019.

[8] J. Roberts, “Future and changing roles of staff in distance education: a study to identify training and professional development needs,” Distance Education, vol. 39, no. 1, pp. 37–53, 2018.

[9] M. S. Murphy and S. Pinnegar, “Shaping community in online courses: a self-study of practice in course design to support the relational,” Studying Teacher Education, vol. 14, no. 3, pp. 272–283, 2018.

[10] C. Dede, “The evolution of distance education: emerging technologies and distributed learning,” American Journal of Distance Education, vol. 10, no. 2, pp. 4–36, 1996.

[11] E. Dahlstrom, D. C. Brooks, and J. Bichsel, The Current Ecosystem of Learning Management Systems in Higher Education: Student, Faculty, and IT Perspectives, ECAR, Louisville, CO, USA, 2014.

[12] T. J. McGill and V. J. Hobbs, “How students and instructors using a virtual learning environment perceive the fit between technology and task,” Journal of Computer Assisted Learning, vol. 24, no. 3, pp. 191–202, 2008.

[13] D. L. DeNeui and T. L. Dodge, “Asynchronous learning networks and student outcomes: the utility of online learning components in hybrid courses,” Journal of Instructional Psychology, vol. 33, no. 4, 2006.

[14] J. Keengwe and T. T. Kidd, “Towards best practices in online learning and teaching in higher education,” MERLOT Journal of Online Learning and Teaching, vol. 6, no. 2, pp. 533–541, 2010.

[15] M. Rizun and A. Strzelecki, “Students’ acceptance of the COVID-19 impact on shifting higher education to distance learning in Poland,” International Journal of Environmental Research and Public Health, vol. 17, no. 18, Article ID 6468, 2020.

[16] T. A. Urdan and C. C. Weggen, Corporate Elearning: Exploring a New Frontier, WR Hambrecht & Co, San Francisco, CA, USA, 2000.

[17] B. Hall, “New study seeks to benchmark enterprises with world-class e-learning in place,” E-learning, vol. 1, no. 1, pp. 18–29, 2000.

[18] I. E. Allen and J. Seaman, Staying the Course: Online Education in the United States, 2008, Sloan Consortium, Newburyport, MA, USA, 2008.

[19] F. Saba, “Critical issues in distance education: a report from the United States,” Distance Education, vol. 26, no. 2, pp. 255–272, 2005.

[20] M. Clark-Ibáñez and L. Scott, “Learning to teach online,” Teaching Sociology, vol. 36, no. 1, pp. 34–41, 2008.

[21] S. Jaschik, D. Lederman, and C. Gallup, Faculty Attitudes on Technology, Inside Higher Education, 2014.

[22] W. Chaiyasoonthorn, “Intention to become digital startups,” in Proceedings of the 2019 9th International Workshop on Computer Science and Engineering, pp. 21–25, Hong Kong, China, June 2019.

[23] H. Benchirifa, A. Asli, and J. Zerrad, “Promoting student’s entrepreneurial mindset: Moroccan case,” Transnational Corporations Review, vol. 9, no. 1, pp. 31–40, 2017.

[24] S. L. Lew and S. H. Lau, “An empirical study of students’ intention to use cloud e-learning in higher education,” International Journal of Emerging Technologies in Learning (IJET), vol. 15, no. 9, pp. 19–38, 2020.

[25] A. N. Al-Tahtah, M. A. Al-Sharafi, and M. Abdulrah, “How COVID-19 pandemic is accelerating the transformation of higher education institutions: a health belief model view,” Studies in Systems, Decision and Control, vol. 348, pp. 333–347, 2021.

[26] Q. AlAjmi, M. A. Al-Sharafi, and A. A. Yassin, “Behavioral intention of students in higher education institutions towards online learning during COVID-19,” Studies in Systems, Decision and Control, vol. 348, pp. 259–274, 2021.

[27] Y. T. Prasetyo, A. K. S. Ong, G. K. F. Concepcion et al., “Determining factors affecting acceptance of E-learning platforms during the COVID-19 pandemic: integrating extended technology acceptance model and DeLone & McLean IS success model,” Sustainability, vol. 13, no. 15, Article ID 8365, 2021.

[28] B. Khalid, S. Chavesusuk, and W. Chaiyasoonthorn, “MOOCs adoption in higher education: a management perspective,” Polish Journal of Management Studies, vol. 23, no. 1, pp. 239–256, 2021.

[29] B. Khalid, M. Lis, W. Chaiyasoonthorn, and S. Chavesusuk, “Factors influencing behavioural intention to use MOOCs,” Engineering Management in Production and Services, vol. 13, no. 2, pp. 83–95, 2021.

[30] A. Charyomchai, “The online technology acceptance model of generation-Z people in Thailand during COVID-19 crisis,” Management & Marketing, vol. 15, 2020.

[31] M. Bosamia and A. Patel, “An overview of cloud computing for e-learning with its key benefits,” International Journal of Information Sciences and Techniques (IJIST), vol. 6, 2016.

[32] P. Divya and S. Prakasam, “Effectiveness of cloud based e-learning system,” International Journal of Computer Application, vol. 119, no. 6, 2015.

[33] Q. Alajmi and A. Sadiq, “What should be done to achieve greater use of cloud computing by higher education institutions,” in Proceedings of the 2016 IEEE 7th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), pp. 1–5, Vancouver, BC, Canada, October 2016.

[34] M. Mohiuddin, N. Halilem, S. A. Kobir, and C. Yuliang, Knowledge Management Strategies and Applications, Intech Publications, London, UK, 2017.

[35] S. L. Lew, S. H. Lau, and M. C. Leow, “Usability factors predicting continuance of intention to use cloud e-learning application,” Heliyon, vol. 5, no. 6, Article ID e01788, 2019.

[36] S. Sukendro, A. Habibi, K. Khaeruddin et al., “Using an extended Technology Acceptance Model to understand students’ use of e-learning during Covid-19: Indonesian sport science education context,” Heliyon, vol. 6, no. 11, Article ID e05410, 2020.

[37] T. Teo, “Examining the influence of subjective norm and facilitating conditions on the intention to use technology among pre-service teachers: a structural equation modeling
of an extended technology acceptance model," *Asia Pacific Education Review*, vol. 11, no. 2, pp. 253–262, 2010.

[38] D. R. Compeau and C. A. Higgins, "Computer self-efficacy: development of a measure and initial test," *MIS Quarterly*, vol. 19, no. 2, pp. 189–211, 1995.

[39] N. Fatih, D. Shannon, and M. Ross, "Expanding the technology acceptance model (TAM) to examine faculty use of learning management systems (LMSs) in higher education institutions," *Journal of Online Learning and Teaching*, vol. 11, no. 2, 2015.

[40] E. W. T. Ngai, J. K. L. Poon, and Y. H. C. Chan, "Empirical examination of the adoption of WebCT using TAM," *Computers & Education*, vol. 48, no. 2, pp. 250–267, 2007.

[41] A. Pitt and Y.-K. Lee, "The influence of system characteristics on e-learning use," *Computers & Education*, vol. 47, no. 2, pp. 222–244, 2006.

[42] M. K. O. Lee, C. M. K. Cheung, and Z. Chen, "Acceptance of Internet-based learning medium: the role of extrinsic and intrinsic motivation," *Information & Management*, vol. 42, no. 8, pp. 1095–1104, 2005.

[43] C.-S. Ong, J.-Y. Lai, and Y.-S. Wang, "Factors affecting engineers' acceptance of asynchronous e-learning systems in high-tech companies," *Information & Management*, vol. 41, no. 6, pp. 795–804, 2004.

[44] C. L. Gan and V. Balakrishnan, "Mobile technology in the classroom: what drives student-teacher interactions?" *International Journal of Human-Computer Interaction*, vol. 34, no. 7, pp. 666–679, 2018.

[45] F. Jabeur, M. Mohiuddin, and E. Karuranga, "Timeline of education research institutions," *Computer Studies*, vol. 13, no. 3, pp. 1–25, 2013.

[46] F. D. Davis, R. P. Bagozzi, and P. R. Warshaw, "User acceptance of computer technology: a comparison of two theoretical models," *Management Science*, vol. 35, no. 8, pp. 982–1003, 1989.

[47] E. Park, J. Lim, and Y. Cho, "Understanding the emergence and social acceptance of electric vehicles as next-generation models for the automobile industry," *Sustainability*, vol. 10, no. 3, p. 662, 2018.

[48] M. Yang, A. A. Mamun, M. Mohiuddin, N. C. Nawi, and N. R. Zainol, "Cashless transactions: a study on intention and adoption of e-wallets," *Sustainability*, vol. 13, no. 2, p. 831, 2021.

[49] I. Ajzen and M. Fishbein, *Understanding Attitude and Predicting Social Behavior*, Prentice-Hall, Englewood Cliffs, NJ, USA, 1980.

[50] M. Fishbein and I. Ajzen, *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*, Addison-Wesley, Boston, MA, USA, 1975.

[51] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly*, vol. 13, no. 3, pp. 319–339, 1989.

[52] V. Venkatesh and F. D. Davis, "A theoretical extension of the technology acceptance model: four longitudinal field studies," *Management Science*, vol. 46, no. 2, pp. 186–204, 2000.

[53] V. Venkatesh and H. Bala, "Technology acceptance model 3 and a research agenda on interventions," *Decision Sciences*, vol. 39, no. 2, pp. 273–315, 2008.

[54] B. Herrenkind, A. B. Brendel, I. Nastjuk, M. Greve, and L. M. Kolbe, "Investigating end-user acceptance of autonomous electric buses to accelerate diffusion," *Transportation Research Part D: Transport and Environment*, vol. 74, pp. 255–276, 2019.

[55] C.-L. Hsu and H.-P. Lu, "Why do people play on-line games? An extended TAM with social influences and flow experience," *Information & Management*, vol. 41, no. 7, pp. 853–868, 2004.

[56] D. Gefen and D. W. Straub, "Consumer trust in B2C e-Commerce and the importance of social presence: experiments in e-Products and e-Services," *Omega*, vol. 32, no. 6, pp. 407–424, 2004.

[57] D. Gefen, E. Karahanna, and D. W. Straub, "Trust and TAM in online shopping: an integrated model," *MIS Quarterly*, vol. 27, no. 1, pp. 51–90, 2003.

[58] J.-W. Moon and Y.-G. Kim, "Extending the TAM for a world-wide-web context," *Information & Management*, vol. 38, no. 4, pp. 217–230, 2001.

[59] S. Chaves, B. Khalid, and W. Chaiyasoot, "Understanding stakeholders needs for using blockchain based smart contracts in construction industry of Thailand: extended TAM framework," in *Proceedings of the 2020 13th International Conference on Human System Interaction (HSI)*, pp. 137–141, Tokyo, Japan, 2020 June.

[60] G. W. H. Tan, K. B. Ooi, J. J. Sim, and K. Phusavat, "Determinants of mobile learning adoption: an empirical analysis," *Journal of Computer Information Systems*, vol. 52, no. 3, pp. 82–91, 2012.

[61] D. C. Yen, C.-S. Wu, F.-F. Cheng, and Y.-W. Huang, "Determinants of users' intention to adopt wireless technology: an empirical study by integrating TTF with TAM," *Computers in Human Behavior*, vol. 26, no. 5, pp. 906–915, 2010.

[62] N. Ozdemir, "How to improve teachers' instructional practices: the role of professional learning activities, classroom observation and leadership content knowledge in Turkey," *Journal of Educational Administration*, vol. 58, 2020.

[63] R. George Saadé, F. Nebebe, and W. Tan, "Viability of the "technology acceptance model" in multimedia learning environments: a comparative study," *Interdisciplinary Journal of e-Skills and Lifelong Learning*, vol. 3, no. 1, pp. 175–184, 2007.

[64] D. C. Yen, C.-S. Wu, F.-F. Cheng, and Y.-W. Huang, "Determinants of users' intention to adopt wireless technology: an empirical study by integrating TTF with TAM," *Computers in Human Behavior*, vol. 26, no. 5, pp. 906–915, 2010.

[65] K. Mathieson, "Predicting user intentions: comparing the technology acceptance model with the theory of planned behavior," *Information Systems Research*, vol. 2, no. 3, pp. 173–191, 1991.

[66] E. M. Rogers, *Diffusion of Innovations*, Simon & Schuster, New York, NY, USA, 2010.

[67] F. D. Davis and V. Venkatesh, "A critical assessment of potential measurement biases in the technology acceptance model: three experiments," *International Journal of Human-Computer Studies*, vol. 45, no. 1, pp. 19–45, 1996.

[68] J. W. Palmer, "Web site usability, design, and performance metrics," *Information Systems Research*, vol. 13, no. 2, pp. 151–167, 2002.

[69] C.-J. Wang, C. Y. Ng, and R. H. Brook, "Response to COVID-19 in Taiwan," *Jama*, vol. 323, no. 14, pp. 1341-1342, 2020.

[70] K. L. Chin, "A study into students' perceptions of web-based learning environment," in *Proceedings of the HERDSA*.
[71] F. Fauzi, D. Antoni, and E. Suwarni, “Mapping potential sectors based on financial and digital literacy of women entrepreneurs: a study of the developing economy,” *Journal of Governance and Regulation*, vol. 10, no. 2, pp. 316–327, 2021.

[72] S. Panda and S. Mishra, “E-Learning in a mega open university: faculty attitude, barriers and motivators,” *Educational Media International*, vol. 44, no. 4, pp. 323–338, 2007.

[73] K. Pajo and C. Wallace, “Barriers to the uptake of web-based technology by university teachers,” *The Journal of Distance Education*, vol. 16, no. 1, pp. 70–84, 2001.

[74] T. T. Teo, C. B. Lee, and C. S. Chai, “Understanding preservice teachers’ computer attitudes: applying and extending the technology acceptance model,” *Journal of Computer Assisted Learning*, vol. 24, no. 2, pp. 128–143, 2008.

[75] M. R. Grant and H. R. Thornton, “Best practices in undergraduate adult-centered online learning: mechanisms for course design and delivery,” *Journal of Online Learning and Teaching*, vol. 3, no. 4, pp. 346–356, 2007.

[76] A. E. Johnson, “A nursing faculty’s transition to teaching online,” *Nursing Education Perspectives*, vol. 29, no. 1, pp. 17–22, 2008.

[77] L. L. Maguire, “Literature review–faculty participation in online distance education: barriers and motivators,” *Online Journal of Distance Learning Administration*, vol. 8, no. 1, pp. 1–16, 2005.

[78] S. J. Nelson and G. W. Thompson, “Barriers perceived by administrators and faculty regarding the use of distance education technologies in preservice programs for secondary agricultural education teachers,” *Journal of Agricultural Education*, vol. 46, no. 4, pp. 36–48, 2005.

[79] T. W. Liew, S.-M. Tan, and R. Seydali, “The Effects of learners’ differences on variable manipulation behaviors in simulation-based learning,” *Journal of Educational Technology Systems*, vol. 43, no. 1, pp. 13–34, 2014.

[80] M. Deimann and J. Keller, “Volitional aspects of multimedia learning,” *Journal of Educational Multimedia and Hypermedia*, vol. 15, no. 2, pp. 137–158, 2006.

[81] X. Wang, Y. Han, C. Wang, Q. Zhao, X. Chen, and M. Chen, “In-edge ai: intelligentizing mobile edge computing, caching and communication by federated learning,” *IEEE Network*, vol. 33, no. 5, pp. 156–165, 2019.

[82] N. Valencia-Vallejo, O. López-Vargas, and L. Sanabria-Rodriguez, “Self-efficacy in computer-based learning environments: a bibliometric analysis,” *Psychology*, vol. 7, no. 14, Article ID 1839, 2016.

[83] E. Alquarshie, “Self-efficacy in online learning environments: a literature review,” *Contemporary Issues In Education Research*, vol. 9, no. 1, pp. 45–52, 2016.

[84] S. Y. Park, M.-W. Nam, and S.-B. Cha, “University students’ behavioral intention to use mobile learning: evaluating the technology acceptance model,” *British Journal of Educational Technology*, vol. 43, no. 4, pp. 592–605, 2012.

[85] J. Santhanamery and T. Ramayah, “Trust in the system: the mediating effect of perceived usefulness of the e-filing system,” in *User Centric E-Government*, pp. 89–103, Springer, Berlin, Germany, 2018.

[86] G. Maheshwari, “Factors affecting students’ intentions to undertake online learning: an empirical study in Vietnam,” *Education and Information Technologies*, vol. 26, no. 6, pp. 6629–6649, 2021.

[87] L. Chen and A. K. Aklikokou, “Determinants of e-government adoption: testing the mediating effects of perceived usefulness and perceived ease of use,” *International Journal of Public Administration*, vol. 43, no. 10, pp. 850–865, 2020.

[88] T. D. Susanto and M. Aljoza, “Individual acceptance of e-Government services in a developing country: dimensions of perceived usefulness and perceived ease of use and the importance of trust and social influence,” *Procedia Computer Science*, vol. 72, pp. 622–629, 2015.

[89] R. B. Kline, *Principles and Practice of Structural Equation Modeling*, Guilford Publications, New York, NY, USA, 2015.

[90] J. Hair, W. Black, B. Babin, and R. Anderson, *Multivariate Data Analysis*, Pearson Education, Englewood Cliffs, NJ, USA, 2010.

[91] S.-Y. Hung, C.-M. Chang, and T.-J. Yu, “Determinants of user acceptance of the e-Government services: the case of online tax filing and payment system,” *Government Information Quarterly*, vol. 23, no. 1, pp. 97–122, 2006.

[92] N. Z. Ismail, M. R. Razak, Z. Zakariah, N. Alias, and M. N. A. Aziz, “E-learners’ intention to use mobile learning,” *International Journal of Technology and Behavioural Science*, vol. 67, pp. 409–415, 2012.

[93] C. Fornell and F. L. Bookstein, “Two structural equation models: LISREL and PLS applied to consumer exit-voice theory,” *Journal of Marketing Research*, vol. 19, no. 4, pp. 440–452, 1982.

[94] F. Hair Jr., M. Sarstedt, L. Hopkins, and V. Kuppelwieser, “Partial least squares structural equation modeling (PLS-SEM),” *European Business Review*, vol. 26, no. 2, pp. 106–121, 2014.

[95] D. Gefen, D. W. Straub, and M. C. Boudreau, “Structural equation modelling and regression: guidelines for research practice,” *Communications of the Association for Information Systems*, vol. 4, no. 7, pp. 1–7, 2000.

[96] J. C. Nunally and I. H. Bernstein, “Validity,” *Psychometric theory*, vol. 3, pp. 99–132, 1994.

[97] C. Fornell and D. F. Larcker, “Evaluating structural equation models with observable variables and measurement error,” *Journal of Marketing Research*, vol. 18, no. 1, pp. 39–50, 1981.

[98] A. M. Farrell, “Insufficient discriminant validity: a comment on bove, pervan, beatty, and shiu (2009),” *Journal of Business Research*, vol. 63, no. 3, pp. 324–327, 2010.

[99] J. F. Hair, G. T. M. Hult, C. Ringle, and M. Sarstedt, *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, Sage Publications, Thousand Oaks, CA, USA, 2016.

[100] P. J. B. Tan, “Applying the UTAUT to understand factors affecting the use of English e-learning websites in Taiwan,” *Sage Open*, vol. 3, no. 4, Article ID 2158244013503837, 2013.

[101] C. L. Gan and V. Balakrishnan, “Predicting acceptance of mobile technology for aiding student-lecturer interactions: an empirical study,” *Australasian Journal of Educational Technology*, vol. 33, no. 2, 2017.

[102] K. J. Preacher and A. F. Hayes, “Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models,” *Behavior Research Methods*, vol. 40, no. 3, pp. 879–891, 2008.

[103] M. Mohiuddin, A. Al Mamun, F. A. Syed, M. Mehedi Masud, and Z. Su, “Environmental knowledge, awareness, and business school students’ intentions to purchase green vehicles in emerging countries,” *Sustainability*, vol. 10, no. 5, Article ID 1534, 2018.

[104] B. J. Landry, R. Griffith, and S. Hartman, “Measuring student perceptions of blackboard using the technology
acceptance model,” *Decision Sciences Journal of Innovative Education*, vol. 4, no. 1, pp. 87–99, 2006.

[105] C. Keeler and M. Horney, “Online course designs: are special needs being met,” *The American Journal of Distance Education*, vol. 21, no. 2, pp. 65–75, 2007.

[106] D. Y. Lee and M. R. Lehto, “User acceptance of YouTube for procedural learning: an extension of the technology acceptance model,” *Computers & Education*, vol. 61, pp. 193–208, 2013.