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# Evaluating the Acceptance of Flexible Online Learning via Extended TAM: The Case of a Developing Economy

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**Abstract**

This study evaluated the acceptance of flexible online learning via an extended technology acceptance model (e-TAM). The authors extended Davis's (1989) TAM with user interface design, social norms, computer literacy, and academic relevance. A total of 1,137 college students from a Philippine state university voluntarily participated in the survey, and the data were analyzed using the covariance-based structural equation modeling (CB-SEM) approach. The findings conform to the proposed model with acceptable model fit measures. Among the 13 hypothesized paths of direct relationships, 12 were reported as significant, indicating various similar findings in the current literature surrounding the acceptance and use of technology of flexible online learning. The results add to different complex structures affecting online learning and provide insights into the post-COVID-19 era, especially from a developing economy perspective. Implications of the study were also discussed.

**Keywords:** *flexible online learning, extended TAM, SEM, user interface design, social norms, computer literacy, and academic relevance.*

## 1. Introduction

The coronavirus disease 2019 (COVID-19) that emerged in late December has spread worldwide. In response to this, many educational institutions suspended face-to-face classroom learning to minimize the spread of the virus, which caused students to be temporarily homebound. Several studies found that the closure of educational institutions would reduce the spread of infectious diseases (Kawano & Kakehashi, 2015;

Wheeler et al., 2010). As a result, different institutions implemented new normal in education, providing quality, inclusive and accessible education for all students (Tria, 2020). The alternative system was designed to support the transition of education from face-to-face to flexible learning, encompassing both asynchronous and synchronous classes that benefit both the students and the teachers (Cahapay, 2020). The sudden shift to flexible online teaching and learning has become the new norm for continuing academic programs during the pandemic.

A flexible online learning system is a learning modality apart from the traditional face-to-face campus and classroom: blended learning, full-online, distance learning (Rasmitadila et al., 2020), and flipped classrooms. Online learning as a flexible approach to education is gaining renewed interest because of its ability to address emerging concerns and opportunities facing higher education. Specifically, online learning addresses the needs of location-bound students due to employment, familial or other responsibilities, needs, preferences, and desires (Houlden & Veletsianos, 2019). Additionally, electronic learning or online learning tools are widely used in education, for this is a tool that uses computer network technology to make it easy for students to reach necessary material for educational purposes via electronic media, such as the Internet (Abdullah & Ward, 2016; Abu-Shanab & Ababneh, 2015).

E-learning involves using information technology (IT) that includes online data services. It offers e-mails, forums, online discussions, assignments, quizzes, and instructional materials, including video, text mediums, and audio, supporting education (Abdullah & Ward, 2016; Drennan et al., 2005; Schindler et al., 2017). Proper tools and an internet connection are vital when using e-learning tools. A good internet connection allows students to access information, and the flow of teaching and learning becomes easy. Teachers effectively enhance teaching strategies, learning management, and versatility for distance students (Abu-Shanab & Ababneh, 2015). By the information stated, there is still a need for research on potential factors affecting students' acceptance of flexible online learning systems.

Past studies have used information technology adoption theories such as the Innovation Diffusion Theory (IDT) (Rogers, 1961), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and the Technology Acceptance Model (TAM) (Davis, 1989). Researchers have shown the need to develop further models to examine other factors that may significantly influence flexible online learning system usage (Drennan et al., 2005; Hussein, 2011). This paper introduced the Extended Technology Acceptance Model (TAM) to determine factors affecting system acceptance which is essential in examining students' experiences, perceptions, and behavioral intentions. Researchers explored adding antecedents to existing models like Davis's TAM that would enhance the understanding of the original model based on theoretically proven antecedent variables. We elucidated the most prevalent endogenous variables to TAM that would explicitly identify the cases for a developing economy.

From a developing economy perspective, emerging literature highlights the more pronounced effects of some behavioral constructs on the acceptance of online learning technologies. For instance, a study by Batucan et al. (2022) revealed that behavioral intention is a critical factor that significantly affects the use of behavior toward online learning in developing economies. Despite the strategies for coping with the limitations of education during the pandemic, it is important to understand students' experience that hinders them from embracing online learning by examining their intentions. Researchers have shown the need to develop other factors that may significantly influence flexible online learning system usage (Drennan et al., 2005; Hussein, 2011). The sudden shift to online learning reminded academic institutions' lack of technology resources, educators' readiness, and geographical situation. Continuous internet connection is necessary for students to engage in online learning fully; however, according to Fabito et al. (2021), the Philippines has the slowest internet speed, ranked 21st out of 22 Asian countries. The insufficient internet access availability (Casillano, 2019), lack of the latest technology, and proper interaction with instructors affected organizational responsiveness and students' ability to participate in online learning (Adnan, 2020; Pastor, 2020). This will affect the behavioral response to the user interface design of the online platforms. Students only communicate digitally and never see one another in person, so the digital learning environment limits the real-time sharing of ideas, knowledge, and information (Adnan, 2020; Gill, 2009). Thus, the social norm is a probable antecedent that would affect the acceptance of online learning. Not all students were competent computer users, and many had only limited Web access (Drennan et al., 2005). Students' competence using computer-based communication may affect their participation in online learning. Also, when students seek relevance to their academic work, they are primarily concerned with whether they can directly apply the knowledge to understand their careers. The applicability and usefulness of students' college experience will give motivation when they see this as relevant for their future employment (Pisarik & Whelchel, 2018). Hence, computer literacy and academic relevance were explored to explain the acceptance of the current flexible online learning.

To examine the factors affecting students' acceptance of a flexible online learning system, the study employs extended TAM with the social norm, user-interface design, computer literacy, and academic relevance as antecedents of the students' perceived usefulness and perceived ease of use towards the attitude to use, behavioral intention in using (BU) the system, and the actual system use (ASU). Further, the paper investigates the moderating effects of age on the paths leading to BU and ASU.

## 2. Hypothesis Development

In 1989, Fred Davis proposed a well-known model related to technology acceptance: the TAM (Figure 1). TAM is derived from Ajzen's Theory of Reasoned Action (TRA), a general theory to predict and explain human behavior across various domains. TAM is famous for predicting users' acceptance of use behavior in information systems. Emerging literature employed TAM in different information system structures, including learning management systems (LMS), with an extensive examination and validation of the model (Surendran, 2012). Although the TAM monitors and predicts technology acceptance and usage, several practitioners of TAM recommended an improvement of the model's theoretical contributions, mainly by adding predictor variables to adequately explain technology adoption usage (Bagozzi, 2007; Benbasat & Barki, 2007).

Furthermore, the TAM's parameters can be constructively modified to evaluate other significant predictors and factors influencing technology adoption and acceptance (Tarhini et al., 2014). Since its development, TAM has been extended in many studies as a research framework in various contexts. This research focused only on educational contexts such as e-learning. Fig. 1 illustrates the original Davis's Technology Acceptance Model.

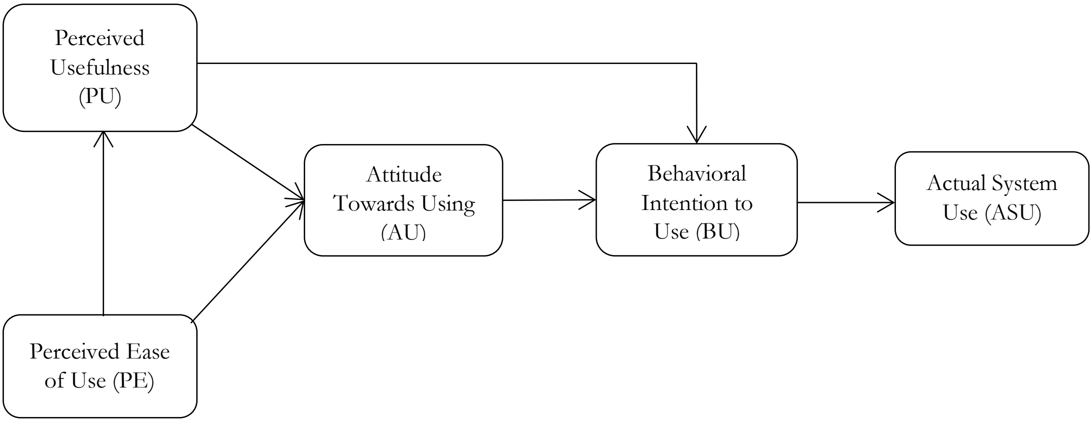


**Figure 1.** Technology Acceptance Model (Davis et al., 1989)

Several researchers identified TAM as effective in explaining the adoption of flexible online learning (FOL) among students (Goh et al., 2013; Tarhini et al., 2014). The study revealed that perceived usefulness (PU) and perceived ease of use (PE) have contributed to the students' adoption of FOL. In this case, the students have different perceptions of FOL elements for ease of use and usefulness. Respondents agree that FOL is easy to use and valuable in helping them for learning. Although various external variables have been used in different TAM adaptations, four distinct variables are the most commonly employed ones. The following are shown in Table 1, along with references from the studies adapted from the study of (Eraslan Yalcin & Kutlu, 2019).

**Table 1.** External Variables with the References

| **Variables** | **References** |
|---|---|
| Social Norm | (Davis et al., 1989), (Park, 2020), (Acarli & Sağlam, 2015a), (Tarhini et al., 2014), (Ahmed & Ward, 2016), (Moreno et al., 2017) |
| User Interface Design | (Davis et al., 1989), (Park, 2020), (Acarli & Sağlam, 2015a), (Tarhini et al., 2014), (Ahmed & Ward, 2016), (Moreno et al., 2017) |
| Computer Literacy | (Raman, 2011) |
| Academic Relevance | (Bhattacherjee & Sanford 2006), (Venkatesh & Davis 2000), (Karahanna et al., 2006), (Saroia & Gao, 2019) |

This study embodies nine variables to explain university students' acceptance of flexible online learning. Figure 2 shows the expected relationships between these nine (9) variables.

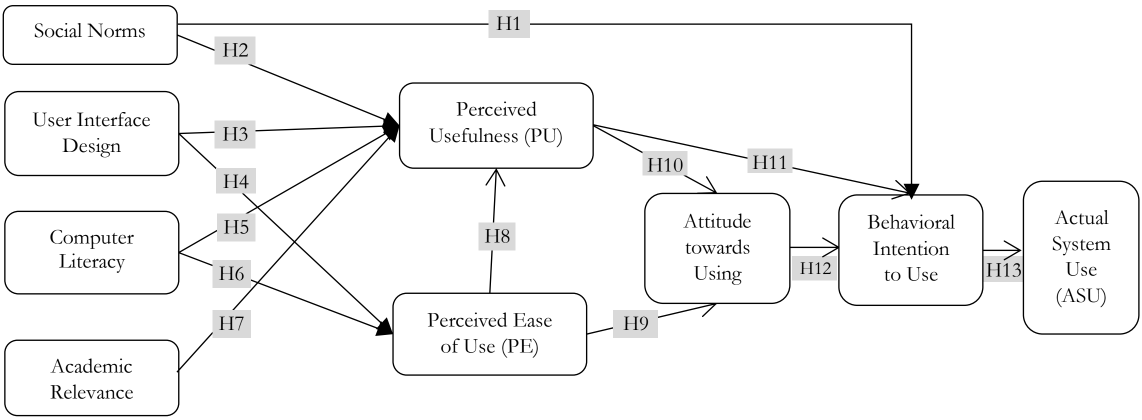


**Figure 2.** Extended Technology Acceptance Model

**Social Norm (SN)** is the perception of whether or not the essential people perform the behavior at issue (Govindasamy, 2001). SN is a form of social pressure that affects students' perceptions of the usefulness of flexible online learning (Davis, 1989; Tarhini et al., 2013) and affects students' perception of PU (Acarli & Sağlam, 2015; Moreno et al., 2017). Additionally, other research has characterized SN as an antecedent of Behavioral Intention to Use (BU) (Tarhini et al., 2014). The direct effect of SN on BU is justified by the fact that people may be influenced by other opinions and hence become involved in a particular behavior even if they don't want to be involved. The work in the developing world context of Lebanon also supported a direct influence of SN on BU (Tarhini et al., 2013). Based on the past findings and bearing in mind the mandatory nature of flexible online learning acceptance within our research context, it is hypothesized that:

**H1**: SN will positively affect the student's BU

**H2**: SN will positively impact the PU

**User Interface Design (UID)** is related to menu design, including control bars, screen design, icons, etc. Many user interface features of an information system, such as menus and icons, are specially intended to improve the usefulness and ease of use of different system functions (Cho et al., 2009). UID's proper use increases technology acceptance, and the usability and technological characteristics affect the systems' benefits and usefulness (Mouakket & Bettayeb, 2015). According to Liu et al.(2010), if the teaching materials contain valuable visual items and exact text, they can easily read and mostly prefer to use them. Also, students can benefit from a user-friendly interface design and easily find the correct learning way (Mouakket & Bettayeb, 2015). In addition, a study by Eraslan and Kutlu (2019) indicates that user-friendly interface design positively affects students' PE and PU using a learning management system. Thus, the following hypotheses are proposed:

**H3**: UID will positively affect the PU

**H4**: UID will positively impact the PE

**Computer Literacy (CL)** is the level of expertise and familiarity with computers someone has. It relates to the ability to use the applications rather than to program. Very computer-literate individuals are sometimes called power users (Raman, 2011). The essential criteria for becoming computer literate have included computer awareness (Battista & Steele, 1984; Johnson et al., 1980), programming ability (Cheng et al., 1985; Gabriel, 1985; Haigh, 1985; Luehrmann, 1981), and competency in computer software applications (Ganske & Hamamoto, 1984). Davis (1989) reported that perceived usefulness significantly correlates with computer usage and future intention to use computers. An increase in user perception of the ease of use of computers through training and experiences will influence their assessment of the relationship between perceived ease of use, effort, and intention to learn and use computers. Adams et al. (1992) suggest that perceived usefulness and perceived ease are important determinants of computer literacy. As flexible online learning is delivered through online networks, it is essential to determine students' perceptions about computers and technologies and assess their competencies in using these technologies for online learning (Rafique et al., 2021). Therefore, the following hypothesis is proposed:

**H5**: CL will positively affect the PU.

**H6**: CL will positively affect PE.

**Academic Relevance (AR)** is defined as how relevant or compatible flexible online learning would be for students' academic lives (Saroia & Gao, 2019). AR means the relevance of flexible online learning in university education generally. Venter et al. (2012) investigated the determinants of using online learning systems in South Africa and found that Major relevance positively influenced PU. Moreover, Venkatesh and Davis (2000) found that Academic relevance positively affected PU. Saroia and Gao S. (2019) study revealed that AR had substantial positive impacts on PU and PEOU of using m-LMS. Consequently, this study argues that R generally affects the PU of flexible online learning. Therefore, this study proposes the following hypothesis.

**H7**: AR will positively affect the PU.

**Perceived Ease of Use (PE)** is defined as the person's belief that using the system will not require physical and mental effort (Davis, 1989). It is seen as the student's perception of the amount of effort and the time needed for system use (Davis & Venkatesh, 1996). As students spend much time on technology and its usage is too hard, they think the system is useless, affecting their usage rate (Davis, 1989; Kiliç, 2014; Sánchez & Hueros, 2010). The students prefer to use user-friendly systems, which are most successful and quickly adopted (Liu et al., 2010). Moreover, students can have more opportunities to improve themselves during their learning period (Abu-Shanab & Ababneh, 2015; Moreno et al., 2017). Prior studies have found that perceived ease of use significantly impacts perceived usefulness (Abdullah et al., 2016; Binyamin et al., 2019; Joo et al., 2018; Zogheib et al., 2015). In addition, previous research found that perceived ease of use was a strong predictor of attitude toward e-learning use (Fokides, 2017; Teo, 2012; Wong, 2015; Zogheib et al., 2015). Thus, the arguments above lead to the following hypotheses:

**H8** PE will positively affect the PU.

**H9:** PE will positively affect the AU.

**Perceived usefulness (PU)** is the extent to which a person believes using the system will improve their performance (Davis, 1989). Various studies have indicated that PU is the primary determinant of using a specific technology (Chow, Herold, Choo, & Chan, 2012). Additionally, the degree to which an individual perceives the system to meet the task requirements is determined by PU. In flexible online learning, if students perceive that an online learning system can help improve their work performance, they are more likely to participate, positively influencing their performance (Teo, 2012).

A study by Damnjanovic et al. (2015) found that PU significantly affects the attitude toward the use of flexible online learning, as the usefulness of online learning affects an individual's interest and the actual use of that flexible online learning. Previous research found that PU had the most significant effect on attitude (Ritter, 2017; Tarhini et al., 2015; Teo, 2012; Wong, 2015; Zogheib et al., 2015). In addition, PU significantly impacted behavioral intention using e-learning (Abdullah et al., 2016; Martinho et al., 2018; Scherer et al., 2019; Wong, 2015). The students' adoption and use of online learning prove that the most crucial determinant of a student's attitude toward adopting and using online learning is their perception of its usefulness (perceived usefulness). Based on the prior studies, we propose the following hypothesis:

**H10:** PU will positively affect the AU.

**H11:** PU will positively affect the BU.

The **Attitude toward Using (AU)** is defined as individuals' positive or negative feelings about performing and how they affect users' particular behavior. Fishbein and Ajzen (1975) assumed that an individual's attitude towards a specific object is a bipolar effect determined by a set of probabilities of beliefs regarding that object. This attitude will then affect a group of intentions corresponding to that object, where meaning represents the probability of the individual performing its specific behavior. Previous research on e-learning acceptance has identified attitude as a determinant factor of BI using e-learning (e.g., Cheung & Vogel, 2013; Tosuntaş et al., 2015). Also, many studies revealed that attitude is considered a dominant factor affecting BI (Chu & Chen, 2016; Hussein, 2017; Teo, 2012; Teo et al., 2017; Zogheib et al., 2015). Based on the findings of those studies, we developed the following hypothesis.

**H12:** AU will positively affect the BU

**Behavioral intention to Use** (BU) is "a measure of the likelihood that a person will employ the application" (Lederer et al., 2000). It refers to the intent of the learners to employ e-learning systems and involves persistent use from the present to the future. Triandis's (1977) Theory of Interpersonal Behavior includes a factor called "habits", predicted by past behavior and which, together with behavioral intention and moderated by facilitating conditions, ultimately determines actual use. An integrated TAM based on social cognitive theory and the theory of planned behavior used by Liaw (2008) suggests a significant correlation between the behavioral intention of students to participate in flexible online learning and the effectiveness of e-learning. Ghosh (2016) found that behavioral intention to use directly and significantly influences the actual system use (AU) of flexible online learning. Therefore, it leads to this hypothesis:

**H13:** BU will positively affect the ASU

**Age as Moderator**. It is suggested that age is an essential demographic variable that directly moderates behavioral intention and acceptance of flexible online learning (Tarhini et al., 2014). In terms of technology acceptance, it has been found that age differences affect people's self-efficacy in using technology (Czaja et al., 2006). Previous research also found that age differences influenced the perceived difficulty of learning new software applications (Morris & Venkatesh, 2000; Morris et al., 2005). They discovered that the relationship between performance expectancy (similar to PU) and BI was more robust for younger ones. Age differences have different levels of computer anxiety, and those lower levels of computer anxiety are associated with less hesitation to engage in opportunities to learn new technology skills (Jung et al., 2010). In terms of computer and Internet self-efficacy, older adults have been found to have low self-efficacy in technology use (Czaja et al., 2006). This could be because many older adults believe they are too old to understand new technology (Turner et al., 2007). Moreover, Tarhini et al. (2014) found that PU and BI have a stronger relationship for younger users than older ones. Thus, we hypothesize the following:

**H14:** Age will moderate all relationships of the proposed model.

## 3. Methods

### *3.1 Participants*

One thousand two hundred (1,2000) college students from chosen universities in the Philippines participated in the study. Data were collected using an online questionnaire (i.e., google forms). In the data quality audit, we excluded 63 responses due to duplication, missing data, failure to hold the sincerity test, and unqualified people as respondents (not students, senior high school students, and students who have already graduated). The total number of respondents in the analysis was 1,137. Table 2 reveals the demography of the final participants.

### 3.2 *Instrument*

The measurement items for the survey questionnaire of each construct were adopted from validated measurements offered in previous work and disseminated among the students of Cebu Technological University. There are two parts to the survey questionnaire: the first part was designed to gather the demographic information of the student participants, and the second part was the construct indicators included in the study. The items in the third section were measured using a five-point Likert scale in different hands.

**Table 2.** Demographic characteristics of the participants ($n = 1{,}137$).

| Category | | Total $n = 1137$ n | % |
|---|---|---|---|
| Age | | | |
| | 18-20 | 618 | 54.35 |
| | 21-23 | 453 | 39.84 |
| | 24-26 | 46 | 4.05 |
| | 27 and above | 20 | 1.76 |
| Gender | | | |
| | Male | 363 | 31.9 |
| | Female | 774 | 68.1 |
| Year Level | | | |
| | First Year | 302 | 26.6 |
| | Second Year | 302 | 26.6 |
| | Third Year | 479 | 42.1 |
| | Fourth Year | 52 | 4.6 |
| | Fifth Year | 2 | 0.2 |

**3.2.1. Social Norm (SN)**. Developed based on Venkatesh et al. (2003), the SN of the students is measured by the following items: "People who influence my behavior think that I should use flexible online learning." "People who are important to me think I should use flexible online learning." "My instructor supports using flexible online learning for my studies." "I use flexible online learning because of the proportion of students who use the system." "In general, the institution has supported online learning." On a five-point Likert scale, responses ranged from "never" (1) to "always" (5). The scale's Cronbach's alpha was 0.841.

**3.2.2. User-Interface Design (UID)**. Developed based on Simon et al. (1996) and Doll & Torkzadeh (1988), we measure the student's User-Interface Design using the following items: "Flexible online learning layout is user-friendly." "Flexible online learning provides the precise information I need." "The information in the flexible online learning is presented clearly." "Flexible online learning is easy to use." "I am satisfied with the accuracy of the flexible online learning." "Flexible online learning provides sufficient information." "Overall, I can use flexible online learning." On a five-point Likert scale, responses ranged from "not at all" (1) to "very much" (5). The scale's Cronbach's alpha was 0.901.

**3.2.3. Computer Literacy (CL)**. Developed based on Kollmann et al. (2009), Bhattacherjee & Sanford (2006), Marcolin et al. (2000), and Harrison and Rainer (1992), we measure the student's Computer Literacy using the following items: "How would you rate your technical knowledge, i.e., your knowledge about specific languages, applications, platforms, and tools?" "How knowledgeable are you on using the following technologies: computers?" "How knowledgeable are you on using the following technologies: word processing?" "How thorough is your current knowledge of spreadsheets?" "How confident are you in using the computer to write a letter or essay?" "How confident are you in getting the software up and running?" "How confident are you moving the cursor around the monitor screen?" Responses were given a five-point Likert scale ranging from "very low" (1) to "very high" (5). Cronbach's alpha for the scale was 0.890.

**3.2.4. Academic Relevance (AR)**. Developed based on Bhattacherjee & Sanford (2006) and Venkatesh and Davis (2000), we measure the students' Academic relevance using the following items: "Using flexible online learning is completely compatible with today's current situation." "Using flexible online learning is compatible with all aspects of my learning." "The use of flexible online learning is relevant (appropriate) for my learning." "The use of flexible online learning will have an effect or is important for my studies." "The use of flexible online learning enables me to work the way I prefer." "Using flexible online learning fits my preferred method for my studies." On a five-point Likert scale, responses ranged from "not at all" (1) to "very much" (5). The scale's Cronbach's alpha was 0.882.

**3.2.5. Perceived Usefulness (PU)**. Developed based on Davis (1989), we measure the student's Perceived usefulness using the following items: "Using the flexible online learning improves [would improve] my performance." "Using the flexible online learning increases [would increase] my productivity." "Using flexible online learning enhances [would enhance] my effectiveness." "Using the flexible online learning makes it [would make it] easier for me to carry out my tasks." "I find [would find] the flexible online learning useful for my studies." On a five-point Likert scale, responses ranged from "never" (1) to "always" (5). The scale's Cronbach's alpha was 0.881.

**3.2.6. Perceived Ease of Use (PE)**. Developed based on Davis (1989), we measure the student's Perceived Ease of Use using the following items: "Learning to operate flexible online learning is [would be] easy." "I find [would find] flexible online learning easy to get to do what I want [would want] it to do." "My interaction with flexible online learning is clear and understandable." "I find [would find] flexible online learning to be flexible to interact with." "It is [would be] easy for me to become skillful at using flexible online learning." "Overall, I find [would find] flexible online learning easy to use." On a five-point Likert scale, responses ranged from "not at all" (1) to "very much" (5). The scale's Cronbach's alpha was 0.884.

**3.2.7. Attitude towards Using (AU)**. Developed based on Taylor and Todd (1995), we measure the student's Attitudes towards Use using the following items: "Using flexible online learning in learning is a good idea." "Using flexible online learning in my learning is a foolish idea." "Using flexible online learning in my learning is [would be] pleasant." "Using flexible online learning in my learning is [would be] unpleasant."

"Overall, I like the idea of using flexible online learning in learning."On a five-point Likert scale, responses ranged from "not at all" (1) to "very much" (5). The scale's Cronbach's alpha was 0.703.

**3.2.8. Behavioral Intension to Use (BU)**. Developed based on Cigdem, H., & Ozturk, M. (2016), we measure the student's Behavioral Intention to Use using the following items: "I intend to use flexible online learning to assist my learning." "I intend to use functions of flexible online learning to assist my learning." "I intend to use flexible online learning as an autonomous tool." "I would like flexible online learning functions implemented further in departmental modules." "I feel confident with flexible online learning and would like to use it more effectively." On a five-point Likert scale, responses ranged from "never" (1) to "always" (5). The scale's Cronbach's alpha was 0.89.

**3.2.9. Actual System Use (ASU)**. Developed based on Mathieson (1991), we measure the students' Actual System Use using the following items: "To what extent did you use flexible online learning last month?" "To what extent did you use flexible online learning last week?" "I use flexible online learning to share/seek course information." "I frequently use flexible online learning to supplement my learning." "Overall, to what extent do you use flexible online learning?" On a five-point Likert scale, responses ranged from "never" (1) to "always" (5). The scale's Cronbach's alpha was 0.879.

Before the data analysis's main procedure, Cronbach's Alpha was computed as the preliminary analysis of the study. Cronbach's alpha was used in measuring the internal reliability of the constructs' items. A reliability coefficient of 0.70 or above is acceptable (Hair, 2014). In this study, Cronbach's alpha values for all the constructs were above 0.7, as shown in Table 3. Therefore, all the constructs were reliable; hence, they can be used in the following data analysis procedure, the Exploratory Factor Analysis (EFA).

## 4. Results

The extended TAM research model and the hypothesized relationships between the constructs were empirically tested using Structural Equation Modeling (SEM) to understand better the student's acceptance of a flexible online learning system. This study was tested using three (3) procedures: Exploratory Factor Analysis, Confirmatory Factor Analysis, and Path Analysis done through AMOS 26®. Finally, the final research model was analyzed and tested to be accepted based on its model fit.

***4.1 Primary Analysis***. The preliminary analysis found the internal reliability indices of each construct using Cronbach's alpha of the original survey items. The instrument reflected the indices range from 0.703 to 0.901. All the indexes showed good to excellent evaluations (Pallant, 2003). Table 3 shows the visual inspection of multicollinearity and discriminant validity using the correlation matrix.

**Table 3**: Correlation Matrix

| Factor | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| PU | 1.000 | | | | | | | | |
| PE | .451 | 1.000 | | | | | | | |
| AU | .250 | .492 | 1.000 | | | | | | |
| BU | .350 | .643 | .547 | 1.000 | | | | | |
| ASU | .474 | .640 | .626 | .590 | 1.000 | | | | |
| SN | .358 | .475 | .549 | .619 | .598 | 1.000 | | | |
| UID | .248 | .359 | .396 | .427 | .386 | .250 | 1.000 | | |
| CL | .414 | .628 | .473 | .544 | .633 | .449 | .446 | 1.000 | |
| AR | .177 | .298 | .347 | .287 | .310 | .425 | .097 | .269 | 1.000 |

Intercorrelations among the constructs ranged from 0.097 to 0.643. The results showed good discriminant validity since the study variables' correlation indices are less than 0.90 (Hair, 2014a); (Lischetzke, T., 2014). The strongest positive correlation was found between CL and ASU (0.633), while there's no negative correlation in the correlation matrix. We also found moderate correlations ranging from 0.310 to 0.475. All other coefficients had low correlations ranging from 0.097 to 0.298.

***4.2. EFA Results.*** Exploratory factor analysis (EFA) was utilized to identify factorial structure among the TAM constructs and external factors (e.g., SN, UID, CL, AR). A total of 1,137 responses were randomly selected from the study sample (n = 1200). Meyers et al. (2016) suggested that an oblique Promax solution was performed for rotation selection. Several indices were used to determine the factorial structure. Items were retained when the highest loading eigenvalue exceeded .40, with at least .15 larger than cross-loadings (Worthington & Whittaker, 2006). The commonality value should not fall below 0.30, and factor loading for each component must be greater than (>) 0.40 (Hair, 2014). But according to Merenda (1997), items with loadings equal to or lesser than 0.3 were not included in consideration for inclusion; loadings greater than 0.3 are considered minimal. The dimensions reduction factor analysis in IBM SPSS 26 was used. The EFA results and the reliability indices by Cronbach's alpha are presented in Table 4.

The EFA procedures removed PU4, PU5, AU1, AU3, AU5, BU4, SN3, SN4, SN5, UID2, UID3, UID4, AR2, AR5, and AR6 due to low factor loading, cross-loading, and low communality indices. After the items were removed, the results showed that the factor loading values ranged from 0.334 to 0.996, which suggests that the factors considered in the research are essential. The KMO value was highly satisfactory at 0.840 for the model, with Bartlett's test of sphericity of 2281.150 (significant at $p<0.01$). Using Promax rotation, we found three factors with eigenvalues from 0.860 to 10.426. Cronbach's alpha has shown high measures ranging from 0.763 to 0.875.

**Table 4.** EFA Results

| Factor | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Commonality | Eigenvalue | $\alpha$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PU1 | | | | .785 | | | | | | .695 | | |
| PU2 | | | | .860 | | | | | | .721 | 10.426 | 0.854 |
| PU3 | | | | .817 | | | | | | .745 | | |
| PU4 | | | | .580 | | | | | | .652 | | |
| PE1 | | | .956 | | | | | | | .731 | | |
| PE2 | | | .888 | | | | | | | .742 | | |
| PE3 | | | .493 | | | | | | | .572 | 3.616 | 0.854 |
| PE4 | | | .564 | | | | | | | .565 | | |
| PE5 | | | .603 | | | | | | | .612 | | |
| AU1 | | | | | | | .734 | | | .692 | | |
| AU3 | | | | | | | .862 | | | .673 | 2.111 | 0.808 |
| AU5 | | | | | | | .831 | | | .709 | | |
| BU1 | | | | | .797 | | | | | .804 | | |
| BU2 | | | | | .817 | | | | | .812 | 1.788 | 0.875 |
| BU3 | | | | | .876 | | | | | .768 | | |
| ASU1 | | | | | | | | .856 | | .793 | | |
| ASU2 | | | | | | | | .922 | | .716 | 1.344 | 0.823 |
| ASU5 | | | | | | | | .652 | | .700 | | |
| SN3 | | | | | | | | | .752 | .736 | | |
| SN4 | | | | | | | | | .837 | .677 | 1.256 | 0.763 |
| SN5 | | | | | | | | | .769 | .747 | | |
| UID1 | | .504 | | | | | | | | .616 | | |
| UID2 | | .931 | | | | | | | | .720 | | |
| UID3 | | .908 | | | | | | | | .746 | 1.067 | 0.867 |
| UID6 | | .839 | | | | | | | | .706 | | |
| UID7 | | .356 | | | | | | | | .553 | | |
| CL2 | .855 | | | | | | | | | .731 | | |
| CL3 | .836 | | | | | | | | | .771 | | |
| CL5 | .773 | | | | | | | | | .612 | 0.994 | 0.872 |
| CL6 | .741 | | | | | | | | | .636 | | |
| CL7 | .741 | | | | | | | | | .590 | | |
| AR1 | | | | | | .701 | | | | .619 | | |
| AR3 | | | | | | .739 | | | | .694 | 0.860 | 0.818 |
| AR4 | | | | | | .730 | | | | .604 | | |

***4.3. Confirmatory Factor Analysis (CFA).*** A total of 1,137 responses were loaded to Amos for the Confirmatory Factor Analysis to validate EFA structures. The appropriate measures used to determine the model strength were the Chi-square test ($\chi 2$), the Root Mean Square Error Approximation (RMSEA), and the Standardized Root Mean Square Residual (SRMR). The Comparative Fit Index (CFI) and the Tucker–Lewis Index (TLI) were relative fit measures. The researchers implement the following cut-off scores to achieve a good model: SRMR must be ≤ 0.080, RMSEA must be ≤ 0.060, TLI must be ≥ 0.900, and CFI must be ≥ 0.900 (Hu & Bentler, 1999).

For CFA analysis, the recommended factor loading is 0.50 or higher (Ahmed & Ward, 2016) and ideally 0.70 or higher (Ahmed & Ward, 2016; Karahanna et al., 2006). Thus, the variable that has a factor loading of less than 0.5 must be deleted for the sake of good results. According to this criterion, the Average Variance Extracted (AVE) and Composite Reliability (CR) can assess the measurement model's convergent validity. AVE values above 0.7 are considered good, whereas a level of 0.5 is acceptable, and the proper values for CR are 0.7 and above (cit.). As a result of our data's CFA, see Table 5, which reflects the standardized factor loadings, Composite Reliability (CR), Average Variance Extracted (AVE), and Cronbach's alpha of the final model.

***4.4. Exploring the Relationship between the Latent Variables for SEM.*** We conducted the correlational analysis through the Pearson correlation coefficient to support the path analysis of the SEM. The study followed the r-value guidelines (Schober et al., 2018): 0.00–0.09, "negligible correlation;" 0.10–0.39, "weak correlation;" 0.40–0.69, "moderate correlation;" 0.70–0.89, "strong correlation;" and 0.90–1.00, "very strong correlation."

Table 6 reflects the correlation matrix among the constructs included in the CFA. All of the correlations are significant correlation at the level of 0.01 ($p < 0.01$). The correlation values ranging from 0.317 (weak correlation) to 0.689 (moderate correlation). It is worth noting that all negligible correlations are insignificant. There are no any negative correlations, seven (7) weak-positive, and 28 moderate correlations. As expected, correlations between constructs were all higher than the zero-order correlation in the preliminary analysis.

***4.5. Structural Equation Modeling.*** We used SEM to examine the relationships between the variables and reported the standardized regression weights in Table 7. The reporting excludes the insignificant paths. All of the fit measures of the final model are acceptable ($\chi2$ [1184.474, N = 1,137], $p < 0.001$, $\chi2/df = 2.378$, TLI = 0.966, and CFI = 0.970). The RMSEA = 0.035 indicates an excellent fit between the hypothesized model and the observed data (Hu & Bentler, 1999).

Table 7 revealed that all hypothesized relationships of the variable were significant to the study except for Hypothesis 3 (H3), which states that "UID will positively affect the PU." In the analysis, we found that H3 failed to hold a significant result and was removed from the path analysis. Based on the analysis results, figure 3 shows the final model of the study.

***4.6. Age as Moderating Variable.*** This research also investigated whether age moderates all constructs in the final model of the study. Moderating effects were analyzed using multigroup analyses in AMOS version 21, where the moderating variable was split into two groups and analyzed using the critical ratios approach (Byrne, 2010). To examine this moderating variable, the age range is grouped into two to get the necessary values and data: The first group (ranging from 18-21 years old) and the Second Group (ranging from 22-36). Table 8 presents the effects of moderating variable.

**Table 5.** CFA Results

| Constructs | Items | Standardized Loadings | CR | AVE | $\alpha$ |
|---|---|---|---|---|---|
| Computer Literacy | CL2 | 0.753 | 0.859 | 0.551 | 0.861 |
| | CL3 | 0.793 | | | |
| | CL5 | 0.743 | | | |
| | CL6 | 0.745 | | | |
| | CL7 | 0.672 | | | |
| User-Interface Design | UID1 | 0.748 | 0.856 | 0.544 | 0.866 |
| | UID2 | 0.750 | | | |
| | UID3 | 0.728 | | | |
| | UID6 | 0.709 | | | |
| | UID7 | 0.752 | | | |
| Perceived Ease of Use | PE1 | 0.696 | 0.856 | 0.543 | 0.861 |
| | PE2 | 0.715 | | | |
| | PE3 | 0.763 | | | |
| | PE4 | 0.748 | | | |
| | PE5 | 0.760 | | | |
| Perceived Usefulness | PU1 | 0.792 | 0.868 | 0.622 | 0.863 |
| | PU2 | 0.818 | | | |
| | PU3 | 0.825 | | | |
| | PU4 | 0.714 | | | |
| Behavioral Intention to Use | BU1 | 0.890 | 0.890 | 0.730 | 0.883 |
| | BU2 | 0.907 | | | |
| | BU3 | 0.758 | | | |
| Academic Relevance | AR1 | 0.706 | 0.819 | 0.602 | 0.812 |
| | AR3 | 0.824 | | | |
| | AR4 | 0.792 | | | |
| Attitude Towards Using | AU1 | 0.761 | 0.814 | 0.593 | 0.812 |
| | AU3 | 0.745 | | | |
| | AU5 | 0.803 | | | |
| Actual System Use | ASU1 | 0.770 | 0.798 | 0.573 | 0.816 |
| | ASU2 | 0.606 | | | |
| | ASU5 | 0.871 | | | |
| Social Norm | SN3 | 0.787 | 0.815 | 0.596 | 0.812 |
| | SN4 | 0.718 | | | |
| | SN5 | 0.808 | | | |

Table 8 compares the values among the two groups and the corresponding z-scores. The result revealed that most of the hypotheses are supported. For instance, BU exerts a stronger relationship with ASU to adopt flexible learning for younger students ($\beta$ = 0.931), while UID has a stronger relationship with PE for older ones ($\beta$ = 0.745). Nevertheless, only the relationship between CL to PU is not affected by the age of both young ($\beta$ = 0.066) and old students ($\beta$ = 0.081).

**Table 6.** Correlation Matrix among CFA constructs

| Study Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| PU | 1.000 | | | | | | | | |
| PE | .626** | 1.000 | | | | | | | |
| AU | .585** | .686** | 1.000 | | | | | | |
| BU | .634** | .604** | .638** | 1.000 | | | | | |
| ASU | .488** | .472** | .417** | .595** | 1.000 | | | | |
| SN | .496** | .480** | .480** | .571** | .603** | 1.000 | | | |
| UID | .563** | .670** | .689** | .598** | .501** | .589** | 1.000 | | |
| CL | .369** | .424** | .358** | .362** | .268** | .317** | .357** | 1.000 | |
| AR | .502** | .533** | .598** | .565** | .468** | .578** | .641** | .361** | 1.000 |

**Correlation is significant at $\rho < 0.01$ (2-tailed).

**Table 7.** SEM Results

| Hypothesis | Path | $\beta$ | SE | CR | $p$ | Label |
|---|---|---|---|---|---|---|
| H1 | SN → BU | 0.427 | 0.037 | 12.126 | <0.001 | Supported |
| H2 | SN → PU | 0.184 | 0.041 | 3.943 | <0.001 | Supported |
| H4 | UID → PE | 0.737 | 0.040 | 18.515 | <0.001 | Supported |
| H5 | CL → PU | 0.067 | 0.038 | 2.170 | <0.05 | Supported |
| H6 | CL → PE | 0.147 | 0.033 | 5.774 | <0.001 | Supported |
| H7 | AR → PU | 0.109 | 0.050 | 2.256 | <0.05 | Supported |
| H8 | PE → PU | 0.504 | 0.041 | 11.511 | <0.001 | Supported |
| H9 | PE → AU | 0.951 | 0.063 | 16.314 | <0.001 | Supported |
| H10 | PU → AU | 0.099 | 0.042 | 2.682 | <0.01 | Supported |
| H11 | PU → BU | 0.252 | 0.038 | 7.799 | <0.001 | Supported |
| H12 | AU → BU | 0.251 | 0.036 | 7.195 | <0.001 | Supported |
| H13 | BU → ASU | 0.946 | 0.044 | 20.734 | <0.001 | Supported |

Correlation is significant at ***$\rho < 0.001$, **$\rho < 0.01$, *$\rho < 0.05$

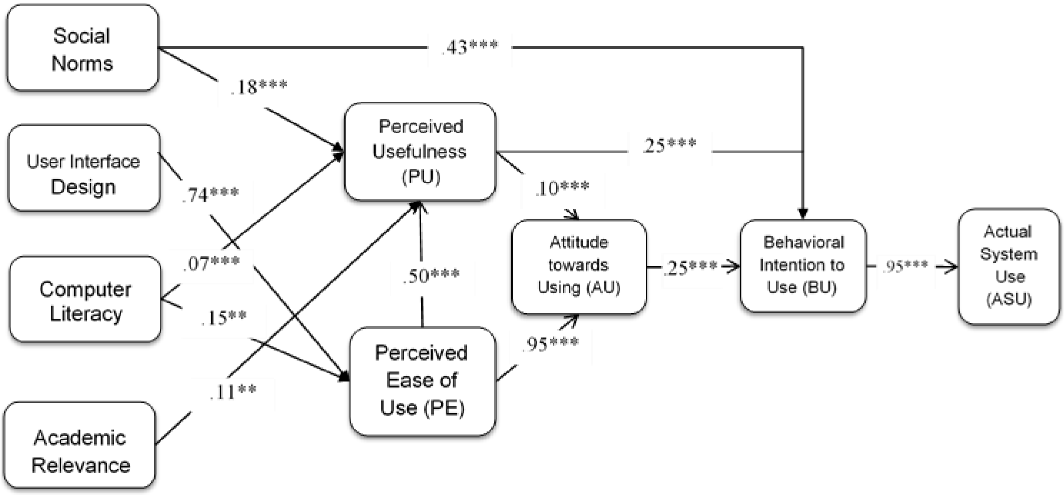


**Figure 3.** Final Model

**Table 8.** Effects of Moderating Variables

| | *Young Estimate* | *Old Estimate* | *z-score* |
|---|---|---|---|
| SN → BU | 0.452*** | 0.469*** | 0.169 |
| SN → PU | 0.146** | 0.211* | 0.63 |
| UID → PE | 0.737*** | 0.745*** | 0.08 |
| CL → PU | 0.066 | 0.081 | 0.178 |
| CL → PE | 0.209*** | 0.213** | 0.052 |
| AR → PU | 0.144* | 0.064 | -0.649 |
| PE → PU | 0.49*** | 0.452*** | -0.387 |
| PE → AU | 0.996*** | 1.02*** | 0.138 |
| PU → AU | 0.143*** | 0.073*** | -0.542 |
| PU → BU | 0.303*** | 0.271** | -0.294 |
| AU → BU | 0.237*** | 0.307*** | 0.742 |
| BU → ASU | 0.931*** | 0.879*** | -0.457 |

Correlation is significant at $^{***}\rho < 0.001$, $^{**}\rho < 0.01$, $^{*}\rho < 0.05$

## 5. Discussion

The paper mainly examines factors contributing to students' actual system use of flexible learning in a developing economy during the COVID-19 outbreak. This study differs from previous studies since it focused on college students in a developing country where students are unfamiliar with flexible learning and the composition of the antecedent variables is proposed and validated for the first time. We used the TAM model to investigate this issue, with external factors as crucial predictor variables in accepting flexible learning. The hypotheses concerning TAM scales and external factors were analyzed. This study shows six essential points of discussion.

First, SN positively affects students' BU and PU. This finding confirms prior studies that suggested that SN affects both BU and PU (Arcali & Sağlam, 2015; Moreno et al., 2017; Tarhini et al., 2014). It indicates that other people may influence students' BU and PU on accepting flexible learning (e.g., friends, classmates, and instructors). Second, UID positively affects PU and PE. Like Eraslan and Kutlu (2019), the study concluded that user-friendly interface design positively affects students' PE and PU using a learning management system. Third, CL positively affects PU and PE. This suggests that PU and PE are essential factors in students' computer literacy of flexible learning.

Fourth, the relationship between AR and PU was found to be significant. This finding was confirmed by a prior study, in which the authors revealed that AR positively affects PU and PEOU using m-LMS (Saroia & Gao 2019). Then, the relationship between BU and ASU is positive and significant. This result was confirmed by Ghosh (2016), which showed behavioral intention directly and significantly influenced the actual system use (AU) of flexible online learning.

Lastly, the investigation of moderating effect of age yields exciting insights. Regarding the impact of CL on PE, it is found that age has a more substantial relationship for younger than for older students. This is also understandable because younger students are more tech-savvy, and their comfort level with flexible learning is higher than their counterparts. In addition, age was found to moderate the relationship between SN to BU and PU and UID to PE. The result indicates that there still exist significant generational gaps despite the rapid growth in internet use, explicitly using flexible learning, among young and old students. On the other hand, the relationship between AR and PU was positively significant for younger students. This indicates that younger students find flexible learning as necessary, compatible, and valuable with their learning compared to older students.

## 6. Implication

We put forward three significant implications based on the results. First, the UID strongly predicts the PEU. This is a welcome development, especially for students and faculty members who implement the flexible learning environment. Students' ability, motivation, and productivity are mostly affected by how good are the interface design of a system (Oweis, 2018), which essentially favors the activities in flexible online learning. On the other hand, Fathema et al. (2015) discussed that faculty members are motivated to learn and use flexible online learning more if they know the learners accept the system in terms of its flexibility in the interface. Thus, it is recommended that faculty self-efficacy may be studied in the context of the use of flexible online learning, and universities should offer periodic training programs and extended online help for flexible online learning.

Secondly, this study will serve as a grounding theory to be applied in enhancing the personnel of educational institutions, specifically in the context of flexible online learning programmers and implementers. System quality is a solid salient factor that shapes faculty members' usage of flexible online learning. Therefore, designers and university policy-makers should concentrate on improving a flexible online learning system to make it more usable for faculty members (Fathema et al., 2015). A continuous quality improvement process should be implemented to maintain a higher level of education quality, collect feedback from flexible online learning users about quality concerns, problems, and recommendations for improvement, and prepare for flexible online learning improvement actions.

Lastly, age's moderating effect is significant for most of the proposed relationships. The study suggests that institutions should review the acceptance of flexible learning by collecting lived experiences among learners and offering relevant solutions to the problems encountered.

## 7. Conclusion

The paper validates an extension of the Technology Acceptance Model (TAM) and explores students' acceptance of the flexible online learning system in a Philippine state university. The main idea is to delineate the effects of the social norm (SN), user interface design (UID), computer literacy (CL), and academic relevance (AR) to the behavioral constructs of Davis's (1989) TAM during the COVID-19 pandemic.

Five (5) original variables and four (4) external variables resulted in being valid and acceptable concerning the fit measures, as suggested by Hair (2014). The structural equation modeling (SEM) results described that each hypothesized variable was significant except on the path from UID to perceived usefulness. Thus, the external variables affect students' acceptance and intention to use flexible online learning. Therefore, SN, UID, CL, and AR, are proper antecedents affecting students' acceptance and intention to use flexible online learning in a developing economy. Even though the Philippine higher education institutions (HEIs), more specifically the state universities, were caught unprepared for the online transition of classes, the model was still validated to describe the phenomenon effectively. As an acceptance measurement tool, TAM allows for exploring antecedent variables in online learning. The emerging aspect of the model is advantageous in extending to various complex structures affecting online learning in the post-COVID-19 era.

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