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Factors Influencing High School Teachers' Adoption of Learning Management Systems: A Study in Northern Luzon, Philippines

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Abstract. The world faced different challenges brought about by the COVID–19 pandemic. The closure of schools brought significant disruptions to the learning process and, in effect, caused learning gaps among students. To adapt and facilitate continued learning, the Philippine Science High School (PSHS) System used the Knowledge Hub (kHub) as its central Learning Management System (LMS). This quantitative study examined factors influencing the acceptance of an extended Technology Acceptance Model (TAM) among teachers at PSHS-CVC. Data was gathered using an online survey and was analyzed using the WarpPLS software. Forty-one teachers, the majority female, with Master's degrees, belong to higher teaching ranks, and with 6 – 10 years of teaching in the institution were the respondents of the study. Analysis of the data gathered indicated that system quality directly impacted both perceived usefulness and perceived ease of use. In turn, perceived ease of use influenced perceived usefulness, while perceived self-efficacy affected perceived ease of use. Perceived usefulness directly affected teachers' attitudes, intentions, and actual use of the LMS, which were also influenced by teaching experience. Of the 29 tested hypotheses, 10 were supported, confirming specific constructs of the extended TAM in this academic setting. Furthermore, the study showed that the adoption of LMS is greatly affected by the teaching experiences of the users, whether it is perceived to be beneficial to them, and if they intend to use the said LMS. This study provides insights into the acceptance factors for LMS adoption, contributing to strategies for effective technology use in education.

Keywords: Educational technology; Extended TAM; Learning Management System; Philippines

1.0 Introduction

Flexible learning is an educational approach that allows students flexibility in time, place, and mode of learning, often utilizing modern technology. It includes both online and offline instructions. Flexible learning implementation may differ depending on technological advancements, device availability, internet connectivity, and digital mastery. Due to the COVID–19 pandemic, the government implemented health protocols like lockdowns and temporary closures of establishments like schools. It intensified the need for flexible learning to ensure continuity of learning, pushing schools to adapt quickly. One widely used approach is distance learning, often supported by Learning Management Systems (LMSs) that enable teachers to continue instruction and students to access learning materials remotely.

LMSs have become a core component of modern education, facilitating in-person and remote teaching. LMS platforms like the knowledge hub (kHub) used by Philippine Science High School – Cagayan Valley Campus (PSHS-CVC) support a variety of instructional tasks. They allow teachers to upload course materials, conduct assessments, and track student progress while providing students with a means to access resources and monitor their performance. However, despite these advantages, LMS adoption and effective use are not guaranteed. Teachers and students may face challenges due to limited digital skills, varying technology accessibility, and differences in user engagement (Zanjani et al., 2016; Ignacio, 2021). PSHS CVC kHub operates using Moodle, a free, open-source software LMS and is used by teachers and students for flexible learning. It has different features like uploading and downloading learning materials and assessments, taking assessments, monitoring students' progress, and participating in forums and chats.

The use of LMSs in the teaching–learning process entails one's mastery of the use of technology. The Technology Acceptance Model and its different versions are a framework to model the extent to which educators adopt technology in their teaching practice (Scherer et al., 2019). The Technology Acceptance Model (TAM) is frequently used to understand technology adoption in educational settings. Initially introduced by Davis et al. (1989), TAM assesses perceived usefulness and ease of use, influencing users' intentions and attitudes toward adopting new technologies. This study utilizes an extended version of TAM, including external factors such as system quality and perceived self-efficacy (Fathema et al., 2015), to examine specific factors affecting LMS acceptance among PSHS-CVC teachers.

Despite extensive global research on LMS implementation, studies examining TAM's applicability in high school LMS adoption in the Philippines remain limited. A study on the applicability of TAM in adopting LMS among high school levels will help the administrator design more programs and policies that will lead to digital transformation and attainment of educational equity among teachers, learners, and stakeholders of basic education. This research addresses this gap by assessing which TAM constructs are most influential for LMS adoption and acceptance by teachers at PSHS-CVC. Figure 1 presents the proposed Technology Model that shows the different hypotheses included in the study.

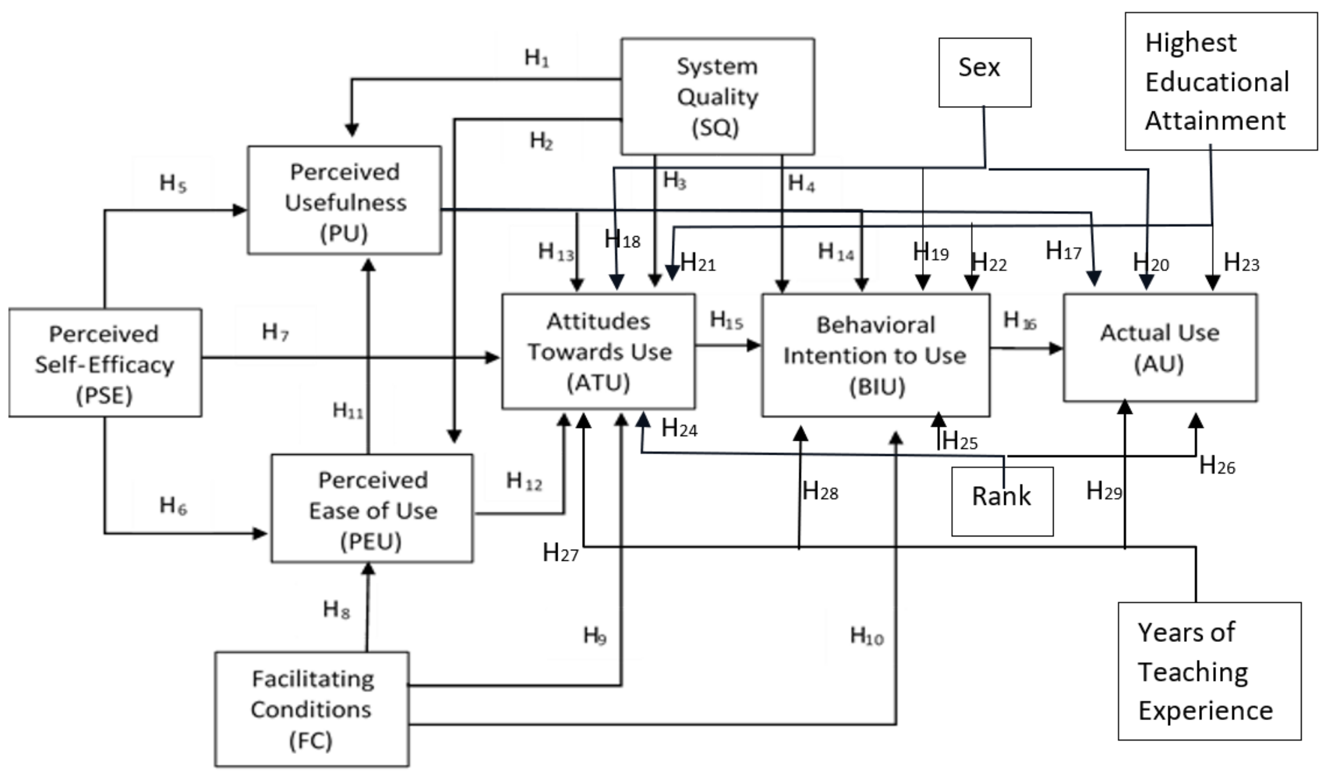

Figure 1: Proposed Technology Model of the Study

The first ten (10) hypotheses address the effects of the external variables System Quality (SQ), Perceived Self-Efficacy (PSE), and Facilitating Conditions (FC) on the original TAM constructs. In this study, "System Quality" (SQ) refers to the users' satisfaction with the performance, responsiveness, features, and contents of the LMS that is currently in use (Mailizar, Burg, & Maulina, 2021). The study's central hypothesis was that teachers would prefer to utilize the LMS in the future if they were satisfied with its quality and had favorable attitudes toward using it.

H1: PU is directly affected by SQ.
H2: PEU is directly affected by SQ.
H3: ATU is directly affected by SQ.
H4: BIU is directly affected by SQ.

Perceived Self – Efficacy (PSE), which is the self–evaluation of a person's ability to perform the tasks necessary to attain the needed results successfully, is another crucial factor in determining whether or not a technology system will be accepted (Nikou & Economides, 2019). PSE refers to a teacher's assessment of or confidence in his or her ability to use the system in the context of the LMS. The effect of "Perceived Self-efficacy" on "Attitudes Towards Use" was included in this investigation. From these, three hypotheses were examined:

H5: PU is directly affected by PSE.
H6: PEU is directly affected by PSE.
H7: ATU is directly affected by PSE.

Facilitating conditions (FC) are influences that can have a good or bad effect on the difficulty people have in successfully finishing a given work (Teo, 2010). In the current study and the context of LMS use, FC is assessed by the accessibility of capacity-building opportunities, technical help and assistance, and related resources to help work in the LMS. Previous studies revealed a weak positive effect of FC on ATU and PEU (Fathema et al., 2015). If suitable facilitating conditions exist, teachers will adopt favorable attitudes toward using LMSs. The study put forth three more hypotheses to investigate the impact of facilitating conditions (FC) on the PEU and ATU in the context of faculty acceptance of LMS. The effect of FC on BIU was also included in this investigation:

H8: Facilitating Conditions have a positive influence on PEU.
H9: Facilitating Conditions' positive influence on ATU.
H10: Facilitating Conditions' positive influence on BIU.

The other seven (7) hypotheses determine the effects of the original TAM variables, namely, Perceived Ease of Use (PEU), Perceived Usefulness (PU), Attitudes Towards Use (ATU), Behavioral Intention to Use (BIU), and Actual Use (AU) with each other. An individual's perception of using a specific technology effortlessly is known operationally as perceived ease of use (PEU). Operationally speaking, perceived usefulness (PU) is the degree to which an individual deliberates that using a specific system would improve their aptitude to accomplish their job (Davis, 1989). In addition, attitude toward use (ATU) refers to a person's good or lousy inclination toward engaging in the target behavior when using a system. Operationally, behavioral intention to use (BIU) is defined as using the features and content of a learning management system (LMS) to support academic activities, both now and in the future. Lastly, Actual Use (AU) refers to the overall extent of use of the LMS:

H11: Perceived Ease of Use has a positive influence on PU.
H12: Perceived Ease of Use has a positive influence on ATU.
H13: Perceived Usefulness has a positive influence on ATU.
H14: Perceived Usefulness has a positive influence on BIU.
H15: Attitude toward Use has a positive influence on BIU.
H16: Behavioral Intention to Use has a positive influence on AU.
H17: Perceived Usefulness has a positive influence on AU.

Other variables included in the model are sex, highest educational attainment, rank, and years of teaching experience. Sex is whether the respondent is a female or male. Highest Educational Attainment refers to the respondents' educational attainment, whether they finished a bachelor's degree, master's degree, or doctorate or post-doctorate degree. The Philippine Science High School System teachers are all Special Science Teachers and are ranked accordingly. In this study, rank refers to whether the respondents are Special Science Teacher I, Special Science Teacher II, Special Science Teacher III, Special Science Teacher IV, or Special Science Teacher V. Years of teaching experience refers to the number of years the respondents are teaching at Philippine Science High School – Cagayan Valley Campus. This does not include the teaching experiences of the respondents outside of Philippine Science High School – Cagayan Valley Campus. The following were the additional hypotheses of the study:

H18: Sex directly affects ATU
H19: Sex directly affects BIU
H20: Sex directly affects AU
H21: Highest Educational Attainment directly affects ATU
H22: Highest Educational Attainment directly affects BIU
H23: Highest Educational Attainment Directly Affects AU
H24: Rank directly affects ATU
H25: Rank directly affects BIU
H26: Rank directly affects AU
H27: Years of teaching experiences directly affect ATU
H28: Years of teaching experiences directly affect BIU
H29: Years of teaching experiences directly affect AU

By studying the effects of these variables on the adoption of LMS, this study seeks to support administrators and policymakers in improving LMS integration, enhancing its usefulness for teachers and students. Understanding these factors can also guide teachers in designing more practical activities, ultimately fostering a supportive learning environment at PSHS-CVC.

2.0 Methodology

2.1 Research Design

This study employed a descriptive-correlational design, utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the relationships among variables within the Technology Acceptance Model (TAM). PLS-SEM was chosen for its efficacy in handling complex path models and its robustness with small sample sizes, aligning well with the study's objectives of examining TAM-related constructs in a specific educational context.

2.2 Research Locale

The study was conducted at the Philippine Science High School Cagayan Valley Campus (PSHS-CVC) in Bayombong, Nueva Vizcaya, Philippines. PSHS-CVC is one of the 16 campuses of the Philippine Science High School System (PSHSS) and serves scholars from Region II and neighboring provinces, including Ifugao and Nueva Ecija.

2.3 Research Participants

The study's participants consisted of PSHS-CVC teachers, totaling 41 individuals. These individuals have firsthand experience using the Learning Management System (LMS). WARP PLS-SEM was used to determine an appropriate sample size, leveraging the inverse square root and gamma-exponential methods. With a significant path coefficient of 0.397, a significance level of 0.05, and a power level of 0.750, the minimum sample sizes required were 35 and 22 participants.

2.4 Research Instrument

Data collection was conducted through an online survey consisting of three sections. The first section provided an overview of the study's purpose and obtained informed consent in compliance with the Data Privacy Act. The second section gathered demographic data, including respondents' gender, educational attainment, rank, and years of experience. The third section contained items measuring LMS-related constructs based on the extended TAM model, adapted from Fathema et al. (2015). The TAM constructs included System Quality (SQ, 4 items), Perceived Self-Efficacy (PSE, 3 items), Facilitating Conditions (FC, 3 items), Perceived Ease of Use (PEOU, 4 items), Perceived Usefulness (PU, 4 items), Attitude Toward Use (ATU, 4 items), Behavioral Intention to Use (BIU, 3 items), and Actual Use (AU, 3 items).

2.5 Data Gathering Procedure

An online survey was distributed to all 52 faculty members through their official Gmail accounts and a group chat. Data collection occurred from June 7 to June 14, 2023, approximately two years after the initial LMS implementation. Informed consent was obtained from all participants, ensuring compliance with ethical standards and transparency regarding the study's purpose. Respondents accessed the survey using their official Gmail accounts, verifying the authenticity of responses.

2.6 Data Analysis

This quantitative study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) using WarpPLS 8.0 software to assess relationships between TAM-related constructs (SQ, PSE, FC, PEOU, PU, ATU, BIU, and AU) and other relevant variables. Frequency and percentage analyses were performed to describe respondents' demographic profiles.

2.7 Ethical Considerations

Throughout the study, ethical standards were rigorously upheld. All procedures followed PSHS-CVC's research policies and adhered to the Data Privacy Act, ensuring that personally identifiable information was accessible only to the primary researcher. Respondents were fully informed of their rights and provided explicit consent before participating.

3.0 Results and Discussions

3.1 Demographic Profile of Respondents

Table 1 presents the descriptive summary of the profile of the study respondents.

Table 1. *Descriptive statistics of the demographic profile of respondents (n=41)*

Category	Frequency	Percentage
Gender		
Male	18	43.9
Female	23	56.1
Highest Educational Attainment		
BA/BS	16	39.0
Master's	18	43.9
Doctorate/Post-Doctorate	7	17.1
Rank		
Special Science Teacher I	6	14.6
Special Science Teacher II	8	19.5
Special Science Teacher III	10	24.4
Special Science Teacher IV	10	24.4
Special Science Teacher V	7	17.1
Teaching Experience		
0–5 years	8	19.5
6–10 years	15	36.6
11–15 years	2	4.9
16–20 years	7	17.1
21 years and above	9	22.0

As shown in Table 1, 56.1% of the respondents were female, while 43.9% were male. Most participants (43.9%) held a Master's degree, and only a minority (17.1%) held a Doctorate or Post-Doctorate degree. Distribution by rank was relatively even, with most respondents holding the ranks of Special Science Teacher III and IV. Regarding teaching experience, many respondents had 6-10 years of service, reflecting a diverse range of professional backgrounds and a heterogeneous sample.

3.2 Tests for Reliability and Validity

The level of uniformity among the reflective items and the intended measures is assessed by construct reliability (Amora & Fearnley, 2020). When composite reliability (CR) and Cronbach's alpha (CA) are both at least 0.70, construct reliability is deemed adequate (Kock, 2020). Convergent validity evaluated whether respondents understood the items related to each variable to the same extent as the instruments' creator intended. There are two ways to evaluate convergent validity in PLS-SEM. Item loadings about the variable must be statistically significant ($p < 0.5$) and have a value of at least 0.50. Item loading indicates the correlation between the item and the variable. Another requirement is that the average variance extracted (AVE) be at least 0.50 (Kock, 2015). AVE compares observational error to the overall dispersion attributable to the construct (Amora & Fearnley, 2020)

Table 2. *Constructs' item loadings, AVE, and reliability*

Constructs	No. of Items	Factor Loadings	AVE	CA	CR
System Quality (SQ)	4	0.367-0.923	0.600	0.747	0.846
Perceived Self-Efficacy (PSE)	3	0.892-0.935	0.849	0.911	0.944
Facilitating Conditions (FC)	3	0.741-0.925	0.673	0.751	0.859
Perceived Ease of Use (PEU)	4	0.654-0.895	0.654	0.818	0.882
Perceived Usefulness (PU)	4	0.902-0.979	0.889	0.958	0.970
Attitudes Towards Use	4	0.895-0.948	0.841	0.937	0.955
Behavioral Intention to Use (BIU)	3	0.895-0.938	0.842	0.906	0.941
Actual Use (AU)	3	0.796-0.923	0.739	0.822	0.894

All factor loadings are significant at 0.001 ($p < 0.001$). AVE = average variance extracted; CA = Cronbach's alpha; CR = composite reliability

The data in Table 2 indicate that one of the eight concepts had a factor loading less than 0.50. System Quality (SQ) had a factor loading of 0.396, the 2nd question in the questionnaire, which asked about the respondents' satisfaction with the campus's internet speed. Internet speed is one of the problems of the Philippines in general. PSHS–CVC is not spared from that. Further analysis showed that during the data–gathering time, PSHS–CVC experienced fluctuation and slow internet speed. This has affected the responses of the respondents to the said questions. The other constructs have factor loadings within the valid value, which is 0.50, which indicates that the given questionnaire is of sound construction. The Cronbach's alpha and composite reliability of the eight different constructs are all above 0.70, exceeding the recommended construct validity threshold of 0.70. Like how item loadings are recorded, AVE values above 0.50 were deemed sufficient for the structural model's constructs' convergent validity. With all these results, it can be concluded that the questionnaire used in this context is valid.

Discriminant validity refers to the ability of the respondents to distinguish one variable from another, particularly in their content and structure (Kock, 2015). A variable's components have a strong correlation if the square root of the AVE of that variable is greater than the number of combinations of that variable with another (Teo, 2010). In this case, only System Quality (SQ) has a diagonal value lower than the related off-diagonal values. This shows seven constructs have satisfactory discriminant validity for all concepts (see Table 3).

Table 3. *Coefficients of correlations and constructs' AVEs*

Constructs	SQ	PSE	FC	PEU	PU	ATU	BIU	AU
System Quality (SQ)	**0.774**							
Perceived Self-Efficacy (PSE)	0.580	**0.921**						
Facilitating Conditions (FC)	0.820	0.641	**0.820**					
Perceived Ease of Use (PEU)	0.706	0.838	0.741	**0.809**				
Perceived Usefulness (PU)	0.702	0.681	0.806	0.806	**0.943**			
Attitudes Towards Use (ATU)	0.663	0.634	0.723	0.714	0.825	**0.917**		
Behavioral Intention to Use (BIU)	0.705	0.704	0.770	0.768	0.868	0.885	**0.918**	
Actual Use (AU)	0.341	0.455	0.089	0.451	0.110	0.140	0.270	**0.860**

The above results showed that the convergent validity, discriminant validity, and reliability tests were all satisfied to ensure their use in estimating the structural model. Other parameters needed to ensure the fitness of the data were also considered. Such parameters, but not limited to, are average path coefficient, average r squared, and nonlinear bivariate causality direction ratio. The following data showed the results of these different parameters.

Average path coefficient (APC)=0.210, P=0.037
Average R-squared (ARS)=0.665, P<0.001
Average adjusted R-squared (AARS)=0.607, P<0.001,

Average block VIF (AVIF)=3.396, acceptable if <= 5, ideally <= 3.3
Average full collinearity VIF (AFVIF)=5.451, acceptable if <= 5, ideally <= 3.3
Tenenhaus GoF (GoF)=0.748, small >= 0.1, medium >= 0.25, large >= 0.36
Sympson's paradox ratio (SPR)=0.828, acceptable if >= 0.7, ideally =1
R-squared contribution ratio (RSCR)=0.931, acceptable if >= 0.9, ideally = 1
Statistical suppression ratio (SSR)=0.897, acceptable if >= 0.7
Nonlinear bivariate causality direction ratio (NLBCDR)=0.931, acceptable if >= 0.7

Overall, the fit and quality indices of the structural model in the present study fell within acceptable limits.

3.2 Test of Structural Model

After testing the validity and reliability of the said constructs, the test for the structural model ensued. The parameter approximations and results for suggested associations in the extended TAM are shown in Table 4. Table 4 contains the hypotheses being tested, the direct path between the constructs being studied, the results of the **β**, p-value, and $f^{2,}$ and whether the data generated supports or not the given assumptions. Only 10 of the twenty – nine (29) hypotheses being tested were confirmed after the collected data were analyzed.

Table 4. *Parameter approximations of the extended TAM for LMS*

Path	β	p-value	f^2	Results
SQ→PU	0.394	0.002	0.303	Supported**
SQ→PEU	0.238	0.049	0.175	Supported*
SQ→ATU	0.094	0.266	0.072	Not Supported
SQ→BIU	-0.108	0.237	0.083	Not Supported
PSE→PU	0.025	0.435	0.018	Not Supported
PSE→PEU	0.611	<0.001	0.521	Supported**
PSE→ATU	0.047	0.380	0.033	Not Supported
FC→PEU	0.148	0.160	0.110	Not Supported
FC→ATU	0.069	0.326	0.054	Not Supported
FC→BIU	0.083	0.292	0.067	Not Supported
PEU→PU	0.522	<0.001	0.425	Supported**
PEU→ATU	0.165	0.132	0.120	Not Supported
PU→ATU	0.525	<0.001	0.443	Supported**
PU→BIU	0.493	<0.001	0.436	Supported**
ATU→BIU	0.471	<0.001	0.418	Supported**
BIU→AU	0.332	0.009	0.188	Supported**
PU→AU	-0.284	0.024	0.131	Supported*
Sex→ATU	-0.189	0.099	0.008	Not Supported
Sex→BIU	0.034	0.414	0.002	Not Supported
Sex→AU	-0.165	0.133	0.012	Not Supported
EducA→ATU	0.113	0.226	0.022	Not Supported
EducA→BIU	-0.071	0.321	0.014	Not Supported
EducA→AU	0.078	0.304	0.005	Not Supported
Rank→ATU	0.162	0.136	0.052	Not Supported
Rank→BIU	-0.112	0.229	0.035	Not Supported
Rank→AU	-0.231	0.055	0.053	Not Supported
Exper→ATU	0.066	0.333	0.014	Not Supported
Exper→BIU	-0.005	0.488	0.001	Not Supported
Exper→AU	0.256	0.038	0.037	Supported*

Table 4 shows that the structural model revealed that SQ positively affects PU (H_1) and PEU (H_2) as shown by their p – p-values, which are 0.002 and 0.049, respectively. The effect of SQ on PU is significant with an $f^2 = 0.303$, whereas the effect of SQ on PEU is moderate, with a value of f^2 equal to 0.175. Positive β values (i.e., path coefficients) indicated that low SQ led to low PU and PEU, a direct positive correlation. This aligns with studies like DelOne and McLean (2003), Cheng (2012), and Ferran (2021) that highlight the importance of system quality in shaping Perceived Usefulness. The moderate effect of SQ on PEU also aligns with studies such as those by Thong et al. (2006), who found that quality aspects of systems reduce the system's complexity and enhance its ease of use. Higher system quality in different platforms reduces the learning curve, making users feel more comfortable and confident using the technology. Moreover, SQ did not significantly influence ATU (H_3) and BIU (H_4), meaning SQ has no direct effect on ATU and BIU. Pynoo et al. (2011) found that although system quality influences PU and PEU, it does not always directly lead to a positive attitude toward use or intentions, as PU often mediates these factors.

For PSE, it can be deduced that PSE significantly influenced PEU (H_6) with a p-value less than 0.001. The amount of the influence of PSE can be described as large on PEU ($f^2 = 0.521$). This implies that individuals with high self–efficacy are more likely to perceive technology as easy to use. The large effect size further confirms that teachers with higher confidence in their technological skills find the LMS easier to navigate. However, PSE did not significantly affect PU (H_5) and ATU (H_7), indicating no correlation between these constructs. The lack of significant correlations between PSE, PU, and ATU contrasts with other studies, such as Venkatesh and Davis (2000), where PSE often influences perceptions of usefulness through its effect on PEU. Ferran (2021) also found that PSE strongly affects the users' perceived ease of use, while perceived ease of use highly influences the students' perceived usefulness. This is also affirmed by Panergayo and Aliazas (2023), who found out that online learning self–efficacy positively impacts both PU and PEU. However, McFarland and Hamilton (2006) mentioned that in some environments, PSE might not always directly influence PU or attitude, especially if the system's usefulness is perceived independently of the user's confidence.

In connection with the findings of Fathema et al. (2015), this study demonstrated that SQ significantly and favorably influences PU. This implies that teachers will consider a high–performing LMS valuable. PEU is significantly influenced by teachers' perceived levels of self–efficacy, which supports earlier research that states that self-efficacy plays a key role in determining whether a technology use will be successful. This finding recommends that educators with high self–efficacy also have high levels of ease and assurance in their ability to use the LMS to further their professional objectives. According to prior research, teachers with high self–efficacy have better perceptions of and more significant aims to employ the LMS (Parkman et al., 2018)

FC did not influence PEU (H_8), ATU (H_9) and BIU (H_{10}). This implies that for teachers, facilitating conditions do not affect their perception of the ease of use of the kHub, actual use of the kHub, and their behavioral intention to use the said LMS. These results on FC's effect on the different constructs are intriguing, given that facilitating conditions such as available support and infrastructure are often viewed as influential in technology adoption models, such as those in Venkatesh et al.'s (2003) Unified Theory of Acceptance and Use of Technology (UTAUT). However, similar to these results are those of Teo (2010), who found out that facilitating conditions may not always play an important role for experienced users, who may rely more on their abilities and the perceived benefits of the system rather than external supports. The research conducted by Ferran (2021) also showed that FC does not affect the users' attitudes toward the use of e-learning tools.

PEU has a significant effect on PU (H_{11}) to a large extent (f^2=00425) but no significant effect on ATU (H_{12}). This shows the mediating role of PEU on PU across multiple contexts. PEU's influence on PU suggests that as teachers find the LMS easier to use, they start seeing it as more beneficial for their tasks. In terms of PU, it had a positive and large effect both on the ATU (H_{13}) and BIU (H_{14}) (f^2=0.443 and 0.436, respectively). This implies that if teachers perceive the LMS to be helpful, then they will use the LMS and will have a strong behavioral intention to use it. Moreover, the large effect sizes for both paths are consistent with TAM's fundamental hypothesis that PU significantly predicts ATU and BIU. Scherer et al. (2019) reinforced these findings in educational technology, where perceived usefulness is a strong motivator for positive attitudes toward technology and actual behavioral intentions to adopt and use it. Garcia (2017) found that PEU and PU significantly affect each other in the acceptance of college students of learning management systems. Additionally, PU has a small direct effect on AU (H_{17}) with a f^2 value equal to 0.131. These findings were corroborated in the study of Panegaryo and Aliazzas (2023), where they found that PEU and PU positively influence ATU. In the same study, PU and ATU significantly predicted BIU. Furthermore, Prasetyo et al. (2021) found that PEU has the most significant impact on AU, followed by the user interface and SQ towards PEU, which subsequently led to BIU and AU. Navarro et al. (2021), in their study among engineering students in the Philippines, found that PU and PEU significantly influence BIU. However, Chatterjee (2023) found that PEU does not affect PU.

On the other hand, ATU positively and significantly affected BIU (H_{15}) at a large extent (f^2=0.418), and in turn, BIU directly affected AU (H_{16}) at a moderate extent (f^2=0.188). The significant and positive relationships between these constructs echo many TAM studies that identify attitude as a key predictor of intention to use and actual usage of the technology. Park (2009) found similar patterns among teachers adopting e-learning platforms: positive attitudes lead to increased behavioral intention to use and the actual usage of the technology. This was further confirmed by the research of Belo et al. (2024), which found that ATU had the most decisive influence on BIU among aviation college students. The positive effect of PEU with PU, PU on ATU, AU, and BIU, ATU on BIU, and the comparable result of BIU on AU align with the works by Sibuea (2018), Amora & Fearnley (2020) and Lavidas, Komis & Achriani (2022). This means that teachers who perceive ease of use with the system will develop promising behaviors toward LMS practice and have higher intentions to use the technology, which will later lead to active actual use. The study's results also showed the positive effect of years of teaching experience on using the LMS. This indicates that the more years of teaching, the greater the chance they will use the said LMS.

Of the additional hypotheses being tested, only years of teaching experience directly affect AU (H_{29}) moderately, with an f^2 value of 0.037. Sex, Educational Attainment, and Rank do not affect the use of LMS. This is partially aligned with the research of Teo (2011), who observed that teaching experience is a significant predictor of actual use of technology in TAM studies, possibly due to more experienced teachers having greater exposure and comfort with technology. However, Tarhini et al. (2014) found that sex and educational attainment could influence technology acceptance in specific contexts, though cultural and institutional factors often mediate these effects.

This study aimed to verify the extended TAM's suitability in a regional educational setting (Fathema et al., 2015). This research supported only 10 hypotheses, even though it confirmed several relationships from the model. After analyzing the model generated and considering only the significant paths, Figure 2 was generated. Figure 2 shows which of the different constructs on the extended TAM and the additional variables are significant with one another. Similar to the original TAM, the study's results showed that attitudes toward use directly affect the behavioral intention to use the LMS, directly affecting the actual use of the LMS. Additionally, Perceived Usefulness also directly influences Attitudes toward use and Behavioral intention to use, and perceived ease of use directly affects perceived usefulness, as indicated in the original TAM. Moreover, from the original TAM, external variables such as system quality, perceived self-efficacy, and facilitating conditions directly affect perceived usefulness and ease of use. Of the said variables, System Quality directly affects Perceived Usefulness and Perceived ease of use. In contrast, Perceived self–efficacy directly affects perceived ease of use. This study did not establish the direct effects of facilitating conditions on the different variables. In addition to the extended TAM, the study was able to show that teaching experience has a direct effect on the actual use of the LMS, and perceived usefulness has a direct effect on Actual use. These two direct relationships were not indicated in the original and extended TAM.

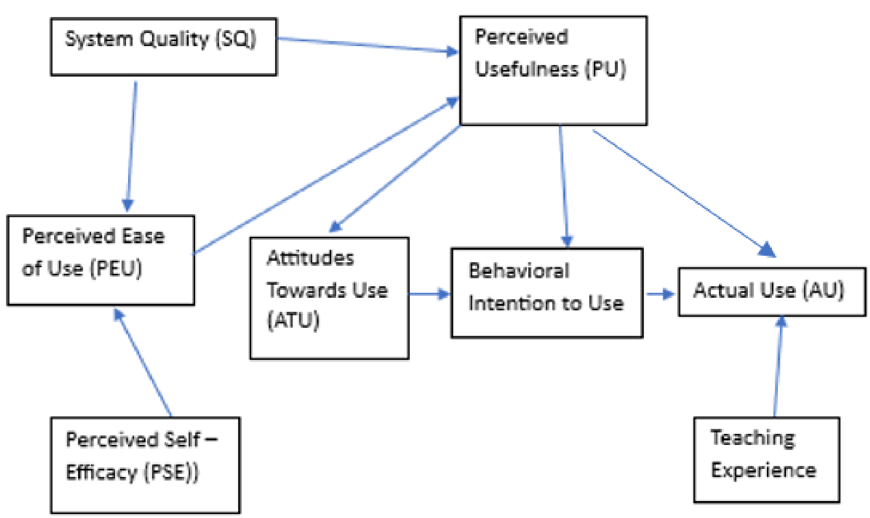

Figure 2. Technology Adoption Model Generated

4.0 Conclusion

The findings of this study offer substantial insights into the Technology Acceptance Model (TAM) as applied to learning management systems (LMS) within educational contexts. Although eight hypothesized relationships among the model's constructs were not statistically supported, the overall results demonstrate significant adherence to TAM's extended and original versions, reinforcing its relevance in educational technology adoption. This partial alignment aligns with Amora and Fearnley's (2020) observation that no universally accepted TAM model exists, as ongoing technological advancements and contextual factors within education—such as shifting behaviors, experiences, and the prominence of external variables—continuously reshape the model's applicability.

Key findings from this research highlight the critical roles of System Quality and Perceived Self-Efficacy. Specifically, System Quality and Perceived Self-Efficacy were positively associated with Perceived Ease of Use, while System Quality also significantly impacted Perceived Usefulness. These results indicate that teachers are more likely to find an LMS that is easy to use when the LMS has high system quality. Furthermore, if teachers perceive themselves to have high self–efficacy in using LMS, they will most likely perceive the LMS as easy to use and navigate. In addition, a high-quality system feature of an LMS enhances teachers' perceptions of the LMS's usefulness. Moreover, the study found a positive relationship between teaching experience and actual LMS usage, suggesting that experienced teachers are more likely to engage and use the system.

The findings further suggest that educators who demonstrate high self-efficacy, positive attitudes, and favorable behavioral intentions toward the LMS could serve as champions of LMS adoption, potentially assisting peers who face challenges in adopting flexible learning technologies. This study emphasizes that enhancing system quality and supporting teachers' self-efficacy are key strategies for increasing Perceived Ease of Use and Perceived Usefulness, both driving positive attitudes and behavioral intentions toward LMS adoption. These findings reaffirm a core principle of TAM: Perceived Usefulness remains a critical determinant of actual system use. The study also notes that demographic factors such as sex, educational attainment, and rank appear to exert minimal influence on LMS adoption, indicating that future strategies should prioritize system quality and intrinsic motivational factors, particularly teachers' belief in the system's usefulness and ease of use.

These results underscore the importance of prioritizing system quality and perceived usefulness as central criteria in LMS selection for university and school administrators responsible for LMS implementation. Future research on TAM may benefit from exploring additional external variables and considering mixed-method approaches, which could yield qualitative insights to enhance understanding of TAM's constructs. This expanded approach may contribute to refining TAM's descriptive power in educational technology, adapting it more effectively to the evolving landscape of digital learning.

5.0 Contributions of Authors

Rosalinda Luwang conceptualized and performed the study, gathered and analyzed the data, and prepared the research manuscript.
Oligo, Jubert: gave input on the conceptualization of the research topic and helped with the analysis of data and finalization of the research manuscript.
Valderama, Julius: gave input on conceptualizing the research topic and helped with data analysis and the research manuscript's preparation.

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7.0 Conflict of Interests

There is no conflict of interest

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