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Research Article

Utilizing Learning Management System Technology: Modelling the Tripartite Relationships Among Previous Technology Use Experience, Technology Self-Efficacy, and Use Behavior

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ABSTRACT

This study sought to find out how previous technology use experience, technology self-efficacy, and use behavior relate among themselves towards learning management system (LMS) technology uptake. This is because LMS has been adopted by higher educational institutions during both the COVID-19 lockdown and post-COVID-19 era. Nonetheless, evidence shows lack of training of tutors in utilizing the LMS technology for pedagogical purposes during the emergency remote learning paradigm. Owing to that, most tutors relied on their previous technology use experiences to cultivate a self-belief towards the actual use behavior of leaning management system for their teaching and learning. Consequently, a quantitative approach based on a survey design was adopted, and questionnaire used to collect data from a purposive sample of 267 tutors in a traditional face-to-face distance setting. Results from a partial least squares structural equation modelling approach proved a positive statistically significant effect of both previous technology use experience and technology self-efficacy on LMS use behavior. Additionally, previous technology use experience positively determined technology self-efficacy with the latter having a significant indirect and mediation effect on the former towards LMS use behavior. The results of this study provided insights into the tripartite relationships existing among these three important variables. Based on the findings, recommendations were made to higher educational institutions towards the adoption of LMSs by tutors.

Keywords: previous technology use experience, technology self-efficacy, LMS use behavior, blended learning, distance higher education, structural equation modelling

INTRODUCTION

Information communication technology (ICT) has pervaded our contemporary society such that every facet of life has been either positively or negatively affected (Roztocki et al., 2019). ICT has been of great importance to current educational system (Buabeng-Andoh, 2015) by altering the curriculum and its delivery (Rambe, 2016). This is because unlike previously where teaching and learning were limited to the boundaries of the classroom, today's pedagogical practices transcend beyond brick wall barriers (Ponners & Asim, 2016). This implies that several modes of delivery have been incorporated into teaching and learning. Some of these common modes are online and blended learning (Park & Shea, 2020; Siemens et al., 2015). While online learning is the form of teaching and learning that purely occur via the internet without any physical face-to-face interaction, the blended mode combines the halves of both face-to-face and online components (Pearson, 2020; Siemens et al., 2015; Stauffer, 2020). According to Siemens et al. (2015), both the traditional mode of face-to-face delivery and the purely online mode of delivery have inherent limitations. This is because, the traditional mode of delivery is beset with geographical and spatial deficiencies while the purely online mode inhibits physical interaction which is an important factor in the pedagogical process (Siemens et al., 2015; Stauffer, 2020). Thus, the blended mode of delivery has become a suitable option for most institutions offering the dual mode higher education (Gambari et al., 2017; Ma'arop & Embi, 2016).

According to Siemens et al. (2015), the blended mode of distance education delivery is the type of delivery where part of the teaching and learning occur in the classroom while the other parts are handled online with the aid of the Internet or Web 2.0 technologies. The implication is that a technology is needed to mediate the blended mode of delivery between instructors and students alike (Rad et al., 2019). One of the most important and commonly used technological platforms that is aiding the blended mode delivery in higher education, is the learning management system (LMS) (Durak & Cankaya, 2019; Tinmaz & Lee, 2020). According to Yakubu (2019, p. 1), "LMS is a web-based system that possesses an extensive range of pedagogical and course administration tools." This definition has been reiterated by Tinmaz and Lee (2020). LMS can also facilitate group chats, discussions, document sharing, assignment submission, quizzes, grading and course evaluations (Bove & Conklin, 2020). Moreover, LMS has a potential to serve students with diverse backgrounds including culture, age, or gender (Tinmaz & Lee, 2020). Since the outbreak of the COVID-19 pandemic coupled with global lockdown situations, there has been a great growth in acquisition and use of LMS technologies by both higher educational institutions and the general educational sector (Heng & Sol, 2020). The LMS technology has been used by higher educational institutions together with other video-conferencing tools such as Zoom, Webex, WebCT, Google Meet, etc. (Camilleri & Camilleri, 2021). Nonetheless, the forced utilization or non-voluntary use of the LMS technology during the COVID-19 era without adequate training or no training for instructors especially, has raised concerns of self-efficacy and actual use behavior by faculty members. Especially, for most institutions, the emergency transition to remote learning via the LMS, took off with little or no training of faculty prior to LMS uptake for online learning (Yan, 2020; Zhao, 2020). According to Rapanta et al. (2020), "in the COVID-19 emergency situation, teachers have, almost overnight, been asked to become both designers and tutors, using technological tools …" (p. 926). This view was re-echoed by Almahasees et al. (2021) as well as Heriyanto et al. (2022) that there was lack of faculty training in the use of technology for teaching and learning during the emergency remote learning transition period. Additionally, Donham et al. (2022) had also cited instructors' technology usage difficulties due to lack of training. Whereas some instructors leveraged on their previous experiences with technology to manage the use of LMS, others had to struggle through. According to Aladsani (2022), higher education institutions across the world were forced to make rapid transition to a fully online education format with no time to prepare. This meant that for most faculty members, their personal previous technology use experience became crucial in determining their self-efficacy beliefs to utilize LMS for pedagogical practices. However, for LMS technology to be adequately used by tutors who are agents of change and to further teach and motivate students to also use such technologies, they must possess the self-belief that they can confidently use it, pass on the usage skills to students as well as direct them when in difficulty within the online learning environment (Barton & Dexter, 2019; Fong et al., 2019; Granziera & Perera, 2019). The afore discussion based on the literature, suggests a possible tripartite relationship existing among these three important variables (previous technology use experience, self-efficacy, and use behavior) for LMS utilization. In view of the potential interplay of effects among the three variables, it warrants an investigation into how instructors' previous technology use experiences can translate into both self-efficacy and use behavior of LMS technology for blended learning. Thus, defining a model to establish a possible relationship among the aforementioned variables was necessary for both theoretical and practical considerations. Such a definite model to unravel these important relationships was missing in the literature. Consequently, this study fills the gap by establishing a hypothesized model on the relationship among previous technology use experience, self-efficacy and use behavior of LMS to be empirically tested through structural equation modelling (SEM). Against this background, the study seeks to answer the following research questions:

1. **RQ1**. What significant predictive relationship exists between previous technology use experience and technology self-efficacy of tutors?
2. **RQ2**. What significant predictive relationship exists between technology self-efficacy and LMS use behavior of tutors?
3. **RQ3**. What significant predictive relationship exists between previous technology use experience and LMS use behavior of tutors?

LITERATURE REVIEW

Theoretical Basis

This study is underpinned by Thompson et al.'s (1991) model of personal computer utilization and Bandura's (1994) self-efficacy theory. Within the model of personal computer utilization, Thompson et al. (1991) argued that an individual's prior experience with technology will induce him to utilize personal computers. Bandura (1994) on the other hand, identified that the construct 'self-efficacy' had a significant influence on individual's intention to use a particular technology if that person has what he termed technology self-efficacy. What is missing in the literature is the theorization and empirical validation that, for technology self-efficacy to be acquired, previous technology experience could be a determinant. Hence, integrating all the three variables together to formulate a definite model to explain their intricate relationships towards technology (LMS) use behavior is imperative.

Hypotheses Formulation and Conceptual Model Development

Relationship between previous technology use experience and technology self-efficacy

Previous technology use experience connotes the experience that individuals accrue overtime in using different technologies for diverse tasks (Bervell & Umar, 2018; Sulaymani et al., 2022). These technologies could range from smart phones, computers, personal digital assistants, etc. (Sung et al., 2016). All these devices are connected to the internet for access to the world wide web. The frequent use of these devices equips individuals with the knowledge, skills, and abilities in surfing the internet. Consequently, as individuals acquire these attributes in using the internet, their self-confidence towards internet usage heightens and culminates into a self-belief that they can use the internet and other technological devices for diverse activities (Elbitar, 2015; Sulaymani et al., 2022). This self-belief or confidence towards technology is what is known as technology self-efficacy (Bandura, 1994). Within this study, technology self-efficacy is thus defined as tutors' self-belief or confidence towards the use of technological devices to access the internet and perform other activities. According to Elbitar (2015), as individuals practice with technologies, they become accustomed and efficacious in their usage. Hence, previous technology use experience would induce in tutors the belief that they can use LMS for blended learning purposes (Bervell & Umar, 2018; Sulaymani et al., 2022). On this basis, we postulated that:

H1: Previous technology use experience has a positive relationship with tutors' technology self-efficacy.

Relationship between technology self-efficacy and LMS use behavior

Technology self-efficacy of tutors represents their belief that they can use technologies for several purposes through different media. Compeau et al. (1999) defined self-efficacy as the judgement of one's ability to use a technology to accomplish a particular job or task. Recently, Pan (2020) opined that technological self-efficacy is "characterized as individuals' perception of their capabilities to utilize technology-related tools" (p. 2). This self-belief has a propensity to instill in tutors the confidence that they can use several platforms that depend on the internet to function (Chu, 2010; Chu & Tsai, 2009). Since LMS is a platform made functional by the Internet technology, tutors are likely to form positive self-outlook towards its usage based on the premise that they are used to other internet technologies (Dogru, 2017). It was envisaged in this study that tutors would be propelled towards LMS usage on the basis of their self-efficacy towards technologies (Hong et al., 2022). Leveraging on this psychological disposition, the likelihood of their usage pattern, frequency and copiousness becomes apparent. Against this backdrop, we hypothesized that:

H2: Technology self-efficacy has a positive relationship with tutors' LMS use behavior.

Relationship between previous technology use experience and LMS use behavior

LMS use behavior is defined in this study as users actual use of LMS platforms for several educational purposes. It also references tutor' frequency and intensity in the use of LMS technology for online pedagogical and other educational purposes. According to Venkatesh et al. (2008), use behavior "is the rate of frequency, duration, and intensity of person and system interaction" (p. 11). Bervell (2018) also provided a specific explanation to LMS use behavior as "tutors' engagement with the LMS system in terms of regularity, time lapse, or intensity to perform blended learning tasks or activities" (p. 155).

Copious and diverse previous technology use experiences by individual tutors may have a potential effect on their inclination towards how they would utilize an LMS platform. In this vein, they are likely to behave as innovators and see LMS technology as just one of the technologies they have been using (Bervell & Arkorful, 2020; Gunasinghe et al., 2018; Mormina, 2019). This innovative drive underpinned by their previous technology use experience could influence them positively to try out LMS for educational purposes such as assessment, teaching, and discussions in their professional practices (Amid & Din, 2021; Pruet et al., 2016; Zwain, 2019). The reverse may be the case if tutors do not possess the needed technology use experience. Their lack of technology use experience could create a sense of unfamiliarity with LMS and lead to a negative use behavior or an anxiety towards LMS usage (Bervell & Umar, 2018; Vo et al., 2022). The ensuing discussion suggest a seeming relationship between previous technology use experience and LMS use behavior. Based on this premise, we proposed that:

H3: Previous technology use experience has a positive relationship with tutors' LMS use behavior

Based on the hypotheses formulated above, a conceptual model was developed below as depicted in **Figure 1**.

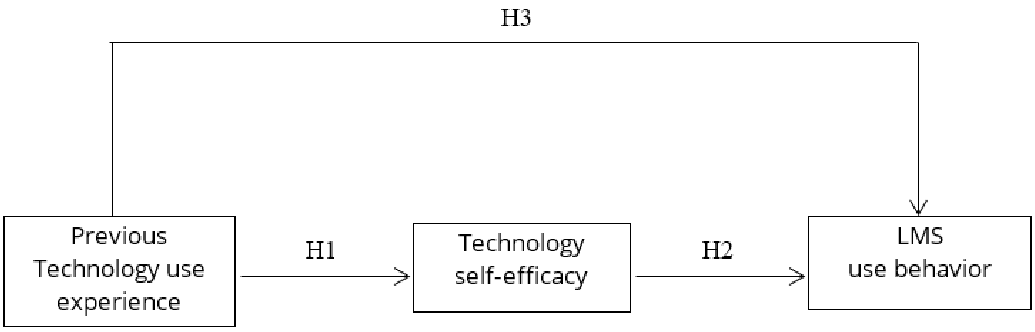

Figure 1. Conceptual model

MATERIALS AND METHODS

A quantitative approach was adopted for this study in accordance with the purpose of the study. Consequently, a survey design was employed, and questionnaire used to obtain data from 267 tutors who formed the representative sample of respondents from a total population of 400 tutors nation-wide. A purposive sampling technique was used to obtain the sample of tutors who were using the LMS for online delivery of teaching and learning activities. The tutors had pilot tested an online blended mode of delivery in a traditional-based distance education. Prior to data collection, participants' consent was individually sought, and voluntariness of participation was ensured for them to have the option to withdraw from the study at any point in time they desired or wished to do so. This was to fulfil part of the ethical standards.

The adequacy of the sample of 267 tutors out of the total population of 400 was statistically determined based on Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Krejcie and Morgan (1970) sampling adequacy thresholds. Questionnaire adopted for this study was from the blended learning acceptance scale (BLAS) developed by Bervell et al. (2021) and was anchored on a five-point Likert scale. The BLAS is an instrument that consists of 45 items across 11 constructs for measuring blended learning acceptance in distance education. It is based on a five-point Likert scale and contains items for both technological, social and personality dimensions. Since the interest of this study revolved around just three variables, only previous technology use experience, technology self-efficacy and use behavior, were used from the BLAS. All the three variables were measured using five items each from the BLAS.

The final questionnaire used for this study consisted of two key sections: demographic and main data sections. The demographic aspect consisted of gender, age, teaching experience, course taught and location while the main data were based on previous technology use experience, technology self-efficacy and use behavior. As suggested by Carpenter (2018), the questionnaire was validated by experts' review, focus group discussion, and statistically verified for reliability through Cronbachs' alpha, composite reliability, and rho A (Hair et al., 2017). Four weeks was dedicated to the data collection process and valid responses were entered into SPSS for data cleaning. The refined data were converted into comma separated values (CSV) file and exported into the SmartPLS software for SEM analysis.

DATA ANALYSIS AND RESULTS

Demographic Data

Preliminary data analysis showed that 164 males and 103 females representing 61.4% and 38.6% respectively, participated in this study. Thus, there were relatively more males than female respondents. The ages of tutors were either less than or equal to 35 years up till 56 years and over. However, the majority of respondents were within the age range of 36-45years. This was confirmed by 38.2% with a corresponding number of 102 respondents. The least age category of respondents comprised those tutors who were 56 years and above. In terms of teaching experience, majority of the tutors had taught between six and 10 years (112; 42.0%).

Few of the tutors had taught for more than 11 years, as more than one half of them had less than 11 years teaching experience. On the type of courses tutors handled, more than half of the respondents, taught education related courses, representing 50.9%. The remaining tutors belonged to business (69; 25.8%); and mathematics & sciences (62; 23.2%). On the level of programs taught, the diploma level had the majority of tutors with 61.4% out of the total respondents. The undergraduate and postgraduate tutors were 87 (33.3%) and 14 (5.2%), respectively. Finally, with respect to the location of tutors, 173 taught in urban study centers while the remaining 94 were in rural study centers.

Model Analysis

Measurement model

Figure 2 and **Figure 3** present results for the confirmatory factor analysis run for the PLS algorithm. In **Figure 2**, all the items measuring the various constructs as used in the questionnaire were all loaded. Thus, five items each were used to measure technology self-efficacy, LMS use behavior and previous technology use behavior.

Meanwhile, not all items loaded achieved the minimum loading of approximately 0.6 suggested by Hair et al. (2017). Thus, all such items were deleted, and the refined results are presented in **Figure 3**. The results presented in **Figure 3** show that all items forming each of the variables of the study obtained the minimum 0.60 approximation and above as suggested by Hair et al. (2017). Even though EXP 1 loaded 0.596, it was not deleted because it was above 0.5 and closer to 0.6 (Kaiser, 1974).

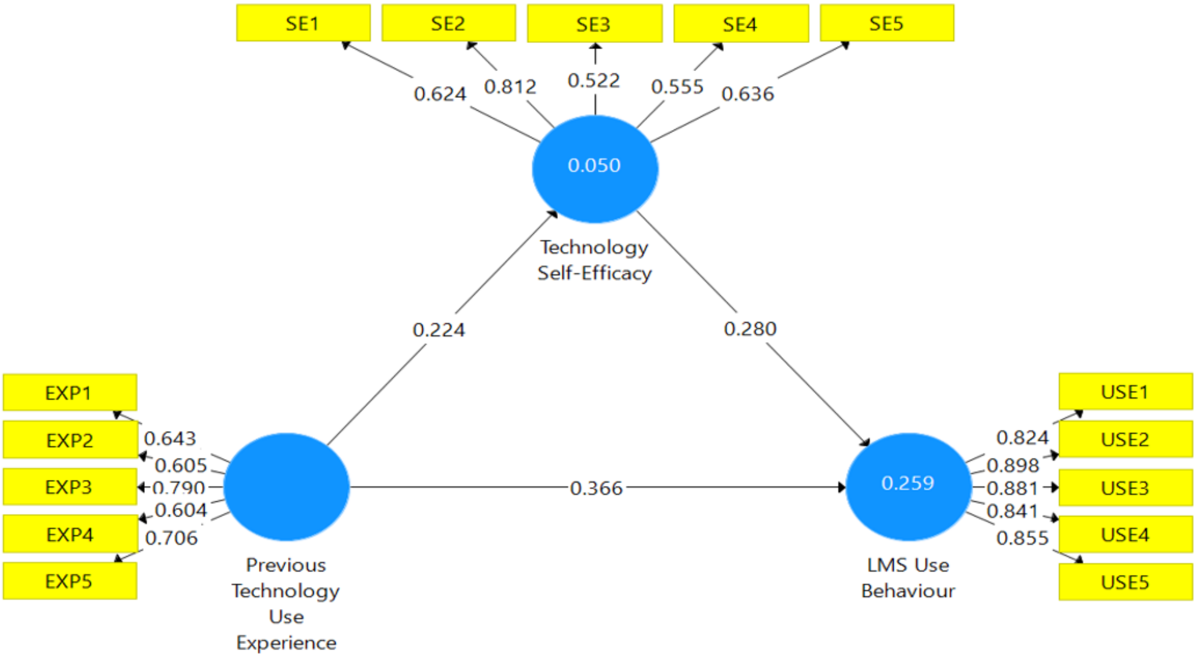

Figure 2. EFA algorithm for all items

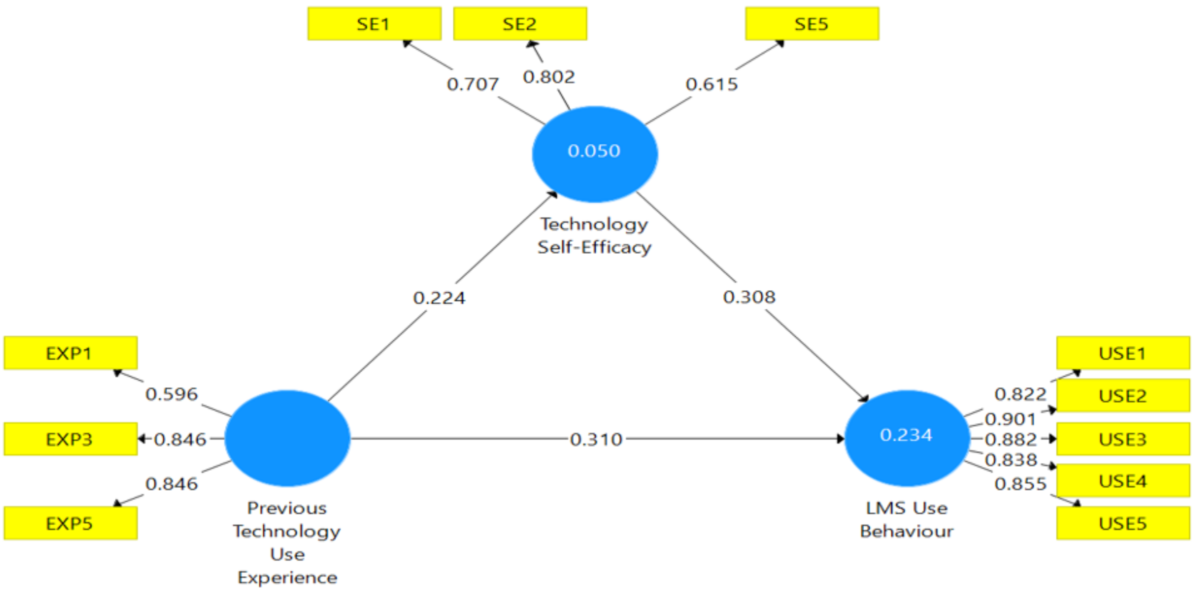

Figure 3. CFA algorithm for items that loaded well

Internal consistency measures for the analysis

Results for the internal consistency of the PLS model using four indicators–Cronbach's alpha, rho A, composite reliability, and average variance extracted (AVE) are presented in **Table 1**.

The reliability and validity results of the model as presented in the model indicate that AVE values for all variables ranged from 0.505 to 0.738, which were above the minimum threshold of 0.50 recommended by Kline (2015). Values obtained for the composite reliability for all constructs were between 0.751 and 0.918; and that of rho A were between 0.537 and 0.883. For Cronbach's alpha, values obtained also ranged between 0.524 and 0.882. Though the Cronbach's alpha and rho A values obtained for the technology self-efficacy variable were below the recommended 0.70 minimum threshold, it was not deleted because the variable attained the minimum threshold under the superior indicators such as composite reliability and AVE. Thus, all variables of the model achieved both reliability and validity standards.

Table 1. Construct reliability and validity

Variables	Cronbach's alpha	Rho A	Composite reliability	AVE
LMS use behavior	0.882	0.883	0.918	0.738
Previous technology use experience	0.700	0.744	0.813	0.597
Technology self-efficacy	0.524	0.537	0.751	0.505

Table 2. Heterotrait-monotrait ratio (HTMT)

Variables	LMS use behavior	Previous technology use experience	Technology self-efficacy
LMS use behavior	**0**		
Previous technology use experience	0.454	**0**	
Technology self-efficacy	0.521	0.307	**0**

Table 3. Collinearity statistics (VIF)

Variables	LMS use behavior	Previous technology use experience	Technology self-efficacy
LMS use behavior			
Previous technology use experience	1.053		1.000
Technology self-efficacy	1.053		

Discriminant validity

Heterotrait-monotrait ratio (HTMT) was used to check the uniqueness of each variable in the study for the discriminant validity as suggested by Henseler et al. (2015). **Table 2** presents the results indicating that all diagonal loadings for the same variable were zero and between variables of study were below 0.85 thresholds (Henseler et al., 2015). This suggested that discriminant validity was achieved for the PLS path model.

Multicollinearity

The study examined the existence of multicollinearity, using the variance inflated factors (VIF) as suggested by Hair et al. (2017). The threshold by Hair et al. (2017) posited that VIF values should be below 3.3 suggesting that the reflective model was multicollinearity-free. **Table 3** thus, shows the results for the multicollinearity analysis. It was clear from the results shown in **Table 3** that there was no presence of multicollinearity since all the inner values were below 3.3 thresholds.

Structural model and hypotheses testing

The study tested significance of hypothesized paths. **Figure 4** presents the results for the bootstrapping sequence of 5,000 samples utilized in the PLS bootstrap procedure as recommended by Hair et al. (2017).

Results of path analysis

Detailed results for path analysis and testing of hypotheses of the study are presented in **Table 4**. The R^2 values as presented in **Table 4**, supported by the adjusted R^2 values, indicate that the model explained about 21.8% variance in LMS use behavior by both technology self-efficacy and previous technology use experience. Results of the hypotheses testing as shown in **Table 4** also indicate that all variables in the model achieved statistical significance. That is previous technology use experience had a statistically significant relationship with LMS use behavior at (β=0.299, t=4.397, p=0.000); previous technology use experience had a positive and significant relationship with technology self-efficacy at (β=0.224, t=2.509, p=0.012). The results in **Table 4** further show that there was a positive and statistically significant relationship between technology self-efficacy and LMS use behavior for hypothesis three at (β=0.298, t=3.102, p=0.002). Finally, the results proved that technology self-efficacy positively and statistically mediated the relationship between previous technology use experience and LMS use behavior at (β=0.069, t=2.068, p=0.039).

The effect sizes obtained for each of the significant paths as represented in Table 4 showed that, f^2 values for the significant paths were also favorable based on Cohen (1988) suggestion that an effect size of 0.02 to 0.662 was acceptable. The unidimensional nature of the confidence intervals for the variables for all significant paths had valid and reliable significance without any spurious effect. Additionally, the significant results were further strengthened by the confidence level of 97.5%, with a minor error margin of only 2.5% indicated by the statistics obtained from the upper and lower boundaries respectively.

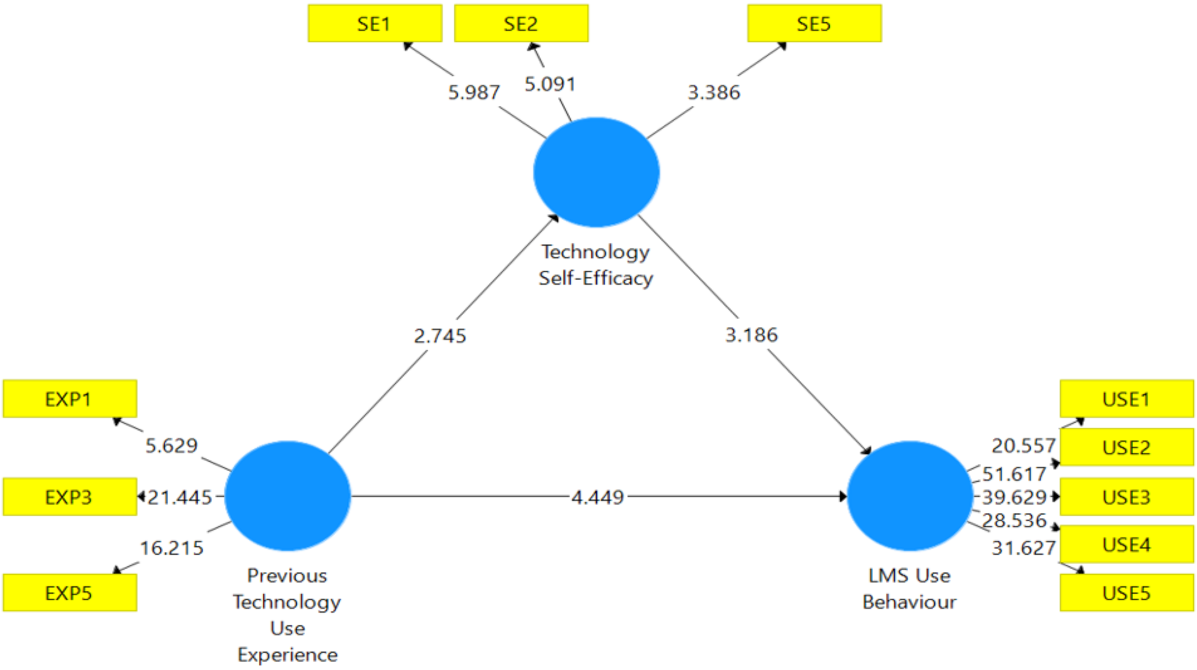

Figure 4. Bootstrapping results

Table 4. Path significance coefficients

	R-S			R-SA				
LMS use behavior	0.218			0.212				
Technology self-efficacy	0.050			0.047				
						CI		
Variables of the study	Beta	M	SD	TS	pV	2.5	97.5	f^2
Previous technology use experience->LMS use behavior	0.299	0.307	0.068	4.397	0.000	0.176	0.432	0.109
Previous technology use experience->Technology self-efficacy	0.224	0.237	0.089	2.509	0.012	0.007	0.386	0.053
Technology self-efficacy->LMS use behavior	0.298	0.299	0.096	3.102	0.002	0.098	0.460	0.108
Specific indirect effect								
Previous technology use experience->Technology self-efficacy->LMS use behavior	0.069	0.070	0.033	2.068	0.039	0.011	0.140	

Note. **p<0.000; *p<0.05 supported; R-S: R-square; R-SA: R-square adjusted; M: Sample mean; SD: Standard deviation; pV: p-values; CI: Confidence intervals; TS: t-values

DISCUSSION

The study determined the underlying causal relationships among the constructs: previous technology use experience, technology self-efficacy and LMS use behavior. The study results revealed significant influence of previous technology use on technology self-efficacy; technology self-efficacy on LMS use behavior as well as significant effect of previous technology use experience on LMS use behavior by distance education tutors in a higher educational institution.

The initial hypothesis of the study that previous technology use experience has a statistically significant relationship with technology self-efficacy means that individual's confidence in their ability to complete a task or achieve a goal was further enhanced by previous exposure to technology use. This is because previous exposure contributed to acquiring the necessary competence necessary for achieving what one wants to use the technology to achieve. The finding suggested that tutors' initial knowledge and experience with technology directly influenced their beliefs in ability to use LMS to achieve learning outcomes and to improve students' learning engagements. This meant that if instructors have prior technological knowledge and skills, they were more self-confident that they could use LMS to successfully accomplish their teaching and learning tasks (Bervell & Umar, 2018). In other words, the tutor's previous knowledge in technology minimized their initial anxiety to use LMS. Hence, tutors' previous knowledge and experiences with technology cannot be swept away when determining their technology self-efficacy. This is because it enabled them to develop deeper interest in using LMS and other technologies to teach. Likewise, the tutors' prior knowledge and experience of technologies helped them to view LMS usage as something worthwhile to be mastered (Elbitar, 2015) and were able to deal with associated challenges.

Additionally, the result of the second hypothesis of the study that technology self-efficacy related to LMS use behavior suggested that the tutors' capabilities to use technology influenced their LMS use behavior. The results meant that people would shun the use of LMS if they did not have self-efficacy or confidence in their ability to use the LMS to achieve their goals. Confidence and belief in one's ability to use LMS for the intended activities thus influence their behavior for the adoption or use of LMS platforms. Thus, any percentage increment or investment in enhancing the self-efficacy of users would lead to the same percentage return or increase in positive behavior of users to adopt and use LMS platforms. In other words, the strength of the tutor's beliefs that he or she is capable of using LMS to perform his or her duties and task, had a direct effect on their LMS use behavior (Chu, 2010; Chu & Tsai, 2009). The finding is in tandem with that of Hong et al.'s (2022) assertion that instructors with technology self-efficacy believe that they would be successful with technology use. Hence, they would try to do what they believed they could do with technology and choose to perform activities according to their technological efficacy.

Furthermore, there was a statistically significant predictive relationship between previous technology use experience and LMS use behavior. This implied that instructors who have had experience or encountered previous technology use had a higher propensity for adopting a behavior that would support LMS usage. Thus, the positive relationship signified that any percentage increase in experience with previous technology use would result in the same percentage increase in developing a positive attitude towards LMS usage. Individuals who were exposed to previous technology tend to overcome the phobia associated with technology use and would have developed the basic skills and interests necessary to operate on the LMS platform. Thus, previous technology use serves as a launchpad for positively influencing LMS use. This is consistent with earlier studies by Pan (2020) and Shih et al. (2006) who suggested that previous technological experience of students influenced how they organized their learning activities online. Specifically, teachers who had previous experience with technology for personal purposes or for teaching and learning, reported of higher use of LMS (Zwain, 2019). The findings added emphasis to the research of Shih et al. (2006) who stressed that people with more experiences with digital technologies used less time to organize their virtual space and had positive attitude towards teaching and learning with technologies (Bervell & Arkorful, 2020, Mormina, 2019).

Finally, finding for the possible mediation effect of technology self-efficacy on the relationship between previous technology use experience and LMS use behavior needed further explanation since it was a serendipity. This result provided the grounds to further argue that it is not enough to be exposed to previous technology use to totally persuade LMS usage behavior. Rather, there is the need for exposure to technology to result in technology self-efficacy to be able to induce a positive behavior for actual LMS use.

Implications

Tutors' previous experiences with technology must be considered for a successful adoption of a LMS platform. This was because tutors with prior technological experiences had higher expectations of using a LMS platform to support their teaching irrespective of the challenges that they might encounter. Additionally, before implementing LMS, it is prudent that tutors are made aware of the technological tools and skills required to use a LMS platform. This would allow them to up tool their competence and upskill the knowledge necessary for using a LMS platform. The result also implied that higher education institutions should endeavor to provide instructors with both technological training and hands-on activities that target specific use of LMS platforms prior to its implementation. Finally, higher educational institutions can automate most of their campus activities with technology in order to make the use of diverse technologies familiar to instructors. This way, the instructors are more likely to develop their technological skills and better have positive beliefs in themselves that they will be more capable of using the LMS to support their teaching and learning activities. This self-efficacy is crucial for LMS technology uptake because of the mediating effect it had on previous technology experience towards LMS use behavior. This presupposes that even though both previous technology use experience and technology self-efficacy significantly predicted LMS use behavior, the ultimate factor that will propel instructors to use LMS was their self-efficacy belief towards the technology.

Limitations and Suggestions for Future Research

The study did not test for any moderating effects (gender, age, course taught, etc.) on the predictors of LMS use behavior to determine the direction of effect. Future studies can look at these interesting findings.

There was no importance-performance map analysis (IPMA) test to statistically differentiate between the important and high performing predictors of LMS use behavior. It is recommended that future studies unravel these results.

The study did not differentiate among the various previous technology use experience (computer, internet, smart devices, etc.) to unravel their individual effects on technology self-efficacy and LMS use behavior. Future research can conduct such categorized analysis for verification of their effects on LMS use behavior.

Finally, the study did not differentiate among the various technology self-efficacy (computer, internet, smart devices etc.) to unravel their individual effects on LMS use behavior. It is suggested that future studies can specify the individual technology self-efficacies and perform their predictive effect analyses on LMS use behavior.

CONCLUSION

This study has made novel strides in defining and validating a definite model that integrated the tripartite effects of three important variables in technology acceptance research which were previous technology experience, technology self-efficacy and LMS use behavior. The results obtained have proven that there was a positive predictive tripartite effect among the three variables and provided an opportunity for further academic discourse within the LMS technology acceptance research. The gap that existed in literature on how these three variables related had been resolved through robust empirical statistical analyses by this study and also suggestions made for further research on the phenomenon for additional clarifications that could lead to certain intricating dimensions of the variables.

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Declaration of interest: Authors declare no competing interest.

Data availability: Data generated or analyzed during this study are available from the authors on request.

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