Utilization decision towards LMS for blended learning in distance education: Modeling the effects of personality factors in exclusivity

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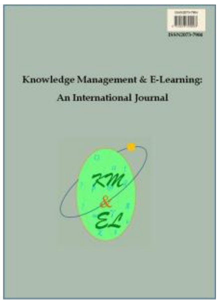

Knowledge Management & E-Learning: An International Journal (KM&EL)
ISSN 2073-7904

Recommended citation:
Bervell, B., & Umar, I. N. (2018). Utilization decision towards LMS for blended learning in distance education: Modeling the effects of personality factors in exclusivity. *Knowledge Management & E-Learning, 10*(3), 309–333.

Knowledge Management & E-Learning, 10(3), 309–333

Utilization decision towards LMS for blended learning in distance education: Modeling the effects of personality factors in exclusivity

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Abstract: Over the decades, personality factors (attitude, self-efficacy, anxiety and computer experience) have pervaded the underpinning determinants of behavioural intentions to accept and use emerging technologies, chiefly in purviews where integration is into the working processes that may be pro traditional. The chasm in the literature has been how these technology personality factors extensively relate within and among themselves in a definite model exclusive to these factors, and their overall variance explained in usage intentions. In view of this, the study adopted a quantitative design and employed the questionnaire for data collection from 267 distance education tutors from a countrywide spread. Findings from structural equation modeling (SEM) technique revealed 'technology attitude' and 'technology experience' to be major predictors of usage intentions. The direct effects of technology anxiety and self-efficacy on behavioural intention were fully mediated by technology attitude. Non-linear relationships showed that technology self-efficacy, experience and anxiety were all antecedents of attitude towards LMS, while 'technology experience' alone determined 'technology self-efficacy'. The Important-Performance Map Analysis (IPMA) revealed attitude as the most important and performing construct in determining behavioural intention. Technology attitude had technology related self-efficacy as its most important and performing construct determinant. The overall variance explained by the derived model was 35%. The study recommended that technology attitude and experience should be prioritized in LMS-related blended learning implementation in distance education. It further proposed that future studies include moderators on technology personality factors in determining usage intentions to further improve the model's robustness.

Keywords: Technology personality factors; Blended learning; Usage intentions; Linear relationships; Non-linear relationships; Distance education

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1. Introduction

The distance education phenomenon has spanned three to four generations (Anderson & Dron, 2010), offering opportunities for non-conventional education outside the walls of several institutions, especially for working adults. This has widened the scope of education for people constrained by time and resources, providing a caveat to accessing higher education. From a modest beginning of paper-based correspondence (Aoki, 2012) to satellite broadcast, audio, video and audio-visual broadcast via television, the advent of the internet, has rather changed the phase of distance education. The internet has made it possible for distance learners to have real time in-class participation, access remote information and interact with both peers and instructors at their own time, pace, space or place. This development has emerged in its trail terms such as online learning and electronic learning (e-learning). According to Smith and Rupp (2004), electronic learning provides such advantages as being less expensive, faster, accessible and promote students' control over the whole learning process.

Falch (2004) proposed a four-stage model approach to e-learning methodologies embedded with a spectrum of illustrated learning. The fourth model rather involves part of the learning process occurring in the classroom (face to face) and the other component being carried outside the classroom via ICT-based facilities and tools. This is the combination of traditional face to face with e-learning, often termed as blended learning, which is most widespread in today's higher educational institutions. According to Garrison and Kanuka (2004), the blended mode of e-learning reinforces both an interactivity and communication learning environment and provide meaningful learning outcomes. It thus provides versatility for both in and outside classroom learning and interaction among students, peers and teachers. Driscoll (2002) for instance, defines blended learning as intermixing of any instructional forms to achieve educational goals, whereas Garrison and Kanuka (2004) explain the term to simply mean integrating classroom teaching with online experiences. This, they opine, facilitates independent and collaborative learning experiences which build a community of enquiry and a platform for free and interactive dialogue. Anderson and Dron (2010) share the importance of technology and pedagogy for the success of distance education, indicating that the former creates the beats while the latter defines the move. However, underpinning the blended learning practice is the Learning Management System (LMS).

Ellis (2009) explains LMS to be a software application for the administration, documentation, tracking, and reporting of training programs, classroom and online events, e-learning programs, and training content. It is also the use of a web-based communication, collaboration, learning, knowledge transfer and training. Yueh and Hsu (2008) assert that LMS supports activities such as presenting information, managing courses materials, collecting information and evaluating students. This provides essential advantages to educational institutions in general and instructors in specific. According to Naveh, Tubin, and Pliskin (2010), the uniqueness and quality of LMS to education has influenced most higher educational institutions to invest heavily in implementing such a 'new' learning approach. Nonetheless, Al-Busaidi (2012), Cigdem and Topcu (2015), suggest that although LMS is widely used by institutions to assist distance learning, the correct use of these tools is crucial for success in course and knowledge management (Wang, Noe, & Wang, 2014; Zhang, de Pablos, & Xu, 2014). This view was earlier supported by Park (2009) that though the institutions are providing blended learning to support distance education learning programmes, they are experiencing enormous difficulties. Again, the increasing trend of LMS acquisition and implementation does not parallel the usage by instructors, as instructor online presence still seems rare.

This, according to Sasseville (2004), could be related to the technology associated changes that are perceived as personal by instructors, rather than social challenges. Earlier in the literature, Walsham (2000) proposed the need to consider human diversities in addition to the technical and technological tendencies. McGill, Kobas, and Renzi (2014) reiterate that instructors play a salient role in specifying the effectiveness, success or inefficacies of LMS usage. Hence, the inability of instructors to understand the impact of LMS enabled blended learning, could be the underlying factor for resistance (Avidov-Ungar & Eshet-Alkalai, 2011). In the view of Nihuka and Voogt (2012), instructors' resistance to this pedagogical-technological change is a personal factor that impedes LMS usage acceptance. This, they believe is a function of their attributes such as attitudes (Teo, Ursavas, & Bahçekapili, 2012), self-efficacy (Ong & Lai, 2006), anxiety due to lack of ICT skills (Buabeng-Andoh, 2012) as well as computer and ICT related experiences based on generational divide (Jones & Shao, 2011). Together, these personal related traits of instructors constitute their personality factors that determine to a larger extent their acceptance or otherwise of LMS for blended learning in distance education.

Erciş and Deniz (2008) define personality as an individual's situational response behaviour. In the view of Erkuş and Tabak (2009), personality is a consistent, stable and conventional relationship of an individual with his internal and external environments and is interrelated with all of the personal characteristics. It also defines "a dynamic organisation within the individual of those psychophysical systems that determine his characteristic behaviour and thoughts" (Allport, 1961).

Personality factors thus seem to affect the totality of life of individuals as a set of characteristics that differentiate them from others in terms of both natural and artificial tendencies. Hence, it can be argued that personality factors are significant traits which cause different perceptions or responses against the similar instances (Erkuş & Tabak, 2009). In technology adoption studies, model developments by earlier authors who made efforts to reveal determinants of individual acceptance of technology, emphasized the influence of technology related personality factors. Fishbein and Ajzen (1975), Ajzen (1985) and Davis, Bagozzi, and Warshaw (1989), all stressed the importance of technology attitude to have an effect on individual acceptance of technology; Compeau, Higgins, and Huff (1999) highlighted on affect (attitude), computer anxiety and self-efficacy, while Thompson, Higgins, and Howell (1991) narrowed on computer experience and affect (attitude). Relatively recent empirical evidence on how personality factors may influence the technology acceptance of individuals could be traced to studies from Erdoğmuş and Esen (2011), Shih and Fan (2013) and others.

Consequently, personality factors have been demonstrated to be associated with technology acceptance in various ways and among several technologies, particularly in higher education. According to Svendsen, Johnsen, Almås-Sørensen, and Vittersø (2013), the personality dimension often defined to be either introversion or extroversion, is related to many aspects of human–computer interaction. In higher education technology acceptance research, the emphasis on personality influence has been towards either faculty members or students in relation to their willingness to interact with technology. Though Venkatesh, Morris, Davis, and Davis (2003) projected a non-effect of personality factors in the UTAUT model, other authors (Tiew, 2014; Oye, Iahad, & Rahim, 2012) have disputed this stance. However, in appreciating the effect of personality factors on behavioural intention to adopting/accepting LMS technology, most studies (Fagan, Neil, & Wooldridge, 2004; Simsek, 2011; Lee & Huang, 2014; Olatubosun, Olusoga, & Shemi, 2014; El-Gayar & Moran, 2016) have not concentrated on personality factors alone but interspersed with other constructs.

Additionally, these studies that attempted modeling personality factors incorporated one, two or at most three of these factors and tested for correlations and causality. They neglected other analyses such as mediation, effect sizes and important–performance map analysis (IPMA) among these technology personality factors in determining LMS behavioural intentions towards usage. This provides a shadow result of the total effects of personality factors in technology acceptance research. Another gap in the literature is on how the modeling of personality factors alone determine the entire variance explained in technology acceptance research in distance education and what significant non-linear relationships exist among personality factors in a definite model (Bervell & Umar, 2017). Finally, most studies have also concentrated overly on main stream university usage of LMS and not in distance education mode environments where instructors and students are scattered across a region or country.

In Social Cognitive Theory (SCT) of Information Systems, Compeau et al. (1999) incorporated computer self-efficacy, anxiety and affect (attitude) in their model. Thompson et al. (1991) in their Model of PC Utilization, modeled a relationship between experience with PC's and affect (attitude) towards PC's. This study thus combines the two models and chooses only the four technology related personality constructs to develop a conceptual model exclusive to them. Against this background, the study is supported by the following research questions:

1. What is the relationship between personality factors and behavioural intention of LMS usage by distance education tutors?
2. What non-linear relationships exist among personality factors in determining LMS usage intentions?
3. What mediation effects exist among personality factors in determining LMS usage intentions?
4. What is the overall variance explained by personality factors in LMS usage intentions?

2. Literature review

2.1. Towards model development and hypotheses formulation

2.1.1. Relationship between technology personality factors and usage intentions

Instructor technology attitude as a contributing factor to usage intention towards technology, has been key in the literature of acceptance research. Attitude represents an individual's favourable or unfavourable assessment of engaging in a behaviour of interest (Ajzen, 2005). Within the technology domain, attitude could be viewed as a potential adoptor's evaluation either adverse or convenient, towards using a particular technology to perform a specific task. In LMS usage intentions for blended learning, instructors have exhibited varied attitudes towards its implementation. For instance, Alghamdi and Bayaga (2016) as well as Park (2009), found positive attitudes of university instructors to be an important factor influencing their usage of LMS for blended learning. Similar results were recorded by Oye et al. (2012) who looked at ICT integration in general. In TAM, Davis (1989) positions attitude to influence users' intention to adopt technology if they are at ease with its usage and find it more useful. Research evidence from Thomas, Singh, and Gaffar (2013) and El-Gayar and Moran (2016) reveal the construct to be a strongest predictor of behavioural intention; an assertion earlier disputed by Venkatesh et al. (2003). Recent results by Dlalisa (2017), Boateng, Mbrokoh, Boateng, Senyo, and Ansong (2016) support findings from the former authors (Thomas et al., 2013; El-Gayar & Moran 2016). In the distance education setting, it is expected that there will be consistency in the effect of attitude on behavioural intentions. Against this premise, the study hypothesizes that:

***H1**: Technology attitude of distance education tutors will have a positive and significant relationship with LMS usage intentions for blended learning.*

Experience in general, depicts the combination of an individual's skills, practice or familiarity with utilization of a specific object or procedural practices that span a period of time. On the other hand, technology experience explains the amount of exposure that a user has obtained with the interaction of a particular technology (Willis, 2008). Ball and Levy (2008) opine that, an individual's computer usage and skills over time has a relationship with usage intention extension to other similar technologies. Thus, individuals who are often in the world of computer usage, embrace computer technologies with ease. In this instance, instructor computer experience over time may provide a basis for accepting LMS technology usage in distance education. The more computer technology exposed distance education instructors are, the more positive their behavioural intentions. In relatively current literature, authors such as De Smet, Bourgonjon, De Wever, Schellens, and Valcle (2012) found individual computer technology experience to determine LMS usage intentions. Similar results were obtained by Usoro, Echeng, and Majewski (2013) as well as Tiew (2014), all in a regular university setting. In the view of Kennedy, Judd, Churchward, Gay, and Krause (2008), preferences of using a technologically oriented pedagogy, is a function of previous positive experiences, skills and abilities with other similar technologies. Hence the hypothesis:

***H2**: Technology experience of distance education tutors will have a positive and significant relationship with LMS usage intentions for blended learning.*

Self-efficacy as a personality factor, defines a person's perceptions of his or her ability to perform a specific task. Bandura (1997) and Zimmerman (2000) explain the construct to be the belief of one's ability to engage in specific actions that result in a desired outcome. However, technology self-efficacy (TSE) which differs from the general psychological term, is the belief in one's ability to successfully perform a technologically sophisticated new task (McDonald & Siegall, 1992). LMS technology has aided most university courses to be both online and face to face (blended) requiring a compulsory teacher-student online interaction component. The online aspect becomes obtainable when instructors are able to perform their task successfully. This to a large extent rides on their knowledge and skills needed for online interactions. The concept of self-efficacy thus comes to the fore to determine willingness. Instructors will be able to use LMS for blended learning if they perceive that they have the ability to use it for such purposes. This is further dependent on how they perceive the usage of LMS to be easier to fulfil online pedagogical practices. According to Bandura (1983), instructors with high technological instructional self-efficacies will provide the necessary scaffolding towards intrinsic interest in students as well as self-directedness. In a similar vein, the technological self-efficacy is likely to be positively related to technology (LMS) integration (Kim, Kim, Lee, Spector, & DeMeester, 2013). Empirical evidence from Park (2009), Lwoga and Komba (2015), Olatubosun et al. (2014) prove a positive relationship between self-efficacy and usage intentions in regular university settings. On this basis, the study proposes that:

***H3**: Technology self-efficacy of distance education tutors will have a positive and significant relationship with LMS usage intentions for blended learning.*

In general psychological terms, anxiety is related to the fear individuals demonstrate towards specific tasks or situations. But an affective emotional response arising from the use of or (thought of using) a technology, represents a potential adoptor's technology anxiety (Cohen, Bancilhon, & Sergay, 2013). Venkatesh et al. (2003) explained the construct to be a degree of individuals' apprehension or even fear when they are faced with the possibility of using computers. This is usually asymptotic of individuals when newly adapted or introduced to technology as a result of difficulty in usage or personal incompetence or lack of technological self-efficacy (Feihn, 2010). Distance education instructors' technology anxiety thus projects a concern in the usage of LMS for blended learning in distance education delivery. In their study of LMS acceptance, Olatubosun et al. (2014) identified anxiety as one of the determinants of intentions to adoption. Their results resonated that of Al-alak and Alnawas (2011) and that of Oye et al. (2012). For distance education tutors, it is envisaged that their technology anxiety levels will negatively influence LMS usage intentions. It is thus hypothesized that:

***H4**: Technology anxiety of distance education tutors will have a negative but significant relationship with LMS usage intentions for blended learning.*

2.2. Non-linear relationships between technology personality factors (attitude, experience, self-efficacy and anxiety)

Non-linear relationships of constructs, capture the explicit variances and commonalities in outcomes for several components of a construct (Roberts ,1986). Kock (2016) explains non-linear models as useful in generating causal explanations and providing reconciliation for inconsistent findings from diverse sources. The underlying literature supporting non-linear modeling provides a basis for unravelling non-linear relationships that may exist among technology personality factors based on theoretical perspectives.

Ajzen and Fishbein (2005) in Theory of Planned Behaviour (TPB), posited that individual behavioural intention to perform a target task depends partly on attitude but explained further that attitude itself is a direct product of other determinants. With respect to other technology personality factors, Thompson et al. (1991), Compeau et al. (1999), Sam, Othman, and Nordin (2005) theorized that attitude is influenced by the combined effects of self-efficacy, experience and anxiety factors. Thus, individuals who possess high technology self-efficacy levels as a result of accumulated computer experience overtime, are likely to generate a positive attitude towards other technology (LMS) usage intentions (Thompson et al., 1991; Sam et al., 2005). The reverse of this relationship is also possible when technology self-efficacy and experience levels are low, creating an atmosphere of high anxiety levels, whereas low technology anxiety levels will produce a positive attitude towards LMS usage.

However, technology anxiety and self-efficacy are a function of computer or technology use experience over time. Copious experiences with technology are likely to generate a high belief of self-efficacy (Elbitar, 2015) and low anxiety towards the use of LMS technology (Bozionelos, 2001) while a reciprocal effect of low anxiety in turn determines an individual's high self-belief in usage of technology and vice versa (Weil & Rosen, 1995). Thus, both technology self-efficacy and experience have a negative relationship with technology anxiety (Compeau et al., 1999; Bozionelos, 2001). The mish mash of relationships between the technology personality factors produce an intertwined model relationship that require empirical testing. However, studies are silent on the possible mediating effect that could arise from the relationships between these factors. Thus, based on the possible non-linear relationships that may exist within these technology personality factors, the study further hypothesizes that:

H5*: Technology self-efficacy of distance education tutors will have a positive and significant relationship with their technology attitude towards LMS usage intentions for blended learning.*

H6*: Technology anxiety of distance education tutors will have a negative but significant relationship with their technology attitude towards LMS usage intentions for blended learning.*

H7*: Technology experience of distance education tutors will have a positive and significant relationship with their technology attitude towards LMS usage intentions for blended learning.*

H8*: Technology self-efficacy of distance education tutors will have a negative but significant relationship with their technology anxiety towards LMS usage intentions for blended learning.*

H9*: Technology experience of distance education tutors will have a negative but significant relationship with their technology anxiety towards LMS usage intentions for blended learning.*

H10*: Technology experience of distance education tutors will have a positive and significant relationship with their technology self-efficacy towards LMS usage intentions for blended learning.*

2.3. Relationship between behavioural intention and use behaviour

Most of the technology adoption models postulate behavioural intention as a covert evidence of actual behaviour, influenced by other environmental, systemic and personality factors. Behavioural intention is proposed as a reflection of an indication of an individual's willingness to engage in a certain behaviour, in relation to a specific object, tool or person (Kim & Hunter, 1993a). Individuals, prior to exhibition of target behaviours, form cognitive intentions (Venkatesh et al., 2003; Ajzen, 1985). Intentions thus become a close antecedent of predictive technological behaviour (Kim & Hunter, 1993b). In effect, once an individual form a positive intention towards a particular technology use, it will lead to the performance of the actual use behaviour which was in mind, making the intentions now explicit. Actual or use behaviour becomes the extent and purposes to which a technology is utilized (Venkatesh et al., 2003) and eventually becomes the product of intentions when there is an extension of the intent motives of technology use to actual use (Davis et al., 1989). Therefore, a direct relationship exists between behavioural intention and use behaviour (Davis, 1989). Thus, the hypothesis:

H11: *Behavioural intention of distance education tutors will have a positive and significant relationship with their use behaviour of LMS for blended learning.*

The final proposed model based on the hypotheses is depicted in Fig. 1.

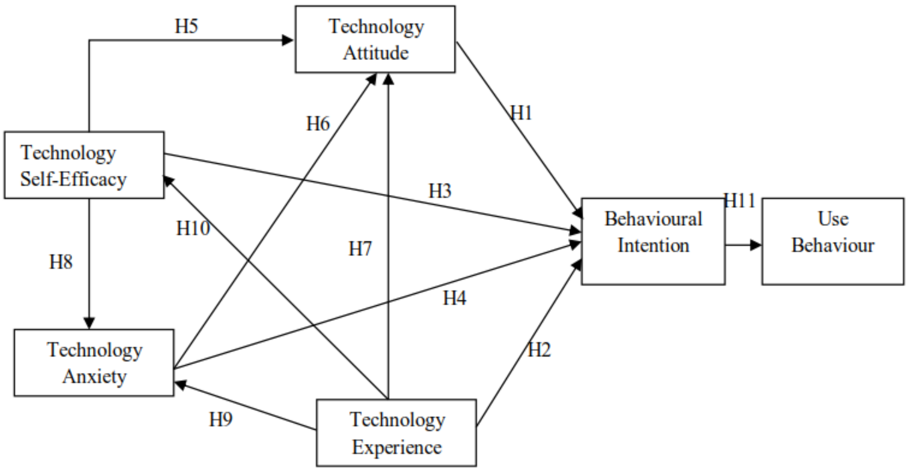

Fig. 1. Proposed model for the study

3. Methodology

3.1. Design and instrument

The study adopted a quantitative design employing the questionnaire as the instrument for data collection. The questionnaire comprised two broad sections, being the demographic section and technology personality factors (technology attitude, anxiety, self efficacy and experience) as well as the dependent (behavioural intention and use behaviour) variables' section. A total number of 24 items were covered in the instrument, anchored on a five-point Likert scale with items modified from Venkatesh et al. (2003), Park (2009), Al-alak and Alnawas (2011).

3.2. Sampling and data collection

The target population was about 1,500 distance education tutors that had a country wide spread in various regional locations. However, the accessible population were 400 tutors who were involved in the piloting process of the Fronter LMS for blended learning. In view of this, a cluster sampling technique was employed to allocate sample sizes to the various regions and their peculiar study centres. The process produced a final sample size of 280 tutors which provided adequate representativeness. Accordingly, 280 questionnaires were distributed across the various regional study centres. Out of this total number, 267 were filled and returned, representing 95.4%. The returned questionnaires were screened and imputed into SPSS version 21 software and then exported as a comma separated values (csv) file into Smart PLS software 3.2.6 for statistical analysis.

4. Analysis

4.1. Respondents' profile

Initial analysis focused on the demographic characteristics of the respondents. This information is presented in Table 1.

Table 1
Profile of respondents

Profile	Frequency	Percentage
Gender		
Male	164	61.4%
Female	103	38.6%
Age		
(≤35)	67	25.1%
(36-46)	102	38.2%
(47-57)	64	24.0%
(≥58)	34	12.7%
Face to face experience		
(≤5yrs)	98	36.7%
(6-11yrs)	112	42.0%
(≥12yrs)	57	21.3%

From Table 1, the 267 tutors comprised 164 males and 103 females representing 61.4% and 38.6% respectively. The age groupings ranged from about 35 years to 58 years and over, with face to face experience ranging from 5 years to 12 years and above. The results from the table signifies a relatively more male respondent than females. The age group (36-46) had the highest frequency with 38.2% out of the total percentage, while those tutors with 6-11 years of face to face experience constituted the majority (N:112, 42.0%) of the entire sample.

4.2. Results for model

This research employed the SmartPLS 3.2.6 software for the statistical analysis of both the measurement and structural model components of the hypothesized model. In Partial Least Squares Structural Equation Modeling (PLS-SEM), the two-stage evaluation of the outer and inner models is the standard for model assessment and relationship testing (Hair, Hult, Ringle, & Sarstedt, 2017). Since the hypothesized model is the reflective type, it was evaluated based on validity and reliability as well as path analysis, coefficient of determination, effect size, predictive relevance and the importance-performance map analysis (IPMA) (Hair, Hult, Ringle, & Sarstedt, 2014).

4.3. Assessment of the measurement (outer) model

In assessing the validity and reliability of the reflective model, the convergent validity, average variance estimate and item loadings were the criteria. From Table 2, the PLS Algorithm results for outer loadings were between 0.61-0.89. All outer loadings of the constructs were higher than the threshold of 0.708 (Hair et al., 2017) except three items from three different constructs (ANX1 0.68; EXP2 0.63 and SE5 0.61) which were below 0.708. However, these items were retained because their deletion did not improve the average variance estimate but rather affected the content validity. According to Hair et al. (2014) when such a condition pertains, the items should be retained in the model. Nonetheless, after PLS algorithm procedure for Confirmatory Factor Analysis, some items were deleted because of low loadings of less than 0.5 (Hair et al., 2014).

Composite reliability values ranged between 0.74 and 0.90, all higher than the 0.7 criterion (Hair et al., 2017). In fulfilling the average variance estimates criteria, all the values from the constructs were between 0.5 and 0.72, satisfying the acceptable minimum values of 0.5 (Hair et al., 2017). Based on the statistics obtained for the measurement model, validity and reliability standards were achieved.

Table 2
Convergent validity and reliability of measurement model

Construct	Items	Loadings	Composite Reliability	Average Variance Extracted (AVE)
Tech. Anxiety	ANX1	0.68	0.88	0.65
	ANX2	0.87		
	ANX3	0.89		
	ANX5	0.77		
Tech. Attitude	ATT1	0.83	0.90	0.67
	ATT3	0.72		
	ATT4	0.86		
	ATT5	0.86		
Behavioural Intention	BI1	0.81	0.87	0.63
	BI2	0.82		
	BI3	0.75		
	BI4	0.80		
Tech. Experience	EXP1	0.70	0.78	0.54
	EXP2	0.63		
	EXP5	0.86		
Tech. Self Efficacy	SE1	0.72	0.74	0.50
	SE2	0.75		
	SE5	0.61		
Use Behaviour	USE1	0.83	0.90	0.72
	USE4	0.86		
	USE5	0.86		

Note. AVE = (summation of squared factor loadings)/ (number of construct's items); Composite reliability = (square of the summation of the factor loadings)/ [(square of the summation of the factor loadings) + (square of the summation of the error variances)] (Yeap, Ramayah, & Soto-Acosta, 2015; Hair et al., 2014)

4.4. Discriminant validity

Constructs in a model have to differ in terms of measurement from other constructs. Fornell and Larcker (1981) recommend the correlation of constructs to be compared with the square root of the average variance estimate for a particular construct. Thus, the diagonal loadings have to be greater than their corresponding vertical loadings for other constructs. Table 3 depicts all bolded diagonal loadings being higher than their vertical counterparts. Items in the constructs within the model measured discriminately, achieving the threshold.

Table 3
Discriminant validity

Construct	ANX	ATTU	BI	EXP	SE	UB
Tech. Anxiety	**0.81**					
Tech. Attitude	-0.17	**0.83**				
Behavioural Intention	-0.13	0.55	**0.80**			
Tech. Experience	-0.11	0.30	0.36	**0.74**		
Tech. Self Efficacy	-0.10	0.55	0.38	0.23	**0.70**	
Use Behaviour	-0.19	0.53	0.52	0.38	0.36	**0.86**

Note. Diagonals (bolded) represent the square root of the average variance extracted while the off-diagonals are correlations among constructs; Diagonal elements should be larger than off-diagonal elements in order to establish discriminant validity (Yeap et al., 2015; Hair et al., 2014); Tech. = Technology

4.5. Heterotrait-Monotrait ratio (HTMT)

A more rigorous measure of discriminant validity is the HTMT (Henseler, Ringle & Sarstedt, 2015). This is the product of the average correlations of the indicators across constructs measuring different phenomena relative to the average of the correlation of the indicators within the same construct, thus the ratio of the between- trait correlations to the within-trait correlations (Hair et al., 2017). As a strict criterion, the HTMT should be less than 0.85 but a more acceptable parameter is less than 0.90. From Table 4, the HTMT values of the constructs were all lower than the 0.85 strict criterion, thus the model satisfied the HTMT strict standard.

Table 4
Heterotrait-Monotrait ratio

Construct	ANX	ATTU	BI	EXP	SE	UB
Tech. Anxiety	**0**					
Tech. Attitude	0.19	**0**				
Behavioural Intention	0.16	0.64	**0**			
Tech. Experience	0.17	0.30	0.46	**0**		
Tech. Self-Efficacy	0.15	0.82	0.58	0.32	**0**	
Use Behaviour	0.22	0.60	0.61	0.46	0.54	**0**

Note. Heterotrait-Monotrait Ratio (HTMT), which is the average of the correlations of indicators across constructs measuring different phenomena, relative to the average of the correlations of indicators within the same construct (Henseler et al., 2015)

4.6. Assessment of structural model

In assessing the structural model, the relationships and significance of path coefficients, coefficient of determination, t-statistics, mediation effects, effect sizes, predictive relevance and IPMA were analyzed (Hair et al., 2017).

4.6.1. Path analysis and hypotheses testing

For path analysis, a bootstrapping procedure of 5000 samples was used to correct for non-normality and calculate for significance of model hypotheses. The graphical results of the bootstrapping analysis are presented in Fig. 2.

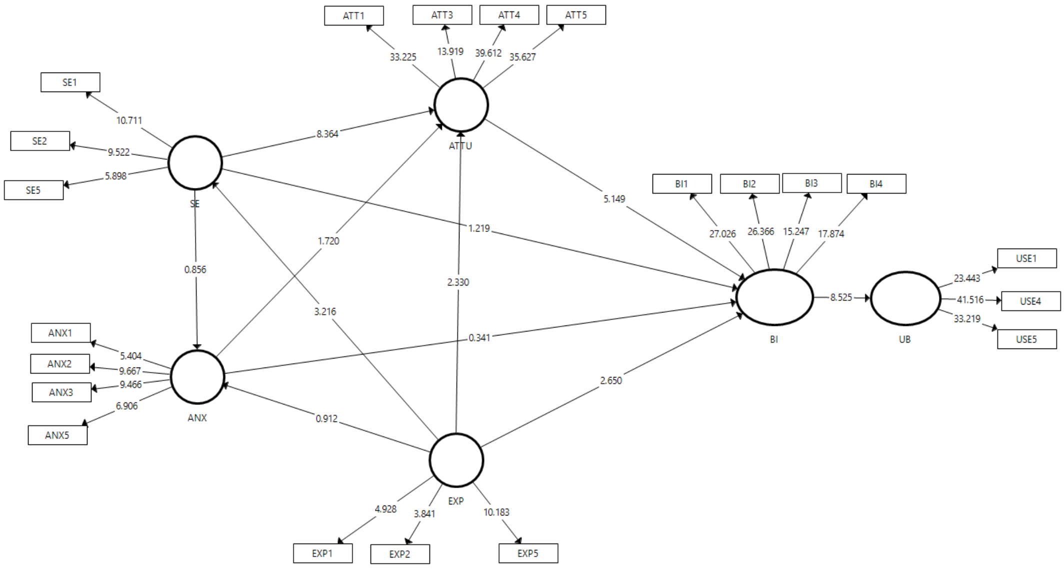

Fig. 2. Results from PLS-SEM bootstrapping procedure

Table 5
Results from structural analysis and hypotheses testing

Hypotheses	**Relationship**	**Std. Beta**	**Std. Error**	**t-value**	**Decision**	**f^2**
H1	ATTU -> BI	0.44	0.08	5.15**	Supported	0.19
H2	EXP -> BI	0.21	0.08	2.65**	Supported	0.06
H3	SE -> BI	0.08	0.07	1.22	Not Supported	
H4	ANX -> BI	-0.02	0.06	0.34	Not Supported	
H5	SE -> ATTU	0.5	0.06	8.36**	Supported	0.37
H6	ANX -> ATTU	-0.11	0.06	1.72*	Supported	0.02
H7	EXP -> ATTU	0.17	0.07	2.33**	Supported	0.04
H8	SE -> ANX	-0.07	0.08	0.86	Not Supported	
H9	EXP -> ANX	-0.11	0.09	0.91	Not Supported	
H10	EXP -> SE	0.23	0.08	3.22**	Supported	0.06
H11	BI -> UB	0.52	0.06	8.53**	Supported	0.37

*Note. $p<0.01$**, $p<0.05$**

The tabulated results from the bootstrapping procedure are exhibited in Table 5.

With respect to Table 5, the initial assessment was the determinants of behavioural intention, proceeded by attitude, anxiety, self-efficacy, and use behaviour. From the table, the beta coefficients and t-statistics indicated that two constructs, technology attitude (β=0.44; t=5.15, p<0.01) and technology experience (β=0.21; t=2.65, p<0.01) were positively related to behavioural intention and the relationships were very significant with the former being the stronger. However, technology anxiety (β=-0.02; t=0.34, p>0.05) and technology self-efficacy (β=0.08; t=1.22, p>0.05) had a negative and positive relationship with behavioural intention respectively, but were insignificant in prediction.

With reference to the antecedents of technology attitude, both the constructs, technology self-efficacy (β=0.5; t=8.36, p<0.01) and technology experience (β=0.17; t=2.33, p<0.01) were positively and significantly related to it. On the other hand, technology anxiety (β=-0.11; t=1.72, p<0.10) had a negative but significant relationship with technology attitude albeit the weakest predictor. Technology self-efficacy proved the strongest predictor of technology attitude.

Interestingly, neither technology self-efficacy (β=-0.07; t=0.86, p>0.05) nor technology experience (β=-0.11; t=0.91, p>0.05) determined technology anxiety, even though as expected, the relationships were negative. Technology experience (β=0.23; t=3.22, p<0.01) nonetheless was positive and the strongest predictor of technology self-efficacy. Finally, behavioural intention (β=0.52; t=8.53, p<0.01) strongly predicted use behaviour and their relationship was positive. In sum, the results from Table 5 confirm that hypotheses H1; H2; H5; H6; H7; H10 and H11 were all supported excluding H3; H4; H8 and H9.

Further assessment was conducted on the predictive significance of the accepted hypothesized constructs' relationships in the model. Information provided by t-statistics and p-values only show the presence or otherwise of effects neglecting the actual size thereof (Sullivan & Feinn, 2012). Kline (2015) recommends effect sizes (f^2) of 0.005, 0.01 and 0.025 to indicate small, medium and large effect sizes respectively (Hair et al., 2017). The f^2 statistics from Table 5 ranged from 0.02 to 0.37 representing medium to large effect sizes of the accepted hypothesized relationships. This means the relationships are reliable for policy and practice.

In addition to the effect sizes, the coefficient of determination and predictive relevance of the model were analyzed. Cohen (1988) suggested an R^2 value of 0.35 and above to indicate a substantial model (Yeap et al., 2015) whereas as a relative measure of predictive relevance, Q^2 values of 0.02, 0.15, and 0.35 indicate that an exogenous construct has a small, medium, or large predictive relevance for a certain endogenous construct (Hair et al., 2014). From Table 6, the coefficients of determination values were 0.34 and 0.35 for technology attitude and behavioural intention respectively, indicating a good model. The Q^2 values of 0.21 and 0.24 signified a good model predictive relevance.

Table 6
Co-efficient of determination and predictive relevance

Construct	**R^2**	**Q^2**
Tech. Attitude	0.34	0.21
Behavioural Intention	0.35	0.24

Note. Q^2 signifies predictive relevance R^2 signifies coefficient of determination

4.7. Mediation effects

The insignificance of technology self-efficacy and technology anxiety in predicting behavioural intention, informed a further mediation analysis. Preacher and Hayes (2008) suggested a bootstrapping of the indirect effects to statistically confirm full mediation or otherwise by an initial predictive construct (Hair et al., 2014). This further proves that the absence of an initial predictive construct (technology attitude) causes the previously insignificant relationship between independent variables (technology self-efficacy and technology anxiety) and a dependent variable (behavioural intention) becomes significant. Results of the bootstrapped indirect effects of technology attitude on both technology self-efficacy and technology anxiety are shown in Table 7.

Table 7
Bootstrapping results of indirect effects

Relationship	Std. Beta	Std. Error	t-value	Decision
ANX ->ATTU-> BI	-0.1	0.0	2.2	Supported
SE->ATTU->BI	0.2	0.0	4.6	Supported

*Note. p<0.01**

Results from Table 7 prove a full mediation effect of technology attitude on technology anxiety and self-efficacy. Thus, the direct effects of technology anxiety and self-efficacy on behavioural intention were fully absorbed by the inclusion of technology attitude in the model. The variables (technology related self-efficacy and anxiety) become direct determinants of technology-related attitude but indirect factors of behavioural intention. Thus, they rather lead to the formation of technology attitude (positive or negative) towards LMS intention behaviour.

4.8. Importance-performance map analysis (IPMA)

The Importance-Performance Map Analysis (IPMA) emphasizes the individual performance and relevance of predictive constructs on their dependent variable, relative to other predictor constructs in a model (Hair et al., 2014). The IPMA utilizes the unstandardized effects to promote a *ceteris paribus* interpretation of predecessor construct's impact on the target construct (Ringle & Sarstedt, 2016). In order to determine the importance of the significant relationships on key dependent constructs in the model, the IPMA was conducted for both behavioural intention and technology attitude. Table 8 and Table 9 display the results.

4.8.1. Importance-performance map analysis for behavioural intention

Table 8
Performance index and important index values

Construct	Importance Index	Performance Index
Tech. Anxiety	-0.18	41.50
Tech. Attitude	0.44	73.14
Tech. Experience	0.36	60.67
Tech. Self-Efficacy	0.31	65.90

From Table 8, the performance index value (73.14) shows that technology attitude had the strongest performance in determining behavioural intention as well as the highest in order of importance (0.44). This was followed by technology experience (importance index, 0.36) as the next most important predictor of behavioural intention, even though in terms of performance (60.67), technology self-efficacy (65.9) was higher. Technology anxiety was the least, relative to performance (41.50) and importance (-0.81) in terms of its relationship with behavioural intention. The graphical IPMA for behavioural intention is depicted in Fig. 3.

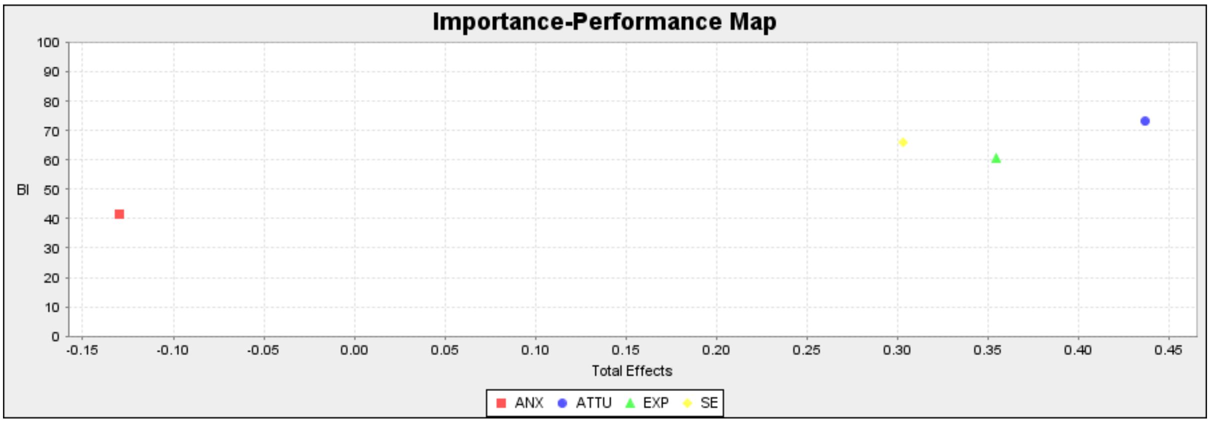

Fig. 3. IPMA for behavioural intention

4.8.2. Importance-performance analysis for technology attitude

The results of both importance index and performance index are represented in Table 9.

Table 9
Performance index and important index values

Construct	Importance Index	Performance Index
Tech. Anxiety	-0.14	41.52
Tech. Experience	0.24	60.67
Tech. Self-Efficacy	0.66	65.9

Results from Table 9 signify that technology self-efficacy was both the strongest performer (65.9) as well as the most important predictor (0.66) of technology attitude. This was proceeded by technology self-efficacy in order of importance (0.24) as well as performance (60.67). The graphical illustration is shown in Fig. 4.

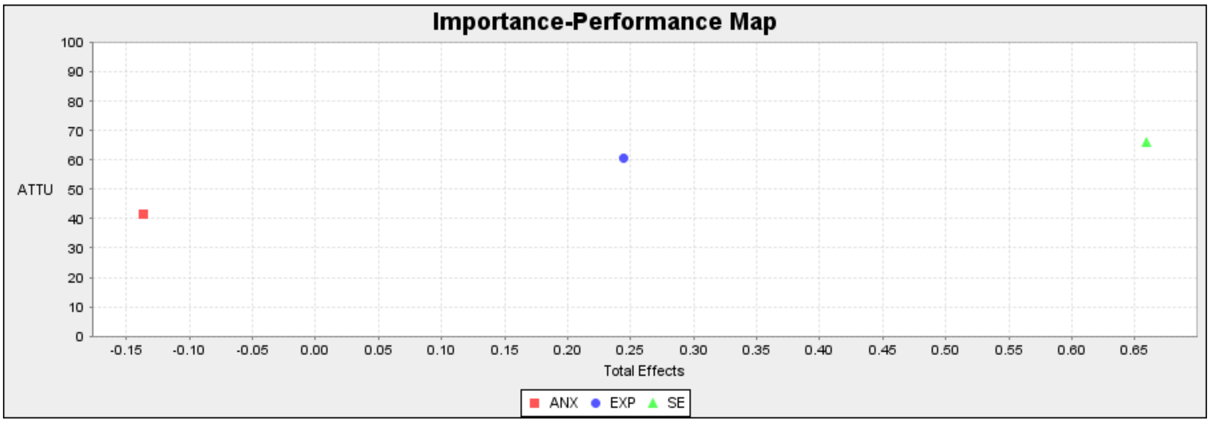

Fig. 4. IPMA for attitude

4.8.3. Graphical representation of the overall PLS path model and IPMA results

The total IPMA results for both behavioural intention and technology attitude are depicted by Fig. 5. The path coefficients and performance values represented in each construct are totally different from the item loadings and R^2 values for PLS algorithm and bootstrapping outputs (Ringle & Sarstedt, 2016). In the image below, the beta values in the outer model represent the importance of each item to the construct and not the loadings. Similarly, the inner values within each of the constructs are the performance indexes in relation to the endogenous variables and not the R^2 values. Ringle and Sarstedt (2016) admonish readers to be cautious not to misinterpret the output of the IPMA.

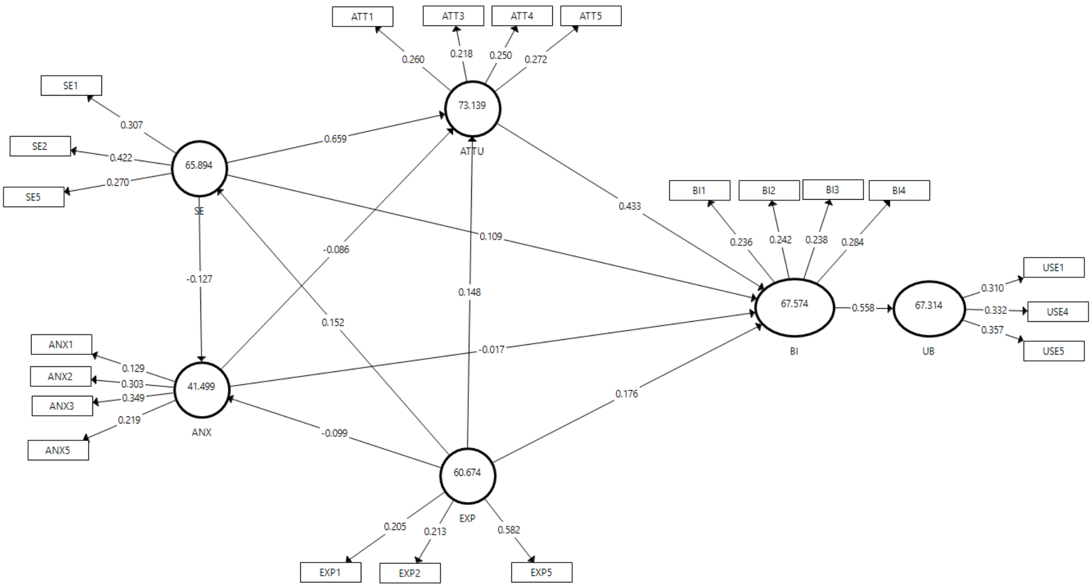

Fig. 5. Overall graphical IPMA results

5. Discussion

5.1. Summary of findings and discussion

This study looked into the predictive abilities of technology personality factors on LMS usage intentions for blended learning in distance education. It further investigated the possible non-linear and mediating relationships within technology personality factors as well as the overall variance explained in determining usage intentions in distance education when these factors are modeled exclusively.

Findings from the analysis of the hypothesized relationships revealed that, key antecedents of LMS usage intentions by distance education tutors were technology attitude and individual technology experience. The direct effect of technology attitude on behavioural intentions, resonates earlier findings by Alghamdi and Bayaga (2016) and Oye et al. (2012), but contradicted that of Venkatesh et al. (2003). Technology related attitude as the strongest performing and important predictor of LMS usage intentions by tutors in this study, was in support of Thomas et al. (2013), El-Gayar and Moran (2016) as well as Davis et al. (1989) in the TAM model but contradicted Venkatesh et al. (2003) in the UTAUT model. However, technology experience as a predictor of behavioural intentions was in agreement with De Smet et al. (2012) and Usoro et al. (2013). Contrary to the expectations of this study, the effects of technology related anxiety and technology self-efficacy were not significant to distance education tutors in determining their intentions towards LMS usage. These outcomes contradicted the findings from Olatubosun et al. (2014) and Al-alak and Alnawas (2011) but supported earlier stance by Venkatesh et al. (2003).

Results from the linear relationships produced in this study provide an indication that, in forming intentions to use LMS for blended learning, distance education tutors were rather motivated by their attitude towards technology which was a product of their previous experience with other technologies that could carve a positive outlook towards LMS usage. Attitude towards technology by instructors has been an effective personality determinant of intention behaviours of other introduced novel technologies within the literature. A positive attitude towards technology or related technology is anticipated to foster positive intentions towards newly introduced technologies. In this instance, if tutors in distance education have positive attitudes towards technology, then they are likely to accept LMS for blended learning. This points to the need for the development of positive attitudes of tutors towards educational technologies, of which LMS is not an exception. However, the formation of distance education tutors' attitude within this study has proven to be a function of their technology related self-efficacy, anxiety and experiences. The favourable nature or otherwise of the aforementioned determinants of tutors' attitude will significantly determine their intention behaviour. In addition to attitude, tutors also related to their previous technology outlook (whether positive, negative, copious or little) as one of the strongest basis to determine their onward LMS usage intentions. This means that if tutors have acquired a positive experience with technologies albeit copiously or otherwise, it serves as a bedrock towards LMS-enabled blended learning. Tutors' individual technology attitude and technology experience, thus become crucial components of their cognitive intention derivatives towards LMS usage for blended learning within the distance education mode.

The non-significance of technology anxiety in deciding tutors' LMS intentions formation was partly explained by the low anxiety levels indicated by the tutors in their responses to their perceived apprehension towards technology usage and thus, had a minor influence on intention determinations. With respect to technology related self-efficacy, tutors exhibited high outlook in terms of exposure to technological innovation use practices over time. This resulted in a positive belief of their technology ability levels. Moreover, the non-predictability of the two technology related personality constructs (anxiety and self-efficacy), in this study, is empirically explained by the non-linear relationships within the derived model.

The results from the non-linear relationships expose technology self-efficacy of tutors as strongly and positively determined by technology experience, confirming an earlier finding by Compeau and Higgins (1995) as well as Elbitar (2015). Nonetheless, this outcome contradicted recent studies by Sarfo, Amankwah, and Konin (2017) and earlier results from Karsten and Roth (1998). Generally, the technology experiences of tutors in this study had an influence on their technology ability beliefs. Technology experience thus becomes an important element in determining distance education tutors' technology self-efficacy levels. The positive nature of the relationship signals that, a high technology experience is likely to result in a high self-efficacy level with other technologies and vice versa. In this case, as tutors engage more and more with LMS technology, there will be a corresponding improvement and positivity in their LMS self-efficacy perceptions. For specificity in terms of LMS self-efficacy, tutors needed to be fully convinced of their LMS usage related experiences before having a positive belief of their abilities with LMS technology.

Of utmost importance to the explanation of the non-predictive nature of technology self-efficacy and technology anxiety is their mediation relationship with technology related attitude. The mediation results from the bootstrapping of their indirect effects proved that, the direct effects of both technology related anxiety and self-efficacy were absorbed by the presence of technology attitude in the definite model. Thus, an occurrence of a full mediation effects. This means, originally, the two technology related personality factors would have predicted behavioural intention towards LMS usage, but the inclusion of the later construct, extinguished their direct effects. The result provides an indication that within the distance education domain, tutors' self-efficacy and anxiety levels were direct agents forming their technology attitudes towards LMS uptake intentions. Their effects rather propelled the attitude factor in intention determination of tutors while offering a strong indirect effect on behavioural intention of tutors.

Two other non-linear relationships insignificant within the model were between technology anxiety and two other constructs (technology self-efficacy and technology experience). These results were interesting as they contradicted that of Bozionelos (2001) and Compeau et al. (1999) although there were correlations between the constructs. The outcome gives an indication that within the context of this study, anxiety levels of tutors reflected other external factors other than the two hypothesized personality constructs. Other factors may serve as reasons for technology anxiety, of which environmentally prone indicators geared towards LMS usage in distance education could be inclusive.

Additionally, all the three technology related factors (anxiety, self-efficacy and experience) predicted distance education tutors' attitude towards LMS usage intentions. This finding support that of Thompson et al. (1991), Compeau et al. (1999) and Sam et al. (2005). This gives an indication that the technology attitude formations of distance education tutors were a final product of the three-aforementioned technology related personality constructs, even though technology self-efficacy was the strongest predictor of the former construct.

Additionally, the original theorized relationship between behavioural intention and use behaviour was not different in this study. Behavioural intentions of tutors strongly determined their LMS use behaviour, supporting the views of Davis et al. (1989) and Venkatesh et al. (2003). Distance education tutors rated their overall behavioural intention as very important in forming their actual LMS usage behaviour, implying that their utilization of LMS for blended learning delivery, bothers to a large extent on the intentions they have formulated over time towards LMS as a platform to promote blended learning. Positive intentions are likely to promote positive and high utilization of LMS and vice versa.

A careful assessment of the p/t-values and the IPMA results provided further information on the most performing and important factors which need managerial attention. For instance, there was a consistency in technology attitude as the strongest predictor (by way of p/t-values) as well as the most important and performing variable in determining tutor's behavioural intention towards LMS-enabled blended learning. This is because, across all the variables, technology attitude obtained highest values across all three-dimensional measures, confirming its dominance in influence when it comes to tutors' intentions. Thus, the attitude of tutors occupied the centre stage in determining their LMS intentions. However, for technology related experience which proved a second most dominant variable in tutors' intention determination justified by p/t-values and important index measures, its performance index was rather overtaken by technology-related self-efficacy. This points to the fact that even though technology related experience is the second most important factor to tutors in distance education, it's performance in the model proved otherwise, creating the need to improve upon tutors' technology experience in order to improve the variable's performance index towards behavioural intention.

Finally, the total variance explained by the personality-based model amounted to 0.35. This implies that 35% of the intentions to accept LMS related blended learning by distance education tutors was explained by personality factors alone. This R^2 value for a behavioural phenomenon is considered large enough to offer value for the effect of personality factors within the acceptance of LMS in distance education. Implicit of this fact is that the total personality makes up of tutors in distance education can explain 35% of their uptake of LMS for blended learning delivery, leaving about 65% to be explained by other technological factors. However, in the acceptance/adoption of LMS studies, models have explained up to a highest of about 70% of behaviour. Based on this, it can be inferred that personality factors of tutors in distance education explains an approximation of half of their intentions towards LMS usage. This makes their personality factors a key antecedent when considering the LMS acceptance phenomenon.

6. Recommendations

6.1. Recommendations for theory

For theory, the results of this study further advance the role attitude in determining intentions towards LMS use behaviour such as indicated by TAM models. It however contradicts that of the UTAUT that relegates all personality factors from the model, giving a direction that personality factors are still needed in acceptance/adoption models.

Additionally, technology experience proves to be a key predictor variable of behavioural intention which should be given attention in model building. In models such as PC utilization and Social Cultural Theory in Information System, the variable predicts actual usage of technology, but the result of this study further indicates that it also predicts intention as well.

For technology-related Self-efficacy and Anxiety, they represent key determinants of attitude towards LMS while having an indirect effect on behavioural intention. The findings provide a new dimension on the role of self-efficacy and anxiety as indirect predictors of intention behaviour rather than actual predictors when the attitude factor is included in a model.

6.2. Recommendations for practice

Distance education top management should focus on forming positive attitudes in tutors towards LMS usage as the construct proves a major LMS usage intentions' determinant. In addition, more training and exposure towards LMS usage is needed to build experiences which will improve upon tutors' LMS technology self-efficacy beliefs and maintain low anxiety levels towards LMS usage for blended learning in distance education.

Furthermore, other environmental enabling conditions surrounding technology usage (such as technical support, availability and accessibility of technological resources such as laptops, power banks, modems, reliable internet supply etc. should be improved. Technical support teams should be readily available to handle user constraints when necessary. In view of this, certain incentives such as extra duty/ inconvenience allowance should be instituted to sustain these teams.

Supplying laptops and power banks to tutors will be necessary to make LMS usage flexible enough for tutors. Where tutors move away from study centres (where there is the presence of WiFi), modem provision should be possible to keep them still active online to foster continuity in tutor-student interaction.

Aside frequent training, tutors can also be motivated with promotion and other incentive packages tied to LMS usage. This will serve as a caveat to make them increase their online presence and engage more in online activities with students. The results of this will be a further boost to their usage experiences, reducing their anxiety tendencies and subsequently deepen their positive attitudes towards LMS for blended-learning in distance education.

6.3. Recommendations for further study

The study recommends that other moderating factors (location, teaching style, course taught etc.) could be added to the model in this study to determine their effects on technology personality factors and also improve the coefficient of determination. Again, what could be the effect of voluntariness or otherwise of blended learning environments on technology attitude and anxiety levels in utilizing LMS?

The mediating effects also suggest that for theory building, other higher order analysis such as first and second hierarchical order modeling of technology personality factors is warranted.

The paper finally recommends that studies employing personality factors in technology acceptance research should also analyze their relationships within the context of the models adopted. This provides a clear dimension of dominant relationships that exist amongst them and readily informs the chain effect reactions among the personality variables in acceptance behaviour within the contexts of individual studies.

7. Limitations

The study was limited to distance education setting and did not cover mainstream university lecturers. Thus, it is devoid of the views of regular campus-based lecturers that may be different from the views expressed by distance instructors.

The study did not also include moderators such as location, course taught, teaching style etc. to be tested for their effects on technology personality factors towards behavioural intentions.

Acknowledgements

The authors acknowledge the support from the College of Distance Education, University of Cape Coast, Ghana, in giving the go ahead for the study to be conducted. The authors also acknowledge the contributions of all study centre coordinators and course tutors for their willingness in responding to the distributed questionnaire.

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