EXAMINING TEACHER ACCEPTANCE OF LEARNING ANALYTICS IN A HIGHER EDUCATIONAL INSTITUTE: A STRUCTURAL EQUATION MODELLING EXPLORATION

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ABSTRACT

Learning analytics has shown promising potential in helping teachers keep track of students' e-learning activities. It can be used to assist teachers in decision-making regarding teaching strategies and courses or curriculum design. However, teachers may not actually utilise this technology in their classes. Therefore, a deeper understanding of teachers' perception of learning analytics use is needed. This study analysed teachers' perceptions of using learning analytics in their teaching by applying the Technology Acceptance Model (TAM) as the fundamental theory. 178 teaching staff from one polytechnic public university completed an electronic questionnaire. Data collected was analysed by using structural equation modelling. The results showed that perceived usefulness and satisfaction were two main factors for teachers' eventual intention to continue using learning analytics in their future teaching. A relatively novel construct for teachers' information and communication technology (ICT) competence for instructional design was introduced to the TAM. It was found that although the competence factor did not significantly and directly affect the behavioural intention to use learning analytics, it was highly influential to the perceived ease of use. This may mean that professional development programs focusing on instructional design topics, particularly with applications of ICT or e-learning, could increase the use of learning analytics among teachers through mediators, which may eventually induce positive effects to students' learning.

Keywords: learning analytics, technology acceptance model, ICT, instructional design, structural equation modelling

INTRODUCTION

The past few years have witnessed an unprecedented exponential growth of the Internet and the use of information and communication technology (ICT). This has inevitably and spontaneously led to the rapid development of online e-learning in higher educational institutes (Chan, et al., 2021a; Cheng & Yuen, 2018), especially in the past three years of the COVID-19 pandemic period, during which all traditional face-to-face lectures were suspended. The use of both asynchronous and synchronous e-learning modes in universities increased during the pandemic. This advancement in online e-learning technology thus opens new possibilities, particularly in relation to students' engagement with online learning resources. Sangrà et al. (2012) defined e-learning as “an approach to teaching and learning that is based on the use of electronic media and devices as tools for improving access to training, communication and interaction and that facilitates the adoption of new ways of understanding and developing learning.” Such e-learning resources are usually accessed via a learning management system (LMS). An LMS can facilitate students to learn at any place, time and pace as they please. It creates a learning environment without physical user presence. Perhaps most importantly, a learning platform or LMS can deliver online e-learning resources with the capability to track and monitor information regarding access and use of these materials via learning analytics (LA) (Ashrafi et al., 2022; Kotzer & Elran, 2012; Mahnegar, 2012). In contrast to the rather vast concept of LA proposed in the 1st International Conference on Learning Analytics and Knowledge (Siemens, 2011), a more holistic definition by Johnson et al. (2016) defines LA as “an educational application of web analytics aimed at learner profiling, a process of gathering and analysing details of individual student interactions in online learning activities.” LA can provide information from e-learning resource access logs and alert teaching staff regarding academically at-risk students. It can also help teachers and researchers to understand the relationship between e-learning material consumption and assessment outcomes (Azcona et al., 2019; Chan et al., 2019, 2021b; Oliveira & Brown, 2016). Teachers and instructional designers can use course feedback from students (Firat, 2016; Rajabalee & Santally, 2021) in conjunction with e-learning usage behaviour information analysis to further improve e-learning content and course module design. For example, by analysing students’ usage logs for watching online videos and their contentment with the videos, researchers can determine why certain types of e-learning videos are watched by a greater number of cohorts and how frequently videos are watched as students transit over time across academic years (Chan et al., 2021a).

While most of the attention has focused on student e-learning usage, teachers are another major stakeholder of online teaching and learning. Teachers or instructional designers design module layouts, create and upload e-learning materials onto the LMS for students to access. They can also analyse LA data to confirm if their designs have met the intended pedagogical aims (Lockyer et al., 2013). Bakharia et al. (2016) developed a conceptual framework for evaluating “learning designs” using LA. They reported that teachers were critical for bridging instructional design and LA, as well as the bringing together of teaching and learning contexts to interpret LA results. While Bakharia et al. (2016) focused on the evaluation of instructional design with LA, Lockyer et al. (2013) proposed that analysis should also target the understanding of specific educational contexts, such as learning or instructional design, in order to produce “accurate predictive models” and “pedagogical recommendations”. These studies highlight the reciprocity of the relationship between instructional design and LA. Considering that current classes in higher educational institutes are very much integrated with online e-learning, full competence in instructional design should also encompass the ability to use ICT in instructional design tasks.

The availability of LA tools alone does not guarantee that teachers will have a high motivation to use them. Previous studies have suggested that motivation is required to “nudge” students (Chan et al., 2021a) to increase their use of a learning technology (Afirando, et al., 2023; Sørebø et al., 2009). Such nudges could also work for teachers. Thus, this poses an interesting question – what factors can motivate teaching staff to (continually) use LA in their teaching? Specifically, does the addition of teachers’ ICT competence for instructional design (ICID) affect their acceptance of using LA in teaching? A more thorough investigation of teachers' acceptance of using LA and their ICID in the higher educational curriculum is therefore needed.

LITERATURE REVIEW

Acceptance of Using LA – Technology Acceptance Model (TAM)

Technology acceptance refers to an individual's willingness to employ a specific technology and has been widely investigated by previous studies. The TAM proposed by Davis (1989) has been applied in multiple disciplines including business, information system, and education. This model has been used to evaluate, including but not limited to, individuals' acceptance of e-learning (Abdullah & Ward, 2016; Mizher & Alwreikat, 2023; Nikou & Economides, 2017; Sukendro et al., 2020), business application (Bach et al., 2016; Pipitwanichakarn & Wongtada, 2021; Shih & Chen, 2011), healthcare technology (Abbas et al., 2018; Cheng, 2021; Karkonasasi, et al., 2023; Wulan et al, 2024) and social media (Al-Qaysi et al., 2020; Bonaretti, 2022; Chintalapati & Daruri, 2017). The TAM is famous for its exceptionally powerful constructs for modelling individuals' acceptance of technology usage (Cheng & Yuen, 2018). Many of these prior studies have focused on technologies implemented in organisational contexts, such as higher education institutions. While numerous studies have explored teachers' acceptance of various e-learning technologies such as LMS (Yuen & Ma, 2008) and mobile learning (Chao, 2019), few investigations have utilised the TAM to evaluate LA use in educational contexts (Mavroudi et al., 2021; Rienties et al., 2018).

The TAM proposed by Davis (1985) is considered an extension of the Theory of Reasoned Action (Fishbein & Ajzen, 1975, 2011) and is used to predict and explain individual users' acceptance of information systems. In this model, perceived ease of use (PEOU), perceived usefulness (PU) and behavioural intention (BI) are the key factors (constructs) for a person's technology acceptance. PEOU and PU both reflect a person's beliefs toward a certain technology. PU is defined as "the degree to which a person believes that using a particular technology would enhance his or her job performance" (Davis, 1989). PEOU is defined as "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989). BI refers to the degree to which an individual's tendency to do or perform a certain behaviour (Bandura, 1986; Fishbein & Ajzen, 1980). Venkatesh and Davis (1996) subsequently confirmed that both PEOU and PU have direct effects on BI and that PU also mediates the effect of PEOU on BI. Although most of the TAM extended models have successfully confirmed the impact of these three major factors, some recent studies have reported a relatively smaller effect for PEOU (Burke, 2013; Scherer et al., 2019). While most tutors and teachers expressed that they appreciated the assistance provided by the LA tools, some were reserved or "skeptical" about the perceived ease of use of those (Ali, et al., 2013; Mavroudi et al., 2021; Rienties et al., 2018). Conflicting results have been reported in the literature for the relationship between PEOU and BI (Ali et al., 2013). While the original version of the TAM included an attitude factor, its removal was suggested by subsequent studies. Davis et al. (1989) found that the attitude factor only had limited effect on BI. Teo et al. (2008) also reported that the attitude factor did not have a significant relationship with student BI.

The expectation-confirmation model (ECM) was developed to understand an individual's continuance use of a technology (Bhattacherjee, 2001a, 2001b). According to the ECM, an individual's satisfaction (SAT) with their experience of a given technology determines their intention to continue using it (Bhattacherjee, 2001a, 2001b; Cheng, et al., 2023; Hsu & Lin, 2015). Based on ECM and TAM, the relationships among SAT, PU, PEOU, and BI were confirmed in previous assessments of technology acceptance (Amin et al., 2014; Islam, 2015; Venkatesh et al., 2011), especially in the context of higher education (Dağhan & Akkoyunlu, 2016; Lin & Wang, 2012). Specifically, Cheng (2021) shown users with higher satisfaction with an online information system will also have greater intention in using it continuously.

Competence in Using ICT for Instructional Design

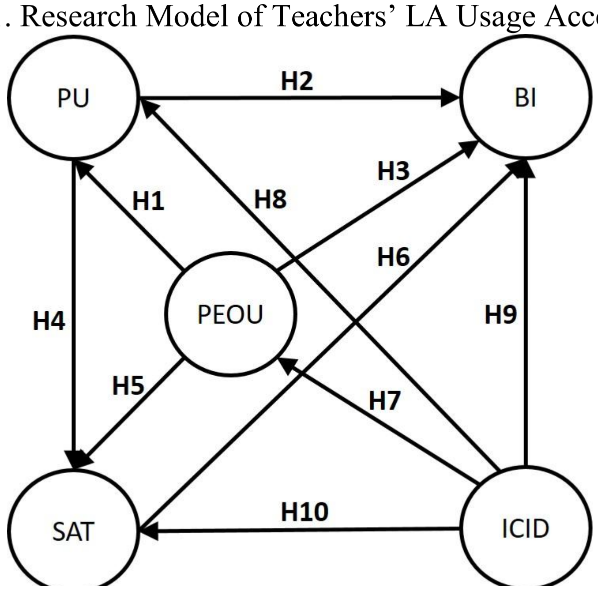
To our knowledge, some teachers at the University have expressed their very limited use of LA in their teaching, despite the institution's mandatory requirement for students to use e-learning either completely online or in hybrid learning mode. A recent internal project (Chan et al., 2022) conducted at the same institution found that a number of teachers were not too aware of any LA promotion activities (e.g., workshops or seminars). Some expressed that they did not feel the need to use LA in their courses extensively. Teachers can use LA data as a source of feedback to modify their courses and LMS modules. For example, every time a student interacts with an LMS, relevant data (e.g., login frequency, chat and thread history, quiz score, video consumption and duration, timestamp of each action) are created and collected; virtually every click a student makes and their related activities are recorded. By evaluating students' consumption of LMS online resources, teachers are able to determine which specific resources and topics have the lowest rate of access and require further amendment or the provision of additional materials (Bakharia et al., 2016; Lockyer et al., 2013; Soffer et al., 2019). Thus, LA data can facilitate the design of e-learning environments, thereby improving the students' overall experience (Chan et al., 2021a). A teacher's lack of intention to use LA may seriously undermine their instructional course design. Conversely, Yalçın et al. (2021) asserted that professionals in the field of instructional design should possess the ability to identify the learning problems of students. This suggests that there may be a significant correlation between a teacher's familiarity with instructional design and their use of LA in teaching. Indeed, an educator's (e.g., teaching staff or instructional designer) application of LA has been confirmed to be highly related to the performance of instructional design tasks (Bakharia et al., 2106; Lockyer et al., 2013).

Contemporary instructional design in higher educational curricula is highly integrated with online e-learning. Although teachers' "competence in instructional design" most likely also encompasses their "capability in using ICT applications", a specifically designed construct that focuses on these two aspects as a cohesive concept could avoid respondent confusion with the questionnaire items. Drawing on the "ICT competence framework" created by the Expertise NetWork (ENW AUGent, 2013), Tondeur et al. (2017) developed a validated instrument to measure pre-service teachers' (i.e., student teachers) ICT competence. This framework was designed to be "applicable and adaptable" for teacher training institutions that aimed to eliminate redundancies from "complex stipulations" of several different ICT frameworks and form "a useful format that could be used in concrete situations". One construct from this instrument is the ICID (originally "ICTC-ID"), which was designed to measure competence in areas that Tondeur and his team deemed essential for the integration of ICT into instructional design. The eight items in this ICID competence construct were combined to measure the magnitude of teachers' competence in using "ICT to support and strengthen their instructional practice" (Tondeur et al., 2017).The present study was prompted by the idea that if teachers are more knowledgeable and competent in using ICT for instructional design, they will also have a greater intention to use and apply LA to their courses. This would enhance their teaching and lead to improved student learning (Amida et al., 2022; Bakharia et al., 2016; Lockyer et al., 2013). An "enhancement" can be a change of teaching strategy that improves student academic performance (Grønlien et al., 2021). For example, teachers can focus on suppling easier to understand learning materials for students based on a "supply chain of information" (Elastika et al., 2021).

To recap, PEOU, PU and SAT have been shown to be major empirical predictors of users' acceptance of technology across various disciplines. In addition, previous studies have suggested the inclusion of additional factors to the TAM to form an extended model (Ali et al., 2013; Papamitsiou & Economides, 2014). In the present study, we applied an additional factor (i.e., teachers' competence in using ICT for performing instructional design practices) (Tondeur et al., 2007; Tondeur et al., 2017) to determine its relationship with LA usage intention. Thus, we proposed an extended TAM (Figure 1) with the following hypotheses:

H1. PEOU is positively related to teachers' PU of LA.
H2. PU is positively related to teachers' intention to use LA (BI).
H3. PEOU is positively related to teachers' intention to use LA (BI).
H4. PU is positively related to SAT with LA use.
H5. PEOU is positively related to SAT with LA use.
H6. SAT is positively related to intention to use LA (BI).
H7. ICID is positively related to teachers' PEOU of LA.
H8. ICID is positively related to teachers' PU of LA.
H9. ICID is positively related to teachers' intention to use LA (BI).
H10. ICID is positively related to SAT with LA use.

Figure 1. Research Model of Teachers' LA Usage Acceptance



* Note: PU, perceived usefulness; PEOU, perceived ease of use; BI, behavioural intention; SAT, satisfaction; ICID, ICT competence for instructional design.

METHODOLOGY

Ethical approval was obtained from the University's Institutional Review Board. E-mail invitations for participation were sent to all the staff who were recorded as instructors, with a URL embedded directing them to a self-administered questionnaire on an online survey platform. Participants were required to complete the informed consent section before proceeding to the questions. Only data from participants who indicated that they used learning analytics and had teaching duties were included in the analysis. This study did not explicitly restrict the use of any online e-learning systems/platforms/tools as a prerequisite.

The study was conducted from January to April 2022. A total of 178 participants completed the questionnaire. Table 1 summarises the roles of the participants played, of which, 67 indicated they were in multiple roles. Participants from 31 various departments (or centres/divisions/units) and faculties answered the questionnaire. The questionnaire comprised 22 items that examined the participants' acceptance of LA usage and their self-perceived competence in using ICT for instructional design purposes: 11 items were adopted from the TAM (Davis, 1989) to measure PU, PEOU and BI; 3 items were adopted from Wu et al.'s study (2010) to measure SAT; and 8 items were from Tondeur et al. (2017) and measured ICID. All constructs were scored on a 5-point Likert scale ranging from "strongly disagree" to "strongly agree". All question items and their original source are listed in Table 2.

SPSS 26 and AMOS 26 were used to perform the data analysis. Structural equation modelling was used to evaluate the causal relationships among the proposed factors.

Table 1. Roles of Participants

n	Role
0	Head of department / Faculty dean
18	Programme leader
79	Subject leader
133	Subject teacher / Lecturer / Instructor
7	Teaching assistant
21	Research staff with teaching duty

*n: not mutually exclusive

Table 2. Construct Abbreviations and Corresponding Measurement Items

Construct name	Item	Question description
Perceived usefulness Davis (1989)	PU1	Using LA would improve my teaching performance
	PU2	Using LA would enhance my effectiveness in teaching
	PU3	Using LA would help me in accomplishing my teaching tasks more quickly
	PU4	Using LA increases my productivity
	PU5	Overall, I find LA useful to my teaching
Perceived ease of use Davis (1989)	PEOU1	Learning to use LA would be easy for me
	PEOU2	It would be easy for me to become skilful at using LA
	PEOU3	The way to use LA is clear and understandable
	PEOU4	Overall, I find using LA is easy

Behavioural intention Venkatesh et al. (2003)	BI1	I intend to use LA in the next 3 months
	BI2	I plan to use LA in the next 3 months
Satisfaction Wu et al. (2010)	SAT1	I am satisfied with the efficiency in using LA
	SAT2	I am satisfied with the effectiveness in using LA
	SAT3	Overall, I am satisfied with LA
ICT competence in instructional design Tondeur et al. (2014)	ICID1	Select ICT-applications in view of a specific educational setting
	ICID2	(Re)design ICT-applications in view of a specific educational setting
	ICID3	Use ICT to differentiate learning and instruction
	ICID4	Track the learning progress of students in a digital way
	ICID5	Evaluate students with the help of ICT
	ICID6	Use ICT appropriately to communicate with students
	ICID7	Design a learning environment with the available infrastructure
	ICID8	Select ICT-applications effectively in creating a learning environment (e.g., in view of the group size)

RESULTS
Validation

Descriptive statistics, including skewness and kurtosis values, for each item are presented in Table 3. According to Kline (2005), the recommended absolute values should not go beyond 3 and 10 for skewness and kurtosis, respectively; these normality thresholds were satisfied for each item. Cronbach's alpha was used to check the internal consistency within each construct (Table 3). Alpha values were all greater than .70, which is the recommended value suggested by previous studies (Bland & Altman, 1997; Nunnally & Bernstein, 1994). In addition, all factor loadings, composite reliability (CR) and average variance extracted (AVE) values (Table 4) were larger than the recommended values of .50, .70 and .50 respectively (Fornell & Larker, 1981; Hair et al., 2006). Thus, good convergent validity was achieved.

Table 3. Descriptive Statistics, Skewness, Kurtosis and Cronbach's Alpha

Item	Mean	s.d.	Skewness	Kurtosis	Cronbach's α
PU1	3.96	.72	-1.12	3.52	.90
PU2	3.95	.71	-.96	2.69	
PU3	3.48	.86	-.46	.38	
PU4	3.43	.87	-.29	.22	
PU5	3.81	.74	-.94	1.94	
PEOU1	3.70	.77	-.49	.88	.91
PEOU2	3.64	.80	-.25	.36	
PEOU3	3.51	.83	-.51	.41	
PEOU4	3.56	.77	-.30	.11	
BI1	3.82	.83	-1.00	2.09	.97

BI2	3.78	.85	-.95	1.72	
SAT1	3.52	.80	-.33	.29	.96
SAT2	3.62	.77	-.40	.23	
SAT3	3.65	.78	-.46	.30	
ICID1	3.63	.78	-.19	.07	.94
ICID2	3.46	.86	-.16	.12	
ICID3	3.53	.78	-.13	.04	
ICID4	3.62	.82	-.43	.32	
ICID5	3.64	.79	-.48	.26	
ICID6	3.81	.79	-.47	.34	
ICID7	3.68	.75	-.31	.36	
ICID8	3.69	.77	-.38	.32	

* Note: PU, perceived usefulness; PEOU, perceived ease of use; BI, behavioural intention; SAT, satisfaction; ICID, ICT competence for instructional design.

Discriminant validity was confirmed if the square root of the AVE exceeded the correlations of a particular construct and the remaining constructs (Fornell & Larker, 1981). The square root of AVE exceeded the Pearson r value for each construct and its off-diagonal counterparts; therefore, discriminant validity was adequate.

The goodness-of-fit was assessed using the Chi-square test ($\chi2$/df), comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA) and standardised root mean square residual (SRMR) (Hair et al., 2006; O'Rourke & Hatcher, 2013). Threshold values of $\chi2/df \leq 5.00$, CFI≥.90, TLI≥.90, RMSEA≤.08 and SRMR≤.08 indicated a good fit between the model and data. The results of the final model indicated a good structural model fit: $\chi2$/df=1.56, CFI=.97, TLI=.97, RMSEA=.06 and SRMR=.06.

Table 4. Factor Loading, CR and AVE

Item	Factor loading	CR	AVE	√AVE
PU1	.86	.89	.63	.79
PU2	.82			
PU3	.68			
PU4	.70			
PU5	.88			
PEOU1	.79	.90	.70	.83
PEOU2	.75			
PEOU3	.89			
PEOU4	.90			
BI1	.95	.97	.94	.97
BI2	.99			
SAT1	.90	.97	.90	.95
SAT2	.97			

SAT3	.94			
ICID1	.81	.94	.66	.81
ICID2	.78			
ICID3	.84			
ICID4	.84			
ICID5	.85			
ICID6	.75			
ICID7	.70			
ICID8	.89			

* Note: PU, perceived usefulness; PEOU, perceived ease of use; BI, behavioural intention; SAT, satisfaction; ICID, ICT competence for instructional design.

Table 5. Discriminant Validity

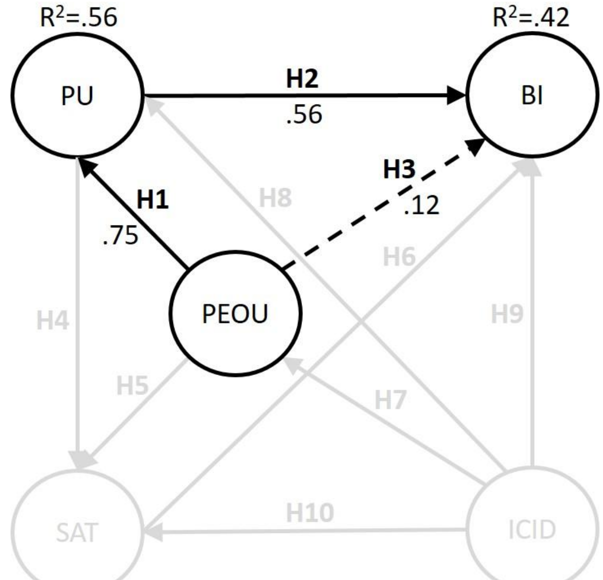
	PU	PEOU	BI	SAT	ICID
PU	**.79**				
PEOU	.74	**.83**			
BI	.65	.53	**.97**		
SAT	.74	.79	.62	**.95**	
ICID	.50	.59	.44	.50	**.81**

* Values in bold are the square root of AVE
** Note: PU, perceived usefulness; PEOU, perceived ease of use; BI, behavioural intention; SAT, satisfaction; ICID, ICT competence for instructional design.

Model Testing Results

The analysis was followed by a series of steps designed to compare the sub-models and a finalised model was shown at the end. Dotted path means not significant ($p>.05$). The original model from Davis (1986) was used to observe the causal relationships of the three fundamental constructs of TAM, namely PU, PEOU and BI (Model 1: see Figure 2). Out of the three paths, two were found to be significant: PEOU→PU (H1: $\beta=.75$; $p<.001$) and PU→BI (H2: $\beta=.56$; $p<.001$). PEOU→BI was insignificant (H3: $\beta=.12$; $p=.28$). The explanatory power of the model (R^2) was .43.

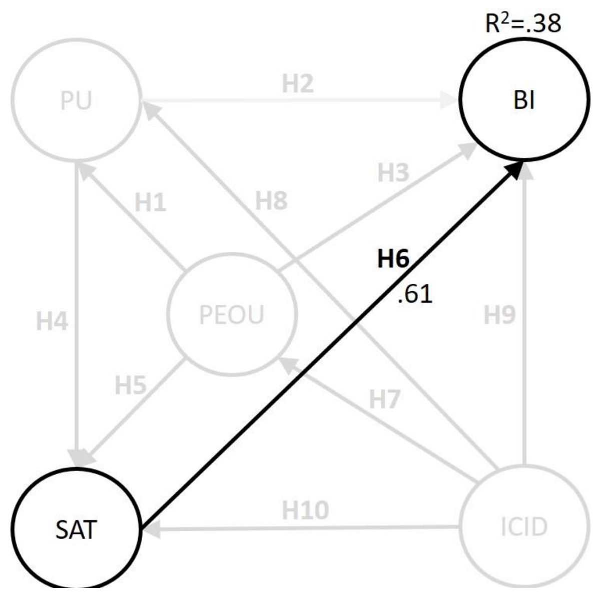
Figure 2. Hypothesis Testing and Results: Model 1



* Note: PU, perceived usefulness; PEOU, perceived ease of use; BI, behavioural intention.

In Model 2, the effect of the SAT construct on BI (H6) was examined. The variance explained (R^2=.38) by the causal path in this model (β=.61; p<.001) was slightly lower than that in the first model (Figure 3).

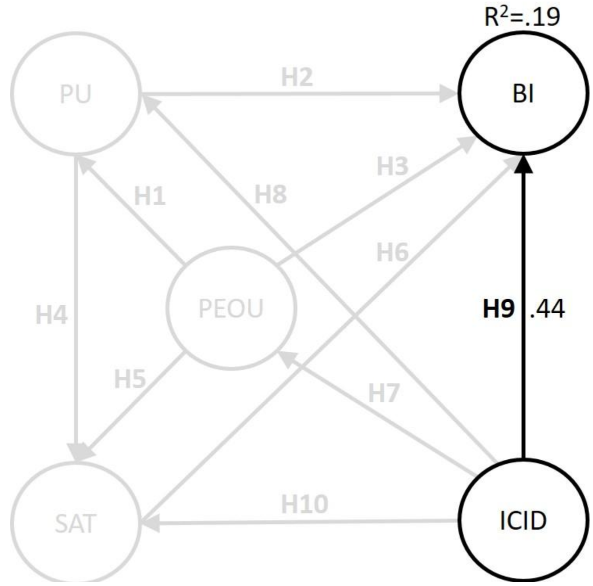
Figure3. Hypothesis Testing and Results: Model 2



* Note: BI, behavioural intention; SAT, satisfaction.

In Model 3, ICID was tested. A significant causal relationship with BI (H9: β=.44; p<.001) was observed, with a weak R^2 (.20) (Figure 4).

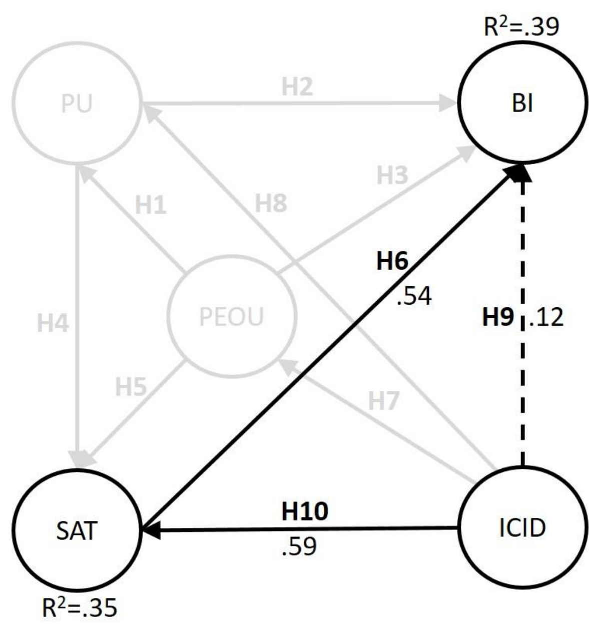
Figure 4. Hypothesis Testing and Results: Model 3



* Note: BI, behavioural intention; ICID, ICT competence for instructional design.

Model 4 consisted of the addition of ICID to Model 2; the variance explained (R^2=.39) was increased by only 1%. The path coefficient of SAT→BI was decreased by .07 (H6: β=.54; p<.001). ICID showed a moderate effect on SAT (H10: β=.59; p<.001), but insignificant effect on BI (H9: β=.12; p=.13) (Figure 5).

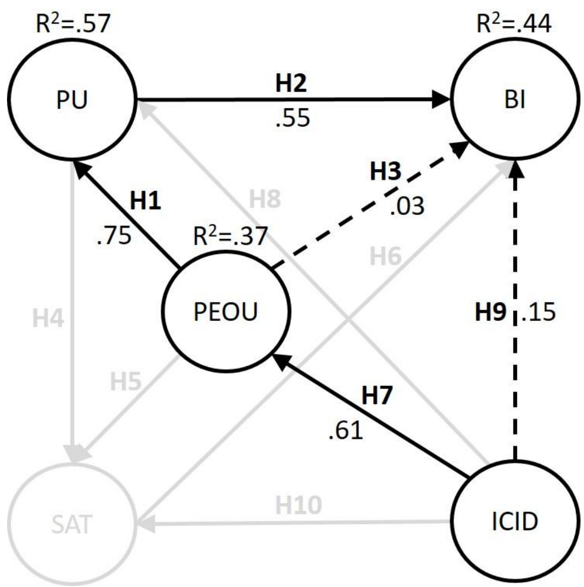
Figure 5. Hypothesis Testing and Results: Model 4



* Note: BI, behavioural intention; SAT, satisfaction; ICID, ICT competence for instructional design.

Model 5 consisted of the three original TAM constructs, with the addition of ICID. PEOU again showed an insignificant effect on BI (H3: β=.03; p=.81). The causal relationships of PEOU→PU (H1) and PU→BI (H2) were on par with Model 1: β=.76 (p<.001) and β=.55 (p<.001), respectively. Furthermore, ICID directly and significantly affected PEOU (H7: β=.61; p<.001), but not BI (H9: β=.15; p=.06). The variance explained was raised slightly in Model 5 (43.5%) compared to Model 1 (42.5%) (Figure 6).

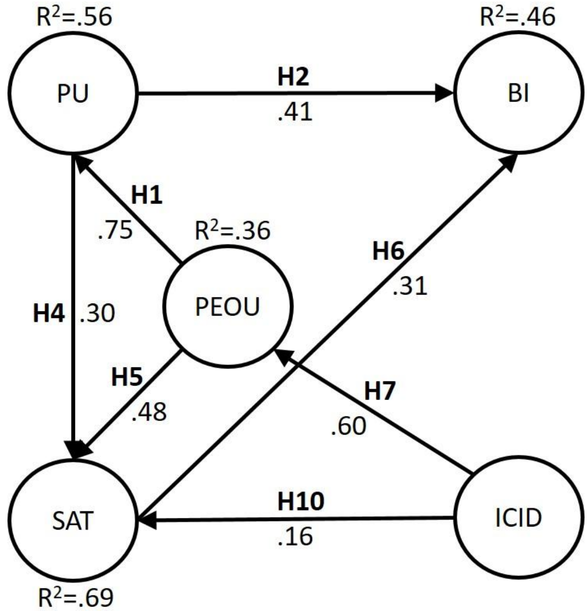
Figure 6. Hypothesis Testing and Results: Model 5



* Note: PU, perceived usefulness; PEOU, perceived ease of use; BI, behavioral intention; ICID, ICT competence for instructional design.

Figure 7 shows the final model (Model 6) – an extended TAM, which included all the aforementioned constructs: PEOU, PU, BI, SAT and ICID. PEOU→BI (H3: β=-.11; p=.42), ICID→BI (H9: β=.10; p=.20) and ICID→PU (H8: β=.10; p=.21) were insignificant and therefore excluded in the final model. The following paths were significant: PEOU→PU (H1: β=.75), PU→BI (H2: β=.41), SAT→BI (H6: β=.31), ICID→PEOU (H7: β=.60), ICID→SAT (H10: β=.16), PU→SAT (H4: β=.30) and PEOU→SAT (H5: β=.48) (all p<.001, except for ICID→SAT (H10), which had a slightly larger p-value of .01).

Figure 7. Hypothesis Testing and Results: Model 6 (Final Model)



* Note: PU, perceived usefulness; PEOU, perceived ease of use; BI, behavioural intention; SAT, satisfaction; ICID, ICT competence for instructional design.

PU was explained by PEOU with an R^2 of .56, while PEOU was explained by ICID with an R^2 of .36. PEOU, PU and ICID explained 69.2% of the variance in SAT. Only PU and SAT directly contributed to the variance in BI. Altogether, the model accounted for 45.5% of the variance in teachers' BI of using LA, thus yielding increases of only 3% compared to Model 1 (PEOU and PU), 6.8% compared to Model 4 (SAT and ICID) and 7.9% compared to Model 2 (SAT). Table 6 shows a list of hypotheses with path coefficients and β values of the finalised model. In summary, there was a good fit between the data and finalised version of the model.

Table 6. Summary of Hypotheses (Final Model)

Hypothesis	Path	Standardised coefficient (β)	Significant
H1	PEOU→PU	.75	Yes
H2	PU→BI	.41	Yes
H3	PEOU→BI	-	No
H4	PU→SAT	.30	Yes
H5	PEOU→SAT	.48	Yes
H6	SAT→BI	.31	Yes
H7	ICID→PEOU	.60	Yes
H8	ICID→PU	-	No
H9	ICID→BI	-	No
H10	ICID→SAT	.16	Yes

* Not significant: p>.05
** Note: PU, perceived usefulness; PEOU, perceived ease of use; BI, behavioural intention; SAT, satisfaction; ICID, ICT competence for instructional design.

DISCUSSION

This study proposed an extended TAM that accounted for teachers' ICT competence in instructional design, in order to explain teachers' perception LA usage and their future intention to use it. The aims of this research were: to explore teachers' acceptance of using LA in their teaching and to study the relationships among the original TAM constructs (with SAT) and an additional construct of ICID, in a hypothesised research model.

The key findings were as follows:
- PU has direct and significant effects on both BI and SAT (H2, H4).
- PEOU has direct and significant effects on teachers' PU and SAT (H1, H5).
- SAT has direct and significant effects on BI (H6).
- ICID has direct and significant effects on both PEOU and SAT (H7, H10).
- H3, H8 and H9 are not significant and are rejected in the present model.

Agreement on PU of using LA in teaching was observed in the majority (82.6%) of participants, while 75.3%, 74.2%, 71.8% and 64.5% of participants expressed agreement on ICID, BI, PEOU and SAT, respectively. The results of this study revealed that while BI was not explicitly affected by PEOU, there were implicit effects through mediation. In the finalised model, PU and SAT were mediators of PEOU in the prediction of BI. This showed that PEOU was a common implicit factor for predicting BI. PU and SAT were the two strongest factors that affected teachers' continuance intention of using LA directly. An understanding of the roles of PU and SAT in predicting teachers' intention to continue using LA is particularly crucial for promoting adoption and effective use of LA for teaching in higher education. It is important to emphasise the potential benefits of these tools in enhancing teaching and learning outcomes, as well as ensuring that teachers have the necessary support and resources to effectively integrate LA use into their pedagogical practices. Furthermore, efforts should be made to ensure that teachers have a positive experience when using LA. For example, teachers could be provided with user-friendly interfaces, clear instructions for the applications, and ongoing support and training. Through these means, higher education institutions can promote a culture of innovation and improvement, where teachers are empowered to use LA and other e-learning tools to enhance the quality of education for their students.

Overall, PU, PEOU and ICID accounted for 69.2% of the variance observed in SAT, with PEOU having the biggest path coefficient (.48). PEOU also solely affected PU with a large β of .750. These findings indicate that an increased PEOU will lead to higher PU and SAT and greater inclination to continue using LA for teaching. Previous studies have reported that PEOU is a key determinant of technology acceptance. Yuen and Ma (2008) found that PEOU of the Interactive Learning Network e-learning platform was "extremely important" amongst in-service teachers. Schoonenboom (2014) concluded that instructors' "high level" ease of use of the Blackboard LMS was one of the primary reasons for a "high level" of intent to use the system. As technology evolves, PEOU will remain a major consideration during product development (Burke, 2013; Vredenburg, 2003). Although PEOU is one of the fundamental constructs of the TAM, recent studies on the other hand have found that it is not a strong factor (Scherer et al., 2019; Schepers & Wetzels, 2007; Zhang et al., 2012). The lower importance of PEOU may be due to the fact that participants had no choice but to use the technology. For example, in the present study, teachers may have felt that LA usage was de facto mandatory, despite the fact that the university or faculties informed them that using LA in their courses was optional. Some teachers may also have felt that the use of LA in their teaching was an inevitable trend. In addition to considering the time needed to use LA effectively, teachers may also have accounted for other factors such as explicit motivations (e.g., student engagement, learning outcomes). Thus, whether LA use was perceived as easy may not have been a deciding factor in their eventual decision to continue using LA.

Conversely, while some recent studies have reported that the impact of PEOU on technology acceptance is relatively low, it may still be highly relevant in certain population groups. In a previous study conducted by Burke (2013), certain groups of consumers were more concerned with the ease of use of a product, rather than its functional features. Consumers who opted for simplicity when purchasing a DVD recorder had less product knowledge. On the other hand, those who already owned a complex smart phone would replace their phone with relatively little concern for whether the phone was easy to use. These findings may help explain the teachers' low concern for PEOU in the present study, as they may have already been proficient in using LA; indeed, LA is not a new technology and has been increasingly used in universities over the past several years (Ifenthaler & Yau, 2018).

ICID is a relatively novel construct specifically created by Tondeur et al. (2007) to understand teachers' competence in using ICT for instructional design purposes. The addition of this construct to the TAM facilitates a deeper understanding of factors that can potentially increase motivation for LA use among teachers. Our findings showed that ICID was a relatively weak factor in the direct prediction of BI, as it only explained 19.5% of the variance. In fact, when combined with SAT into the model (see Model 4), the path from ICID to BI became insignificant and R^2 was only increased by 1%, although the path coefficient (ICID on SAT) was still significant with an intermediate effect. While we hypothesised that ICID would be a direct factor influencing BI, this was contradicted by our results. Indeed, PU and SAT overshadowed the effects of ICID on BI within the model. In light of the potential impact of teachers' ICID on their eagerness to use LA in their teaching, it is important to consider the design and implementation of professional development programs that aim to enhance these skills. Rather than conducting separate workshops for LA and instructional design, an integrated approach may be more effective in promoting the adoption of LA in higher education. To achieve this, it may be necessary to review and rethink the existing professional development offerings for teachers. An integrated approach that combines instruction in both LA and instructional design may better equip educators to implement LA tools effectively in their teaching. Such an approach may also have the added benefit of reducing the time and resources required to deliver separate training on both topics. Providing teachers with a deeper understanding of the pedagogical underpinnings of LA and how it can be effectively integrated into instructional design may increase their eagerness to adopt LA tools in teaching practices.

Nevertheless, ICID was a significant factor for predicting both PEOU and SAT; ICID explained 35.7% of the variance in PEOU (β=.60), reflecting a decent, albeit not strong, predictive ability. These findings indicated that teachers who felt that they were more competent in using ICT for instructional design tasks also found it easier to use LA and were more satisfied with its use. A previous internal study reported that teachers who were more competent in ICT, or particularly keen on designing and making use of their courses' LMS modules, were also more inclined to engage with LA professional development workshops and seminars (Chan et al., 2022). Thus, if a teacher's ICID can be demonstrated to be a valid factor (whether implicitly or explicitly) in motivating teacher eagerness in using LA to teach, then more resources should be diverted to train teachers in instructional design tasks. Therefore, the provision of additional instructional design training for teachers (using ICT/e-learning) may increase their competence and lower their PEOU and SAT thresholds, thereby promoting their intention to use LA.

Limitations

Some limitations are acknowledged in this study. First, the sampling frame was limited to teaching staff at a single university. Future studies may also consider the inclusion of teachers from other institutes, if we want to further increase the generalisability of the study results. In this study participants from 31 units (including faculties and departments/centres) completed the questionnaire, this suggests a reasonable level of representation across departments and strengthens the generalisability of our findings.

Although invitations were sent to all staff who were registered as teachers involved in online LMS courses, this approach may have only attracted participants who were attentive to emails, particularly mass promotional emails from various departments and faculties. Other means of recruitment such as cold calling may resolve this issue.

This study utilised a cross-sectional design. Future studies may consider using a longitudinal design and extending the observation period to a subsequent academic year or semester to determine for example whether a teacher's perception in future intention of LA use in the current semester will have an effect on their subsequent perception of using LA in the next semester.
While the focus of the present study was to understand the effect of various factors on teachers' continuance in LA use, to better understand the complexity of teachers' attitude to LA, future studies should consider evaluating the impact of faculty requirements for LA use and how these are enforced.

CONCLUSIONS

This study demonstrated that PU and SAT were significantly related to teachers' intention to continue using LA in teaching. PEOU of LA and ICID were not found to be meaningful factors in the expressed intent to subsequent use of LA, but contributed implicitly via mediation. Nevertheless, ICID significantly affected PEOU and SAT. The results of this study could facilitate the exploration of novel ways to promote LA implementation in teaching. This would be particularly relevant for higher education settings, where instructional design tasks primarily involve the use of LA.

The results of this study may fill a gap in the literature in terms of whether teachers' competence in instructional design using ICT will motivate and affect their intention to use LA in teaching. This research contributes empirical evidence on teachers' acceptance and utilisation of LA, which is particularly relevant for university stakeholders and policy makers, and provides directions for future studies in this field.

Disclosure Statement

No conflict of interest was reported by the authors.

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