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Antecedents of intention to use project management among educational institution: Empirical study in Jordan

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The present study examined the perception of users towards the role of artificial intelligence (AI) in improving personal learning profile (PLP), personal learning network (PLN) and personal learning environment (PLE). Additionally, the impact of PLP, PLN and PLE on perceived ease of use, perceived effectiveness and perceived usefulness in improving the general attitude and satisfaction of users in their intention to use project management was examined. Results showed the impact of PLE on perceived ease of use and perceived usefulness, significant impact of PLP on perceived effectiveness, and impact of student pressure on intention to use project management. Data were obtained from professionals and students with experience in the use of project management modules. Notably, the obtained data were fully based on the perceptions of the respondents, resulting in potential self-perception bias. Perceptions of users towards PLP, PLN and PLE were integrated into the technology acceptance model framework of this study, to understand their impact on the general attitude and satisfaction of learners. Using AI can enhance learner attitude and satisfaction while creating more engaging e-learning, proving the crucial role of AI in forming the right environment through learner profile match.

1. Introduction

Globalization brings continuous challenges to educational institutions in their efforts towards maintaining and improving their performance. Meanwhile, organizational performance of educational institutions is significantly affected by a number of factors such as project management skills improvement, IT integration, supply chain coordination, process innovation, and communication strength (Masa'deh et al., 2025). When these factors are effectively balanced, the educational institutions could effectively meet the needs of both students and the community while improving its performance in general. In their study, Oke and Takeda (2022) had indicated the importance of project management skills in the improvement of organizational systems, achievement of continuous improvements and utilization of innovations, to increase performance sustainably. Online learning is in fact advantageous. Firstly, it could overcome the time and space limitations so often associated with conventional education (Bates, 2005). Another advantage of online learning, as described by Paulsen (1993), is that, learner is able to utilize various available contents, online spaces and technologies, and all of these could maximize learning. More importantly, online learning usage during the pandemic is an effective way to curb the disease from spreading because there is no face-to-face or physical contact in this type of learning. Fittingly, Jones and Issroff (2005) and Bekele (2010) indicated the importance of motivation, not only in conventional learning, but in online learning as well, as it drives learning. In fact, lack of motivation could impair learning, both in conventional face-to-face learning and in e-learning. Clearly, motivation is a vital component in learning. Notably, e-learning is a remote form of learning that involves the use of a vast range of applications and processes, like virtual classrooms, digital collaboration, computer assisted learning as well as web-based training (ASTD, 2010).

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Additionally, artificial intelligence (AI), which encompasses a group of technologies, is also increasingly popular in use in e-learning; this tool provides the right environment for learning and connects learner to the correct learner network (Al-Rawashdeh, 2025; AlSokkar et al.,2025).

E-learning has been a popular subject among scholars and this form of learning has been examined in various aspects, including its usage aspect such as its acceptance and perceived ease of use, among others. In examining these aspects and some other aspects of e-learning, many studies have employed the technology acceptance model (TAM) introduced by Davis in 1989. TAM facilitates the understanding of the connection between perceived ease of use and perceived usefulness and user attitude and actual usage of e-learning. Additionally, the framework of personal learning network (PLN), personal learning profile (PLP) and personal learning environment (PLE) by Montebello (2017) was employed in this study to understand their impact on the many aspects of TAM in the e-learning context.

Based on the user profile, AI could improve e-learning. In this regard, AI can somewhat replace the facilitator in performing this task, i.e., identify learner's specific needs based on learner profile. Accordingly, this study examined the perception of learners towards PLN, PLE and PLP, as well as the effect of their perception on their attitude and satisfaction levels. In particular, this study explored the relation of these components with perceived ease of use, perceived usefulness and perceived effectiveness, which are the elements necessary in the formation of the right attitude of learner and consequently learner satisfaction, and the predictors of learner's intention towards the utilization of e-learning module. Accordingly, the following research questions guided this study:

RQ1. Do personal learning environments, network and profile influence their perceived ease of use, perceived effectiveness and perceived usefulness of learners towards e-learning modules?

RQ2. What are the factors that determine a learner's overall intention to use the e-learning platform?

2. Literature Review and Hypotheses

2.1 E-learning and Technology Acceptance Model (TAM)

E-learning is regarded as a major development in information and communications technology (ICT), as noted in Liu et al. (2009). This form of learning facilitates learners in actively learning and collaborating with their peers and/or instructors no matter where they are (Ijazdar & Hu, 2004). Those who have a job or have family commitments are now able to further their studies through e-learning because this form of learning is flexible as it allows learners to learn regardless of time and place (Pratt, 1999). For educational institutions, the use of e-learning allows the institutions to reach learners who are not able to take part in the old-fashioned face-to-face learning environments (Maddux & Johnson, 2001).

Studies on e-learning that employed TAM reported significant impact imparted by perceived ease of use and perceived usefulness on the behavioral intention of a person towards e-learning systems utilization (Liu et al., 2009). In TAM, perceived usefulness, ease of use, and attitudes are noted as the three main variables that determine adoption of technology (Davis, 1989). In examining the satisfaction of user towards e-learning, the use of TAM is appropriate as it could show how perceived usefulness, ease of use, and attitudes – the constructs in this model – affect the enjoyment of learners (Arbaugh & Duray, 2002).

Technology acceptance is also affected by factors such as gender, psychological characteristics and socioeconomic backgrounds. For instance, women and men seem to differ in terms of what affects them in technology acceptance; women are more likely to be impacted by subjective norms and organization culture, whereas their male counterparts are more likely to be impacted by perceived usefulness (Venkatesh & Morris, 2000). Technology acceptance is also affected by age; younger people are more likely to accept new technology in comparison to older people (Meyer, 2011).

2.1.1 Perceived Effectiveness

In the context of e-learning, perceived effectiveness can be understood as the belief of the user that the e-learning is a valuable instructional tool in both training programs and learning modules, as indicated by Huprich (2016). However, those who are yet to go through the entire e-learning module may not have the confidence towards the value and effectiveness of this type of learning as a tool of training (Liaw & Huang, 2013). In their study, Chan et al. (2003) evaluated the effectiveness of e-learning using four factors and indicated the complexity of this type of learning because it involves various interconnected issues that need to be taken into account (before its evaluation could be ascertained).

2.1.2 Perceived Usefulness

Perceived usefulness which can be understood of the degree to which one is certain that using specific systems would make them perform better (Davis, 1989), has been regarded as a great determiner of use behavior (Davis et al., 1992). Those who learn using e-learning can learn flexibly; they can learn at any time and location of their convenience. In other words, e-learning provides learners with convenience. Not only that, there is no rush or delay in e-learning, because learners would be able to learn at the pace most appropriate for them. Through e-learning, Liu et al. (2009) mentioned that those far from one another could virtually assemble to learn, work together and share knowledge. Additionally, those perceiving the usefulness of e-learning are more likely to use this type of learning as their learning method.

2.1.3 Perceived Ease of Use

Perceived ease of use refers to the degree to which one believes that using specific systems will be effort-free (Davis, 1989). For learners, perceived ease of use would indirectly affect their intent towards the utilization of Internet-based learning through perceived usefulness and perceived enjoyment (Lee et al., 2005; Qatawneh et al., 2024). The significant impact of perceived ease of use on both the attitudes and perceived usefulness of students has been affirmed (Lee et al., 2005).

2.1.4 Attitude

It is vital to provide users with the correct e-learning environments to motivate and ease learning. For this reason, Liu et al. (2009) highlighted the need to understand the attitudes of users towards e-learning. In understanding the attitudes of individuals toward e-learning, Liaw (2002, 2007) indicated the need to come up with an approach comprising various disciplines. Wang (2003) indicated that e-learning should be measured using various aspects of personal perceptions, so that a correct instrument for determining attitude levels could be created.

2.1.5 Satisfaction

Satisfaction encompasses the difference between the anticipated and the real gain or advantage (Tsai et al., 2007). In system implementation, pleasure is regarded as a vital element. In learning settings, Teo (2014) mentioned that there are factors affecting pleasure, and these factors have linkage to the student, teacher, technology, direction design, system design as well as the environment. Appositely, user satisfaction is an antecedent in system success prediction (Liaw & Huang, 2013; Esterhuyse et al., 2016), while e-learning in itself is a system (Charlier et al., 2010). Notably, e-learning is a highly user-oriented system, and so, it is important that users could successfully use it. As such, the perception of users on their satisfaction level towards the use of the system is essential (Shee & Wang, 2008). Hence, high satisfaction towards a system can be interpreted as high readiness towards the usage of the system (Liaw & Huang, 2013). Hence, the following hypotheses were proposed:

H_{1a}: *Perceived ease of use of learners towards e-learning impacts his/her attitude towards learning.*

H_{1b}: *Perceived ease of use of learner towards e-learning impacts his/her satisfaction towards learning*.

H_{2a}: *Perceived effectiveness of learner towards e-learning impacts his/her attitude towards learning*.

H_{2b}: *Perceived effectiveness of learner towards e-learning impacts his/her satisfaction with learning*.

H_{3a}: *Perceived usefulness of learner towards e-learning impacts his/her attitude towards learning.*

H_{3b}: *Perceived usefulness of learner towards e-learning impacts his/her satisfaction towards learning.*

2.1.6 Intention to Use

Initiatives of e-learning are creatable via e-learning (Mohammadi, 2015; Esterhuyse, 2016), and many studies on intention to use were looking into the experiences that increase the intent of users towards future usage of technology (Armenteros et al., 2013). The intent to use technology was found to have positive linkage to factors including perceived usefulness (Davis, 1989; Jacques et al., 2009), perceived enjoyment (Wang et al., 2010), subjective norms and openness to experience (Schepers & Wetzels, 2007). Considering these findings, the following two hypotheses were put forth:

H_{4a}: *The attitude of the learner towards e-learning impacts his/her intention to use it.*

H_{4b}: *The satisfaction of e-learning impacts his/her intention to use it.*

2.2 Artificial Intelligence (AI) and E-learning

Since its introduction many years ago, artificial intelligence or famously known as AI has been effectively providing users with general technologies to resolve real-life problems (Stone & Hirsh, 2005), in various domains including the domain of education (Beck et al., 1996) in which the use of AI is increasingly common. Within the context of e-learning, AI enables personalization, resulting in improved learning outcomes. A number of studies (Luckin et al., 2016; Montebello, 2017) accordingly have highlighted the value of AI in improving student learning. Indeed, AI has been incorporated in various learning systems. For instance, AI is incorporated into computer-assisted learning (CAL) to facilitate learning. Indeed, AI improves the learning process, as highlighted by Luckin et al. (2016) and Montebello (2017) in their study on artificial intelligence applied to education or also known as AIEd.

In a study by Kim et al. (2018), a concept of smart classroom was envisaged. In this classroom, data acquisition, preprocessing systems and computing components for high-quality computation become its major components. An ontology of smart classrooms for improving self-learning, was discussed by Uskov et al. (2015). As described by the authors, the classroom provides a different maturity level of smartness for the purpose (improve self-learning). In a study Montebello (2019), a concept of ambient intelligent classroom was illustrated. The classroom employs devices including desktop computers, laptops and mobile phones with sensors (eye tracers, motion detectors, click-stream records, engagement log-files, keystroke counts) to detect activities of users during text reading and video viewing. Relevantly, Cope and Kalantzis (2015, 2019) discussed an AI-enabled assessment on customized learning in their study, focusing on the incremental progress of learners. The instrument comprises intelligence tutoring systems as described by Nye (2015). The systems employ games and simulation to establish constant engagement (Shute & Ventura, 2013), log files and clickstream analyses to view success achieved by learner (Crossley et al., 2016), text mining for text and speech comprehension (Zhai & Massung, 2016), in addition to computer peer evaluation (Carlson & Berry, 2003). AI facilitates e-learning by connecting learners to the correct network of people with a personal learning network (PLN) based on the information from the learner's personal learning profile (PLP), and then providing these learners with a personal learning environment (PLE) (Montebello, 2017). PLP, PLN and PLE can all be embedded into the e-learning platform.

2.2.1 Personal Learning Network (PLN)

The satisfaction outcomes are affected by various factors including the environmental factors. Increasing the interaction and connection of learners could increase learner satisfaction towards e-learning (Arbaugh, 2000). In this regard, the use of a personal learning network (PLN) provides users with access to the entire vital input sources and output devices in order to achieve most effective communication and operation in the virtual world. Clearly, e-learning needs a good support system comprising web resources and information from social networks (Leone, 2013).

Learners today are more active in participating in learning; they share knowledge with others. Today, there are tools that facilitate knowledge distribution, sharing and connection, and these tools have been widely in use within the academic domain (O'Reilly, 2013). Sclater (2008) appositely indicated the effective utilization of these tools for the said purposes. The web can become the platform on which learners willingly share information and collaborate with their peers. Gurzick and White (2013) pertinently mentioned that these supportive networks allow knowledge staff to share information with others. Within the context of this study, the ability of PLN in enhancing perceived ease of use, perceived effectiveness and perceived usefulness could be expected, affecting the attitude and satisfaction level of users. Therefore:

H_{5a}: *The perception of learners about AI-enabled personal learning networks (PLN) has an impact on the learner's perceived ease of use towards e-learning.*

H_{5b}: *The perception of learners about AI-enabled PLN has an impact on the learner's perceived effectiveness towards e-learning.*

H_{5c}: *The perception of learners about AI-enabled PLN has an impact on the learner's perceived usefulness towards e-learning.*

2.2.2 Personal Learning Profile (PLP)

A personal learning profile (PLP) is the digital or electronic form of what is captured by a learner profile. In other words, PLP encompasses a digital profile describing the learner (Baumgartner, 2012). In an online setting, PLP can facilitate the access of users to the correct resources. In an academic setting, Gooren-Sieber and Henrich (2012) described a learning portfolio as the academic documentation of a student that correctly captures the tasks that the student has completed and the accomplishments that the students have gained over the years. The description provided by Gooren-Sieber and Henrich (2012), based on Lorenzo and Ittelson (2005), can be regarded as one functionality – out of six functionalities – of PLP. PLP allows the identification of certain academic content that would meet the specific needs of learners. Also, PLP can be a practical tool because it could boost self-directed learning, reflecting certain academic achievements for learners (Daunert & Price, 2014). Additionally, the use of PLP could improve online user motivation (Noesgaard & Ørngreen, 2015).

Studies have shown the ability of PLP in increasing enthusiasm among learners, because PLP can motivate learners to initiate and take part in new learning processes, in their network especially (see: Attwell, 2007; D'Alessandro, 2011). In a related study, Vargas-Vera and Lytras (2008) employed an e-learning environment in identifying learner's tendencies in learning and creating learner's impending educational experiences, to improve the learning process. All these findings demonstrate the ability of PLP in affecting the perceived ease of use of learners towards e-learning and the perceived effectiveness and usefulness of learners towards e-learning, if the system corresponds with the specific needs and interest of the learner. As reported by Arbaugh (2002) and Arbaugh and Duray (2002), the attitude of learners toward computers significantly predicts learner satisfaction. As such, the use of PLP in e-learning is expected to increase the attitude and satisfaction of users toward e-learning. Hence:

H_{6a}: *The perception of learners towards AI-enabled personal learning profile (PLP) has an impact on learner's perceived ease of use towards e-learning.*

H_{6b}: *The perception of learners towards AI-enabled personal learning profile (PLP) has an impact on learner's perceived effectiveness towards e-learning.*

H_{6c}: *The perception of learners towards AI-enabled personal learning profiles (PLP) has an impact on learner's perceived usefulness for e-learning.*

2.2.3 Personal Learning Environment (PLE)

The personal learning environment (PLE), which combines PLN and PLP, demonstrates the principle of personalized education. Together, personal network and portfolio could result in an environment of learning that is both successful and healthy; the learning environment feels close and personal to the learner. PLE has been studied by many. In a study by Attwell

(2007), it was reported that PLE encourages the use of new and different learning methods. Furthermore, in comparison to virtual learning environments (VLE), PLE is more flexible and less resource bound (Charlier et al., 2010). PLE is learner-centered and thus, it is the learner that decides on the resources and format to be used in the presentation of academic materials (Charlier et al., 2010).

In a study by Dabbagh and Kitsantas (2012) on PLE, a framework was proposed. The authors proposed the implementation of a PLE that supports self-regulated learning, stressing on learner-educator relationship and educators taking the transformative approach to motivate learners. In another study, Fiedler and Väljataga (2013) indicated the need to provide highly accessible institutional learning environments and VLEs, considering the high availability of information today. PLE forms a positive learning climate. It also affects ease of use, usefulness and learners' effectiveness, resulting in a more favorable attitude towards learning and increased satisfaction towards e-learning. This study hence proposed the following:

H_{7a}: *The perception of learners towards AI-enabled PLE has an impact on learner's perceived ease of use towards e-learning.*

H_{7b}: *The perception of learners towards AI-enabled PLE has an impact on learner's perceived effectiveness towards e-learning.*

H_{7c}: *The perception of learners towards AI-enabled PLE has an impact on learner's perceived usefulness towards e-learning.*

2.2.4 Student Pressure

Student satisfaction is a major goal for business organization, and the achievement of student satisfaction requires understanding of student needs and demand. When the student is satisfied, it could mean that the business organization employs a satisfactory system. Perceived customer pressure and overall satisfaction have inverse correlation (Chong, 2008). Appositely, customer pressure entails demands and behaviors that result in adoption of new technology by companies (Hasani et al., 2017). End consumers and business consumers as major stakeholders of business organizations frequently demand that the organization would improve in terms of its environmental and social performance (Gualandris & Kalchschmidt, 2014). Among business organizations, the adoption of ISO standards is strongly motivated by customer pressure. This implies a positive relationship between customer pressure and quality control performance (Ueki, 2016). Adoption intention of SMEs is positively and significantly correlated with customer pressure (Maduku et al., 2016). Green innovation of SME is also significantly affected by customer pressure (Mangula, 2017). Also, customer pressure also is a main determinant in the environmental performance of firms (Chong, 2008). Hence:

H_8: *Students' pressure has a positive impact on Intention to use.*

2.3 Research Model

Review on past relevant studies showed impacts of AI-enhanced PLN, PLP and PLE on perceived ease of use, perceived effectiveness and perceived usefulness of learner, which consequently will impact the attitude and satisfaction of learner and also the intent of learner towards pursuing e-learning. A conceptual model was proposed, as in the following Fig. 1.

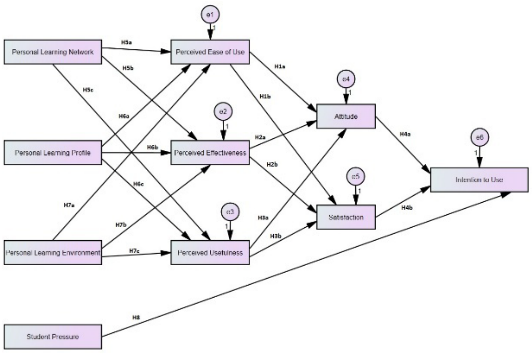

Fig. 1. Research model

3. Research Methodology

The present study employed a questionnaire as the tool for obtaining the study data. The questionnaire items were adopted from relevant literature, and they covered ten study constructs as illustrated in Fig. 1. The items were supplemented with 5-point Likert scales to ease the respondents in providing their most accurate response. The scales were anchored from 1 to denote "Strongly Disagree" to 5 to denote "Strongly Agree." To ease understanding of the respondents whose native language is Arabic, the questionnaire, which was originally in English, was translated into Arabic. The translation process followed the back-translation method. Firstly, the original questionnaire which was in English, was translated into Arabic. Then, the Arabic version was translated back into English. After that, the original English questionnaire and the translated English questionnaire were compared. The comparison allowed the researcher to assure that both versions were identical, and hence, reliable. A pretest to the questionnaire was carried out as well, involving fifteen students with e-learning systems experience in school. Aside from answering the questionnaire, these students were asked to provide feedback as necessary. Based on these feedbacks, the questionnaire was refined, and the finalized questionnaire was produced.

3.1 Measures

In this study, measures of the variables followed prior studies. Specifically, measures for perceived effectiveness were based on Huprich (2016), measures for perceived usefulness, perceived ease of use and attitude were based on Liu et al. (2009), while measures for satisfaction and intention to use were based on Esterhuyse et al. (2016). Perceived ease of use, perceived usefulness and attitude towards behavioral intention to use were based on the original TAM (Davis,1989). Additionally, measures for PLP, PLN and PLE were based on a book titled "AI Injected e-Learning: The Future of Online Education" authored by Montebello (2017). There were four items representing PLP including "AI can recommend material and methodology," and "AI can provide personalized feedback and self-evaluation." There were three items representing PLN including "AI can connect the learner with people with similar interests," and "AI can help learners exchange knowledge with similar others." There were two items representing PLE including "AI can make the learning environment more conducive" and "AI can make learning more enjoyable." Measures on student pressure were based on Berns (2009).

3.2 Sample and Data Collection

The questionnaire was delivered to the study respondents online, via a link on a Facebook post. Students with e-learning use experience were the study respondents. The researcher had gathered 800 usable responses for the data analysis stage. The following Table 1 presents the respondents' demographic profile information.

Table 1
Description of the respondents' demographic profiles

Category	Category	Frequency	Percentage%
Gender	Male	680	0.85
	Female	120	0.15
	Total	800	100
Age (Year)	20 years old or younger	550	0.68
	20 - 29 years	200	0.25
	30 – 39 years	50	0.07
	Total	800	100
University Sector	Public	450	0.56
	Private	350	0.44
	Total	800	100
College	Scientific	120	0.15
	Humanities	100	0.13
	Health	250	0.31
	Education	330	0.41
	Total	800	100
Academic Level	Bachelor	600	0.76
	Master	100	0.12
	Doctorate	100	0.12
	Total	800	100
Resident Place	The Capital (Amman)	200	0.25
	Northern Region	180	0.23
	Middle Region	150	0.19
	Southern Region	270	0.33
	Total	800	100
Technology Type to Use eLearning	Personal computer	220	0.28
	Smartphone	580	0.72
	Total	800	100
Internet Evaluation	Excellent	300	0.38
	Very good	50	0.06
	Good	450	0.56
	Total	800	100

4. Data Analysis and Results

4.1 Normality and Multicollinearity

Using AMOS 22.0, the univariate normality was examined for each study variable. Skewness-kurtosis test was carried out based on Kline (2005) and Byrne et al. (2010). Here, skewness values were all smaller than 3 as the cut-off value, while all kurtosis values achieved were less than 8 as the cut-off value endorsed by West et al. (1995) and Kline (2005). Normality of univariate distribution was hence affirmed. Reliability of SEM is impacted by multicollinearity, and inside a regression model, Kline (2005) stated that multicollinearity means that the independent variables are highly correlated between them. This study accordingly examined multicollinearity using SPSS, and the values of tolerance and VIF were calculated. Results showed tolerance value of below 0.10, and value of VIF greater than 10 – both values are classed as tolerable.

4.2 Common Method Bias

This study examined common method bias (CMB) potential using Harman's single-factor as advised by Harman (1976) and Podsakoff et al. (2003). There were 8 constructs involved and they were: PLP, PLN, PLE, ATT, SP, SA, PE, PU, PEOU and

INP represented by 39 items. From the results, the researcher found no identification of any single factor. Also, the first component symbolized 41.65% of variance, which was smaller than the 50% recommended cut-off value of Podsakoff et al. (2003). As can be deduced, the study data did not suffer from CMB.

4.3 SEM Analysis

The present study employed SEM for hypotheses testing. The following subsections present the details.

4.4 Measurement Model

In examining the items' properties, confirmatory factor analysis (CFA) was executed in this study. Additionally, as indicated in Bagozzi and Yi (1988) and Hair et al. (2006), the measurement model illustrates the assessment of latent variables or hypothetical constructs particularly on the observed variables, signifying the reliability and validity of the responses of the observed variables for the latent variables. Accordingly, factor loadings, Cronbach's alpha, composite reliability and also Average Variance Extracted (AVE) were computed for the study variables, and they can all be viewed in Table 2.

Table 2
Properties of the final measurement model

Constructs and Indicators	Factor Loadings	Std. Error	Square Multiple Correlation	Error Variance	Cronbach's Alpha	Composite Reliability	AVE
Personal learning Network(PLN)					0.901	0.81	0.91
PLN1	0.811	***	0.810	0.311			
PLN2	0.877	0.012	0.644	0.366			
PLN3	0.922	0.033	0.301	0.158			
Personal learning Profile (PLP)					0.822	0.89	0.80
PLP1	0.771	0.034	0.722	0.311			
PLP2	0.654	0.031	0.766	0.111			
PLP3	0.822	0.011	0.531	0.508			
PLP4	0.680	0.055	0.702	0.576			
PLP5	0.821	0.066	0.555	0.510			
Personal learning Environment (PLE)					0.811	0.81	0.77
PLE1	0.722	0.020	0.490	0.411			
PLE2	0.666	0.040	0.399	0.453			
PLE3	0.511	0.032	0.507	0.122			
PLE4	0.572	0.011	0.502	0.290			
PLE5	0.666	0.039	0.045	0.470			
Perceived Ease of Use (PEOU)					0.880	0.80	0.91
PEOU1	0.751	0.065	0.605	0.523			
PEOU2	0.922	0.030	0.561	0.520			
PEOU3	0.613	0.019	0.832	0.441			
PEOU4	0.821	0.024	0.611	0.695			
Perceived Effectiveness (PE)					0.829	0.83	0.87
PE1	0.621	0.039	0.822	0.711			
PE2	0.524	0.011	0.831	0.209			
PE3	0.622	0.022	0.366	0.222			
PE4	0.311	0.044	0.005	0.311			
PE5	0.666	0.071	0.409	0.210			
Perceived Usefulness (PU)					0.910	0.86	0.90
PU1	0.811	0.038	0.704	0.311			
PU2	0.902	0.021	0.899	0.347			
PU3	0.540	0.021	0.780	0.222			
PU4	0.976	0.010	0.733	0.144			
PU5	0.510	0.021	0.205	0.134			
Attitude (ATT)					0.944	0.81	0.73
ATT1	0.750	0.029	0.521	0.366			
ATT2	0.819	0.015	0.632	0.409			
ATT3	0.754	0.066	0.570	0.548			
Satisfaction (SA)					0.910	0.94	0.86
SA1	0.861	0.037	0.716	0.234			
SA2	0.736	0.011	0.889	0.286			
SA3	0.812	0.028	0.820	0.279			
Student pressure (SP)					0.881	0.91	0.84
SP1	0.822	0.021	0.721	0.111			
SP2	0.773	0.013	0.806	0.223			
SP3	0.801	0.014	0.776	0.305			
Intention to Use Project management (IN)					0.821	0.90	0.86
INP1	0.889	0.011	0.774	0.103			
INP2	0.843	0.221	0.811	0.226			
INP3	0.803	0.041	0.888	0.338			

The table shows that the factor loadings indicators are all larger than 0.50, denoting convergent validity, as recommended by Bagozzi and Yi (1988) and Creswell (2009). Furthermore, values of AVE were greater than 0.50, affirming convergent validity, as proposed by Bagozzi and Yi (1988) and Hair et al. (2010). Furthermore, the values of composite reliability were higher as opposed to the cut-off value of 0.60, affirming high-level internal consistency of the latent variables. Table 3 shows the intercorrelations between construct pairs being smaller in value compared to the AVE estimates square root of both constructs, and so, discriminant validity is affirmed (Hair et al., 2006). As such, the convergent and discriminant validity of the measurement items used in this study were of sufficient levels.

Table 3
Correlations of constructs

Constructs	PLN	PLP	PLE	PEOU	PE	PU	ATT	SA	SP	INP
PLN	0.93									
PLP	0.661	0.91								
PLE	0.827	0.791	0.77							
PEOU	0.801	0.622	0.605	0.88						
PE	0.591	0.651	0.620	0.816	0.86					
PU	0.823	0.666	0.643	0.827	0.670	0.93				
ATT	0.711	0.801	0.609	0.701	0.722	0.701	0.73			
SA	0.632	0.611	0.641	0.732	0.670	0.608	0.644	0.70		
SP	0.604	0.705	0.666	0.721	0.777	0.746	0.633	0.718	0.80	
INP	0.699	0.832	0.723	0.660	0.730	0.651	0.620	0.777	0.689	0.77

4.5 Structural Model

The study hypotheses were tested in this study. Structural equation modeling was used for the purpose, and it was run using Amos 22. SEM was appropriate for the study context because the researcher could simultaneously test all the hypotheses, both direct and indirect effect hypotheses. Summarized results of the study hypotheses are shown in Table 4.

Table 4
Summary of proposed results for the theoretical model

Research Proposed Paths	Coefficient Value	t-value	p-value	Empirical Evidence
H1a: PEOU → ATT	0.340	13.111	0.001	Supported
H1b: PEOU→ SA	0.122	1.235	0.040	Supported
H2a: PEF→ ATT	0.034	1.055	0.102	Not Supported
H2b: PEF → SA	0.040	1.269	0.112	Not Supported
H3a: PU → ATT	0.011	1.033	0.103	Not Supported
H3b: PU→ SA	0.014	1.225	0.161	Not Supported
H4a: ATT→ INP	0.075	1.201	0.270	Not Supported
H4b: SA → INP	0.212	8.222	0.001	Supported
H5a: PLN → PEOU	0.031	1.273	0.113	Not Supported
H5b: PLN → PEF	0.015	1.220	0.213	Not Supported
H5c: PLN→ PU	0.024	1.101	0.111	Not Supported
H6a: PLP → PEOU	0.721	0.224	0.202	Not Supported
H6b: PLP → PEF	0.333	0.444	0.004	Supported
H6c: PLP → PU	0.011	0.182	0.123	Not Supported
H7a: PLE→ PEOU	0.526	0.302	0.003	Supported
H7b: PLE→ PEF	0.044	0.116	0.222	Not Supported
H7c: PLE → PU	0.291	0.504	0.040	Supported
H8: SP → INP	0.199	0.337	0.005	Supported

5. Results

Results, as displayed in Table 4, demonstrate path coefficients, where perceived ease of use affects both attitude and satisfaction significantly. As such, H1a, H1b were supported. In addition, perceived effectiveness affects both attitude and satisfaction insignificantly. As such H2a, H2b were not supported. Moreover, perceived usefulness affects both attitude and satisfaction insignificantly. As such H3a and H3b were not supported. Furthermore, attitude did not affect intention to use project management, so H4a was not supported. Satisfaction was the only factor that affects intention to use project management. Therefore, H4b was supported. For PLN, results showed no impact of this construct on perceived ease of use, perceived effectiveness and perceived usefulness. As such, H5a, H5b, and H5c were not supported. For PLP, results showed that it had an impact only on perceived effectiveness. This means that H6b was supported, while H6a and H6c were not. Results showed the impact of PLE on perceived ease of use and perceived usefulness, and so, H7a and H7c were supported. However, PLE had no impact on perceived effectiveness, and so, H7b was not supported. Finally, results showed that students' pressure had an impact on intention to use project management, and so, H8 was supported.

6. Discussion and Implications

For educational organizations, investing in the development of robust project management capabilities, integrating the innovative IT solutions and establishing relationships with external suppliers would be beneficial in improving their operational efficiency and in maintaining their competitiveness and adaptability in today's erratic environment.

At present, the rate of e-learning course enrolment is really high, and yet, the rate of e-learning course completion is very low. This phenomenon can be attributed to learners' lack of motivation or loss of interest towards completing the course owing to the rather discouraging environment of learning provided by this type of learning. In e-learning, there is no facilitator or teacher available to guide learners, as opposed to the traditional face-to-face classroom learning. To many learners, this situation has made learning through e-learning very challenging. Understanding such challenges is crucial because otherwise, e-learning cannot become a major mode of learning today. Notably, e-learning has gained importance owing to the situations today, especially, after the outbreak of COVID-19 that has made face-to-face classroom learning risky.

PLP, PLN and PLE have been proven to affect learning and teaching in this modern era. This study accordingly examined the perception of learners towards PLP, PLN and PLE and the impacts of these factors on numerous aspects of learning. With the emergence of AI, this study specifically looked into how the integration of AI into PLP, PLN and PLE could effectively improve learning, and be included in TAM of e-learning. The discovery of the direct impact of PLP on learner satisfaction implies that the correct match between the profile of learner to the courses offered could increase satisfaction of learner. The enhancement of the learning process through PLP was also affirmed by Luckin et al. (2016) and also by Montebello (2017).

Additionally, the impact of PLE on perceived ease of use and perceived usefulness denotes the need to establish a conducive and supportive learning environment for users. Notably, e-learning can appear dull and monotonous, and for this reason, learners need to be motivated consistently, through the use of methods such as rewards and points for their accomplishments and task completions. Additionally, the learning environment has a significant impact on the ease of use and usefulness of the e-learning module. Also, PLP has an effect on perceived effectiveness, because the match between the profile of learner and the learning pace will make learning more effective.

The use of artificial intelligence (AI) allows suggestions of fitting material and methodology to the learning style of learners. Through its intelligent system, AI could suggest the courses most fitting to the learner (VanLehn, 2011; Nye, 2015). Not only that, AI facilitates personalized feedback and self-evaluation. The suggestion of a learning module by AI based on the profile of the learner could increase the learner's perceived effectiveness and satisfaction of the learner towards e-learning. Additionally, Cope and Kalantzis (2015, 2019) indicated that AI-enabled assessment focusing mainly on customized learning facilitates the tracking of learners' accrued progress. Crossley et al. (2016) further added that success of learners could be checked using click-streams analysis. Furthermore, Montebello (2019) proposed the use of "ambient intelligent classroom" in which information is captured using a number of methods including engagement log files, motion detectors, eye trackers, click-stream record, as well as keystroke counts.

6.1 Limitations and Future Scope

The present study explored the perception of users towards the use of e-learning in completing their courses, and the impact of AI usage in current e-learning in matching the portfolio of learners with the learning modules, on the future of e-learning. PLP, PLN and PLE empowered by AI, were examined in this study, on perceived ease of use, perceived effectiveness and perceived usefulness of learners. Results showed that PLN did have a significant impact on perceived ease of use, perceived effectiveness and perceived usefulness of learners, but the effect of this construct should be explored more deeply in future studies. AI-empowered PLN could facilitate learners in connecting with the correct individuals and interest groups, and consequently establish the correct network for knowledge and information interchange, to improve learning outcomes.

In the arena of e-learning, AI has tremendous implications, as can be exemplified by the use of its 3-D visualization in the construction of realistic learning with virtual and augmented reality. Additionally, the use of AI's biometric recognition system in e-learning allows the gathering of learner data to create accurate learner profiles. Apart from that, gamification is effective in engaging learners in the system. Still, AI-enabled e-learning has challenges. For instance, data usage and data privacy are delicate issues that need to be handled cautiously. Also, for teachers and educators, AI should just be a support system, not their substitute. Furthermore, for many institutes of learning, it is not easy to come up with the content and curriculum that can appropriately fit into the AI-enabled e-learning module.

References

Al-Rawashdeh, S.A.A. (2025). The role of artificial intelligence systems in combating cybercrime: A field study in Jordan. *Jordan Journal of Business Administration, 21*(1), 121-141.

AlSokkar, A. A., Al-Gasawneh, J. A., Alamro, A., Binkhamis, M., AlGhizzawi, M., & Hmeidan, T. A. (2025). The Effectiveness of E-Marketing on Marketing Performance in Jordanian Telecommunications Companies: Exploring the Mediating Role of the Competitive Environment. *SN Computer Science*, *6*(1), 1-15.

Arbaugh, J.B. (2000). Virtual classroom characteristics and student satisfaction with internet-based MBA courses. *Journal of Management Education, 1*(24), 32-54.

Arbaugh, J.B. (2002). Managing the online classroom: A study of technological and behavioral characteristics of web-based MBA courses. *Journal of High Technology Management Research, 2*(13), 203-223.

Arbaugh, J.B., & Duray, R. (2002). Technological and structural characteristics, student learning and satisfaction with web-based courses– An exploratory study of two online MBA programs. *Management Learning,* pp. 331-347.

Armenteros, M., Liaw, S.S., Fernandez, M., Dıaz, R.F., & Sanchez, R.A. (2013). Surveying FIFA instructors' behavioral intention toward the multimedia teaching materials. *Computers and Education, 61*(1), 91-104.

ASTD (2010). *E-learning*, available at: http://www.astd.org/LC/glossary.htm.

Attwell, G. (2007). E-Portfolios the DNA of the personal learning environment?. *Journal eLearning Knowledge Society, 3*(2), 39-61.

Bagozzi, R., & Yi, Y. (1988). On the evaluation of structural evaluation models. *Journal of the Academy of Marketing Science, 16*(1), 74-94.

Bates, A. (2005). *Technology, E-Learning and Distance Education*. Routledge Falmer.

Baumgartner, P. (2012). *Eine Taxonomie for E-Portfolios, Department of Interactive Media and Educational Technologies*. Danube University Krems.

Beck, J., Stern, M., & Haugsjaa, E. (1996). Applications of A.I. in education. *The ACM Magazine for Students, 3*(1), 11-15.

Bekele, T.A. (2010). Motivation and satisfaction in internet-supported learning environments: A review. *Educational Technology and Society, 2*(13), 116-127.

Berns, M. (2009). English as lingua franca and English in Europe. *World Englishes, 28*(2), 192-199.

Byrne, S.M., Allen, K.L., Lampard, A.M., Dove, E.R., & Fursland, A. (2010). The factor structure of the eating disorder examination in clinical and community samples. *International Journal of Eating Disorders, 43*(3), 260-265.

Carlson, P.A., & Berry, F.C. (2003). *Calibrated peer review and assessing learning outcomes*. Frontiers in Education Conference, STIPES, 2, F3E-1.

Chan, A.Y., Chow, K.O., & Jia, W. (2003). *A framework for evaluation of learning effectiveness in online courses*. In The International Conference on Web-Based Learning, Springer, Berlin, Heidelberg, 383-395.

Charlier, B., Henri, F., Peraya, D., Gillet, D., & Barcelona (2010). *From personal environment to personal learning environment*. In the 5th European Conference on Technology Enhanced Learning.

Chong, S. (2008). Success in electronic commerce implementation: A cross-country study of small and medium-sized enterprises. *Journal of Enterprise Information Management, 21*(5), 468-492.

Cope, B., & Kalantzis, M. (2015). *Assessment and pedagogy in the era of machine-mediated learning.* Education as social construction: contributions to theory, research, and practice, 350-374.

Cope, B., & Kalantzis, M. (2019). Education 2.0: Artificial intelligence and the end of the test. *Beijing International Review of Education, 1*(2-3), 528-543.

Creswell, J. (2009). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. 3rd ed., Thousand Oaks: Sage Publications.

Crossley, S., Paquette, L., Dascalu, M., McNamara, D.S., & Baker, R.S. (2016). *Combining click stream data with NLP tools to better understand MOOC completion.* Proceedings of the Sixth International Conference on Learning Analytics and Knowledge, 6-14.

D'Alessandro, M. (2011). Connecting your radiology learning to your clinical practice: Using personal learning environments, learning portfolios and communities of practice. *Pediatric Radiology, 41*(1), 245.

Dabbagh, N., & Kitsantas, A. (2012). Personal learning environments, social media, and self-regulated learning: A natural formula for connecting formal and informal learning. *The Internet and Higher Education, 15*(1), 3-8.

Daunert, A.L., & Price, L. (2014). *E-portfolio: A practical tool for self-directed, reflective, and collaborative professional learning.* Discourses on Professional Learning, Springer, Dordrecht, 231-251.

Davis, F.D. (1989). Usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 3(13), 319-340.

Davis, F.D., Bagozzi, R.P., & Warshaw, P.R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology, 22*(14), 1111-1132.

Esterhuyse, M. (2016). Intention to use and satisfaction of e-learning for training in the corporate context. *Interdisciplinary Journal of Information, 11*, 347-365.

Esterhuyse, M., Scholtz, B., & Venter, D. (2016). Intention to use and satisfaction of e-learning for training in the corporate context. *Interdisciplinary Journal of Information, Knowledge, and Management, 11*, 347-365.

Fiedler, S., & Väljataga, T. (2013). Personal learning environments: A conceptual landscape revisited. *E-Learning Papers, 35*, 1-16.

Gooren-Sieber, S., & Henrich, A. (2012). *Systems for Personalised Learning: Personal Learning Environment vs. E-Portfolio?.* In: Cheung, S.K.S., Fong, J., Kwok, LF., Li, K., Kwan, R. (eds) Hybrid Learning. ICHL 2012. Lecture Notes in Computer Science, 7411. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-32018-7_28

Gualandris, J., & Kalchschmidt, M. (2014). Customer pressure and innovativeness: Their role in sustainable supply chain management. *Journal of Purchasing and Supply Management, 20*(2), 92-103.

Gurzick, D., & White, K.F. (2013). *Online personal networks of knowledge workers in computer supported collaborative learning.* Computer-Supported Collaborative Learning at the Workplace, Springer, Boston, MA, 225-239.

Hair, J., Black, W., Babin, B., Anderson, R., & Tatham, R. (2006). *Multivariate Data Analysis*. 6th ed., New Jersey: PrenticeHall.

Hair, J., Black, W., Babin, B., Anderson, R., & Tatham, R. (2010). *Multivariate Data Analysis*. 7th ed., New Jersey: PrenticeHall.

Harman, W.W. (1976). *An incomplete guide to the future*. San Francisco Book Company.

Hasani, T., Bojei, J., & Dehghantanha, A. (2017). Investigating the antecedents to the adoption of SCRM technologies by start-up companies. *Telematics and Informatics, 34*(5), 655-675.

Huprich, J. (2016). *Perceived Effectiveness of E-Learning for Technology Instruction in Public Library Staff Development Programs: A Survey Based on the Technology Acceptance Model*. Master of Science in Information Technology Theses, Kennesaw State University.

Ijazdar, R., & Hu, Y. (2004). *How Banks Manage CRM: A B2B Perspective*. Lulea University of Technology.

Jacques, P.H., Garger, J., Brown, C.A., & Deale, C.S. (2009). Personality and virtual reality team candidates: The roles of personality traits, technology anxiety and trust as predictors of perceptions of virtual reality teams. *Journal of Business Management, 15*(2), 143.

Jones, A., & Issroff, K. (2005). Learning technologies: Affective and social issues in computer-supported collaborative learning. *Computers & Education, 44*(4), 395-408.

Kim, Y., Soyata, T., & Behnagh, R.F. (2018). Towards emotionally aware A.I. smart classroom: Current issues and directions for engineering and education. *IEEE Access, 6*, 5308-5331.

Kline, R.B. (2005). *Principles and Practice of Structural Equation Modeling*. 2nd ed. New York: Guilford.

Lee, M.K., Cheung, C.M., & Chen, Z. (2005). Acceptance of Internet-based learning medium: The role of extrinsic and intrinsic motivation. *Information & Management, 42*(8), 1095-1104.

Leone, S. (2013). *Characterisation of a Personal Learning Environment as a Lifelong Learning Tool*. Springer, Ancona.

Liaw, S.S. (2002). An Internet survey for perceptions of computer and World Wide Web: Relationship, prediction, and difference. *Computers in Human Behavior, 18*(1), 17-35.

Liaw, S.S. (2007). Understanding computers and the internet as a work assisted too. *Computers in Human Behavior, 23*(1), 399-414.

Liaw, S.S., & Huang, H.M. (2013). Perceived satisfaction, perceived usefulness and interactive learning environments as predictors to self-regulation in e-learning environments. *Computers and Education, 60*(1), 14-24.

Liu, S.H., Liao, H.L., & Pratt, J.A. (2009). Impact of media richness and flow on e-learning technology acceptance. *Computers and Education, 52*(3), 599-607.

Lorenzo, G., & Ittelson, J. (2005). An overview of e-portfolios. *Educause Learning Initiative, 1*(1), 1-27.

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L.B. (2016). *Intelligence Unleashed: An Argument for A.I. In Education.* Pearson, London.

Maddux, C., & Johnson, D. (2001). *The Web in Higher Education: Assessing the Impact and Fulfilling the Potential.* The Haworth Press, New York, NY.

Maduku, D.K., Mpinganjira, M., & Duh, H. (2016). Understanding mobile marketing adoption intention by South African SMEs: A multi-perspective framework. *International Journal of Information Management, 36*(5), 711-723.

Mangula, I. (2017). *A meta-analysis of IT innovation adoption factors: the moderating effect of product and process innovations diffusion of SaaS adoption view project*. In the Pacific Asia Conference on Information System.

Masa'deh, R., Albalawneh, D., Warrad, L., Thurasamy, R., & Almajali, D. (2025). The impact of information technology application on project performance: The mediating role of knowledge management. *Journal of Project Management, 10*(2), 221-228.

Meyer, J. (2011). Workforce age and technology adoption in small and medium sized service firms. *Small Business Economics, 37*(3), 305-324.

Mohammadi, H. (2015). Investigating users' perspectives on e-learning: An integration of TAM and IS success model. *Computers in Human Behavior, 45*, 359-374.

Montebello, M. (2017). *A.I. Injected E-Learning: The Future of Online Education*. Springer, Berlin.

Montebello, M. (2019). *The Ambient Intelligent Classroom: Beyond the Indispensable Educator*. Springer, Vol. 840.

Noesgaard, S., & Ørngreen, R. (2015). The effectiveness of e-learning: An explorative and integrative review of the definitions, methodologies and factors that promote e-learning effectiveness. *Electronic Journal eLearning, 13*(4), 278-290.

Nye, B. (2015). Intelligent tutoring systems by and for the developing world: A review of trends and approaches for educational technology in a global context. *International Journal of Artificial Intelligence in Education, 25*(2), 177-20.

O'Reilly, T. (2013). *What is web 2.0 design patterns and business models for the next generation of software*, available at: http://www.oreilly.com/pub/a/web2/archive/what-is-web-20.html.

Oke, A., & Takeda, S. (2022). The role of IT in supply chain process innovation. *International Journal of Production Research, 60*(14), 4519-4535.

Paulsen, M.F. (1993). The hexagon of cooperative freedom: A distance education theory attuned to computer conferencing. *DEOS News, 3*(1e9).

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y., & Podsakoff, N.P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879-903.

Pratt, R.P. (1999). *Building Learning Communities in Cyberspace: Effective Strategies for the Online Classroom.* Jossey-Bass Publishers, San Francisco.

Qatawneh, A.M., Al-Lozi, E.M., & Al-Lozi, N.M. (2024). Internet of things "IoT" and the quality of decision-making during the Covid-19 pandemic: A perspective of accounting managers within the Jordanian industrial sector. *Jordan Journal of Business Administration, 20*(2), 291-308.

Schepers, J., & Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effect. *Information & Management, 44*(1), 90-103.

Sclater, N. (2008). Web 2.0, personal learning environments and the future of learning management systems. *Research Bulletin, 13*, Boulder, CO: EDUCAUSE Center for Applied Research, 2008, available fromhttp://www.educause.edu/ecar

Shee, D., & Wang, Y. (2008). Multi-criteria evaluation of the web-based e-learning system: A methodology based on learner satisfaction and its applications. *Computers and Education, 50*(3), 894-905.

Shute, V., & Ventura, M. (2013). Stealth Assessment: Measuring and Supporting Learning in Video Games. *The MIT Press, 102*.

Stone, M., & Hirsh, H. (2005). Artificial intelligence: the next twenty-five years. *AI Magazine, 26*(4), 85.

Teo, T. (2014). Preservice teachers' satisfaction with e-learning. *Social Behavior and Personality: An International Journal, 42*(1), 3-6.

Tsai, P.C., Yen, Y., Huang, L., & Huang, I. (2007). A study on motivating employees' learning commitment in the post-downsizing era: Job satisfaction perspective. *Journal of World Business, 42*(2), 157-169.

Ueki, Y. (2016). Customer pressure, customer-manufacturer-supplier relationships, and quality control performance. *Journal of Business Research, 69*(6), 2233-2238.

Uskov, V.L., Bakken, J.P., & Pandey, A. (2015). *The Ontology of Next Generation Smart Classrooms*. Smart Education and Smart E-Learning, Springer, Cham, 3-14.

VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational Psychologist, 46*(4), 197-221.

Vargas-Vera, M., & Lytras, M. (2008). Exploiting semantic web and ontologies for personalised learning services: Towards semantic web-enabled learning portals for real learning experiences. *International Journal of Knowledge and Learning, 4*(1), 1-17.

Venkatesh, V., & Morris, M.G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly, 24*, 115-139.

Wang, Y.S. (2003). Assessment of learner satisfaction with asynchronous electronic learning systems. *Information & Management, 41*(1), 75-86.

Wang, Y.S., Lin, H.H., & Liao, Y.W. (2010). Investigating the individual difference antecedents of perceived enjoyment in the acceptance of blogging. *World Academy of Science, Engineering and Technology, 67*(1), 1014-1023.

West, S.G., Finch, J.F., & Curran, P.J. (1995). *Structural equation models with nonnormal variables: Problems and remedies*. In: Hoyle, R.H., Ed., Structural Equation Modeling: Concepts, Issues, and Applications, Sage, Thousand Oaks, 56-75.

Zhai, C., & Massung, S. (2016). Text data management and analysis: A practical introduction to information retrieval and text mining. *Association for Computing Machinery and Morgan and Claypool, 12*.