



Facebook/Meta usage in higher education: A deep learning-based dual-stage SEM-ANN analysis

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Abstract

The paper's main aim is to investigate and predict major factors in students' behavioral intentions toward academic use of Facebook/Meta as a virtual classroom, taking into account its adoption level, purpose, and education usage. In contrast to earlier social network research, this one utilized a novel technique that comprised a two-phase analysis and an upcoming the Artificial Neural Network (ANN) analysis approach known as deep learning was engaged to sort out relatively significant predictors acquired from Structural Equation Modeling (SEM). This study has confirmed that perceived task-technology fit is the most affirmative and meaningful effect on Facebook/Meta usage in higher education. Moreover, facilitating conditions, collaboration, subjective norms, and perceived ease of use has strong influence on Facebook usage in higher education. The study's findings can be utilized to improve the usage of social media tools for teaching and learning, such as Facebook/Meta. There is a discussion of both theoretical and practical implications.

Keywords Facebook/Meta · Social media · Social networking sites · Structural equation modeling · Artificial Neural network · Deep Learning · Higher education · Online learning Turkey

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1 Introduction

Over time, Facebook/Meta has emerged as one of the software that has been implemented for generating and sharing information with Internet users. As a result of the evolution of Web 2.0, it is now widely acknowledged as the most widely utilized Social Networking Site (SNS) for disseminating information among students in higher education (Ajjan & Hartshorne, 2008; Lampe et al., 2011; Hew & Cheung, 2012; Deng & Tavares, 2013; Albayrak & Yildirim, 2015; Purvis et al., 2016; Sharma et al., 2016).

Students and teachers may use social networking sites, particularly Facebook/Meta, to exchange knowledge, disseminate learner-created material, increase student engagement, communicate, and interact socially (Bowman & Akcaoglu, 2014; Deng & Tavares, 2013; Gabarre et al., 2013; Jong et al., 2014; Junco, 2012; Khan et al., 2014; Lampe et al., 2011; Pérez et al., 2013; Wang et al., 2012; Wu et al., 2013). Researchers and academics in higher education were influenced by the growing usage of SNSs in the role of technology (Albayrak & Yildirim, 2015; Boyd & Ellison, 2007; Cheung et al., 2011; Hargittai, 2007; Hew, 2011; Junco, 2012; Madge et al., 2009; Selwyn, 2009). The higher penetration of Facebook/Meta provides the crucial and numerous benefits for students of utilizing Facebook/Meta for learning and teaching purposes (Ainin et al., 2015; Gao et al., 2012; Golder et al., 2007; Leong, Ibrahim, et al., 2018; Leong, Jaafar, et al., 2018; Manca & Ranieri, 2013, 2017; Milosevic et al., 2015; Moorthy et al., 2015; Rodríguez-Hoyos et al., 2015; Stutzman, 2006; Tan et al., 2012; Tess, 2013; Wang & Du, 2014; Wong et al., 2015). The benefits of mobile SNSs include its accessibility without regard to time or place, making the technologies useful as cutting-edge learning aids (Aillerie & McNicol, 2016; Beer & Burrows, 2007; Bicen & Cavus, 2011; de-Marcos et al., 2016; Leong et al., 2018; Leong, Jaafar, et al., 2018; Madge et al., 2009). As previously stated, the superiority of using Facebook/Meta are founded on the notions of “every time and everywhere,” “context-awareness,” and even “ubiquitous learning.” (Hwang et al., 2008; Leong et al., 2018a, 2018b; Wai et al., 2016).

There are several motivations for this study. First, to predict the students' intention to accept Facebook/Meta as a learning medium in higher education. Second, propose a novel hybrid model by using proven models Technology Acceptance Model (TAM), The Unified Theory of Acceptance and Use of Technology (UTAUT), and Theory of Planned Behavior (TPB), etc. Third, previous researches on social networks have used a single step of analysis, mostly using SEM analysis (Ainin et al., 2015; Boticki et al., 2015; Chaouali, 2016; Cheung et al., 2011; Kabilan et al., 2010; Leong, Ibrahim, et al., 2018; Leong, Jaafar, et al., 2018; Lockyer & Patterson, 2008; Lu & Yang, 2014; Mazer et al., 2007; Mazman & Usluel, 2010; Milosevic et al., 2015; Mufadhal et al., 2018; Roblyer et al., 2010; Wang & Du, 2014; Wong et al., 2015). SEM is a popular linear model used in numerous research to investigate major drivers or factors. However, these basic linear models may be insufficient for representing the complexity of real-world decision-making challenges. To overcome this issue, an AI technique

that can produce reasonably advanced non-linear regression models with higher accuracy as a supplement to linear models may be used (Sim et al., 2014; Wong et al., 2011). Despite the fact that some academics have adopted a more robust and stable average of distinct ANN analysis as the second phase to aim to achieve this issue (Akgül, 2019; Sharma et al., 2016; Tiruwa et al., 2018). Their ANN study is limited to one-hidden layer architectures, which Huang and Stokes (2016) raised one hidden layer architectures is a shallow ones. Other study fields that employ the two-phase SEM-ANN analysis encounter a similar issue (e.g., Lee et al., 2020; Leong et al., 2019). A deep ANN design, rather than a shallow ANN, should be used, according to Wang et al. (2017), because it can result in more accurate of a non-linear model by using two or more hidden layers. Given these objections, the authors have correctly utilized PLS-SEM with ANN to the existing study's problems to leverage the potential of deep learning based two-phased hybrid SEM-ANN analysis. Finally, universities, particularly public ones in emerging countries such as Turkey, frequently suffer from inadequate facilities and lack communication technologies and formal electronic techniques to engage with their students. Furthermore, they continue to rely on the traditional Learning Management System (LMS) of one-way communication inside the classroom and do not fully utilize the advantages of social media in engaging students in virtual learning. The teaching–learning activity was a perishable service that had to be consumed in the moment it was supplied. It was also traditionally restricted by geographical location-the instructor and student being in the same location. With the advancement of technology, these time and space limits have gained some wiggle room. According to statistics, Turkey ranks in the top 15 nations in terms of the number of Facebook/Meta accounts generated (Statista.com, 2021). COVID-19 Pandemic has revealed gaps in online education. With many school education systems suddenly shifting to online lessons. In general, e-learning is the best solution during the lockdown. In the context of the COVID-19 pandemic, the closure of colleges and institutions, as well as scientific platforms such as classrooms and others, the use of social media, the most prominent of which is Facebook/Meta, as a method of e-learning. This study was undertaken to perform research with a sample of six Turkish state university students in Turkey to throw some light on this issue.

2 Theoretical Background

As stated Lu et al. (2014), “*an extension of social networking where individuals with similar interests converse and connect through their mobile phones and/or tablets*”. Increased use of mobile devices as an educational tool to support vocabulary activities (Lan & Huang, 2012; Stockwell, 2010). Using mobile devices, according to Kim et al. (2014), would improve learning experiences since the technology allows teachers to be more flexible in giving tailored instructional messages to students. Furthermore, when mobile SNSs are employed in educational activities, the learning process is characterized by “knowledge sharing, information reference, online/offline interactions, and visual/verbal connection

exchanges” (Wong et al., 2015: 764). Currently, the academic community is utilizing social media platforms efficiently, such as blogs and the sharing of instructional films, updates, and academic materials (Berger, 2017). Many students and staff are still unfamiliar with using Facebook/Meta for learning and teaching reasons, and, as previously said, research on Facebook/Meta usage in higher education and continued intentions are scarce (Wong et al., 2015; Milosevic et al., 2015; 2018 Moorthy et al., 2015; Leong, Ibrahim, et al., 2018; Leong, Jaafar, et al., 2018).

Adoption of new information technology or systems is required for successful system deployment; hence, factors of user acceptance can help to improving system design and affecting system efficacy (Agarwal & Prasad, 1998; Davis, 1989; Mathieson, 1991). How users’ views of a system impact adoption and how people embrace new technologies has long been a topic of study (Venkatesh et al., 2003). Many important theories have been proposed in the past to investigate user adoption of any new technology or information system. The study approach in this work is based on three fundamental theories of behavior intention in technology adoption: TAM and UTAUT which has been extended by adding three more variables: hedonic motivation, price value, and habit as UTAUT2 (Davis, 1989; Venkatesh et al., 2003, 2012) and TPB (Ajzen, 1991). Recent bibliometric analyses conducted by Hew (2011), and Tamilmani et al., (2021) indicated rising interest in the scientific world in the continuance intention to utilize an information system.

Several studies into various social network systems have revealed a variety of important factors influencing students’ behavioral intentions toward academic use of Facebook/Meta. Table 1 summarizes the primary papers recognized as academic use literature in a researcher’s evaluation of social networking sites and identifies the characteristics of crucial variables that explain intention to use. For instance, Moorthy et al., (2015) showed that intention and behavior to use Facebook/Meta for learning are determined by four factors: perceived enjoyment, perceived usefulness, perceived ease of use, and self-efficacy. Sharma et al., (2016) investigated and assessed collaboration (C), perceived enjoyment (PE), perceived usefulness (PU), resource sharing (RS), and social influence (SI) in the evaluation of academic use of Facebook/Meta in higher education. Leong, Ibrahim, et al. (2018), Leong, Jaafar, et al. (2018)) showed that perceived task-technology fit (PTTF), PU, and PE have significant relationships with the intention to use social network sites. The same year, Tiruwa et al., (2018) indicated that cooperation is the most powerful predictor of Facebook/Meta use for collaborative learning in higher education, followed by variables such as critical mass (CM), PU, PE, and material and resource sharing. In this sense, According to Akgül (2019), CM, compatibility (COMP), membership (M), perceived ease of use (PEU), PU, and trust (T) all have significant correlations with the intent to utilize Facebook/Meta in higher education. The same year, Al-Sharafi et al., (2019) posited that factors such as SI, PE, PU, and PEU are especially vital for behavioral intention to use online social networks for higher institutions’ students. Finally, Raza, Kumar, et al. (2020), Raza, Qazi, et al. (2020)), recently assessed the uses & gratification theory and theory of planned behavior impact on Facebook/Meta usage among students.

Table 1 Studies about the intention to use Facebook/Meta

Author(s)/ Year	Technique applied	Area	Number of Hidden Layers	Variables	How was the number of hidden neurons deter- mined?	Network Struc- ture	Activation Function Hidden Layer	Output Layer
Sharma et al., (2016)	TAM, UTAUT and etc SEM-NN	Facebook/Meta usage in higher education		Collaboration, Social Influence, Perceived useful- ness, Perceived enjoyment, Resource sharing, Intention to use Facebook/Meta,	Automatically by software	5–10-1	Hyperbolic Tangent	Identity
Tiruwa et al., (2018)	SEM-NN	Modelling Facebook/ Meta usage for collaboration and learning in higher education	1	Critical mass, Perceived useful- ness, Perceived enjoyment, Material and resource shar- ing, Collabora- tion, Intention to use Facebook/Meta	Automatically by software	5–10-1	Hyperbolic Tangent	Identity
Al-Shihi, Sharma, & Sarrab, (2018)	ANN	Mobile learning acceptance	1	Flexibility learn- ing, Social learning, Efficiency learn- ing, Entertain- ment, suitability learn- ing, Economic learn- ing M-learning acceptance	Automatically by software	6–5-1	Hyperbolic Tangent	Identity

Table 1 (continued)

Author(s)/ Year	Technique applied	Area	Number of Hidden Layers	Variables	How was the number of hidden neurons deter- mined?	Network Struc- ture	Activation Function Layer	Output Layer
Algüil (2019)	SEM-NN	Facebook/Meta Adoption in Higher Educa- tion	1	Critical Mass, Compatibility, Membership, Perceived ease of use, Perceived useful- ness, Trust Intention to use,	Automatically by software	5–3–1	Hyperbolic Tangent	Identity

TAM: Technology Acceptance Model; **UTAUT:** The Unified Theory of Acceptance and Use of Technology; **SEM:** Structural Equation Modelling; **NN:** Neural Network.

2.1 Hypotheses Development

The following hypotheses were established focused on the students' intentions to use Facebook/Meta for learning purposes:

2.2 Collaboration (C)

C fundamentally outlines how environmental and cognitive elements work together to influence a person's learning and behavior patterns (Ainin et al., 2015). The use of social media sites might be a new type of collaboration. According to studies, Facebook/Meta users may generate and receive information, as well as join new groups for collaborative learning through debates and interactive sharings (Hung & Cheng, 2013; Selwyn, 2007). Social media has the conversational, collaborative, and communal capacity to help the learning process by allowing users to join various educational groups and exchange assignments, projects, and so on (Maloney, 2007; Mazman & Usluel, 2010; DeAndrea et al., 2012; Ractham & Firpo, 2011; Sanchez et al., 2014; Sharma et al., 2016). As a result, it is crucial to allow students to engage, communicate, and work with one another via Facebook/Meta to create stronger relationships between students and professors. Thus, students can be involved with their direction substances that are relevant to their studies (Ainin et al., 2015). Hamid et al., (2015) students benefit from increased engagement with other students and professors as a result of social technology. Considering C's considerable influence on academic use of Facebook/Meta, the following hypothesis is proposed:

H₁ C has a positively and significantly influences on BI.

2.3 Facilitating Conditions (FC)

FC is a broad notion that encompasses many various aspects, including knowledge, training, infrastructure, and assistance. It is defined as follows: "*the degree to which an individual believes that an organizational and technical structure exists to support use of the system*" (Venkatesh et al., 2003). The degree to which a person feels that there are appropriate living conditions and appropriate technological infrastructure to facilitate educational usage of Facebook/Meta is referred to as facilitating conditions (Milosevic et al., 2015; Sanchez et al., 2014). Considering FC's considerable influence influence on academic use of Facebook/Meta, the following hypothesis is proposed:

H₂ FC has a positively and significantly influences on BI.

2.4 Perceived Enjoyment (PE)

Enjoyment is defined as "*the extent to which the activity of using the computer is perceived to be enjoyable in its own right, apart from any performance*

consequences that may be anticipated” (Davis et al., 1992:1113). In another definition, Moon and Kim (2001) described enjoyment as “*the pleasure the individual feels objective when committing a particular behavior or carrying out a particular activity*”, they also observed that “enjoyment” is a crucial element in Internet adoption. In other words, the critical factor of PE in understanding users’ purpose to use in the literature, social media has been widely recognized as a pleasure-oriented information system (Davis et al., 1992; Van der Heijden, 2004; Hong, Tam, et al., 2006; Hong, Thong, et al., 2006; Hong Tam, & Kim, 2006; Hong, Thong, et al., 2006; Sledgianowski & Kulviwat, 2009; Kang & Lee, 2010; Merhi, 2015). According to Hamid et al. (2015), when compared to traditional classroom-based teaching and learning, employing Online Social Networking (OSN) offers learners with a significantly more enjoyable learning environment. Yang et al., (2016) conducted the study in which the authors found a strong influence of PE on users’ mobile SNSs participation. “*Therefore, users who experienced enjoyment from using these applications are more likely to adopt them*” (Lin et al., 2013). Considering PE’s considerable influence on academic use of Facebook/Meta, the following hypothesis is proposed:

H₃ PE has a positive and significant influence on the academic usage of Facebook/Meta.

2.5 Perceived Ease of Use (PEOU)

PEOU refers to “*the degree to which an individual believes that using a particular system would be free of physical and mental efforts*” (Davis, 1989). In this sense, PEOU can be considered to be a crucial driver, one of the qualities of greatest impact on the acceptance, and antecedent of adoption intention of new technology (Kim et al., 2010; Moore & Benbasat, 1991). In the study of Bataineh et al., (2015), it has been empirically proved perceived ease of use significantly enhances the intention to use Facebook/Meta as a learning tool. Zaki and Khan (2016) investigated the factors that impact on students’ use of Facebook/Meta for educational purposes. Another aspect that influences the decision to utilize Facebook/Meta for learning is perceived ease of usage. Considering PEOU’s considerable influence on academic use of Facebook/Meta, the following hypothesis is proposed:

H₄ PEOU positively and significantly affects on BI.

2.6 Perceived Task-Technology Fit (PTTF)

The initial determinant of actual behavior, according to TRA (Fishbein & Ajzen, 1975), is behavioral intention. In this study, Task-Technology Fit (TTF) was defined as “*the degree to which a technology assists an individual in performing his or her portfolio of tasks*” (Baleghi-Zadeh et al., 2014; Goodhue & Thompson, 1995). Lu and Yang (2014) have indicated that PTTF considerably impacts the aim of people to adopt innovations. Authors reported achieving learning requirements impact

on the perceived fit (Goodhue & Thompson, 1995; Lee & Lehto, 2013; Leong, Ibrahim, et al., 2018; Leong, Jaafar, et al., 2018; Lin & Wang, 2012; Pagani, 2006). Considering PTTF's considerable influence on academic use of Facebook/Meta, the following hypothesis is proposed:

H₅ PTTF positively and significantly influences on BI.

2.7 Perceived Usefulness (PU)

According to TAM, the key motivators for embracing and using new technologies are PU and PEOU. PU can be defined as “*the degree to which an individual believes that using a particular system would enhance his/ her job performance*” (Davis, 1989). Nowadays, Facebook/Meta more frequently has been used for many different aspects; it has easy to use, usefulness, and social influence factors (Milosevic et al., 2015; Sanchez et al., 2014). According to Sanchez et al., (2014), PU has a significant impact on college students' use of Facebook/Meta. According to Zaki and Khan (2016), perceived usefulness may influence the intention to use Facebook/Meta for academic objectives. Considering PU's considerable influence on academic use of Facebook/Meta, the following hypothesis is proposed:

H₆ PU positively and significantly influences on BI.

2.8 Resource Sharing (RS)

Students commonly exchange study materials, projects, beneficial resources, and papers using text, audio, video, and photos, as well as connections to other resources or Websites (Mazman & Usluel, 2010; Ractham & Firpo, 2011; Sharma et al., 2016). Facebook/Meta is a significant platform for sharing many cultures, beliefs, rituals, and traditions (Ainin et al., 2015; Sharma et al., 2016). Students and faculty have exchanged study and educational resources on Facebook/Meta to enhance formal learning for group assignments or by reacting to comments (Ainin et al., 2015; Boud et al., 2001; Hamid et al., 2015; Milosevic et al., 2015; Sanchez et al., 2014; Sharma et al., 2016). The usage of Facebook/Meta has been emerged as a virtual classroom for sharing knowledge and academic material with other students by many academic institutions (Milosevic et al., 2015; Sanchez et al., 2014). Considering RS's considerable influence on academic use of Facebook/Meta, the following hypothesis is proposed:

H₇ RS positively and significantly influences on BI.

2.9 Social Influence (SI)

SI can be defined as “*the degree to which an individual is acting under the influence of some other person, group or social events*” (Venkatesh et al., 2003). Another definition of SI is “*one's predetermined opinion of how others will judge a specific*

behavior of a person” (Fishbein & Ajzen, 1975; Venkatesh et al., 2003). Triandis (1980) defined as “the individual’s internalization of the reference groups’ subjective culture, and specific interpersonal agreements that the individual has made with others, in specific social situations”. SI is explained as “the degree to which an individual perceives that important others believe she or he should use the new system.” (Teo, 2009). According to Sanchez et al. (2014), Social Influence is the most important factor in predicting the adoption of Facebook/Meta. Milosevic et al. (2015), revealed that social influence has a significant influence on a person’s intention to use social media. Considering BU’s considerable influence on academic use of Facebook/Meta, the following hypothesis is proposed:

H₈ SI positively and significantly influences on BI.

2.10 Subjective Norm (SN)

SN refers to “the perceived social pressure to perform or not to perform a behavior” (Ajzen, 1991). Arteaga Sánchez and Duarte Hueros (2010) subjective norm had been reported to have stronger impact on behavioral intention, which is incorporated into TAM. Kim (2011) and Yoon and Rolland (2015) investigated the influence of subjective norms on continuance intention to use social networking services. The influence of interpersonal behaviors, friends, and colleagues of word-of-mouth, mass media reports, and experienced people determined the subjective norms (Bhattacharjee, 2000). Normative beliefs should be multidimensional in the IT usage area (Ajzen, 1991; Davis, 1989; Fishbein & Ajzen, 1975; Mathieson, 1991; Taylor & Todd, 1995). Considering SN’s considerable influence on Facebook/Meta usage in higher education, the following hypothesis is proposed:

H₉ SN positively and significantly influences on BI.

3 Research Methodology

3.1 Measurement of variables

The study employed previously validated measures and was amended to fit into the context of Facebook/Meta usage. Social influence (SI), which was taken from Park et al., (2014) and Teo (2012). The items for facilitating conditions (FC) and Subjective norm (SN) were derived from Teo (2012). Perceived usefulness (PU) adapted from Park et al., (2014), Teo (2012), Davis (1989), and Venkatesh and Davis (2000). Perceived enjoyment (PE) was adopted from Park et al., (2014). Resource sharing (RS) was derived from Park et al. (2014) and Bock et al., (2005). Collaboration (C) was adapted from So and Brush (2008). Perceived task-technology fit (PTTF) was taken from Lu and Yang (2014). Perceived ease of use (PEU) was adopted from Park et al., (2014), Davis (1989), and Venkatesh and Davis (2000). Finally, the intention to use Facebook/Meta (INT) was adopted from Bock et al., (2005).

The participants responded their attitudes on a five-point Likert scale aside from demographic characteristics. 29 questions were used to measure predictors, while three questions were used to test students' expected usage of social media in higher education, and the usage intention factors.

According to the descriptive data of the sample, females account for 46 percent of Facebook/Meta users, while males account for 54 percent. The age group between 21 and 30 years old accounted for 78.5 percent of the total. 15.5 percent of those polled were over the age of 31. Six percent of those under the age of 20 were in this age category. The majority of participants have a bachelor's degree and represented 75%, followed by vocational school degree (19%), graduate degree (6%).

3.2 Sample and Data Collection

Participants with existing social media experience were chosen for sample collection. Both offline and online approaches were used to acquire the sample data. The offline strategy, which was employed in a pilot research phase, aided in obtaining immediate replies from participants without any interruption. The last stage of data collection comprises collecting completed online questionnaires from participants.

The survey was published online, and the link was sent by email. The technique was successful in reaching a significant number of students and deleting duplicate and/or incomplete survey answers. Multiple forms submitted from the same IP address were blocked, preventing repetition.

A non-random and convenience sample of 343 students from six Turkish state universities was used in an empirical study. Despite its modest size, the sample size is sufficient for SEM analysis to be performed (Myers et al., 2011). This sample size meets ten times the minimum threshold recommended by Bentler and Chou (1987), and Hair, Hollingsworth, et al. (2017). G*Power was applied to determine the minimum size of the sample, as recommended by Hair, Hult, et al. (2017). It was calculated that the sample size for this study is 166 when 9 predictors were used, 15% effect size, 5% alpha level, and 95% power were used. Overall, 343 replies were received, much above the recommended minimum sample size.

4 Empirical Findings:

4.1 PLS-SEM Analysis and Results

4.1.1 Measurement model

Smart PLS (Version 3.3.2) software was executed to analyze data using the PLS-SEM approach. First, the outer loadings of the items surpassed the ≥ 0.70 criterion (Hair et al., 2010). Second, Table 2 provides that Cronbach's alpha and composite reliabilities (CR) have cut-off values that are all greater than the threshold 0.70 and that all average variance extracted (AVE) values exceeded the threshold 0.50, maintaining construct reliability, convergent validity, and divergent validity. Third,

Table 2 Internal consistency reliability, convergent validity results

Lat.V	Indic	Reliability		VIF = <5	Validity		
		Indicator Reliability			Internal Consistency Reliability		Conv Validity
		Factor			$\alpha \geq .70$	CR $\geq .70$	
		Loading ≥ 0.70					
C	C1	,854	2,165		,856	,912	,777
	C2	,925	2,963				
	C3	,863	1,998				
FC					,742	,854	,662
	FC1	,852	1,697				
	FC2	,834	1,633				
	FC3	,750	1,311				
INT					,864	,917	,787
	INT1	,884	2,118				
	INT2	,901	2,485				
	INT3	,875	2,177				
PE					,785	,874	,699
	PE1	,818	1,545				
	PE2	,821	1,693				
	PE3	,867	1,715				
PEOU					,846	,907	,765
	PEOU1	,811	1,739				
	PEOU2	,910	2,737				
	PEOU3	,899	2,309				
PTTF					,904	,940	,839
	PTTF1	,921	2,865				
	PTTF2	,929	3,374				
	PTTF3	,898	2,688				
PU					,719	,840	,637
	PU1	,761	1,306				
	PU2	,804	1,655				
	PU3	,827	1,468				
RS					,882	,927	,809
	RS1	,890	2,290				
	RS2	,910	2,707				
	RS3	,898	2,497				
SI					,686	,816	,601
	SI1	,764	1,288				
	SI2	,646	1,323				
	SI3	,896	1,485				
SN					,797	,907	,830
	SN1	,895	1,781				
	SN2	,927	1,781				

Table 2 (continued)

α = Cronbach’s Alpha; **CR** = Composite Reliability; **C**: Collaboration; **FC**: Facilitating Conditions; **INT**: Intention to Use Facebook/Meta; **PE**: Perceived enjoyment; **PEOU**: Perceived Ease of Use; **PTTF**: Perceived Task-Technology Fit; **PU**: Perceived Usefulness; **RS**: Resource Sharing; **SI**: Social Influence; **SN**: Subjective Norm

the Fornell–Larcker and HTMT-ratio requirements for discriminant validity were evaluated; AVEs were greater than squared inter-construct correlations (Fornell & Larcker, 1981), and the heterotrait-monotrait (HTMT) correlation ratio was less than 0.95. (Henseler et al., 2015) See Table 3. The third method utilized to test discriminant validity was cross-loadings. See Table 4.

4.1.2 Structural Model Path Analysis

Hair et al., (2010) suggested four steps to assess the structural model. First, the Variance Inflation Factor (VIF) values were generated to assess collinearity issues. All of the VIF values retrieved are inside the cut-off range (VIF < 5). As a result, collinearity was not an issue in our study (Table 2). Second, the bootstrapping method (5000 resamples) was used to test the hypothesized relationship at a significance level of 0.05. Results of the bootstrapping algorithm are depicted in Table 5. C ($\beta=0.161$; t-value = 2.490; significance at $p < 0.013$; $f^2=0.03$), FC ($\beta=0.186$; t-value = 3.418; significance at $p < 0.001$; $f^2=0.005$), PEOU ($\beta=0.076$; t-value = 1.754; significance at $p < 0.080$; $f^2=0.01$), PTTF ($\beta=0.278$; t-value = 4.649; significance at $p < 0.000$; $f^2=0.08$), and SN ($\beta=0.134$; t-value = 2.191; significance at $p < 0.029$; $f^2=0.03$) have significant and positive impact with a small effect size was found on intention to use Facebook/Meta. Therefore, H1, H2, H4, H5, and H9 hypotheses were supported. However, four of the nine hypothesized paths, from PE to Facebook/Meta intention (H3), PU to Facebook/Meta intention (H6), RS to Facebook/Meta intention (H7), and SI to Facebook/Meta intention (H8), were not supported by statistically

Table 3 The Fornell-Larcker discriminant validity and The HTMT correlation matrix

	C	FC	INT	PE	PEOU	PTTF	PU	RS	SI	SN	C	FC	INT	PE	PEOU	PTTF	PU	RS	SI	SN			
C	,88																						
FC	,53	,81									,66												
INT	,58	,52	,89								,67	,65											
PE	,46	,40	,44	,84							,56	,52	,52										
PEOU	,33	,37	,30	,21	,88						,39	,46	,34	,24									
PTTF	,65	,43	,57	,44	,11	,92					,73	,53	,64	,52	,12								
PU	,53	,41	,48	,57	,27	,50	,80				,67	,55	,59	,76	,34	,61							
RS	,57	,44	,47	,60	,46	,37	,60	,90			,67	,55	,54	,71	,53	,41	,75						
SI	,17	,12	,24	,33	-,02	,26	,43	,23	,78		,20	,15	,29	,44	,10	,31	,61	,29					
SN	,40	,42	,46	,51	,23	,35	,51	,46	,32	,91	,49	,55	,54	,63	,27	,41	,67	,55	,39				

Table 4 The indicator loadings and cross-loadings

	C	FC	INT	PE	PEOU	PTTF	PU	RS	SI	SN
C1	,854	,456	,467	,427	,372	,455	,493	,578	,145	,368
C2	,925	,477	,535	,422	,315	,554	,488	,526	,154	,394
C3	,863	,456	,528	,379	,194	,693	,429	,424	,158	,300
FC1	,393	,852	,446	,349	,302	,352	,339	,332	,101	,353
FC2	,516	,834	,433	,304	,441	,340	,370	,458	,096	,331
FC3	,370	,750	,398	,332	,159	,367	,291	,285	,099	,340
INT1	,549	,487	,884	,426	,295	,512	,445	,475	,148	,459
INT2	,477	,444	,901	,378	,215	,538	,443	,370	,308	,394
INT3	,515	,461	,875	,355	,277	,472	,387	,398	,198	,353
PE1	,381	,332	,359	,818	,248	,301	,518	,543	,223	,403
PE2	,338	,284	,316	,821	,084	,407	,436	,367	,341	,436
PE3	,434	,385	,410	,867	,178	,398	,480	,570	,280	,429
PEOU1	,229	,232	,223	,088	,811	,050	,179	,302	-,013	,135
PEOU2	,306	,334	,246	,183	,910	,107	,227	,427	-,076	,205
PEOU3	,320	,394	,298	,252	,899	,129	,287	,465	,020	,246
PTTF1	,666	,399	,572	,401	,129	,921	,479	,369	,222	,345
PTTF2	,579	,403	,513	,425	,081	,929	,451	,341	,236	,309
PTTF3	,524	,388	,481	,383	,096	,898	,438	,295	,261	,313
PU1	,408	,219	,388	,373	,090	,433	,761	,406	,404	,376
PU2	,358	,322	,290	,485	,242	,319	,804	,488	,358	,392
PU3	,483	,428	,441	,513	,307	,420	,827	,537	,289	,450
RS1	,466	,359	,425	,498	,404	,322	,539	,890	,182	,372
RS2	,543	,407	,422	,589	,361	,352	,551	,910	,239	,430
RS3	,542	,428	,417	,530	,485	,320	,529	,898	,205	,442
SI1	,117	,123	,174	,301	,033	,149	,400	,231	,764	,299
SI2	,049	,050	,093	,150	-,082	,152	,238	,102	,646	,100
SI3	,189	,098	,251	,290	-,031	,274	,357	,188	,896	,280
SN1	,361	,369	,377	,400	,191	,319	,425	,392	,289	,895
SN2	,370	,394	,448	,511	,223	,324	,503	,445	,287	,927

significant path coefficients. Table 5 provides a concise summary of these findings (Fig. 1).

Third, we revealed that the coefficient of determination R^2 value for the Intention is 0.492 (49.2%), highlighting that the study model has a moderate but significant predictive power (Hair et al., 2011; Henseler et al., 2009). Fourth, the Q^2 values for behavioral intention to use Facebook/Meta (0.359) are more than zero, showing that the model is predictively relevant. The research model’s predictive relevance has been assessed by utilizing a blindfolding procedure with omission distance (OD)=8. Also, the results of small (q^2) effect size. C, FC, PE, PEOU, PTTF, PU, SI, and SN have a small effect size (q^2) on intention to use Facebook/Meta. And also, resource sharing has no effect size on intention to use Facebook/Meta.

Table 5 Results of path analysis and hypothesis testing

H	Path	β coefficients	T Statistics	Effect size ¹ f^2	P Values	Effect size ² q^2	Support
H1	C→INT	,161	2,490**	,03	,013	,02	Accepted
H2	FC→INT	,186	3,418***	,05	,001	,03	Accepted
H3	PE→INT	,015	,250	0	,803	-,01	Rejected
H4	PEOU→INT	,076	1,754*	,01	,080	,01	Accepted
H5	PTTF→INT	,278	4,649***	,08	,000	,05	Accepted
H6	PU→INT	,024	,412	0	,680	-,01	Rejected
H7	RS→INT	,059	,910	,01	,363	-,01	Rejected
H8	SI→INT	,052	1,119	,01	,263	0	Rejected
H9	SN→INT	,134	2,191**	,03	,029	,01	Accepted

*** $p < .01$, ** $p < .05$, * $p < 0.1$.

¹ f^2 : R^2 included - R^2 excluded / $1 - R^2$ included.

² q^2 : Q^2 included - Q^2 excluded / $1 - Q^2$ included

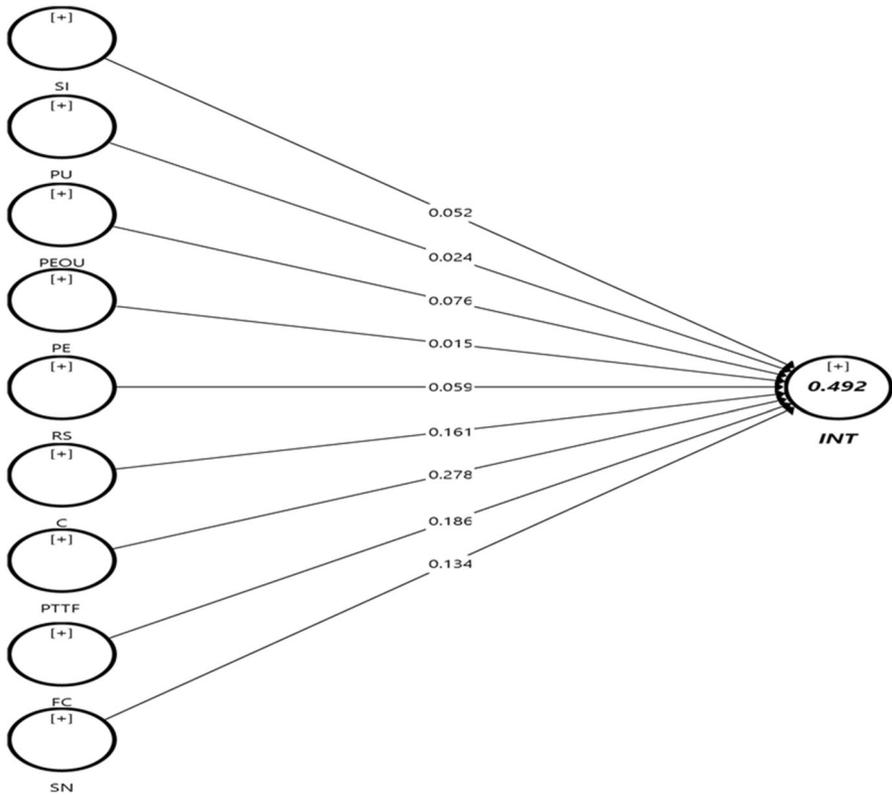


Fig. 1 Structural model path coefficients

Finally, after evaluating the model's predictive capability, the model fit is evaluated. Model fit is concerned with how well the best model for representing the data fits the underlying theory (Hooper et al., 2008). The model fit evaluation in PLS-SEM was done using the five criteria listed below.

Standardized Root Mean Square Residual (SRMR), an absolute measure of model fit, is the first criterion established to avoid model misspecification (Henseler et al., 2015). For SRMR, the cut-off value is 0.08. The SRMR for the study was calculated by SmartPLS and is 0.063, which is less than the cut-off value stated in the literature. The second criteria, Root Mean Square Residual (RMS_{theta}), evaluates “the degree to which the outer model residuals correlate” (Henseler et al., 2015). To demonstrate a satisfactory model fit, this value should be ≤ 0.12 (Hair et al., 2010; Henseler et al., 2015). Using Smart PLS RMS_{theta} is 0.15, which indicates a not good model fit. The third criterion, Unweighted Least Squares (*d*ULS) is 1.737, The fourth criterion, Geodesic Discrepancy (*d*G) is 0.671, the cut off values of the third and fourth criterion indicates a high degree of goodness-of-fit and is regarded trustworthy. Last criterion, a global fit measure for PLS path modeling has been suggested (Tenenhaus et al., 2005). The model's GoF for the current research to be 0.61, which is considered large.

4.1.3 PLS Predict

Following that, PLS predict analysis was performed using the default parameters (10 folds and 10 repetitions) to assess the model's out-of-sample predictive power (Shmueli & Koppius, 2010). The Q^2 predict values of the PLS analysis, the Mean Absolute Error (MAE) values, and the RMSE values based on the PLS and the Linear Model (LM) analyses were utilized to assess the outcomes. As shown in Table 6, all of the Q^2 values in PLS analysis were greater than zero, suggesting that the PLS-SEM results had lower prediction errors than merely utilizing mean values. Furthermore, in terms of MAE values at the indicator level, the amount of out-of-sample predictive power was rather low, as three items of intention in the PLS-SEM analysis provided no larger prediction errors than the LM benchmark.

Table 6 PLS predict assessment

Methods	PLS			LM			PLS-LM		
	RMSE	MAE	Q^2	RMSE	MAE	Q^2	RMSE	MAE	Q^2
INT2	1,088	,871	,346	1,122	,911	,305	-,034	-,040	,042
INT1	1,046	,825	,394	1,090	,855	,341	-,045	-,030	,053
INT3	1,170	,909	,322	1,203	,951	,283	-,033	-,042	,039

RMSE and MAE metric in PLS must produce smaller values than that of LM, thus generating negative values in PLS-LM; Q^2 metric in PLS must produce larger values than that of LM, thus generating positive values in PLS-LM

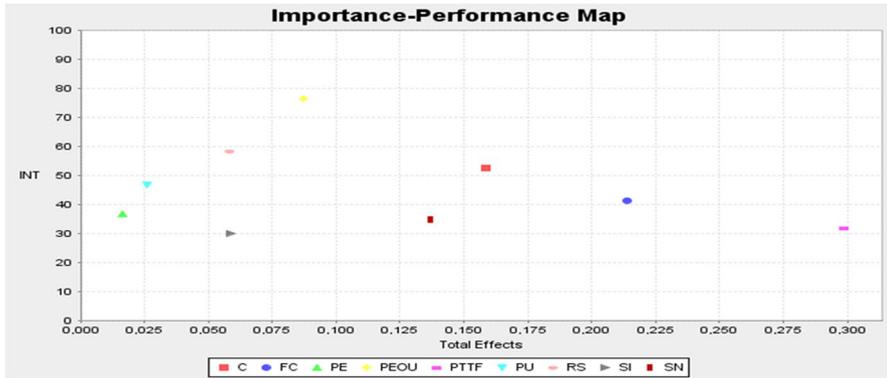


Fig. 2 Importance-performance map analysis for the intention. C: Collaboration; FC: Facilitating Conditions; PE: Perceived enjoyment; PEOU: Perceived Ease of Use; PTTF: Perceived Task-Technology Fit; PU: Perceived Usefulness; RS: Resource Sharing; SI: Social Influence; SN: Subjective Norm

Table 7 IPMA results full data set

Latent Variable	Intention	
	Total Effect (Importance)	Index Value (Performance)
C	,158	52,707
FC	,214	41,375
PE	,016	36,569
PEOU	,087	76,373
PTTF	,298	31,689
PU	,026	46,805
RS	,058	58,222
SI	,059	30,079
SN	,137	34,789

4.1.4 Importance-Performance Map Analysis (IPMA)

Figure 2 and Table 7 show the results of an IPMA run for the major goal construct of intention to use Facebook/Meta, as well as its directly associated antecedents.

4.1.5 Artificial Neural Network Analysis (ANN)

ANN is “a machine that is invented to model the manner in which human brain performs a specific task or function” (Haykin, 2004:24). Recently, the deep learning paradigm has made remarkable advances (Liu et al., 2017; Siyal et al., 2020). A Multi-Layer Perceptron (MLP) is a popular choice in technology adoption studies because it offers various advantages (Sim et al., 2014). One of the most often

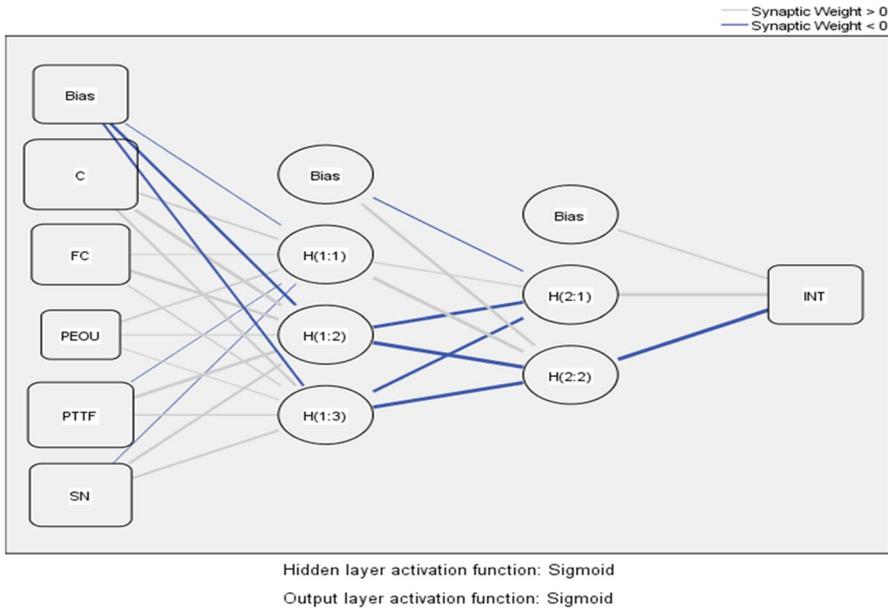


Fig. 3 The ANN Model

utilized deep NNs (with more than two layers) (Fig. 3) has certain intrinsic benefits over the linear models, such as its notable nonlinear fitting capabilities and excellent predictive capacity. As a result, for the objectives of the study, the feedforward back-propagation multilayer perceptron was used as the foundation ANN model, which consists of three layers: input, hidden, and output (Akgül, 2018; Lee et al., 2020). The input layer involved five independent significant factors from SEM (i.e. C, FC, PEOU, PTF, and SN), the number of hidden neurons was computed spontaneously by the SPSS Neural Network algorithm, whereas intention to use Facebook/Meta was included as a dependent variable in the output layer of the model with the standardized range [0, 1] Fig. 3. To leverage for deeper learning, a two-hidden-layer deep ANN architecture for the output neuron node has been developed (Bekker & Goldberger, 2016; Bekker and Goldberger, 2016; Lee et al., 2020, Mahdaviyar & Ghorbani, 2019; Wang et al., 2017). As depicted in Fig. 3, one ANN model was constructed for intention to use Facebook/Meta in this study. The sigmoid function was assigned as the activation function, and the number of hidden neuron nodes was let to develop on its own, as in Lee et al., (2020). In addition, a ten-fold cross-validation process was applied to avoid over-fitting. 10% of the data utilized for testing and the remaining 90% data utilized for training processes by using SPSS 24 Neural Network algorithm (Akgül, 2019; Chong, 2013; Chong et al., 2015; Hew, et al., 2019; Kokkinos & Margaritis, 2018; Liébana-Cabanillas et al., 2017).

The prediction accuracy of the ANN model was used to calculate Root Mean Square Error (RMSE) values (Fig. 3) (Akgül, 2018). As indicated in Table 8, the RMSE mean-values for training and testing are relatively small at 0.159 and 0.157, respectively. The small and similar RMSE mean values verify high prediction

Table 8 RMSE values

(R² = 84,60%)
Input neurons: C, FC, PEOU, PTTF, SN; Output neuron: Intention to use Facebook/Meta

Training			Testing			Total samples
N1	SSE	RMSE	N2	SSE	RMSE	N1 + N2
303	7,563	,158	40	,693	,132	343
306	7,409	,156	37	,854	,152	343
309	7,313	,154	34	1,121	,182	343
303	7,105	,153	40	,996	,158	343
306	6,751	,149	37	1,446	,198	343
297	8,056	,165	46	1,057	,152	343
315	7,915	,159	28	,674	,155	343
306	7,798	,160	37	,857	,152	343
300	7,873	,162	43	,675	,125	343
314	9,246	,172	29	,772	,163	343
Mean	7,703	,159	Mean	,915	,157	
Sd	,676	,007	Sd	,246	,022	

N: Number of samples; **SSE**: Sum square of errors; **RMSE**: Root mean square of errors; **C**: collaboration; **FC**: facilitating conditions; **PEOU**: perceived ease of use; **PTTF**: perceived task-technology fit; **SN**: subjective norm

accuracy and fit the model. Similar to Lee et al., (2020), Leong, Ibrahim, et al. (2018), Leong, Jaafar, et al. (2018)), Leong et al., (2019), Leong et al., (2020), Philips et al., (2015), Wong et al., (2019) R² was computed and that found the ANN models explain 0.846% of the variance in behavioral intention to use Facebook/Meta. $R^2 = 1 - RMSE / S^2$, where S² is the intended output variance for the test data. To further assess the efficacy of the ANN models, a goodness-of-fit coefficient similar to the R² in the PLS-SEM study was produced. The R² value achieved in the ANN analysis is much higher than the R² value obtained in the PLS-SEM analysis, revealing that the endogenous constructs are best portrayed in the ANN analysis. We believe that this result is mostly due to the two-hidden-layer deep learning architecture and the capacity of ANN to capture the non-linear relationships.

A sensitivity analysis was also utilized for the ANN model to rank the input neuron nodes (i.e., the exogenous variables) based on their normalized importance (NI). The sensitivity analysis was used to determine the relative relevance and normalized importance of the predictors. The relative importance of a predictor is divided by the biggest value of the relative importance among the predictive factors. A bit of different sensitivity analysis was utilized by the researchers, who has argued that motor response recruiting prefrontal areas would support the idea that the learning modelling of the task has not a linear function influenced by the learning parameter, the greater the maze size for goal-task the more steps to get an optimal pathway. The attention are guided by cluster of neurons between occipital, temporal and prefrontal cortex (Mugruza-Vassallo, & Potter, D., 2019; Mugruza-Vassallo et al., 2021). Table 9 depicts

Table 9 Sensitivity analysis with normalized importance

Independent variable importance		
Constructs	Importance	NI
C	,24	,86
FC	,25	,89
PEOU	,09	,32
PTTF	,28	100
SN	,16	,57

Table 10 The total contribution of the hidden layer

Predictor	Predicted						Total Contribution
	Hidden Layer 1			Hidden Layer 2		Output Layer	
	H(1:1)	H(1:2)	H(1:3)	H(2:1)	H(2:2)	INT	
Input Layer	(Bias)	,021	,273	1,026			1,320
	C	,311	1,000	-1,702			3,014
	FC	,322	,799	-1,760			2,881
	PEOU	,844	1,070	-0,190			2,105
	PTTF	1,052	,975	-1,863			3,891
	SN	,553	,952	-1,036			2,542
Hidden Layer 1	(Bias)				-,047	-,114	
	H(1:1)				-,376	1,246	
	H(1:2)				,117	-,262	
	H(1:3)				2,546	-5,301	
Hidden Layer 2	(Bias)						-,004
	H(2:1)						-2,916
	H(2:2)						3,234

C: Collaboration; **FC:** Facilitating Conditions; **PEOU:** Perceived Ease Of Use; **PTTF:** Perceived Task-Technology Fit; **SN:** Subjective Norm; **INT:** Intention

that, similarly to the PLS-SEM analysis, perceived task-technology fit to be the most important drivers for academic use of Facebook/Meta, followed by facilitating conditions (NI=89%), collaboration (NI=86%), subjective norm (NI=57%), and perceived ease of use (NI=32%). This is supported even further by the overall contribution of the input neurons. (Table 10) (Lee et al., 2020; Teo et al., 2015; Varzaru and Bocean, 2021; Mugruza-Vassallo, et al., 2021).

5 Discussion

According to the SEM findings, perceived task-technology fit is the most influential construct academic use of Facebook/Meta. The first and most important factor influencing academic use of Facebook/Meta is PTF. It is consistent with previous research findings (Baleghi-Zadeh et al., 2014; Leong, Ibrahim, et al., 2018; Leong, Jaafar, et al., 2018; Wu & Chen, 2017).

The second most significant variable impacting academic use of Facebook/Meta is FC. It is consistent with the study done by (Ainin et al., 2015; Sánchez et al., 2014).

The third most influential component is C. The conclusions of this study are consistent with the findings of previous researches (Ainin et al., 2015; Arshad & Akram, 2018; Mazman & Usluel, 2010; Sánchez et al., 2014; Sharma et al., 2016; Tiruwa et al., 2018). The conclusions of this study contradict the findings of previous research done by (Shmueli & Koppius, 2010).

SN is the fourth most influencing factor. This is consistent with previous studies on the direct effect of SN on behavioral intention to use Facebook/Meta for academic purposes (Abbad, Morris & de Nahlik, 2009; Cheung & Vogel, 2013; Dhume et al., 2012; Dumpit & Fernandez, 2017; Lou et al., 2000; Mouakket, 2015). The result inconsistent with the studies done (Hadizadeh Moghadam & Bairamzadeh, 2009; Ma et al., 2005; Motaghian et al., 2013; Yuen & Ma, 2008).

PEOU is the fifth most influencing factor. Consistent with Al-Sharafi et al., (2019), Arshad and Akram, (2018), Al-rahmi et al., (2015), Al-Ammary et al., (2014), Abbad, Morris, & de Nahlik, (2009), Baleghi-Zadeh et al., (2014), Chintalapati and Daruri (2016), Dhume et al., (2012), Dumpit and Fernandez (2017), Milošević et al., (2015), Lenhart and Madden (2007), Moorthy et al., (2015), Motaghian et al., (2013), Sánchez et al., (2014) perceived ease of use in predicting behavioral intention to use was found significant in the context of Facebook/Meta usage. Surprisingly, though these empirical outcomes are contradictory to the classic findings of Akgül (2019), Leong, Ibrahim, et al. (2018), Leong, Jaafar, et al. (2018), Mohammadi (2015).

On the other hand, it is interesting to note that PU, PE, RS, and SI have no significant impact on INT to use Facebook/Meta. PU does not significantly influence intention to use Facebook/Meta. Surprisingly, PU, PE, RS, and SI were found insignificant towards to use Facebook/Meta (Abbad, Morris & de Nahlik, 2009; Akgül, 2019; Al-Ammary et al., 2014; Al-Sharafi et al., 2019; Arshad & Akram, 2018; Al-rahmi et al., 2015; Baleghi-Zadeh et al., 2014; Chintalapati & Daruri, 2016; Dhume et al., 2012; Dumpit & Fernandez, 2017; King & He, 2006; Lenhart & Madden, 2007; Leong, Ibrahim, et al., 2018; Leong, Jaafar, et al., 2018; Mazman & Usluel, 2010; Milošević et al., 2015; Mohammadi, 2015; Motaghian et al., 2013; Mouakket, 2015; Ngai et al., 2007; Sánchez et al., 2014; Sharma et al., 2016; Tiruwa et al., 2018; Van Raaij & Schepers, 2008). On the other hand, the findings of this work are compatible with the findings of Moorthy et al (2015).

PE does not significantly influence INT to use Facebook/Meta, which is in the same line with Padilla-Meléndez et al., (2013), Sánchez-Franco et al., (2009).

This result contradicts the study of many researchers in the different scientific areas (Al-Sharafi et al., 2019; Byoung-Chan et al., 2009; Chong, 2013; Dumpit & Fernandez, 2017; Kim, 2011; Lee et al., 2005; Leong, Ibrahim, et al., 2018; Leong, Jaafar, et al., 2018; Mouakket, 2015; Roca et al., 2006; Sharma et al., 2016; Tiruwa et al., 2018).

On the other hand, no significant effect of RS on INT to use Facebook/Meta was confirmed in this study. There are four relationships, which are not in line with previous researches (Arshad & Akram, 2018; Kim et al., 2014; Mazman & Usluel, 2010; Sanchez et al., 2014; Sharma et al., 2016; Tiruwa et al., 2018).

SI does not significantly influence INT to use Facebook/Meta. The findings of the research model are not parallel with several studies from literature (Al-Sharafi et al., 2019; Al-Ammary et al., 2014; Kim, 2011; Raza, Kumar, et al., 2020; Raza, Qazi, et al., 2020; Sánchez et al., 2014; Sharma et al., 2016; Yoon & Rolland, 2015). On the other hand, this finding justifies the earlier claims of several scholars of previous researches done in various contexts Cheung et al., (2011), Lenhart and Madden (2007), Lin and Lu (2015), Milošević et al., (2015), Shmueli and Koppius (2010).

The neural network modeling utilized in this study aids in understanding the aspects that drive academic use of Facebook/Meta (Akgül, 2019; Sharma et al., 2016; Tiruwa et al., 2018). According to the results of the neural network modeling, PTF is the most important predictor of Facebook/Meta adoption in higher education. FC is the second most important predictor of Facebook/Meta adoption, according to the same results as SEM. Following this are the letters C, SN, and PEOU.

The neural network study, on the other hand, validated many SEM findings while also providing a somewhat different order of importance for a number of relevant predictors. The findings of the neural network modeling revealed that C is the most important predictor of Facebook/Meta adoption in higher education. Unlike the SEM results, RS is the second most important predictor of Facebook/Meta adoption. RS was found to be the most influential factor on INT to use of Facebook/Meta, which was the case in results from the SEM analysis (Sharma et al., 2016). The neural network modeling results revealed that collaboration was the most influencing factor and RS was the second important predictor. This indicates that the ANN design better explains the variation of BI to utilize (Tiruwa et al., 2018). According to the results of an ANN study by Akgül (2019), PU is the most important predictor of Facebook/Meta use in higher education. In contrast to the SEM results, critical mass is the second most significant predictor of Facebook/Meta adoption. According to the SEM research results, critical mass was shown to be the most significant factor on Facebook/Meta intention to use. These and other modest discrepancies between SEM and ANN findings might be explained by the neural network models' greater prediction accuracy due to their nonlinear and non-compensatory nature (Lee et al., 2020).

Furthermore, the R^2 of the deep ANN model is much greater than the R^2 of the PLS-SEM study. This suggests that the variation of BI to utilize in this study is better explained by the two-hidden-layer deep ANN architecture. We believe that the higher R^2 values obtained from ANN research are connected to the deep ANN architecture's capability for deep learning and capturing non-linear correlations between components. Researchers, not just those from the disciplines of social networking

sites, are thus encouraged to carefully watch and address the non-linearity issue using a multi-stage data analysis with deep learning.

6 Conclusion and study implications

The environment of higher education has evolved dramatically, and Internet technologies have played a critical role. With the advent of Web 2.0 technologies, Internet users may now produce their own material and interact with other users; when utilized appropriately, these elements have enormous potential to improve the learning experience. Despite the promise for Web 2.0 tools to assist the learning process, their use in virtual classrooms has not made major gains. Researchers sought to investigate the elements that may inspire students to embrace and use Web 2.0 platforms, notably Facebook/Meta, for educational purposes in order to throw some light on the subject. Facebook/Meta and other social media platforms are an essential and extremely valuable component of Web 2.0. Unfortunately, university academics have not paid enough attention to Facebook/Meta and other social media technologies. As a result, the goal of this study was to investigate and forecast factors influencing Facebook/Meta usage among students at academic institutions. Collaboration, facilitating conditions, perceived ease of use, perceived task-technology fit, and subjective norm have a statistically significant influence on Facebook/Meta usage in higher education. In Turkey, with the rise of the COVID-19 epidemic, this is the first and unique study assessing students' perceptions on Facebook/Meta usage in higher education.

The main contribution of this study to the current state of knowledge by serving as a forerunner in integrating TAM, UTAUT, and TPB with the incorporation of two other constructs-PTTF and PE to investigate the behavioral intention of students towards the adoption of Facebook/Meta as a learning tool in higher education. The existing study provides several practical and managerial implications for how the antecedents may motivate Facebook/Meta usage in higher education. First, unlike other studies (Acarli & Sağlam, 2015; Al-Sharafi et al., 2019; Lacka & Chong, 2015; Leong, Ibrahim, et al., 2018; Leong, Jaafar, et al., 2018; Mazman & Usluel, 2010; Milosevic et al., 2015; Sanchez et al., 2014; Tarhini et al., 2016; Wu & Chen, 2017), educational administrators and service providers may devise an appropriate strategy based on the significance of the variables discovered in this study to urge more students to use Facebook/Meta for academic purposes rather than merely entertainment. Since the majority of students use Facebook/Meta or other social media, the findings of this study may strengthen e-learning activities in Turkey. By performing a deep learning-based two-phase SEM-ANN analysis, our work has contributed to the current literature. Furthermore, the R^2 of the deep ANN model is much greater than the R^2 of the PLS-SEM study. This suggests that the variation of INT to utilize in this study is better described by the two-hidden-layer deep ANN design.

Second, the study's findings revealed that PTTF and FC variables are the strongest determinants of desire to utilize Facebook/Meta in higher education. This research reveals a notable discovery that PTTF has a stronger influence on users' intention to use; this finding shows that establishing a match between users' tasks

and Facebook/Meta, as well as their effectiveness as an e-learning tool, is more significant than enjoying the apps. As a result, developer businesses should employ proper marketing and promotion strategies, as well as adequate measures of pleasure factors, while developing learning features for social networks in order to improve utilization intention. Developers should put more effort into building programs that are more pleasant and pleasurable to use for learning objectives, because in real situations searching and learning are often conducted while internal and external factors compete for our attention resources (Savage et al., 2018). According to student answers, facilitating conditions such as the help menu or support services for managing Facebook/Meta activity are important drivers of Facebook/Meta adoption. Because PTF is a strong predictor of intent to use, marketing initiatives should emphasize the applicability of mobile SNSs for facilitating learning activities. This method will significantly boost the use of mobile SNSs in learning communities.

Recent advances in stimulus-driven neural networks and learning systems are rekindling interest in multimodal learning systems (Mugruza-Vassallo, et al., 2021). As a result, Facebook/Meta service providers must pay attention multimodal systems and place a greater emphasis on collaboration and subjective norms while upgrading the design of the learning tool. SN implies that while deciding whether to continue using Facebook/Meta, individuals rely greatly on the people they care about. As a result, marketing managers and Web developers must understand group psychology and allow users to share their good feelings about the site in order to persuade other users to continue using it. This has the potential to expand the number of users. C implying that students believe that using Facebook/Meta would be free of physical and mental efforts and will allow them to improve their collaboration.

Finally, the findings of this study may be utilized to provide suggestions and provide directions for the establishment of student–teacher policies at six Turkish public institutions. Teachers at universities may be recommended to encourage their students to utilize Facebook/Meta in order to promote collaboration and resource sharing. It is a significant problem for researchers to discover a suitable approach to use Facebook/Meta’s social component to enhance our students’ learning experiences without making them feel uncomfortable. Before utilizing Facebook/Meta for class purposes, the scholar should offer particular instruction on the Facebook/Meta capabilities that will be utilized in the course and address any student concerns.

Therefore, future studies can consider replicating this study into a longitudinal one. This will allow for the comparison of variances over different periods which would lead to a more comprehensive study. Lastly, this study developed the research model according to the TAM, UTAUT, TPB, and etc. frameworks. With that said, the factors that represented the TAM, UTAUT, TPB, and etc. frameworks were hypothesized to have any direct effect on the intention to use. Therefore, future studies can look into making alterations to this study’s research model in addition to the inclusion of moderators and mediators to address the below mentioned limitations.

We anticipate that our research will provide light on the developing field of distance education. In addition to the practical contribution, the newly proposed deep learning-based two-phase SEM-ANN analysis in this study is expected to add to the current body of research, notably in the domains of distance education and Artificial Intelligence. We hope that by doing so, we might stimulate

researchers to identify further possible applications for the deep learning-based two-phase SEM-ANN analysis.

7 Limitations

The current study has managed to unveil the impacts of TAM, UTAUT, and TPB theories on Facebook/Meta adoption. Applying a multi-analytical methodology by utilizing PLS-SEM as linear and ANN as non-linear relationships detected within the model. Nevertheless, the study is not longitudinal, which is limited to a certain time frame. Future researchers are recommended to collect longitudinal data to study the post-adoption behavior of users and further examine the role of experience on their usage behavior. A longitudinal approach may reconsider the effect of time. In addition, since the study was conducted in Turkey therefore the findings are limited to the six Turkish state universities' context and cannot be generalized to other university types, nations, or geographical regions. Data from public and private universities might be collected and compared in future studies. A fascinating extension of this research would be to compare students' impressions of Facebook/Meta in small and big colleges. Future research with students from various countries would also be interesting to see if cultural differences in socio-cultural settings impact Facebook/Meta adoption and use. Hofstede's (1991) cultural aspects theory and compare the results to other countries. This study was limited to Facebook/Meta. It can be suggested that further research should perform this study for other types of Web 2.0 technologies and their use and impact on teaching could differ such as Twitter, Instagram, wikis, blogs, or social bookmarking, and MySpace. Another weakness of this study is that it relied on an easy sampling strategy to acquire data. In addition, in this study, the utilization of sigmoid function as the activation function, thus the results of ANN analysis have limited to the used activation function. The performance of hyperbolic tangent, identity, and softmax activation functions may produce better results. The methodological approach may utilize hyperbolic tangent, identity, and softmax types of activation functions. It would be beneficial to perform for disabled pupils (i.e. visually impaired individuals may need specialized materials, hard of hearing students may need to have the teaching materials in text, etc.). This allows students and instructors to connect in real-time and provides extra student assistance. It is crucial for teachers to test their equipment, make reminders for the class, and create a precise agenda. Although we established in this study that the deep ANN architecture might result in lower RMSE values and better R^2 values by employing the same set of data and similar parameters, such outcomes may vary under other data sets and ANN architecture designs. Scholars are then recommended to compare the findings obtained by the shallow ANN architecture with the deep ANN architecture in order to choose the optimum design for their situations.

7.1 Future studies

Furthermore, future researchers are recommended to incorporate other theoretical models and factors such as learning theories, technology adoption theories, diffusion and innovation, social presence theory, theory of rational addiction or social support theories from the psychology domain, gratification theories (Chakraborty et al., 2021; Guan et al., 2021; Lou et al., 2021; Rogers et al., 2014). And also, social overload, information overload, life invasion, and privacy invasion, and two organisms (i.e., technostress and exhaustion) constructs to examine this subject matter from the perspective of the stimulus–organism–response theory (Fu et al., 2020; Loh et al., 2021) and other moderating variables and other critical constructs such as privacy and computer self-efficacy to understand users' acceptance behavior of Facebook/Meta for learning purposes and academic improvements (Aldhahi et al., 2021; Aldheleai et al., 2021; Calaguas and Consunji, 2022).

Finally, in order to acquire more accurate results, future study should investigate the influence of demographic features or individual differences, such as personality traits, age, and gender, on actual usage behavior.

Authors' contributions These authors contributed equally to this work.

Declarations

Competing interest None.

References

- Abbad, M. M., Morris, D., & De Nahlik, C. (2009). Looking under the bonnet: Factors affecting student adoption of e-learning systems in Jordan. *The International Review of Research in Open and Distributed Learning*, 10(2), 1–25. <https://doi.org/10.19173/irrodl.v10i2.596>
- Acarli, D. S., & Saglam, Y. (2015). Investigation of pre-service teachers' intentions to use of social media in teaching activities within the framework of technology acceptance model. *Procedia- Social and Behavioural Sciences*, 176, 709–713. <https://doi.org/10.1016/j.sbspro.2015.01.530>
- Agarwal, R., & Prasad, J. (1998). The antecedents and consequences of user perceptions in information technology adoption. *Decision Sciences*, 22, 15–29. [https://doi.org/10.1016/S0167-9236\(97\)00006-7](https://doi.org/10.1016/S0167-9236(97)00006-7)
- Aillerie, K., & McNicol, S. (2016). Are social networking sites information sources? Informational purposes of high-school students in using SNSs. *Journal of Librarianship and Information Science*, 50(1), 1–12. <https://doi.org/10.1177/0961000616631612>
- Ainin, S., Naqshbandi, M. M., Mogavvemi, S., & Jaafar, N. I. (2015). Facebook usage, socialization and academic performance. *Computers & Education*, 83, 64–73. <https://doi.org/10.1016/j.compedu.2014.12.018>
- Ajjan, H., & Hartshorne, R. (2008). Investigating faculty decisions to adopt Web 2.0 technologies: Theory and empirical tests. *Internet and Higher Education*, 11(2), 71–80.
- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211. [https://doi.org/10.1016/0749-5978\(91\)90020-T](https://doi.org/10.1016/0749-5978(91)90020-T)
- Akgül, Y. (2018). A SEM-neural network approach for predicting antecedents of factors influencing consumers' intent to install mobile applications. Mtenzi, F. J. et al. (Eds), in *Mobile technologies and*

- socio-economic development in emerging nations*, IGI Global. (262–308). <https://doi.org/10.4018/978-1-5225-4029-8.ch012>
- Akgül, Y. (2019). Understanding and predicting the determinants of the Facebook usage in higher education: a two staged hybrid sem- neural networks approach, in *11th International Conference of Strategic Research on Scientific Studies and Education (ICoSReSSE) November, 08–10, 2019 Antalya – Belek*, pp.9–22.
- Al-Ammary, J., Al-Sherooqi, A. K., & Al-Sherooqi, H. K. (2014). The acceptance of social networking as a learning tools at University of Bahrain. *International Journal of Information and Education Technology*, 4, 208–214. <https://doi.org/10.7763/IJIEET.2014.V4.400>
- Aldheleai, Y. M., Al-Sharafi, M. A., Al-Kumaim, N. H., & Al-Rahmi, W. M. (2021). Investigating the Impact of the Sense of Privacy on the Correlation Between Online Learning Interaction and Students' Academic Performance. In *Recent Advances in Technology Acceptance Models and Theories* (pp. 485–496). Springer, Cham. https://doi.org/10.1007/978-3-030-64987-6_28
- Al-rahmi, W. M., Othman, M. S., & Yusuf, L. M. (2015). Social media for collaborative learning and engagement: Adoption framework in higher education institutions in Malaysia. *Mediterranean Journal of Social Sciences*, 6(3), 246–252. <https://doi.org/10.5901/mjss.2015.v6n3s1p246>
- Al-Sharafi, M., Mufadhil, M. E., Arshah, R. A., & Sahabudin, N. A. (2019). Acceptance of online social networks as technology-based education tools among higher institution students: Structural equation modeling approach. *Scientia Iranica*, 26(1), 136–144. <https://doi.org/10.24200/SCI.2018.51570.2256>
- Al-Shihi, H., Sharma, S. K., & Sarrah, M. (2018). Neural network approach to predict mobile learning acceptance. *Education and Information Technologies*, 23, 1805–1824. <https://doi.org/10.1007/s10639-018-9691-9>
- Albayrak, D., & Yildirim, Z. (2015). Using social networking sites for teaching and learning: Students' involvement in and acceptance of facebook® as a course management system. *Journal of Educational Computing Research*, 52(2), 155–179. <https://doi.org/10.1177/0735633115571299>
- Aldhahi, M. I., Alqahtani, A. S., Baattaiah, B. A., & Al-Mohammed, H. I. (2021). Exploring the relationship between students' learning satisfaction and self-efficacy during the emergency transition to remote learning amid the coronavirus pandemic: A cross-sectional study. *Education and Information Technologies*, 1-18<https://doi.org/10.1007/s10639-021-10644-7>
- Arshad, M., & Akram, M. S. (2018). Social media adoption by the academic community: Theoretical insights and empirical evidence from developing countries. *International Review of Research in Open and Distributed Learning*, 19(3), 243–262. <https://doi.org/10.19173/irrodl.v19i3.3500>
- Arteaga Sánchez, R., & Duarte Hueros, A. (2010). Motivational factors that influence the acceptance of Moodle using TAM. *Computers in Human Behavior*, 26(6), 1632–1640. <https://doi.org/10.1016/j.chb.2010.06.011>
- Baleghi-Zadeh, S., Ayub, A. F. M., Mahmud, R., & Daud, S. M. (2014). Behaviour intention to use the learning management: Integrating technology acceptance model with task-technology fit. *Middle-East Journal of Scientific Research*, 19, 76–84. <https://doi.org/10.5829/idosi.mejrs.2014.19.icmrr.12>
- Bataineh, A. Q., Al-Abdallah, G. M., & Alkharabsheh, A. M. (2015). Determinants of continuance intention to use social networking sites SNS's: Studying the case of Facebook. *International Journal of Marketing Studies*, 7(4), 121. <https://doi.org/10.5539/ijms.v7n4p121>
- Beer, D., & Burrows, R. (2007). Sociology and of and in Web 2.0: some initial considerations. *Sociological Research Online*, 12(5), 67–79. <https://doi.org/10.5153/sro.1560>
- Bekker, A. J., & Goldberger, J. (2016). Training deep neural-networks based on unreliable labels. *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2682–2686. <https://doi.org/10.1109/ICASSP.2016.7472164>
- Bekker, A. J., Shalhon, M., Greenspan, H., & Goldberger, J. (2015). Multi-view probabilistic classification of breast microcalcifications. *IEEE Transactions on Medical Imaging*, 35(2), 645–653. <https://doi.org/10.1109/TMI.2015.2488019>
- Bentler, P. M., & Chou, C. P. (1987). Practical issues in structural modeling. *Sociological Methods & Research*, 16(1), 78–117. <https://doi.org/10.1177/0049124187016001004>
- Berger, P. (2017). Beyond plain acceptance or sheer resistance: A typology of university instructors' attitudes to students' media use in class. *Teaching and Teacher Education*, 67, 410–417.
- Bhattacharjee, A. (2000). Acceptance of internet applications services: The case of electronic brokerages. *IEEE Transactions on Systems Man and Cybernetics-Part A Systems and Humans*, 30(4), 411–420. <https://doi.org/10.1109/3468.852435>

- Bicen, H., & Cavus, N. (2011). Social network sites usage habits of undergraduate students: Case study of Facebook. *Procedia-Social and Behavioral Sciences*, 28, 943–947. <https://doi.org/10.1016/j.sbspro.2011.11.174>
- Bock, G. W., Zmud, R., Kim, Y. G., & Lee, J.-N. (2005). Behavioral intention formation in knowledge sharing: Examining the roles of extrinsic motivators, social-psychological forces, and organizational climate. *Management Information Systems Quarterly*, 29(1), 87–111. <https://doi.org/10.2307/25148669>
- Boticki, I., Baksa, J., Seow, P., & Looi, C. K. (2015). Usage of a mobile social learning platform with virtual badges in a primary school. *Computers and Education*, 86, 120–136. <https://doi.org/10.1016/j.compedu.2015.02.015>
- Boud, D., Cohen, R., & Sampson, J. (Eds.). (2001). *Peer learning in higher education: Learning from & with each other*. Psychology Press.
- Bowman, N. D., & Akcaoglu, M. (2014). “I see smart people!”: Using Facebook to supplement to cognitive and affective learning in the university mass lecture. *Internet and Higher Education*, 23, 1–8. <https://doi.org/10.1016/j.iheduc.2014.05.003>
- Boyd, D. M., & Ellison, N. B. (2007). Social network sites: Definition, history, and scholarship. *Journal of Computer-Mediated Communication*, 13(1), 210–230. <https://doi.org/10.1111/j.1083-6101.2007.00393.x>
- Byoung-Chan, L., Jeong-Ok, Y., & In, L. (2009). Learners’ acceptance of e-learning in South Korea: Theories and results. *Computers & Education*, 53(4), 1320–1329. <https://doi.org/10.1016/j.compedu.2009.06.014>
- Calaguas, N. P., & Consunji, P. M. P. (2022). A structural equation model predicting adults’ online learning self-efficacy. *Education and Information Technologies*, 1–17. <https://doi.org/10.1007/s10639-021-10871-y>
- Chakraborty, T., Kumar, A., Upadhyay, P., & Dwivedi, Y. K. (2021). Link between social distancing, cognitive dissonance, and social networking site usage intensity: A country-level study during the COVID-19 outbreak. *Internet Research*. <https://doi.org/10.1108/INTR-05-2020-0281>
- Chaouali, W. (2016). Once a user, always a user: Enablers and inhibitors of continuance intention of mobile social networking sites. *Telematics and Informatics*, 33, 1022–1033. <https://doi.org/10.1016/j.tele.2016.03.006>
- Cheung, C. M., Chiu, P. Y., & Lee, M. K. O. (2011). Online social networks: Why do students use Facebook? *Computers in Human Behavior*, 27(4), 1337–1343. <https://doi.org/10.1016/j.chb.2010.07.028>
- Cheung, R., & Vogel, D. (2013). Predicting user acceptance of collaborative technologies: An extension of the technology acceptance model for e-learning. *Computers & Education*, 63, 160–175. <https://doi.org/10.1016/j.compedu.2012.12.003>
- Chintalapati, N., & Daruri, V. S. K. (2016). Examining the use of YouTube as a learning resource in higher education: Scale development and validation of TAM model. *Telematics and Informatics*, 34(6), 853–860. <https://doi.org/10.1016/j.tele.2016.08.008>
- Chong, A. Y. L. (2013). A two-staged SEM-neural network approach for understanding and predicting the determinants of m-commerce adoption. *Expert Systems with Applications*, 40(4), 1240–1247. <https://doi.org/10.1016/j.eswa.2012.08.067>
- Chong, A. Y. L., Liu, M. J., Luo, J., & Keng-Boon, O. (2015). Predicting RFID adoption in healthcare supply chain from the perspectives of users. *International Journal of Production Economics*, 159, 66–75. <https://doi.org/10.1016/j.ijpe.2014.09.034>
- Davis, F. D. (1989). Perceived Usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- 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, 1111–1132. <https://doi.org/10.1111/j.1559-1816.1992.tb00945.x>
- de-Marcos, L., García-López, E., García-Cabot, A., Medina-Merodio, J. A., Domínguez, A., Martínez Herráiz, J. J., & DiezFolledo, T. (2016). Social network analysis of a gamified e-learning course: Small-world phenomenon and network metrics as predictors of academic performance Computers in Human. *Behaviour*, 60(312), 321. <https://doi.org/10.1016/j.chb.2016.02.052>
- DeAndrea, D. C., Ellison, N. B., LaRose, R., Steinfield, C., & Fiore, A. (2012). Serious social media: On the use of social media for improving students’ adjustment to college. *The Internet and Higher Education*, 15(1), 15–23. <https://doi.org/10.1016/j.iheduc.2011.05.009>

- Deng, L., & Tavares, N. J. (2013). From Moodle to Facebook: Exploring students' motivation and experiences in online communities. *Computers & Education*, 68, 167–176. <https://doi.org/10.1016/j.compedu.2013.04.028>
- Dhume, S.M., Pattanshetti, M.Y., Kamble, S.S., and Prasad, T. Adoption of social media by business education students: Application of technology acceptance model (TAM)", in *Technology Enhanced Education (ICTEE), 2012 IEEE International Conference on*, pp. 1–10 (2012).
- Dumpit, D.Z. & Fernandez, C.J. (2017). Analysis of the use of social media in higher education institutions (HEIs) using the technology acceptance model, *International Journal of Educational Technology in Higher Education*, 14(1). <https://doi.org/10.1186/s41239-017-0045-2>
- Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies*, 59(4), 451–474. [https://doi.org/10.1016/S1071-5819\(03\)00111-3](https://doi.org/10.1016/S1071-5819(03)00111-3)
- Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behaviour: An introduction to theory and research*. Reading: Addison-Wesley.
- Fornell, C., & Larcker, D. F. (1981). Evaluation structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.2307/3151312>
- Fu, S., Li, H., Liu, Y., Pirkkalainen, H., & Salo, M. (2020). Social media overload, exhaustion, and use discontinuance: Examining the effects of information overload, system feature overload, and social overload. *Information Processing & Management*, 57(6), 102307. <https://doi.org/10.1016/j.ipm.2020.102307>
- Gabarre, S., Gabarre, C., Din, R., Shah, P. M., & Karim, A. A. (2013). Using mobile Facebook as an LMS: Exploring impeding factors. *GEMA Online Journal of Language Studies*, 13(3), 99–115.
- Gao, F., Luo, T., & Zhang, K. (2012). Tweeting for learning: A critical analysis of research on micro-blogging in education published in 2008–2011. *British Journal of Educational Technology*, 43(5), 783–801. <https://doi.org/10.1111/j.1467-8535.2012.01357.x>
- Golder, S.A., Wilkinson, D. & Huberman, B.A., 2007. Rhythms of social interaction: messaging within a massive online network. In: Steinfeld, C., Pentland, B.T., Ackerman, M., Contractor, N. (Eds.), *Communities and Technologies 2007 Proceedings of the Third Communities and Technologies Conference*. Springer-Verlag Limited, London, pp. 41–66.
- Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, 19(2), 213–236. <https://doi.org/10.2307/249689>
- Guan, L., Zhang, Y., & Zhu, J. J. (2021). Predicting information exposure and continuous consumption: Self-level interest similarity, peer-level interest similarity and global popularity. *Online Information Review*. <https://doi.org/10.1108/OIR-10-2020-0475>
- Hadizadeh Moghadam, A., & Bairamzadeh, S. (2009). Extending the technology acceptance model for e-learning: A case study of Iran. In *Sixth International Conference on Information Technology: New Generations* (pp. 1659–1660).
- Hair, J. F., Black, W. C., Babin, B., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Prentice Hall.
- Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, 19(2), 139–152. <https://doi.org/10.2753/MTP1069-6679190202>
- Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017a). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management and Data Systems*, 117(3), 442–458. <https://doi.org/10.1108/IMDS-04-2016-0130>
- Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2017b). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Sage Publications.
- Hamid, S., Waycott, J., Kurnia, S., & Chang, S. (2015). Understanding students' perceptions of the benefits of online social networking use for teaching and learning. *The Internet and Higher Education*, 26, 1–9. <https://doi.org/10.1016/j.iheduc.2015.02.004>
- Hargittai, E. (2007). Whose space? Differences among users and non-users of social network sites. *Journal of Computer-Mediated Communication*, 13(1), 276–297. <https://doi.org/10.1111/j.1083-6101.2007.00396.x>
- Haykin, S. (2004). *Neural networks: A comprehensive foundation* (2nd ed.). Upper Saddle River, NJ: Prentice Hall.
- Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). *The use of partial least squares path modeling in international marketing*. Emerald Group Publishing Limited. [https://doi.org/10.1108/S1474-7979\(2009\)0000020014](https://doi.org/10.1108/S1474-7979(2009)0000020014)

- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Hew, K. F. (2011). Students' and teachers' use of Facebook. *Computers in Human Behavior*, 27(2), 662–676. <https://doi.org/10.1016/j.chb.2010.11.020>
- Hew, K. F., & Cheung, W. S. (2013). Use of Web 2.0 technologies in K-12 and higher education: The search for evidence-based practice. *Educational Research Review*, 9, 47–64. <https://doi.org/10.1016/j.edurev.2012.08.001>
- Hew, K. F., & Cheung, W. S. (2012). Use of Facebook: A case study of Singapore students' experience. *Asia Pacific Journal of Education*, 32(2), 181–196. <https://doi.org/10.1080/02188791.2012.685560>
- Hofstede, G. (1991). *Cultures and organizations: Software of the mind*. McGraw-Hill.
- Hong, S.-J., Tam, K. Y., & Kim, J. (2006a). Mobile data service fuels the desire for uniqueness. *Communications of the ACM*, 49(9), 89–94. <https://doi.org/10.1145/1151030.1151034>
- Hong, S., Thong, J. Y., & Tam, K. Y. (2006b). Understanding continued information technology usage behavior: A comparison of three models in the context of mobile Internet. *Decision Support Systems*, 42(3), 1819–1834. <https://doi.org/10.1016/j.dss.2006.03.009>
- Hooper, D., Coughlan, J., & Mullen, M. (2008). Structural equation modeling: Guidelines for determining model fit. *Electronic Journal of Business Research Methods*, 6(1), 53–60. <https://doi.org/10.1016/j.compedu.2012.09.017>
- Huang, W., & Stokes, J. W. (2016). MtNet: a multi-task neural network for dynamic malware classification. In *International conference on detection of intrusions and malware, and vulnerability assessment* (pp. 399–418). Springer, Cham.
- Hung, S. W., & Cheng, M. J. (2013). Are you ready for knowledge sharing? An empirical study of virtual communities. *Computers & Education*, 62, 8–17. <https://doi.org/10.1016/j.compedu.2012.09.017>
- Hwang, G.-J., Tsai, C.-C., & Yang, S. J. (2008). Criteria, strategies, and research issues of context-aware ubiquitous learning. *Educational Technology & Society*, 11, 81–91.
- Jong, B., Lai, C., Hsia, Y., Lin, T., & Liao, Y. (2014). An exploration of the potential education value of Facebook. *Computers in Human Behavior*, 32, 201–211. <https://doi.org/10.1016/j.chb.2013.12.007>
- Junco, R. (2012). The relationship between frequency of Facebook use, participation in Facebook activities, and student engagement. *Computers & Education*, 58(1), 162–171. <https://doi.org/10.1016/j.compedu.2011.08.004>
- Kabilan, M. K., Ahmad, N., & Abidin, M. J. Z. (2010). Facebook: An online environment for learning of English in institutions of higher education? *Internet and Higher Education*, 13(4), 179–187. <https://doi.org/10.1016/j.iheduc.2010.07.003>
- Kang, Y. S., & Lee, H. (2010). Understanding the role of an IT artifact in online service continuance: An extended perspective of user satisfaction. *Computers in Human Behavior*, 26(3), 353–364. <https://doi.org/10.1016/j.chb.2009.11.006>
- Khan, M. L., Wohn, D. Y., & Ellison, N. B. (2014). Actual friends matter: An internet skills perspective on teens' informal academic collaboration on Facebook. *Computers & Education*, 79, 138–147.
- Kim, B. (2011). Understanding antecedents of continuance intention in social networking services. *Cyberpsychology, Behavior, and Social Networking*, 14(4), 199–205. <https://doi.org/10.1089/cyber.2010.0009>
- Kim, C., Mirusmonov, M., & Lee, I. (2010). An empirical examination of factors influencing the intention to use mobile payment. *Computers in Human Behavior*, 26(3), 310–322. <https://doi.org/10.1016/j.chb.2009.10.013>
- Kim, J., Hwang, D., Park, S. I., Lee, H., Hong, C., & Kim, W. (2014). Personalized interactive e-learning system using expanded SCORM. *Applied Mathematics & Information Sciences*, 8(1), 133–139. <https://doi.org/10.12785/AMIS/081L17>
- King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management*, 43(6), 740–755. <https://doi.org/10.1016/j.im.2006.05.003>
- Kokkinos, Y., & Margaritis, K. G. (2018). Managing the computational cost of model selection and cross-validation in extreme learning machines via Cholesky. *SVD, QR, and Eigen Decompositions, Neurocomputing*, 295, 29–45. <https://doi.org/10.1016/j.neucom.2018.01.005>
- Lacka, E., & Chong, A. (2016). Usability perspective on social media sites' adoption in the B2B context. *Industrial Marketing Management*, 54, 80–91. <https://doi.org/10.1016/j.indmarman.2016.01.001>
- Lampe, C., Wohn, D. Y., Vitak, J., Ellison, N. B., & Wash, R. (2011). Student use of Facebook for organizing collaborative classroom activities. *International Journal of Computer-Supported Collaborative Learning*, 6(3), 329–347.

- Lan, Y.-F., & Huang, S.-M. (2012). Using Mobile Learning to Improve the Reflection: A Case Study of Traffic Violation. *Educational Technology & Society, 15*(2), 179–193.
- Lee, D. Y., & Lehto, M. R. (2013). User acceptance of YouTube for procedural learning: An extension of the technology acceptance model. *Computers & Education, 61*, 193–208. <https://doi.org/10.1016/j.compedu.2012.10.001>
- Lee, K. O. M., Cheung, C. M. K., & Chen, Z. (2005). Acceptance of internet-based learning medium: The role of extrinsic and intrinsic motivation. *Information & Management, 42*(8), 1095–1104. <https://doi.org/10.1016/j.im.2003.10.007>
- Lee, V. H., Hew, J. J., Leong, L. Y., Tan, G. W. H., & Ooi, K. B. (2020). Wearable payment: A deep learning-based dual-stage SEM-ANN analysis. *Expert Systems with Applications, 157*, 113477. <https://doi.org/10.1016/j.eswa.2020.113477>
- Lenhart, A., Madden, M., (2007). *Social networking websites and teens: An overview*. Washington: DC: Pew Research Center
- Leong, L. W., Ibrahim, O., Dalvi-Esfahani, M., Shahbazi, H., & Nilashi, M. (2018a). The moderating effect of experience on the intention to adopt mobile social network sites for pedagogical purposes: An extension of the technology acceptance model. *Education and Information Technologies, 23*(6), 2477–2498. <https://doi.org/10.1007/s10639-018-9726-2>
- Leong, L. Y., Hew, T. S., Ooi, K. B., Lee, V. H., & Hew, J. J. (2019). A hybrid SEM-neural network analysis of social media addiction. *Expert Systems with Applications, 133*, 296–316. <https://doi.org/10.1016/j.eswa.2019.05.024>
- Leong, L. Y., Hew, T. S., Ooi, K. B., & Chong, A. Y. L. (2020). Predicting the antecedents of trust in social commerce—A hybrid structural equation modeling with neural network approach. *Journal of Business Research, 110*, 24–40. <https://doi.org/10.1016/j.jbusres.2019.11.056>
- Leong, L. Y., Jaafar, N. I., & Ainin, S. (2018b). Understanding facebook commerce (F- Commerce) actual purchase from an artificial neural network perspective. *Journal of Electronic Commerce Research, 19*(1), 75–103.
- Liébana-Cabanillas, F., Marinkovi, V., & Kalinić, Z. (2017). A SEM-neural network approach for predicting antecedents of m-commerce acceptance. *International Journal of Information Management, 37*(2), 14–24. <https://doi.org/10.1016/j.ijinfomgt.2016.10.008>
- Lin, K.-Y., & Lu, H.-P. (2015). Predicting mobile social network acceptance based on mobile value and social influence. *Internet Research, 25*(1), 107–130. <https://doi.org/10.1108/IntR-01-2014-0018>
- Lin, W. S., & Wang, C. H. (2012). Antecedences to continued intentions of adopting e-learning system in blended learning instruction: A contingency framework based on models of information system success and task-technology fit. *Computers & Education, 58*, 88–99. <https://doi.org/10.1016/j.compedu.2011.07.008>
- Lin, X., Li, Y., Califf, C.B., & Featherman, M. (2013). Can Social Role Theory Explain Gender Differences in Facebook Usage? *2013 46th Hawaii International Conference on System Sciences*, 690–699. <https://doi.org/10.1109/HICSS.2013.125>
- Loh, X. K., Lee, V. H., Loh, X. M., Tan, G. W. H., Ooi, K. B., & Dwivedi, Y. K. (2021). The dark side of mobile learning via social media: how bad can it get?. *Information Systems Frontiers*, 1–18.
- Lockyer, L. & Patterson, J. (2008). Integrating Social Networking Technologies in Education: A Case Study of a Formal Learning Environment. *Eighth IEEE International Conference on Advanced Learning Technologies*, pp. 529–533, <https://doi.org/10.1109/ICALT.2008.67>
- Lou, H., Luo, W., & Strong, D. (2000). Perceived critical mass effect on groupware acceptance. *European Journal of Information Systems, 9*, 91–103. <https://doi.org/10.1057/palgrave.ejis.3000358>
- Lou, J., Deng, L., & Wang, D. (2021). Understanding the deep structure use of mobile phones—an attachment perspective. *Behaviour & Information Technology, 1-19*<https://doi.org/10.1080/0144929X.2021.1975822>
- Lu, H.-P., & Yang, Y.-W. (2014). Toward an understanding of the behavioural intention to use a social networking site: An extension of task-technology fit to social-technology fit. *Computers in Human Behaviour, 34*, 323–332. <https://doi.org/10.1016/j.chb.2013.10.020>
- Lu, X., Yu, Z., Guo, B., & Zhou, X. (2014). Predicting the content dissemination trends by repost behavior modeling in mobile social networks. *Journal of Network and Computer Applications, 42*, 197–207. <https://doi.org/10.1016/j.jnca.2014.01.015>
- Ma, W.W.-K., Andersson, R., & Streith, K.-O. (2005). Examining user acceptance of computer technology: An empirical study of student teachers. *Journal of Computer Assisted Learning, 21*, 387–395. <https://doi.org/10.1111/j.1365-2729.2005.00145.x>

- Madge, C., Meek, J., Wellens, J., & Hooley, T. (2009). Facebook, social integration, and informal learning at university: It is more for socializing and talking to friends about work than for actually doing work. *Learning, Media and Technology*, 34(2), 141–155. <https://doi.org/10.1080/17439880902923606>
- Mahdaviifar, S., & Ghorbani, A. (2019). Application of deep learning to cybersecurity: A survey. *Neuro-computing*, 347, 149–176. <https://doi.org/10.1016/j.neucom.2019.02.056>
- Maloney, E. (2007). What Web 2.0 can teach us about learning. *Chronicle of Higher Education*, 53(18), 130–142. <https://doi.org/10.2478/eurodl-2014-0024>
- Manca, S., & Ranieri, M. (2013). Is it a tool suitable for learning? A critical review of the literature on Facebook as a technology-enhanced learning environment. *Journal of Computer Assisted Learning*, 29(6), 487–504. <https://doi.org/10.1111/jcal.12007>
- Manca, S., & Ranieri, M. (2017). Networked scholarship and motivations for social media use in scholarly communication. *The International Review of Research in Open and Distributed Learning* 18(2). <https://doi.org/10.19173/irrodl.v18i2.2859>
- Mathieson, K. (1991). Predicting user intentions: Comparing the technology acceptance model with the theory of planned behavior. *Information Systems Research*, 2(3), 173–191. <https://doi.org/10.1287/isre.2.3.173>
- Mazer, J. P., Murphy, R. E., & Simonds, C. J. (2007). I'll see you on "Facebook": The effects of computer mediated teacher self-disclosure on student motivation, affective learning, and classroom climate. *Communication Education*, 56, 1–17. <https://doi.org/10.1080/03634520601009710>
- Mazman, S. G., & Usluel, Y. K. (2009). Adoption of Web 2.0 tools in distance education. *Procedia Social and Behavioral Sciences*, 1(1), 818–823. <https://doi.org/10.1016/j.sbspro.2009.01.146>
- Mazman, S. G., & Usluel, Y. K. (2010). Modeling educational usage of Facebook. *Computers & Education*, 55(2), 444–453. <https://doi.org/10.1016/j.compedu.2010.02.008>
- Merhi, M. I. (2015). Factors influencing higher education students to adopt podcast: An empirical study. *Computers & Education*, 83, 32–43. <https://doi.org/10.1016/j.compedu.2014.12.014>
- Milosevic, I., Zivkovic, D., Arsic, S., & Manasijevic, D. (2015). Facebook as virtual classroom-social networking in learning and teaching among Serbian students. *Telematics and Informatics*, 32(4), 576–585. <https://doi.org/10.1016/j.tele.2015.02.003>
- Mohammadi, H. (2015). Investigating users' perspectives on e-learning: An integration of TAM and IS success model. *Computers in Human Behavior*, 45, 359–374. <https://doi.org/10.1016/j.chb.2014.07.044>
- Moon, J. W., & Kim, Y. G. (2001). Extending the TAM for a World-Wide-Web context. *Information & Management*, 38(4), 217–230. [https://doi.org/10.1016/S0378-7206\(00\)00061-6](https://doi.org/10.1016/S0378-7206(00)00061-6)
- Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, 2(3), 192–222. <https://doi.org/10.1287/isre.2.3.192>
- Moorthy, V. S., Karam, G., Vannice, K. S., & Kieny, M. P. (2015). Rationale for WHO's new position calling for prompt reporting and public disclosure of interventional clinical trial results. *PLoS Medicine*, 12(4), e1001819. <https://doi.org/10.1371/journal.pmed.1001819>
- Motaghian, H., Hassanzadeh, A., & Moghadam, D. K. (2013). Factors affecting university instructors' adoption of web-based learning systems: Case study of Iran. *Computers & Education*, 61, 158–167. <https://doi.org/10.1016/j.compedu.2012.09.016>
- Mouakket, S. (2015). Factors influencing continuance intention to use social network sites: The Facebook case. *Computers in Human Behavior*, 53, 102–110. <https://doi.org/10.1016/j.chb.2015.06.045>
- Mufadhil, M. E., Sahabudin, N. A., & Al-Shara, M. A. (2018). Conceptualizing a model for adoption of online social networks as a learning tool. *Advanced Science Letters*, 24(10), 7747–7750. <https://doi.org/10.1166/asl.2018.13011>
- Mugruza-Vassallo, C., & Potter, D. (2019). Context dependence signature, stimulus properties and stimulus probability as predictors of ERP amplitude variability. *Frontiers in Human Neuroscience*, 13(39). <https://doi.org/10.3389/fnhum.2019.00039>
- Mugruza-Vassallo, C.A., Potter, D.D., Tsiora, S. et al. (2021). Prior context influences motor brain areas in an auditory oddball task and prefrontal cortex multitasking modelling. *Brain Informatics*, 8(5). <https://doi.org/10.1186/s40708-021-00124-6>
- Myers, N. D., Ahn, S., & Jin, Y. (2011). Sample size and power estimates for a confirmatory factor analytic model in exercise and sport: A Monte Carlo approach. *Research Quarterly for Exercise and Sport*, 82(3), 412–423. <https://doi.org/10.1080/02701367.2011.10599773>

- Ngai, E. W. T., Poon, J. K. L., & Chan, Y. H. C. (2007). Empirical examination of the adoption of WebCT using TAM. *Computers & Education*, 48(2), 250–267. <https://doi.org/10.1016/j.compedu.2004.11.007>
- Padilla-Meléndez, A., Del Aguila-Obra, A. R., & Garrido-Moreno, A. (2013). Perceived playfulness, gender differences, and technology acceptance model in a blended learning scenario. *Computers & Education*, 63, 306–317. <https://doi.org/10.1016/j.compedu.2012.12.014>
- Pagani, M. (2006). Determinants of adoption of high-speed data services in the business market: Evidence for a combined technology acceptance model with task technology fit model. *Information Management*, 43, 847–860. <https://doi.org/10.1016/j.im.2006.08.003>
- Park, E., Baek, S., Ohm, J., & Chang, H. J. (2014). Determinants of player acceptance of mobile social network games: An application of extended technology acceptance model. *Telematics and Informatics*, 31(1), 3–15. <https://doi.org/10.1016/j.tele.2013.07.001>
- Pérez, T., Araiza, M. J., & Doerfer, C. (2013). Using Facebook for learning: A case study on the perception of students in higher education. *Procedia Social and Behavioral Sciences*, 106, 3259–3267. <https://doi.org/10.1016/j.sbspro.2013.12.375>
- Phillips, P., Zigan, K., Silva, M. M. S., & Schegg, R. (2015). The interactive effects of online reviews on the determinants of Swiss hotel performance: A neural network analysis. *Tourism Management*, 50, 130–141. <https://doi.org/10.1016/j.tourman.2015.01.028>
- Purvis, A., Rodger, H., & Beckingham, S. (2016). Engagement or distraction: The use of social media for learning in higher education. *Student Engagement and Experience Journal*, 5(1), 1–5.
- Racham, P., & Firpo, D. (2011). Using social networking technology to enhance learning in higher education: a case study using Facebook. In System Sciences (HICSS), 2011 44th Hawaii International conference on IEEE (pp. 1e10).
- Raza, A., Kumar, U., Hassan, J., et al. (2020a). A comparative study of dirac 2D materials, TMDCs, and 2D insulators with regard to their structures and photocatalytic/sonophotocatalytic behavior. *Applied Nanoscience*, 10, 3875–3899. <https://doi.org/10.1007/s13204-020-01475-y>
- Raza, S. A., Qazi, W., Shah, N., Qureshi, M. A., Qaiser, S., & Ali, R. (2020b). Drivers of intensive Facebook usage among university students: An implications of U&G and TPB theories. *Technology in Society*, 62, 101331. <https://doi.org/10.1016/j.techsoc.2020.101331>
- Roblyer, M. D., McDaniel, M., Webb, M., Herman, J., & Witty, J. V. (2010). Findings on Facebook in higher education: A comparison of college faculty and student uses and perceptions of social networking sites. *Internet and Higher Education*, 13(3), 134–140. <https://doi.org/10.1016/j.iheduc.2010.03.002>
- Roca, J. C., Chiu, C. M., & Martinez, F. J. (2006). Understanding e-learning continuance intention: An extension of the technology acceptance model. *International Journal of Human-Computer Studies*, 64(8), 683–696. <https://doi.org/10.1016/j.ijhcs.2006.01.003>
- Rodríguez-Hoyos, C., Haya, I., & Fernández-Díaz, E. (2015). Research on SNS and education: The state of the art and its challenges. *Australasian Journal of Educational Technology*, 31(1), 100–111.
- Rogers, E. M., Singhal, A., & Quinlan, M. M. (2014). *Diffusion of innovations* (pp. 432–448). Routledge.
- Sánchez-Franco, M. J., Martínez-López, F. J., & Martín-Velicia, F. A. (2009). Exploring the impact of individualism and uncertainty avoidance in web-based electronic learning: An empirical analysis in European higher education. *Computers and Education*, 52(3), 588–598. <https://doi.org/10.1016/j.compedu.2008.11.006>
- Sánchez, R. A., Cortijo, V., & Javed, U. (2014). Students' perceptions of Facebook for academic purposes. *Computers & Education*, 70, 138–149. <https://doi.org/10.1016/j.compedu.2013.08.012>
- Savage, S. W., Potter, D. D., & Tatler, B. W. (2018). The effects of array structure and secondary cognitive task demand on processes of visual search. *Vision Research*, 153, 37–46. <https://doi.org/10.1016/j.visres.2018.09.004>
- Selwyn, N. (2007). 'Screw blackboard... do it on Facebook!': An investigation of students' educational use of Facebook. Ponencia. En: Poke <http://www.scribd.com/doc/513958/Facebookseminar-paper-Selwyn>. Accessed 10 October 2021.
- Selwyn, N. (2009). Faceworking: Exploring students' education-related use of Facebook. *Learning, Media and Technology*, 34(2), 157–174. <https://doi.org/10.1080/17439880902923622>
- Sharma, S. K., Joshi, A., & Sharma, H. (2016). A multi-analytical approach to predict the Facebook usage in higher education. *Computers in Human Behavior*, 55, 340–353. <https://doi.org/10.1016/j.chb.2015.09.020>
- Shmueli, G., & Koppius, O. (2010). Predictive analytics in information systems research. *MIS Quarterly*, 35(3), 553–572. <https://doi.org/10.2307/23042796>

- Sim, J. J., Tan, G. W. H., Wong, J. C. J., Ooi, K. B., & Hew, T. S. (2014). Understanding and predicting the motivators of mobile music acceptance-A multi-stage MRA-artificial neural network approach. *Telematics and Informatics*, 31(4), 569–584. <https://doi.org/10.1016/j.tele.2013.11.005>
- Siyal, A. W., Chen, H., Chen, G., Memon, M. M., & Binte, Z. (2020). Structural equation modeling and artificial neural networks approach to predict continued use of mobile taxi booking apps: the mediating role of hedonic motivation. *Data Technologies and Applications*, 55(3), 372–399. <https://doi.org/10.1108/DTA-03-2020-0066>
- Siyal, A. W., Hongzhuang, C., & Gang, C. (2021). From consumer satisfaction to recommendation of mobile app-based services: An overview of mobile taxi booking apps. *SageOpen*, 11(1), 1–14. <https://doi.org/10.1177/21582440211004179>
- Sledgianowski, D., & Kulviwat, S. (2009). Using social network sites: The effects of playfulness, critical mass and trust in a hedonic context. *Journal of Computer Information Systems*, 49(4), 74–83.
- So, H.-J., & Brush, T. A. (2008). Student perceptions of collaborative learning, social presence, and satisfaction in a blended learning environment: Relationships and critical factors. *Computers & Education*, 51(1), 318–336. <https://doi.org/10.1016/j.compedu.2007.05.009>
- Statista.com, (September 22, 2021). *Leading countries based on Facebook audience size as of July 2021*. Retrieved from <https://www.statista.com/statistics/268136/top-15-countries-based-on-number-of-facebook-users/>
- Stockwell, G. (2010). Using mobile phones for vocabulary activities: Examining the effect of the platform. *Language, Learning, and Technology*, 14(2), 95–110.
- Stutzman, F. (2006). An evaluation of identity-sharing behavior in social network communities. *International Digital Media and Arts Association Journal*, 3(1), 14–24.
- Tamilmani, K., Rana, N. P., Dwivedi, R., et al. (2021). The extended unified theory of acceptance and use of technology (UTAUT2): A systematic literature review and theory evaluation. *International Journal of Information Management*, 57, 102269.
- Tan, G. W. H., Ooi, K. B., Sim, J. J., & Phusavat, K. (2012). Determinants of mobile learning adoption: An empirical analysis. *The Journal of Computer Information Systems*, 52, 82–91.
- Tarhini, A., Hone, K., Liu, X., & Tarhini, T. (2016). Examining the moderating effect of individual-level cultural values on users' acceptance of E-learning in developing countries: A structural equation modeling of an extended technology acceptance model. *Interactive Learning Environments*, 25(3), 306–328. <https://doi.org/10.1080/10494820.2015.1122635>
- Taylor, S., & Todd, P. A. (1995). Understanding IT usage: A test of competing models. *Information Systems Research*, 6(2), 144–176.
- Tenenhaus, M., Vinzi, V. E., Chatelin, Y. M., & Laura, C. (2005). PLS path modeling. *Computational Statistics & Data Analysis*, 48(1), 159–205. <https://doi.org/10.1016/j.csda.2004.03.005>
- Teo, T. (2012). Examining the intention to use technology among preservice teachers: An integration of the technology acceptance model and theory of planned behavior. *Interactive Learning Environments*, 20(1), 3–18. <https://doi.org/10.1080/10494821003714632>
- Teo, T. (2009). The impact of subjective norm and facilitating conditions on pre-service teachers' attitude toward computer use: A structural equation modeling of an extended technology acceptance model. *Journal of Educational Computing Research*, 40(1), 89–109. <https://doi.org/10.2190/EC.40.1.d>
- Teo, A. C., Tan, G. W. H., Ooi, K. B., Hew, T. S., & Yew, K. T. (2015). The effects of convenience and speed in m-payment. *Industrial Management & Data Systems*, 115(2), 311–331. <https://doi.org/10.1108/IMDS-08-2014-0231>
- Tess, P. A. (2013). The role of social media in higher education classes (real and virtual) – a literature review. *Computers in Human Behavior*, 9(5), 60–68. <https://doi.org/10.1016/j.chb.2012.12.032>
- Tiruwa, A., Yadav, R., & Suri, P. K. (2018). Modelling Facebook usage for collaborative learning in higher education. *Journal of Applied Research in Higher Education*, 10(3), 357–379. <https://doi.org/10.1108/JARHE-08-2017-0088>
- Triandis, H. C. (1980). Values, attitudes, and interpersonal behavior. In H. Howe, & M. Page (Eds.), *Nebraska symposium on motivation*, 27, (pp:195–259). Lincoln, NB: University of Nebraska Press.
- Van der Heijden, H. (2004). User acceptance of hedonic information systems. *MIS Quarterly*, 28, 695–704. <https://doi.org/10.2307/25148660>
- Van Raaij, E. M., & Schepers, J. J. L. (2008). The acceptance and use of a virtual learning environment in China. *Computers & Education*, 50(3), 838–852. <https://doi.org/10.1016/j.compedu.2006.09.001>

- Värzaru, A. A., & Bocean, C. G. (2021). A Two-Stage SEM–Artificial Neural Network Analysis of Mobile Commerce and Its Drivers. *Journal of Theoretical and Applied Electronic Commerce Research*, 16(6), 2304–2318. <https://doi.org/10.3390/jtaer16060127>
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186–204. <https://doi.org/10.1287/mnsc.46.2.186.11926>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
- Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157–178.
- Wai, I. S. H., Ng, S. S. Y., Chiu, D. K. W., Ho, K. K. W., & Lo, P. (2016). Exploring undergraduate students' usage pattern of mobile apps for education. *Journal of Librarianship and Information Science*, 50(1), 34–47. <https://doi.org/10.1177/0961000616662699>
- Wang, J. G., Cao, Z. D., Yang, B. H., Ma, S. W., Fei, M. R., Wang, H., Yao, Y., Chen, T., & Wang, X. F. (2017). A method of improving identification accuracy via deep learning algorithm under condition of deficient labeled data. *36th Chinese Control Conference*, 2281–2286.
- Wang, Q., Woo, H. L., Quek, C. L., Yang, Y., & Liu, M. (2012). Using the Facebook group as a learning management system: An exploratory study. *British Journal of Educational Technology*, 43(3), 428–438. <https://doi.org/10.1111/j.1467-8535.2011.01195.x>
- Wang, R.-B., & Du, C.-T. (2014). Mobile social network sites as innovative pedagogical tools: Factors and mechanism affecting students' continuance intention on use. *Journal of Computers in Education*, 1, 353–370. <https://doi.org/10.1007/s40692-014-0015-9>
- Wong, T. C., Wong, S. Y., & Chin, K. S. (2011). A neural network-based approach of quantifying relative importance among various determinants toward organizational innovation. *Expert Systems with Applications*, 38(10), 13064–13072. <https://doi.org/10.1016/j.eswa.2011.04.113>
- Wong, C.-H., Tan, G.W.-H., Loke, S.-P., & Ooi, K.-B. (2015). Adoption of mobile social networking sites for learning? *Online Information Review*, 39(6), 762–778. <https://doi.org/10.1108/OIR-05-2015-0152>
- Wong, L. W., Leong, L. Y., Hew, J. J., Tan, G. W. H., & Ooi, K. B. (2020). Time to seize the digital evolution: Adoption of blockchain in operations and supply chain management among Malaysian SMEs. *International Journal of Information Management*, 52, 101997. <https://doi.org/10.1016/j.ijinfomgt.2019.08.005>
- Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior*, 67, 221–232. <https://doi.org/10.1016/j.chb.2016.10.028>
- Wu, J. H., & Wang, S. C. (2005). What drives mobile commerce? an empirical evaluation of the revised technology acceptance model. *Information and Management*, 42(5), 719–729. <https://doi.org/10.1016/j.im.2004.07.001>
- Wu, S., Hou, H., Hwang, W., & Liu, E. Z. (2013). Analysis of learning behavior in problem-solving-based and project-based discussion activities within the seamless online learning integrated discussion (solid) system. *Journal of Educational Computing Research*, 49(1), 61–82. <https://doi.org/10.2190/EC.49.1.c>
- Yang, S., Wang, B., & Lu, Y. (2016). Exploring the dual outcomes of mobile social networking service enjoyment: The roles of social self-efficacy and habit. *Computers in Human Behaviour*, 64(C), 486–496. <https://doi.org/10.1016/j.chb.2016.07.010>
- Yoon, C., & Rolland, E. (2015). Understanding continuance use in social networking services. *Journal of Computer Information Systems*, 55(2), 1–8. <https://doi.org/10.1080/08874417.2015.11645751>
- Yuen, A. H. K., & Ma, W. W. K. (2008). Exploring teacher acceptance of e-learning technology. *Asia-Pacific Journal of Teacher Education*, 36(3), 229–243. <https://doi.org/10.1080/13598660802232779>
- Zaki, M. Z. M., & Khan, A. (2016). Intention to use Facebook for learning support: The case of college students. *Journal of Information & Knowledge Management*, 6(2), 1–14.