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Educational Technology Adoption: A systematic review

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Abstract

During the past decades a respectable number and variety of theoretical perspectives and practical approaches have been advanced for studying determinants for prediction and explanation of user's behavior towards acceptance and adoption of educational technology. Aiming to identify the most prominent factors affecting and reliably predicting successful educational technology adoption, this systematic review offers succinct account of technology adoption and acceptance theories and models related to and widely applied in educational research. Recognised journals of the Web of Science (WoS) database were searched with no time frame limit, and a total of 47 studies published between 2003 and 2021 were critically analysed. The key research findings revealed that in educational context a vast majority of selected studies explore the validity of Technology Acceptance Model (TAM) and its many different extensions (N=37), along with TAM's integrations with other contributing theories and models (N=5). It was exposed that among numerous predictors, thematically grouped into user aspects, task & technology aspects, and social aspects, self-efficacy, subjective norm, (perceived) enjoyment, facilitating conditions, (computer) anxiety, system accessibility, and (technological) complexity were the most frequent predictive factors (i.e. antecedents) affecting educational technology adoption. Considering types of technologies, e-learning was found to be the most common validated mode of delivery, followed by m-learning, Learning Management Systems (LMSs), and social media services. The results also revealed that the majority of analysed studies were conducted in higher education environments. New directions of research along with potential challenges in educational technology acceptance, adoption, and actual use are discussed as well.

Keywords Technology acceptance · Technology adoption · Predictive factors · Education · Systematic review

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1 Introduction

Over the last half-century, a vast number of adoption theories and technology acceptance models, along with a plethora of their extensions and modifications has been advanced. Aiming to explore their applicability, as well as to enhance their predictive validity, proposed theories and models have been extensively used in assessment of various Information and Communication Technology (ICT) products and services. Commonly, technology adoption is a term that refers to the acceptance, integration, and embracement of any types of new technology. Technology acceptance, as the first step of technology adoption, is an attitude towards technology, and it is influenced by various factors. According to the Innovation Diffusion Theory (IDT) (Rogers, 1962, 1995), adoption is a decision to make full use of technology innovation as the best course of action available. The key to adoption is that the adopter (individual or organization) must perceive the idea, behavior, or product as new or innovative. As for technology adoption research at the individual level, numerous theories and models have been used to predict and explain human behavior towards technology acceptance, adoption and usage.

Education presents an area of great interest in incorporating new technologies, thus technology acceptance and adoption theories and models are often used to inform research in educational context. Such setting is characterised by a great variety of potential users of various types of technology embraced in the process of learning, teaching, and assessment. Some of the most influential theoretical approaches involve (listed in chronological order with relevant illustrative example research):

- *Technology Acceptance Model* (TAM) (Davis, 1986, 1989), the widely used reliable model, to explore new facilitating technologies in educational context, ranging from social media platforms (Yu, 2020) to the technology aimed at helping the learning process through teaching assistant robots (Park and Kwon, 2016), simulators (Lemay, Morin, Bazelais & Doleck, 2018), and virtual reality (Jang, Ko, Shin & Han, 2021);
- *Decomposed Theory of Planned Behavior* (DTPB) (Taylor & Todd, 1995) to understand university students' adoption of WhatsApp in learning (Nyasulu & Chawinga, 2019), to explore factors that influence teachers' intentions to integrate digital literacy (Sadaf & Gezer, 2020), as well as to examine factors that impact the acceptance and usage of e-assessment by academics (Alruwais, Wills & Wald, 2017);
- *Unified Theory of Acceptance and Use of Technology* (UTAUT) (Venkatesh, Morris, Davis & Davis, 2003) to study core factors affecting the university students' attitude towards adoption of online classes during COVID-19 (Tiwari, 2020), to explore the factors that influence preservice teachers' acceptance of ICT integration in the classroom (Birch & Irvine, 2009), and students' usage of e-learning systems in developing countries (Abbad, 2021);
- *Extended UTAUT* (UTAUT2) (Venkatesh, Thong & Xu, 2012) to evaluate acceptance of blended learning in executive education (Dakduk, Santalla-Banderali & van der Woude, 2018), and to examine preservice teachers' acceptance of learning management software (Raman & Don, 2013).

Several reviews and meta-analysis that summarize empirical research have been focused on specific topics in the field of education, for example: (i) *particular technology adoption model*, like the meta-analysis dealing with TAM in prediction of teachers' adoption of technology (Scherer, Siddiq & Tondeur, 2019), and the quantitative meta-analysis to identify the most commonly used external factors of TAM in the context of e-learning adoption (Abdullah & Ward, 2016); (ii) *specific type of users*, like reviews conducted to understand factors influencing academics' adoption of learning technologies (Liu, Geertshuis & Grainger, 2020), to explore factors that affect teachers' acceptance and use of ICT in the classroom (Gamage & Tanwar, 2018), as well as to study factors affecting students' adoption and continuation of technology use in online learning (Panigrahi, Srivastava & Sharma, 2018); (iii) *particular technology and mode of delivery*, like reviews carried on to explore factors affecting blended learning adoption and implementation in higher education (Anthony, et al. 2020), to study technical factors affecting users' intentions to use mobile phones as learning tools (Alghazi, Wong, Kamsin, Yadegaridehkordi & Shuib, 2020), as well as to examine the most prominent external factors affecting learning management systems (LMSs) adoption in higher educational institutions (Al-Nuaimi & Al-Emran, 2021). Besides, some theoretical work aimed to identify determinants of learning technology acceptance, but it was more focused on original constructs of reviewed technology adoption theories, like in the study conducted by Kaushik and Verma (2020).

However, to the best of authors' knowledge, currently there is hardly a holistic view of factors that affect and reliably predict successful acceptance and adoption of technology engaged in educational process. Understanding these aspects can be beneficial and can help in an improvement of both, research and educational practices. Hence, this concept-centric review aims at addressing this concern with the following two main research questions (RQs):

- RQ1. Which technology acceptance and adoption theories and models are widely applied in educational research?
- RQ2. Which are the most prominent predictive factors (i.e. antecedents) affecting educational technology adoption?

2 Research Approach

The research scope of this systematic review is narrowed and piloted towards understanding the most recognized and applied theoretical models, as well as the most influential predictive factors affecting various technologies used to support the process of knowledge transfer and acquisition. Due to massive work worldwide, this study is used to offer succinct account of predominant predictors in educational technology adoption, and certainly cannot be all-encompassing. With the aim to filter and narrow the search, but at the same time to cover representative literature from recognised journals, the Web of Science (WoS) Current Contents Connect (CCC) database was searched. The search was not limited to a precise timespan. To denote different technology acceptance models and theories, the search was conducted using relevant terms connected with Boolean operators "OR" and "AND", specifically *("theor*" OR "model") AND ("technolog*") AND ("adoption" OR "acceptance")*. To locate education related studies, *("education*" OR "learn*")* search terms were joined with the aforementioned ones by means of the operator "AND". Truncation was used to cover all variations of some keywords, for example, the search term "*technolog**" was used to search for literature that included the word "technology" as well as "technologies".

It was searched for studies that have specified search terms in publication title (the filter "TITLE" was selected). For the purpose of this review, specified *inclusion criteria* enabled selection of studies that report on technology acceptance and adoption theories and models in which some type of ICT products and services to support the process of learning and teaching was used (in this context indicating all classes of technologies, interactive systems, environments, tools, applications, services, platforms, and devices). To be included, studies had to report on empirically evaluated research model and related research hypothesis. Besides, studies must be published as peer-reviewed journal articles written in English language. On the subject of *exclusion criteria*, studies that do not clearly and credibly describe model/theory constructs or variables, and the relationships among them, were not considered as valid to be selected and included in the analysis. In addition, theoretical studies published as peer-reviewed journal articles, specifically reviews and meta-analysis, were excluded as well.

The literature search was conducted in August 2021. No time frame period was specified; 1998-2021 is the full range of the CCC database search engine. In this inquiry, 71 publications that included specified search terms in the publication title were identified. Considering only peer-reviewed journal articles written in English, the number of 67 journal and review articles was reached. Title, abstract and full text of the filtered literature were screened to ensure publication suitability and relevance. Accordingly, the qualified publications were retained and eleven unrelated ones were excluded, thus narrowing the number and leaving for further detailed analysis 56 publications. Out of 56 identified journal articles, 47 publications were found to be compliant with the purpose of this study, while 9 publications offered theoretical work which summarized empirical research focused on specific topics in educational technology acceptance and adoption.

In view of the identified theoretical work, the majority of studies offered meta-analysis and reviews of Technology Acceptance Model (TAM) based studies in education (N=6), specifically (Dimitrijević & Devedžić, 2021; Granić & Marangunić, 2019; Kemp, Palmer & Strelan, 2019; Scherer et al., 2019; Al-Emran, Mezhuyev & Kamaludin, 2018; Abdullah & Ward,2016), while just few publications addressed other acceptance models and theories, in particular Unified Theory of Acceptance and Use of Technology (UTAUT) (Bervell & Umar, 2017), Senior Technology Exploration, Learning and Acceptance (STELA) model (Tsai, Rikard, Cotton & Shillair, 2019), along with Straub's (2009) study in a context of informal learning which examined adoption processes through the lenses of Innovation Diffusion Theory (IDT), Concerns-Based Adoption Model (CBAM), TAM and UTAUT.

3 Results and Discussion

The analysis of 47 publications found to be compliant with the purpose of this study is presented and discussed in the following.

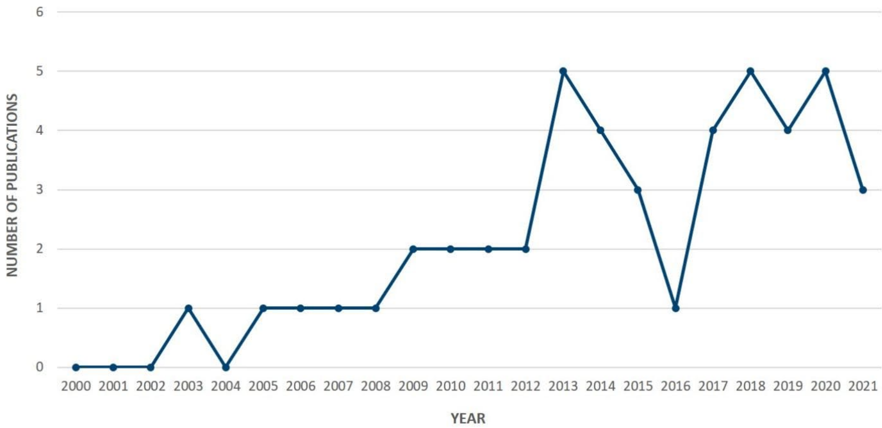

Fig. 1 Publication history

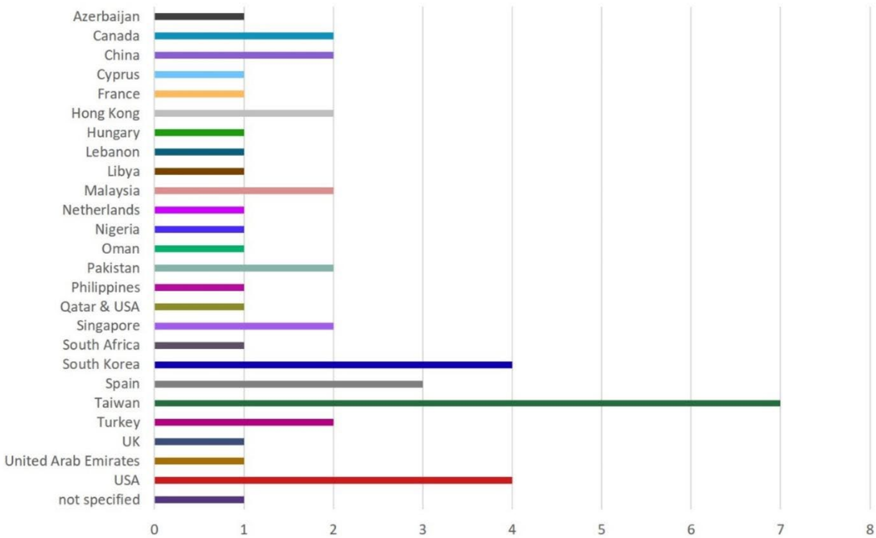

Fig. 2 Distribution of selected articles by countries

3.1 Publication History and Distribution by Countries

Considering the history of publishing, Fig. 1 shows the trend of publication frequency which started in 2003, and can be followed until 2021. The majority of studies has been published in the last decade thus reflecting an increased attention given to the researched domain. It can be noticed that there are only three identified studies in 2021, but this is connected with the fact that the search was undertaken in August 2021, and several potentially relevant articles/studies are not published yet.

The interest of researchers worldwide in educational technology acceptance and adoption is evident (see Fig. 2). Most of the identified studies were conducted in Taiwan (N=7), followed by relevant research carried out in South Korea and USA (N=4), Spain (N=3), Canada, China, Hong Kong, Malaysia, Pakistan, Singapore and Turkey (N=2). In the rest of illustrated countries only single studies were piloted (alphabetical order): Azerbaijan, Cyprus, France, Hungary, Lebanon, Libya, Netherlands, Nigeria, Oman, Philippines, South Africa, UK, United Arab Emirates, as well as Qatar & USA.

3.2 Type of Technologies and Modes of Delivery

This research revealed a diversity of ICT products and services employed in educational context, here referring to all classes of technologies, interactive systems, environments, tools, applications, services, platforms, and devices used in the selected research. Considering types of technologies and modes of delivery used to support the process of learning and teaching, it is noticeable that almost half of the analysed studies (N=20) validated e-learning technologies, in selected research referred to as e-learning systems (Hanif, Jamal & Imran 2018), e-learning platforms (Song & Kong, 2017), e-learning environments (Esteban-Millat, Martinez-Lopez, Pujol-Jover, Gazquez-Abad & Alegret 2018), e-learning tools (Tarhini, Hone, Liu & Tarhini 2016), web-based learning systems (Calisir, Gumussoy, Bayraktaroglu & Karaali 2014), Internet-based learning systems (Saade & Bahli, 2005), or just e-learning (Abdou & Jasimuddin, 2020). Many studies dealt with mobile learning (N=6) in which context mobile computing devices (Lai, 2020), mobile technology and apps (Briz-Ponce & Garcia-Penalvo, 2015), tablet personal computers (Moran, Hawkes & El Gayar, 2010), or just m-learning (Iqbal & Bhatti, 2015) was validated. Learning Management Systems (LMSs) in general, along with specific LMSs in particular, like Blackboard (Yi & Hwang, 2003), Moodle (Nagy, 2018), and Moodle gamification training platform (Vanduhe, Nat & Hasan, 2020), were also frequently researched (N=6).

Besides, some studies (N=5) counted on social media services/platforms at large (Al-Rahmi, Shamsuddin, Alturki, Aldraiweesh, Yusof, Al-Rahmi & Aljeraiwi, 2021), as well as on WeChat (Yu, 2020) and YouTube (Lee & Lehto, 2013) in particular. Since educational possibilities of virtual reality (VR) and augmented reality (AR) are getting more attention, few studies (N=3) were focused on VR technology (Lin and Yeh, 2019), VR and AR technology (Jang, Ko, Shin & Han, 2021), while one earlier study concerned virtual world Second Life (Chow, Herold, Choo & Chan, 2012). Use of computer technology in general was examined in a couple of studies

(N=2) (e.g. Teo, 2010), while a number of single studies considered also assistive technology (Nam, Bahn & Lee, 2013), collaborative technology, specifically Google applications for collaborative learning (Cheung & Vogel, 2013), simulation-based learning environment (Lemay, Morin, Bazelais & Doleck, 2018), university communication model (UCOM) which works similar to Massive Open Online Course (MOOC) (Tawafak, Romli & Arshah, 2018), as well as Open Educational Resources (OER) (Kelly, 2014). Figure 3 provides insight into a variety of validated technologies and modes of delivery.

3.3 Type of Participants & Sample Size

Another aspect refers to different types of involved participants/users. In a great majority of analysed research (N=29) university students were the most commonly chosen sample group, since most data from web-based questionnaires and/or mailed surveys was collected from the universities (e.g. Salloum, Alhamad, Al-Emran, Monem & Shaalan, 2019; Park, 2009). Several studies involved employees (N=7) from a variety of organizations/companies, specifically faculty & educational stakeholders (Aburagaga, Agoyi & Elgedawy, 2020), bank officials (Abdou & Jasimuddin, 2020), business workforce (Lee, Hsieh & Hsu, 2011), blue-collar workers (Calisir et al., 2014), health nurses (Chen, Yang, Tang, Huang & Yu, 2008), along with employees from four international agencies of the United Nations (Roca, Chiu & Martinez, 2006), as well as from four industries, specifically manufacturing, information technology, marketing and government agencies (Lee, Hsieh & Chen, 2013). Quite a few studies engaged teachers (N=5), to be specific pre-service (Teo, 2010) and in-service teachers (Jang et al., 2021), special education teachers (Nam et al., 2013), as well as K-12 educators (Kelly, 2014). A small number of research also involved other partici-

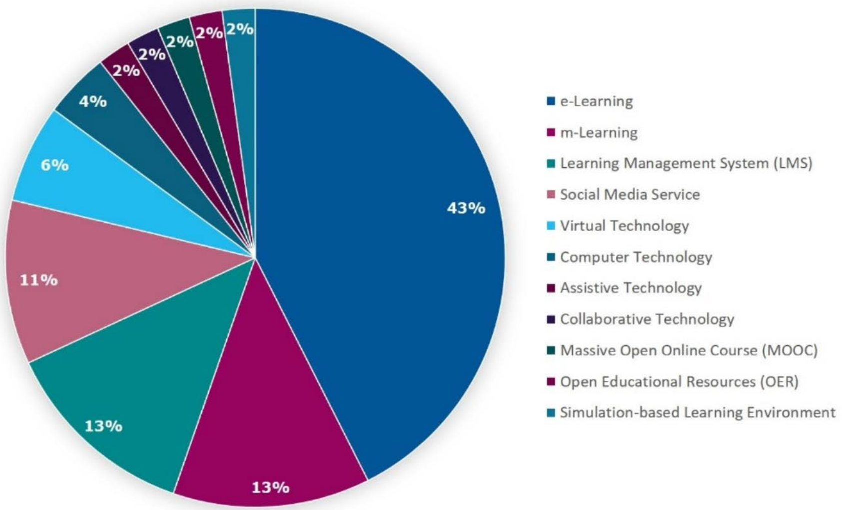

Fig. 3 Validated technologies and modes of delivery

pants, in particular university instructors (N=2) (Vanduhe et al., 2020), older adults (Lai, 2020), and senior high school students (Prasetyo, Ong, Concepcion, Navata, Robles, Tomagos, Young, Diaz, Nadlifatin & Redi, 2021). Finally, in one study information about the type of participants who took part in the conducted research was not provided (see Fig. 4).

It can be seen that sample size varied from the smallest sample of 72 students (Lin & Yeh, 2019) to the largest one of 2574 students involved in the study conducted by Esteban-Millat et al. (2018). However, the domination of smaller sample sizes up to 400 participants (N=30) compared to the number of larger sample sizes is notable.

3.4 Employed Technology Acceptance and Adoption Models

The conducted review clearly indicated that the vast majority of identified research used TAM model (N=42), in particular the core TAM (N=1), the extended TAM (N=36), along with some studies which integrated TAM with other individual models/theories aiming to advance TAM's explanatory power (N=5), in particular with:

- Innovation Diffusion Theory (IDT) proposed by Rogers (1962, 1995) as the most popular model in investigating innovation acceptance and adoption (N=2), specifically (Lee et al., 2011; Al-Rahmi, Yahaya, Aldraiweesh, Alamri, Aljarboa, Alturki & Aljeraiwi, 2019),
- Information Systems Success Model (ISSM) introduced by DeLone and McLean (1992) as a robust theoretical basis for the study of technology post-adoption (N=2), specifically (Prasetyo et al., 2021; Al-Rahmi et al., 2021),
- combination of ISSM and Expectation-Confirmation Theory (ECT), a post-adoption theory offered by Oliver (1980), in work conducted by Roca, Chiu, and Martinez (2006).

Besides TAM-based research, a few studies explored also the core (N=2) and the extended (N=2) UTAUT model, along with a single research which employed extended UTAUT2 model (refer to Fig. 5).

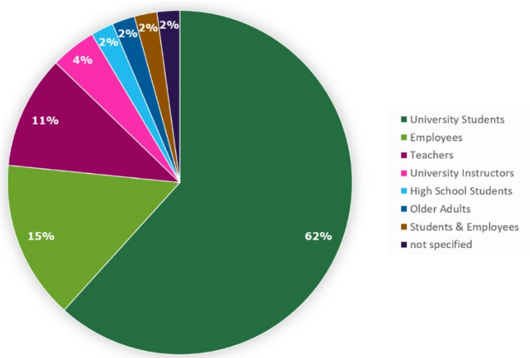

Fig. 4 Type of involved participants

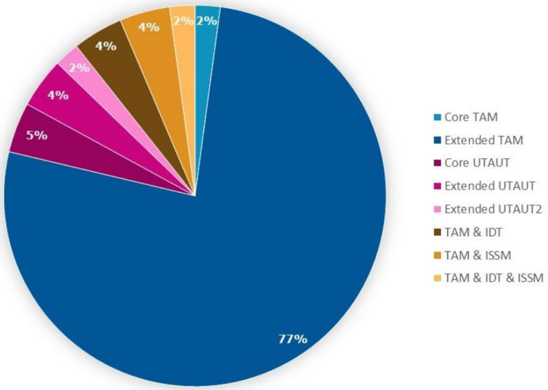

Fig. 5 Used technology acceptance and adoption models

3.5 Factors Affecting Educational Technology Adoption

This study revealed that, aiming to increase the predictive validity of TAM and UTAUT, in most selected studies (N=44) the models have been extended with different *predictive (antecedent) factors*. In view of UTAUT model on the one hand, those factors are related to the behavioral intention (BI) variable/construct. On the other hand, when considering TAM, the majority of identified factors represent antecedents of the two core variables of TAM, perceived ease of use (PEU) and perceived usefulness (PU), while a minor number predicts behavioral intention (BI). Among selected research, only three studies have used original models without any modifications and enhancements, in particular the core TAM (Chipps, Kerr, Brysiewicz & Walters, 2015) and the core UTAUT (Lai, 2020; Yakubu & Dasuki, 2019).

In addition, besides a variety of introduced predictors for the core TAM constructs, as well as TAM's and UTAUT's behavioral intention variable, the results exposed also a number of incorporated *supplementary factors* which aimed to moderate relationships among TAM's constructs. Consequently, categorization of identified factors from models' modifications and enhancements included in this review is conducted, and three pools of factors affecting educational technology adoption are documented:

- antecedents of perceived ease of use (PEU) and perceived usefulness (PU),
- behavioral intention (BI) antecedents, and.
- moderating factors.

To shed-light-on, numerous identified predictive factors are thematically grouped into: (i) *user aspects* (individual attributes, and pleasure & usefulness), (ii) *task & technology aspects*, and (iii) *social aspects*. The categorised antecedents of TAM variables (PEU and PU), as well as TAM's and UTAUT's BI antecedents, along with related illustrative example research are presented in Tables 1 and 2, respectively.

Antecedents of Perceived Ease of Use and Perceived Usefulness. By analysing the selected publications, *self-efficacy* was found as the most widely introduced predictive factor of TAM (N=16). In various empirical studies conducted in educational context it was revealed that self-efficacy, i.e. an individual judgement of one's capability to use computer (e.g. Salloum et al., 2019; Teo, 2009), Internet (e.g. Nagy, 2018), m-learning (e.g. Park, Nam & Cha, 2012), e-learning (e.g. Chen et al., 2008) or specific application (e.g. Yi & Hwang, 2003), had a significant impact on the perceived usefulness and the perceived ease of use. Another widely researched predictive factors were *subjective norm* (N=9), defined as the degree to which an individual believes that people who are important to him/her think he/she should or should not perform the behavior in question, as well as *perceived enjoyment* (N=8) considered 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. It has been revealed that the subjective norm (Song & Kong, 2017), and enjoyment (Salloum et al., 2019), positively and significantly influence students' perceived usefulness of e-learning, as well as perceived ease of use of e-learning systems (Hanif et al., 2018; Chang, Hajiyev & Su, 2017)

The results indicated that *system quality* (e.g. Salloum et al., 2019) and *system accessibility* (e.g. Park et al., 2012; Hanif et al., 2018), along with *technological complexity* (e.g. Teo, 2009) have a significant influence on perceived ease of use. Besides, *facilitating conditions*, which originally provide resource factors (such as time and money needed) and technology factors regarding compatibility issues that may constrain usage, were indicated to be an essential factor that affect e-learning system (e.g. Song & Kong, 2017) or computer technology (e.g. Teo, 2009) acceptance. Finally, while the perceived playfulness, which operationalizes the question of how intrinsic motives affect the individual's acceptance of technology, had a direct impact on the variables perceived usefulness and perceived ease of use (e.g. Padilla-Melendez, del Aguila-Obra & Garrido-Moreno, 2013), *anxiety* as a personal trait explained as evoking anxious or emotional reactions when it comes to performing a behavior, negatively affects the two core TAM variables (e.g. Chang et al., 2017; Calisir et al., 2014)

Behavioral Intention Antecedents. Both self-efficacy and subjective norm were among frequently employed factors affecting attitude towards technology and behavioral intention. The results indicated that *self-efficacy* was found to have a direct effect and a positive influence on behavioral intention to use e-learning (e.g. Tarhini, Hone & Liu, 2014; Yi & Hwang, 2003), m-learning (e.g. Moran et al., 2010; Park et al., 2012), as well as collaborative technology (e.g. Cheung & Vogel, 2013), and computers (e.g. Nam et al., 2013; Teo, 2009). *Subjective norm*, as another important construct in providing an understanding of the determinants of usage in educational context, is shown to have strong influence on the behavioral intention to use e-learning systems/platforms (e.g. Song & Kong, 2017). It has been revealed that subjective norm represented by peers significantly moderate the relationship between attitude and intention toward the technology (Cheung & Vogel, 2013)

Furthermore, *perceived playfulness* is found to be one of the key drivers for the adoption and use of blended learning system depending of user's gender (Padilla-

Table 1 Predictors of the two core TAM variables (PEU and PU) along with relevant example research

Category	Antecedents of PEU & PU	Illustrative Sample Research
User Aspects		
Individual Attributes	self-efficacy (N=16)	Nagy, 2018
	(computer) anxiety (N=4)	Chang et al., 2017.
	cognitive absorption (N=2)	Saade & Bahli, 2005.
	(prior) experience (N=2)	Chang et al., 2017.
	user characteristics (N=1)	Chen et al., 2008.
	flow (N=1)	Esteban-Millat et al., 2018.
	privacy (N=1)	Aburagaga et al., 2020.
	self-esteem (N=1)	Yu, 2020.
	major relevance (N=1)	Park et al., 2012.
	student readiness (N=1)	Iqbal & Bhatti, 2015.
	technological, pedagogical & content knowledge (N=1)	Jang et al., 2021.
Pleasure & Usefulness	(perceived) enjoyment (N=8)	Salloum et al., 2019.
	(perceived) playfulness (N=3)	Padilla-Melendez et al., 2013.
	(perceived) system accessibility (N=4)	Hanif et al., 2018.
	(perceived) system quality (N=3)	Prasetyo et al., 2021.
	(perceived) content quality (N=2)	Calisir et al., 2014.
	information quality (N=2)	Salloum et al., 2019.
	content richness (N=1)	Lee & Lehto, 2013.
	relative advantages (N=2)	Lee et al., 2011.
	result demonstrability (N=2)	Hanif et al., 2018.
	confirmation (N=1)	Roca et al., 2006.
	perceived mobility value (N=1)	Huang et al., 2007.
	perceived e-government learning value (N=1)	Shyu & Huang, 2011.
	perception of external control (N=1)	Hanif et al., 2018.
Task & Technology Aspects		
	(technological) complexity (N=4)	Teo, 2010.
	compatibility (N=3)	Lee et al., 2011.
	trialability (N=2)	Lee et al., 2011.
	task-technology fit (N=2)	Lee & Lehto, 2013.
	task importance (N=1)	Schoonenboom, 2014.
	task equivocality (N=1)	Lee et al., 2013.
	fidelity (N=1)	Lemay et al., 2018.
	vividness (N=1)	Lee & Lehto, 2013.
	user interface (N=1)	Prasetyo et al., 2021.
	perceived resource (N=1)	Cheung & Vogel, 2013.
	access devices (N=1)	Aburagaga et al., 2020.
	infrastructure (N=1)	Aburagaga et al., 2020.
	Internet access factors (N=1)	Chen et al., 2008.
Social Aspects		

Table 1 (continued)

Category	Antecedents of PEU & PU	Illustrative Sample Research
	subjective norm (N=9)	Song & Kong, 2017.
	facilitating conditions (N=5)	Song & Kong, 2017.
	social influence (N=2)	Vanduhe et al., 2020.
	observability (N=2)	Al-Rahmi et al., 2019.
	image (N=1)	Calisir et al., 2014.
	social norm (N=1)	Jang et al., 2021.
	social recognition (N=1)	Vanduhe et al., 2020.
	recommendation (N=1)	Briz-Ponce & Garcia-Penal-vo, 2015.
	organization factors (N=1)	Chen et al., 2008.
	quality of work life (N=1)	Tarhini et al., 2016.
	institutional support (N=1)	Aburagaga et al., 2020.
	organisational support (N=1)	Lee et al., 2013.
	motivational support (N=1)	Jang et al., 2021.

Table 2 Predictors of TAM's and UTAUT's behavioral intention (BI) variable along with example research

Category	Antecedents of BI	Illustrative Sample Research
User Aspects		
Individual Attributes	self-efficacy (N=7)	Nam et al., 2013.
	anxiety (N=1)	Moran et al., 2010.
	self-esteem (N=1)	Yu, 2020.
	conformity behavior (N=1)	Yu, 2020.
	trust (N=1)	El-Masri & Tarhini, 2017.
	major relevance (N=1)	Park et al., 2012.
	attitude toward using technology (N=1)	Moran et al., 2010.
Pleasure & Usefulness	perceived playfulness (N=2)	Lin and Yeh, 2019.
	perceived enjoyment (N=1)	Yu, 2020.
	user satisfaction (N=1)	Lee & Lehto, 2013.
	system accessibility (N=2)	Park, 2009.
	system quality (N=1)	Al-Rahmi et al., 2021.
	information quality (N=1)	Al-Rahmi et al., 2021.
Task & Technology Aspects		
	technology integration (N=1)	Tawafak et al., 2018.
	perceived technology fit (N=1)	Al-Rahmi et al., 2021.
Social Aspects		
	subjective norm (N=4)	Song & Kong, 2017.
	social influence (N=1)	Briz-Ponce & Garcia-Penalvo, 2015.
	social norm (N=1)	Tarhini et al., 2014.
	recommendation (N=1)	Briz-Ponce & Garcia-Penalvo, 2015.
	sharing (N=1)	Cheung & Vogel, 2013.
	top management support (N=1)	Abdou & Jasimuddin, 2020.

Melendez et al., 2013). Also, direct and indirect effect of perceived playfulness on the intention to use a computer-assisted training program has been confirmed (Lin & Yeh, 2019). Finally, the research has exposed that *system accessibility* was one of the dominant exogenous constructs affecting behavioral intention to use mobile learning (e.g. Park et al., 2012)

Moderating Factors. Although the majority of selected research has been focused on finding PEU, PU and BI antecedents, there is also a growing need for understanding incorporated supplementary factors aiming to moderate the relationships among

TAM variables, on the one hand, as well as those which have an impact on the model itself, on the other. In the investigation of the moderating effect of gender and age on e-learning acceptance Tarhini and colleagues (2014) have found that *age* moderates the effect of perceived ease of use, perceived usefulness and self-efficacy on behavioral intention, and that *gender* moderates the effect of perceived ease of use and social norms on behavioral intention. Yet, unexpectedly, no significant moderating effect of age on the relationship between social norms and behavioral intention was found; results also revealed no moderating of gender on perceived usefulness or self-efficacy and behavioral intention. Padilla-Melendez et al. (2013) argued that there exist gender differences in attitude and intentions to use. The main contribution of their study is provided evidence that there exist gender differences in the effect of playfulness in the student attitude toward technology and the intention to use it. In females, playfulness influences attitude toward using the system. In males, playfulness influences attitude moderated by perceived usefulness

When examining the moderating effect of *individual-level cultural values* on users' acceptance of e-learning in developing countries, Tarhini et al. (2016) demonstrated that the relationship between social norms and behavioral intention was particularly sensitive to differences in individual cultural values, with significant moderating effects observed for all studied cultural dimensions, in particular *masculinity/femininity*, *individualism/collectivism*, *power distance* and *uncertainty avoidance*. As a final point, in an empirical study of the use of the General Extended Technology Acceptance Model for E-learning (GETAMEL) to determine the factors that affect students' intention to use an e-learning system, Chang and colleagues (2017) found that *technological innovation* significantly moderates the relationship between subjective norm and perceived usefulness, as well as perceived usefulness and behavioral intention to use e-learning.

3.6 Integration with Other Models & Theories

Although TAM proved to be a powerful model applicable to various technologies and contexts at the individual level, research also revealed its successful integration with other contributing theories and models within a range of different application fields (Al-Emran & Granić, 2021). To evaluate students' adoption of smartwatches for educational purposes, TAM has been successfully combined with Goodhue and Thompson's (1995) *Task-Technology Fit* (TTF) (Al-Emran, 2021), and Rogers (1975) *Protection Motivation Theory* (PMT) (Al-Emran, Granić, Al-Sharafi, Nisreen & Sarrab, 2021). In addition, the *Innovation Diffusion Theory* (IDT) has been combined with TAM in an empirical investigation on university students' intention to use e-learning systems (Al-Rahmi et al., 2019), to investigate factors affecting business employees' behavioral intentions to use the e-learning system (Lee et al., 2011), as well as to explore diffusion and adoption of an open source learning platform (Huang, Wang, Yang & Shiau, 2020). The *Information Systems Success Model* (ISSM), as one of the post-adoption theories, has been integrated with TAM to help in determining factors which affected acceptance of e-learning platforms during the COVID-19 pandemic (Prasetyo et al., 2021), and in exploring students' behavioral intention to use social media, specifically the perception of their academic performance and satisfaction (Al-Rahmi et al., 2021). Lastly, to understand e-learning continuance intention, TAM has been integrated with ISSM and Oliver's (1980) *Expectation-Confirmation Theory* (ECT) (Roca et al., 2006).

3.7 Limitations of the Conducted Review

In the conducted review, specific criteria were used to search the WoS CCC database for relevant studies to be included and analysed. The applied research approach allowed to capture and cover only a representative selection of studies published in numerous recognized journals, and undoubtedly cannot be all-inclusive. Specification of other search criteria along with a selection of other databases might bring more and/or slightly different selection of relevant journal articles and proceeding papers. Hence, this review should be regarded as an attempt to explore relevant challenges and emerged topics in educational technology adoption field during the past. Finally, it should be noted that this study does not describe or pass any judgement on research methods and approaches employed in the analysed literature since this is out of the scope of this review.

4 Conclusion and Future Research

Over the past decades a variety of theoretical perspectives have been advanced to provide an understanding of the determinants of acceptance, adoption and usage of various technologies used to support the process of knowledge transfer and acquisition. However, it has been shown that over the years TAM has emerged as a leading scientific paradigm for studying the determinants affecting human behavior and usage of various technologies through beliefs about two factors: the perceived ease of use and the perceived usefulness (Al-Emran & Granić, 2021; Marangunić & Granić, 2015). Moreover, the conducted review once again exposed TAM predomination in educational context as well; refer also to (Granić & Marangunić, 2019). This study confirmed that TAM is the most widely used powerful and valid model for prediction and explanation of user's behavior towards acceptance and adoption of various technologies used to support the process of learning and teaching.

Continuous development of new technologies, along with a growing number and diversity of users in educational context, opens new directions of research that could raise understanding of the technology acceptance, adoption, and actual use. Thus, despite the fact that extensive work has already been conducted, there is still a huge potential for further advancements, exploration and practice in this field of research. In light of current research findings, future work could follow new research directions:

- to explore predictive validity of technology acceptance models and theories when applied to various supporting ICT technologies employed in a number of emerging *teaching strategies*, like flipped learning, gamification-based learning, and visual scaffolding, favourable *communication support*, like chats, discussion forums, and discussion boards, as well as relevant *facilitative tools*, like blogs and wikis used in educational context;

- to further empirically validate predictive factors (antecedents) influencing the acceptance and adoption of technology in education which have not been so widely explored, for example *perceived playfulness* which has been associated with a high level of perceived usefulness (Lin & Yeh, 2019), *social media usage* which has indicated a positive and constructive influence on satisfaction and academic performance (Al-Rahmi et al., 2021), as well as psychological influence factors such as *conformity behavior* and *self-esteem* due to their positive and direct effect on perceived ease of use, perceived usefulness, perceived enjoyment and continuance intention (Yu, 2020);
- to explore some possibly significant predictive factors that still have not been adequately examined, but could be important in understanding educational technology adoption as for example, the factor dealing with task & technology aspects, that can be described as *cost-effective/pennyworth*, here referring to employment of efficient solutions in educational context with relatively limited budget (e.g. simulation, VR, AR, visual scaffolding/visualization);
- to advance the explanatory power of individual technology acceptance and adoption models by reviewing and integrating them with already established theories and models from other fields, like social psychology – Bagozzi and Warshaw's (1990) *Theory of Trying* (TofT), cognitive psychology – Bhattacherjee's (2001) *Expectation-Confirmation Model* (ECM), along with information technology – Goodhue and Thompson's (1995) *Task-Technology Fit* (TTF).

Declarations

Statements on Open Data, Conflict of Interest and Ethics The data of the systematic review consist of articles published in journals and conferences. Many of these are freely available online, others can be accessed for a fee or through subscription.

The authors declare no conflicts of interest.

No ethics review was required to undertake this literature review.

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