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ONLINE LEARNING ACCEPTANCE IN HIGHER EDUCATION – DO WE KNOW EVERYTHING?

AZ ONLINE TANULÁS ELFOGADOTTSÁGA A FELSŐOKTATÁSBAN – ISMERÜNK-E MINDENT?

Research on the acceptance of educational technologies in higher education has become a high priority in recent years, particularly in the context of COVID-19. Numerous articles have been published on the subject, building on basic technology adoption models to investigate the impact of a wide range of factors on adoption. The proliferation of variables frequently makes it challenging to interpret results and may generate confusion. In order to synthetize and organize this knowledge, the authors collected 143 variables from 47 systematically selected studies. Based on the results of an in-depth analysis of the content and effects of each variable, they developed a framework that helps provide insights into state-of-the-art research on technology acceptance in higher education. The results of their study not only summarize what they know so far but also point to gaps where new findings in the field are expected.

Keywords: **online learning, technology acceptance models, higher education**

A technológiaelfogadás kutatása a felsőoktatásban az utóbbi években kiemelt jelentőségűvé vált, különösen a COVID-19 kontextusában. Számos cikk jelent meg a témában, amelyek a technológia elfogadásának alapvető modelljeire építve vizsgálják a különböző, használat során fontosnak bizonyuló tényezők elfogadásra gyakorolt hatását. A változók nagy számossága gyakran kihívást jelenthet és zavart okozhat az eredmények értelmezésében. A rendelkezésre álló kutatási eredmények szintetizálása és rendszerezése érdekében 47 szisztematikusan kiválasztott tanulmányból 143 változót gyűjtöttek össze a szerzők. Az egyes változók jelentéstartalmának és hatásainak mélyreható elemzését követően kidolgoztak egy olyan keretrendszert, amely segít betekintést nyújtani a technológiaelfogadással kapcsolatos legmodernebb kutatásokba a felsőoktatás kontextusában. Tanulmányuk eredményei nemcsak összefoglalják az eddigi ismereteinket, hanem rámutatnak azokra a hiányosságokra is, ahol új eredmények várhatók a területen.

Kulcsszavak: **online tanulás, technológiaelfogadási modellek, felsőoktatás**

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The use of digital technology and information and communication technology (ICT) based teaching tools has long been part of higher education (HE). Numerous studies have examined the advantages and disadvantages of using technology in HE (Fidalgo et al., 2020). Since spring 2020, however, the use of ICT tools in education in general, and in HE in particular, is no longer an issue (Szabó et al., 2022). In parallel with the outbreak and the continuing threat of COVID-19, HE globally switched to distance learning. Consequently, the question of what influences the acceptance of technology-based education in HE and what factors will make students effectively and willingly use online learning has become particularly important.

There is a wealth of study on technology adoption in HE contexts; a wide range of models and variables have been studied. These factors have now become so diverse that it is often difficult to see them in a coherent way, thus, it is hard to tell if something has been investigated or if there's more to discover. Singh and Thurman (2019) found 46 definitions of online learning alone. Accordingly, many factors have been identified that influence technology adoption in some way. These variables are often education-related, but in some cases, they refer to the general acceptance of technology. The multiplicity of variables means that variables with similar meanings are often included in the models under different names. Research results on the same factor are not published under the same name, generating confusion, and making it difficult to generalize the results and formulate a common vision. As research on technology adoption has become an important topic in HE, it is essential to contextualize the variables already studied, their interrelationships, and the research gaps that emerge from them.

Research, which explores and categorizes the variables that appear in online learning technology adoption research, has not yet been performed. The purpose of this study is to offer a framework that identifies and categorizes the factors that affect the acceptance of online learning. Based on these considerations the main research questions of this study are:

RQ1: What are the factors that emerge in HE online learning acceptance research using technology adoption models?

RQ2: What is the exact content (definition or description) of these variables and what is their relationship to each other? How do they affect adoption?

RQ3: Based on the interrelationships of the variables used, what are the main nodes and themes that emerge in the research of online learning?

RQ4: What research gaps are outlined based on the examination and grouping of the variables?

In order to answer our research questions, on the basis of a thorough analysis of the variables found in the articles collected, we determine and categorize the factors contributing to the adoption of online learning in higher education using the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Keszey & Zsukk, 2017). These two models are the dominant technology adoption models in general and in online learning. We developed a framework that helps understand the interrelationships and differences between these factors. In the analysis, we grouped 143 variables (127 antecedent, 11 outcome, and 5 moderating variables) of different titles based on 47 articles and created 6 categories in total. We provide tables detailing the results already available on the factors of technology acceptance and help identify the nodes, gaps, and contradictions. The detailed analysis and the resulting implications of the established framework provide future direction in the research of the topic.

Method

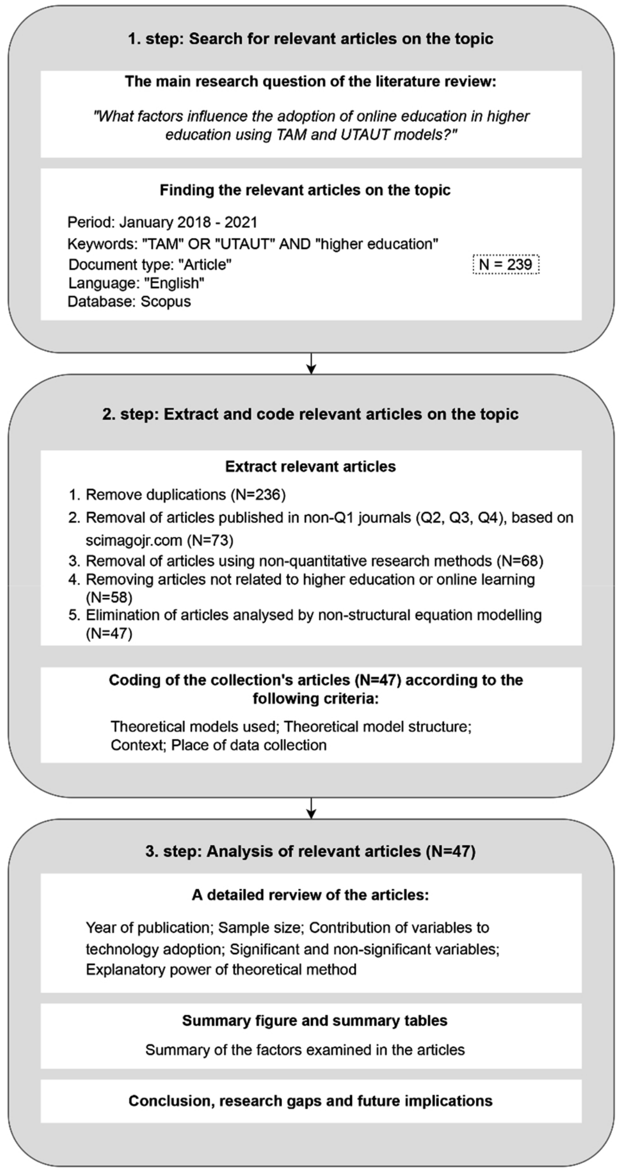
Sample selection process

Our goal is an in-depth understanding of the factors used in the articles to explain the acceptance and adoption of online learning. Based on this goal, our approach to analyzing the selected studies is more in a framework-based than in a bibliometric way (Paul & Criado, 2020), therefore a more qualitative focus was applied. Accordingly, the aim of the selection process was not to identify and analyze all the articles published on the topic but to develop a sample from which to build the framework. To ensure that our sample was still based on a sufficiently systematic choice. We collected articles for the analysis using the process shown in Figure 1 (PRISMA; Moher et al., 2009).

In an educational context, Abdullah and Ward (2016) found that 85% of research used TAM or UTAUT while 15% used other models. Similarly, based on systematic reviews, Kaushik and Verma (2019) and Granić and Marangunić (2019) found that studies on online learning adoption predominantly use TAM or UTAUT. In our analysis of factors that relate to online learning adoption, we draw on TAM and UTAUT and present those articles that examine the adoption factors of online learning with the application of these two models.

Figure 1

Process flow of the article selection process



Source: own compilation

As our objective was not to present publication trends or provide statistics on the publications within the topic but rather to comprehend the underlying meaning of the variables used, we had to decide how to narrow down the number of studies. To this end, we restricted the range of articles in the study, both in terms of quality and time span.

As a first step, we used the Scopus search engine with the keywords "TAM" or "UTAUT" and "higher education". In addition to the three keywords, the restriction "article" was also applied; we only analyzed research published in this format. The search included the language "English" as input. Finally, we filtered the period to the interval from January 2018 until December 2021, the date of the selection process. First, this timeframe resulted in a sufficient number of publications containing the most recent research findings, second, previous literature reviews of technology adoption in HE online learning have collected and analyzed academic work until 2018 (Kaushik & Verma, 2019; Sarker et al., 2019; Martin et al., 2020).

We subjected the resulting proprietary database of 239 articles based on the search options to the PRISMA filtering criteria to retain only research relevant to the research question. Of the 239 hits, 3 duplicate items were detected, leaving 236 items after filtering. We further narrowed down the range of articles and created a selection of the 237 articles based on journal ranks. We ranked articles (by journal) using the Scimago Journal Rank website (www.scimagojr.com), filtering out Q2, Q3, and Q4 ranked articles, leaving only Q1s (Keszey, 2020). Subsequently, we filtered out articles that did not use a quantitative research method. In combing through the 68 remaining articles, we excluded 10 that did not relate to higher education or online learning. From the remaining 58 articles, we removed 11 that were not based on the testing of structural effects of TAM or UTAUT.

A list of the selected 47 studies can be found in the Supplementary material.

Overview of the studies

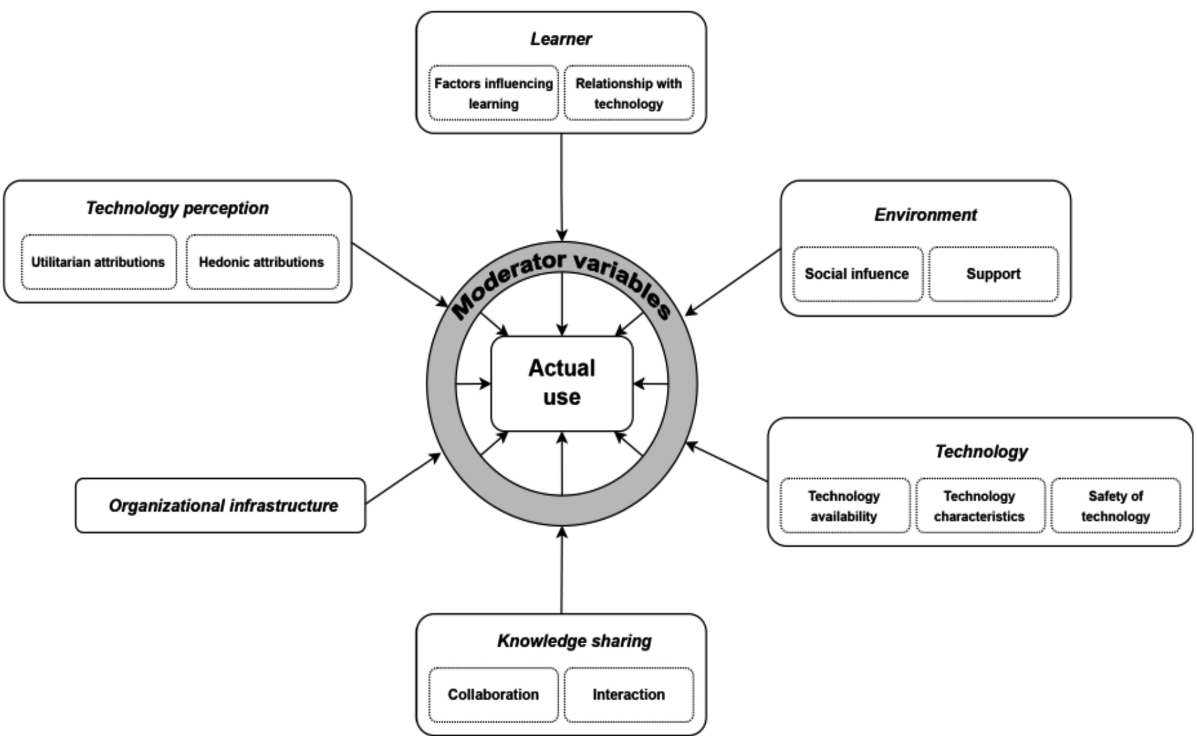
We coded the 47 selected articles according to the following aspects: theoretical models used, context (online learning, mobile learning, social media, online learning environment), size of the sample, theoretical model structure (dependent, moderator, mediator, and independent variables), contribution of variables to technology adoption, and significant and non-significant effects.

The articles can be grouped into four themes based on their context. In the 16 articles classified under online learning, the authors focus on the adoption of online learning or tools to support it. Fourteen studies relate to mobile learning, examining the use and adoption of mobile phones as smart devices for learning. The central theme of seven studies is technology adoption related to social media, which functioned as a platform for collaboration and interaction in online classes. The online learning environment (OLE) context was the focus of ten papers.

In terms of sample sizes, the studies vary between 150 and 1,385. Articles belonging to the categories TAM and UTAUT. TAM alone was used in 30 articles, UTAUT in 13, while the two models were combined in 4 articles. Besides TAM and UTAUT, some articles involved other technology acceptance models (e.g. Diffusion of Innovations, Theory of Planned Behavior).

Figure 2

Meta-framework



Source: own compilation

Meta-framework

Our study summarizes and organizes the variables that may affect technology adoption using an iterative coding procedure. Research on technology acceptance in higher education has investigated the contribution of different independent, mediating, and moderating variables to the outcome variables, most often intention to use and actual use. To organize these variables into a meaningful structure, we created a meta-framework (Figure 2) following an iterative process.

First, as the name of the variables alone often did not properly indicate its real meaning, we collected the definitions or, when it was not provided, the description (i.e. scales) of the 143 variables and grouped them accordingly. Based on the definitions or descriptions, both researchers independently created groups covering the meanings of the variables. After grouping the variables separately, we discussed the result and redesigned the groups together. If there was a discrepancy, we modified existing groups or created new groups. After a new round of the individual grouping process, we reviewed the groups and redesigned them again. We continued this process until we both agreed on the groups and the grouping of the variables. After the classification process, small groups of variables with similar meanings began to emerge. We then created subcategories of these similar variables, which we further grouped together to form the main categories.

In the next section, we present the main and sub-categories into which we classified the variables based on their definitions. Variables with similar meanings are indicated and analyzed in one batch. The articles that included the variables under study are referred to by the numbers found in the reference list. We also present the variables and their

Table 1

Learner main category

					Number of tested effects		Role(s) of the variable in the models			
Main category	Sub-categories	Variables	Articles	Number of appearances in the articles	Number of significant effects	Number of insignificant effects	Antecedent	Mediator	Outcome	Moderator
Learner	Factors influencing learning	Self-regulated Learning	[4]	1	1			1		
		Engagement for Learning	[10]	1	1		1			
		Understanding	[22]	1		1	1			
		Cognitive gratification	[3]	1	1		1			
		Interest	[22]	1		1	1			
		Learning and applying learned knowledge capability	[22]	1	1		1			
		Grade Improvement	[22]	1		1	1			
		Programming Capability	[22]	1	1		1			
		Family responsibilities	[22]	1		1	1			
		Employment status	[22]	1		1	1			
	Relationship with technology	Self-efficacy	[13], [17], [20], [42]	4	4	1	5			
		Perceived self-efficacy	[31]	1	1		1			
		Computer self-efficacy	[4], [16], [25], [34], [36]	5	5	2	7			
		Self-motivation and confidence	[22]	1		1	1			
		Self-computer competency	[34]	1	2		2			
		Experience	[42]	1	1	1	2			
		Computer anxiety	[29]	1	1			1		
		Anxiety	[26], [27]	2	2		1	1		
		Perceived awareness	[13]	1	1		1			
		Innovativeness	[18], [25]	2	2	1	3			
		Personal innovativeness	[20], [38], [39]	3	2	1	3			
		Resistance to change	[37]	1	1		1			
		Attitude strength	[30]	1	1		1			
		Compatibility	[11]	1	1			1		
		Perceived compatibility	[8], [9], [13]	3	3	1	4			
		Job relevance	[24]	1	1		1			
		Attachment	[37]	1	1	1	2			
		Familiarity with classical digital tools	[29]	1	1		1			
		Familiarity with high-tech digital tools	[29]	1	1		1			

Source: own compilation

effects on the outcome variable in systematic tables. These role of the variables can be either antecedent, mediator, moderator or outcome, and the effect can be significant or non-significant depending on the strength of the evidence. Summary of the resulting tables are presented as each category is discussed.

Learner main category

The Learner category includes variables that are closely related to the inherent personal characteristics or knowledge of the learner. Based on the definitions of variables in the selected studies, we divided this main category into two subcategories: *Factors influencing learning* and *Relationship with technology*. Variables in the subcategories are summarized in Table 1.

Factors influencing learning

Factors influencing learning include personal characteristics that may specifically affect an individual's learning effectiveness and learning outcomes. These variables are essential factors for online learning, as the reduced presence of an instructor compared to face-to-face teaching requires the ability to self-manage, and a certain level of engagement and motivation to complete the learning process (Martin et al., 2020). *Self-regulated learning* [4] helps the ability to work, learn, manage time, and plan independently, since in online learning environments with little instructor presence, learners need to manage their learning workflow autonomously. *Engagement for learning* [10] not only affects their performance but also their behavior and intentions and is therefore an important factor in the acquisition of knowledge and skills. *Cognitive gratification* [3] refers to the focus on acquiring and understanding information, knowledge and understanding, self-education, and learning.

Relationship with technology

The characteristics of relationships with technology are independent of the given technology (online education), referring to the general personal characteristics and knowledge of the learner that existed before the specific technology was used. In this subcategory, we include those variables that reflect a general user attitude, behavior, emotions, or knowledge of technology in general.

Self-efficacy [13, 17, 20, 42], *Perceived self-efficacy* [31], and *Computer self-efficacy* [4, 16, 25, 34, 36] are the learner's self-belief in their ability to perform tasks with the help of technology. Researchers have concluded that self-efficacy is a key component of the acceptance of educational systems; learners with low self-efficacy will not be able to cope with a complex system, will not put in much effort, and will therefore be less likely to overcome the challenges they may face when using the system [13]. Contrary, *Computer anxiety* [29] is a response to perceived threats of technology when it is too difficult to use or when the benefits of use outweigh the user's efforts. This significantly affects the user's behavior, makes them less willing to think about using the technology, and increases their anxiety about using it. These variables can affect technology acceptance in the initial, so-called phase 0, as even trying can be sabotaged by fear and anxiety.

Perceived awareness [13] refers to the extent to which users are aware of, understand, and subsequently exploit the beneficial features of the technology through its adoption. *Innovativeness* [18, 25] and *Personal innovativeness* [20, 38, 39] indicate that users who are willing to innovate are more willing to try to use technology than those who are reluctant to change their habits [18, 39]. *Resistance to change* [37] refers to the difficulty of breaking with routine and the emotional stress that this entails, making this variable a barrier to technology adoption.

The intention to use technology can be significantly influenced by the values, norms, current needs, intentions, or past experiences of the learner, which is by definition the *Compatibility* variable [11, 8, 9, 13]. *Compatibility* can also be linked to *Attachment* [37], i.e., the bond connecting a person's self and the device that is developed in the user because of object-human interaction. When designing and implementing technical parameters and features, hardware and software developers should also focus on the user's goals and needs when using the system.

Environment main category

The Environment category includes those variables whose content is related to the role of a third party, beyond the scope of the learner or the technology itself. Based on their content, the variables in this main category could be sorted into two subcategories, *Social influence* and *Support*. Variables in the subcategories are summarized in Table 2.

Social influence

Social influence includes variables that refer to the role of the community that may impact the user's acceptance of the technology. *Social characteristics* [6] is the umbrella term that includes social influence, relational capital, and social impact. *Social influence* is one of the main variables in UTAUT measuring the extent to which a learner is interested in what the people most important to them (e.g. peers, tutors and friends) think about the new system they are using.

The variables *External factors* [389], *External influence* [39], and the TAM2 variable *Subjective norms* [14, 17, 24, 35, 36, 37] are also similar in meaning to this variable. When users start to use and gradually learn about a technology, they encourage their peers to use it. For the variables *Social recognition* [43], P*ersonal integrative gratification* [3], and *Social image* [35], not only opinions but also recognition of the external environment matter. Users expect to be recognized for their skills and abilities when using the system or innovation and seek to develop a positive image of themselves through subjective norms or peer influence.

Support

The variables in the Support subcategory may play an important role in the implementation, operation, and support of the system and, although not directly for all vari-

Table 2

Environment main category

					Number of tested effects		Role(s) of the variable in the models			
Main – category	Sub-categories	Variables	Articles	Number of appearances in the articles	Number of significant effects	Number of insignificant effects	Antecedent	Mediator	Outcome	Moderator
Environment	Social influence	Social Characteristics	[6]	1	1		1			
		Social Influence	[1], [5], [13], [16], [20], [21], [23], [26], [27], [30], [32], [33], [40], [43], [46], [47]	16	12	10	15	2		
		Peer influence	[25]	1		1	1			
		External factors	[38]	1	1			1		
		External Influence	[39]	1	1		1			
		Subjective Norms	[14], [17], [24], [35], [36], [37]	6	4	3	6	1		
		Social recognition	[43]	1	1		1			
		Personal Integrative gratification	[3]	1		1	1			
		Social Image	[35]	1	1	1	1			
		Social trust	[14]	1	1		1			
		Reputation	[25]	1		1	1			
	Support	Government support	[19], [20]	2	2		2			
		Learning Tradition	[4]	1	1		1			
		Senior leadership support	[19]	1	1		1			
		Employer encouragement	[27]	1	1	1	1			
		Institutional Support	[2]	1	1	1	2			
		School support	[25]	1	1		1			
		Vendor support	[19]	1	1		1			
		Technical Support	[17]	1	1	1	2			
		Content Quality	[15], [36]	2	1	2	3			
		Learning Content Quality	[20]	1	1		1			
		Information Quality	[15], [17], [36]	3			2	3		
		Perceived Information Quality	[13]	1			1			

Source: own compilation

ables, may impact the user's acceptance of the technology. Support can come from several sources. On a macro level, it can be from the state or government; on a micro level, it can be the university, either by creating a supportive environment or through content development.

Government support [19, 20] is defined as the influence of the governing bodies of the country, as a measure of support for technology. Another variable with a social context is *Learning traditions* [4], which encompasses long-established educational cultures, learning habits, traditions, and routines (e.g. students are grouped by age; a teacher teaches, and students listen; instruction is delivered in a classroom). Innovation can also disrupt or change these practices; thus, learning traditions may serve as a barrier to the adoption of a new system, as it can lead to resistance to innovation.

The variables *Senior leadership support* [190] and *Institutional support* [2], however, can impact adoption at the micro level, closer to the learner. If users see that the leadership is committed and involved in the dissemination of technology; if they ensure that the right environment, rules, and policies are in place to ensure quality online learning activities (e.g. technical infrastructure, technical requirements, incentives); and if the use of technology is included in the long-term vision of the management, then organizational resistance to adopting new technology will be lower [19].

Vendor support [19] condenses the operator's general service tasks into a single variable, including user education, infrastructure provision, security control, and data accessibility. *Technical support* [17] examines the impact of the existence of a team providing technical support and advice from the university. The meaning of vendor support and technical support covers the institutional and human side of service delivery and refers to the extent to which the organization supports the learner in using technology.

The variables *Content quality* [15, 36], *Learning content quality* [20], *(Perceived) Information quality* [13, 15, 17, 36], provided by the organization (university), refer to the relevance, reliability, quality, and timeliness of the materials and information (e.g. lectures, exercises, tests) provided to the users (students) for learning purposes.

Technology main category

Technology includes variables where researchers focused more on the specific characteristics and physical properties of the technology to be implemented and used (i.e., not only a device but also a complete system). We created three further subcategories for ease of interpretation: *Availability*, *Characteristics*, and *Safety*. Variables in the subcategories are summarized in Table 3.

Technology availability

Technology availability variables refer to characteristics related to the usability and availability of technology. *Availability of resources* [13], *Perceived accessibility* [36], and *Access device* [2] are related to the availability of the necessary technological resources, such as hardware, software, or internet connection; the availability of the system; and the technology. On the contrary, *Perceived barriers* [29] and *Mobile device limitations* [20] include factors that hinder adoption, like costs, short battery life, software problems, inadequate user interface, or low bandwidth on the internet connection for mobile devices.

Technology characteristics

Technology characteristics [6] and *Task-technology fit* [6, 11, 43] indicate the extent to which a given technology supports and assists an individual in performing a given task. Experienced users select the tools and technologies that offer the greatest benefits to perform their job, while those that cannot provide the right value (e.g. better results) are ignored. *Competitive advantage* [19] shows how much more advantage a given device or system offers over other systems in possession of similar characteristics based on the objective features of technology. For example, in the

Table 3

Technology main category

					Number of tested effects		Role(s) of the variable in the models			
Main category	**Sub-categories**	**Variables**	**Articles**	**Number of appearances in the articles**	Number of significant effects	Number of insignificant effects	Antecedent	Mediator	Outcome	Moderator
Technology	**Technology availability**	Availability of Resources	[13]	1	1		1			
		Perceived Resource	[24]	1	1		1			
		Perceived Accessibility	[36]	1	1		1			
		Accessibility	[22]	1	1		1			
		Access Device	[2]	1	1	1	2			
		Perceived barriers	[29]	1	1			1		
		Mobile Device Limitations	[20]	1		1	1			
	Technology characteristics	Technology Characteristics	[6]	1	1		1			
		Task-Technology Fit	[6], [11], [43]	3	3	1	2	2		
		Competitive advantage	[19]	1	1		1			
		Storage Mechanism	[22]	1	1		1			
		Personalization	[45]	1	1	1	2			
		User Interface	[20]	1	1		1			
		Trialability	[8], [9]	2	2	2	4			
		Observability	[8], [9]	2	2	1	3			
		Complexity	[8], [9]	3	2	2	4			
		Technological complexity	[25]	1	1		1			
		Mobility	[45]	1	1	1	2			
		Perceived Mobility Value	[31]	1	1		1			
		Sharing	[22]	1	1		1			
		Attendance	[22]	1		1	1			
		Submissions	[22]	1	1		1			
		Cost advantage	[19]	1	1		1			
		Price value	[5]	1	1	2	3			
		Financial factor	[38]	1	1			1		
	Safety of technology	Privacy	[2]	1	2		2			
		Perceived Security	[13]	1	1		1			
		Security concerns	[19]	1	1		1			
		Perceived Trust	[13]	1	1		1			
		Trust	[5], [20], [32]	3	4	1	4	1		

Source: own compilation

case of a cloud-based system, this could be faster service, simpler installation and upgrade process, lower payment, or more flexible access.

Several studies have used technology-specific variables that refer to the characteristics of the technology: *Personalization* [45], *User interface* [20], *Trialability* [8, 9], *Observability* [8, 9], *Complexity* [8, 9, 19], and *Mobility* [45] are all attributes that can affect technology adoption. Indeed, the design of a given device can play a major role in technology acceptance, as *Personalization* and *Observability* can help to create a user's intention to use it [45, 8, 9], and the *Trialability* and *Testability* of the technology can reduce uncertainty and possible resistance [8, 9].

and *Trust* [5, 20, 32] can be defined as the user's confidence in the system's ability to provide a reliable and efficient service. Several factors can affect the user's trust, such as the level of security of data and transactions, or the level of privacy protection.

Knowledge sharing main category

In this main category, we included variables that relate to how knowledge is shared among the participants of the learning process with the help of technology. This main category distinguished itself from the others, as the ability to transfer and share knowledge is a very important part of the perception of technology in an educational context. We have further broken down this category into

Table 4

Knowledge sharing main category

					Number of tested effects		Role(s) of the variable in the models			
Main category	**Sub-categories**	**Variables**	**Articles**	**Number of appearances in the articles**	**Number of significant effects**	**Number of insignificant effects**	**Antecedent**	**Mediator**	**Outcome**	**Moderator**
Knowledge sharing	**Collaboration**	Engagement	[7], [27]	2	2		1	1		
		Active collaborative learning	[7]	1	1			1		
		Collaboration for learning	[10]	1	1			1		
		Collaboration and engagement	[11]	1	1			1		
		Collaborative learning	[12]	1	1		1			
		Collaboration	[45]	1	1		1			
		Social media use	[7], [12]	2	2			2		
		Social networking sites usage	[11]	1	1			1		
	Interaction	Interactivity	[20]	1	1		1			
		Interaction	[18], [22]	2	2		2			
		Interaction with peers	[7], [11]	2	2		2			
		Interaction with lecturers	[7], [11]	2	2					
		Social integrative gratification	[3]	1	1		1			
		Learning community	[27]	1		1	1			
		Interaction for learning	[10]	1	1		1			
		Online communication	[10]	1	1			1		
		Student motives to communicate	[10]	1	1		1			
		Social Isolation	[33]	1	1		1			

Source: own compilation

The monetary characteristics of the technology are incorporated into the models through the variables *Price value* [5], *Cost advantage* [19], and *Financial factor* [38]. While the latter refers to the need for financial inputs indispensable for the user to use the technology (e.g. purchase of software and hardware), cost advantage refers to the characteristics of the technology that allow certain costs to be saved (e.g. operating and maintenance costs).

Safety of technology

Privacy [2], *Perceived security* [13], and *Security concerns* [19] all focus on the importance of, and concerns about, information and data security. *Perceived trust* [13]

Interaction and *Collaboration* subcategories. Variables in the subcategories are summarized in Table 4.

Interaction

Interaction variables focus on communication between the individual learner and community, or individual-community and instructor. We have grouped several variables with related meanings here. *Interactivity* [20], *Interaction* [18, 22] *Interaction with peers and lecturers* [7, 11], *Interaction for learning* [10], *Satisfaction with social integrative gratification* [3], and *Online communication* [10] deal with the exchange of messages, communication with lecturers and peers, and possibilities and perception during online learning.

In contrast, *Social isolation* [34] has the opposite meaning, i.e., an individual's social absence or a low number of meaningful interactions with others that make them socially isolated. The lockdown imposed by COVID-19 reduced opportunities for contact and interaction, leading to isolation at a global level. In such an environment, for example, the variable *Student motives to communicate* [10] can be important because the cooperation that develops during learning can positively influence students' motivation to communicate, which in turn contributes to reducing drop-out.

Collaboration

Collaboration includes variables that are closely related to learner collaboration and knowledge sharing. *Engagement* [7, 27], *Active collaborative learning* [7], *Collaboration and engagement* [11], *Collaborative learning* [12], *Collaboration for learning* [10], and *Collaboration* [46] all refer to a teaching method whereby students and learners work together, sharing information, ideas, and opinions, and understanding each other's perspectives to achieve a learning goal. In contrast to individual learning, those who actively learn together can exploit each other's strengths. Hence, the participants' communication skills, self-esteem, motivation, critical thinking, and learning outcomes are enhanced.

Collaboration using social networking sites and social media is cited as a specific example. *Social media use* [7, 12] and *Social networking sites usage* [11] are factors in the development of collaborative learning and engagement.

Organizational infrastructure main category

In the Organizational infrastructure main category variables not only focus on the human resources and organizational support needed for technology adoption (part of the Environment main category), but also on the adequacy and availability of the technology, provided by the organization (here mainly by the HE institutes). We included variables that emphasize the integration of technology into the organization. Variables in this category were not further disaggregated as they all related to a specific aspect of infrastructure. Variables in the category are summarized in Table 5.

Most of the variables here are linked to the facilitating conditions of using the technology. *Facilitating conditions* is a main UTAUT variable (occurs in 15 articles) and refers to the extent to which an individual believes that the use of the system is supported by the organization and an efficient technical infrastructure [47]. *System quality* [17, 36], *Quality of the system* [15], *Service quality* [15], and *Quality of services* [39] were almost identical in definition to the *Facilitating conditions* in the articles.

Facilitating conditions can therefore be described as the organizational *Infrastructure* [2], defined as the set of basic systems and technical services necessary for the proper and efficient functioning of the organization (i.e., university). Infrastructure includes, for example, the availability of internet, electricity, communication facilities, or computer rooms and laboratories, just like *Connected classroom climate* [47]. Similarly, the variables *Technology readiness* [19] of the organization, *Technology compatibility* [19], and *Task characteristics* [6] attempt to describe the degree of connection and fit between the organization and the technology from two angles. On the one hand, they measure the readiness of the organization to adopt the new technology (e.g. availability of the necessary platforms, technical infrastructure or specialized human resources). On the other hand, they also indicate

Table 5

Organizational infrastructure main category

Main category	Sub-categories	Variables	Articles	Number of appearances in the articles	Number of tested effects: Number of significant effects	Number of tested effects: Number of insignificant effects	Role(s) of the variable in the models: Antecedent	Role(s) of the variable in the models: Mediator	Role(s) of the variable in the models: Outcome	Role(s) of the variable in the models: Moderator
Organizational infrastructure	–	Infrastructure	[2]	1	1	1	2			
		Facilitating Conditions	[1], [13], [16], [20], [21], [23], [25], [26], [27], [32], [33], [40], [41], [46], [47]	15	10	8	18			
		Connected Classroom Climate	[39]	1	1					
		Technology compatibility	[15]	1	1					
		Task Characteristics	[17], [36]	2	1	2	2	1		
		Technology readiness	[15]	1	1			1		
		Quality of Services	[47]	1	1			1		
		Service quality	[19]	1	1			1		
		System Quality	[6]	1	1			1		
		Quality of the system	[19]	1	1			1		

Source: own compilation

the degree of fit of the new technology with the organization's current technology, systems, processes, problems to be solved, tasks, activities, culture, etc.

Technology perception main category

The variables herein refer to the learner's perceptions and feelings related to a given educational technology. These are not objective characteristics of the technology (as in Technology main category) but the subjective perception of the user. Within this category, we separated two additional subcategories for ease of interpretation. Variables in the subcategories are summarized in Table 6.

Utilitarian attributions

Utilitarian attributes deal with the utility or functional value of an object (Batra and Ahtola, 1991). The variables were assigned to this subcategory according to the extent to which the individual considers the technology to be functional and useful in the learning process. This subcategory includes the basic TAM and UTAUT variables, thus, most of the studies included them in the research. *Perceived ease of use*, one of the main variables of TAM (was used in 32 studies) and similarly, *Effort expectancy*, the main variable of UTAUT (in 14 studies), are both refer to the amount of energy and effort required to use the technology as perceived by the user. *Recognized usability* [19] has a similar meaning but with a different name.

Perceived usefulness (part of TAM – 32 studies) and *Performance expectancy* (part of UTAUT – 14 studies) refer to the perceived performance improvement achieved by the user using the technology. *Recognized usefulness* [19] has a similar meaning. It is noteworthy that all the 47 articles used these two UTAUT or TAM baseline variables in their theoretical models, either as independent or mediating variables.

Relative advantage(s) [8. 9. 25] is also a variable in this subgroup; it indicates the extent to which the learner assumes that the new system or innovation is better than the old, traditional technology.

Hedonic attributions

Hedonic attributes of a technology deal with the emotional or sensory experiences of the user (Batra & Ahtola, 1991). We use this subcategory to classify variables that deal with a learner's sense of satisfaction or pleasure when using the technology. *Perceived enjoyment* (TAM-3) [6, 8, 9, 10, 12, 31, 36], *Enjoyment* [19, 22, 42] *Hedonic motivation* (UTAUT-2) [1, 5, 40], and *Hedonic gratification*

Table 6

Technology perception main category

Main – category	Sub-categories	Variables	Articles	Number of appearances in the articles	Number of tested effects		Role(s) of the variable in the models			
					Number of significant effects	Number of insignificant effects	Antecedent	Mediator	Outcome	Moderator
Technology perception	Utilitarian attributions	Relative Advantage(s)	[8], [9], [25]	3	3					
		Perceived Usefulness	[1], [2], [3], [4], [6], [7], [8], [9], [10], [11], [12], [14], [15], [18], [20], [22], [24], [25], [28], [29], [31], [34], [35], [36], [37], [38], [41], [42], [43], [44], [45]	32	30	3	9	24		
		Performance Expectancy	[5], [13], [16], [21], [23], [26], [27], [30], [32], [33], [39], [40], [46], [47]	14	14	3	13	4		
		Perceived Ease of Use	[1], [2], [3], [4], [6], [7], [8], [9], [10], [11], [12], [14], [15], [18], [20], [22], [24], [25], [28], [29], [31], [34], [35], [36], [37], [38], [41], [42], [43], [44], [45]	32	32	2	12	22		
		Effort Expectancy	[5], [13], [16], [21], [23], [26], [27], [30], [32], [33], [39], [40], [46], [47]	14	13	6	17	2		
		Recognized usability	[5], [13], [16], [21], [23], [26], [27], [30], [32], [33], [39], [40], [46], [47]	1		1	1			
		Recognized usefulness	[19]	1		1	1			
	Hedonic attributions	Perceived Enjoyment	[6], [8], [9], [10], [12], [31], [36]	7	8		8			
		Enjoyment	[18], [22], [42]	3	2	1	3			
		Hedonic Motivation	[1], [5], [40]	3	4		3	1		
		Hedonic Gratification	[3]	1	1		1			
		Student Satisfaction	[6], [11]	2	2			2		
		Satisfaction	[22], [27]	2	2	1	3			
		Research Students Satisfaction	[7]	1	1			1		
		Perceived Playfulness	[1]	1	1		1			
		Computer Playfulness	[36]	1	1	1	2			
		Perceived Convenience	[4]	1	1		1			

Source: own compilation

[3] carry the meaning of the user's perceived enjoyment, pleasure, and fun when using the system. For example, in mobile learning, emoticons and games can help to make learning more enjoyable, which can reinforce the intention to use [3]. Similarly, *Perceived playfulness* [1] and *Computer playfulness* [36] are associated with feelings of curiosity, exploration, and enjoyment. *Perceived convenience* [4] encapsulates the convenience factors experienced during use (e.g. temporal, and spatial freedom in the case of MOOCs). *Student satisfaction* [6, 11] and *Research students' satisfaction* [7] are defined as the sense of successful and satisfactory learning experiences used as independent variables in the studies.

Moderator variables

The variables presented were all the main effects in the research models. We found very few studies that included any moderating variables [11, 17, 33, 42], in which a total of four moderating variables were examined. These are factors that can influence the strength and even direction of the relationships between variables. [11] and [17] examine three moderating variables (*Age, Gender,* and *Experience*). Fear of the virus (*Corona fear*; [33]) has an attenuating effect on the relationship between *Expected performance* and *Intention to use*, and a strengthening effect on the relationship between *Peer influence* and *Intention to use*. *Geographical areas* in article [42] does not significantly moderate the impact of most predictors on their exogenous constructs.

Outcome variables

Our aim was primarily to present the variables that affect the adoption of online learning, but it is important to note that the output variables were different in many cases, with different variables measuring technology adoption. Table 7 presents the moderator and outcome variables.

Based on TAM, *Attitude* is one possible consequence of the factors listed previously. In the context of technology adoption research, it is defined as an individual's general affective, i.e., emotional, mood response to the use of new technology, and is usually included as a mediating variable between independent variables and *Intention to use*. In the studies listed, attitudes of students toward online learning and learning technologies were investigated in 16 articles.

(Behavioral) Intention to use is defined as a deliberate, thoughtful decision to make an effort to carry out an action. The variable is a significant predictor of actual use, which is evidenced by the fact that in all 18 articles in which it is used as a mediating variable, it has a positive, significant effect on final use. *Behavioral intention to use* was used not only as a mediating but also as an outcome variable in 18 articles, followed by *Actual use* or *Actual usage behavior* in 15 articles, indicating that the user actually uses the technology.

The variables related to adoption, *Acceptance* [1, 47] and *Intention to adopt* or *Adoption* [19, 45], examine the literal adoption of the technology as an outcome variable. *Performance* [6, 7, 10, 11] is used in the articles as a vari-

Table 7

Moderator and outcome variables

Main category	Sub-categories	Variables	Articles	Number of appearances in the articles	Number of tested effects: Number of significant effects	Number of tested effects: Number of insignificant effects	Role(s) of the variable in the models: Antecedent	Role(s) of the variable in the models: Mediator	Role(s) of the variable in the models: Outcome	Role(s) of the variable in the models: Moderator
Moderator variables		Age	[17], [26]	2						2
		Gender	[17], [26]	2						2
		Experience	[17], [26]	2						2
		Geographical areas	[42]	1						1
		Corona Fear	[33]	1						1
Outcome variables		Quality of use	[28]	1					1	
		Quantity of use	[28]	1					1	
		Acceptance	[1], [47]	2					2	
		Actual Use	[2], [13], [14], [16], [17], [36], [41], [42], [44], [46]	10					10	
		(Behavioral) Intention to use	[1], [2], [3], [4], [6], [8], [9], [10], [13], [14], [15], [16], [17], [18], [20], [21], [22], [23], [24], [25], [27], [29], [30], [31], [32], [33], [35], [36], [37], [38], [39], [40], [41], [42], [43], [46]	32				18	18	
		Actual/Usage/Use Behaviour	[21], [22], [23], [24], [33]	5					5	
		Performance	[6], [7], [10], [11]	4					4	
		Collaborative Authoring	[12]	1					1	
		Adoption / Intention to adopt	[19], [45]	2					2	
		Persistence in online courses	[26], [27]	2					2	
		Attitude	[1], [2], [9], [14], [16], [21], [23], [25], [31], [34], [36], [37], [41], [42], [43], [44]	16				15	1	

Source: own compilation

ety of variables, such as academic, learning, and student performance. *Collaborative authoring* [12] is explained by the variables examining the collaboration required for researchers as academic actors to work online. The use of *Quantity of use* and *Quality of use* [28] variables refer to the quantity and quality of students' participation in online learning. These variables are included in the studies as final outcome variables.

Discussion

In this study, we analyzed and categorized the variables that were found to affect the adoption of educational technologies in the selected studies as explanatory or explained variables using either UTAUT or TAM. We found 127 independent, 11 outcome, and 5 moderating variables in the 47 articles. We created a framework to shed light on the relationships between the variables and trends in their use. The research resulted in a meta-framework with six main categories. We further subdivided these six categories into subcategories to provide a complete picture of the variables under study. In addition to the presentation and grouping of the variables, some implications became apparent during the development of the meta-framework.

Of the six main categories, *Technology* had the same number of variables as *Learner*, resulting in the two most populous categories (30 variables). This is somewhat surprising as in the field of online learning past frameworks concentrate mainly on the learner, course+instructor, and organization (Martin et al., 2020; Martin & Bolliger, 2022). While these are important elements of online learning, the role of technology is brought to the fore in research on online learning technology adoption.

Technology has not only a large number of variables but also a high number of unique variables, i.e., used by only one study. Thus overall, the variables associated with the different technologies are not universally accepted factors and it is difficult to generalize about their role. However, some important implications emerge.

Although with different designations, the availability of technology was identified as an important aspect in many of the studies. While the use of some technologies in education is obvious to many, it is also necessary to consider circumstances and technical requirements that are not yet available or not self-evident for certain social groups or countries. When designing a system, it is worth considering and investigating factors that may be barriers to technology adoption at the device level.

Variables related to technology safety and trust have received relatively little attention in the research. This is interesting for several reasons. First, a high proportion of the effects examined are significant (only 1 out of 10 effects was not significant) (Table 3). To gain students' trust, online learning systems must offer high-quality services in a secure manner. On the other hand, in most technology acceptance models, the perceived risk and trust factor (Siegrist, 2021) is considered significant, thus it may be worthwhile strengthening this factor in the case of education through further research.

The variables classified in the *Learner* category appear just as often as the technology-related variables, which is surprising given that the key actor in technology acceptance is the learner who experiences and uses technology. Without knowledge of the learner's intentions, needs, feelings, and experiences, there is no point in introducing a new technology, as individual characteristics are essential to the development of adoption. This main category was the only one in which the factors related to education were distinctly separated. Although variables related to the industry context, i.e., education, also appeared in the other main categories, they were only clearly distinguishable in the *Learner* category. Individual characteristics may become particularly important in the context of online learning, as the learner must achieve results independently without personal presence.

In terms of the number of variables, the third main category, *Environment,* included variables that might influence adoption in some external way beyond the learner and technology characteristics. Social influence is part of both TAM2 (subjective norms) and UTAUT (social influence) and the selected studies examined their effects often (29 effects in total), yet in many cases (13) this factor was not significant (Table 2). This may be because, although peer pressure or the presence of key people may have a strong effect on the adoption of certain technologies, these variables may be less important in the adoption of an educational system. The use of educational technologies is in many cases (and particularly during the pandemic) a mandatory and essential condition for course completion.

The other subcategory of *Environment* refers to support. The extent to which the student is supported in the use of online technologies plays a significant role in the selected studies (12 variables). The implementation of technologies represents a major investment in terms of financial, technical, and human resources, both at the national and institutional levels. Governmental and organizational leadership has a strong influence in supporting and disseminating educational technologies. At the same time, at the organizational level, the transition to online education must not lead to a deterioration in the quality of education. To ensure high standards, the HE institution should provide human and organizational support, and ensure the quality of the teaching material. Many of the teaching materials used in face-to-face teaching cannot be used in one-to-one online classes and need to be adapted.

Knowledge sharing between the educators, the learner and peers seems to be an important aspect of online learning based on the number of variables investigated. The two subcategories, *Collaboration* and *Interaction*, appeared to be the most homogeneous in the analysis in terms of meaning. Interaction and cooperation are basic prerequisites of successful traditional learning; thus, researchers considered it important to investigate whether knowledge transfer and sharing in an online environment can be developed through communication and discussion. This has an important role to play in the research on technology acceptance in online learning in terms of learning outcomes and system effectiveness. Variables related to interaction can be considered pillars of cooperative learning, without which there is no collaboration, task sharing among students, or feedback from instructors.

Organizational infrastructure refers to the quality and quantity of the technology that is provided by the organization (HE institution). While the UTAUT factor, facilitating conditions, has a similar meaning, organizational infrastructure includes the quality of services as well as the fit of technology with the available infrastructure of the organization. These variables reveal that without the right infrastructure and its integration with existing systems, it is not possible to provide any online education.

Finally, when learners meet the specific educational technology, they develop their subjective perception of the given technological solution. The perception of ease of use (effort expectancy) and usefulness (performance expectancy), are the most often investigated variables of the selected studies, as these are the basic factors of both TAM and UTAUT. Although education is fundamentally a utilitarian service, it is important to see that the more enjoyable the student feels their education is, the more willing they will be to learn. Although not as numerous as in the case of utilitarian characteristics, several studies have investigated the effect of hedonic characteristics of educational technology, and only 3 of the 26 effects examined were found to be non-significant (Table 6). With the rise of online technologies, gamification can be easily integrated into the teaching and learning process, creating intrinsic motivation for active participation. Although external motivators are important in learning (grades, scores, ladders), long-term engagement in learning requires an internal drive that can be more easily created through hedonistic factors, like games.

Finally, we should also mention the outcome variables. Although *Behavioral intention to use* was used in most of the studies (32 cases), *Actual use* (15 cases) also appeared in several cases. There were relatively few measures of *Performance*, which suggests that most studies have insisted on the original models (TAM, UTAUT) in this respect. Although the output variables of technology adoption are logically actual use or intention to use, it would be important to also examine the factors that impact the learning outcome, at least as a mediating variable, and measure its impact on adoption.

Limitations

In addition to its contribution, the study has limitations. The selection process was limited to articles that used TAM or UTAUT. Although these are the two most used models in the literature, other models may include other types of variables. Based on the quantitative nature of TAM and UTAUT, only quantitative research was selected, thus, variables from qualitative research were not integrated into the model. The selection process has been limited to four years, in order to examine the most recent results. Finally, we limited the search to articles in English, so we did not examine variables from research available in other languages.

Conclusions and future perspectives

The meta-framework we created based on the selected studies aims to help researchers in the field of online learning to understand the variables and their effects that have already been researched in the field, and to include new variables to identify research gaps. In the following, we highlight some additional gaps and identify new research directions.

Variables related to education and learning are few among all variables. It may be worthwhile investigating pedagogy-related individual characteristics that could influence the process and effectiveness of learning. This could be the perception of innovation (webinars, Kahoot, virtual reality (VR), serious games) in the structure of the curriculum and the lesson, which could be a motivating force. Factors related to learning styles (Kolb's learning styles) could also provide exciting results, as well as explore the extent to which synchronous/asynchronous learning styles help the outcome. Although no educational technology-related variables were found in the collection, it could be worth exploring whether the provided technology is compatible with education. The online platforms most used for distance learning, such as Teams or Zoom, were originally designed for maintaining friendships or work contacts and conducting meetings; many features (e.g. quality projection of video material and reporting functions) were not available at the beginning or after the start of distance learning. However, the technologies that were already in place (e.g. Moodle) were not necessarily integrated with these systems. In many cases, this created a multi-platform problem, making life difficult for both students and educators.

In the context of technology, it may be a surprising finding that trust in and security of the technology are studied in only a few research articles, even though the topic is relevant, as proven by the selected studies. It would be worthwhile including these factors in further models, as either the perception of security related to data protection or the stability of the system can be compromised in real, everyday situations (e.g. loss of learning outcomes, temporary failure of a platform for collaboration or task submission).

It is noticeable that the hedonistic perception of technology has been investigated by different variables, but the articles do not discuss the eudemonic dimension of the perception of technology, which is best described in terms of self-fulfillment, well-being, and flourishing (Ryan & Deci, 2009; Meybri et al., 2022). By considering and applying these factors, the learning process can be not only effective but also meaningful.

Concerning the design of the models, we consider it important to highlight the negligible number of moderating variables in the set. Several factors may influence the strength or direction of the effects, such as educational attainment, type of degree, field of education, or interests. It would be important to take these contextual aspects into account using moderating variables.

Although one limitation of our research is that it only looked at selected articles from a limited period, model (TAM and UTAUT), and set, we believe that the meta-framework, based on more than 100 variables, can provide a basis for further analysis. Variables from additional articles written since our analysis or using different models can be easily incorporated into the framework and thus further enriched with these variables. Nevertheless, based on the experience of the analysis, in some cases the variables used in the research are new in name only, and have strong similarities in meaning. For future research to make a further contribution, it is important to create a certain coherence in the naming of variables, and thus facilitate both literature analyses and the development of new models, not to mention meta-analyses.

Note

1 The articles in detail, extracting year of publication, specific theoretical model, context, sample size, and explanatory power of the tested model R2 can be found in the Supplementary material.

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Supplementary Table Description of the selected articles

ID	Author(s)	Year	Basic models			Context	Sample size	Journal	R2 value
			T	U	O				
[1]	Abdul Rabu et al.	2018	X	X		Online learning	204	Education and Information Technologies	0.641
[2]	Aburagaga et al.	2020	X			Social Media	382	IEEE Access	0.18
[3]	Aburub & Alnawas	2019	X		X	Mobile learning	820	Education and Information Technologies	0.47
[4]	Al-Adwan	2020	X			Online Learning Environment	403	Education and Information Technologies	0.507
[5]	Al-Azawei & Alowayr	2021		X		Mobile learning	469	Technology in Society	0.511 & 0.419
[6]	Al-Maatouk et al.	2020	X			Social Media	162	IEEE Access	-
[7]	Al-Rahmi et al.	2018	X		X	Social Media	723	Computers and Education	-
[8]	Al-Rahmi et al.	2019	X		X	Online learning	1286	IEEE Access	-
[9]	Al-Rahmi et al.	2019	X		X	Online learning	1148	Interactive Learning Environments	-
[10]	Alalwan et al.	2019	X		X	Social Media	863	IEEE Access	-
[11]	Alamri et al.	2020	X			Social Media	602	IEEE Access	-
[12]	Alenazy et al.	2019	X			Social Media	1118	IEEE Access	-
[13]	Almaiah et al.	2019		X		Mobile learning	697	IEEE Access	-
[14]	Alshurafat et al.	2021	X		X	Online Learning Environment	274	Education and Information Technologies	0.020
[15]	Alshurideh et al.	2021	X			Mobile learning	566	Informatics	0.726
[16]	Altalhi	2020	X	X		Online learning	169	Education and Information Technologies	0.661
[17]	Ameen et al.	2018	X	X		Online learning	181	British Journal of Educational Technology	0.45
[18]	Balouchi & Samad	2020	X			Online learning	218	Education and Information Technologies	0.749
[19]	Bhardwaj et al.	2021	X		X	Online learning	465	Computers, Materials and Continua	-
[20]	Chavoshi & Hamidi	2019	X	X		Mobile learning	257	Telematics and Informatics	0.437
[21]	García Botero et al.	2018		X		Mobile learning	587	Journal of Computing in Higher Education	0.13
[22]	Gupta et al.	2021	X			Online Learning Environment	300	IEEE Access	-
[23]	Hoi	2020		X		Mobile learning	293	Computers and Education	0.19

[24]	Kaewsaiha & Chanchalor	2020	X			Online Learning Environment	584	Education and Information Technologies	-
[25]	Khlaisang et al.	2019	X			Mobile learning	1339	Interactive Learning Environments	0.84
[26]	Lakhal & Khechine	2021		X		Online learning	430	Education and Information Technologies	0.291
[27]	Lakhal et al.	2021		X		Online learning	759	International Journal of Educational Technology in Higher Education	0.245
[28]	Larmuseau et al.	2018	X			Online Learning Environment	161	Interactive Learning Environments	0.12
[29]	Lazar et al.	2020	X			Online learning	310	PLoS ONE	0.62
[30]	Nistor et al.	2019		X		Online Learning Environment	225	British Journal of Educational Technology	0.29
[31]	Qashou	2020	X			Mobile learning	402	Education and Information Technologies	0.514
[32]	Rahman et al.	2021		X		Social Media	300	Educational Technology Research and Development	0.577
[33]	Raza et al.	2020		X		Online Learning Environment	516	Journal of Educational Computing Research	0.289
[34]	Reddy et al.	2020	X			Online learning	1385	Education and Information Technologies	0.374
[35]	Rejón-Guardia et al.	2019	X			Online Learning Environment	267	Journal of Computing in Higher Education	0.75
[36]	Salloum et al.	2019	X			Online learning	435	IEEE Access	0.681
[37]	Sánchez-Prieto et al.	2019	X			Mobile learning	222	British Journal of Educational Technology	0.712
[38]	Shorfuzzaman et al.	2019	X			Mobile learning	160	Computers in Human Behavior	0.62
[39]	Sidik & Syafar	2020		X		Mobile learning	284	Education and Information Technologies	-
[40]	Sitar-Tăut	2021		X		Mobile learning	311	Human Behavior and Emerging Technologies	0.576
[41]	Sukendro et al.	2020	X			Online learning	974	Heliyon	0.389
[42]	Syahruddin et al.	2021	X			Online learning	1291	Heliyon	0.351
[43]	Vanduhe et al.	2020	X		X	Online Learning Environment	375	IEEE Access	0.547
[44]	Wai et al.	2018	X			Mobile learning	150	Journal of Librarianship and Information Science	0.164
[45]	Yadegaridehkordi et al.	2018	X			Online learning	209	Education and Information Technologies	0.412
[46]	Yakubu & Dasuki	2018		X		Online learning	286	Information Development	-
[47]	Yang et al.	2018		X		Online Learning Environment	289	Journal of Educational Computing Research	-

Basic models: T- TAM; U- UTAUT; O- other

Source: own compilation