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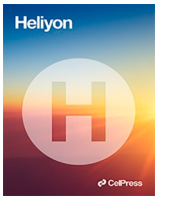

Analysis of factors affecting the effectiveness of face-to-face marketing learning via TikTok, YouTube and video conferencing

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ABSTRACT

After the COVID-19 pandemic, the use of virtual platforms, social networks and online applications has been totally modified by returning to face-to-face systems. The mandatory use of these tools in the period of social distancing has led to their extensive development. This paper analyzes the effects of the use of ICTs in a purely face-to-face environment. Therefore, it analyzes the factors that affect student satisfaction and effectiveness in marketing learning through the use of digital tools and online applications in face-to-face classes, and this analysis is from a dual perspective of user and learning dissatisfaction. Using a learner-centered approach in university classes, the use of the digital platform Blackboard, the digital tool YouTube and the social network TikTok in university marketing teaching is analyzed. The study is carried out on a sample of 327 university students of different levels. The analysis is performed through a mixed methodology using a symmetric (PLS-SEM) and non-symmetric (fsQCA) approach, allowing a better generalization of the results. In the measurement of effectiveness, both user assessment and student learning assessment are significative, the two being affected in a similar way. However, they are not related to each other, acting independently. Attitude is the construct that has the greatest impact on both types of satisfaction. Perceived enjoyment also exerts a notable influence, especially on learning satisfaction. The study presents one of the first post-pandemic approaches to the analysis of the effectiveness of technological tools (ICT tools) in the face-to-face setting of university marketing classes.

1. Introduction

The Internet has inevitably changed our way of life, both at work and in our communications, entertainment, shopping, and learning. Education, in particular, has adapted to the new technological scenario, benefiting from the advantages of new information and communication technologies (ICTs) to facilitate communication between teachers and students and the exchange of knowledge [1–3]. Hence, the concept of e-learning (i.e., electronic-learning) emerges as the integration of technology and education, becoming an effective learning medium nowadays [4,5].

In addition, the COVID pandemic has also provided a boost to the further development of e-learning tools, as teachers were forced to use the e-learning platform to teach students [6–8]. Therefore, the suggestion by Ref. [9] to incentivize teachers to teach their students with the support of digital technologies to achieve better learning is worth noting. Hence, it is not surprising that, in order to

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foster student learning, modern universities have supplemented their traditional offline classes with web-based online educational tools by incorporating webinars or learning management systems (LMSs), such as web course tools (WebCT) or Blackboard, Moodle, It's learning, Fronter, etc., into their curricula (Abdullah et al., 2016; Chen & Tat Yao, 2016; Daultani et al., 2021; Ebner & Gegenfurtner, 2019; Eom, 2012; Findik-Coşkunçay et al., 2018; Sharma & Chandel, 2013a; Sørebø et al., 2009).

Much has been learned from marketing education in the pandemic stage, its being especially important to maintain what has been done well and remember what has been done badly, in order to design appropriate teaching strategies for the crisis stages [10]. In this way [11], propose a crisis management model for marketing education, derived from best practices and decisions made during the COVID-19 crisis.

On the other hand, we agree with Costado Dios and Piñero Charlo, (2021) that face-to-face teaching can be enriched with e-learning tools. It is key, therefore, to remember that student satisfaction with the learning process through ICT assumes the role of learning facilitator [12]. Lower student satisfaction with the use of the ICT tool is related to poorer performance, therefore, it is interesting to investigate student satisfaction with the ICT tools used during learning [13]. The adoption of any technology is not in itself a panacea for higher education, changes should be supported by studies in relation to learning outcomes [14].

However, it is sometimes the case that the results of different research on students' satisfaction with ICT have been inconsistent due to the lack of a proper selection of measurement instruments [15]. As further explained in the literature review of this paper, student satisfaction has been measured with items related to the technological tool [16–19], with learning achieved through the tool [20,21], or a mixture of user satisfaction and learning satisfaction [22–24]. We have not found studies that analyze satisfaction with the tool (i.e., user satisfaction) and satisfaction with learning (i.e., learning satisfaction) simultaneously and independently, as well as the relationship between the two. Taking into account that in face-to-face university teaching, the use of e-learning tools is optional, and it is the teacher who decides whether or not to use it in the teaching-learning process, not the student, we believe it is important to differentiate between the two learner satisfactions. Therefore, we intend this study to be a pioneer in analyzing both types of student satisfaction separately and in relation to each other.

Research has been conducted on the similarities and differences between face-to-face and e-learning, based primarily on student and teacher perceptions and attitudes, as well as e-learning achievement and performance [7]. Recalling that the pandemic has promoted the development of e-learning tools and that in order to turn e-learning initiatives into sustainable forms of learning, we must ensure their success [25], we believe it is interesting to delve into student satisfaction with the use of online tools in a face-to-face learning environment beyond the COVID-19 meta period.

Furthermore, given that the incorporation of new ICT tools in education aims to enhance student learning, we agree with [3] on the need for further research on the factors affecting the acceptance of e-learning tools, and we also believe that it is necessary to test the LE achieved with these tools. In this regard, we also agree with [22] on two key points: (1) to keep learners engaged with the course they are taking, interest-generating elements can be included to support the course content, and the range of e-learning tools offers many possibilities to be further explored; and (2) since the impact of these interest-generating elements in marketing courses has been studied only to a limited extent, there remains a notable research gap.

On the other hand, to measure the success of e-learning, the literature suggests DeLone and McLean's information systems (IS) success model, the technology acceptance model (TAM), user satisfaction models, and e-learning quality models [4,26]. The first two have perhaps been the most widely used in the context of IS [5], however research has been designed with variables from the different models to achieve a better explanation of learning effectiveness (LE). As can be seen from the research presented so far, satisfaction has been extensively studied in the context of e-learning tools. This is not surprising, as its assessment is necessary to test the use of the learning tool [25]. Specifically, perceived learner or instructor loyalty [4], or intention for continued use, intended use, or actual use [27–32] have been investigated. These constructs focus mainly on the tool used and sometimes less on the learning gained. In this regard, the literature also offers research that studies constructs more related to concrete learning achievements, such as learner benefits [17,26,33], learning achievement [6], impact on performance [5,34], LE [35,36], or learner scores [5,8,37,38]. Given that e-learning aims to enhance learning, this study believes that it is worthwhile to extend research on LE as a result of e-learning tools used in face-to-face settings.

Accordingly and striving to be concrete, we hope to contribute to the literature on marketing learning in the university setting by (1) analyzing the background of LE through three different technological tools that generate e-learning interest, namely TikTok, YouTube and videoconferencing, (2) investigating the use of these e-learning tools in a face-to-face setting beyond the COVID-19 meta period, (3) testing the LE of these tools, (4) exploring learner satisfaction through two constructs, namely user satisfaction (US) and learning satisfaction (LS), (5) discovering the relationship of the two satisfaction types with the other constructs of the model, and (6) testing the relation between LS and US.

Hence, our research question would be "What are the factors that influence the effectiveness of marketing learning in a face-to-face environment through TikTok, YouTube and video conferencing?". Accordingly, the main objective of the research is to determine the effectiveness of university learning through a dual perspective of satisfaction, personal and learning. This objective is articulated through two secondary objectives. First, to find out what are the main antecedents affecting both types of satisfaction and, second, to determine whether both types of satisfaction are related to each other.

Therefore, based on the literature, our study proposes a research model composed of three independent variables perceived ease of use (PEU), perceived enjoyment (PE) and attitude toward the use of a technology (ATT), two satisfaction variables (LS and US) and one dependent variable (LE). Hence, this study aims to deepen our understanding of the variables that determine learning efficacy (LE) when using ICT in the face-to-face environment of university education in marketing.

Consequently, we structure our paper in such a way that after this introduction, this study delves into the literature review that leads us to propose our research model and our hypotheses. Subsequently, we analyze the results obtained, and finish with the

conclusions, future research lines, and our study's limitations of.

2. Related work

The development of information and communication technology (ICT) has triggered e-learning, which is ICT-supported learning, having become an important enabler of the teaching-learning process [3,6,39]. In addition, ICT has facilitated the paradigm shift from teacher-centered to learner-centered education, so that learning becomes active by involving students in the learning process [1,40,41]. Meanwhile, the COVID-19, which introduced the term "new normal", has accelerated this paradigm shift with a rapid transition from traditional face-to-face learning to online learning in higher education [42,43]. Moreover [44], term the first semester of the 2021–2022 academic year (prior to the end of the pandemic) as the "meta-COVID-19 period" given that it is a period of disruption, but one that offers many exciting opportunities in academia, followed by a general health phenomenon. The authors explain that by adjusting the ICT applied during the epidemic, academic institutions will be able to move toward sustainable educational models that support the active participation of students in achieving educational goals. In addition, student perceptions of face-to-face and e-learning, which show positive aspects of both, has led to the development of hybrid teaching models (i.e., blended learning) to get the best of both teaching models [45].

Until the first decade of the 21st century it seemed that students were more in favor of using traditional tools, while teachers expressed a greater preference for the use of digital technologies [46]. In this sense [47], take a critical approach to the way ICTs were handled in marketing education, arguing that they were not adequately used to promote student engagement, enhance learning and provide them with all the skills they need to perform their jobs when they enter the labor market. In addition, e-learning also has some disadvantages, such as the cost of multimedia materials, frustration, anxiety and confusion, or the possibility of isolating learners [39,40,48,49]. Even now, although students have the latest technologies at their disposal, some do not use them to learn as much as they could, which means that the full potential of ICT is not realized [2]. It is no surprise, therefore, that [50]emphasized that it would make sense that the use of technological tools employed in marketing classrooms would change rapidly to adapt to swift technological change. This appears to have been the case, as evidence shows that students are increasingly using ICT to collaborate in the educational process [51,52].

Ali and Maksum, (2020) clarify that e-learning is an umbrella term for technology that enables learning using a variety of teaching and learning tools, but that e-learning cannot be separated from the use of the Internet. Therefore, it refers to tools that require the use of the Internet to deliver learning materials electronically to students. Being economical, flexible and accessible without barriers of time and distance, different innovative techniques are emerging in the field of learning systems [53,54,51,48,55,56].

According to Costado Dios and Piñero Charlo, (2021), face-to-face teaching requires full presence in the classroom, both for theoretical and practical classes, although it allows the complementary use of online tools for sending notices, chats, forums, e-mails, sharing documentation, student assignments, etc. Meanwhile, the online teaching model refers to totally online educational training supported by ICT, without a physical presence in the classroom, so that the students must continuously use their computers, tablets or cell phones to follow their teaching-learning process from home. For its part, the hybrid or blended learning model is halfway between the online and face-to-face models, since it combines teaching in the physical classroom and in the virtual classroom. As we have already mentioned, the COVID-19 pandemic has highlighted the essential role of ICT in education, as well as the comparison between face-to-face, online and blended education models. For example, Jacques et al., (2021) found that there is no difference in the performance of the students in face-to-face and online education. However, students were much less enthusiastic about the forms of teaching that require the implementation of electronic systems, especially in the development of projects and practical work. Kanetaki et al. (2022) compared the use of YouTube in online training, in face-to-face and blended learning and found that interest in videos decreases in face-to-face training because students can solve their doubts in the class.

Considering, therefore, that the use of ICT in education is due to the achievement of better learning Duffy and Ney, (2015), it is essential that changes are supported by studies in relation to the learning outcomes Cavanaugh and Jacquemin, (2015). Specifically, Sharma and Chandel, (2013) and Dikcius et al. (2021) argue that research is needed on the acceptance of ICT in the learning environment and on the LE achieved. In this regard, it should also be considered that students' satisfaction with the learning process through ICT assumes the role of learning facilitator [12]. Consequently, the proliferation of studies on the most innovative ICTs related to e-learning in the second and current decade of the 21st century is not surprising.

Therefore, many of the studies that have contributed to understanding the success of e-learning are related to the technology acceptance model and the expectations and confirmation model [57]. Masadeh et al. (2023) explain that the first studies of the 21st century focused on technology (e.g., intention to use, adoption, usability, course content, and e-learning personalization), and from 2007 onwards included satisfaction. In the second decade, studies have already focused more on learner and instructor attitudes and interactions.

The Technology Acceptance Model (TAM) by Davis, (1989), which is framed within the theories of Social Action Psychology, has been the most widely used theory to measure the success of new technology in terms of the acceptance and use of technology [1,25,26,29]. This model presents the perceived usefulness and the PEU as the main determinants of ATT and intention of use, which determines actual use. In addition, perceived usefulness and PEU are conditioned by factors of a social, cultural, and political nature. In order to improve the explanatory and predictive power of the TAM, the model has been widely extended, giving rise to different versions such as TAM2 by Ref. [58], TAM3 by Ref. [59], the Unified Theory of Acceptance and Use of Technology (UTATUT) by Ref. [60] and UTAUT2 by Ref. [60]. In the e-learning domain, TAM has been widely extended and used [53].

As we have discussed, learner satisfaction has also been used to evaluate the success of e-learning. The Expectation-Confirmation Theory (ECT) from Ref. [61] explains that when customers confirm that the purchase lives up to expectations, they would feel satisfied

and could cement their loyalty by generating more purchases [25,32]. Several studies have confirmed that learner satisfaction with e-learning can be widely used to assess the success of e-learning [5]. In this sense [62], highlights the critical role of satisfaction for the intention of continued use and declares that this has been well established in IS models in marketing and reference disciplines through studies such as those of [61] or [63].

Given that the search for synergies between contributions from different theories is common in scientific research, in this literature review we found many studies investigating the relationship between some of the variables of the TAM or some of its extensions or versions and student satisfaction. In the field of e-leaning courses, the literature offers studies such as those of Arbaugh (2000), Alraimi et al. (2015), Alrawabdeh et al. (2023), Butt et al. (2023), Chen and Tat Yao (2016), Chugh et al. (2023), Joo et al. (2018), Masadeh et al. (2023), Sørebø et al. (2009), Sun et al. (2008), and Kadek and Sugianingrat (2021). Regarding learning management systems (LMS) (e.g., BlackBoard, Canvas, Moodle, etc.), we find studies such as those of Abdel-Maksoud (2018), Al-Fraihat et al. (2020), Ghazal et al. (2018), Sunkara and Kurra (2017), and Xu and Mahenthiran (2016). Specifically in the use of video-based instructional material, we remark the research by Donkor (2011) and Nagy (2018). Among the studies on mobile-learning we note that of Alrawabdeh et al. (2023) and Chao (2019).

However, an inadequate selection of the measurement instruments could have generated inconsistent results in the different studies on student satisfaction with ICT, so it is necessary to precisely define each variable to be studied and choose the appropriate instrument [15]. Consequently, this study aims to be a pioneer in the differentiation of two types of satisfaction for the educational environment.

The literature offers various definitions of student satisfaction. The concept of e-learning as an IS seems to guide some of the definitions in the learning environment. Hence [64], describe satisfaction in terms of the usability of the system, technical aspects and content quality. In this sense, Ghazal et al. (2018) argue that learner satisfaction indicates the happiness and the agreement with system use. However, Lin et al. (2008) support that learner satisfaction not only shows the learner's level of enjoyment, but also assesses the effectiveness of the education they experience. Hence [65], define satisfaction as the expected amount of learning accumulated through a particular e-learning system and Lin et al. (2008) refer to the satisfaction of personal learning needs in the learning process.

Consequently, in the context of our study, US can be conceptualized as the level of gratification generated in the learner by the educational tools used in the learning process. LS is defined as a psychological state that arises from the result of the confirmation or disconfirmation in the comparison between the academic expectations related to the learning to be achieved and that achieved by the learner, in the educational experience, which the learner values as favorable or unfavorable.

When analyzing learner satisfaction, there is not always a clear differentiation between the two concepts in the literature. Some papers seem to follow the US concept, as they analyze aspects such as the quality of the tool, the pleasure with the experience of using the tool, the enjoyment of the learning experience through the tool used, etc. [39,66,67,68,16–19,24,30,30,32,34,36,69,70,71,72–74]. Other studies analyze aspects such as the fulfillment of learning objectives, the acquisition of relevant competencies, appropriateness to the way of learning, etc. In these cases, they refer more to the LS [20,21,75]. Other papers seem to include both US and LS aspects, as they use a combined scale to ask whether the respondent learned much more, whether the lesson was clear, whether it was a delightful or enjoyable experience, etc. [4,22–24,26,76,77,78].

We propose to establish a clear differentiation between the two constructs since in the field of education the learning tools used by the teacher may affect US and LS differently.

On the other hand, e-learning refers to the intervention of technology in the learning process [26] and although it seems to have become an effective learning medium today [4,5], researchers remain interested in measuring its effectiveness. Something that is not

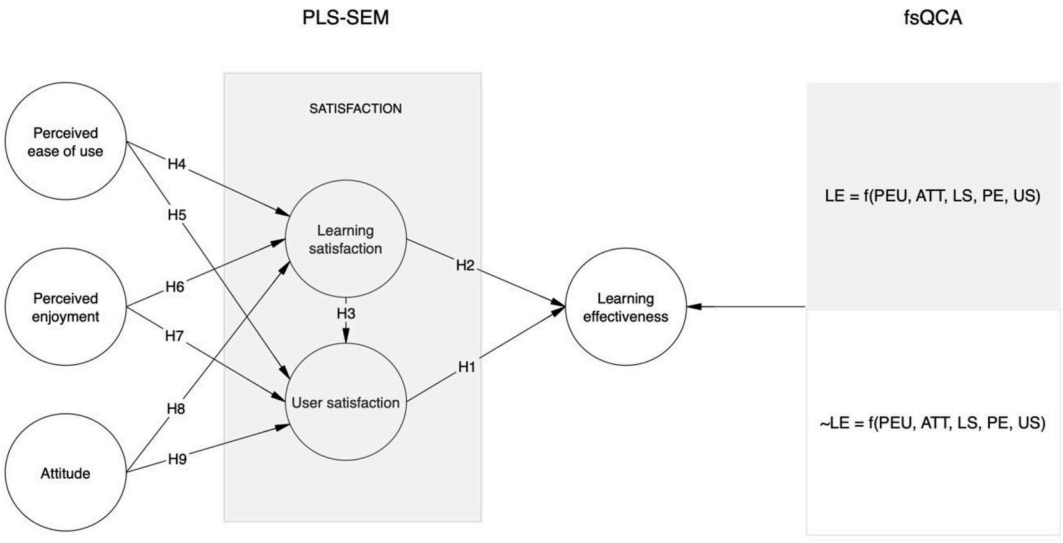

Fig. 1. Proposed model.

uncommon if we remember that technology is not in itself a panacea for higher education, the changes must be supported by studies on learning outcomes [14,22].

Therefore, some research studies students' perception of its benefits [17,26,33], learning achievements [6], performance impact [5,34], LE [35,36]. Others prefer more objective data using student scores.

In our paper, we are measuring the effectiveness of learning from the learner's point of view and conditioned by his or her satisfaction with the experience of using tools chosen by the teacher. In this sense, we have selected the three variables that we believe can help explain student satisfaction in this context. We have therefore tried to propose a model that includes the antecedent variables of satisfaction that are directly related to its use in face-to-face training sessions.

With the idea that e-learning tools, more abundant due to the pandemic [5–8,37,38], can enrich face-to-face learning [45], this study believes that research on LE as a result of e-learning tools used in face-to-face settings is worth expanding.

3. Materials and methods

To conduct this research, we have selected three types of representative ICT tools used in teaching, two of which have been widely used and proven to be effective in learning. Firstly, to represent online teaching platforms we have chosen our university's [79–81]. To represent video tools, we have selected YouTube, [82–84]. Then, to represent social networks we have used TikTok, as it is one of the most widely used at present [85–87]. The first two have been widely used and have been proven to be effective in learning. The following model is proposed (Fig. 1).

The present research uses a mixed methodology between PLS-SEM and fsQCA. In decision-making analysis using statistical methods, such as PLS-SEM, there can be an oversimplification due to the fact that only linear relationships are examined. To address this limitation, the fsQCA technique is used. This allows for a deeper understanding of complex substances in combination with PLS-SEM [88]. While PLS-SEM establishes causal relationships between related constructs, fsQCA investigates the necessary and sufficient conditions for the factors in PLS-SEM analysis to lead to a result [89]. To obtain more precise and clearer conclusions from the PLS-SEM results, it is combined with fsQCA [90]. The PLS-SEM results with fsQCA are highly promising because they allow for a unique analysis that combines both symmetric and asymmetric perspectives, while accounting for measurement error inherent in the measurements. The goal of this multi-method approach is to provide a more detailed and complex view of the causal relationships between the antecedent constructs and the selected key target constructs [91,92]. In addition, the combination of PLS-SEM and fsQCA makes it possible to evaluate the predictive power of a model with careful development based on theory and logic [93]. By combining these two prediction-focused methods, more actionable management recommendations can be obtained, as the prescriptions derived from these models are often predictive in nature [94]. The amount of uncertainty and variability makes the process dynamic, characterized by interdependent, non-proportional and non-continuous decision-driven choices (Misangyi et al., 2017). We argue that these factors operate in conjunction with the concept of causal complexity [95].

Because of this causal complexity, qualitative comparative analysis (QCA) provides a tool that aims to support and/or complement the information obtained at the aggregate level by adopting symmetrical methods [96], since QCA does not start from the basis of the usual techniques, which consider causal conditions to be independent variables, with linear and additive effects on the outcome. Adding this methodology to the analysis of human behavior is necessary, as the understanding of student behavior is limited when exclusively symmetric methodologies are used [97]. Human behavior is naturally complex and the amount of uncertainty makes the process dynamic, characterized by interdependent and non-proportional decision-driven choices [98]. The fs/QCA method has attracted the attention of researchers in various fields of research and its use has been growing consistently since 2007 [99]. Its main objective is to detect causal relationships between the chosen conditions and the expected results after the comparative analysis of the cases [100].

The analysis consists of creating all the combinations of conditions and, by applying logical inference, establishing which constellations of factors imply the expected results (LE). Therefore, with this method, we start by considering for this methodology all the factors introduced in the model, to observe which are the possible combinations that can lead to the expected result of LE.

LE = f (PEU, ATT, LS, PE, US), and ~ LE = f (PEU, ATT, LS, PE, US).

Table 1
Sample distribution.

Gender	
Men	42.51%
Women	57.49%
Age	
Under 25 years	95.72%
Over 25 years old	4,28%
Cycle	
Frist	45.87%
Second	23.85%
Third	23.85%
Fourth	7.34%

3.1. Sample

To test the previously defined hypotheses, a questionnaire was developed. In this study, we employed a non-probability convenience sampling technique. This approach acknowledges that each member of the population does not have an equal chance of being chosen, and the decision of selection is left to the researcher's judgment [91]. This method is commonly utilized in the fields of social sciences, business and education [101]. In our specific case, the convenience of using the non-probabilistic method is rooted in the aim to ensure a balanced participation of students from different subjects and age groups, thereby enhancing the generalizability of the results. Scales from the literature were used for the study. All the scales used are made up of several items that score additively, 7-point Likert-type: (1) "Strongly disagree"; (2) "Disagree"; (3) "Somewhat disagree"; (4) "Undecided"; (5) "Somewhat agree"; (6) "Agree" and (7) "Strongly agree". The questions included in this questionnaire have been validated by different authors adapted from: (1) PEU [102,103]; (2) ATT [104]; (3) LS [105]; (3) PE [106]; (4) US [107]; (5) LE [35]. The population selected for this research were students of the Marketing Degree of the University of Seville, from different courses where ICT tools had been used. The distribution of the questionnaire was between March and April 2022, being an online and anonymous form. A total of 349 questionnaires were answered (Table 1), of which 22 were eliminated because they were incomplete.

3.2. Common method bias

Common method bias (CMB) is a term used to describe the difference between a trait score and the measured score, which can be attributed to the use of the same method to measure one or more traits [108]. This can be a problem in social science research, as it can lead to bias and error [109], systematic problems that may affect the accuracy of the results. To avoid CMB, the procedural remedies suggested by Podsakoff, MacKenzie and Podsakoff have been implemented [110], as well as a statistical technique called variance inflation factors (VIF) [111]. This test can detect possible CMB situations by assessing vertical and lateral collinearity. The Kock and Lynn guidelines [112] recommend a VIF value of less than 3.3 to avoid pathological collinearity. The present model has a maximum VIF of 2.11, indicating that it is free of CMB [111]. Table 2 shows the values described above.

3.3. -SEM

The researchers used a statistical technique called PLS-SEM to analyze their model, a multivariate analysis technique whose purpose is to test structural models [113]. They chose this method because it is effective for small to moderate sample sizes and provides parameter estimates even with small sample sizes [114], exploratory research and predictive applications [115]. PLS-SEM is especially useful for examining new structural pathways in studies that build on previous models or propose new relationships and measurements [116], as in the case of this study.

The structural equation modeling (SEM) process consists of two stages: the evaluation of the measurement model and the evaluation of the structural model [117]. The evaluation of the measurement model is the first step, which ensures that each construct is measured correctly. The robustness of the proposed model is measured by assessing reliability and validity, which are the main requirements, even in articles whose object of study is education [118]. The vast majority of the research used composite reliability and Cronbach's alpha for the internal consistency of the measurement model [119]. To assess the validity of the constructs, it used techniques such as average variance extracted (AVE) and cross-factorial loadings, which under the recommendation of [120] and others, including in the education sector [121,122]. Constructs with a reliability score above 0.7 are considered to have satisfactory internal consistency.

3.4. Hypotheses

Therefore, we will now delve a little deeper into the variables that constitute the research model of this study in order to support the hypotheses with the existing literature.

3.4.1. Learning effectiveness (LE)

Although the success of a system cannot be limited to a single dependent factor [123], perceived effectiveness is a clear indicator of the success of the educational process [123].

As we have already noted, after the pandemic phase, there has been a rapid transition of learning modes and its influence on LE needs to be investigated [43]. LE refers to the level of achievement of learning objectives and is a reflector of the quality of teaching and learning performance [124]. LE contributes to learners' acquisition of knowledge [125].

[126] propose that learning performance is the most critical reflector of the success of an educational process. However, effectiveness should be measured by students' self-perception and not by performance in tests or exams [127].

Table 2
Full collinearity VIF.

Variables	Attitude	Learning Effectiveness	Learning satisfaction	Perceived ease of use	Perceived enjoyment	User Satisfaction
VIF	2.04	1.29	1.68	1.54	2.09	1.89

3.4.2. User satisfaction (US)

Satisfaction is considered an individual's emotional evaluation that is a consequence of experiences and beliefs (Rahman et al., 2017). According to the Uses and Gratifications Theory, consumers have evolved from being passive subjects to becoming a conscious and motivated use of communication [128]. US can be defined as the level of gratification that a technology generates in the user once it has satisfied their needs [129]. Therefore, in the context of our study, US can be conceptualized as the level of gratification that the training tools used in the learning process generate in the learner.

In the educational field, US is considered one of the main indicators of success of the educational tool used [130]. The lack of satisfaction could be an impediment to the successful adoption of any technology and the improvement of learning [23]. Research on e-learning tools has revealed that satisfaction with those tools is always positively related to use intentions (retention and continuation), regardless of the setting or study [22]. To achieve US, it is essential that the needs of the learner be fulfilled [17].

In the context of learning, perceived US with ICT is a very strong predictor of system effectiveness [67,17,131]. US and its relationship with perceived effectiveness has been analyzed within the scope of the hybrid model [39]. Additionally, in the e-learning setting, Ho and Dzeng, 2010), and Basith et al. (2020) proved that satisfaction has a positive and significant relationship with academic performance.

As a result, the following hypothesis is proposed.

Hypothesis H1. US is positively related to LE

3.4.3. Learning satisfaction (LS)

Satisfaction refers to the judgement after consumption of a product or service, considering the overall experience of consumption [132]. LS specifies the modalities of learners' personal internal feelings in the learning process [133]. Therefore, LS is defined as a psychological state that arises from the confirmation or disconfirmation between academic expectations and the learner's educational experiences that he or she values as favorable or unfavorable [51]. The learner has prior expectations with the learning process. If the experience exceeds those expectations, he or she will feel satisfied, whereas if those expectations are not met, the outcome will be "dissatisfied".

In the field of technology use in the learning process, LS has been conceptualized not only with the learning experience, but also with the consistency with the values and needs of the learners [134,135].

LS is considered a clear predictor of academic performance [136], due to the fact that it facilitates students' active and continual participation in learning activities [137].

From these arguments, the following hypotheses are derived.

Hypothesis H2. LS is positively related to LE

Hypothesis H3. LS is positively related to US

3.4.4. Perceived ease of use (PEU)

PEU is defined as "the degree to which a person believes that using a particular system would be free of effort" [138]. PEU is a crucial factor in determining user acceptance and adoption of ICT [49], as it is a personal belief that predicts ATT [139,140]. Therefore, users are likely to choose the application that they perceive to be easier to use rather than another one (Davis, 1989). In addition, PEU is considered a cognitive belief [141].

With respect to ICT in education, PEU refers to the extent to which a student perceives that using ICT does not require much effort. Therefore, if students perceive the use of information technologies for learning to be effortless, they will be more likely to use them; but if they perceive their use to be laborious, they will possibly be reluctant to use them, despite their benefits for their learning [139]. Hence, for instance Ref. [51], proved that PEU is a good predictor of students' behavioral intention toward LMSs. The large number of studies regarding the acceptance of technology in educational settings reflects the relevance of this variable in the use of new technologies [51,31,56,133,139–143].

(Donkor, 2011) argued that PEU should be of prime concern if the learners are to be satisfied with e-learning. In the context of education, different studies have not only verified that PEU promotes the intention to use ICT, but also that it is well suited to predict students' US [74]. PEU is also an antecedent of LS [21]. Hence, it is not surprising that the studies by Refs. [39,51,24,57,69,143] have also verified the relationship between PEU and satisfaction.

These arguments from the literature help in setting out the following hypotheses.

Hypothesis H4. PEU is positively related to LS

Hypothesis H5. PEU is positively related to US

3.4.5. Perceived enjoyment (PE)

PE is defined as the "degree to which the activity of using technology is perceived as enjoyable in itself, apart from any anticipated performance consequences" [144]. PE is considered an emotional belief [22,145]. According to the technology acceptance model (TAM) and self-determination theory framework, PE is similar to the intrinsic motivation that drives the performance of an activity due to the genuine interest or enjoyment of the process of performing it [68,42,146]. Furthermore, this intrinsic motivation is related to the satisfaction of the three basic psychological needs (i.e., relatedness, competence, and autonomy), being able to trigger students' engagement in achieving learning goals [42].

PE has been widely used in education [53,51,31,140,142,143,146]. In this environment, studies on student satisfaction with new forms of technology or gamification for learning often need to include emotional factors such as PE of the new technology and gamification [143]. In particular, PE is a commonly used external factor in technology acceptance research [49,145].

Research has found that PE is an antecedent of student satisfaction [143]. Some studies have tested the relationship of PE with US [68,16,32,131] and others its relationship with combined satisfaction scales [57,145,143].

Based on the findings of the previous literature, the following hypotheses were proposed.

Hypothesis H6. PE is positively related to LS

Hypothesis H7. PE is positively related to US

3.4.5.1. Attitude toward the use of a technology (ATT). ATT is defined as an individual's positive or negative feelings toward the use of a technology [146]. In education, most studies report that attitude toward a particular ICT tool has a direct and positive impact on the intention to use it [49,141,147,148]. In this regard [141], argues that the triple facet of attitude, i.e., cognitive, affective, and behavioral, explains its relationship with students' intention to use ICT in learning.

Attitude also helps to shape the expectations that will condition satisfaction; therefore, LS is conditioned by learners' attitudes toward learning and by emotions and affect toward the educational process [149], Li, 2018. Furthermore, students who have a positive ATT are more satisfied and productive when following e-learning programs [40].

[18] verified the relationship between students' ATT and students' US with e-learning tools. On the other hand [21], demonstrates the positive relationship between ATT and LS. In addition [39,57], and (Wang et al., 2022) also studied the relationship of ATT with satisfaction.

Accordingly, the following hypotheses are formulated.

Hypothesis H8. ATT is positively related to LS

Hypothesis H9. ATT is positively related to US

4. Main results

4.1. results

A two-step process has been outlined to evaluate reflective models with PLS-SEM [150]. Firstly, the evaluation of the measurement model is performed and, secondly, the evaluation of the structural model is carried out. The results show that the measurement model meets all the general requirements. Firstly, all the individual items reach the reliability requirement because all the standardized loadings are higher than 0.7, as recommended by Refs. [120,151].

Subsequently, as regards the reliability of the model, the composite reliability and Cronbach's alpha index were used for the analysis. In all the cases, the indicators are greater than the 0.7 recommended by Refs. [120,152]. In addition, the average variance extracted (AVE) is analyzed to ensure the validity of convergence. As advocated in Ref. [153], all the indicators in our sample offer levels above 0.5. Table 3 shows that all constructs meet the objectives.

Next, we used the Fornell and Larcker test in which we compared the square root of the AVE of each variable with the correlations of that variable [154]. Similarly, we assessed validity with a Heterotrait-Monotrait (HTMT) study. [155], and it has been found that in all the cases the levels are below the recommended 0.9 (Table 4).

The square root normalization of residuals (SRMR) was used as a criterion for the overall model fit. This criterion serves to adjust the indices in the covariance structure model, i.e., sensitivity to misspecification of the under-metered model [156]. This study follows the cut-off criteria for fit indices in the analysis of covariance structure, where its SRMR must be less than 0.08 [157]. This is shown in Table 5.

The coefficient of determination R^2 applies only to endogenous or dependent latent variables. This coefficient measures the amount of variance of the endogenous latent variable explained by its latent independent variables. For both LE and LS, the effect is significant (greater than 0.75). For US, we consider it moderate [113]. Table 6 is shown.

For the evaluation of the structural model, the strength of the relationship between the dependent variable and the independent variable was studied. The resampling technique (Bootstrapping) used was 10,000 samples (Table 7).

In view of the table showing the significance of the relationships tested, we can intuit some interesting elements that will be

Table 3
Statistics.

	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted (AVE)
Attitude	0.831	0.833	0.899	0.749
Learning Effectiveness	0.950	0.953	0.968	0.910
Learning satisfaction	0.905	0.917	0.934	0.781
Perceived ease of use	0.895	0.896	0.935	0.826
Perceived enjoyment	0.915	0.929	0.946	0.854
User Satisfaction	0.918	0.921	0.948	0.858

Table 4
Validity of constructs.

	Attitude	Learning Effectiveness	Learning satisfaction	Perceived ease of use	Perceived enjoyment	User Satisfaction
Attitude	0.865					
Learning Effectiveness	0.753	0.954				
Learning satisfaction	0.767	0.868	0.883			
Perceived ease of use	0.699	0.528	0.538	0.909		
Perceived enjoyment	0.670	0.604	0.596	0.515	0.924	
User Satisfaction	0.813	0.737	0.719	0.616	0.792	0.927

Table 5
Overall model fit.

	Saturated model	Estimated model
SRMR	0.068	0.069
d_ULS	0.875	0.912
d_G	0.589	0.591
Chi-square	1108.567	1093.332
NFI	0.837	0.839

Table 6
Coefficient of determination R2.

	R square	Adjusted R-squared
Learning Effectiveness	0.780	0.779
Learning satisfaction	0.599	0.596
User Satisfaction	0.773	0.771

Table 7
P values.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	t-statistics (|O/STDEV|)	P Values
Attitude - > Learning satisfaction	0.675	0.675	0.058	11.556	0.000
Attitude - > User Satisfaction	0.480	0.478	0.047	10.138	0.000
Learning satisfaction - > Learning Effectiveness	0.700	0.696	0.044	15.807	0.000
Learning satisfaction - > User Satisfaction	−0.010	−0.007	0.051	0.199	0.842
Perceived ease of use - > Learning satisfaction	0.052	0.050	0.042	1.217	0.224
Perceived ease of use - > User Satisfaction	0.147	0.145	0.055	2.685	0.007
Perceived enjoyment - > Learning satisfaction	0.443	0.447	0.040	11.070	0.000
Perceived enjoyment - > User Satisfaction	0.234	0.240	0.050	4.676	0.000
User Satisfaction - > Learning Effectiveness	0.675	0.675	0.058	11.556	0.000

Table 8
Indirect effects.

	t-statistics (|O/STDEV|)	P Values
Perceived enjoyment - > Learning satisfaction - > User Satisfaction - > Learning Effectiveness	1.883	**0.060**
Perceived enjoyment - > Learning satisfaction - > User Satisfaction	2.206	**0.028**
Attitude - > Learning satisfaction - > User Satisfaction	3.198	**0.001**
Attitude - > Learning satisfaction - > Learning Effectiveness	9.033	**0.000**
Attitude - > Learning satisfaction - > User Satisfaction - > Learning Effectiveness	2.512	**0.012**
Perceived ease of use - > Learning satisfaction - > User Satisfaction	0.157	**0.875**
Perceived ease of use - > Learning satisfaction - > Learning Effectiveness	0.165	**0.869**
Learning satisfaction - > User Satisfaction - > Learning Effectiveness	2.687	**0.007**
Perceived ease of use - > User Satisfaction - > Learning Effectiveness	1.231	**0.219**
Attitude - > User Satisfaction - > Learning Effectiveness	4.033	**0.000**
Perceived enjoyment - > User Satisfaction - > Learning Effectiveness	4.527	**0.000**
Perceived enjoyment - > Learning satisfaction - > Learning Effectiveness	2.606	**0.009**
Perceived ease of use - > Learning satisfaction - > User Satisfaction - > Learning Effectiveness	0.155	**0.877**

analyzed later. For example, perceived ease of use is not significant with LS but is with use satisfaction, and the importance of LS, as well as ATT and PE.

For a better understanding of the relationships within the model, especially the possible mediation of some variables, we analyzed the specific indirect effects (Table 8).

These results indicate that to achieve the goal of LE, the construct that makes the relationship between LS and US significant is ATT. Once the model calculations have been performed, we represent them in Fig. 2.

4.2. *fsQCA results*

The analysis using fsQCA aims to capture the complexity of the behavior in this case of the students as well as to complement the linear results obtained using the PLS-SEM methodology. To run the fs/QCA the data must be converted from the original 7-point Likert scale into a data set suitable for calibration. The conversion process included the following: 1) calculating the mean for each construct, based on student responses and corresponding factor loadings; 2) calibrating the resulting data based on the percentile of the mean score for each construct; 3) calibrating the resulting data based on the percentile of the mean score for each construct; and 4) calibrating the data based on the percentile of the mean score for each construct [158]. After a thorough analysis of the data [159], the choice of our cut-off points is based on the 90th, 50th and 10th percentiles, which is in line with [160]. Table 9 shows the descriptive statistics of the result.

Next, we analyze in Table 10 the necessary conditions regarding the presence and denial of LE. According to Ref. [161], the necessary conditions that QCA analysis establishes must be analyzed through the view of empirical consistency, empirical relevance and conceptual significance. FsQCA establishes that the necessary conditions for LE are those that have a level of consistency above 0.9, being in this case PEU, ATT and US in the case of the presence of LE, and ~LS in the case of the denial of effectiveness (~LE).

The next step is to construct a truth table (Table 11) containing all possible combinations of conditions and outcomes. At this stage, it is necessary to determine which of the combinations of conditions we consider significantly influence the expected outcome. This decision is made by determining two important parameters [162], the consistency and frequency thresholds. The choice of cut-off points for consistency is made in accordance with the indications of [162,163]. However, we use the indications provided in the work of [164] to select the frequency cut-off thresholds. In the last step of the fs/QCA procedure, the number of combinations is logically minimized, each of which leads to the result independently of the others [165]. The analysis of the truth tables allows us to know the set of combinations of elements susceptible to reach the same solution. Looking at the table of the presence of LE, there are five combinations of solutions. (Table 11).

These five combinations of solutions, in the case of factors associated with human behavior as in the case of the study where student attitudes are analyzed, can be interpreted as profiles of students with similar attitudes for the implementation of a new learning methodology. In terms of the core conditions (i.e., those present in both the intermediate and the parsimonious solution).

In the same way, we construct the truth table for the negation of LE (Table 12). This allows us to effectively compare the importance of the different variables against opposite solutions, in order to obtain a better quality of the results.

5. Discussion

In general terms, the research achieves the previously stated objectives of determining the effectiveness of university marketing

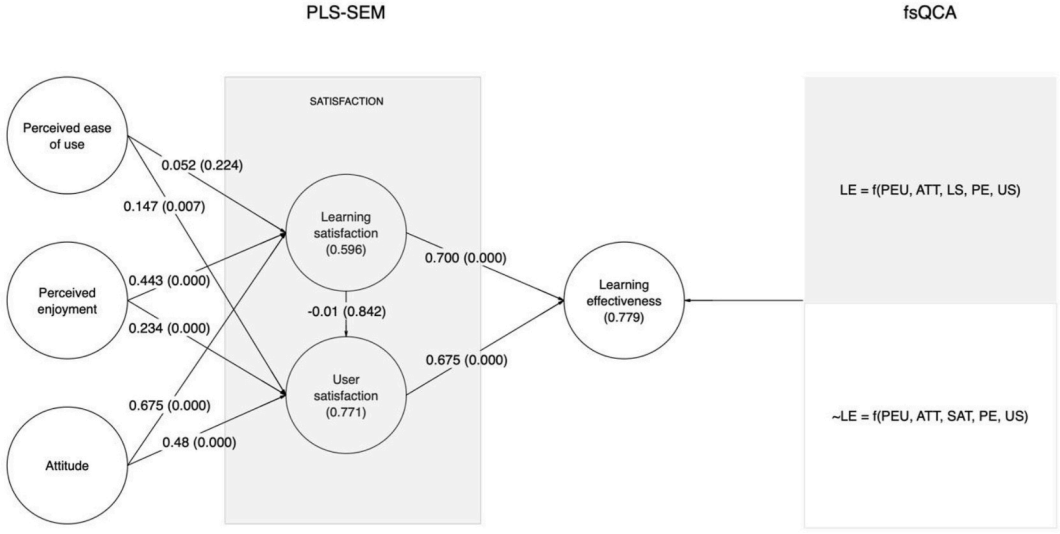

Fig. 2. Proposed model with loadings, p value and explained variance.

Table 9
Descriptive statistics.

		Mean	Std. Dev.
PEU	Perceived ease of use	0.8550	0.187
ATT	Attitude	0.7540	0.255
LS	Learning satisfaction	0.5851	0.297
PE	Perceived enjoyment	0.6457	0.313
US	User Satisfaction	0.7426	0.258
LE	Learning effectiveness	0.6277	0.312

Table 10
Necessary conditions.

Final Variable: LE			Final Variable: ~LE		
Learning effectiveness (LE)			Learning effectiveness (~LE)		
Tested conditions	Consistency	Coverage	Tested conditions	Consistency	Coverage
PEU	0.982607	0.721326	PEU	0.867669	0.377776
~PEU	0.152392	0.660058	~PEU	0.359946	0.924668
ATT	0.973740	0.810635	ATT	0.726795	0.358858
~ATT	0.229854	0.586523	~ATT	0.616477	0.932993
LS	0.876937	0.940684	LS	0.526121	0.334727
~LS	0.379811	0.574714	~LS	0.906768	0.813785
PE	0.859544	0.835567	PE	0.634138	0.365617
~PE	0.347413	0.615536	~PE	0.714801	0.751143
US	0.968284	0.818407	US	0.720059	0.360964
~US	0.243934	0.595008	~US	0.637752	0.922638

Table 11
Truth table LE.

Solutions ~ LE	1	2	3	4	5
PEU	◯	●	●		◯
ATT		●		●	●
LS	○	●	●	●	○
PE	●	○	○	●	●
US	●		●	●	◯
Consistency	0.8876	0.9402	0.9512	0.9654	0.9131
Raw coverage	0.1335	0.3113	0.3060	0.7721	0.1971
Unique coverage	0.0032	0.0072	0.0021	0.4967	0.0062
Overall solution consistency	0.9279				
Overall solution coverage	0.8471				

Note. Black ("●") and hollow circles ("◯") show the presence and absence of a condition, respectively. Moreover, large and small circles show core and peripheral conditions, respectively. Blank cells show a "do not care" situation.

learning through a personal and LS perspective, posing interesting challenges with respect to previous research in the field of university education and technological applications. To this end, we assessed our first secondary objective to find out what are the main antecedents affecting both types of satisfaction, analyzing the different relationships established between them. Regarding PEU and its relationship with LS (H_4), this is not significant in the research. Although it is true that this relationship has been extensively analyzed in educational contexts, it is not significant [2,22]. Since the COVID-19 pandemic, the results have been somewhat contradictory [166, 167], being also strongly influenced according to the platform used [168], so that, to some extent, the contradictory results in the current research make sense. Another justification may come from the use in previous research of LS measurement scales and other combined scales, as discussed in the theoretical framework of this work.

In addition, the different applications, according to their characteristics, demand different efforts from the students in their work and development, thus generating different sensations of difficulties. Precisely related to the above, the hypothesis raised between PEU and US (H_5) is significant. That is, the platform used, in principle, is perceived by students as satisfactory [169] possibly because they consider it a more pleasant way to achieve their educational objectives than traditional tools. This situation may generate diverse results, especially since the background of PEU in educational contexts may not be entirely clear [2]. Nevertheless, our results are in line with recent research [170], which confirms that the relationship exists even in the opposite direction, i.e., US has a positive and significant effect on PEU. For a complete overview, a summary of the hypotheses of this research can be found in Table 13.

Table 12
Truth table ~ LE.

Solutions ~ LE	1	2	3	4
PEU	●		●	◯
ATT	◯	◯		
LS	◯	◯	◯	◯
PE		◯	◯	●
US		◯	◯	●
Consistency	0.9562	0.9815	0.9616	0.9459
Raw coverage	0.5050	0.4817	0.4800	0.0689
Unique coverage	0.0905	0.0739	0.0689	0.0183
Overall solution consistency	0.9434			
Overall solution coverage	0.6789			

Note. Black ("●") and hollow circles ("◯") show the presence and absence of a condition, respectively. Moreover, large and small circles show core and peripheral conditions, respectively. Blank cells show a "do not care" situation.

Table 13
Summary table.

Attitude - > Learning satisfaction	Supported
Attitude - > User Satisfaction	Supported
Learning satisfaction - > Learning Effectiveness	Supported
Learning satisfaction - > User Satisfaction	Not Supported
Perceived ease of use - > Learning satisfaction	Not Supported
Perceived ease of use - > User Satisfaction	Supported
Perceived enjoyment - > Learning satisfaction	Supported
Perceived enjoyment - > User Satisfaction	Supported
User Satisfaction - > Learning Effectiveness	Supported

The PEU construct, considered in this research as an independent antecedent construct, has been recurrently related in the literature to ATT in different fields. However, this relationship has sometimes shown inconsistencies, both in areas of adoption of educational innovations and in other fields [171]. establish, in a study on adoption of technology products, that PEU does not have a significant relationship with ATT. Focusing on educational settings [172], do not either find a significant relationship between the two variables, indicating that it is above all the path of usefulness and not that of ease of use that influences ATT. Along the same lines, they refer to Ref. [173], who justify in a complete model the non-use of the relationship between the two variables (see also [174]), The results are similar, suggesting that if the majority of students know of the technologies used and how they work, they shift their attitude toward other factors. It is therefore a factor that can present disparate results depending on the context.

As for PE, it is found to be related in the model with LS (H_6) and US (H_7). Both relationships are significant, although it is true that there is an important imbalance, since with respect to LS (t-value 11.070) the intensity is greater than with US (t-value 4.676). The significance of the first relationship (LS) coincides with studies such as that of [175] that analyze it, in the teaching context, even from a perspective of mediation of shared knowledge. With respect to the direct relationship, our results coincide with those of [176], that in an e-learning environment, they indicate that "the more they perceive pleasure in using a computer solely for its own sake, and regardless of its instrumental value, the more positive their judgement of its use is" [176]. Regarding the power of the relationship in our research, it is possible that the tool used was very novel for the students in the learning context, being highly valued due to this [177]. This fact is also confirmed by the fs/QCA analysis. LS is present in all five proposed solutions, showing its strength in the model, with a coverage of 0.9406.

Although the relationship between PE and US (H_7) has been extensively analyzed in the consumer field [178], analyses related to the teaching field are not so frequent. Recently, in a meta-analytical study [179], indicate that all the papers analyzed confirmed this relationship, to a greater or lesser extent, which is in line with the results of the present research. This work also adds confirmation to this relationship, since US appears as a necessary condition in the QCA analysis and is also reflected in the five solutions proposed for LE, making it another key variable in the model. However, the relationship of PE with US (t-value 4.676) is of lower intensity than with LS. Students have shown greater enjoyment when that enjoyment or gratification has come from the sensation of learning, and not from any other type. However, this is a relationship that needs to be further developed and tested, since recent studies show results contrary to those obtained [180].

The ATT of students is profoundly modified during the use of e-learning systems, as indicated by the analysis of [181], establishing that the improvement of this ATT enhances the general results of learning. This fact is related to technological progress and the ability of new applications and systems to involve students in learning methods, since the current results are inconsistent with those obtained when the first e-learning systems were implemented [182]. In the case of the study, the relationship of ATT with LS (H_8) and with US (H_9) is significant, with a similar intensity (T-values 11.556 and 10.138, respectively). In the particular case of LS, the results are in line

with research that points out the positive relationship between the two variables [183]. Yet, analyses in COVID times have shown that the relationship between ATT and satisfaction with learning was not so clear, due to the fact that students had no other choice [184]. The satisfaction was therefore conditioned by the obligatory use of the learning tool. We found that in the face-to-face context the inconsistency of the results from the COVID-19 stage has been eliminated.

The analysis of Cheok & Wong (2015) on predictors of satisfaction in learning environments indicates that the learner will feel more comfortable if he/she is prepared or challenged. In the case of the relationship between ATT and US (H_9), which is also significant in the study, this may be due to the fact that the application used is widely known by the students, so their predisposition toward it will be positive. Precisely, this ATT is reflected in the similar value of both LS and US in the model. In other learning environments, such as the technological one, the relationship has also turned out to be positive. [185], indicating that when good use of the application is perceived, personal satisfaction levels increase.

Another objective of the work was to determine the existence of a relationship between LS and US (H_3). This does not present clear results, starting with the fact that some studies consider one of them more important than the other [186]. In our analysis, the relationship is not significant, at least not directly. Although some authors have hypothesized that LS leads to US (Basith et al., 2020), other studies have indicated that the relationship may be inverse, i.e., that personal satisfaction may lead to system recognition and thus to LS [187]. These contradictory results may stem from the different determinants of both types of satisfaction. In the case of US, elements such as the system, the information received or the quality of service may be determinants of satisfaction [188], eliciting an emotional response that requires indirect analysis. However, LS establishes student allegiance to the system, not specifically to the application [189], and its assessment is based on elements such as relevance, usefulness, accuracy, reliability, timeliness, etc. [190], very different from US. In addition, some analyses have indicated that if the system receives poor student evaluation, satisfaction will be low regardless of the learning outcomes [191]. Nevertheless, our analysis of the indirect effects of the three constructs preceding satisfaction in the model reveals that ATT is the only one that makes the relationship between the two types of satisfaction significant (H_3). The existence of studies certifying the relationship between ATT and the intention to use ICT is definite [140], but its relationship with satisfaction had not been analyzed, and, above all, as a link between professional and personal vision in the face of learning. We know that ATT helps to shape the expectations that condition satisfaction [137], but now we know that in the field of learning with the application of ICT satisfaction will be of a double component.

Taking into account the above regarding the relationship between US and LS, the present study justifies according to the literature the direction of the discrete relationship tested, and subsequently the results in the non-symmetric model indicate its presence in two solutions (Solutions 3 and 4). However, when we analyze the indirect effects, we find that both variables vary their behavior with respect to LE, and the mediating effect of US does not occur in all the hypothesized relationships. Our research has developed the hypothesis in that direction since it was intended that the weight of effectiveness would be placed on factors of satisfaction with learning, derived from the student's educational experience rated as favorable or unfavorable, and the balance of his or her expectations. Furthermore, this orientation of the hypothesis has determined a relevant theoretical fact, which is the functioning of the ATT as a link between both variables, since the mediation of the US does not occur either for PE or PEU, but does in the case of ATT. However, the consideration that it gives us regarding its inclusion as a hypothesis in the review can be established in future research. In fact, our intention is to replicate the study in future courses, with a view to improving the model and the research and theoretical and practical contribution.

Regarding the relationship of LS with LE, studies have shown different results [54]. indicate that the highest level of satisfaction in student learning takes place through face-to-face teaching, although within their analysis of multiple teaching systems, they also find the relationship between learning and effectiveness with different platforms to be significant. This relationship has as well been analyzed with respect to the vision of students and teachers, without finding significant differences between the two groups, but resulting significant in both cases [192]. It has also been analyzed in times of pandemic, proving significant too, at least for the Zoom or Google Classroom platforms [184], although the vision of these studies contemplates the use of digital platforms as an emergency option in the face of circumstances. The present analysis, which also finds the relationship significant, is carried out in a post-pandemic period where the use of digital media responds to planned academic planning criteria, and not to unexpected and unforeseen situations. However, subsequent studies begin to show higher levels of effectiveness in learning through satisfaction with the implementation of digital media [193]. In the case of the present study, the relationship has a high statistical significance (t-value 15.807). This fact is further complemented once the indirect effects are analyzed. Within them, we observe how LE obtained through LS is relevant when the antecedents are PE or ATT, but not PEU. This fact may be motivated in the case of the study by the intervention and encouragement of the teachers, as indicated by Ref. [194] when they say that "student satisfaction and engagement are essential elements that define their learning experiences" [194].

The relationship of US with LE has also been demonstrated in other research [195]. indicates that student motivation, concentration and participation have the potential to generate better results. Likewise, other studies have corroborated this relationship and even that mediated by motivation [196]. The results of the research show that students are favorable to the use of digital tools in the classroom in the post pandemic period, reflected in their personal and LS, so that the potential of ICT still has much room for exploitation in its development in the classroom [2].

6. Conclusions

After the pandemic period caused by COVID-19, higher education systems have tried to recover the conditions they had previously, including those related to teaching methodologies with digital tools. This process has been conditioned by the acceleration in the implementation of these tools in academic and university environments, which has meant that in the post-pandemic period their

development has been marked by a lack of knowledge of their true impact on students. The objective with respect to their development has been to achieve a balance between quality in education, student engagement and knowledge resource management, aiming to ensure that the teaching opportunities received by students increase their autonomy, engagement, ability, connectivity and, above all, the improvement of academic results. Derived from this objective, there is a need to evaluate the effectiveness of classroom technology implementation models to improve academic outcomes, as well as the characteristics that produce student engagement and satisfaction.

From an academic point of view, the present work presents interesting contributions in the field of research. Effectiveness in learning is measured with respect to two variables, from a perspective not only of academic satisfaction, by the learning achieved, but also from a user perspective through US. The research, approached in this way, overcomes an important gap in the literature regarding whether to consider the variables of effectiveness in ICT learning systems in isolation or collectively, providing a dual performance measure that will enable the development of more comprehensive future models. Satisfaction with learning demonstrates a stronger influence on effectiveness than US. This result opens the door to future research perspectives that seek to validate the difference between the two types of satisfaction, and its impact on other digital tools implemented in the classroom.

Previous analyses have raised the problem of an inconsistency of results due to the conditions of use with respect to face-to-face use, conditioned by the pandemic. The study makes a contribution to the literature in that it proposes conditions for on-site use, overcoming the conditions established up to now due to the pandemic. Stability and planning, once the previous period has passed, will allow the results to be more stable and lasting, and contextually more generalizable. Despite the preference shown so far by students for traditional tools, the present study offers ways to convince them of the convenience of using ICT tools, also in face-to-face training.

This research also presents an important academic advance by analyzing the two types of satisfaction, both separately and in the relationship of one with the other, and by establishing ATT as a link between the two, so that academic development programs for the implementation of ICTs should take into account the triple cognitive, affective and behavioral facet, both from the learning and user point of view, in order to achieve better results in terms of effectiveness. US only acts as a mediator in the relationship of satisfaction with learning and effectiveness only in the case of the presence of ATT. This is neither the case with PEU nor with PE. Therefore, the ATT construct should be a primary focus of future model development for better understanding.

The research also represents progress from a university management point of view. After the pandemic, a process of standardization has started, which has been affected by the drastic previous experience regarding the mandatory use of distance learning systems, as well as the different digital tools. These tools, which have proven their effectiveness, must be developed in face-to-face environments considering some aspects, which this research analyzes. First of all, the implementation of digital tools in face-to-face university teaching environments and, above all, their effectiveness will be very much determined by ATT, so institutions should analyze, depending on the tool they want to implement, the cognitive, affective and behavioral relationship that it implies for students, making prior evaluations regarding this situation in order to improve effectiveness.

Secondly, institutions should consider the personal component in the process of implementing digital tools. This circumstance will enable evaluation systems to consider individual aspects to enhance and promote the effectiveness of the implementation of digital and blended learning systems. It is imperative to take into account emotional elements in the evaluation of learning systems, so that the student goes from being a passive factor in the analysis to becoming an active participant, assessing the levels of user satisfaction obtained from the learning process. Therefore, future academic strategies in terms of effectiveness should balance user and learning criteria, thus boosting assessment procedures. Similarly, motivational incentives for students should transcend the simple valuation of their academic achievements, including incentives that promote their well-being and growth as individuals.

7. Limitations and future research directions

The research is not without limitations. The sample was limited to a single university, so it would be necessary for future research to include a larger sample of universities, which would also make it possible to determine possible differences between different types of teaching, thus improving the effectiveness of programs by adapting them to different contexts. Regarding the relationship between the variables, the present study indicates that ATT, LS and PE are the elements that appear most frequently in the solutions. That is, from the students' point of view, they are those that most influence, through different combinations, effectiveness. This fact would allow future research to better predict the effectiveness orientation of students, by determining their importance, order and serving as a basis for the improvement of future models, and establishing a possible order among them according to the different university environments.

In addition, it would be advisable to expand the study with more digital platforms, since each of them has its own learning particularities, and this fact could generate distortions in the results of the study. In the future, the approach of longitudinal research would also allow a better generalization of the conclusions. In this respect, virtual systems, social networks and online applications are going to be highly conditioned in the future by the rapid implementation of artificial intelligence [197], as a new paradigm in higher education. The present study may represent a starting point in the determination of the conditions of effectiveness of this teaching technology. This is in order to compare and establish the areas of modification of effectiveness in student learning, as well as a comparative element regarding the characteristics and dimensions that will affect effectiveness in the future, and the balance that may be established between current technologies and those associated with artificial intelligence.

A large number of studies have evaluated the effectiveness of platforms in virtual environments, while the present analysis refers to their use, but within the classroom, i.e., in a fully face-to-face environment. Subsequent research could carry out a comparative study of the different components of effectiveness in both environments, confirming or not the presence and significance of the variables present, and complementing the results with a view to possible hybrid teaching systems. This would allow a greater generalization of

the results and conclusions. The research has been carried out using digital tools in a fully face-to-face environment. These conditions will allow longitudinal studies to be carried out in the future to evaluate the effectiveness and consistency of the results of the model.

The development of the present model, according to the literature and the results obtained, especially those derived from the non-symmetric fsQCA methodology, may raise the use of alternative relationships that complement it, and contribute to the development of the theory in this area, especially after the pandemic period, as well as relationships that have been widely covered in previous research but whose results show the opposite. Therefore, further research should consider possible hypotheses between constructs such as PEU on ATT and conduct an analysis of their complementarity in new educational settings, helping to discern the apparent inconsistency of results that has occurred so far, and analyzing more deeply the causes of the absence of the PEU construct in the proposed solutions. This is especially the case with the application of technologies that are more unfamiliar to students. Similarly, as a future research line, we propose to extend the model to include the variables of perceived usefulness and system quality as antecedents of satisfaction.

One of the objectives of the present work was to test the relationship between LS and US. The results indicate the non-significance of the direct relationship in that sense, although the results of the indirect effects show different results in the mediating effect of US. Future work should consider the analysis of US on LS. US is based on elements such as the system, the information received or the quality of the service, which could condition the effectiveness of learning, so its consideration could broaden the theoretical perspective of future work.

Author contribution statement

All authors listed have significantly contributed to the investigation, development and writing of this article.

Additional information

No additional information is available for this paper.

Data availability statement

The data is protected by the data protection law according to Spanish regulations.

Ethics approval and consent to participate

We have had the consent of the persons to carry out the database, complying with the ethical directives of the University of Seville. Participants gave their informed consent.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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