

Students' adoption of e-learning: evidence from a Moroccan business school in the COVID-19 era

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Abstract

Purpose – This article aims to study the determinants of e-learning acceptability by university students based on their experiences with distance learning during the coronavirus disease 2019 (COVID-19) pandemic.

Design/methodology/approach – A questionnaire was used to collect data from 448 students enrolled in a Moroccan business school's fourth and fifth years. The technology acceptance model (TAM) was the primary framework used for this analysis, into which variables from the expectation confirmation model were injected, namely facilitating conditions, social influence, expectation confirmation and satisfaction. The proposed conceptual model was tested and evaluated using the partial least squares structural equation modeling (PLS-SEM) technique. Then the authors have offered an in-depth analysis by employing the importance-performance map analysis (IPMA) approach.

Findings – The investigation suggested that the proposed measurement scale effectively assesses the factors impacting students' decision to continue using e-learning in the future. This study's results show that e-learning acceptance depends significantly on the students' satisfaction, perceived ease of use (PEU) and perceived usefulness (PU). In contrast, the facilitating conditions are not a valid measurement scale to determine students' attitudes toward e-learning.

Originality/value – This is one of the first studies in the Moroccan context to evaluate e-learning acceptability by management students after COVID-19 using a unique research model.

Keywords E-learning, Technology acceptance, Digital, Higher education, IPMA

Paper type Research paper

1. Introduction

Globally, numerous countries placed restrictions in reaction to the coronavirus disease 2019 (COVID-19) pandemic, such as closing universities and educational institutions to maintain the healthcare system's stability. Worldwide, universities have shifted from traditional to online education (Al-Tahitah, Al-Sharafi & Abdulrab, 2021). Most governments implemented quarantine or mobility restrictions to prevent the widespread coronavirus, which substantially influenced our lives. Besides the economy, one of the most significant reversals of COVID-19 was the education sector. For the 2019–2020 academic season, all higher education institutions in Morocco have switched to distance learning as a cost-cutting measure. Despite e-learning's benefits, this learning mode is not widely used for various reasons (Alismaiel, 2021). In the context of an unpredictable health crisis in 2020, digital learning systems were developed on short notice without any prior instruction to train the Moroccan academic staff in e-learning. According to Al-Tahitah *et al.* (2021), using e-learning during COVID-19 has contributed to raising a new philosophy where the



traditional education approach could be replaced by new orientations that may become essential in the nearest future.

The complete transition to online learning could be inevitable in the near future because classroom settings are becoming extinct in the information and communication technologies (ICT) era, as [Al-Qaysi, Mohamad-Nordin, Al-Emran, and Al-Sharafi \(2019\)](#) stated. Establishing a regional education hub depends primarily on the complete integration of digital technologies into the national educational ecosystem. The COVID-19 pandemic has reshaped the Moroccan educational system toward using more ICT tools in higher education. The main reason for favoring this transmission is that the new Moroccan development model constructed in 2021 focuses on universal access to high-quality education. This action requires a significant upgrade of the digital broadband infrastructure nationally.

In today's world, all higher education institutions are digitalizing their courses curriculum, relying heavily on the progress of the ICT sector ([Alajmi, Al-Sharafi & Abuali, 2020](#)). All these efforts are deployed to take advantage of e-learning's benefits which could reduce universities' costs and enhance their flexibility toward contextual changes. Online education can allow students to enhance their networking capacities with peers across nations or even different continents. Besides that, e-learning pushes teachers and researchers to be more effective by making them operate out of their comfort zone. Moreover, an online education platform might give students access to specialized degree courses that may not be available in their local higher education institution, especially for graduate students looking to develop their competencies. Generally, e-learning has all it takes to replace traditional education, expanding the reach of students beyond the boundaries, time and space ([Baylari & Montazer, 2009](#)). Especially with the right attitude from instructors and students toward e-learning ([Baber, 2021](#)) because no matter how sophisticated the technology gets, what matters the most is the user's positive attitude towards it ([Huang & Liaw, 2005](#)). Also, the lack of students' motivation can dull e-learning's success. Therefore, students' attitudes and feelings toward e-learning play a major role in its success because e-learning could have severe flaws such as connectivity concerns and social isolation problems threatening students' psychological health ([Sá & Serpa, 2020](#)).

On a national scale, we have identified a shortage of pedagogical engineering to promote e-learning as a reliable educational model. Practically, the implementation of e-learning is not always smooth and effective ([Mailizar, Almanthari, Maulina & Bruce, 2020](#)). During the COVID-19 outbreak, business schools have rapidly implemented e-learning. According to [Zaharah, Kirilova and Windarti \(2020\)](#), a step like that without the proper e-learning experience and resources could paralyze the learning system. Nevertheless, given the efforts made by academic institutions during the COVID-19 crisis, we have witnessed a broad social consensus among all stakeholders. Accordingly, most higher education students were partially familiar with distance learning. National authorities have actively pursued all available options to improve the use of digital dispositive to ensure the continuation of studies through the effective transmission of courses to students via the Internet and provide valuable experiences that enhance students' learning processes through academic knowledge enrichment.

According to the literature, different scholars have conducted various types of studies regarding e-learning acceptance worldwide. Some have analyzed e-learning acceptance during the pandemic ([Abbasi, Ayoob, Malik & Memon, 2020](#); [Baber, 2021](#); [Bouyzem, Ghilane, Moustakim & Tsouli, 2022](#); [Favale, Soro, Trevisan, Drago & Mellia, 2020](#); [Mailizar et al., 2020](#); [Oujdoui, Chafik & Boubker, 2021](#); [Sukendro et al., 2020](#)). In contrast, most studies in the Moroccan context were conducted during normal times before the coronavirus ([Ben Romdhane, 2013](#); [Bouhaji, Ait Mouddene, Benloubir, Serhier & Bennani Othmani, 2014](#); [Lebzar & Jahidi, 2017](#); [Riyami, 2018](#)), posing many challenges but at the same time highlighting the importance of investigating e-learning acceptance factors for emerging countries during pandemics as [Sukendro et al. \(2020\)](#) stated. Without knowledge of students'

continuous usage, it is impossible to enhance e-learning in Morocco or support its programs, systems, regulation policies and sustainability.

Empirically, e-learning is not without limitations, and there is a knowledge gap regarding students' attitudes toward using e-learning as a studying tool in the future. This highlights the need to study the acceptance factors that could emerge to promote students' acceptance. Therefore, this study was conducted to understand factors predicting the use of e-learning through the PLS-SEM approach among the students of the National School of Business and trade of Tangier. The research adopted technology acceptance model (TAM) and expectation confirmation model (ECM) as a guiding academic model to determine the main factors influencing students' e-learning acceptability. Moreover, the main factors impacting students' intentions were detected using the importance-performance map analysis (IPMA) analysis.

This paper's findings will help to advance our understanding of e-learning acceptance barriers amid COVID-19 in the context of an emerging country business school. Therefore, this study adds valuable insight to the e-learning acceptance literature and provides meaningful suggestions for policymakers to improve e-learning sustainability in the Moroccan context. In other words, we seek to investigate the determinants of e-learning adoption to ensure its sustainability in higher education institutions as a mode of learning not only during a crisis but also in normal circumstances, and this is through the adoption of a mixed or hybrid system that combines face-to-face and distance learning. To achieve those objectives, this study aspires to answer the following research questions:

- (1) What factors influence and motivate students' behavioral intention toward e-learning?
- (2) Does combining the TAM and ECM theories offer an excellent research framework in the Moroccan context?
- (3) Do the PLS-SEM and the IPMA approaches empirically provide reliable results in the e-learning research field?

We have structured our paper into five main sections to carry out this study. The first is devoted to contextualizing distance learning in Morocco during the health crisis. The second section will deal with the theoretical foundations of technical acceptability. The third and fourth sections will be devoted to developing the conceptual research model, the hypotheses that result from it and the methodological framing. Finally, the last section will be devoted to the presentation and the discussion of the study's results.

2. Higher education in Morocco during the COVID-19 crisis

Due to the global paralysis created by the advent of the COVID-19 pandemic in early 2020, higher education institutions worldwide have faced obstacles in providing adequate learning continuity for their students. Consequently, significant changes have been incorporated into teaching processes (Murphy, 2020). The social distancing measures applied to limit the propagation of the virus have forced higher education institutions to move towards virtual systems to ensure the continuity of pedagogical programs, which makes the online learning ecosystem an alternative to the traditional classroom environment (Liguori & Winkler, 2020). However, this transformation comes with implementation and management obstacles. For some universities, this transmission has been more difficult (Abdur Rehman, Soroya, Abbas, Mirza & Mahmood, 2021), and the adaptation challenges in this crisis context arise for both faculty and students.

Digitization is a crucial dimension of education worldwide (Singh & Thurman, 2019). In the era of globalization, the world's prestigious universities have proceeded to internationalize their programs, relying on digital technology as a delivery mechanism for

educational content and as a channel for knowledge transmission. However, distance and even hybrid education pose problems in the case of emerging and developing countries. This is generally due to the technological infrastructure weakness, the educational system aridity, and the students' and teachers' resistance to adopting e-learning technologies either because of confidence lack or because of the missing utility or facilities of access.

Resorting to distance learning was the only option for maintaining the academic year during the COVID-19 pandemic. During the crisis management phase, academics faced severe challenges imposed by the COVID-19 circumstances. Therefore, it is compelling to study the issues and challenges that face all stakeholders by offering suggestions for improvement, especially since we are in an open preparatory phase on the concept of digital-based education. Indeed, [Bojović, Bojović, Vujošević and Suh \(2020\)](#) propose five steps to move from a traditional to a fully digitalized learning model. Based on their thesis, the first two phases, namely preparation and planning, require an assessment of the needs and capabilities of all stakeholders. This pre-implementation assessment of e-learning is vital to the success of the digital transition outputs, as most organizations have not been given enough time to thoroughly consider how to incorporate new technologies into their strategies ([Carroll & Conboy, 2020](#)).

The changes in the educational environment due to the coronavirus have become evident, and as a result, academic learning has entered a new phase of development and maturity ([Han & Sa, 2021](#)). On the other hand, [Toquero \(2020\)](#) states that it is essential for academic institutions to improve their programs and use new teaching strategies and methods, stating the importance of using new technologies in education. In Morocco, the authorities have implemented programs to promote ICT since the launch of the "NAFID@" operation in 2005. In fact, several initiatives have been launched in the perspective of generalization and integration of information technologies in higher education, including "Maroc Numéric 2013 and 2015", "LAWHATI," and many other measures that aim to promote the use of ICT in higher education in the country.

Similarly, the Moroccan Higher Council of Education, Formation and Scientific Research recommended in 2019 the inclusion of ICT in the public policies of the educational system as a sort of pedagogical innovation by proposing a legal framework that guides this political action. However, despite the authorities' efforts, the results of [Hamdani's \(2021\)](#) survey with 358 students in Moroccan public higher education institutions show that students are unsatisfied with the experience of distance learning because of the technological infrastructure weaknesses, mainly the poor connectivity quality and the high Internet costs in Morocco compared to other European partners. Under these circumstances arises the question of the total acceptability of e-learning as an independent learning system by Moroccan students, especially in a period of full convergence towards using ICT in all fields, mainly those related to professional learning.

In general, it is necessary to invest more in technologies to successfully manage the new organizational requirements imposed by the arrival of the COVID-19 pandemic, which will allow the creation of digitalized courses in line with the current educational system or even virtual universities.

3. Theoretical aspects of technology acceptance

According to [Bobillier Chaumon \(2016\)](#), investigating the acceptability of technology serves to assess and predict the motivations and determinants of future users' acceptance. The topic of technology acceptability has been addressed through three fundamental approaches: practical acceptability, social acceptability and situational acceptability ([Sagnier, Loup-Escande & Valléry, 2019](#)). Indeed, operational acceptability aims to ensure, following [Brangier, Hammes-Adelé, and Bastien \(2010\)](#), the compatibility between users, their tasks

and the technology. Generally, the first two approaches are based on several factors such as reliability, overall cost, utility, usability and compatibility. This approach seeks to improve the ergonomic aspects of technology and optimize the interactions between users and the technology to promote its adoption (Bobillier Chaumon, 2016; Sagnier *et al.*, 2019). However, we can identify two model streams from the theoretical conceptualization of social acceptability: those that conceive of acceptability in terms of satisfaction and those based on the user's perception of the technology (Dubois, Bobillier-Chaumon & Ngom-Dieng, 2015).

Acceptability as user satisfaction is based on the assumption that user satisfaction can be considered a measure of the success of a technology. DeLone and McLean's (1992, 2003) model of technology success was developed based on this perspective. According to the latter authors, satisfaction refers to assessing the quality of the technology based on the user's experience (Ben Romdhane, 2013).

Models based on the perception of technology by users integrate social cognitions into the acceptance process of technologies. Indeed, Davis (1989) invented a model entirely in line with this approach: the TAM. This model is considered an extension of Fishbein and Ajzen's (1975) theory of reasoned action. TAM is a theoretical framework for studying how perceived usefulness (PU) and perceived ease of use (PEU) of new technology affect its acceptance. In other words, the TAM states that intentions to use technology depend on the ease of use of the technology itself and users' perceptions of usefulness. When TAM was first introduced by Davis (1989), it was conceived as a theory explaining technology acceptance. Since then, it has been used in various fields, including new technologies and services (Venkatesh, 2006). In the same year, King and He (2006) confirmed that it is the most widely used model in scientific research to assess the acceptability of technologies. In the TAM, PU refers to the level at which the user believes that the technology will improve their work performance, while PEU refers to the degree of comfort the potential user feels when using the technology. According to Davis (1989), these two factors are considered the main determinants of users' attitudes and directly influence their intentions to use the technology.

This model has undergone two essential mutations with scientific progress, namely, TAM2 and TAM3. Researchers attempted to incorporate external determinants of PU in the second model through a longitudinal study of four organizations. However, in the third one, the authors tested eight theoretical models presenting the technology acceptance paradigm to extract four determinants of technology acceptance intention. The determinants are expected performance, expected effort, social influence and facilitating conditions. Generally, these two extensions of the TAM model are considered an essential enhancement to Davis's (1989) research.

Finally, the situational acceptance approach invented by Bobillier Chaumon and Dubois (2009) is founded on the contextualization principle, which aims to analyze the contributions and determine the limits of technology in its context of use. This approach determines a technology's usefulness without detaching it from the specificities of the users' projects.

4. Conceptual model

To identify the main factors influencing students' intentions to use e-learning systems, such as fully digitalized courses, this section is devoted to studies addressing similar topics to develop our conceptual research model and test it in the Moroccan context.

The development of e-learning, particularly in higher education institutions during the COVID-19 crisis, has been widely debated and researched in various studies from different angles and contexts (Abdur Rehman *et al.*, 2021; Al-Samraie, Teng, Alzahrani & Alalwan, 2018; Druke, Mainz, Lemos, Wirtz & Boecker, 2021; Han & Sa, 2021; Mailizar, Burg & Maulina, 2021; Muthuprasad, Aiswarya, Aditya & Jha, 2021; Núñez-Canal, de Obesso & Pérez-Rivero, 2022). By way of illustration, Abdur Rehman *et al.* (2021) argue that the shift to

digital technology in the teaching profession has been accelerated mainly in emerging countries by the global pandemic, whereas this is not the case for advanced countries that have invested heavily in the digital transition and digital transformation. For his part, [Simpson \(2018\)](#) points out that digitalization is the main trigger for the worldwide higher education ecosystem change. Generally, contextual and cultural dispersions are behind the success of e-learning between developed and emerging countries. In this sense, [Muries and Masele \(2017\)](#) suggested exploring the factors of e-learning adoption in developing countries, especially in higher education institutions.

In the same vein, [Saeed Al-Marroof et al. \(2020\)](#) studied the continuous intention to use e-learning of 30 teachers and 342 students in one of the universities in the United Arab Emirates. They highlighted a huge gap in the existing literature regarding using multiple theories to understand the predictive power behind students' intentions.

We will combine the TAM and the ECM to explain the acceptance and predict the future usage intention of e-learning platforms in Morocco. The main reason explaining our theoretical positioning is that ECM is rooted in the expectancy-confirmation paradigm ([Hong, Thong, & Tam, 2006](#)). This model relies primarily on the idea that users' continued usage decisions are similar to consumers' repeated purchase decisions. Therefore, ECM could explain students' intentions to continue using distance learning by mobilizing three antecedents, namely satisfaction, confirmation and PU.

Furthermore, we constructed a mixed model because each theory has separate roots and is founded on different antecedent factors. They each partially comprehend students' cognitive processes connected to e-learning usage. As a result, it is feasible that when these theories are integrated, they will give a better and more comprehensive explanation of the cognitive processes and behaviors associated with e-learning usage than when each theory is evaluated alone ([Ho, 2010](#); [Hong et al., 2006](#); [Lee, 2010](#); [Nicholas, Hartono, Vincent & Gui, 2022](#); [Saeed Al-Marroof et al., 2020](#)).

4.1 Facilitating conditions

Facilitating conditions are defined by [Venkatesh, Morris, Davis and Davis \(2003\)](#) as the degree to which the user believes that the technical infrastructure is necessary for using the system. Furthermore, they are considered predictors of the actual use of technology and information systems, as they directly influence the behavior or the intention to use ([Venkatesh et al., 2003](#)). Empirically, facilitating conditions have been confirmed to significantly influence PEU among users ([Alismaiel, 2021](#); [Nikou, 2021](#); [Venkatesh et al., 2003](#)). Generally, a supportive educational environment characterized by a developed technological infrastructure and providing quality technical support for students is an essential facilitator for users' acceptance of e-learning, as they feel that the digital system is easy to use. Within this framework, the following hypothesis can be formulated:

H1. Facilitating conditions positively impact PEU.

4.2 Social influence

The developed version of the TAM incorporates social influence as a predictor of technology adoption. However, the first implementation of this variable in its current format was in the unified theory of acceptance and use of technology (UTAUT) in 2003. Based on the theory of reasoned action, [Venkatesh et al. \(2003\)](#) posited that social influence may impact technology adoption as a function of users' expectations that may be objects of social pressures from their environment. Theoretically, social influence describes a condition that determines users' intention and behavior regarding the utilization of technology by considering the influence of the people closest to them. According to [Venkatesh et al. \(2003\)](#), the encouragement from these

people becomes a social pressure to adopt the technology because users search to legitimate their existence within the social coalitions.

Furthermore, social influence positively impacts users' perceptions of the system's usefulness (Nikou, 2021; Nikou & Economides, 2017; Wu & Chen, 2017). Indeed, students who have never used e-learning as a learning approach before the COVID-19 pandemic may need to appreciate the opinions of their teachers, parents or others who influence their behavior. In the context of e-learning acceptance, we can hypothesize the following:

H2. Social influence positively impacts the e-learning's PU.

4.3 Perceived ease of use

Venkatesh *et al.* (2003) defined PEU as the degree to which the user believes the system would be easy to exploit. According to Nikou (2021), when users of a web-based system believe it is easy to operate, they are more likely to continue their experience by using it frequently in the future. This makes PEU one of the main determinants of technology acceptance. In the context of e-learning, Lin, Chen and Fang (2011) defined PEU as the extent to which users believe that using an e-learning system will be effortless. In addition, previous studies have shown that PEU strongly predicts attitude toward e-learning adoption (Mailizar *et al.*, 2021; Nikou, 2021; Zogheib, Rabaa'i, Zogheib & Elshaheli, 2015). Furthermore, a panoply of research has confirmed a significant causal relationship between PEU and PU (Abdullah, Ward, & Ahmed, 2016; Binyamin, Rutter & Smith, 2019; Druke *et al.*, 2021; Han & Sa, 2021; Mailizar *et al.*, 2021). Considering the above discussion, we propose the following two research hypotheses:

H3a. Perceived ease of use positively affects PU.

H3b. Perceived ease of use positively affects the continued usage of e-learning.

4.4 Confirmation

Confirmation of expectations is the perception or direct result of user evaluations, comparing their initial expectations with the expected performance after using the technology or the actual performance (Bhattacharjee, 2001). This construct was designed to measure the degree to which students' expectations before experiencing e-learning for studying were consistent with their confirmations after using distance learning platforms as a learning mode during COVID-19. Theoretically, being derived directly from experience and interaction with the information system, confirmation of initial expectations can positively affect users' PU of the technology according to the ECM. Several studies have found a significant causal relationship between expectation confirmation and students' PU (Daneji, Ayub & Khambari, 2019; Lee, 2010; Nikou, 2021; Sørebo, Halvari, Gulli & Kristiansen, 2009).

Expectation confirmation theory suggests that users' successful technology experiences enhance user satisfaction. Indeed, if students believe that the digital system is advantageous and the user experience matches or exceeds their initial expectations, then the occurred confirmation leads to user satisfaction (Daneji *et al.*, 2019). Therefore, achieving the expected goals improves the PU and satisfaction of e-learning users. Hence, the following hypotheses are formulated:

H4a. Confirmation significantly influences PU.

H4b. Confirmation positively impacts students' satisfaction regarding e-learning.

4.5 Perceived usefulness

Conceptually, Davis (1989) defines perceived utility as the degree to which a user believes that operating a system would improve their future performance. According to Lin *et al.* (2011),

PU can be described in our analysis as the degree to which students believe that e-learning can help them achieve their academic goals. Generally, users are more likely to use an information system when they think it is worthwhile (Nikou, 2021). Previous research has shown that PU is the primary motivator of initial acceptance and continued use of online learning systems (Beldad & Hegner, 2018; Lee, 2010; Lin *et al.*, 2011; Wu & Chen, 2017).

In the context of our study, the expectancy confirmation paradigm argues that students' PU regarding e-learning can positively affect their satisfaction, serving as a baseline for confirmation judgments. This relationship is supported by Helson's (1964) adaptation level theorem, which proposes that users perceive stimulus only at an adequate or appropriate level (Lee, 2010; Sørebo *et al.*, 2009). Based on this examination of PU, we propose the following hypotheses:

H5a. PU positively impacts the continuance use of e-learning.

H5b. PU positively impacts the students' satisfaction regarding e-learning.

4.6 Satisfaction

Theoretically, satisfaction guarantees continued use in management sciences and ensures the user's intention to use. Similarly, the ECM model considers satisfaction a powerful determinant of users' continued use in the information systems literature. Concerning our study, Han and Sa (2021) suggest that student satisfaction positively affects the behavioral intentions of these users toward future e-learning use. Indeed, satisfaction has significant importance in the literature related to online services, as this satisfaction influences users' decision whether to continue using the service in question (Lin & Sun, 2009). Szymanski and Hise (2000) consider e-satisfaction as users' judgment of their overall online experience over a given period.

Furthermore, several empirical studies have shown that student satisfaction can be an essential determinant of continued use and full adoption of e-learning (Daneji *et al.*, 2019; Lee, 2010; Lin *et al.*, 2011; Nikou, 2021; Sørebo *et al.*, 2009). Based on these studies, we can formulate the following hypothesis:

H6. Students' satisfaction has a positive effect on e-learning adoption.

5. Research methodology

In the present study, which aims to identify the main factors of the continuity of e-learning usage by Moroccan students, we have followed an epistemological approach that conditions our empirical investigation and the sampling method. We will present successively in this section our epistemological positioning and methodological choices.

5.1 Methodology

As for our study, the most appropriate approach to studying the causal relationship between the different variables of our conceptual model is the deductive approach, based essentially on the hypothetico-deductive method, which consists of formulating hypotheses based on theoretical and empirical contributions, then testing them empirically. Consequently, our study is fully positioned in the post-positivist paradigm.

The mode of investigation deployed in this research is the questionnaire survey. According to Boudali and Jebabli (2019), this is the most appropriate method for collecting data in empirical studies based on the hypothetico-deductive approach. According to Baumard, Donada, Ibert and Xuereb (2014), data collection through the questionnaire allows dealing with large samples and establishing statistical relationships between several

variables. Indeed, the different questions of our investigation instrument are articulated around all the axes of our conceptual model. This study's measurement scales are of Likert type with five points selected from previous literature on the same topic dealing with information systems and e-learning. It is crucial to mention that we contextualized the different items according to the COVID-19 pandemic and the intrinsic specificities of the sample.

5.2 Statistical background of the business school during COVID-19

Before exploring the characteristics of our sample, it is appropriate to review the context experienced by the business school during the COVID-19 period in terms of preparations and arrangements to manage the crisis and ensure educational continuity. In the Moroccan business school, we are studying in the current research, several actions were initiated to keep the learning process as fluid as possible. Right after the crisis advent, our business school started generalizing professional email addresses for all students, teachers and administrative staff, installing a web-based server and enhancing the connectivity speed by installing broadband infrastructure in order to record online courses in a professional studio inside the Business School campus. Moreover, they improved the school's network's security system and started organizing several workshops about e-learning platforms for teachers and administrators. To ensure that the students have a great experience with e-learning, they offered them full-paid subscriptions to different digital libraries such as ScholarVox.

Professors' production using e-learning in 2020 at the business school during the period from March 16th to June 19th is counted for 1,135 supports (i.e. 57.27% were digital supports such as PowerPoint slides and PDFs, 380 distances learnings courses that were held using Google Meet Classroom and Zoom, 30 voice recordings, and 75 permanents videos on the school's platform). Notably, around 619 documents were published using the business school's e-learning platform.

5.3 Data collection

To answer our research problem, test the hypotheses formulated, and empirically verify our conceptual research model, we relied on a quantitative approach by administering a questionnaire to the students. The questionnaire survey allowed us to collect data on a representative sample of the business school's students. The participants ($n = 466$) were totally finance and audit students in their fourth and fifth years at the school's finance and audit programs. First, we intentionally targeted those students because they used the school's e-learning platform during their second and third years. Thus, participants were identified as having sufficient experience in using e-learning platforms. Second, we have distributed the questionnaire to the students during the winter semester of 2021/2022, using surveys at the National School of Business and trade of Tangier from December 1st to December 4th 2021.

The perspective sample size was 466 students representing a population of 2,381 students at the business school. Therefore, the aggregated response rate was around 96% because only 448 questionnaires were correctly filled out and recovered. This means that 18 questionnaires were rejected because of conformity issues. According to [Adam \(2020\)](#), our sample size is suitable to represent a population of even 3,000 students because the calculated sample at 95% confidence level and 5% margin of error is 341 students. Moreover, our argument meets the minimal requirements of [Krejcie and Morgan \(1970\)](#), who specified a sample of 331 individuals to represent a population of 2,400. Thus, our research could be reviewed using PLS-SEM to verify the hypotheses according to the ten times rule ([Kock & Hadaya, 2018](#); [Hair, Black, Babin & Anderson, 2014](#)).

5.4 Demographic description

Due to the lack of a random sample frame, we used a non-probabilistic sampling method. This technique is used for practical reasons of accessibility. Our sample comprises 448 students, 277 females, representing 61.8% of the total sample. More than half of the respondents to our questionnaire are fourth-year students (i.e. 290 students), compared to 138 students in the fifth academic year. Almost half of the students are 21 years old, while the rest are 20 to 26 years old. Notably, 73.9% of the respondents indicated that they were not using any e-learning platform before COVID-19. It is noteworthy that students who used e-learning platforms before the pandemic used Coursera, LinkedIn Learning, Udemy, Moodle and other platforms.

Furthermore, 62.7% of the students forming our sample attest that they spend an average of more than 4 hours of Internet usage per day. Regarding the representative quality of the study sample, it is necessary to point out that the fourth-year questioned students present 55.87% of all students enrolled in the fourth year. The students in the fifth year, which are part of the study, present nearly 37% of students enrolled in the fifth year for the academic year 2021–2022, and they are enrolled in the options financial management and accounting and audit and management control (see [Table 1](#)).

5.5 Measurement model

We used structural equation modeling with PLS as the primary estimation method to empirically validate our conceptual research model. These structural equations were initially developed to facilitate the modeling of multiple causal relationships before being used to analyze the validity of latent constructs. By mobilizing the PLS algorithm integrated into SmartPLS software (v.3.3.3) designed by [Ringle, Wende, and Becker \(2015\)](#) on all observations from the 448 students in our sample, we checked for internal validity to ensure the reliability of our constructs. We checked for convergent and discriminant validity for each construct for model robustness.

Variable	Description	Frequency	Percentage	Accumulated percentage
Gender	Female	277	61.8%	61.8%
	Male	171	38.2%	100%
Academic level	Master	20	4.5%	4.5%
	4th-year	290	64.7%	69.2%
	5th-year audit	52	11.6%	80.8%
	5th-year finance	86	19.2%	100%
Age	20	40	8.9%	8.9%
	21	208	46.4%	55.4%
	22	147	32.8%	88.2%
	23	39	8.7%	96.9%
	24	9	2%	99.8%
	25	4	0.9%	99.8%
	26	1	0.2%	100%
	e-learning use before COVID-19	No	331	73.9%
Yes		117	26.1%	100%
Daily Internet usage frequency	Less than one hour	5	1.1%	1.1%
	Between 1h–2h	36	8%	9.1%
	Between 2h–4h	126	28.1%	37.3%
	More than four hours	281	62.7%	100%

Source(s): Authors' calculations

Table 1.
Sample's demographic characteristics

6. Empirical analysis

According to [Sarstedt, Ringle and Hair \(2017\)](#), it is mainly necessary to assess indicators' reliability, internal reliability, and convergent and discriminant validity of the different variables of a reflective model.

6.1 Convergent validity

The first step in assessing constructs' reliability and validity is eliminating items with factorial contributions or loadings below 0.70 (i.e. all items of "Facilitating Conditions," the SI4 and PEU2 items). The decision to eliminate items not fulfilling the convergent validity criteria comes after careful analysis of counter effects caused by eliminating these items on composite reliability and construct validity, which are significantly improved after removing the items mentioned above (i.e. the level of significance of the factorial contributions generated by the PLS algorithm are above 0.70). Generally, the convergent validity of a construct can be ensured when each item shares more variance with its latent construct than with its measurement error. According to [Fornell and Larcker \(1981\)](#), convergent validity can be justified when the average variance between the construct and its items, designated as the average variance extracted (AVE), is larger than 0.50. The composite reliability has values higher than 0.847, which is acceptable since it exceeds the normative minimum of 0.70. In addition, Cronbach's alpha values are between 0.727 and 0.889, which is duly accepted. The study's results suggest that the internal consistency of the empirical model is guaranteed (see [Table 2](#)).

Similarly, the discriminant validity of our model is ascertained using the Fornell–Larcker criterion ([Table 3](#)). Discriminant validity measures how a latent construct is distinct from other latent constructs ([Hair et al., 2014](#)). At this point, the square root value of the AVE

Constructs	Items	Items' loadings (>0.7)	Cronbach's alpha (>0.7)	rho_A (>0.7)	CR (>0.7)	AVE (>0.5)
Social influence	IS1	0.733	0.727	0.730	0.847	0.650
	IS2	0.860				
	IS3	0.821				
Perceived ease of use	PEU1	0.716	0.831	0.842	0.881	0.597
	PEU3	0.767				
	PEU4	0.795				
	PEU5	0.830				
Perceived usefulness	PEU6	0.750	0.848	0.848	0.898	0.688
	PU1	0.789				
	PU2	0.865				
	PU3	0.856				
Confirmation	PU4	0.806	0.761	0.763	0.863	0.677
	CON1	0.853				
	CON2	0.835				
Satisfaction	CON3	0.779	0.791	0.799	0.877	0.705
	SAT1	0.806				
	SAT2	0.870				
E-learning continuity	SAT3	0.842	0.889	0.894	0.919	0.693
	CUT1	0.860				
	CUT2	0.850				
	CUT3	0.760				
	CUT4	0.861				
	CUT5	0.829				

Table 2.
PLS-SEM assesement results

Source(s): Authors' calculations

mentioned at the diagonal of Table 3 must be greater than the construct's correlations with the other constructs, meaning that its inner items better explain its variance than any other construct (see Table 4).

6.2 Estimating the structural model

Given that the validity and reliability of the construct measures are empirically verified, we proceed to evaluate the results of the structural model (inner model). Figure 1 shows the PLS-SEM estimates for the measurement model purified of items that do not meet the reliability requirements.

After verifying the prediction quality of the endogenous variables by evaluating the determination coefficient and measuring the significance of the correlation coefficients using the *t*-statistic, we can attest that our model is highly relevant (see Figure 2).

Fornell–Larcker criteria	CON	CUT	PEU	SI	SAT	PU
Confirmation	0.823					
E-learning continuity	0.548	0.833				
Perceived ease of use	0.574	0.591	0.773			
Social influence	0.467	0.551	0.471	0.806		
Satisfaction	0.693	0.720	0.617	0.582	0.840	
Perceived usefulness	0.512	0.674	0.647	0.561	0.667	0.830

Note(s): The values in the diagonal represent the square roots of the AVEs, and the other values represent the inter-construct correlations

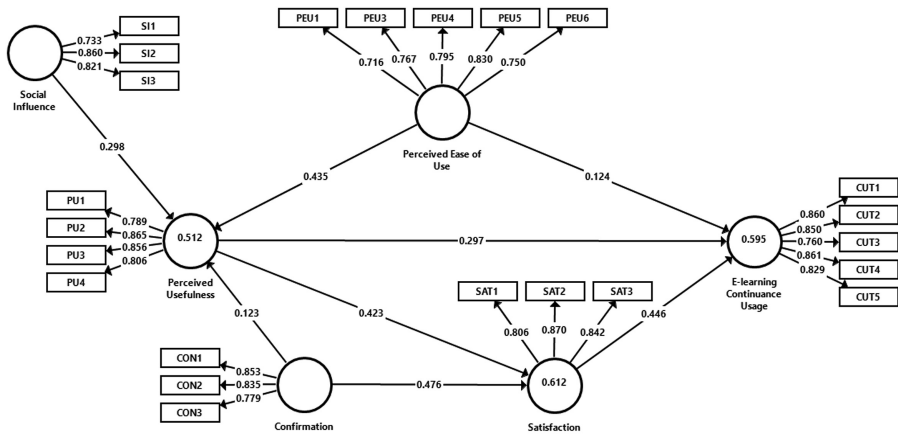
Source(s): Authors' calculations

Table 3. Model's discriminant validity

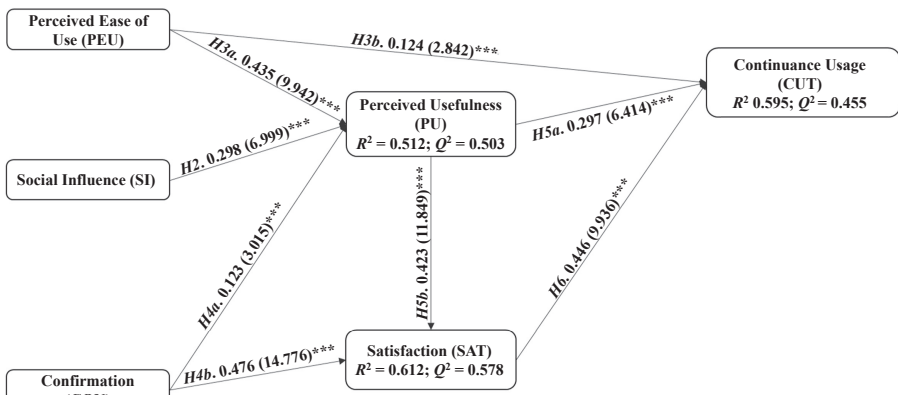
	CON	CUT	PEU	SI	SAT	PU
CON1	0.853	0.510	0.458	0.440	0.591	0.453
CON2	0.835	0.425	0.450	0.358	0.573	0.333
CON3	0.779	0.411	0.506	0.350	0.544	0.469
CUT1	0.477	0.860	0.476	0.431	0.628	0.593
CUT2	0.456	0.850	0.511	0.485	0.646	0.564
CUT3	0.421	0.760	0.447	0.334	0.476	0.485
CUT4	0.439	0.861	0.513	0.510	0.574	0.589
CUT5	0.483	0.829	0.512	0.515	0.656	0.569
PEU1	0.365	0.400	0.716	0.326	0.402	0.447
PEU3	0.484	0.460	0.767	0.349	0.515	0.471
PEU4	0.441	0.424	0.795	0.365	0.459	0.495
PEU5	0.477	0.564	0.830	0.430	0.550	0.599
PEU6	0.443	0.411	0.750	0.337	0.441	0.464
SI1	0.268	0.350	0.352	0.733	0.341	0.441
SI2	0.417	0.472	0.381	0.860	0.527	0.468
SI3	0.442	0.509	0.406	0.821	0.533	0.444
SAT1	0.624	0.484	0.474	0.485	0.806	0.479
SAT2	0.597	0.665	0.583	0.465	0.870	0.633
SAT3	0.530	0.651	0.491	0.520	0.842	0.556
PU1	0.431	0.554	0.566	0.397	0.544	0.789
PU2	0.379	0.544	0.525	0.474	0.549	0.865
PU3	0.389	0.550	0.494	0.469	0.547	0.856
PU4	0.493	0.585	0.556	0.514	0.570	0.806

Source(s): Authors' calculations

Table 4. Cross-loadings analysis



Note(s): R² inside the circles



Note(s): ***Means the relationship is significant at 1%. (t-value in parentheses)

Figure 2.
Determinants of
e-learning acceptance

As shown in the two figures above, the coefficient of determination of all endogenous constructs, namely PU, satisfaction and continuity of use, is moderate, with values between 0.503 and 0.612. Systematically, our analysis reveals that our model could explain 59.5% of the variance in students' decisions on the continuity of use of e-learning platforms.

Furthermore, the second figure shows our structural model's predictive relevance (Q^2) results. According to Sarstedt *et al.* (2017), the closer the predicted values are to the collected values, the higher the Q^2 criterion; therefore, the model's predictive quality is considered relevant. In general, a Q^2 value greater than zero for an endogenous construct indicates that the prediction power of the causal model is acceptable for that construct. For our case, the values of Q^2 are all greater than zero, concluding that the model has sufficient predictive power.

As shown in Table 5, most size effect values f^2 are acceptable. Indeed, confirmation has no significant effect on PU (i.e. $f^2 = 0.019$). Similarly, PEU and PU seem to have no significant size effect on e-learning continuance usage because the f^2 value is less than 0.150. In contrast, social influence has a size effect close to the mean threshold on PU.

6.3 Importance-performance map analysis (IPMA)

The IPMA approach is considered an excellent extension for the PLS-SEM modeling, especially for e-learning post-acceptance, because it could offer a great framework to analyze the significance and performance of each factor (Elnagar, Afyouni, Shahin, Nassif, & Salloum, 2021). Moreover, this approach offers an in-depth comprehension of PLS-SEM's results by contrasting the total effects representing the predecessor constructs' importance in shaping, in our case, the e-learning continuous intention to use with latent variables' performance expressed as scores (Ringle & Sarstedt, 2016). Thus, we ran IPMA using Table 6 depicts the total effects (importance) and index values (performance) used for the IPMA.

The IPMA analysis in Figure 3 shows that the most performing interaction factor determining students' intentions to use e-learning is PU (0.486; 59.192). Satisfaction has the second-highest importance in determining a student's intention, whereas it has the fourth performance level. Results showed a medium level of importance for PEU and confirmation, although the first latent variable has the most superior performance level (69.567). Thus, for managerial implications, social influence is not an important factor. Figure 3 depicts the index values and total effect scores.

The importance-performance map showed that PU and satisfaction are the most important factors to be taken into managerial consideration. In contrast, PEU and confirmation have a medium level of importance and performance in determining students' intentions to accept e-learning.

7. Results discussion

The hypothesis test examines the path coefficients' significance between the latent variables forming our structural model, using the bootstrapping technique recommended by Chin (1998). Table 7 represents a summary of the hypotheses testing results.

Constructs		f^2	Decision
Confirmation	Satisfaction	0.431	Large effect size
	Perceived usefulness	0.019	Small effect size
Perceived ease of use	E-learning continuity	0.020	Small effect size
	Perceived usefulness	0.240	Medium effect size
Social influence satisfaction	Perceived usefulness	0.131	Small effect size
	E-learning continuity	0.243	Medium effect size
Perceived usefulness	Satisfaction	0.341	Large effect size
	E-learning continuity	0.101	Small effect size

Note(s): According to Cohen's (1988) guidelines, $f^2 \geq 0.02$, $f^2 \geq 0.15$, and $f^2 \geq 0.35$ represent small, medium, and large effect sizes, respectively

Table 5. Cohen's size effect test

	Importance	Performance
Perceived usefulness	0.486	59.192
Satisfaction	0.446	50.979
Perceived ease of use	0.336	69.567
Confirmation	0.272	53.714
Social influence	0.145	50.468

Source(s): Authors' calculations

Table 6. IPMA values for CUT

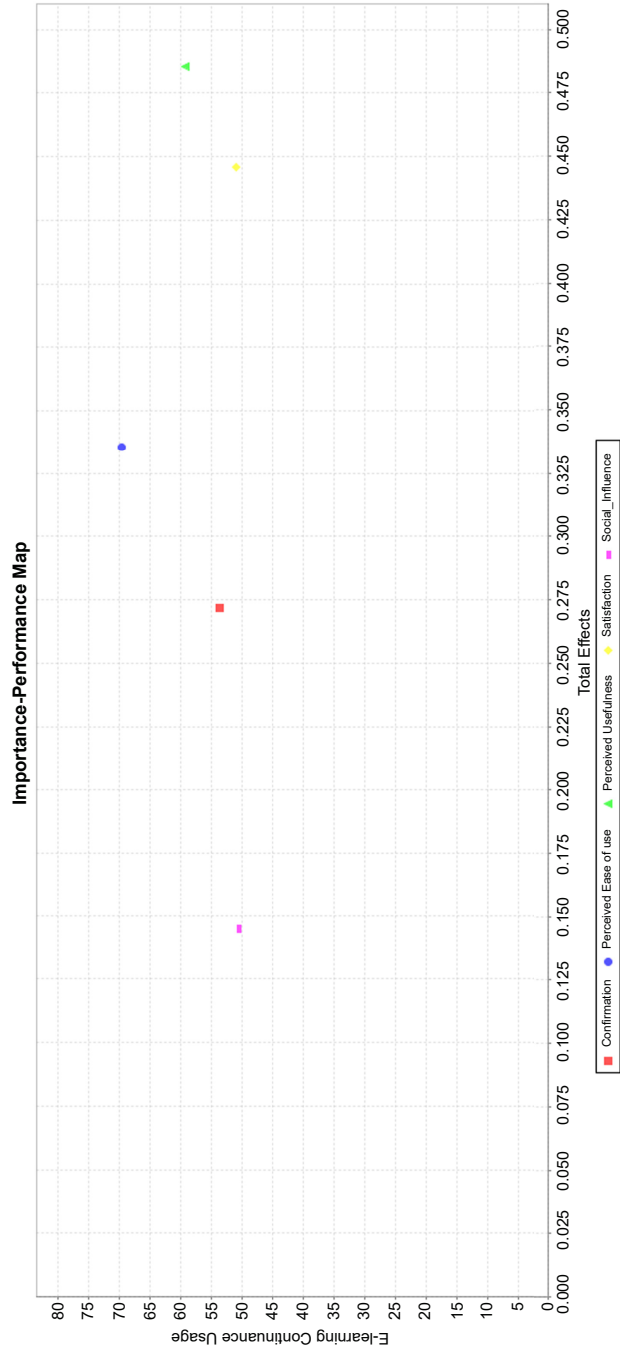


Figure 3.
IPMA for e-learning
continuance usage

Table 7 indicates that social influence positively affects students' PU ($\beta = 0.298; p = 0.000$) which supports the [second hypothesis](#) of our conceptual model. This result explains that students' PU is influenced by up to 29.8% by the blessing of their surroundings and mainly their peers about using e-learning platforms. Therefore, it can be concluded that when students receive suitable guidance and incentives from their peers, they perceive that e-learning platforms are important. This conclusion is consistent with the findings of [Nikou \(2021\)](#), [Nikou and Economides \(2017\)](#), and [Wu and Chen \(2017\)](#).

Our study highlights the significant positive effect of PEU on PU ($\beta = 0.435; p = 0.000$), validating the hypothesis (H3a). This result confirms that the e-learning PU is strongly impacted by the students' degree of ease of use based on their technological and technical knowledge and experiences. Consequently, as PEU increases, PU increases. If students think that an e-learning platform is easy to use, they will use it systematically. It should be noted that although students used e-learning during the last health crisis without adequate prior preparation, our empirical results indicate that PEU positively impacts students' continuity of use, which leads us to accept the hypothesis (H3b). This finding is aligned with the literature on technology acceptance ([Abdullah et al., 2016](#); [Binyamin et al., 2019](#); [Drueke et al., 2021](#); [Han & Sa, 2021](#); [Nikou, 2021](#); [Mailizar et al., 2021](#); [Zogheib et al., 2015](#)).

Similarly, confirmation resulting from a usage experience during COVID-19 pandemic, has a positive effect on satisfaction ($\beta = 0.476; p = 0.000$) and PU ($\beta = 0.123; p = 0.002$). These results converge with the findings of [Bhattacharjee \(2001\)](#), [Daneji et al. \(2019\)](#), [Lee \(2010\)](#), [Nikou \(2021\)](#) and [Sørøbo et al. \(2009\)](#). This result leads us to admit that the students' good experience with the e-learning imposed by the COVID-19 pandemic was above the students' expectations, improving their overall judgment. In this sense, the business school's students affirmed that the pedagogical services during COVID-19 exceeded the expected performance.

The perception of e-learning importance seems to be the most potent determinant when it comes to confirming students' expectations before full acceptance of technology in general and pedagogy in particular. This conclusion can be explained by the fact that technical skills and knowledge can make pre-acceptance expectations more realistic and post-acceptance use more effective. Thus, hypotheses (H4a) and (H4b) can be accepted by assuming that a high level of confirmation may be present when realistic expectations are associated with correct and effective use.

The empirical results show that it is plausible that PU also influences subsequent e-learning acceptance decisions ($\beta = 0.297; p = 0.000$). It is noteworthy that ex-post beliefs of e-learning usefulness assess how a technology such as distance learning platforms provides access to increased educational performance, while post-acceptance satisfaction assesses students' positive, indifferent or hostile experiences following their experience. Paradoxically, lower-than-expected performance after initial uses of e-learning platforms creates a "negative experience" and, thus, dissatisfaction among students. Our study

	β	Mean	t-value	p-value	Decision
CON → SAT	0.476	0.476	14.58	0	(H4b) is accepted
CON → PU	0.123	0.127	3.075	0.002	(H4a) is accepted
PEU → CUT	0.124	0.129	2.954	0.003	(H3b) is accepted
PEU → PU	0.435	0.432	10.08	0	(H3a) is accepted
SI → PU	0.298	0.300	7.048	0	(H2) is accepted
SAT → CUT	0.446	0.445	9.586	0	(H6) is accepted
PU → CUT	0.297	0.294	6.317	0	(H5a) is accepted
PU → SAT	0.423	0.422	12.13	0	(H5b) is accepted

Source(s): Authors' calculations

Table 7. Summary of hypotheses testing results

confirms that PU positively influences student satisfaction ($\beta = 0.423; p = 0.000$), in line with the findings of Lee (2010) and Sørebo *et al.* (2009). We can accept the hypotheses (H5a) and (H5b) based on the above discussion and especially after running the IPMA analysis that suggested that the PU is the essential latent variable in our research model that determines e-learning continuance usage.

On the other hand, satisfaction can be classified as an important determinant of technological acceptance in the context of e-learning in Morocco ($\beta = 0.446; p = 0.000$). This result confirms those of Limayem, Hirt and Cheung (2007) and Roca, Chiu and Martínez (2006), but it remains in contradiction with the conclusion of Sørebo *et al.* (2009). Therefore, the sixth hypothesis of our conceptual model is accepted. One possible explanation for this statement is the consistency between satisfaction, PU and intrinsic motivations that can be triggered by positive confirmation after an experience, whether deliberate or imposed. Since satisfaction, as conceptualized in this study, is based on a broad experience that generates positive, indifferent or negative perceptions about e-learning, the IPMA matrix confirmed that the students' satisfaction after COVID-19 could be the second-highest latent variable contributing to adopting e-learning in our context.

8. Conclusion

This study attempted to measure students' intention to adopt e-learning as a distance learning mode based on their experiences during the COVID-19 pandemic. This learning approach was imposed by the Moroccan government's lockdown and social distancing measures. In this paper, we were able to identify the main determinants of e-learning's adoption and acceptance. Through a quantitative study deploying the questionnaire to collect information, we found that facilitating conditions cannot be classified as a determinant of e-learning adoption in the context of business schools in Morocco because most of the 448 interviewed students expressed their technical abilities and knowledge in this area. In other words, nowadays, IT tools' availability and the students' technical skills cannot constitute a determining criterion of e-learning acceptance, given that the digital services have become a vital dimension of our daily life, instead of a set of tools that serve to facilitate learning goals.

By mobilizing a quantitative methodology, we proposed a structural model capable of explaining 59.5% of the decision to accept e-learning as a distance learning mode. Our results suggest that PEU strongly influenced students' PU and decisions regarding e-learning. Furthermore, prior experience with distance learning during the COVID-19 pandemic significantly influenced students' PU of online learning through the variable expressing students' confirmation of their favorable experiences derived from interactions with the different e-learning platforms used by higher education institutions in Morocco. In addition, students' behavioral intention to use e-learning after the COVID-19 is mainly ensured by their expressed satisfaction levels, which seems to be one of the most significant e-learning determinants since 61.2% of students' satisfaction stems from the initial positive perception of e-learning and the confirmation based on past experiences.

Our paper suggests that in order for students who are not familiar with distance learning in higher education in Morocco (i.e. 73.9% of the students in our sample) to continue using this mode of learning during and after the pandemic, the quality of the system and their attitude towards online learning are vital. Therefore, this study indicates that it is crucial to ensure that higher education institutions have a high-quality distance learning system. In addition, these institutions must maintain a positive attitude towards e-learning, which is essential in predicting its use by students. Our research states that students' satisfaction is significantly influenced by their perception of e-learning' usefulness and their confirmations after experiencing e-learning platforms during the two academic years, 2019–2020 and 2020–2021. Based on these connections, we can conclude that in order to ensure sustainable use of

e-learning not only during the pandemic but also in the *post*-COVID-19 period, the quality of the e-learning system is crucial since the majority of respondents manifested the low presence of technical assistance (i.e. item FC3, see [Appendix](#)). Therefore, the authorities in charge are invited to maintain and improve systems quality, contributing to the fact that the students' close environment favors their adoption of technology for learning either in parallel with their university studies or independently after their academic training. Overall, our study concluded that the business school students had accepted e-learning and intended to use it to develop their professional careers in the future (i.e. item CUT3, see [Appendix](#)). However, half of the interviewed students affirm that they prefer and will always choose the face-to-face mode for the rest of their university studies (i.e. item CUT5, see [Appendix](#)).

8.1 Practical implications

E-learning is one of the principal development axes for the Moroccan government in order to integrate technologies into higher education. Since policymakers in Morocco rely on e-learning to shape the future of education nationwide, we must identify the primary factor favoring students' acceptability. The findings of this study revealed that behavioral factors such as satisfaction, confirmation and social influence could explain students' intentions.

Also, the IPMA analysis that we carried out implies that universities and policymakers should focus on improving students' satisfaction. The study draws the attention of policymakers to carefully deal with students' current interaction with e-learning platforms to guarantee their good intentions toward adopting e-learning. We have highlighted in this research that students' PU and satisfaction could be an excellent way to promote e-learning adoption in the Moroccan context. Finally, as this study has shown, facilitating conditions are by no means a valid scale for determining students' degree of e-learning acceptability. Therefore, we recommend that authorities promote other e-learning drivers since connectivity and IT conditions do not impact students' intentions.

8.2 Theoretical implications

Regarding theory building, we developed an integrated model that combines two practical models: TAM and ECM. Compared to other studies examining the e-learning acceptance by students in the Moroccan context, this is one of the first studies in the Moroccan context to evaluate e-learning acceptability by management students after COVID-19 using a unique research model. This enabled further examination of other antecedents influencing e-learning continuance usages, such as social influence, confirmation and satisfaction, especially for students' satisfaction that is rooted in their confirmation post-use of e-learning during COVID-19.

In terms of methodology, contrasting prior empirical studies in Morocco that mainly depended on PLS-SEM analysis, this study used a double analysis combining the PLS-SEM with the IPMA. For theoretical formulation, it can be admitted that PU according to IPMA's results is more powerful in determining e-learning acceptance, contradicting the findings of PLS-SEM, suggesting that students' satisfaction has a path coefficient more significant than the other latent variables. The enormous explanatory power of these three variables makes it essential for their inclusion as the main variables in technology acceptance in the Moroccan context.

8.3 Limitations and future research

In conclusion, it is noteworthy that there are some limitations to this study, including the fact that the participants were all from a single Moroccan school of higher education with regulated access, which could influence results generalization for all Moroccan students,

especially those from open-access institutions whose study conditions are challenging even in face-to-face mode. Another limitation of this study is that it did not consider external factors, such as e-learning platforms' quality and the quality of the Moroccan educational system, which could have significant impacts on the practical adoption of e-learning.

Owing to these limitations, we think future studies should include more higher education institutions in Morocco to form more significant evidence on e-learning acceptance. Thus, it will be imperative to engage more students in participating in research. Furthermore, teacher interviews and focus groups would provide a reliable research framework. Moreover, theoretically adding moderating variables such as age and gender should reveal significant results. Besides adding more variables and expanding the sample size, testing our model in other emerging countries in the African and Gulf regions could be interesting to examine the significance of this research's results.

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Variables	Codes	Means (responses)	Items	Sources
Facilitating conditions	FC1	4.344	I have the technological and financial resources to use e-learning platforms	Tajudeen, Basha, Michael, and Mukhtar (2013), Karaali, Gumussoy, and Calisir (2011), Nikou (2021), Nikou and Economides (2017)
	FC2	4.333	I have the knowledge and technical skills to use e-learning platforms	
	FC3	2.156	I quickly got technical assistance when I needed help with my e-learning platforms experience during the COVID-19 period	
	FC4	3.136	The necessary instructions (technical guide) for the successful use of e-learning are available on my school's website	
	FC5	4.013	The platform my school chose during the COVID-19 pandemic was easy for me to use	
Social influence	SI1	3.357	The people around me think I should continue using e-learning to improve my knowledge and enrich my experiences	Nikou and Economides (2017), Karaali <i>et al.</i> (2011), Lassoued and Hofaidhllaoui (2013)
	SI2	2.882	My colleagues at the business school are convinced of the benefits and advantages of e-learning (distance learning)	
	SI3	2.83	Most of my peers affirm their ability to take comprehensive distance learning courses	
	SI4	4.022	My business school generally supported using distance learning during the COVID-19 crisis	
Perceived ease of use	PEU1	3.951	Learning to attend shared courses on e-learning platforms would be easy for me	Davis (1989), Karaali <i>et al.</i> (2011), Masrom (2007)
	PEU2	3.214	I think the interaction with my teachers would be easy for me in e-learning	
	PEU3	3.518	My interaction with the e-learning platforms' content would be clear and apprehensible	
	PEU4	3.708	I think the interaction with the e-learning platforms would be flexible	
	PEU5	3.69	I find it easy to take courses on e-learning platforms	
	PEU6	4.047	I would find e-learning platforms easy to operate	
Perceived usefulness	PU1	3.556	Online learning platforms would allow me to complete my educational tasks more quickly	Davis (1989), Park (2009), Ouajdouni <i>et al.</i> (2021), Mailizar <i>et al.</i> (2021)
	PU2	3.312	Using e-learning platforms will improve the quality of my academic training	
	PU3	3.243	Online learning would increase my academic skills and productivity	
	PU4	3.357	Using e-learning platforms would generally be advantageous for me, as it was during the COVID-19 pandemic	
Confirmation	CON1	3.163	My experience using e-learning during COVID-19 was better than I expected	Bhattacharjee (2001), Lee (2010)
	CON2	3.009	The quality of online educational delivery during COVID-19 was better than I expected	
	CON3	3.254	E-learning platforms can meet needs that go beyond my expectations of distance learning	

(continued)

Table A1. Questionnaire addressed to the business school students

Variables	Codes	Means (responses)	Items	Sources
Satisfaction	SAT1	3.141	I am satisfied with my e-learning training via the business school's platforms	Bhattacharjee (2001), Lee (2010)
	SAT2	3.241	E-learning makes my learning activities easier than I thought	
	SAT3	2.717	E-learning has significantly impacted my learning background compared to face-to-face training	
E-learning continuance usage	CUT1	3.201	I plan to take e-learning courses in the coming years	Bhattacharjee (2001), Lee (2010), Suzianti and Paramadini (2021), Agbanglanon and Adjanohoun (2020)
	CUT2	2.891	I prefer that my business school continue to use distance learning even after COVID-19	
	CUT3	3.926	I am willing to take online training as my professional career evolves	
	CUT4	3.426	I would highly recommend e-learning to others	
	CUT5	2.493	If I had to choose between face-to-face training and e-learning, I would frequently opt for e-learning	

Table A1.

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