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Cross-cohort analysis of how COVID has changed the online learning experience of business students

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ABSTRACT

The COVID-19 pandemic reshaped the educational landscape and brought online learning into the mainstream. As management education adapts to this new reality, understanding how the experience of online learning influences students is vital—especially when comparing students exposed to online university education during the pandemic with those who went to university afterward. This study examines how the personal characteristics of business students, particularly self-management and the need for interaction, shape their perceptions of online learning. By surveying two cohorts—students from the height of the pandemic in 2020 and a post-pandemic cohort in 2022—we uncover how these characteristics shape the adoption of online learning. Our findings reveal that the need for interaction remains a priority for students, unaffected by the novelty of online education. Meanwhile, the influence of self-management has weakened, suggesting it is a skill that can—and should—be cultivated in online courses. In addition, students increasingly value the enjoyment of online learning (hedonic motivation) over its perceived effectiveness (performance expectancy), emphasizing the need for engaging, well-designed course experiences. This cross-cohort analysis highlights critical shifts in how students engage with online learning, offering valuable insights for the future of management education in a post-pandemic world.

1. Introduction

Universities have always been an integral part and starting point of innovation, technological advancement, and progress. Lifelong learning is not just a buzzword in today's world; thanks to the rapid information and technological development of the 21st century, the use of digital tools has increased in the workplace, in education, and even in personal knowledge acquisition. For the "Net Generation," the efficient use of technology and the application of innovative teaching and learning methods are essential parts of university education (Yadegaridehkordi, Shuib, Nilashi, & Asadi, 2018).

In most countries in the spring of 2020, due to the COVID-19 virus, employees and students in higher education had to switch to online working and learning virtually overnight to maintain physical distance. It became vital for universities to ensure that students could smoothly transition to using the technological tools used in online education and that the education delivered through these tools was of at least the same quality and effectiveness as in-person teaching. However, this period was not only about the success and difficulties of transitioning; it was also decisive in shaping the attitudes and future commitments of students in higher education

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toward online learning. Consequently, what occurred throughout the transition period also determined what the future of higher education would be like.

Since the pandemic, several theoretical and empirical papers have been written on the impact of the COVID-19 virus on higher education (Raza, Qazi, Khan, & Salam, 2021; Zhang et al., 2023). Nevertheless, the new understandings, behaviours, needs and attitudes of university students who have started their studies in a new educational environment due to COVID still have exciting research potential (Chutiphongdech, Phengkona, Roopklom, & Sawangdee, 2024; Fang, Pechenkina, & Rayner, 2023; Madani, Adhikari, & Hodgdon, 2024). Research has shown that online learning acceptance in education, as in other industries, is determined by how easy, effective, and enjoyable users, in this case students, find it (Lakhal, Khechine, & Mukamurera, 2021; Moorthy, Tzu Yee, Chun T'ing, & Vija Kumaran, 2019). Since these variables are fundamentally perceptual, their perception depends not only on the technology itself but also on the user. What has been less researched is an examination of the personal characteristics that influence students' perceptions, i.e., what determines whether someone finds online learning useful, useable, and fun. In addition to these questions, few studies have examined how the impact of these factors varies over time. This raises the question of whether the characteristics of students who studied online at a university under COVID-19 are different from those who have already been exposed to online education before university.

Based on these considerations our objective with this research is twofold. The first is to investigate which personal characteristics influence perceptions of online learning, by using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT-2) as our baseline model (Venkatesh, Thong, & Xu, 2012). Answering this question is particularly important if we want students to accept technological innovations and feel more successful in online education. We incorporate two variables into our research model that are specifically related to learning and describe students' abilities and characteristics: self-management and the need for interaction. While the former is relatively frequently studied in an educational context (Al-Adwan, Al-Madadha, & Zvirzdinaite, 2018; Al-Rahmi et al., 2022), the investigation of the latter has not been given significant importance. The contribution of our study is to link the UTAUT-2 model with personal characteristic variables that are of particular importance in education, thus providing an explanation of which factors influence the perception of online learning and its acceptance.

The second objective of our research is to answer the question of whether the experience gained during online learning changes the effect of the influencing variables.

To achieve these objectives, we conducted a cross-cohort study among Hungarian business students. Prior to the COVID-19 pandemic, the prevalence of online learning or education in Hungary's higher education landscape was rare. In practice, educators applied digital tools and platforms mainly for semester administration, comprehending the course material, and enhancing it (Dunajeva, 2022). Although there were examples of online education in Hungarian higher education before (K-MOOC, webuni.hu, online courses of universities) (Molnar, Namesztovszki, Glusac, Karuovic, & Major, 2020), there was no precedent of all educational institutions closing down suddenly and immediately and of students and teachers conducting their educational activities only online (Pinter, Fenyvesi, & Pinter, 2021). One of the most dominant phenomena has been the unfairness of access to online learning, also known as digital inequality. According to Pinter et al. (2021) there is indeed a technical dimension to digital inequalities, but it is also important to consider that the degree of user self-reliance and the quality of digital experiences may vary, which may also be sources of inequalities. Our study is focused on business students, given the major transformations the pandemic has induced in the business area. Different business sectors, including retail and personal services, have had to rapidly adapt to these changes and begin operating entirely online (Krishnamurthy, 2020). The sudden appearance of the pandemic has initiated a notable shift towards digital transformation in the business landscape. Therefore, it is crucial to investigate how students who aspire to enter the business world, establish themselves, and even become managers or leaders in a company, can thrive in an almost entirely digitalized environment. Specifically, what factors influence their acceptance of technology in a fully online work environment?

Using cross-cohort analysis gave us the opportunity to compare the answers of those who learned online during the COVID-19 pandemic in 2020 with those who participated in it for a longer period, between 2020 and 2022. The students who filled out the questionnaire studied at the same university, with the same specialization, admitted after the same admission procedure. The only difference between them was the life event they had encountered: online education during COVID-19. We assume that the cohort of business students who were asked in 2020 and faced distance learning without significant experience perceived the characteristics of online learning differently. The personality characteristics we investigated had a different effect on acceptance than the business students with the same background but with more than two years of online learning experience who were asked in 2022. The cross-cohort approach allows the variable "experience" to be included in the model, not as a self-reported variable, but as a real lived reality. Thus, the main contribution of our research is to understand how different life events – which we investigated by researching different cohorts – influence the adoption of online learning.

Based on these objectives, we defined three main research questions.

RQ1: What are the main characteristics of online learning that help or hinder its acceptance?
RQ2: Which personal characteristics of business students affect how perception and acceptance of online learning change?
RQ3: Are there differences in business students' acceptance of online learning based on their experience of online learning?

The structure of our article is as follows. In the first section, we summarize existing research related to online learning and integrate technology acceptance models. Based on these studies, we outline our hypotheses. In the second section, we present our empirical research, in which we tested the same model on two different cohorts of first-year university students in both 2020 and 2022. We describe the scales used and test our hypotheses using structural equations. In the final section, we summarize our results and make suggestions for their potential applications.

2. Literature review and hypotheses

2.1. Technology acceptance of online learning in higher education

Singh and Thurman (2019) found 47 definitions of online learning in a systematic literature review. Based on their review they define the concept as "education being delivered in an online environment through the use of the internet for teaching and learning. This includes online learning on the part of the students that is not dependent on their physical or virtual co-location. The teaching content is delivered online and the instructors develop teaching modules that enhance learning and interactivity in the synchronous or asynchronous environment" (Singh & Thurman, 2019, p. 302). In adopting their definition, the focus of our research is not on the technology, or the various platforms and systems (Romero Martínez, Ordóñez-Camacho, Guillen-Gamez, & Bravo Agapito, 2020), but on the online learning itself, in which students learn at a distance supported by digital technology (the internet and information and communication technology (ICT)).

However, to explore the drivers of online learning adoption, we need to go back to models of technology adoption. In education, digital technology innovations are subject to the same fundamental technology acceptance models as any other technological innovation. In the literature on information technology acceptance, several research directions examine how and why users adopt new technologies (Šumak, Heričko, & Pušnik, 2011). Although several models of technology acceptance have been proposed since the 1960s, the Technology Acceptance Model (TAM) developed by Davis (1986) is the most widely recognized and published model in the field. According to this model, the intention to use a particular technology – and therefore actual usage – can be explained by two factors: perceived usefulness and perceived ease of use, through the attitude to using. TAM became popular in the field of education over the years due to its simplicity, ease of application, and robustness (Al-Emran, Mezhuyev, & Kamaludin, 2018; Granić & Marangunić, 2019). By the 2000s, TAM had slowly been replaced by another widely accepted and applied theory, the UTAUT model, which was developed from eight previous technology acceptance models (Yakubu & Dasuki, 2019). The UTAUT-1 model includes four factors (expected performance, expected effort, social influence, and facilitating conditions) that influence behavioral intention, and therefore use behavior. Later, Venkatesh et al. (2012) added three factors (hedonic motivation, price value, and habit), thereby extending the UTAUT-1 model to UTAUT-2. The UTAUT models have been applied several times in academic contexts, and the results have significantly contributed to understanding the application and acceptance of ICT tools (Ikhsan, Prabowo, & Yuniarty, 2021).

The UTAUT model has already demonstrated its relevance in several fields. In recent years it has been applied to the examination of educational innovations (Herodotou, Maguire, McDowell, Hlosta, & Boroowa, 2021; Hoi, 2020). In our theoretical model, we have incorporated three variables from the UTAUT-2 model –performance expectancy, effort expectancy, and hedonic motivation – which, according to previous studies (Abdul Rabu, Hussin, & Bervell, 2019; Raza et al., 2021; Sidik & Syafar, 2020; Terblanche, Lubbe, Papageorgiou, & van der Merwe, 2023), can have a direct impact on online learning usage intention. These variables primarily refer to the perception of online learning by the individual user, in our case students. Thus, the investigation of their impact can contribute to a better understanding of the online learning adoption process in education.

In the following, we present the three variables that could affect the acceptance of online learning.

2.2. Performance expectancy

According to Venkatesh, Morris, Davis, and Davis (2003), performance expectancy is a measure of the user's belief in the extent to which the system assists them in achieving better results and goals. The authors suggest that performance expectancy is the most influential determinant of technology acceptance and has been used as a variable in numerous studies since its development. In the field of education, Hoi (2020) and Salem and Elshaer (2023) have investigated the effect of performance expectancy in the context of mobile learning, while AL-Nuaimi, Al Sawafi, Malik, and Al-Maroof (2022) have examined the impact of performance expectancy in an online learning environment context. Perceived usefulness – a similar factor to performance expectancy – has a significant direct effect on online learning intentions in the case of a programming course (Rafique, Majeed, Ahmed, & Dou, 2020). The findings from these studies suggest that students who perceive mobile learning or online learning environments as supportive of their learning process and improving their academic performance are more likely to use them compared to those with a lower performance expectancy.

As with traditional education, efficiency is also important in online education (e.g., in terms of mastering the course content and achieving learning goals). The online system must provide support for these aspects at least as effectively as traditional education if the university management intends to introduce online courses in the future. On this basis, we assume that if students find online education effective, they are more inclined to use it.

H1. Performance expectancy positively influences the behavior intention of using online learning technologies in the future.

2.3. Effort expectancy

Effort expectancy represents the extent to which an individual perceives the system as easy to use (Venkatesh et al., 2003). In traditional education, higher education students generally have a clear understanding of how to learn and accomplish learning goals, as they already possess metacognitive knowledge and strategies for managing their learning process. However, online learning requires different strategies and attitudes, whether for processing the course material or adapting to the new learning environment and the changed social interactions. Therefore, it is essential to examine whether the use of the online system poses a challenge for students before introducing online education.

In the studies conducted by Hoi (2020), Raza et al. (2021), Yakubu and Dasuki (2019), AL-Nuaimi et al. (2022), and Salem and Elshaer (2023), effort expectancy has a positive, significant effect on behavior intention, which means that the more users perceive the system as easy to use, the more they are inclined to actually use it.

In our model, we assume that the less effort required and the easier the learning process is for students, the more they prefer to learn online.

H2. Effort expectancy positively influences the behavior intention of using online learning technologies in the future.

2.4. Hedonic motivation

The pleasure associated with online learning is represented by the hedonic motivation variable in the UTAUT-2 model. This variable relates to how much the user perceives the use of the system as enjoyable or as fun (Venkatesh et al., 2012).

In this study, we hypothesize that an individual may enjoy learning and find pleasure in mastering it, even if the learning process is not easy for them to achieve their learning goals. Research in the field of education proved the direct positive effect of enjoyment or hedonic motivation on behavior intention in their research model (Alam, Mahmud, Hoque, Akter, & Sohel Rana, 2022; Arain, Hussain, Rizvi, & Vighio, 2019; Moorthy et al., 2019). Similar to these studies, we assume that the feeling of joy and pleasure percepted during online learning positively influences and motivates the user to accept and use the online learning platform. Thus, our research model included hedonic motivation as a direct variable influencing behavioral intention.

H3. Hedonic motivation positively influences the behavior intention of using online learning technologies in the future.

In the following sections, we present the personal characteristics that may affect the perception of performance, effort, and enjoyment of online learning, thus proposing hypotheses to answer our second research question.

2.5. Personal characteristics

An individual's personal characteristics and personality can influence the intention to use through cognitive and psychological processes (Sindermann, Riedl, & Montag, 2020). It is not a coincidence, therefore, that in the context of online learning, research models often include individual personal traits and characteristics as factors influencing usage (Baber, 2021). Personality traits are often included in online learning studies, like the Big Five Personality Traits (Abe, 2020), mental health-related factors like stress especially in COVID-related studies (Chu & Li, 2022) or personality traits related to technology, like self-efficacy or computer anxiety (Siron, Wibowo, & Narmaditya, 2020; Syahruddin et al., 2021). Besides these factors, education-related aspects are also of great importance. One of the most researched among these is self-regulated learning (Wang & Zhang, 2019, pp. 32–37) since in an online learning environment, instructional presence is less pronounced compared to traditional education.

While there can be numerous personal characteristics to include, our study focuses on one factor that is a general technology-oriented factor – the need for interaction – and one that is relevant to education – self-management of learning.

2.6. Need for interaction

Although internet technologies were already being used for communication prior to the COVID-19 pandemic, the majority of users were more likely to prefer and organize in-person meetings to maintain relationships. Distance education thus posed new challenges for participants who could work and learn together only through online communication, with all the advantages and disadvantages that this entails.

In the past, the strongest criticisms of online education and learning have been related to the method of communication and interaction, or the complete lack thereof. Fortunately, with the development of technology, collaboration and communication opportunities have improved and expanded, resulting in a proportional increase in the learning experience (Dailey-Hebert, 2018). In online learning, communication can occur between learner-learner, learner-content, and teacher-learner. The latter, according to Dailey-Hebert (2018), can be a significant factor in learner satisfaction. Online learning provides the learner with a range of new experiences (both positive and negative) that can even influence the success of learning. For example, in Kuong's (2015) qualitative research, students found online education to be more comfortable and flexible, providing more time to master the course material. However, they missed face-to-face interactions, personal contact, and immediate feedback, which were undoubtedly reinforced by the lack of synchronous education. The results of Kang & Park's research also emphasize the importance of instuctor's feedback (Kang & Park, 2022) which have a bold effect on student satisfaction. A lack of personal interaction is also reported by Grothaus (2023) in her qualitative research, where German students referred to a lack of affective engagement due to ineffective communication with peers and lecturers.

The need for personal interaction is a widely studied factor in the field of acceptance of self-service technologies (Curran & Meuter, 2005; Dabholkar & Bagozzi, 2002; Rose & Fogarty, 2006; Walker & Francis, 2003). The variable, which is an important factor in the adoption of self-service technologies, refers to an individual characteristic that determines the degree to which the consumer considers personal interaction important while using the service (Dabholkar, 1996).

According to Dabholkar and Bagozzi (2002) and Rose and Fogarty (2006), consumers who value personal interaction with service providers perceive the service as less efficient and less easy to use in the absence of such interaction, which suggests a negatively related variable. Chavoshi and Hamidi (2019) demonstrate the importance of online communication and interaction for ease of use and effectiveness in education. Thus, we believe that the importance of interaction is even more pronounced when it comes to the personal need for interaction. Based on these findings, we hypothesize that the importance of and need for personal interaction have a negative effect on the student's effort and performance expectancy.

H4a. Need for interaction negatively influences performance expectancy.

H4b. Need for interaction negatively influences effort expectancy.

Alalwan et al. (2019), Demoulin and Djelassi (2016), Raman (2021) found that various forms of pleasure and interaction variables influence technology use, either as independent variables or as moderator variables influencing relationships between other constructs. However, we believe that the user's need for interaction can directly influence their perception of enjoyment during online learning, as in the gaming industry (J. Lee, Kim, & Choi, 2019), and also in the case of university courses.

H4c. Need for interaction negatively influences hedonic motivation.

2.7. Self-management of learning

With online education, the previous role of instructors as providers and facilitators of knowledge has transformed, increasing the responsibility of students to master the course material (Shreaves, Ching, Uribe-Florez, & Trespalacios, 2020). In March 2020, higher education stakeholders had to rapidly switch from face-to-face to online education, which represented a sudden, significant change for the students as well. As the new situation required a completely different learning attitude, style, and time management, we were interested in examining how autonomy, self-organization skills, and the sudden high degree of "freedom" influence the transition to online learning, and the acceptance of it in the future. As Means and Neisler (2021) reported the main problem for students during the COVID-19 online learning was how to stay motivated during the course.

Recently, self-directed learning and self-regulated learning have become popular constructs for researchers to investigate (Yeh et al., 2019), but these concepts can extend beyond the possibilities of online learning introduced in March 2020. Students did not have the opportunity to personalize their tasks and learning environment or set ambitious learning goals on the online platform, which although aligned with traditional frameworks, was still significantly different from the traditional format and continued to be regulated by instructors, subject coordinators, university operational schedules, and regulations. Thus, students' self-regulation opportunities were limited to time and resource management for learning tasks. Zhu, Bonk, and Berri (2022) studied these two student learning strategies in relation to the use of massive open online courses. As self-management is defined in the literature as "the degree to which a student is self-disciplined with the capability of engaging in learning autonomously" (Abdallah, Abdallah, & Bohra, 2021; Al-Adwan, 2020; Al-Adwan, Al-Adwan, & Berger, 2018; Al-Adwan, Al-Madadha, & Zvirzdinaite, 2018; Al-Rahmi et al., 2022; Alasmari & Zhang, 2019), we assume that this personal characteristic is the most appropriate for examining students' online learning acceptance in the aforementioned educational situation.

While self-management is a key individual characteristic in research on the adoption of online learning, it is rarely used in this context. We assume that students who can independently and autonomously organize their learning process, adjusting their learning pace, time management, and preferences to accomplish their tasks, will find online education more effective and easier. In addition to usefulness and ease of use, intrinsic, hedonic motivation derives from the pleasure and satisfaction of the task or activity itself (Lin, McKeachie, & Kim, 2003; Sharif & Raza, 2017). In our research, we hypothesize that students who are able to organize and control their learning process autonomously will perceive online learning as more enjoyable and pleasurable.

H5a. Self-regulated learning positively influences effort expectancy.

H5b. Self-regulated learning positively influences performance expectancy.

H5c. Self-regulated learning positively influences hedonic motivation.

2.8. Impact of prior experience on acceptance: a cross-cohort approach

To answer our third research question, we propose a cross-cohort approach to compare students with different backgrounds in online learning. Cross-cohort analysis is a research method that compares two or more distinct groups (or cohorts) that are defined by specific characteristics, such as the time period they experienced a particular event or their exposure to certain conditions. The goal is to identify similarities, differences, and trends between these groups to understand how their experiences or characteristics influence outcomes (Gnambs & Hanfstingl, 2016; McElroy et al., 2021).

Although, the role of experience in internet and computer use is highlighted as a crucial factor in e-learning acceptance (Abdullah & Ward, 2016), relatively few studies have examined it. Prior experience is integrated in the original UTAUT2 model as a moderator (Venkatesh et al., 2012), while experience is often included in models as a self-reported observed (Asarta & Schmidt, 2020) or latent variable (Al-alak & Alnawas, 2011; Y.-H. Lee, Hsieh, & Chen, 2013). Landrum (2020) has proved that the number of previous online learning courses has significantly effected satisfaction with online learning. We propose a different approach by investigating the various life experiences of different student cohorts as a proxy for experience. The objective is to investigate the distinctions between students with actual online learning encounters and those lacking any pertinent prior exposure. A worldwide event, the introduction of online education during COVID-19, provided an opportunity for this investigation. In 2020, educational institutions around the world had to switch from traditional education to distance education overnight to ensure the health of their teachers and students. While online education was already available in some countries and universities before 2020, a significant portion of teaching at most universities was done in person (Majewska & Zvobgo, 2023). Most teachers and students had to adapt to distance education without significant prior experience. In contrast, for those who entered university in later years, online education was a familiar, natural experience since they had become accustomed to it during their high school and/or previous university years. Through cohort analysis, the respondents share similar parameters in all aspects, except for the effects of the 2020 COVID-19 pandemic. Our research objective is to examine how the online learning acceptance model presented changed in the two different cohorts.

We assume that personal characteristics are less important for those who already have significant online learning experiences. Since there was no significant experience in online learning in 2020, we believe that those who already had a strong self-management ability perceived online learning more positively, found it less difficult to use effectively, and enjoyed it more than those who did not have this ability. In contrast, by 2022, most students had learned how to study independently and effectively during their high school/university years due to necessity, so this ability did not have such a significant impact on their perception of online learning. Similarly, the effect of the need for interaction may have diminished with the experience that personal contact is not necessarily required for effective and enjoyable online learning.

H6a. The impact of personal characteristics is stronger for those business students who are less experienced compared to those who already have experience with online learning technologies.

In line with the results of Venkatesh et al. (2012), our initial assumption regarding the perceived characteristics of online learning is that there has been no significant change in its effects: Those who perceive online learning as enjoyable, efficient, and easy to use also have higher acceptance rates, whether they have prior experience (2022 cohort) or not (2020 cohort). With this assumption, we argue for the robustness and generalizability of the UTAUT model.

Table 1
Scale items, means, factor loadings, and sources.

Construct	Item	Factor loadings		Means		Scales
		2020	2022	2020	2022	
Need for interaction	I would miss the collaborative thinking that can be achieved in a seminar during online education.	0.83	0.81	5.05	5.19	Based on Dabholkar and Bagozzi (2002), Collier and Kimes (2013)
	Personal contact with the lecturer is an important part of university education.	0.83	0.79	5.24	5.47	
	For me, it contributes to my studies at university to hear the opinions and comments of my fellow students in class.	0.78	0.71	5.35	5.41	
	Personal attention by the lecturer is an important part of university education for me.	0.76	0.83	4.87	5.04	
	The personality of the lecturer and their ability to convey their knowledge in person is important to me.	0.74	0.74	5.06	5.13	
	Personal meetings with my fellow students are an important part of university education for me.	0.77	0.73	6.14	6.04	
Hedonic motivation	Learning online is fun.	0.84	0.87	3.94	3.55	Based on Venkatesh et al. (2012)
	Learning online is enjoyable.	0.74	0.76	4.01	3.78	
	Learning online is very entertaining.	0.72	0.65	4.03	3.83	
Performance expectancy	I find online learning more useful than face-to-face learning.	0.87	0.86	3.68	3.88	Based on Venkatesh et al. (2012)
	Learning online increases my productivity.	0.56	0.58	4.02	4.02	
	Learning online helps me accomplish the course material more quickly than in face-to-face form.	0.80	0.85	3.62	3.84	
Self-management of learning	In my studies, I am not self-disciplined and I do not find it easy to set aside reading and homework time.	0.85	0.84	4.05	4.55	Based on Al-Adwan, Al-Adwan, and Berger (2018)
	I can manage my study time effectively and easily complete assignments on time.	0.83	0.79	4.39	4.52	
	I am not self-directed when it comes to studying.	0.72	0.73	3.95	4.35	
Effort expectancy	Learning online is not easy for me.	0.85	0.85	5.28	5.29	Based on Venkatesh et al. (2012)
	I find online learning easy to use.	0.81	0.75	5.35	5.62	
	It is easy for me to become skillful at learning online.	0.80	0.79	5.19	5.13	
Behavioral intention	In my opinion, universities should increasingly adopt online learning instead of the traditional form of education.	0.74	0.79	3.63	3.52	Based on Venkatesh et al. (2012)
	I would like to take online classes where I do not meet the teacher in person, only in a distance learning format.	0.68	0.67	4.47	3.94	
	I do not intend to continue learning online.	0.79	0.67	4.62	4.58	
	If I have the opportunity, I definitely intend to continue learning online.	0.74	0.79	4.35	4.38	
	I would like the university to allow online learning for as many courses as possible.	0.79	0.78	4.60	4.31	
	Online learning is the future.	0.71	0.78	4.27	4.08	

H6b. Perceived performance expectancy, effort expectancy, and hedonic motivation have the same impact on future behavior intention for those business students who are less experienced compared to those who already have experience with online learning technologies.

3. Research method

3.1. Research design and sample

To answer our first two research questions we employed a questionnaire-based survey. In the survey, we measured the variables in the theoretical model with the help of previously validated scales. To answer our third research question and to compare those business students who already had online experience with those who had not, we undertook a cross-cohort analysis.

We collected data from the same type of business students in the same life-cycle of their studies at two different time points. First-year undergraduate students in Business and Management Specialization were randomly selected in May 2020 and May 2022. They filled in the questionnaire in the frame of a Principles of Marketing course for course credit. They were students at the same Hungarian university, with the same specialization, admitted after the same admission procedure. The only distinction between them was the life event they encountered: online education amid the COVID-19 pandemic. Those students who completed the 2020 questionnaire were in the middle of their first semester of online education when they were confronted for the first time and in full reality with distance learning. The sample in 2022 had undergone online education throughout their high school years and entered university with two years of prior online learning background. While in 2020, online education was compulsory, in 2022 some classes were online, but most of the classes were offline. To test our theoretical model, we collected data with the same questionnaire at the two data points using Qualtrics. The 2020 questionnaire was completed by 293 first-year students (73% response rate). The average age of the respondents was 19.96 years (SD = 1.12); 64.2% of the sample was female. The 2022 questionnaire was completed by 283 first-year students (80% response rate). Respondents had an average age of 19.89 years (SD = 0.96), and 50.5% of the sample was female.

3.2. Measures

To measure the constructs of the research model and to test our hypotheses, we developed a survey instrument with measurement scales. The questionnaire consisted of six constructs using a seven-point Likert scale from 1-strongly disagree to 7-strongly agree. We adopted the scales from previous studies (Appendix 1). We based six items for need for interaction on Dabholkar and Bagozzi (2002) and Collier and Kimes (2013), and three items for self-management of learning on Albelbisi (2019). We based the scale for behavior intention on Venkatesh et al. (2012) and adapted it to online learning. A detailed description of the scales is given in Table 1.

3.3. Analysis method

We applied a two-stage approach to testing our research model (Anderson & Gerbing, 1988). First, we tested the validity and reliability of our measurement model with the help of confirmatory factor analysis. The internal reliability and convergent and discriminant validity of the latent variables, just as the goodness of fit of the measurement model were assessed. Second, we adopted structural equation modeling to test the hypothesized relationships between the latent variables. Structural equation modeling is an adequate method to simultaneously analyze all relationships between all latent and observed variables in the model (Hayes, 2013).

SEM combines elements of multiple regression and factor analysis. It is a comprehensive statistical modeling tool capable of analyzing multivariate data with intricate relationships between variables. SEM has various strengths over traditional multivariate techniques like regression. It allows multiple relationships and endogenous variables to test in one model. SEM accommodates measurement error and allows researchers to assess the alignment between the theoretical model and sample data, a capability not as easily achievable with conventional multivariate methods. The primary focus of SEM in this investigation is to analyze causal relationships described in the hypotheses. SEM has its advantages but also its limitations. One such limitation is that, as with any regression-based model, it cannot be used to test the direction of causal relationships, which must always be driven by the theory. Another limitation is that, like most self-report methods, it works with perceived data, making it difficult to capture real, objective behavior.

As our model is based on a cross-cohort analysis comparing answers from business students in 2020 and 2022, we performed a multi-group moderation analysis. Although not using multi-group analysis, Hansen-Brown, Sullivan, Jacobson, Holt, and Donovan (2022) showed that comparing two different cohorts obtained useful results. To make the two groups comparable with the same measurement model, we tested the two cohorts with the help of a series of invariance tests. We compared the baseline model with nested models to check the invariance across the two groups. Once we reached measurement invariance, we tested structural invariance and compared the structural paths of the two models with the help of chi-square difference tests. For confirmatory factor analysis and structural equation modeling analyses, we used SPSS Amos version 27.00.

4. Results

4.1. Confirmatory factor analysis and measurement model invariance testing

We performed confirmatory factor analysis on the two groups separately. First, we tested internal consistency and reliability of the composite measures. We checked the internal consistency and reliability of the indicators by linking each scale item to its corresponding latent constructs and estimating the covariances between them for both groups. All factor loadings were above the threshold level of 0.5 and all weights were significant ($p < 0.001$), supporting convergent validity. Table 2 shows that the average variance extracted (values are above the 0.5 threshold value, fulfilling the convergence validity criterion in each sample (Fornell & Larcker, 1981). Both Cronbach α and composite reliability CR) indicators are above 0.7 for each variable, thus, corresponding to the threshold (Nunnally, 1967). In addition, the correlation between any two constructs was less than the square root of the average variance extracted value, indicating that discriminant validity was satisfied for each sample; the scales were sufficiently different from each other (Fornell & Larcker, 1981). We also used confirmatory factor analysis to examine the model fit (Table 3). The χ^2_{2020} was 475.138 with df = 235 degrees of freedom and their ratio was 2.022, while the χ^2_{2022} was 481.211 with df = 235 and the χ^2/df ratio was 2.048, which is less than 3 in both cases, thus meeting criterion validity (Byrne, 2010). The comparative fit index, CFI = 0.963 for sample 2020 and CFI = 0.944 for sample 2022 are above 0.9. threshold (Hu & Bentler, 1999). The Root Mean Square Errors of Approximation (RMSEA) in the calculation were 0.059 (2020) and 0.061 (2022), which were below the threshold of 0.08 (Hu & Bentler, 1999).

To test measurement invariance between the two cohorts, we performed a multi-group analysis and ran invariance tests with nested models. Configural invariance refers to the factor structure of the models (Kline, 2016). We estimated the least restrictive model, the configural model with all parameters freely estimated across the two cohorts. Based on the above-documented goodness of fit indexes, both models fit well. Thus, configural invariance is supported; the same factor structure is identified for both groups. Next, we examined metric invariance by constraining the factor loadings to be equal in the cohort groups and tested the model against the baseline (configural) model. Metric invariance is reached when the difference between the constrained and unconstrained model is non-significant. To test the difference ΔChi-square and delta ΔCFI are suggested (Cheung & Rensvold, 2002). As in our case $\Delta\chi 2(18) = 20.186$, $p = 0.001$ is significant based, so we checked the difference in the values of CFI. When $\Delta CFI \leq 0.01$, the decrease in model fit is not substantial with the imposition of the equality constraints. In our case ΔCFI is less than 0.01 (CFI(configural)-CFI(metric) = 0.95-0.949 = 0.001). Thus, metric invariance is indicated between the two cohorts (Chen, 2007).

4.2. Structural model assessment

Before testing our hypotheses, we checked the structural model's fit indexes. Based on our results, χ^2_{2020} was 519.353 with df = 239 degrees of freedom and χ^2/df ratio was 2.173 ($p = 0.000$), while the χ^2_{2022} was 594.993 with df = 241 degrees of freedom and the χ^2/df ratio was 2.469, which is less than 3, meeting the threshold in both cases. The CFI = 0.963 for sample 2020 and CFI = 0.92 for sample 2022 also meet the criterion (above 0.9). RMSEA was 0.063 for model 2020 and 0.072 for model 2022, which are below the threshold of 0.08. The predictive index for the model strength is $R^2 = 0.706$ for sample 2020 and $R^2 = 0.617$ for sample 2022. The exogenous variables thus explain 70.6% and 61.7% of the variance of the endogenous variable in each model, ceteris paribus.

Table 4 presents the results of the hypotheses testing. The effects of the antecedent variables on the endogenous variables are significant at a 5% significance level with two exceptions; the relationship between need for interaction and effort expectancy in both models and the relationship between effort expectancy and behavioral intention were not significant in model 2020. Hypothesis H1 is accepted, i.e. it is true that performance expectancy has a positive effect on behavioral intention ($\beta_{2020} = 0.412$, $p < 0.001$; $\beta_{2022} = 0.211$, $p < 0.001$). Contrary, based on model 2020, hypothesis H2 has to be rejected. Thus it cannot be confirmed that effort expectancy has a positive effect on behavioral intention ($\beta_{2020} = -0.014$, $p = 0.798$). However, in model 2022, hypothesis H2 is accepted ($\beta_{2022} = 0.268$, $p < 0.001$). Hypothesis H3 is also supported: The experienced pleasure while learning online has a positive effect on behavioral intention in both cohorts ($\beta_{2020} = 0.439$, $p < 0.001$; $\beta_{2022} = 0.616$, $p < 0.001$). Hypotheses H4b ($\beta_{2020} = -0.731$, $p < 0.001$; $\beta_{2022} = -0.352$, $p < 0.001$) and H4c ($\beta_{2020} = -0.538$, $p < 0.001$; $\beta_{2022} = -0.541$. $p < 0.001$) regarding the need for interaction are also supported, as the variable has a negative effect on performance expectancy and hedonic motivation. Nevertheless, hypothesis H4a is rejected in both models concerning the relationship between the need for interaction and effort expectancy ($\beta_{2020} = 0.008$. $p = 0.927$; $\beta_{2022} = -0.139$. $p = 0.125$). Self-regulated learning has a significant effect on the three perceived online learning variables, the hypothesized positive effects in H5a ($\beta_{2020} = 0.345$, $p < 0.001$; $\beta_{2022} = 0.327$, $p < 0.001$), H5b ($\beta_{2020} = 0.794$, $p < 0.001$; $\beta_{2022} = 0.446$, p

Table 2
Results of the reliability and validity analysis.

	Cohort	CRα	CR	AVE	EE	NI	PE	HM	SM	BI
EE	2020	0.802	0.805	0.579	**0.761**					
	2022	0.768	0.769	0.527	**0.726**					
NI	2020	0.908	0.906	0.619	−0.09	**0.787**				
	2022	0.895	0.892	0.582	−0.247	**0.763**				
PE	2020	0.863	0.865	0.682	0.297	−0.476	**0.826**			
	2022	0.865	0.873	0.698	0.277	−0.413	**0.836**			
HM	2020	0.938	0.939	0.837	0.395	−0.411	0.652	**0.915**		
	2022	0.915	0.917	0.786	0.262	−0.431	0.648	**0.887**		
SM	2020	0.832	0.842	0.645	0.328	−0.301	0.621	0.524	**0.803**	
	2022	0.815	0.817	0.598	0.455	−0.392	0.544	0.445	**0.773**	
BI	2020	0.93	0.929	0.687	0.309	−0.653	0.701	0.771	0.48	**0.829**
	2022	0.915	0.914	0.642	0.402	−0.602	0.605	0.758	0.398	**0.801**

EE – Effort expectancy, NI – Need for interaction, PE – Performance expectancy, HM – Hedonic motivation, SM – Self-management, BI – Behavioral intention.

Table 3
Fit indexes for the measurement model.

CFA	2020	2022	Threshold
CMIN	475.138	481.211	–
DF	235	235	–
CMIN/DF	2.022	2.048	Between 1 and 3
CFI	0.954	0.944	>0.9
NFI	0.914	0.897	>0.9
IFI	0.955	0.945	>0.9
TLI	0.946	0.934	>0.9
RMSEA	0.059	0.061	<0.08

Table 4
Results of hypothesis testing.

	B		β (std.)		S.E.		p		Result	
	2020	2022	2020	2022	2020	2022	2020	2022	2020	2022
PE → BI	0.41	0.21	0.47	0.18	0.05	0.06	***	***	H1 is supported	H1 is supported
EE → BI	−0.01	0.27	−0.01	0.19	0.05	0.08	0.798	***	H2 is **not** supported	H2 is supported
HM → BI	0.44	0.62	0.51	0.62	0.05	0.06	***	***	H3 is supported	H3 is supported
NI → EE	0.01	−0.14	0.01	−0.11	0.08	0.09	0.927	0.125	H4a is **not** supported	H4a is **not** supported
NI → PE	−0.73	−0.35	−0.41	−0.25	0.11	0.09	***	***	H4b is supported	H4b is supported
NI → HM	−0.54	−0.54	−0.30	−0.32	0.11	0.11	***	***	H4c is supported	H4c is supported
SM → EE	0.34	0.33	0.36	0.41	0.07	0.07	***	***	H5a is supported	H5a is supported
SM → PE	0.79	0.45	0.57	0.48	0.09	0.07	***	***	H5b is supported	H5b is supported
SM → HM	0.67	0.41	0.47	0.37	0.09	0.08	***	***	H5c is supported	H5c is supported

EE – Effort expectancy, NI – Need for interaction, PE – Performance expectancy, HM – Hedonic motivation, SM – Self-management, BI – Behavioral intention.

< 0.001), and H5c ($\beta_{2020} = 0.667$, $p < 0.001$; $\beta_{2022} = 0.41$, $p < 0.001$) are all supported. Fig. 1 summarizes the results of the structural model testing. Fig. 1 shows the standardized betas based on Table 4; the relationships where significant differences were observed between the two cohorts are indicated in **bold**.

4.3. Multi-group moderation with the two cohorts

Examining the paths in the structural model, we find that there are three cases where there is a difference between the two groups: the relationship between self-management and performance expectancy ($\Delta\chi2(1) = 3.888$, $p = 0.049$), the relationship between self-management and hedonic motivation ($\Delta\chi2(1) = 3.997$, $p = 0.046$), and the relationship between effort expectancy and behavioral intention ($\Delta\chi2(1) = 6.321$, $p = 0.012$) (Table 5). Based on these results, we partially accept hypothesis H6a. Prior experience moderates the effect of self-management and performance expectancy ($\beta_{2020} = 0.566$, $\beta_{2022} = 0.478$), and the effect of self-management and hedonic motivation ($\beta_{2020} = 0.469$, $\beta_{2022} = 0.368$). For these relationships, it is confirmed that the impact of personal characteristics is stronger for those students who are less experienced compared to those who already have experience with online learning. Similarly, we can partially accept hypothesis H6b, as only performance expectancy ($\beta_{2020} = 0.469$, $\beta_{2022} = 0.179$), and hedonic

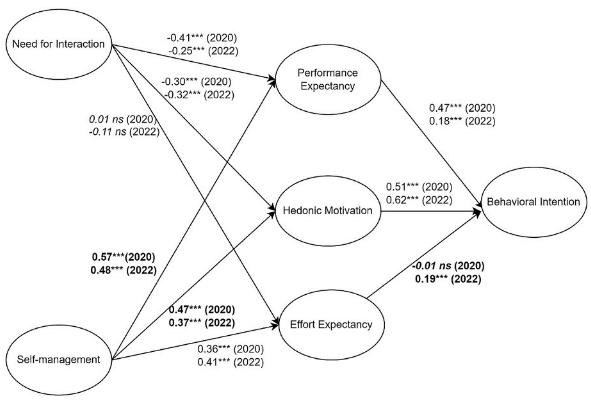

Fig. 1. Results of the structural model for the two cohorts
***p < 0,001; ns – not significant
Bold: Significant difference between the two cohorts; Italic: not significant.

motivation ($\beta_{2020} = 0.507$, $\beta_{2022} = 0.623$) have the same impact on acceptance for those students who are less experienced compared to those who already have experience, as the cohort analysis results did not show a difference in these relationships.

5. Discussion

In our research, we examined the factors influencing the acceptance of online management education in two cohorts of students. Based on our findings, we make several important observations.

First, our results show that students' perception of the performance, effortlessness, and enjoyment of online learning has a significant effect on their adopting it. Second, we can conclude that these effects change depending on experience.

After testing the hypotheses, we found that performance expectancy had a significant positive effect on behavioral intention to learn online in the future. Therefore, the more effective students in management higher education perceive online education to be, the more likely they will use it in the future. This aligns with most of the results of previous studies on performance expectancy (Hoi, 2020; Salem & Elshaer, 2023). The effect of performance expectancy holds for both cohorts. Thus, we can state that the expected improvement in learning performance caused by online learning has a positive effect independent of past experiences.

Hedonic motivation also contributes positively and significantly to the behavioral intention in both tested models, indicating that the more enjoyable students perceive online learning to be, the more they will want to participate in it. This effect was also reported in previous research, so the results of this study confirm prior findings (Arain et al., 2019; Kaisara, Atiku, & Bwalya, 2022; Moorthy et al., 2019). Even if the 2022 model shows a stronger relationship between hedonic motivation and behavioral intention, based on the results of the moderation analysis, there is no significant difference between the two groups.

Although the results of the moderation analysis confirm no significant difference in the paths in terms of performance expectancy and hedonic motivation, it seems that the gap between the two is increasing, which may be a future trend. We imply that when it was necessary to develop a new learning strategy and focus on achieving learning goals and results during the unexpected situation in 2020, efficiency played a more important role, and the opportunity to enjoy online learning was less emphasized. In contrast, two years later, for students who had already gained some routine in high school after several semesters of online or hybrid education and also had the option of completing university classes online, the enjoyment of online learning became more important.

Based on the results of hypothesis testing, effort expectancy did not have a significant effect on behavioral intention to learn online for the 2020 cohort. This result is not surprising according to the literature, as authors such as Altalhi (2021), Alowayr (2022), and Doleck, Bazelais, and Lemay (2018) have all reported non-significant results when examining the impact of effort expectancy on technology acceptance. Most of the authors explain the surprising result by the fact that as students are already conscious of the technological background of online learning, it is not challenging for them to use online learning.

Among the explanations, it is worth highlighting that provided by (Doleck et al., 2018). They argue that in situations where both efficiency and performance may be essential in the use of technology but where performance expectancy is a more important factor to the user than effort expectancy, then effort expectancy may not appear as a significant result in the tested model. In these performance-critical systems, the need for performance exceeds the necessary extra effort. In the course of education, even in traditional forms, there are many situations where students have no other option to meet the learning requirements necessary to achieve the learning objective but within the given educational framework, as was the case in the context of the present study in 2020 when mandatory online learning was introduced. Thus, the non-significant effect of effort expectancy in the 2020 model can also be explained by the sudden, radical changes that required focusing on learning outcomes and striving for efficiency, trumping expectations for ease of use. However, in 2022, when online courses became more optional, and students had learned to study effectively online, the ease of use in the online learning environment became a significant influencing factor for the behavioral intention to learn online. The different results of the two models are also supported by the cohort analysis, showing a significant difference between the two groups in the relationship between effort expectancy and behavioral intention.

The third important contribution of our study is the inclusion of personal characteristics in the UTAUT model. The results suggest that both the need for interaction and self-management have important effects but with different impacts depending on experience.

The impact of self-management on performance expectancy, effort expectancy, and hedonic motivation proved to be significant for both cohorts. Students who are able to manage their time and tasks successfully perceive online learning as more effective, enjoyable,

Table 5
Moderation χ^2 difference test.

	$\Delta\chi^2$	Δdf	p	Result
NI → PE	1.008	1	0.315	No difference
NI → HM	0.000	1	0.982	No difference
NI → EE	1.241	1	0.265	No difference
SM → PE	3.888	1	0.049	Difference
SM → HM	3.997	1	0.046	Difference
SM → EE	0.011	1	0.915	No difference
EE → BI	6.321	1	0.012	Difference
HM → BI	0.548	1	0.459	No difference
PE → BI	1.116	1	0.291	No difference

EE – Effort expectancy, NI – Need for interaction, PE – Performance expectancy.
HM – Hedonic motivation, SM – Self-management, BI – Behavioral intention.

and easier, and are therefore more likely to choose it and use it. Online education makes it more difficult to achieve the same level of instructor control compared to traditional education. In addition, in 2020, the usual frameworks were changed. For example, timetables were no longer in place in many universities; changes in the familiar environment also altered previous study patterns, thus it was harder to concentrate on tasks in the comfort of home, close to family (Dung, 2020; Hasan & Khan, 2020). Therefore, the capability to self-manage learning turned out to be a crucial factor for students and became decisive in the perception and acceptance of online learning.

While the importance of interaction and collaboration for achieving learning goals is often researched, fewer studies have focused on how the need for interaction, as a fundamental personality trait of students, influences their attitude toward online learning.

Based on our results, the personal characteristic of students' desire for direct interaction has a significant negative effect on performance expectancy and hedonic motivation in both structural models. Thus, students who value personal interaction and communication with peers and instructors find online learning less efficient and less enjoyable. Although qualitative research by Kuong (2015) and Otter et al. (2013) has highlighted the fact that students found the lack of face-to-face communication a frustrating perception and were therefore unlikely to use distance learning in that form in the future, our research demonstrates the importance of this factor in an educational context with the help of a quantitative model. Based on our findings, we can conclude that the need for interaction is an important factor in the acceptance of online learning.

While in the case of performance expectancy and hedonic motivation, the relationship with the need for interaction was significant; in the case of effort expectancy, it was not significant in either model. Therefore, the importance of personal interaction for the student does not have consequences for how much effort they perceive in using online learning. Students can handle the online learning environment on their own and do not rely on the presence of instructors or peers.

An important result of the cohort analysis is that the effect of personal characteristics has split into two aspects for the two variables: the need for interaction and self-management. The need for interaction proved to be equally important as a personal characteristic in both periods, which cannot be overruled by experience. If a student has a high need for personal interaction, this need does not change even if they gain sufficient experience and routine in online learning. Thus, the need for interaction can be considered a stable personal characteristic in terms of how students perceive online learning. On the other hand, based on the moderation analysis, the effect of self-management, except for effort expectancy, has significantly weakened in its effect on hedonic motivation and performance expectancy. According to this result, over the past two years, the "post-COVID-students" have more or less learned to manage themselves, and the effect of this personal characteristic has weakened in this regard.

6. Implications and future research

Our research has shown that the future adoption of online learning in management education is influenced by the perceived performance, effortless use, and enjoyment of online learning and the personal characteristics of the students. From the perspective of online learning, how enjoyable students perceive it appears to be highly important. Beyond the fact that it was slightly more important than performance expectancy for business students receiving online education in 2020, by 2022 its impact had far exceeded that. This result draws our attention to the fact that for business students, online learning is not enough to be an effective solution for acquiring knowledge; it also needs to be entertaining if we want them to be satisfied and choose this type of educational format in the future. Furthermore, the requirement of efficiency of the applied technology has gained value through experience. If online education is not mandatory but a genuine choice, it needs to be user-friendly and not require significant effort from students to use the application.

In addition to the perceived characteristics of online learning, we can draw important conclusions regarding the changing impact of students' personal attributes. Based on our findings, in management education, the performance and personal well-being of students who require personal interaction can be negatively affected by a learning system in which students do not meet face-to-face with their instructors and peers. Besides highlighting the importance of personal interaction, our results demonstrate the importance of self-management. Students who can independently and autonomously organize their learning process, adjusting their learning pace, time management, and preferences to accomplish their tasks, will find online education easier, more effective, and more enjoyable. Based on the results of the cohort analysis, it is apparent that the need for interaction is a personal characteristic, the importance of which has not changed remarkably over time, and which can be a deeply ingrained psychological need for certain students that must be considered when organizing education. Consequently, it may be beneficial for policy-making and curriculum design to implement a blended or hybrid educational format. This approach allows students to engage with one another in class while also providing them the flexibility to schedule their preparation time for tasks independently. If the introduction of hybrid education is not feasible or desired for business schools, it may be worth increasing feedback from the instructor (Kang & Park, 2022) and/or changing the current structure of online classes or communication blocks (Chavoshi & Hamidi, 2019; Meletiou-Mavrotheris, Eteokleous, & Stylianou-Georgiou, 2022), combining synchronous and asynchronous communication forms, and choosing the appropriate ratio of each to ensure optimal learning conditions (Dailey-Hebert, 2018). However, it is important to consider the type of tasks and the skills of the learners (Tu & McIsaac, 2002). Neglecting these factors can easily lead to a decrease in learning effectiveness. In synchronous forms, the emotional charge of interactions is stronger. Through immediate response opportunities, differences in opinion can be discussed, collective thinking can be fostered, and knowledge construction can be facilitated through reflection on each other's ideas. On the other hand, solving complex tasks requiring concentration may be more effective in the case of asynchronous learning.

In contrast to the need for interaction, self-management was found to be a personal characteristic that could be improved by experience, according to the cohort analysis, as the effect of the variable weakened over the years. Therefore, policy-makers, so the universities should provide opportunities for students to develop their self-management skills, such as through training sessions. Additionally, it is important to consider that for those who have difficulty independently managing their learning processes, providing frameworks such as a class schedule, and multiple opportunities for assessment, monitoring, and consultations can be crucial. This aspect is also important because the ability to learn to effectively use online learning can give students an important advantage in the world of work. From this perspective, it is therefore important to draw attention to the responsibility of universities in training future workers and teaching them the skills needed to work online.

The limitation of our research is that we only surveyed students from one university's business program; a future research project could be to expand the sample to other universities or other fields of study. Additionally, it may be worthwhile to conduct a cross-cultural analysis by comparing data collected from countries with more advanced and less advanced online education systems. Another potential perspective for future research is to extend the study to additional years to observe the effects of the constructs examined on the acceptance of online education over a longer period. In the post-COVID context, the research model can be enhanced by integrating additional factors. Experiences in online education can influence business students' confidence in applying technology. For instance, with the rise of distance learning, numerous students encountered challenges in presenting in virtual environments, managing video recordings, or engaging effectively in conference calls, which are now essential skills in both online education and online work. In the post-COVID period, the strengthening of digital soft skills during the pandemic may have changed students' self-confidence, i.e. self-efficacy in using technology, which may also have an impact on the effort expectancy and self-management variables we are studying. Considering the development of students' skills and characteristics, it is important to explore factors associated with students' mental health and cognitive load in the post-COVID context. These factors may have significantly influenced satisfaction with technology use during COVID and remain relevant in the current "ordinary" online learning as well as in the job and business realm (e.g., isolation, digital fatigue, anxiety). The mandatory distance learning during the pandemic required students to develop various coping strategies to address these challenges. It could be beneficial to explore how business students in distance learning programs during the post-COVID period manage mental health issues and how this influences their technology usage. Expanding the study's scope, we could investigate the impact of extrinsic and intrinsic motivation on students' well-being in the post-COVID period, taking into account the factors mentioned above within the context of no longer mandatory online education. For instance, a student with an introverted personality might show an increased intrinsic motivation to engage in learning within a hybrid or blended format, particularly when afforded the autonomy to select the balance between synchronous and asynchronous tasks. Regarding external motivational factors, examining grading in the online environment, incentives, and social influence could prove to be particularly insightful in the post-COVID context.

CRediT authorship contribution statement

Ágnes Halász: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Zsófia Kenesei:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Funding acquisition, Data curation, Conceptualization.

Ethics approval

Permission to conduct research with human subjects was granted by the ethics board of the Corvinus University of Budapest, Hungary (KRH/112/2020 and KRH 125/2022)

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Declaration of compenting interest

There is no issue related to the journal's policy and no conflicts of any potential competing interests.

Data availability

Data will be made available on request.

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