Predicting behavioural intention among graduate students in emergency remote teaching: evidence from a transition country

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Abstract Emergency remote teaching (ERT) is a new concept that describes the context in which instructional delivery is switched entirely online due to crisis circumstances. Recent research in such a context has been focused either on exploring the unique learning environment and enabling factors or on instructors’ intended behavior, with few studies exploring the students’ perspective. This study aims to contribute to the literature on technology-mediated teaching and learning by deepening the knowledge of the factors determining students’ behavioral intentions (BI) in ERT settings, using a survey of 487 graduate students attending public and non-public universities in Albania conducted during the COVID-19 pandemic lockdown period. The Technology Acceptance Model (TAM) was employed to explore the chain relationship between ease of use (EASYUSE), expected efficiency (EE), attitudes (ATT), and BI. We expand the TAM model and increase its explanatory power by introducing new variables, such as co-presence (CP), and emergent variables, such as lack of learning materials and time constraints. Variance-based partial least squares techniques were used to validate our conceptual model. As hypothesized,

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EE and EASYUSE have a direct, positive effect on BI and an indirect effect via ATT. CP does not influence the BI directly but only indirectly via ATT and EE. Finally, the lack of learning materials is shown to negatively affect EE. While some of the findings have limited generalizability the specific research setting provides a unique opportunity to investigate the critical role of interactive teaching methods and learning barriers on students’ intentions and ATT. The fresh insights gained from the extended TAM model have important implications concerning the effective and systematic use of online modalities in similar settings.

**Keywords**  Technology Acceptance Model · Co-presence · Material constraints · Time constrain · Emergency remote teaching · Variance-based partial least squares (PLS-SEM)

**Introduction**

The abrupt migration of tertiary education from face to face to fully remote due to the lockdown during the COVID-19 pandemic in March 2020 offered a unique opportunity to explore the behavior of students, instructors, and institutions in higher education (HE) in Albania, a middle-income, post-communist, transition country, with low technology penetration and low public spending on education at only 2.9% of GDP compared to 4.5%, the EU average (Psacharopoulos, 2017). As expected, the country’s HE institutions were unprepared for the switch to online learning. The situation was exacerbated by the challenges brought by the lockdown during the COVID-19 pandemic, such as learner exclusion and losses in human capital investment (OECD, 2020; World Bank, 2020). However, the problems of learning in such challenging conditions were multifaceted. Empirical research worldwide has underlined the pedagogical challenges of online learning due to the lack of face-to-face interaction with instructors and peers, difficulties accessing technology, and financial and organizational obstacles (Adnan & Anwar, 2020; Lassoued et al., 2020). While in Albania, to the best of our knowledge, except for the descriptive–comparative research of Xhelili et al. (2021) and a study exploring the geography and mathematics teacher experience with online teaching of Dhimitri et al. (2021), this is the first study to fully investigate the experience of HE students of technology-supported remote teaching during the first months of the COVID-19 lockdown.

While the terms ‘online’ and ‘e-learning’ are often used to describe the teaching and learning modality used during the lockdown, the terms are somewhat misleading as education programs in Albania (and elsewhere) were not designed to be fully delivered online. Emergency remote teaching (ERT) is a new concept that has emerged since the dramatic increase in the use of technology for education during the COVID-19 pandemic and describes a context in which instructional delivery is switched entirely online due to crisis circumstances (Hodges et al., 2020). While online learning, compared to ERT, is more structured, better planned, and delivered via purposeful methods and materials following the learning goals, ERT is an ad hoc and short-term solution aiming to continue the learning process. From the student’s
perspective, online learning is an option that can be chosen, while in the case of ERT, it is an obligation since no other face-to-face class is available (Bozkurt & Sharma, 2020). Therefore, our study builds on recent research related to online learning and teaching in the ERT context.

Research on online and distance learning is extensive and covers a variety of topics, including the comparison of online learning with classroom instruction (Bernard et al., 2004), the effectiveness of online learning (Tallent-Runnels et al., 2006), the course environment, including technologies used, learner reflection, and characteristics, outcomes, and institutional and administrative factors (Means et al., 2009; Tallent-Runnels et al., 2006), types of interaction and their impact on online learning (Bernard et al., 2009), and the way distance and online education is measured (Calatano, 2018). Empirical work in the ERT context is somewhat limited however, and studies relating to HE have focused mostly on developed countries (Aguilera-Hermida, 2020; Iglesias-Pradas et al., 2021; Shima & Lee, 2020) and less on emerging economies (Cahyadi et al., 2021). Furthermore, many studies have focused on the instructor’s perceptions (Li, 2022; Nikou, 2021; Xu et al., 2021). Following the call of Mouloudj et al. (2021) for further research from other countries with different socio-economic, cultural, and education development experiences, our study includes important contextual factors related to specific circumstances created by the COVID-19 pandemic in a middle-income, transition country and focuses on students’ online learning experience.

The sudden switch to technology-assisted learning in the context of ERT, as an intense and disruptive experience, is a suitable setup in which to observe student behavior. As suggested by Mezirow’s (1991) transformative learning theory, this sudden change leads students to question, critically reflect, and fundamentally change their views on education and learning. To capture the role of technology and the reflection process, the Technology Acceptance Model (TAM) is used in this study. The TAM model was developed to determine behavioral intention (BI) and behavioral outcomes. It suggests that technology-supported learning can be explained as a process developed to estimate the adoption and utilization of information technologies in learning. An individual’s intention to use the technology is influenced by their attitude (ATT) toward using it, which is influenced by fundamental beliefs, such as perceived usefulness (PU) and ease of use (EASYUSE). The model has been validated in different contexts, including ERT (Aguilera-Hermida, 2020; Hong et al., 2021; Xu et al., 2021; Zhou et al., 2021). The most advanced models of the theory, the TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008), along with the empirical research that validates the models (e.g., Tarhini et al., 2013), increase the explanatory power of the initial model by adding antecedents of PU and EASYUSE. This development is suitable for our research context (ERT), where instructions and planning for the transfer to online teaching and learning were almost entirely lacking. Moreover, these advanced models are suitable for evaluating research that focuses on the context, inputs, and process elements rather than the product (e.g., learning), in the line with the suggestions put forward by Hodges et al. (2020) on investigating online learning in the ERT context. Investigating the process of learnings under such circumstances can contribute to the design of a distance learning environment that can affect users’ intended future
behavior toward system use (Nikou, 2021). Furthermore, students cannot choose whether they use e-learning tools during ERT and thus their intention might not capture all the variance in how technology is employed (Moreno et al., 2016). Such circumstances imply that other factors might affect students’ expected behavior. That is why this research adds circumstantial factors related to pedagogy (throughput or process) and the learning environment to our adjusted TAM model.

Successful online learning requires a deep and involving pedagogical approach (see Swan & Shih, 2005). In light of this, the role of co-presence (CP), a term that refers to the linking of an individual’s perception of belonging in a course (Picciano, 2002) with how they feel interacting with others (Kim, 2011), both peers and the instructor (Swan & Shih, 2005), is added as an external variable. The first stage of this study was an exploratory survey of 470 students conducted in April 2020. The survey included many open questions that aimed to identify factors that affected the experience of learning during the lockdown. The most commonly articulated constraints were access to quality materials and the learning schedule, both added as emerging variables in the study second stage. Based on previous research indicating the importance of instructional materials (Alquarsi, 2018; Kuo et al., 2014) and time management (Tallent-Runnels et al., 2006) in online learning and especially in the ERT context (Vladova et al., 2021; Zhou et al., 2021), we expect that the inclusion of these factors in the TAM model, applied in the context of ERT, will increase the model’s explanatory power.

In sum, the current study aims to examine the relationships of teaching and learning models with the acceptance of new technology, predicting HE students’ behavior in an ERT context. More specifically, we build a comprehensive conceptual model based on an extended TAM with CP and constraints to online learning, such as access to suitable learning materials (MATCON) and time constraints (TIMECON), responding to Venkatesh and Davis (2000) call to better explain the determinants of technology-assisted learning, ultimately increasing the explanatory power of the TAM model. Such an approach is in line with recent research conducted in the ERT context, especially during the COVID-19 expanding the TAM model by introducing antecedents, such as e-learning system quality (Mailizar et al., 2021), students characteristics (Mailizar et al., 2021; Siron et al., 2020), time flexibility, learning flexibility and social isolation (Vladova et al., 2021), organizational and technical support (Sukendro et al., 2020; Wang et al., 2021), predictive fear (Akour et al., 2021), technological competency, and subjective norms (Khan et al., 2020). Evidence of students’ expected behavior, we believe, would lead to important insights and replication opportunities in the HE arena for similar countries and contexts. As noted by Andersson and Grönlund (2009) in their comprehensive literature review on online learning, in developing countries compared to developed ones, research focuses mainly on the technical infrastructure, student technological capabilities, and the pedagogical contexts. The rest of this paper is organized as follows. The next section reviews the theoretical premises informing the hypotheses. Section 3 provides extended methodological explanations for the PLS-SEM approach chosen. The fourth section then reports model fit, measurement model testing, and results. The fifth and final section includes a discussion of the theoretical and practical implications of the study, limitations, and future research recommendations.
Theoretical premises and hypotheses development

TAM, initially developed by Davis et al. (1989), is among the most cited models of technology use and acceptance (Davis & Wong, 2007), including in HE (Baki et al., 2018; Šumak et al., 2011; Taylor & Todd, 1995). The model is based on the Theory of Reasoned Actions (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975) and explains the user’s acceptance and expected behavior in the adoption and use of new IT-based systems. The first and most cited model suggested that PU and EASYUSE affect students’ ATT, which, in turn, influences the intention to use, with the latter impacting actual system use. Additionally, PU also affects BI (Davis et al., 1989). The model was extended with general determinants of EASYUSE and PU in TAM2 (Venkatesh & Davis, 2000). Other attempts were made to extend TAM with situational variables categorized as individual differences, system characteristics, social influence, and facilitating conditions (Marangunić & Granic, 2014). TAM3 was a more comprehensive model in view of pre- and post-implementation actions that can make IT systems more adaptable and used (Venkatesh & Bala, 2008). Venkatesh et al. (2003), in their attempt to develop a Unified Theory of Acceptance and Use of Technology (UTAUT), argued that the direct determinants of user acceptance and usage behavior are as follows: performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy includes PU and is defined as the degree that someone believes using a technology can result in improvement in professional performance (Venkatesh & Bala, 2008). Following TAM2 logic, our extended TAM model includes determinants of perceived efficiency (PE) such as CP (Swan & Shih, 2005) and typical constraints in ERT settings, such as learning materials (Alqurashi, 2018) and time (Tallent-Runnels et al., 2006).

The relationship between perceived efficiency, attitudes, and behavioral intentions

The TAM model suggests that PU affects the user’s ATT, reflecting feelings of favorableness or non-favorableness toward using an IT-based system. This relationship has been widely examined in the context of technology use both in distance education and in supplementary classroom learning (Pituch & Lee, 2006). The more that students believe that the IT system supporting their learning is instrumental to their learning, the more positive their ATT. Such a relationship has been observed in the ERT context too (Mouloudj et al., 2021). When TAM is applied to explain users’ behavior toward educational technologies, PE and usefulness are often used interchangeably and represent the facets of perceived learning quality (Venkatesh et al., 2003). However, more comprehensive terms than PU are used in the ERT context (Xu et al., 2021). For inexperienced users, PE, focusing on the quality of teaching and learning assisted by technology, is a more comprehensive term than PU since it relates to the use of technology with a more direct expected outcome. Organizational studies have extensively investigated the positive effect of PE on BI in the use of IT.
systems (Venkatesh & Davis, 2000). This relationship has been tested worldwide in different HE environments, theoretical and practical disciplines, and technologies, from mobile learning to virtual reality simulation (Althunibat, 2015; Tselios et al., 2011; Martinez-Torres et al., 2008). The relationship has also been validated in the ERT context (Xu et al., 2021). Based on the results of previous research, the following hypothesis is advanced:

**Hypothesis 1a** PE positively affects ATT.

**Hypothesis 1b** PE positively affects BI.

Based on the Theory of Reasoned Action (Fishbein & Ajzen, 1975) and Theory of Planned Behavior (Ajzen, 1991), ATT positively affects BI. Empirical research has also corroborated the positive effects of ATT on BI in the context of education research context (Song & Kong, 2017; Moreno et al., 2016; Meléndez et al., 2013; Park et al., 2012; Tselios et al., 2011; Martins & Kellermanns, 2004; Davis et al., 1989), although some authors suggest that this relationship is more nuanced. Capece and Campisi (2011), examining this relationship in HE in Italy and Portugal, found that ATT toward weak usage of online learning has a greater impact on BI than ATT toward intense online learning system usage. Nevertheless, according to Taylor and Todd (1995), ATT may not be an essential determinant of BI if other TAM model factors (such as PE) are considered. Despite the lack of consensus, we expect that students with a positive ATT toward online learning are more motivated to engage in this learning modality. Thus, we hypothesize that

**Hypothesis 2** ATT positively affect BI.

The TAM model suggests that BI is jointly determined by the person’s ATT toward using the system and PE. Moreover, the arguments regarding the positive relationship between PE and ATT suggest a partial mediation of ATT in the relationship between PE and BI. In our research context, we posit that students who have a positive ATT to the online technologies made available during the pandemic, perceiving them to be beneficial to the learning process, would have greater intention to continue to use the systems in future. Thus, the following hypothesis is proposed:

**Hypothesis M1** The positive effects of PE on BI are mediated by ATT.

**Ease of use**

Perceived EASYUSE is the degree to which a person believes that using technology will be free from effort (Davis et al., 1989). According to Bandura (1977), the easier a system is to interact with, the greater self-efficacy. There is a direct relationship between EASYUSE and ATT in the TAM model, suggesting an intrinsically motivating aspect of EASYUSE (Davis et al., 1989). Empirical research has established the positive direct effect of EASYUSE on ATT for different technologies used
in different research contexts, both in distance education (Li & Yu, 2020; Moreno et al., 2016; Meléndez et al., 2013; Sanchez et al., 2013; Park et al., 2012; Tselios et al., 2011; Martins & Kellermanns, 2004) and in supplementary classroom learning (Pituch & Lee, 2006). The positive relationship was corroborated even among first-time users (Zhang et al., 2007), as is the case in our study. Based on the extensive empirical findings reported above, we propose the following hypothesis:

**Hypothesis 3a** Ease of use of online platforms (EASYUSE) positively affects ATT.

In addition to the positive relationship between EASYUSE and ATT, there is some evidence of its role in positively affecting BI (Martinez-Torres et al., 2008). Using longitudinal data from four systems used by different organizations, Venkatesh and Davis (2000) confirmed the central proposition of the TAM2 model but also corroborated that EASYUSE positively influences intention to use such systems. Various empirical studies have found support for the positive relationship between EASYUSE and BI in different learning environments, systems, and teaching strategies in HE (e.g., Althunibat, 2015; Cheng, 2014; Liu et al., 2010) with a few exceptions (e.g., Venkatesh & Bala, 2008). Based on the characteristics of our research context, where students and in many cases their professors have minimal to no experience with online learning, we propose that EASYUSE might affect their intention; thus, we posit that

**Hypotheses 3b** Ease of use of online platforms (EASYUSE) positively affects BI.

According to Taylor and Todd (1995), ATT and EASYUSE explain BI. Moreover, as argued above, there is a positive relationship between EASYUSE and ATT. We expect ATT toward online learning to partially mediate the relationship between EASYUSE and BI; thus, we hypothesize as follows:

**Hypothesis M2** The positive effects of Ease of use of online platforms (EASYUSE) on BI are mediated by ATT.

**The role of co-presence**

Lately, the interest in throughput or process as an indicator of technology-assisted learning quality measurement (Joosten & Cusatis, 2019) has increased. According to Vygotsky’s social development theory (1978), built on Bandura’s theory of social learning (1977), social interaction is indispensable to cognition development. According to this theory, learning is triggered first by the interaction on a social level through the exchange between people and later individually, through awareness and internalization. CP in technology-mediated teaching and learning has attracted the interest of researchers because both synchronous and asynchronous online learning is significantly different from face-to-face discussion and possesses poorer communication cues (Swan & Shih, 2005), although despite their inherent shortcomings,
learning management systems are developing to allow community building and interaction with classmates, instructors, and content. In their meta-analysis, Bernard et al. (2009) concluded that online classrooms provide an opportunity for social presence and satisfaction. However, much depends on instructors, who do not always have the pedagogical and technical skills to adapt to the new environment and may replicate the traditional instructor and content-centered, one-way didactic models, similar to that used in distance education (Joosten & Cusatis, 2019). This lack of adaptation can be exacerbated in the ERT context, where the time to adapt is limited. Many studies have examined and corroborated the proposed positive effect of CP on student satisfaction with both the online course and instructor, as well as on their perceptions of the quality and quantity of learning (Gunawardena & Zittle, 1997; Kim, 2011; Muilenburg & Berge, 2005; Picciano, 2002; Richardson & Swan, 2003; Swan & Shih, 2005; Swan et al., 2000). The relationship is also seen in the augmented reality-mediated learning environment (Chen & Wang, 2017).

Recent studies conducted during the COVID-19 pandemic have shown that instructors’ presence and interactive pedagogy were the highest-ranking factors positively linked with students’ satisfaction (Fatani, 2020). Besides, social isolation negatively impacts students’ PU of online learning (Vladova et al., 2021). Based on the findings of two meta-analyses (Bernard et al., 2009; Richardson et al., 2017), as well as the results of the studies referred to above, we advance the following hypothesis:

Hypotheses 4a  CP positively affects PE.

In addition to the relationship between CP and PE, the CP or social presence impact on ATT has also been examined, but results are mixed. Several studies suggest a strong effect of social presence in changing students’ ATT (Watson et al., 2016). Similarly, Hernandez et al. (2011) found that social influence is one of the key drivers of a learner’s ATT toward online learning, while the sense of community has a positive but insignificant effect. Recent research in the ERT context corroborates the positive impact of social presence on learners’ ATT (Zhou et al., 2021). Based on these arguments, we expect CP to have a strong impact on ATT as lockdown following the pandemic excluded all means of interaction, aside from that digitally mediated. Thus, we pose the following hypothesis:

Hypothesis 4b  CP positively affects ATT.

Venkatesh and Sykes’s (2013) research inspired by social network theories suggested that individual ability to influence others and a user’s closeness to the social network positively influences technology use. There is some evidence in the literature for such a proposition. For example, Rodriguez-Ardura and Artola (2016), using a sample of 1198 European university students, found that CP directly impacts BI. Similarly, Ros et al. (2015) argue that interaction determines students’ intentions to use specific systems. However, Peregrina et al. (2014) found that interaction positively affects BI to continue to use the online learning system in HE setup, but the relationship was not validated in the virtual training company context, while earlier
research from Liu et al. (2010) found a positive but not strong relationship between perceived interaction and BI to use the online learning system. Following Venkatesh and Sykes (2013) arguments we hypothesize that:

**Hypothesis 4c** CP positively affects BI.

Based on the literature suggesting a positive relationship between CP and PE, ATT and BI and TAM model validated relationships among these variables (Davis et al., 1989; Taylor & Todd, 1995), we advance the following mediation hypothesis:

**Hypothesis M3** The positive effects of CP on BI are mediated by, respectively, (a) ATT and (b) PE via ATT.

**Hypothesis M4** The positive effects of CP on ATT are mediated by PE.

**Access to effective teaching and learning materials**

Some studies emphasize the importance of learning materials and their effect on student satisfaction (Lee, 2014), while well-structured learning materials can replace a teacher’s one-to-one interaction in receptive learning (Lee & Rha, 2009). Kuo et al. (2014) found that learner–content interaction had a significant and robust positive relationship with student satisfaction. Similarly, Alquarashi (2018) determined that the learning material is “the most critical predictor of student satisfaction, as well as a significant predictor of perceived learning” (p. 13). In attempting to expand the TAM model, Almaiah et al. (2016) showed that content quality positively affects PE. Access to diverse and rich media had a significant positive effect in the ERT context (Zhou et al., 2021).

Because of the sudden lockdown following the start of the COVID-19 pandemic and the sudden shift to online learning, most students had no possibility of accessing textbooks or other learning materials. Moreover, online teaching materials were unavailable (e.g., tutorials, electronic books). The latter appears to be very instrumental to the process of learning. Studies in the ERT context showed that access to online materials facilitated learning (Ho et al., 2021), especially interactive video supplemented with reading materials (Muthuprasad et al., 2021). Therefore, considering our research context, we expect that the lack of learning materials (MATCON) to negatively affect PE. Thus, we posit as follows:

**Hypotheses 5** Material constraints (MATCON) negatively affect PE.

Considering the relationship between PE with BI and ATT, we propose that the adverse effects of MATCON on PE extend beyond the perceived learning, affecting ATT and BI. Shortcomings in ease of access and the provision of quality materials might affect the ATT to using the system and intentions to use it in future. Thus, we advance the following mediation hypothesis:
Hypothesis M5  The negative effects of MATCON on BI are mediated by, respectively, (a) PE and (b) PE via ATT.

Hypothesis M6  The negative effects of MATCON on (a) ATT are mediated by PE.

Time constraint

Although many studies suggest that online learning has its advantages, by providing flexibility, saving time, and reducing the amount of time spent on online assignments (Garrison, 2011), much depends on how the time is effectively managed. Tallent-Runnels et al.’s (2006) meta-analysis results suggest that online learning is likely to be welcomed by students because it provides them with more convenience and autonomy. It offers a higher flexible schedule and saves time and energy (Panigrahi et al., 2018), especially for those students living far away from their universities (Hubackova & Golkova, 2014). However, some studies suggest that students may struggle with time management and procrastination (Davis et al., 2019), converting time into a barrier for effective online learning. Similarly, Muilenburg and Berge (2005) pointed out that time management can be a barrier to online learning. Despite the advantages, if not correctly scheduled and planned, online learning time can be counterproductive to learning and negatively impact personal and professional lives. For example, too many changes in class schedules during the emergency phase or inappropriate timing of some sessions (e.g., in the evening) can be considered a barrier to effective learning. These changes were more frequent in our context since many instructors struggled to find a work–life balance or share resources with their family members (e.g., share workspace within the house or computers). Recent studies in the ERT context considered time as an accessibility factor and rated it among the critical factors impacting the learning experience during the COVID-19 pandemic (Ho et al., 2021). We consider TIMECON as another external variable in our extended TAM model, thus advancing the following hypothesis:

Hypothesis 6  TIMECON negatively affect PE.

Similar to the argumentation for MATCON, we propose that the negative effect of TIMECON goes beyond its impact on PE, affecting ATT and BI. Thus, we advance the following mediation hypothesis:

Hypothesis M7  The negative effects of TIMECON on and BI are mediated by, respectively, (a) PE and PE via ATT.

Hypothesis M8  The negative effects of TIMECON on (a) ATT by PE.

Summarizing the above hypotheses, Fig. 1 describes the TAM model’s resulting structure, outlining the direct and indirect relationships.
Following Creswell (2009), this research presents the findings of the last stage of an exploratory sequential mixed methods research design composed of three stages. First, we surveyed 470 students. The survey included many open questions that aimed to identify relevant factors that affected online learning during the lockdown following the COVID-19 pandemic. In addition to traditional factors affecting BI and ATT, data analysis indicated that online learning barriers such as lack of learning materials and the excessive flexibility of classes schedule have a negative effect on the overall learning results. In the second stage, we used the first-stage findings to develop composite indicators to capture these phenomena, expanding the theory-based structured questionnaire. Finally, in the third stage, we administrated the enriched questionnaire to the population of graduate students. As suggested by Marangunić and Granic (2014), there is a need for further research focused on adults. This design was deemed appropriate for exploring a relatively new phenomenon for our country (online learning) in the context of ERT during lockdown (with all its implications) and introducing new composite measures into our research instrument.

Sampling and data collection

The data for this research were acquired by surveying graduate students attending eleven programs in eleven public and private universities during the spring and early
summer of 2020. We used an online survey to collect our data. The survey remained open for responses for 1 month. Three questionnaires were removed from the dataset since they were only partially completed.

The survey questionnaire was pre-tested with 13 students using online interviews with students from various Universities. The aim was twofold. First, to ensure face validity, we needed to clarify the questions developed initially in English and determine if respondents understood the questions. The second was to explore the different facets of the new emerging variables (MATCON and TIMECON). Accordingly, we modified some questionnaire items.

Considering the high variability of online learning solutions adopted by various universities, we aimed to have a broad representation of universities and faculties. Thus, 11 lecturers were engaged to facilitate data collection by contacting their students using the email accounts list at their disposal. However, the lack of a sampling frame that includes all students of various did not allow for applying a probability sampling technique. Hence, while we have obtained a high variability sample, the convenience sampling technique limits the research findings’ generalizability to the entire population of students (Table 1). Data were collected in collaboration with university authorities and according to the code of ethics for research. Participation of students in the survey was voluntary and participants were informed that the survey data would be confidential and used only for academic purposes.

### Table 1 Sample descriptives

|                          | Valid (%) |
|--------------------------|-----------|
| Gender                   |           |
| Female                   | 85        |
| Male                     | 15        |
| Type of university       |           |
| Public                   | 71.3      |
| Private                  | 28.7      |
| Attendance year          |           |
| First                    | 80.9      |
| Second                   | 19.1      |
| Status of employment     |           |
| Employed                 | 49.5      |
| Not employed             | 51.5      |

**Missing data, outliers, and bias examination**

We examined the dataset for (i) missing data, (ii) suspicious response patterns, and (iii) outliers (Hair et al., 2017). Firstly, there were no missing data among the items measuring the constructs used in our model. In general, the amount of missing data did not exceed 1%. Secondly, since we are interested in e-learning, we excluded all those cases where the respondents had not used an online platform. As a result, our
sample was reduced from 529 to 509. Thirdly, using the “straight-lining” strategy, we identified unengaged responses. As a result, eight further cases were removed. Using the modified Z-score method (Iglewicz & Hoaglin, 1993), fourteen outliers were identified and removed from the dataset. The final dataset consists of 487 cases.

Since data were collected based on the students’ voluntary participation, we tested for the non-response bias using wave analysis (Van Der Stede et al., 2006). We compared early versus late respondents by splitting respondents into two equally sized groups depending on the time online responses were recorded. No difference was found in terms of respondents’ attributes, such as residence area (urban vs. rural) ($\chi^2$ test, $P = .946$), gender ($\chi^2$ test, $P = .128$), average grade ($\chi^2$ test, $P = .062$), attendance year ($\chi^2$ test, $P = .762$), and employment status ($\chi^2$ test, $P = .059$). Thus, based on wave analysis, non-response bias is not a problem in our study.

Data were collected using a self-reporting questionnaire. Therefore, techniques to control for common method bias (CMB) were used (Podsakoff et al., 2003). We used both ex ante and ex post remedies. Firstly, the questionnaire was pre-tested to adapt questions to the study’s focal context and improve the clarity and accuracy of all items. Secondly, students were informed that their answers would remain anonymous. Thirdly, we used Harman’s single-factor technique to identify whether a single factor emerges that would account for most covariance among variables in our model. This analysis showed eight factors, in which the first accounted for 41.95% of the variance, below the threshold of 50%. The other seven factors contributed to the remaining 42.84% of the variance. We conducted a full collinearity assessment following Kock and Lynn’s (2012) procedure. Full collinearity VIFs are under the threshold of 5 suggested by the authors for algorithms that incorporate measurement error. These results suggest that CMB is not a threat in our study.

**Structural equation modeling (SEM) approach**

Between the two types of SEM methods, covariance-based techniques (CB-SEM) and variance-based partial least squares (PLS-SEM), the first is used for confirmatory purposes, while the second is exploratory (Hair et al., 2017). PLS-SEM was deemed a better choice since our research has a strong exploratory component and PLS-SEM is not concerned with the identification of problems in case complex models, as in our case. Furthermore, this method makes no assumptions about the data distributions (ibid). Although our data are not excessively non-normal, we observed mild levels of kurtosis and skewness.

Despite the advantages of PLS-SEM over CB-SEM regarding sample size, we examined the minimum sample size requirements. In our model, the maximum number of independent variables in any structural path is six, including the control variables. Therefore, assuming the commonly used statistical power level of 80%, we needed at least 171 data sets to detect $R^2$ values of at least 0.1 with a conservative error probability of 1%. Hence, the acquired 487 data sets are sufficient (ibid).
Operationalization of constructs

All variables were operationalized using multi-item self-assessed indicators on a seven-point Likert-type scale adapted from previous research, except for two external variables proposed by the authors, MATCON and TIMECON. Variables were selected from the literature on technology acceptance and distant/online education. Table A1 (see Online Resource A) presents all items adapted from the literature. PE was measured using the two items—the perception of learning and quality—based on Davis et al.’s (1989) items adjusted for online learning, following Cho et al. (2009), keeping those items that resulted unambiguous during the pre-testing phase. Further, ATT was measured using the original scale of Taylor and Todd (1995). One item from the original four-item construct was dropped during the questionnaire’s pre-testing phase due to it being almost identical to another item. BI and EASYUSE were measured using the scale of Li and Yu (2020). Following Kim (2011), CP was measured using three items (one was dropped during the questionnaire’s pre-testing phase). Finally, both MATCON and TIMECON were measured using two items. During the exploratory phase of the study, we identified (i) non-effective sharing of learning materials (MAT) and (ii) the lack of electronic course textbooks (NOBOOK) as substantial constraints to the PE of online learning. Similarly, (iii) inappropriate timetables for online learning sessions (TIMET) and (iv) no fixed schedule for online learning sessions (FLEXT) were identified as TIMECON to the PE of online learning.

To account for potentially confounding variables, two control variables were introduced in the model—gender and employment status of students.

Analysis and results

Survey sample properties and goodness of model fit

In the final sample of 487 students, 85% were female and 15% male. 71.3% of the students surveyed attend public universities and around half were employed. The majority were in the first year of graduate studies (80.9%).

We began analyzing the estimated model focusing our interest on several measures of overall goodness of fit (GoF; Henseler, 2018; Henseler et al., 2014). We examined the standardized root mean-squared residual (SRMR), unweighted least squares (ULS) discrepancy (dULS), and geodesic discrepancy (dG) for the saturated model. We started our model assessment by examining the SRMR, whether the estimated model fits the collected data. A value smaller than 0.08 is a good fit for SRMR (Hu & Bentler, 1999). The SRMR measure for the estimated model was 0.0252 and the saturated model is 0.0236. Also, the resulting SRMR should be lower than the 95% of bootstrap quantile (HI95) or at least lower than the 99% bootstrap quantile (HI99) (Henseler et al., 2016). SRMR and dULS for both the saturated and estimated models are below both bootstrap quantiles, while the geodesic discrepancy is below HI99 only (see Table B1 in Online Resource B). Based on these overall fit indices, the model fit can be deemed satisfactory.
Tests of the measurement model

The evaluation of the measurement model starts with a confirmatory composite/factor analysis to check the model’s adequacy for reflective and emergent variables (Henseler, 2018; Henseler & Schuberth, 2020; Henseler et al., 2014). Assessing a model with reflective constructs requires the evaluation of the indicator reliability, internal consistency, convergent validity, and discriminant validity (Ali et al., 2018; Hair et al., 2017; Ringle et al., 2012), while assessing a model with composite constructs requires the assessment of the overall model fit and the assessment of the model locally (Henseler & Schuberth, 2020). Our model, being mixed, includes five reflective variables, three being endogenous and two composite.

Following Henseler and Schuberth (2020), we first assessed our model by examining the model fit indices and then the emergent variables separately. Firstly, the saturated model tests described above provide the first empirical support for the structure of the proposed model’s factors and composites. Secondly, loadings of the observable variables comprising our emergent variable, MATCON, and TIMECON were shown to be appropriate (above 0.6631). Thirdly, weights were also shown to be acceptable (above 0.3452). T-values of weights and loadings show that observable variables significantly contribute to their emergent variable (see Table B2, Online Resource B).

We examined indicator reliability, internal consistency, convergent validity, and discriminant validity for our reflective measures. Item ATT3, CP3, and AC2 were removed due to, respectively, low loading, cross-loading with items of the ATT measure, and indicator redundancy (loading over 0.95) (Hair et al., 2019). As suggested by the authors, the standardized indicator’s outer loading of the remaining items is between 0.6 and 0.95 (see Table B3, Online Resource B). Collinearity was measured using correlation weights (mode A) to increase stability (Dijkstra & Henseler, 2011). Variance inflation factor (VIF) values are usually below the threshold of 5 (Hair et al., 2019). To evaluate construct internal consistency, we used Dijkstra–Henseler’s $\rho_A$ and Jöreskog $\rho_C$ as reliability measures (Dijkstra & Henseler, 2015a). However, Cronbach’s $\alpha$ has also been reported. The different loadings of the indicator variables show acceptable composite reliability values for $\rho_A$ and $\rho_C$, above 0.7533 and 0.7407, respectively (see Table B4, Online Resource B). Convergent validity was tested using the average variance extracted (AVE). The obtained AVE values for all constructs are higher than 0.5 (Hair et al., 2017), indicating the establishment of convergent validity (see Table B4, Online Resource B). Discriminant validity was tested using the Fornell–Larcker criterion (1981) and by looking at the heterotrait–monotrait ratio of correlations (HTMT) and the HTMT inference as proposed by Henseler et al. (2015). The Fornell–Larcker criterion was satisfied since even the highest correlations between constructs are smaller than the root square of the AVE value (see Table B5, Online Resource B) (Fornell & Larcker, 1981). Moreover, the HTMT correlation values are below the conservative criterion of 0.85 (see Table B6, Online Resource B), indicating the establishment of discriminant validity. Further, the indicator’s loadings on a construct are higher than all its cross-loadings with other constructs (see Table B5, Online Resource B). In all, the model assessment results (summarized in Table B1 to B6, Online Resource B) suggest that there...
was no significant empirical evidence against the proposed model and that all measures were valid and reliable.

**Structural model: direct effects**

The next step required the evaluation of the structural model results by assessing the $R^2$ values of endogenous constructs, the $f^2$ effects, the magnitude, and the significance of the standardized regression coefficients (Benitez Amado et al., 2020; Hair et al., 2017; Ringle et al., 2012). The $R^2$ value enables us to assess our model’s predictivity power (in-sample prediction) for dependent constructs. The (Cohen’s $f^2$) effect size was calculated to assess how substantial the direct effect is (see Cohen, 1988).

We obtained the structural model results, including $t$-values and percentile confidence intervals, using the factor weighting scheme, bootstrapping based on 5000 subsamples (Chin, 1998), and the stop criterion parameter set at $10^{-7}$ with 5000 maximum iterations. We used PLS-c to correct factor attenuation (Dijkstra & Henseler, 2015b).

Figure 2 shows the explained variance (adjusted $R^2$) in the endogenous variables and the path coefficients. The adjusted $R^2$ was used to avoid bias toward complex models since it considers the sample size and compensates for the exogenous variables added to the model (Hair et al., 2017). The variance explained for the three endogenous variables is moderate since adjusted $R^2$ values are above 0.6 (Chin, 2010; Hair et al., 2019).

Table 2 shows the results of the hypothesized relationships, effect sizes and standardized coefficients, their respective standard errors and $t$-values, and the lower and upper bounds of 95% and 99% confidence intervals.

The PLS-SEM results, presented in Table 2, show that PE has a medium positive effect on ATT ($\beta = 0.3614$, $P < .0001$, $f^2 = 0.1612$) and a weaker one on BI ($\beta = 0.3297$, $P < .001$, $f^2 = 0.0992$). Therefore, hypothesis H1a and H1b are supported. Further, ATT has a medium positive effect ($\beta = 0.4862$, $P < .0001$, $f^2 = 0.2060$) on BI, supporting hypothesis H2. EASYUSE has a small positive effect ($\beta = 0.1178$, $P < .01$, $f^2 = 0.0272$) on BI and an even weaker positive effect on ATT ($\beta = 0.1575$, $P < .01$, $f^2 = 0.0601$) supporting hypothesis H3a and H3b. CP has a large positive effect ($\beta = 0.6157$, $P < .0001$, $f^2 = 0.9932$) on PE, supporting hypothesis H4a. CP has a medium positive effect ($\beta = 0.4255$, $P < .0001$, $f^2 = 0.2313$) on ATT, supporting hypothesis H4b, but has no significant effect on BI, thereby not supporting hypothesis H4c. Further, MATCON has a medium negative effect ($\beta = -0.3593$, $P < .0001$, $f^2 = 0.2142$) on PE, supporting hypothesis H5. Finally, TIMECON has no significant effect on PE, therefore, hypothesis H6 is rejected.

**Mediating effects**

We tested our mediation hypothesis by applying the analytical approach proposed by Nitzl et al. (2016). The authors suggest that to demonstrate mediation, bootstrapping is needed to test the significance of the indirect effect. Moreover, in the case
of multiple mediations, it is necessary to employ the Hair et al. (2017) procedure using a spreadsheet application to test the complementary or competitive nature of mediations. Pseudo-$t$-value and the $P$-value based on the pseudo-$t$ tests were calculated to analyze whether the indirect effect is significantly different from zero using the standard errors derived from the bootstrap statistics (see Table 3). These results are bias corrected since the mean of the bootstrap distribution is different from the original mean of the indirect effects (see Hair et al., 2017; Nitzl et al., 2016).

ATT mediates the relationship between PE and BI, supporting hypothesis M1. As expected, the effect is positive and significant ($\beta = 0.1757$, $P < .001$, see Table 3). Further, EASYUSE relationship with BI is both a direct (as described by hypothesis H3b) and an indirect one ($\beta = 0.0766$, $P < .001$), suggesting a complementary partial mediation. Hence, hypothesis M2 is supported. The compounded indirect effect of CP on BI via ATT and two consecutive mediators, PE and ATT, is strong and significant ($\beta = 0.5181$, $P < .001$). The effect of the two paths is complimentary, as indicated in Table 4, therefore, supporting both hypotheses M3a and M3b. Considering that the direct relationships described by H4c are not significant, our results seem to indicate that the influence of CP on BI is not direct but only indirect. Besides, PE mediates the relationship between CP and ATT ($\beta = 0.2225$, $P < .001$), supporting hypothesis M4. The effect of our composite variable MATCON on BI both via PE and via two consecutive mediators, respectively, PE and ATT, is significant, although relatively weak ($\beta = -0.1696$, $P < .0001$). As shown in Table 4, the two mediation paths are complementary, thereby supporting both hypotheses M5a and M5b. Similarly, the effect of MATCON on ATT via PE is negative and significant ($\beta = -0.1212$, $P < .001$), supporting hypothesis M6. The mediating effect of our

Note: Dotted line represents hypotheses with mediation

Fig. 2 The model results
| Hypothesis | Path     | Path co-efficient(\(\beta\)) | Effect size (\(f^2\)) | Standard error | \(t\)-value | \(P\)-value (2-sided) | Percentile bootstrap quantiles |
|------------|----------|-------------------------------|------------------------|----------------|-------------|------------------------|--------------------------------|
| H1a        | PE \(\rightarrow\) ATT  | 0.3614                       | 0.1612                 | 0.0868         | 4.1627      | 0***                   | 0.1511 0.2053 0.5485 0.6192 |
| H1b        | PE \(\rightarrow\) BI   | 0.3297                       | 0.0992                 | 0.0909         | 3.6394      | .0003                  | 0.1029 0.1659 0.5276 0.5985 |
| H2         | ATT \(\rightarrow\) BI  | 0.4862                       | 0.2060                 | 0.0865         | 5.6186      | 0***                   | 0.2583 0.321 0.6598 0.7246 |
| H3a        | EASYUSE \(\rightarrow\) ATT | 0.1575                    | 0.0601                 | 0.0572         | 2.7532      | .0059                  | 0.0174 0.0452 0.2686 0.3072 |
| H3b        | EASYUSE \(\rightarrow\) BI | 0.1178                    | 0.0272                 | 0.0429         | 2.7443      | .0061                  | 0.0056 0.0292 0.1968 0.2279 |
| H4a        | CP \(\rightarrow\) PE   | 0.6157                       | 0.9932                 | 0.0405         | 15.1986     | 0***                   | 0.5095 0.5337 0.6936 0.7125 |
| H4b        | CP \(\rightarrow\) ATT  | 0.4255                       | 0.2313                 | 0.0837         | 5.0854      | 0***                   | 0.1848 0.2508 0.5771 0.6283 |
| H4c        | CP \(\rightarrow\) BI   | -0.0894                      | 0.0071                 | 0.0848         | -1.054      | .2919                  | -0.3281 -0.266 0.0635 0.1207 |
| H5         | MATCON \(\rightarrow\) PE | -0.3354                    | 0.2142                 | 0.0509         | -6.5945     | 0***                   | -0.465 -0.4288 -0.2323 -0.201 |
| H6         | TIMECON \(\rightarrow\) PE | -0.0447                    | 0.0040                 | 0.0497         | -0.8988     | .3688                  | -0.1791 -0.1498 0.0445 0.0747 |

*CP* Co-presence, *BI* Behavioral Intention, *PE* Perceived Efficiency, *EASYUSE* Ease of use, *ATT* Attitudes, *MATCOM* Material Constraints, *TIMECON* Time Constraints

\(***P < .0001\)
Table 3  Results of mediation analysis

| Hypothesis | Path | Path co-efficient ($\beta$) | Standard error | $t$-value | $P$-value (2-sided) | Percentile bootstrap quantiles | Type of mediation |
|------------|------|-----------------------------|----------------|-----------|---------------------|-------------------------------|------------------|
|            |      |                             |                |           |                     | 0.50%  | 2.50%  | 97.50% | 99.50% |                     |                  |
| M1         | PE $\rightarrow$ ATT $\rightarrow$ BI | 0.1757          | 0.0445         | 3.9517    | .0001               | 0.0754 | 0.0964 | 0.2709 | 0.3131 | Complementary partial mediation |
| M2         | EASYUSE $\rightarrow$ ATT $\rightarrow$ BI | 0.0766          | 0.033          | 2.3192    | .0204               | 0.0063 | 0.0192 | 0.1472 | 0.1713 | Complementary partial mediation |
| M3         | (a) CP $\rightarrow$ ATT $\rightarrow$ BI  
             (b) CP $\rightarrow$ PE $\rightarrow$ ATT $\rightarrow$ BI | 0.5181          | 0.07           | 7.402     | .0001               | 0.3674 | 0.3978 | 0.6745 | 0.74     | Full mediation |
| M4         | CP $\rightarrow$ PE $\rightarrow$ ATT | 0.2225          | 0.0581         | 3.8289    | .0001               | 0.0939 | 0.122  | 0.3533 | 0.4017 | Full mediation |
| M5         | (a) MATCON $\rightarrow$ PE $\rightarrow$ BI  
             (b) MATCON $\rightarrow$ PE $\rightarrow$ ATT $\rightarrow$ BI | −0.1696         | 0.0422         | −4.0212   | .0001               | −0.2931| −0.2624| −0.0968| −0.0768| Full mediation |
| M6         | MATCON $\rightarrow$ PE $\rightarrow$ ATT | −0.1212         | 0.0353         | −3.4311   | .0006               | −0.2314| −0.1992| −0.0613| −0.046   | Full mediation |
| M7         | (a) TIMECON $\rightarrow$ PE $\rightarrow$ BI  
             (b) TIMECON $\rightarrow$ PE $\rightarrow$ ATT $\rightarrow$ BI | −0.0226         | 0.026          | −0.8677   | .3856               | −0.099 | −0.0803| 0.0239 | 0.0398   | No mediation |
| M8         | TIMECON $\rightarrow$ PE $\rightarrow$ ATT | −0.0162         | 0.0195         | −0.829    | .4072               | −0.0821| −0.0606| 0.0168 | 0.0281   | No mediation |

*CP* Co-presence, *BI* Behavioral Intention, *PE* Perceived Efficiency, *EASYUSE* Ease of use, *ATT* Attitudes, *MATCOM* Material Constraints, *TIMECON* Time Constraints

***$P < .0001$***
| Hypothesis | Path | Original sample ($O$) | Sample mean ($M$) | Stand devia- tion (STDEV) | Standard error (STERR) | $t$-value ($|O/STERR|$) | $P$-value (2-sided) |
|------------|------|-----------------------|-------------------|--------------------------|------------------------|-------------------------|---------------------|
| M1a        | CP→PE→BI | 0.207 | 0.205 | 0.065 | 0.003 | 71.625 | .000*** |
| M1b        | CP→PE→ATT→BI | 0.108 | 0.107 | 0.028 | 0.001 | 85.665 | .000*** |
| M4a        | MATCOM→RES→BI | −0.111 | −0.115 | 0.038 | 0.002 | −65.155 | .000*** |
| M4b        | MATCOM→RES→ATT→BI | −0.059 | −0.058 | 0.017 | 0.001 | −76.057 | .000*** |

CP Co-presence, BI Behavioral Intention, PE Perceived Efficiency, EASYUSE Ease of use, ATT Attitudes, MATCOM Material Constraints

***$P < .0001$
other composite variable, TIMECON, on BI and ATT is not significant. Since there is no mediation in the path TIMECON→PE→ATT, there cannot be any path with two mediators, MATCON→PE→ATT→BI. Hence, there is no point in comparing the effects of the two different paths suggested by M7a and M7b. Thus, hypotheses M7a, M7b, and M8 are rejected.

The PLS-SEM results for the control variables, presented in Table D1 (Online Resource D), indicate that being an unemployed student negatively affects BI ($\beta = -0.0900$, $P < .05$) and PE ($\beta = -0.0903$, $P < .01$). Being a female student increases the likelihood of continuing with the online learning experience since gender positively affects BI ($\beta = 0.0738$, $P < .05$) but does not affect ATT and PE.

**Discussion**

This paper explores the relationships of learning models with the acceptance of new technology in specific online learning settings during ERT at the start of the COVID-19 pandemic, in order to predict HE students’ future behavior. An extended TAM model was proposed, adding external factors such as CP and constraints related to learning materials (MATCON) and time management (TIMECON). Findings enrich the research in the ERT context by addressing the gap in the literature concerning empirical studies focused on students’ experience with online learning and provide valuable insights for policymakers and HE institutions in their transformation and adapting to the new reality after COVID-19 pandemics. Similar to other studies that have applied the TAM model (Xu et al., 2021; Tselios et al., 2011; Althunibat, 2015; Cheng, 2014; Liu et al., 2010; Martinez-Torres et al., 2008; Venkatesh & Davis, 2000; Davis et al., 1989; Taylor & Todd, 1995), our predictor variables, PE and EASYUSE, have a direct effect and indirect positive effect on BI. The indirect relationship is mediated by ATT, suggesting that if ERT experience is perceived as efficient (PE) and tools are easy to use (EASYUSE), students are predisposed to continue with this modality of learning (BI) if the attitudes regarding the platforms used are positive (ATT). However, in comparison to the classical model, our extended version of the TAM model explains more of the BI variance (above 66%), representing an improvement of the original TAM model of Davis et al. (1989) and empirical research of Taylor and Todd (1995) (explaining 51% and 52% of BI variance, respectively). These results suggest possible directions to improve the explanatory power of the TAM model.

As expected, our results show that CP is a strong determinant of efficiency, as suggested by many studies (Baki et al., 2018; Richardson et al., 2017; Kim, 2011; Muilenburg & Berge, 2005; Swan & Shih, 2005; Richardson & Swan, 2003; Swan et al., 2000; Picciano, 2002; Gunawardena & Zittle, 1997). Such a result supports the proposition of social learning and development theories (Bandura, 1977; Vygotsky, 1978), according to which interaction is indispensable to cognitive development. Furthermore, in line with previous research (Hernandez et al., 2011; Watson et al., 2016), our study findings suggest that students experiencing higher CP have a more positive ATT toward using e-learning platforms. These results are in line with similar research in the ERT context (Zhou et al., 2021). Besides, PE mediates...
the relationship between CP and ATT, suggesting that if e-learning systems and platforms facilitate the creation of a learning community (supporting interaction between students and the professor), it increases e-learning quality, which in turn has a positive effect on students’ ATT toward e-learning. In contrast with the findings of other studies (e.g., Liu et al., 2010; Peregrina et al., 2014; Rodriguez & Artola, 2016; Ros et al., 2015), CP was not shown to influence the BI directly but only indirectly. As expected, ATT and PE mediate the positive effect. These results show that interactive classes are insufficient to influence students’ intention to continue to use e-learning if the process is not instrumental in their learning and if the interactivity itself does not affect their overall ATT toward e-learning.

Our study findings indicate that the lack of learning materials (MATCON) negatively affects PE, demonstrating the importance of access to effective learning materials to achieve learning outcomes, confirming previous research (e.g., Alquarashi, 2018; Lee & Rha, 2009; Kuo et al., 2014; Lee, 2014). Moreover, the lack of learning materials (e.g., electronic books and tutorials) negatively affects both ATT and BI. These results suggest that students display a negative attitude toward e-learning (ATT) if the shared learning materials are not relevant or easily accessible, contributing negatively to learning and course quality (PE). Also, students’ intent to continue with the e-learning modality in future (BI) is reduced because of the negative effect that lack of learning materials has on quality of learning (PE) and ATT. Although having appropriate e-learning materials in the ERT context is a challenge, adopting e-learning more extensively in future would require adjusting learning materials to the new modality, using the advantages that learning management systems offer, as indicated by other studies in similar context (Muthuprasad et al., 2021; Zhou et al., 2021).

Contrary to our expectations and to previous research (e.g., Davis et al., 2019; Muilenburg & Berge, 2005), TIMECON does not seem to affect PE or BI negatively. Although the evidence collected during the first stage of this study is anecdotal, we argue that the specific ERT context during the lockdown following the COVID-19 pandemic might explain these specific results. Students were forced to stay at home during this period, making time management not the most pressing issue. Even if 49.5% of students are employed, they appear to have had a flexible working schedule that did not interfere with their university obligations. However, the effects of TIMECON need to be further investigated in e-learning under ‘normal’ circumstances.

Our results on the effects of control variables on the main outcome variables confirm our initial propositions based on the anecdotal evidence collected in this study’s first stage. Working students (EMPL) have a higher intention to continue with e-learning (BI) and appreciate more the learning outcomes and quality (PE). It appears that for this category of students, e-learning is more convenient because they save commuting time since many of them can access the technology supporting e-learning from different locations, whether at home or the workplace. Also, our study findings confirm that female and male students respond differently to online environments, as suggested by previous online learning research (e.g., Sullivan, 2001, 2002). Female students appear to appreciate more the features and advantages of e-learning. Sullivan (2001, 2002) argued that e-learning offers the possibility for a
more reflective and less improvisational style in asynchronous learning, its anonymity, and social engagement level. This explains the female students’ higher intention to continue with e-learning (BI). However, in line with previous research (e.g., Richardson, 2006), we did not find meaningful gender differences in university students’ ATT toward e-learning in our specific context.

Contributions to research on e-learning

This study responds to various calls in the e-learning literature to increase the explanatory power of the TAM model (Davis et al., 1989; Venkatesh & Davis, 2000) by introducing three additional predictors. In line with social development theory on the role played by interaction in BI, we introduced CP as a predictor of PE, ATT, and BI. Furthermore, we introduced two hindering factors to these three outcomes. This study also enriches the ERT research agenda, responding to Hodges et al.’s (2020) call for more evidence regarding external/input factors and processes of teaching and learning remotely assisted by online technology. Moreover, it fills the existing gap in empirical research by exploring the learning process and its outcomes from the students’ perspective. From a theoretical standpoint, our study suggests that the inclusion of CP and hindering factors in the TAM model increases its explanatory power. The findings confirm the first TAM model suggested propositions. Moreover, our results partially align with social development theory arguments on the critical role of CP as a direct predictor of PE and ATT and its indirect effects on BI via these two outcomes. Finally, our findings confirm the significant effect of MATCON on PE and its indirect negative effect on BI via PE and ATT. These findings are noteworthy.

Practical implication

Examining the experience of Albanian students with e-learning during the COVID-19 pandemic lockdown is instrumental to future successful initiatives to expand teaching and learning modalities in HE in transition countries. This is particularly important when the shift to e-learning is quick and not combined with other more traditional modalities. Our findings show that e-learning requires a new constructivist approach to curricula design and delivery to be effective. Students will be willing to continue to choose this modality if the learning process is engaging and there is an opportunity to interact with each other and the professor. This new approach is needed, especially in countries with teacher-focused instruction, like Albania. Additionally, e-learning management systems and platforms should be practical, easy to use, and facilitate synchronous and asynchronous teaching and learning. Access to appropriate teaching and learning materials (such as electronic books, tutorials, instructional videos, interactive content, online quizzes, and assignments) is a precondition for successful online instruction; thus, additional efforts should be put into creating and adapting digital online materials.

Universities should also consider designing and providing some of their programs online, either fully or partially, meeting the needs (in particular) of working students
who can access study programs from any location and at any time. For these initiatives to be successful, an enabling environment needs to be created in advance to introduce students to online systems and improve the technical and pedagogical skills of teaching staff, in addition to the provision of organizational support, in order to increase know-how and access to technology.

Our findings’ implication might extend beyond the university environment boundaries. Companies adapting to the new world of hybrid working would need to innovate their training and development approaches and build knowledge management systems. The e-learning environment for employee training should be designed to ensure the possibility of interaction, knowledge sharing, and co-design with the instructor in a facilitative role. Furthermore, these systems should allow for time flexibility and host interactive, possibly multimedia-based materials, to attract the users’ attention, as Arghode et al. (2017) suggested.

Limitations and further research

The study has several limitations. Firstly, the inclusion of MATCON and TIME-CON, while justified considering the specific time period in which our study was conducted (immediately after the lockdown), might be less important in a different context. Longitudinal studies might shed some light on how MATCON can transform from hindering factors into, eventually, positive determinants of PE and BI. Secondly, there are limitations in generalizing the findings since we have examined a single ERT environment in a particular context—immediately after the lockdown. Testing the proposed model in a different modality (e.g., blended learning) or under different circumstances (not under such stringent measures related to the lockdown) can further validate our findings. Thirdly, many studies in the ERT context have analyzed the online learning process and outcomes from the instructors’ lens (e.g., Li, 2022; Nikou, 2021; Xu et al., 2021). Our study does not control for the effect of different pedagogical approaches and choices. Future studies need to account for interactive effects with predictors or their confounding effects, perhaps using experimental design as suggested by Nikou (2021). Fourthly, the sample was not randomly selected, limiting the generalization of findings to the entire student population. While our findings have a broader theoretical significance, they should be tested in other contexts, preferably using probabilistic sampling techniques. Finally, some variables are measured with two items, which introduces some bias and model identification problems, as suggested by Iacobucci (2009). Even the emergent constructs are measured with only two items identified during the exploratory stage of our study. Therefore, future research might examine the different facets of the constructs measured, increasing reliability and predictive validity.

Another exciting area for future research would be an investigation of the factors that potentially moderate the relationship between the ease of use of a platform’s PE, such as access to a reliable Internet connection and quality of devices.

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Declarations

Competing interests  The authors declare that they have no competing interests.

Ethical Statements  We hereby declare that this manuscript is the result of our independent creation under the reviewers’ comments. Except for the quoted contents, this manuscript does not contain any research achievement that have been published or written by other individuals or groups. We are the only authors of this manuscript and bear the responsibility of this statement.

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