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The influence of educational and emotional support on e-learning acceptance: An integration of social support theory and TAM

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Abstract

Flexible education is considered the primary function of e-learning, however, empirical evidence during the COVID-19 pandemic has also demonstrated that students may seek emotional comforts in e-learning to alleviate their negative emotions. This study aims to provide a holistic view of the antecedents of college students' e-learning acceptance by integrating social support theory with the technology acceptance model. Specifically, drawing upon social support theory, this study adopted perceived educational support and perceived emotional support as two driving factors and examined their influences on students' continuous intention in e-learning. The model was empirically validated using survey data from 512 college respondents in China during the first wave of the pandemic. Our results suggested that while perceived educational support exerts a major influence on e-learning acceptance, perceived emotional support also has an important role to play. Besides, the analytics results suggested that the two facets of support had different influencing patterns: perceived educational support has a positive and significant relationship with both perceived ease of use and perceived usefulness, whereas perceived emotional support solely has a significant relationship with perceived ease of use. Additionally, compared with the prior studies, the effect size (β) between perceived ease of use and perceived usefulness is larger in the present study (COVID-19 context). These findings stress the need to better understand the mechanism by which social support influences college students' e-learning acceptance and to make use of various kinds of social supports to enhance perceived ease of use (e.g. human-computer interface), promote perceived usefulness, and ultimately motivate more students' continuance intention in e-learning.

Keywords E-learning · TAM · Social support theory · SEM · The COVID-19 pandemic

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1 Introduction

The COVID-19 pandemic has dramatically boosted the use of e-learning. Lockdown and social distancing measures due to the COVID-19 pandemic have led to the disclosure of campuses and forced universities to adapt and adopt e-learning for education delivery. Yet, while its accessibility and flexibility in venues are repeatedly highlighted in the literature (Bao, 2020; Dhawan, 2020; Grey et al., 2020; Mailizar et al., 2021; Szopiński & Bachnik, 2022), the overall performance of e-learning remained unclear. This is because the success of e-learning is not merely dependent on the technology readiness (the supply side), but also on students' actual acceptance (the demand side). Indeed, E-learning is pointless unless college students use it. It is, therefore, necessary to revisit the success of e-learning from the perspective of student acceptance.

Students' acceptance of e-learning can be explained by the technology acceptance model (TAM), where perceived usefulness (PU) and perceived ease of use (PEOU) are two key predictors of individual attitude and behavioral intention (Mailizar et al., 2021; Szopiński & Bachnik, 2022). However, the prevailing e-learning studies have suggested that the TAM constructs can be further influenced by other external variables as well (e.g., subjective normal/social influence, enjoyment, and computer anxiety) (Abdullah & Ward, 2016; Baby & Kannammal, 2020). While these studies are majorly emphasized how the educational function of e-learning is connected to students' e-learning acceptance. The COVID-19-related research highlights the necessity for e-learning to cope with negative emotions (Hu et al., 2022b, c). The need for incorporating emotional antecedents to unravel the e-learning acceptance mechanism is highlighted in the COVID-19 pandemic-related literature. Scholars (Hu et al., 2022c; Pedrosa et al., 2020) argued that e-learning acceptance is not only affected by educational factors, but also negative emotions. This is because negative emotions such as depression, anxiety, or distress are prone to distract students' attention and impede their attitudes toward e-learning. On the other hand, e-learning can serve as a conduit for seeking emotional support, expressing emotions, and voicing fear among college students. The feeling of being cared for, accompanied, and comforted will, in turn, elevate students' attitudes toward e-learning (Hu et al., 2022b, c). In light of this, the influence of emotional antecedents on students' e-learning acceptance cannot be ignored. Although the pandemic will ultimately die off, negative emotions imposed by the external environment (e.g., social distancing) are likely to sustain beyond the pandemic (Apker, 2022; Szopiński & Bachnik, 2022). A need, therefore, emerges to explore the impact of emotional factors to provide a more holistic view of e-learning acceptance (Hsu et al., 2018).

The impact of educational-related and emotional-related antecedents on e-learning acceptance can be separately explored using the theoretical lens of Social support theory. E-learning, like other online communities such as social media (Hu et al., 2022a; Yan & Tan, 2014), can foster an important conduit for social support exchange (Hu et al., 2022b; Weng et al., 2015), where university students may share not just course-related knowledge and materials but also feelings of empathy, love, and caring. In light of this, it is intriguing and essential to explore how such social support provision can influence students' e-learning acceptance. In so doing, drawing upon social support theory, this study introduces two constructs – perceived educational support and perceived emotional support to denote the influence of the technological and emotional antecedents respectively in college students' e-learning intention. Perceived education support, which is adapted from the perceived information support and perceived instrumental support from social support theory, refers to the provision of information, advice, and other tangible support the problem-solving (Semmer et al., 2008), is deployed to denote the impact of educational related factors. Perceived emotional support, referring to the provision of empathy, friendliness, encouragement, esteem, love, and caring (Federici & Skaalvik, 2014), on the other hand, proxies the impact of emotion-related factors. Thus, the research question that this study going to address is: *what are the influential mechanisms of both education and emotional antecedents on students' e-learning acceptance?*

2 Theoretical background

In this section, the background of e-learning during the COVID-19 pandemic and the concept of e-e-learning is first introduced and clarified. Then, the rationale behind our choice of the TAM model to unravel the students' acceptance of e-learning is then described. Hypotheses related to the relationships among TAM constructs are proposed. Last, but not least, with the special need to address both the educational need and psychological need in e-learning during the COVID-19, social support theory is selected as a grounded framework to investigate the influential mechanism of social interaction in e-learning acceptance. The hypothesized relationships between the two facets of social support and TAM constructs are proposed.

2.1 E-learning during the COVID-19

During the COVID-19 pandemic, the unprecedented scale, the impacts, as well as the prolonged duration of the virus, has dramatically forced the use of e-learning to keep education functional. Universities in China, as well as worldwide, had to shift overnight from traditional classroom-based education to online learning (Bao, 2020). A massive amount of ICT tools (e.g., Zoom, Tencent Meeting) have been extended or developed to facilitate such a need. These ICT tools have to great extent addressed the three challenges, namely distance, scale, and personalization, proposed by Dhawan (2020) for e-learning. However, since the dramatic adoption of e-learning during the COVID-19 has caused tremendous difficulties for e-learning, numerous scholars have questioned not only the e-learning readiness (Rapanta et al., 2020; Scherer et al., 2021) but also the ICT suitability (Luo et al., 2017) of ICT. Before further discussing e-learning readiness and ICT suitability during the COVID-19 pandemic, it is necessary to clarify the concept of e-learning and its characteristics.

The term e-learning can be originated from different terms in literature such as distant learning, e-learning, web-based learning, blended learning, etc. In a general sense, all of these terms refer to the use of ICT as a medium to support the learning process (Al-Fraihat et al., 2020; Sun et al., 2008). In general, as an alternative educational paradigm, generally offers two compelling advantages. The majority of the authors posited that e-learning can support distant accessibility, which contributes to enhanced educational opportunities (Moore & MacKenzie, 2020). Another vein of scholars discussed that e-learning revolutes the teaching-learning process by improving student-centered and more flexible learning (Dhawan, 2020). With the compelling advantages, Hsu et al. (2012) argued that e-learning has become the burgeoning standard in education. Nevertheless, the disadvantage of e-learning is non-negligible. Numerous scholars are concerned that e-learning cannot deliver quality and effective educational outcomes (Szopiński & Bachnik, 2022), and they argue that the absence of face-to-face social interactions in e-learning may impede its education functions (Luo et al., 2017).

Particularly in this study, we focus on the massive overnight adoption of ICT to make learning accessible and available during the COVID-19 pandemic. The concept of e-learning used in this study has nuanced differences from those in non-pandemic literature. Regarding e-learning readiness, online learning approaches, such as MOOC, requires consistent planning and development of the ICT to provide quality education (Szopiński & Bachnik, 2022). During the COVID-19 pandemic, however, courses are not pre-planned nor pre-designed for such an abrupt mass migration to e-learning (Carey, 2020). In addition, e-learning takes care and time for both students and teachers to be trained and prepared for online interaction (Cong, 2020). The sudden adoption of e-learning during the COVID-19 pandemic has put both teachers and students under unprecedented pressure. Regarding ICT suitability, online learning has been criticized for failing to foster a sense of community (Luo et al., 2017) and failing to trigger social interaction among students (Mpungose, 2020). Additionally, the negative impact of social interaction absence in e-learning is likely to be exacerbated by the COVID-19 pandemic. Lacking social interactions, coupled with the mental health issues caused by home isolation (Hu et al., 2022a), are prone to degrade the effectiveness and the quality of e-learning.

It is true that e-learning is the panacea for education in the time of the COVID-19 crisis (Dhawan, 2020), but only because it may be the only few options to keep education available or accessible due to the strict quarantine measures such as campus lockdown, and home isolation. In this time of the pandemic, It is imperative to reconsider e-learning's performance from its acceptance. Thus, the TAM is selected to investigate students' e-learning acceptance.

Further, the need to address negative emotions arising from the external environment has been repeatedly highlighted in the literature, particularly during the COVID-19 (Dhawan, 2020; Grey et al., 2020; Shensa et al., 2020; Szopiński & Bachnik, 2022; Yao et al., 2021), but there is limited research (Hsu et al., 2018; Weng et al., 2015) connecting social support with e-learning considering e-learning as a conduit for negative emotions addressing. Nevertheless, both studies highlighted the need to incorporate social support theory with the TAM model to better reveal e-learning acceptance, but neither study examines the direct influence of emotional support or social support on e-learning. A need, therefore, emerges to revisit the social support theory and investigate how incorporating social support into e-learning can stimulate better e-learning motivation.

2.2 Technology acceptance model

Among many behavior models (e.g., the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB)), the technology acceptance model (TAM) was selected as the grounded framework for this study. This is because compared to the TRA and TPB that major emphasized the influence of individual characteristics (e.g., attitude, perceived behavior control, social norms) on behavior (Qu et al., 2023), we argued that e-learning is a context where attitude meets technology innovations: it is important to incorporate human-computer interaction factors (e.g., perceived usefulness, perceived ease of use) for dissecting the behavior (Davis, 1985). In so doing, TAM uses two human-computer interaction factors, namely perceived usefulness and perceived ease of use, to predict the technology adoption behavior. Upon this classic formulation, TAM has been substantially extended to a wide range of information systems applications such as online business systems (Taherdoost, 2018), healthcare information systems (Kamal et al., 2020), learning systems (Sánchez-Prieto et al., 2016), automated vehicles (Zhang et al., 2019), etc. In general, TAM has become a dominant model in investigating predictors of human behavior toward the potential acceptance or rejection of information systems (Marangunić & Granić, 2015; Surendran, 2012).

According to (Mailizar et al., 2021), considering e-learning as a technology, students will have a higher intention to use that technology if they believe that such technology will improve their performance, or if they think that the use of e-learning will be free of effort. Therefore, the following four hypothesizes are proposed (Fig. 1):

H1: Students' attitude toward e-learning has a positive effect on their continuous intention.

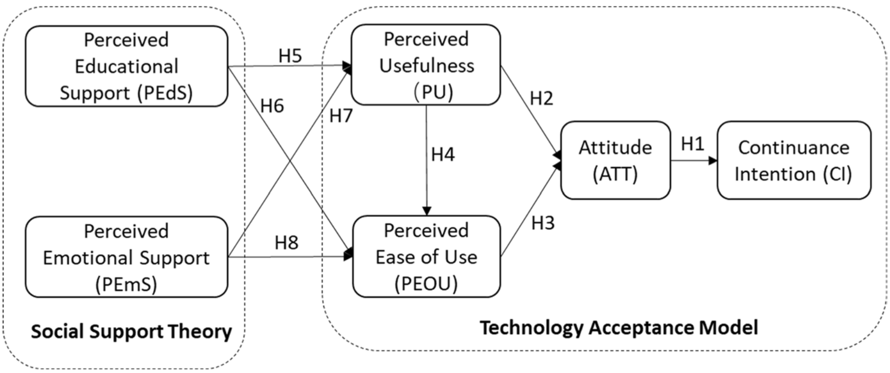

Fig. 1 Research model

H2: Students' perceived usefulness of e-learning has a positive effect on their attitude.
H3: Students' perceived ease of use of e-learning has a positive effect on their attitude.
H4: Students' perceived ease of use of e-learning has a positive effect on their perceived usefulness.

2.3 Social support

Social support is defined in the literature as the assistance and protection given to others, shielding them from precarious events and adverse effects (Wortman & Dunkel-Schetter, 1987). It can be broadly considered as the resources or aids exchanged (Cohen & Hoberman, 1983). Although the support may not contribute directly to the actual problem-solving, it has been repeatedly identified as an important buffer of mental health and a critical nudge for well-being (Cobb, 1976; Hu et al., 2022a; Lin et al., 2015). Investigation of social support has traditionally emphasized the exchange of behavior among interpersonal ties (Cohen & Hoberman, 1983), and has recently been extended to the online context (Liu & Ma, 2020; Yao et al., 2021). Particularly, the online community can create a mutual aid environment, offering an alternative outlet for social interaction, and social exchange, contributing to the mental health resilience of the members against negative emotions (Cobb, 1976; Marzouki et al., 2021).

The invaluable of social support in the online community has been stressed in literature (Yan & Tan, 2014; Yao et al., 2021). Particularly in the e-learning context, there is only sporadic discussion (Hsu et al., 2018; Weng et al., 2015). For instance, By analyzing the impact of various social support sources (from peers, supervisors, and family), Weng et al. (2015) stressed the importance of social support in e-learning acceptance. In another study, Hsu et al. (2018) posited that social support enhances individuals' mental resilience against challenges, pressures, and difficulties, which further contributes to enhanced cognitive processes and improves the engaging experience for learners. Nevertheless, while both studies have implied that perceived social support can impact e-learning acceptance, they considered social support as a general concept rather than investigating the impacts of each type of social support.

Indeed, social support is a multidimensional construct (Lin et al., 2015) and scholars (Cohen & Syme, 1985; House, 1983) have proposed different taxonomies of social support. For instance, House (1983) classified social support into four types: informational, emotional, instrumental, and appraisal support. In another study, Cohen and Syme (1985) proposed another four-dimensional formulation of social support including informational, instrumental, social companionship, and esteem support. Following this taxonomy, in the special context of e-learning, this study divides all types of social support into two main categories: educational support and emotional support. Education support refers to those supports that is offer to directly enhance the education function of e-learning (including informational support and instrumental support). Emotional support, on the other hand, is defined as those supports that contributed not directly to the educational function, but rather to cope with the negative emotions associated with e-learning environment. Social support attributing to emotional support includes social companionship, esteem support, emotional support, appraisal support.

2.3.1 Educational support

Educational support is the provision of tangible assistance (e.g., the assistance of a teacher in helping students to accomplish specific tasks, course material sharing from peer students) (Federici & Skaalvik, 2014), which is directed provided to address the course learning issues. Effective educational support makes it easier for students to solve course problems, therefore has a positive impact on the perceived ease of use. Further, when students perceive a sense of educational support (e.g. teachers explaining the problem), they are more likely to engage in the course study and value them, making them self-regulated (Federici & Skaalvik, 2014). Therefore, it is believed that educational support can contribute positively to learning performance. Based on the above, it is proposed that:

H5: Students' perceived educational support has a positive effect on their perceived usefulness.
H6: Students' perceived educational support has a positive effect on their perceived ease of use.

2.3.2 Emotional support

Emotional support is the provision of empathy, friendliness, encouragement, esteem, love, and caring (Federici & Skaalvik, 2014), which is not directly provided to address the course issues, but rather the stress and other uncomfortable experience during the e-learning. Effective emotional support can attenuate the mental effort needed to cope with the negative, resulting in fewer difficulties in adapting to e-learning. Cognitive load theory explains that this is because less amount of mental effort is needed to be allocated to address the negative emotions which in turn makes more mental effort available for actually adapting to the e-learning (Porumbescu et al., 2017). Similarly, emotional support decreases the effort for students to cope with negative emotions, making more mental effort available for students to understand the course content and therefore contribute to better learning efficiency and effectiveness. Based on the above, it is proposed that:

H7: Students' perceived emotional support has a positive effect on their perceived usefulness.
H8: Students' perceived emotional support has a positive effect on their perceived ease of use.

3 Methodology

3.1 Participants and procedure

In this study, the background was set as e-learning for university students during the first wave of the COVID-19 outbreak in China (spring semester of 2020). Data were collected through online surveys. We selected six cities as the scope of this study, including Beijing and Qingdao in the north, Xiamen in the south, Wuhan in the center, Shanghai in the east, and Chongqing in the west China. We use data from China because the massive adoption of e-learning during the COVID-19 pandemic is a typical representative of an e-learning environment with high technological readiness and insufficient face-to-face social interaction. We argued that the findings and implications in this study can be extended to other countries that share similar characteristics as well.

The survey is conducted from June to August 2020, immediately after their e-learning experience during the first wave of the pandemic. The link to the questionnaire was sent through WeChat to university students that have undergone e-learning during the spring semester of 2020. Besides, to cover areas, not in the abovementioned cities, we recruit respondents on the online (Weibo) platform. In the survey, we explained the objective of this study and clarified that all the information in the survey is confidential and for research purposes only. In sum, a total of 613 respondents were recruited and the survey yielded a total of 512 complete, valid responses (response rate 84%) for the data analysis.

3.2 Construct measurement

The measurement items were adopted from prior studies and adapted to suit the context of this study. The detailed constructs and measurements are listed in Appendix 1. All of the measurement items used a five-point Likert scale, anchored from strongly agree (1) to strongly disagree (5). Moreover, since the survey is in Chinese, this study followed the back-translation method (Bhalla & Lin, 1987). Before the questionnaire was made available online, four graduate students and two undergraduate students reviewed its phrasing, readability, and appropriateness.

3.3 Data analysis

The study employs the two-step Structural Equational Model (SEM) approach recommended by Anderson and Gerbing (1988) for the data analysis. First, by evaluating reliability, convergent validity, and discriminant validity, the fitness and construct validity of the proposed measurement model are examined. Then, the eight hypotheses of the structural model were tested collectively using structural equation modeling (SEM) implemented via the maximum likelihood (ML) algorithm in the

AMOS 26. These techniques allow us the analysis both the measurement model and the structure model.

4 Results and discussions

4.1 Measurement model

The confirmatory factor analysis (CFA) was applied to assess the construct validity of the six contracts. The reliability was assessed by indexes of the factor loading, Cronbach's α, and composite reliability (CR). The factor loading measures the indicator reliability of the model. According to Hair (2009), outer loading for the indicators above 0.7 is considered good reliability while between 0.35 and 0.7 is considered acceptable. The internal consistency reliability was measured using Cronbach's α, composite reliability (CR). Referring to Urbach and Ahlemann (2010), the recommended value for both should be above 0.7. The reliability analysis results of this study are listed in Table 1. All factor loading exceeds 0.7 (good reliability) except for PEdS3 (0.672, acceptable), suggesting good internal reality. CR and Cronbach's α values for all constructs are larger than 0.7, indicating good internal consistency reliability.

Table 1 Reliability and convergent validity analysis

Constructs	Items	Factor Loading	CR	α	AVE
Continuance intention (CI)	CI1	0.892	0.941	0.940	0.843
	CI2	0.941			
	CI3	0.920			
Attitude toward using (ATT)	ATT1	0.904	0.918	0.913	0.789
	ATT2	0.921			
	ATT3	0.838			
PU (PU)	PU1	0.901	0.940	0.939	0.839
	PU2	0.928			
	PU3	0.919			
Perceive ease of use (PEOU)	PEOU1	0.853	0.895	0.893	0.740
	PEOU2	0.895			
	PEOU3	0.831			
Perceived Educational Support (PEdS)	PEdS1	0.905	0.886	0.881	0.663
	PEdS2	0.892			
	PEdS3	0.672			
	PEdS4	0.765			
Perceived Emotional Support (PEmS)	PEmS1	0.925	0.913	0.923	0.726
	PEmS2	0.913			
	PEmS3	0.768			
	PEmS4	0.791			

According to Nunnally (1978), a Cronbach's α above 0.7 is considered a good reliability

Table 2 Discriminant validity analysis

	CI	ATT	PU	PEOU	PEdS	PEmS
CI	**0.918**					
ATT	0.850	**0.888**				
PU	0.746	0.840	**0.916**			
PEOU	0.531	0.723	0.611	**0.860**		
PEdS	0.497	0.588	0.547	0.588	**0.814**	
PEmS	0.412	0.519	0.466	0.561	0.859	**0.852**

Bold figures are the square root of AVEs.

The validity of the measurement model is assessed based on convergent validity and discriminant validity. The convergent validity is measured based on the average variance extracted (AVE). The recommended value for AVE should be ≥ 0.5 (Fornell & Larcker, 1981). The discriminant validity is assessed based on the cross-loadings. As suggested by Urbach and Ahlemann (2010), the square root of the AVE from the construct should be greater than the correlation shared between the construct and other constructs in the model. The convergent validity and the discriminant validity results of the constructs are listed in Tables 1 and 2, respectively. Based on the results, criteria for both convergent validity and discriminant validity are met, indicating good model validity.

4.2 Structural model

The structural model reflecting the assumed linear, causal relationships among constructs was tested. Model fit indices including the chi-square test statistic, the goodness of fit index (GFI), the non-normed fit index (NNFI), the comparative fit index (CFI), and the root mean square error of approximation (RMSEA) are used to assess the model fit. Table 3 listed the recommended value, and the reference for all the model fit indices. By comparing the results and recommended value in Table 3, the proposed model was within accepted thresholds.

Table 3 Model fit indices for the structural model

Model fit indices	Results	Recommended value	Reference
Chi-Square statistics χ^2/df	4.202	≤ 5	Hartwick and Barki (1994)
GFI	0.883	≥ 0.8	Hsu et al. (2018)
MNFI	0.938	≥ 0.9	Hartwick and Barki (1994)
CFI	0.952	≥ 0.9	Hartwick and Barki (1994)
RMSEA	0.079	≤ 0.08	Hsu et al. (2018)

4.3 Technology acceptance model effects

In this study, a model is proposed to understand how educational and emotion-related antecedents affect students' e-learning acceptance. The structural equation analysis of the proposed model is displayed in Fig. 2. In the model, eight hypotheses are developed and the hypotheses testing results are depicted in Table 4.

All TAM effects (H1 to H4) were statistically supported by the empirical results. The significant relationship confirms that the TAM is a good explanatory model for understanding the students' e-learning acceptance, which is in line with previous studies (Abdullah et al., 2016; Agudo-Peregrina et al., 2014; Baby & Kannammal, 2020; Cheng, 2011; Hsu et al., 2018; Tarhini et al., 2016). Specifically, H1 was supported, thus, the higher the students' attitude towards e-learning, the stronger their continuance intention. While Bhattacherjee (2001) argued that there is a significant difference between the initial attitude and the continuance use, our empirical result suggests that the attitude can be a strong determinant ($\beta = 0.848, p < 0.001$) of the continuance use of the e-learning.

In addition, the significant and positive relationships (H2, H3, H4) among the PU, PEOU, and attitude were also confirmed. PEOU was found a significant ($p < 0.001$) and positive relationship ($\beta = 0.427$) with the PU (H4). The relationship ($\beta = 0.312$) between PEOU and attitude (H3) is significant ($p < 0.001$), but weaker than that

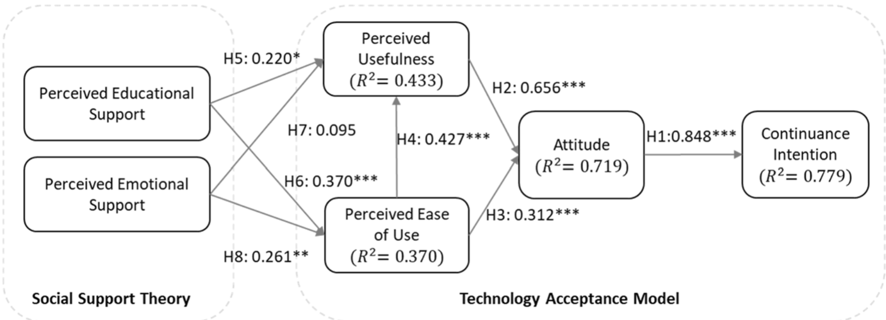

Fig. 2 Structural equation modeling analysis results (***$p<0.001$, **$p<0.01$, *$p<0.05$)

Table 4 Hypotheses testing results

Hypothesis	Standardized coefficient	Supported?
H1: ATT -> CI	0.848	Supported
H2: PU -> ATT	0.656	Supported
H3: PEOU -> ATT	0.312	Supported
H4: PEOU -> PU	0.427	Supported
H5: PEdS -> PU	0.220	Supported
H6: PEdS -> PEOU	0.370	Supported
H7:PEmS -> PU	0.095	Rejected
H8: PEmS -> PEOU	0.261	Supported

($\beta = 0.656$) between PU and attitude (H2). It overlaps with the previous study, Hsu et al. (2018) for instance, however, there is a minor difference. In Hsu et al. (2018), the regression weight for H2, H3, and H4 is 0.940, 0.315, and 0.136 while they are 0.656, 0.312, and 0.427 respectively in this study. By comparison, the relationship between PU and attitude tends to decrease and the relationships between PEOU and PU tend to increase.

One possible explanation behind this is that students during the COVID-19 pandemic are prone to be subjected to negative emotions from both the lacking of face-to-face social interactions and uncertainty in the development of the virus (Dhawan, 2020). The negative emotions tend to distract students from learning course material (Hu et al., 2022c). Thus even if they perceived that learning is useful, the negative emotions may still impede their attitude toward e-learning because they need to allocate their mental efforts to cope with the negative emotions, leading to an attenuation in the PU-attitude relationship (H2). Meanwhile, if students perceived less effort is required to adapt to the e-learning or higher perceived ease of use, the perception of more abundant mental efforts available to understand the course content is prone to improve their self-efficacy (Mailizar et al., 2021), which in turn promotes their perceived usefulness on e-learning, resulting in reinforcement in the PEOU-PU relationship (H4).

4.4 Social support effects

The results in Table 4 also support that the perceived social support is positively related to the TAM constructs. The standardized direct, indirect, and total effects are depicted in Table 5. Both dimensions of perceived social support have positive effects (indirect) on students' e-learning acceptance (indicated by ATT and CI). In particular, on one hand, the effect sizes of PEdS on ATT and CI are both larger than PEmS, suggesting that seeking educational resource remain the primary motivation for students' participation in e-learning. On the other hand, the effects of PEmS on ATT and CI are 0.217 and 0.183, respectively, which are smaller than those of PEdS, but not negligible. This result stresses the need of addressing students' emotional issues during e-learning. As such, in line with Lin et al. (2015), we argued that e-learning acceptance can be affected by two facets of influencing mechanisms.

Table 5 Standardized direct, indirect, and total effects

Antecedents	Direct	Indirect	Total
PEmS -> PEOU	0.261	-	0.261
PEdS -> PEOU	0.370	-	0.370
PEmS ->PU	0.095	0.111	0.206
PEdS -> PU	0.220	0.158	0.378
PEmS -> ATT	-	0.217	0.217
PEdS -> ATT	-	0.363	0.363
PEmS -> CI	-	0.184	0.184
PEdS - > CI	-	0.308	0.308

The education supporting mechanism is measured by the construct of perceived educational support (e.g., informational support, instrumental support, tangible support) that is offered directly to address e-learning task issues. H5 and H6 are attributed to this category. Both hypotheses in combination confirm that the education-supporting mechanism is a driving force of students' e-learning acceptance. Specifically, the perceived educational support is found a positive and significant relationship with both PU ($H5, \beta = 0.220, p < 0.05$) and PEOU ($H6, \beta = 0.370, p < 0.001$). This result partially overlaps with the findings in prior studies, where the perceived educational support are studied using other derivatives such as course content quality and support service quality (Cheng, 2012), perceived capability with students' task (Escobar-Rodriguez & Monge-Lozano, 2012), perceived functionality (Cho et al., 2009).

On the other hand, H7 and H8 are attributed to the emotion-supporting mechanism, which is not intended to address the course studying issues directly, but indirectly through coping with negative emotions. According to the results of this study (Fig. 2; Table 4), H7 is rejected while H8 is supported. While COVID-19-related studies (Dhawan, 2020; Mailizar et al., 2021; Szopiński & Bachnik, 2022) have consistently pointed to the necessity to address emotion-related issues in e-learning, few of them offer nuanced insights into the emotion-supporting mechanism. To address this, the empirical study suggested that the emotional support-PEOU relationship should be the emotion-supporting mechanism. Not surprisingly, in line with previous studies (Abdullah & Ward, 2016; Karaali et al., 2011; Šumak et al., 2011), the significant correlation between perceived emotional support and PU (H7) is rejected. On the other hand, the association between perceived emotional support and PEOU ($H8, \beta = 0.370, p < 0.001$) is confirmed. In a broad context, the emotion supporting mechanism is frequently investigated through other constructs such as anxiety. Earlier studies (Karaali et al., 2011; Šumak et al., 2011) revealed that anxiety had a significant influence on PEOU. Despite their similarities in revealing the impact of negative emotions, the two constructs are distinct. According to Venkatesh, et al. (2003), the term anxiety is defined as "evoking anxious or emotional reactions when it comes to performing a behavior", which is emphasized the negative emotions induced by technology. Perceived emotional support encompasses empathy, and caring (Federici & Skaalvik, 2014), which include addressing negative emotions from both the technology and the environment (COVID-19 pandemic).

4.5 The importance of students' acceptance in e-learning success

In this study, we emphasized the importance of deploying students' acceptance as a proxy for e-learning success. Specifically, we argued that for e-learning to succeed, the emphasis must be shifted from the supply side (e-learning readiness) to the demand side (students' acceptance), much like the diffusion of other technologies (e.g., e-government) (Zhao et al., 2018). This means that while the infrastructure, computerization, and system may provide a grounding basis for e-learning, its success should also embrace the actual engagement or acceptance of its users. Thus, in line with previous studies (Abdullah & Ward, 2016; Hsu et al., 2018), we made the case that it is critical to reassess the e-learning success in light of students' acceptance.

Further, the current study deploys continuous intention rather than intention or participation to proxy students' acceptance. We argued that the initial adoption of e-learning during the COVID-19 pandemic could more or less be deemed a mandatory process, where students are compelled to shift to online education (Bao, 2020; Dhawan, 2020). Under such circumstances, it is impossible to gauge how well e-learning is addressing students' needs for educational support or emotional support if participation is a mandatory process. Like any other behavior, if students' participation in e-learning is not mandated, they must be motivated (Linders, 2012). As such, students' level of self-motivation is a demand-side indicator of e-learning success: students satisfied with their e-learning experience are prone to result in high continuous intention, and the opposite is also likely to be true (Hsu et al., 2018; Szopiński & Bachnik, 2022). Therefore, from the perspective of the demand side, continuous intention (CI) could be a more appropriate indicator for e-learning success.

4.6 Theoretical implications

We first contributed to the e-learning studies by highlighting the importance of revisiting e-learning success from the perspective of student acceptance. While numerous prevailing studies (Bao, 2020; Dhawan, 2020; Grey et al., 2020; Mailizar et al., 2021; Szopiński & Bachnik, 2022) stressed that e-learning success from the supply side: facilitates education accessibility and flexibility, we emphasize that the technology is useless unless the users from the demand side fully embrace with the technology. In doing so, we introduced a behavioral model from the demand side to provide nuanced insights into the cognition process of students' acceptance of e-learning during the COVID-19 pandemic. The findings indicate that TAM is a well-established model with excellent explanatory power in students' e-learning acceptance. Indeed, in line with Hsu et al. (2018), it is necessary to revisit the demand side of e-learning (students' acceptance) to provide a holistic view of e-learning success.

This study also stressed the need to consider the technological perspective of e-learning. In this study, the proposed TAM model explained 71.9% and 77.9% of the variance of the attitude and the continuance intention respectively among the surveyed students. Indeed, e-learning is where education meets technology, the technology feature should not be overlooked. According to the empirical results of this study, PEOU and PU are significantly associated with both students' attitudes and continuance intention in e-learning. This means that we cannot regard e-learning as a paradigm that only focuses on education; rather, as it is a new technology, its perceived usefulness and perceived ease of use are crucial.

Additionally, we also contributed to a more comprehensive understanding of the antecedents of e-learning acceptance. Specifically, while most of the e-learning research has stressed that the educational function is the primary driving force of e-learning use, this study supports the argument by Lin et al. (2015) that the e-learning environment should also account for the psychological needs of students. Drawing upon social support theory, we introduced educational support and emotional support to separately investigate the influence of educational and emotional support on e-learning acceptance. Our findings suggest a different influence pattern of the two facets of social support: perceived educational support is significantly associated with both perceived ease of use and perceived usefulness; perceived emotional support is only significantly associated with perceived ease of use.

4.7 Practical implication

The study has three major implications for practitioners. First, for universities and higher education, an important implication of this study is that e-learning implementation needs to incorporate students' acceptance from the demand side. Despite the fact that e-learning technologies are rapidly evolving, it is critical to reevaluate whether these technologies satisfy the demands of their intended users—students. Based on our empirical findings, it is plausible to expect that students' attitudes and continuance intentions in e-learning can be positively impacted by a high level of perceived emotional support or emotional support. Therefore, when introducing e-learning technology, universities and higher education should take students' emotional and educational needs into better consideration.

Our findings have crucial ramifications for teachers and instructors regarding how to effectively inspire college students to e-learning. It is argued that students'' continuance in e-learning is not only affected by how well the education is provided (perceived educational support), but also the existing level of perceived emotional support. Especially in an environment with stress (e.g., COVID-19) or social interaction is insufficient, students may have a low level of perceived ease of use, in addition to the educational support, leverage emotional support can also potentially promote students' perceived ease of use in e-learning. As a result, instructors' and teachers' responsibilities in online learning should go beyond merely imparting knowledge to include more emotional support tasks such as keeping company, expressing empathy, and providing care.

Our last piece of advice is that technology developers need to improve the human-computer interface in order to support more social interactions. The lack of face-to-face interaction is one of the main issues with e-learning. An enhancement of the human-computer interface may help to attenuate the detriment impact of insufficient social interaction because human-computer interface is associated with PEOU (Nielsen, 1994) and PEOU is identified to associated with the perception of both emotional support and educational support according to our empirical evidence. Two ideas might be useful for technology developers. First, e-learning technologies should not be implemented as a one-way video broadcasting from the teachers to the students, but rather they should encompass more instant interactive features (e.g., quizzes, audio files, videos, simulations, gamification etc.) to get students actively involved in the learning process. Features supporting a higher level of perceived educational support would contribute to a higher level of perceived ease of use and perceived usefulness. Additionally, a higher level of perceived emotional support would also lead to a higher level of reported ease of use, therefore to boost social interactions, instant communication features (e.g., instant messenger) to support students better voicing their fears, expressing their feelings, exchanging supports may also necessary since a higher level of perceived emotional support would also contribute to a higher level of perceived ease of use.

5 Conclusion

The objective of this study was to examine how emotional antecedent in addition to educational antecedent can motivate students' e-learning acceptance. In doing so, a research model integrating social support theory with the TAM was proposed to explore the two facets of influencing mechanisms, namely education-supporting and emotion-supporting mechanisms. The proposed model was empirically tested using survey data from 512 university students regarding their experience of e-learning during the first wave of the COVID-19 pandemic in China. Findings reveal that while the perceived educational support has a significant positive effect on both the PU and PEOU of the e-learning, the perceived emotional support only has a significant positive effect on the PEOU. In contrast to prior studies conducted in the general context, the effect size (β) between PU and PEOU is larger in this study (negative emotional environment). These findings contribute to a better understanding of students' e-learning acceptance and highlight the importance of incorporating emotional support in addition to educational support to motivate more students to e-learning acceptance, particularly in a negative emotional environment (e.g., COVID-19).

This study is not without limitations. First, cross-sectional data from the first wave of the COVID-19 outbreak were used to examine the proposed model. The continuance intention is measured using self-report data. It is argued that the self-reported measurement might not necessarily reflect the actual behavior (Lin et al., 2015). Therefore, future studies are encouraged to validate the proposed model by collecting multiple-wave data. Second, it is important to note that the findings and implications of this study should be interpreted with caution since the survey data is collected in China only. However, we argued that the massive adoption of e-learning in China during the COVID-19 pandemic is a typical example of an e-learning environment with high technological readiness and insufficient face-to-face social interaction. Thus, the results of this study have broad implications for understanding e-learning acceptance in other countries with similar characteristics. For countries that share different characteristics, we believed that the explanatory power of the proposed model can also be extended, however, further empirical data are needed. Finally, the cognitive process underlying students' e-learning acceptance might be non-linear rather than linear, as better explained by expectation confirmation theory (ECT) (Bhattacherjee, 2001). It is, therefore, necessary to further compare TAM with ECT to provide nuanced insights into the cognitive process behind students' e-learning acceptance.

Appendix 1 Constructs and measurements

Constructs	Items	Measures	References
Technological Acceptance Model			
Perceived Usefulness (PU)	PU1	I believe E-learning improves my learning performance.	Wu and Zhang (2014); Kim et al. (2010); Wu and Chen (2017)
	PU2	Using E-learning enhances my learning effectiveness.	
	PU3	Using E-learning easily translates the learning material into specific knowledge	
Perceive ease of use (PEOU)	PEOU1	Learning to use MOOCs is easy.	Chang (2010); Wu and Chen (2017);
	PEOU2	It is easy to become proficient in using MOOCs.	
	PEOU3	The interaction with MOOCs is clear and understandable	
Attitude toward using (ATT)	ATU1	I believe that using MOOCs is a good idea.	Chang (2010); Wu and Zhang (2014) Wu and Chen (2017);
	ATU2	I believe that using MOOCs is advisable	
	ATU3	I am satisfied with using MOOCs.	
Continuance intention (CI)	CIIU1	I intend to continue to use MOOCs in the future	Wu and Zhang (2014) Wu and Chen (2017);
	CIIU2	I will continue using MOOCs increasingly in the future.	
	CIIU3	I intend to continue using MOOCs in the future, at least as active as today	
Perceived Social Support			
Perceived Educational Support (PEdS)	PEdS1	When I use the e-learning services, peers will provide information, advice, and guidance.	Weng et al. (2015)
	PEdS2	When I am using the e-learning service, my supervisors will provide the relevant information and help me improve my performance.	
	PEdS3	When there is something I do not understand, my supervisor will be there to help me.	Federici and Skaalvik (2014)
	PEdS4	When there is something I do not understand, I can always turn to my peers for help	

Constructs	Items	Measures	References
Perceived Emotional Support (PEmS)	PEmS1	When I am using the e-learning service, my peers will encourage and praise me.	Weng et al. (2015)
	PEmS2	When I encounter difficulties during e-learning, my supervisors are willing to listen and provide the emotional support I need.	
	PEmS3	My close friend nicely tells me the truth about how I do on things	Malecki and Demaray (2003); Tan et al. (2019)
	PEmS4	My teachers nicely tell me the truth about how I do on things	

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Declarations

Conflict of interest None.

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