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Influence of Individual-technology-task-environment Fit on University Student Online Learning Performance: The Mediating Role of Behavioral, Emotional, and Cognitive Engagement

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Abstract
The present study aimed to examine whether and to what extent university student online learning performance was influenced by individual-technology fit (ITF), task-technology fit (TTF), environment-technology fit (ETF), and whether the influence was mediated by their behavioral, emotional, and cognitive engagement. A theoretical research model was developed by integrating the extended TTF theory and student engagement framework. The validity of the model was assessed using a partial least squares structural equation modeling approach based on data collected from 810 university students. Student learning performance was influenced by TTF ($\beta = 0.25$, $p < 0.001$), behavioral engagement ($\beta = 0.25$, $p < 0.001$), and emotional engagement ($\beta = 0.27$, $p < 0.001$). Behavioral engagement was affected by TTF ($\beta = 0.31$, $p < 0.001$) and ITF ($\beta = 0.41$, $p < 0.001$). TTF, ITF, and ETF were observed as significant antecedents of emotional engagement ($\beta = 0.49$, $p < 0.001$; $\beta = 0.19$, $p < 0.001$; $\beta = 0.12$, $p = 0.001$, respectively) and cognitive engagement ($\beta = 0.28$, $p < 0.001$; $\beta = 0.34$, $p < 0.001$; $\beta = 0.16$, $p < 0.001$, respectively). Behavioral and emotional engagement served as mediators between fit variables and learning performance. We suggest the need for an extension to the TTF theory by introducing ITF and ETF dimensions and demonstrate the important role of these fit variables in facilitating student engagement and learning performance. Online education practitioners should carefully consider the fit between the individual, task, environment, and technology to facilitate student learning outcomes.

Keywords Task-technology fit · Individual-technology fit · Environment-technology fit · Student engagement · Online learning · Learning performance

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1 Introduction

Online learning refers to a learning environment that uses the Internet and other technological devices and tools for instructional delivery and management of academic programs (Barrot et al., 2021). Although it has various benefits in terms of convenience and flexibility (Isaac et al., 2019; Zapata-Cuervo et al., 2022), student online learning performance is not always good. This has therefore given rise to research studies on the quality of online learning and best practices for delivering effective online education.

Several recent studies have explored various factors affecting student learning performance (Baltà-Salvador et al., 2021; Yu, 2021; Zapata-Cuervo et al., 2022). For instance, Zapata-Cuervo et al. (2022) found that students perceived their online learning as not particularly effective or rigorous; factors such as student self-efficacy and mental health significantly influenced their levels of engagement and study outcomes. Baltà-Salvador et al. (2021) carried out research on students in Spain and found that most students were not satisfied with the quality of online learning they received during the COVID-19 pandemic. Results of that study indicated that student academic development is associated with several factors, including quality of classes, adaptation of the courses to the online format, and student working environment. Yu (2021) investigated the effects of gender, educational attainment level, and personality on online learning outcomes; the results indicated that postgraduate students and learners with agreeable, conscientious, and open personalities were more likely to outperform undergraduate students and learners with extroverted and neurotic personalities.

Although previous studies have achieved valuable insights into factors affecting online learning outcomes, they focused mainly on either individual or technological factors, and ignored the “fit” among technology, tasks, individuals, and environments (i.e., task-technology fit (TTF), individual-technology fit (ITF), and environment-technology fit (ETF)), which is widely recognized as the key to successfully implementing online learning (Baltà-Salvador et al., 2021; Wu & Chen, 2017). TTF has been widely discussed in previous literature across various contexts and its importance in affecting task performance has been well documented (Isaac et al., 2019; Khan et al., 2018; Wu & Chen, 2017). For instance, Isaac et al. (2019) studied factors affecting the use of student online learning and found that the role of TTF was the primary antecedent with the most meaningful effect on student academic performance. Furthermore, ITF determines if online learning fits student capabilities. Wu and Chen (2017) examined the role of ITF in MOOC settings. They pointed out that ITF is associated with perceived ease of use, and that more experienced users are more likely to perceive MOOCs as easy to use. Studies conducted during the COVID-19 pandemic have reported that some students, especially those living in developing countries, have experienced difficulties in using online learning technologies independently (Barrot et al., 2021; El-Sayad et al., 2021; Tao et al., 2022). However, studies on the effects of ITF on student learning performance have been limited. Lastly, the effects of ETF, having not received much attention in online learning before the pandemic, should now be considered, as online learning during COVID-19 has significantly changed the learning environment (Baltà-Salvador et al., 2021). Many students took online courses in their own homes, university residences, or libraries during this time. Unsuitable learning environments may have a detrimental impact on student comfort, well-being, and learning performance (Baltà-Salvador et al., 2021; Braat-Eggen et al., 2017; Parvez et al., 2019; Zhong et al., 2019). Accessing a suitable learning environment has also been reported as the greatest challenge that students faced in online learning during the pandemic (Barrot et al., 2021). Therefore, the impact of ETF on student learning performance warrants further examination.

In addition, previous studies have indicated that the level of student engagement is a key factor influencing student learning outcomes (Lei et al., 2018; Soffer & Cohen, 2019). Compared with traditional face-to-face instruction, the engagement of students in online learning is more challenging (Gillett-Swan, 2017; Salas-Pilco et al., 2022; Yu, 2021). Student engagement has been found to be a mediator between individual/technological factors and student learning outcomes in previous literature. For instance, Chhetri and Baniya (2022) reported that student engagement mediated the relationship between student-faculty interaction and their academic outcomes. However, the way student engagement mediates the relationships between fit dimensions and student learning outcomes remains unknown.

To fill in the research gaps, the present study aimed to examine whether and to what extent TTF, ITF, ETF, and student engagement influence the online learning performance of students. We also examined the mediating role of student engagement between the fit variables and student learning performance.

2 Literature review and research hypotheses

Applying the theoretical background of the TTF fit theory and student engagement framework, we proposed a research model that identifies the causal relationships between TTF, ITF, ETF, student engagement, and learning performance (see Fig. 1).

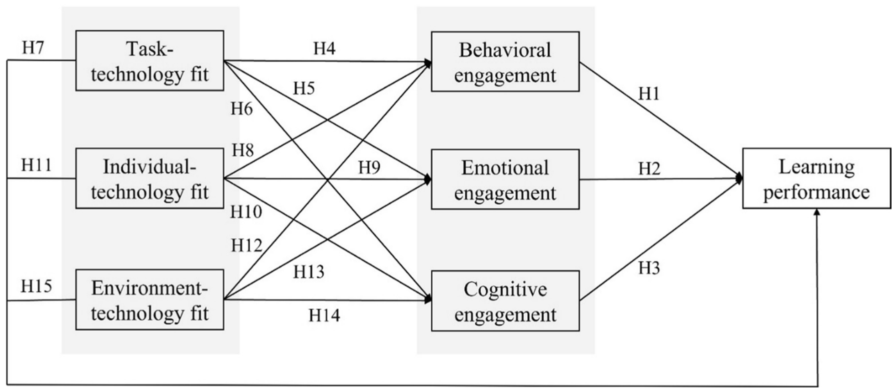

Fig. 1 The proposed research model

2.1 Learning performance

In the present study, learning performance is defined as the extent to which online learning influences student performance in terms of competence, knowledge acquisition, productivity, and resources savings (Isaac et al., 2019).

2.2 Student engagement

Student engagement refers to the time, energy, thought, and effort invested by students in their learning process to achieve their desired learning goals (Dixson, 2015; El-Sayad et al., 2021; Ma et al., 2015). Previous studies have consistently stressed the importance of students' engagement in facilitating their academic achievement (Luan et al., 2020; Soffer & Cohen, 2019), because engaged students are more likely to show perseverance, to self-regulate their behavior toward achieving their goals and to enjoy learning and challenges (Klem & Connell, 2004). Student engagement is a multidimensional concept; however, the number and types of engagement deemed important varied across research literature (Chhetri & Baniya, 2022). In this study, we adopt the three-component conceptualization (i.e., behavioral engagement, emotional engagement, and cognitive engagement) because this framework is most widely accepted (Chhetri & Baniya, 2022; Ding et al., 2017; Fredricks et al., 2004).

2.2.1 Behavioral engagement

Behavioral engagement, in our study, refers to the extent to which students are actively participated in online learning activities (e.g., listening and reading carefully, and participating in online class discussions) (Chiu, 2022; Ding et al., 2017; El-Sayad et al., 2021). Behavioral engagement was found to have a positive influence on academic performance in many previous studies (Bråten et al., 2018; Kokoç, 2019; Morris et al., 2005). For instance, Morris et al. (2005) examined students' participation in, and the duration and frequency of, online courses; they found that student participation has a positive effect on their learning performance. Wang (2017) examined how online behavior engagement influences student achievement in a flipped classroom, and he found that students' engagement in problem-solving activities has a positive impact on their achievement levels. Accordingly, the following hypothesis was proposed.

H1: Behavioral engagement has a significant positive effect on students' learning performance.

2.2.2 Emotional engagement

In the present study, emotional engagement was defined as the extent to which students hold positive feelings about online learning (Chiu, 2022). Previous studies examining the effect of emotional engagement on academic performance yielded mixed results (Lee, 2014). In some studies, emotional engagement was found to be positively associated with academic success (King, 2015; Shernoff & Hoogstra, 2001). However, Ozhan et al. (2020) indicated that emotional engagement was not found to significantly influence success in a gamified online learning environment. In a meta-analysis conducted by Lei et al. (2018), behavioral, emotional, and cognitive engagement were all found to have a positive correlation with students' academic achievement with the effect size of emotional engagement being the lowest. Considering previous evidence, the following hypothesis was proposed.

H2: Emotional engagement has a significant positive effect on students' learning performance.

2.2.3 Cognitive engagement

Cognitive engagement refers to the extent to which students have made cognitive efforts to acquire complex knowledge and gain problem-solving skills (Jung & Lee, 2018; Luan et al., 2020). It relates to their motivation to learn, as well as self-regulation and critical thinking (Lester, 2013; Schindler et al., 2017). Previous literature indicated that students who are behaviorally but not cognitively engaged may not be so successful in their learning process (Casimiro, 2016; Davis et al., 2012). For instance, Pietarinen et al. (2014) reported that there is a positive correlation between cognitive engagement and academic achievement. Cognitive engagement was also found to be associated with student goal orientation and investment in learning (Greene et al., 2004), which in turn affected students' academic achievement (Miller et al., 1996). However, Appleton et al. (2006) indicated that the correlation between cognitive engagement and academic achievement is weak. Based on the previous evidence, the following hypothesis was proposed.

H3: Cognitive engagement has a significant positive effect on students' learning performance.

2.3 Individual-technology-task-environment fit

2.3.1 Task-Technology Fit (TTF)

The TTF theory, developed by Goodhue and Thompson (1995), holds that information technology is more likely to be utilized if the capabilities of the technology fit with the tasks it supports, and subsequently have a positive influence on performance. TTF is defined as "the degree to which a technology assists an individual in performing his or her portfolio of tasks" (Goodhue & Thompson, 1995). In our research context, it refers to the extent to which online learning systems match students' learning tasks. In the past decade, the TTF theory has been extensively applied to understand technology use and impact across various research contexts (Cane & McCarthy, 2009; D'Ambra et al., 2013; Furneaux, 2012; Isaac et al., 2019; McGill & Klobas, 2009; Oliveira et al., 2014; Tao et al., 2022; Wang et al., 2020). In online learning context, many previous studies have examined the positive effects of TTF on online learning behaviors and performance. For instance, Wu and Chen (2017) indicated that TTF was found to play an important role in affecting students' intention to continually use MOOCs. Isaac et al. (2019) indicated that TTF positively influences learning performance in the context of online learning. Moreover, when the online learning systems closely match students' learning tasks, the use of the technology may stimulate student engagement, which in turn may improve students' learning performance. Therefore, the following hypotheses were proposed.

H4: TTF has a significant positive effect on behavioral engagement.
H5: TTF has a significant positive effect on emotional engagement.
H6: TTF has a significant positive effect on cognitive engagement.
H7: TTF has a significant positive effect on students' learning performance.

2.3.2 Individual-Technology Fit (ITF)

In recent years, the TTF theory has been extended by introducing a new construct of ITF (Liu et al., 2011; Parkes, 2013; Wu & Chen, 2017). ITF stressed the match between individual capabilities and technology characteristics. In the context of online learning, it refers to the extent to which students can participate in online learning courses independently and actively (Wu & Chen, 2017). Previous literature indicated that ITF was associated with users' attitude towards the technology (Al-Emran, 2021; Parkes, 2013; Wu & Chen, 2017). However, the exact manner in which ITF affects student engagement and their learning performance remains unknown. Based on previous findings, the following hypotheses were proposed.

H8: ITF has a significant positive effect on behavioral engagement.
H9: ITF has a significant positive effect on emotional engagement.
H10: ITF has a significant positive effect on cognitive engagement.
H11: ITF has a significant positive effect on students' learning performance.

2.3.3 Environment-Technology Fit (ETF)

In the context of online learning, ETF is recognized as another significant factor that may influence students' engagement and learning performance. This factor had rarely been discussed before the pandemic; however, widespread online learning during the pandemic has given rise to studies on whether students had suitable working environment for online learning (Baltà-Salvador et al., 2021). Due to lockdown policies, many students had to study in their own homes. Many recent studies reported that an unsuitable learning environment was a critical impediment to successful online learning (Bączek et al., 2021; Baltà-Salvador et al., 2021; Barrot et al., 2021; Gelles et al., 2020; Realyvásquez-Vargas et al., 2020). For example, students reported being frequently distracted by their roommates or family members during online classes (Barrot et al., 2021; Gelles et al., 2020). Some students, especially those from families in lower socio-economic groups, had limited learning space and facilities at home (Barrot et al., 2021). Other environmental factors, including lighting, noise, and temperature were also found to be associated with student online learning performance during the pandemic (Realyvásquez-Vargas et al., 2020). We believe that if the characteristics of the physical environment are more suitable for online learning, students would be more likely to engage in online learning and achieve better learning outcomes. Therefore, the following hypotheses were proposed.

H12: ETF has a significant positive effect on behavioral engagement.
H13: ETF has a significant positive effect on emotional engagement.
H14: ETF has a significant positive effect on cognitive engagement.
H15: ETF has a significant positive effect on students' learning performance.

3 Materials and methods

3.1 Design

A questionnaire survey was employed to test the before-mentioned hypotheses. Data were collected in April 2022 through a professional web-based survey company in China (www.sojump.com). We targeted university students who had online learning experiences after the outbreak of COVID-19 pandemic. A total of 810 valid samples (954 returned questionnaires, 144 were excluded because of ineligibility) were used for data analysis. The study was approved by the Institutional Review Board of Tianjin University (No. TJUE-2022–193).

3.2 Measures

A self-administered questionnaire was designed for empirical data collection. The questionnaire consisted of two sections. The first section measured participants' demographic information, including gender, grade, major, self-rated academic level, perceived computer literacy, and online learning experience prior to COVID-19 pandemic. The second section measured constructs in the proposed research model. The constructs were measured with items adapted from previous literature (Baltà-Salvador et al., 2021; Chiu, 2022; Liu et al., 2022; Reeve, 2013; Skinner et al., 2009; Wang et al., 2016, 2021; Wu & Chen, 2017) (see Appendix Table 5). All the items were measured using 7-point Likert scales ranging from 1 (strongly disagree) to 7 (strongly agree).

3.3 Data analysis

Partial least squares structural equation modeling (PLS-SEM) approach was employed to examine the proposed research model. Evaluating PLS-SEM results requires performing two stages, namely measurement model assessment and structural model assessment (Hair et al., 2011). For measurement model assessment, the following criteria were used (Hair et al., 2011, 2019): (1) Internal consistency reliability of each construct was assessed by using Cronbach's alpha and composite reliability, with a value greater than 0.7 considered as satisfactory; (2) Convergent validity was assessed by measuring the average variance extracted (AVE) and the AVE values should be higher than 0.5; (3) Discriminant validity was assessed by the Fornell-Larcker criterion that the square root of AVE for each construct should be greater than its correlation with other constructs (Fornell & Larcker, 1981). As for the structural model assessment, path coefficients were estimated, and bootstrapping approach (bootstrap sample = 5,000) was employed to assess the path coefficients' significance. Coefficients of determination (R^2) of the endogenous constructs were calculated to indicate the amount of variance explained by the independent variables. All the analyses were performed by Smart PLS 3.0.

4 Results

4.1 Sample characteristics

The demographic characteristics of the participants are presented in Table 1.

4.2 Model assessment

The constructs' internal consistency was acceptable, as the Cronbach's alpha values and composite reliability of the constructs were greater than 0.7, except that the Cronbach's alpha of ITF (0.61) was lower than 0.7 (see Appendix Table 6). The AVE values of the constructs were all greater than 0.5, indicating satisfactory convergent validity. The Fornell-Larcker criterion was fulfilled for all the constructs, indicating satisfactory discriminant validity (see Appendix Table 7).

4.3 Structural model assessment

All the hypotheses were supported except H3, H11, H12, and H15 (see Table 2 and Fig. 2). TTF had the largest total effect on learning performance (see Table 3), followed by emotional engagement, behavioral engagement, ITF, and ETF. Cognitive engagement did not have significant total effect on learning performance. The proposed model explained 50.3% of the variance in learning performance. TTF, ITF, and ETF together explained 43.5%, 48.6%, and 41.8% of the variance in behavioral engagement, emotional engagement, and cognitive engagement, respectively.

4.4 Mediating effect analysis

We observed that behavioral engagement partially mediated the effects of TTF on learning performance and fully mediated the effects of ITF on learning performance (see Table 4). Emotional engagement was found to partially mediate the effects of TTF on learning performance, and fully mediate the effects of ITF and ETF on learning performance.

Table 1 Characteristics of the study sample(n = 810)

Characteristics	n (%)
Gender	
Male	366 (45.2%)
Female	444 (54.8%)
Grade	
Year 1	103 (12.7%)
Year 2	284 (35.1%)
Year 3	271 (33.5%)
Year 4 and above	152 (18.8%)
Major	
Philosophy	5 (0.6%)
Economics	104 (12.8%)
Law	21 (2.6%)
Education	68 (8.4%)
Literature	58 (7.2%)
History	10 (1.2%)
Natural Science	120 (14.8%)
Engineering	162 (20.0%)
Agriculture	12 (1.5%)
Medicine	80 (9.9%)
Management Science	139 (17.2%)
Arts	30 (3.7%)
Military	1 (0.1%)
Self-rated academic level	
Top 25%	286 (35.3%)
25%-50%	384 (47.4%)
50%-75%	127 (15.7%)
Last 25%	13 (1.6%)
Perceived computer literacy	
High	482 (59.5%)
Moderate	318 (39.3%)
Low	10 (1.2%)
Online learning experience prior to COVID-19	
Never	78 (9.6%)
Sometimes	451 (55.7%)
Very often	281 (34.7%)

5 Discussion

5.1 Main findings and theoretical implications

Our findings make a positive contribution to the literature by exploring how ITF, TTF, and ETF are associated with student online learning performance, and how the

Table 2 Path coefficient estimation and bootstrapping results of the research model

Hypothesis: path	Path coefficient	t-value	*p* value	Supported? (Yes/No)
H1: BE→LP	0.25	6.31	< 0.001	Yes
H2: EE→LP	0.27	6.36	< 0.001	Yes
H3: CE→LP	0.06	1.62	0.11	No
H4: TTF→BE	0.31	8.36	< 0.001	Yes
H5: TTF→EE	0.49	14.23	< 0.001	Yes
H6: TTF→CE	0.28	7.37	< 0.001	Yes
H7: TTF→LP	0.25	6.54	< 0.001	Yes
H8: ITF→BE	0.41	11.50	< 0.001	Yes
H9: ITF→EE	0.19	5.36	< 0.001	Yes
H10: ITF→CE	0.34	9.01	< 0.001	Yes
H11: ITF→LP	-0.05	1.37	0.17	No
H12: ETF→BE	0.03	0.87	0.38	No
H13: ETF→EE	0.12	3.35	0.001	Yes
H14: ETF→CE	0.16	4.01	< 0.001	Yes
H15: ETF→LP	0.07	1.86	0.06	No

LP, learning performance; BE, behavioral engagement; EE, emotional engagement; CE, cognitive engagement; TTF, task-technology fit; ITF, individual-technology fit; ETF, environment-technology fit

associations are mediated by student engagement dimensions. The findings highlight the importance of individual-technology-task-environment fit in the online learning context and suggest the need for an extension to the TTF theory by introducing ITF and ETF dimensions. The three fit dimensions had a significant total effect on student online learning performance, with TTF yielding the strongest total effect. Consistent with previous studies (Isaac et al., 2019; Wu & Chen, 2017), the significant relationship between TTF and learning performance indicates that university students are more likely to perform well academically if they feel that the manner

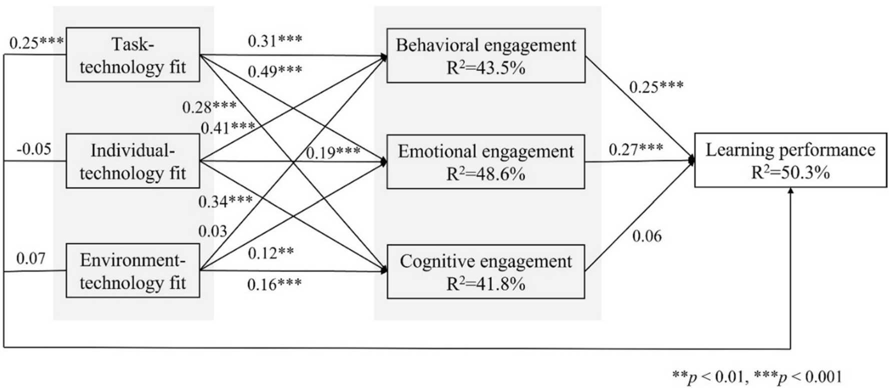

Fig. 2 Structural model evaluation results

Table 3 The direct, indirect, and total effects of predictors on learning performance

	Direct effect	Indirect effect	Total effect
BE→LP	0.25***	-	0.25***
EE→LP	0.27***	-	0.27***
CE→LP	0.06	-	0.06
TTF→LP	0.25***	0.23***	0.48***
ITF→LP	-0.05	0.18***	0.13***
ETF→LP	0.07	0.05***	0.12***

LP, learning performance; BE, behavioral engagement; EE, emotional engagement; CE, cognitive engagement; TTF, task-technology fit; ITF, individual-technology fit; ETF, environment-technology fit

*$p<0.05$, **$p<0.01$, ***$p<0.001$

in which online learning is delivered fits their approach to learning. Moreover, we found that TTF influences online learning performance through the mediating role of behavioral and emotional engagement. The results suggest that students who perceived that the online learning system matched their learning tasks are more likely to actively participate in online learning activities and enjoy online learning, subsequently achieving better learning outcomes. In addition, we observed that TTF has a meaningful effect on cognitive engagement, indicating that when the degree of TTF becomes greater, students put in more cognitive effort during online learning. Contrary to our hypothesis, ITF fails to have a direct effect on online learning performance; however, it does influence learning performance through behavioral and emotional engagement. Our results also indicate that, if online learning technology is designed to fit students' expertise level, students would be more likely to actively participate in online course activities, enjoy online classes, and subsequently achieve better learning outcomes. The results are in line with research conducted by Parks

Table 4 Results of mediating effect tests of engagement

Direct effect		Mediating effect		Mediating role of engagement factors
TTF→LP	0.25***	TTF→BE→LP	0.08***	Partial mediation (complementary#)
		TTF→EE→LP	0.13***	Partial mediation (complementary)
		TTF→CE→LP	0.02	-
ITF→LP	-0.05	ITF→BE→LP	0.10***	Full mediation
		ITF→EE→LP	0.05***	Full mediation
		ITF→CE→LP	0.02	-
ETF→LP	0.07	ETF→BE→LP	0.01	-
		ETF→EE→LP	0.03**	Full mediation
		ETF→CE→LP	0.01	-

LP, learning performance; BE, behavioral engagement; EE, emotional engagement; CE, cognitive engagement; TTF, task-technology fit; ITF, individual-technology fit; ETF, environment-technology fit

#mediated effect and direct effect point at the same direction

*$p<0.05$, **$p<0.01$, ***$p<0.001$

(2013) that ITF would directly affect an individual's attitude towards the technology, but not technology performance.

Similarly, we found that ETF does not directly affect online learning performance, but indirectly influences learning performance through emotional engagement. Previous literature has emphasized that environment should be considered as a separate dimension because it may help to explain why a technology works in one setting but not in another setting (Prgomet et al., 2019). In online learning context, we found that unsuitable learning environments may result in creating a negative emotional experience with online learning, which may in turn have a detrimental impact on student learning performance. In addition, ETF significantly affected cognitive engagement, indicating that when students perceive that the physical environment is suitable for online learning, students will be more cognitively engaged.

The present study demonstrated that behavioral and emotional engagement were both critical factors affecting student learning outcome. The results implied that students who actively participated in online learning activities, especially those who had a positive attitude toward online learning, were more likely to achieve better learning performance (Lei et al., 2018). Unexpectedly, we failed to observe a significant relationship between cognitive engagement and learning performance. A possible explanation for this result is, compared with traditional face-to-face instruction, online learning requires students to invest more effort (El-Sayad et al., 2021; Kim et al., 2018). However, even those students who felt they had put in more cognitive effort did not necessarily achieve positive learning outcomes. Another possible explanation is that students who achieved better learning outcomes had developed skills that allowed them to learn quickly and effectively; however, students with poor learning outcomes did not have good learning skills, making it difficult for them to achieve higher grades even if they tried to be more cognitively engaged (Lei et al., 2018).

5.2 Practical implications

In addition to theoretical contributions, several implications can be drawn from the fit perspective. Online learning practitioners must be aware that learning outcomes depend on the fit between individual, technology, task, and environment. First, TTF was the most important aspect. Our findings strongly suggest that online learning should be designed to fit student requirements. Instructors should not simply transfer an existing in-person course to an online learning platform, but instead need to ensure that the course content and design match student requirements and are suitable for online learning (Aristovnik et al., 2020; Baltà-Salvador et al., 2021). Second, online learning systems should be designed to fit student expertise and expectations. The design of online courses should be based on levels of requisite prior knowledge and the availability of resources for students (Wu & Chen, 2017). Third, a suitable working environment may enhance student learning performance (Baltà-Salvador et al., 2021). Ergonomics issues should also be considered in online learning context (Baltà-Salvador et al., 2021). Therefore, it is recommended that academic institutions and students' families offer a more suitable study environment for students. Previous literature has also indicated that one of the key challenges in achieving a suitable working environment is access to the Internet and related technology (Lockee, 2021). To address this issue, universities should make enquiries of students about their study conditions and offer more support. For example, studies show that school buses have been used to provide mobile hotspots, while students have also been allowed to borrow computers from the university to solve the problem of access (Baltà-Salvador et al., 2021; Lockee, 2021).

5.3 Limitations

First, we only examined student perceptions of online learning in a cross-sectional manner; however, these perceptions may change over time. Longitudinal studies are required to understand how the effects of individual-technology-task fit on student engagement and online learning performance change over time. In addition, we measured student learning outcomes through subjective surveys. Future studies may consider examining students' objective learning performance (e.g., using their grade point average). Third, the survey was conducted during an exceptional public health crisis; therefore, the results of the present study might not be replicable in other online learning settings.

5.4 Conclusions

Investigating how online courses may best be designed to avoid detrimental effects on student learning performance is necessary and important. The findings of our study highlight the important roles of TTF, ITF, and ETF in influencing student engagement and learning performance. Our results indicate that the better the fit between the individual, task, environment, and technology employed, the greater the chance that online learning will facilitate student learning outcomes.

Appendix Table 5

Constructs and measurement items

Constructs	Items
Learning performance (LP) (Wang et al., 2021)	LP1: I have a good grasp of the knowledge on the online course
	LP2: I fully understand what I have learned on the online course
	LP3: I will be able to cope well with the exam
	LP4: Online learning enriches my learning style
Behavioral engagement (BE) (Chiu, 2022; Skinner et al., 2009)	BE1: When I am on online learning, I listen and read very carefully
	BE2: I try hard to do well in online learning activities
	BE3: When I'm in online learning, I participate in class discussions
	BE4: When I'm in online learning, I work as hard as I can
	BE5: I pay attention in online learning
Emotional engagement (EE) (Chiu, 2022; Skinner et al., 2009)	EE1: When I'm in online learning, I feel good
	EE2: When we work on something in online learning, I feel interested
	EE3: Online learning is fun
	EE4: I enjoy learning new things in online learning
	EE5: When we work on something in online learning, I get involved
Cognitive Engagement (CE) (Reeve, 2013; Wang et al., 2016)	CE1: When I'm in online learning, I try to connect what I am learning with my own experiences
	CE2: I try to make all the different ideas fit together and make sense when I'm in online learning
	CE3: When we work on something in online learning, I try to relate what I'm learning to what I already know
	CE4: I make up my own examples to help me understand the important concept I study when I'm in online learning
Task-technology fit (TTF) (Wu & Chen, 2017)	TTF1: Online learning systems are fit for the requirements of my learning
	TTF2: Using online learning systems fits with my educational practice
	TTF3: It is easy to understand which tool to use in online learning systems
	TTF4: Online systems are suitable for helping me complete online courses
Individual-technology fit (ITF) (Wu & Chen, 2017)	ITF1: I can independently complete courses in e-learning systems
	ITF2: I actively participate in various types of discussions and evaluation in online courses
	ITF3: I try to win the awards for outstanding performance of my learning

(continued)

Constructs	Items
Environment-technology fit (ETF) (Baltà-Salvador et al., 2021; Liu et al., 2022)	ETF1: My workspace condition had been suitable for online learning
	ETF2: My workspace condition had been silent for online learning
	ETF3: There is enough space in your workplace for online learning
	ETF4: It is possible to find a space for online learning
	ETF5: My workspace condition had been bright for online learning

Appendix Table 6

Means, SDs, Cronbach's Alphas, CRs, and AVEs of the constructs

Constructs	Items	Mean	SD	Cronbach's Alpha	CR	AVE
Learning performance (LP)	LP1	4.13	1.40	0.71	0.82	0.54
	LP2	4.47	1.30			
	LP3	4.88	1.32			
	LP4	5.09	1.31			
Behavioral engagement (BE)	BE1	4.59	1.40	0.82	0.87	0.58
	BE2	4.79	1.31			
	BE3	4.90	1.35			
	BE4	5.27	1.23			
	BE5	4.70	1.45			
Emotional engagement (EE)	EE1	4.74	1.26	0.79	0.86	0.54
	EE2	4.96	1.32			
	EE3	4.63	1.37			
	EE4	4.91	1.33			
	EE5	5.00	1.30			
Cognitive engagement (CE)	CE1	5.05	1.28	0.72	0.83	0.54
	CE2	4.96	1.26			
	CE3	5.13	1.23			
	CE4	5.08	1.27			
Task-technology fit (TTF)	TTF1	4.85	1.31	0.74	0.84	0.57
	TTF2	4.51	1.48			
	TTF3	5.17	1.24			
	TTF4	4.90	1.30			
Individual-technology fit (ITF)	ITF1	5.40	1.22	0.61	0.79	0.56
	ITF2	4.98	1.31			
	ITF3	4.78	1.47			
Environment-technology fit (ETF)	ETF1	4.82	1.39	0.81	0.87	0.57
	ETF2	5.11	1.40			
	ETF3	5.28	1.25			
	ETF4	5.34	1.29			
	ETF5	5.30	1.31			

CR, composite reliability; AVE, average variance extracted

Appendix Table 7

Square roots of average variance extracted (AVEs, in bold) and correlations among the constructs

	LP	BE	EE	CE	TTF	ITF	ETF
Learning performance (LP)	**0.74**						
Behavioral engagement (BE)	0.59	**0.76**					
Emotional engagement (EE)	0.64	0.64	**0.74**				
Cognitive engagement (CE)	0.50	0.59	0.58	**0.74**			
Task-technology fit (TTF)	0.61	0.56	0.66	0.55	**0.75**		
Individual-technology fit (ITF)	0.45	0.60	0.53	0.57	0.56	**0.75**	
Environment-technology fit (ETF)	0.43	0.41	0.48	0.48	0.52	0.52	**0.75**

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Data availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that they have no competing interests.

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