External and Internal Predictors of Student Satisfaction with Online Learning Achievement

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Abstract
Building and testing a framework of interactive and indirect predictors of student satisfaction would help us understand how to improve students' online learning experiences. The current study proposed that external predictors such as poor technological, environmental, and pedagogical factors would be internalized as negative psychological traits and indirectly predict student satisfaction in online learning. Results of multivariate regressions with 5824 Chinese undergraduate students demonstrated that instructors' online teaching experience and communication with students had a stronger predictive effect on student satisfaction than wireless network quality and learning environment. Structural equation modeling analysis results showed that inferior technological, environmental, and pedagogical factors would be internalized into negative attitudes and emotions toward online learning and indirectly predict student satisfaction. Third, providing after-class learning materials to students or having longer self-learning time would not buffer students from negative external factors. Our study has implications for better understanding the extensive influence of online learning barriers caused by external conditions and building preventive mechanisms through the improvement of instructors' teaching experience and communication with students.

To respond to the public health emergencies caused by Covid-19 in 2020, most higher education institutes (HEIs) transferred their regular education activities online. The sudden burden caused by extra studying time (Fang, Lu, & Chen, 2020), psychological and physical unpreparedness (Razai et al., 2020), and social isolation (Akuratiya & Meddage, 2020) has enlarged the challenges that already existed in online learning for students. As a result, the Covid-19 global pandemic has created the largest-ever online learning practice worldwide, and also brought up a unique opportunity to investigate the quality of online learning during a time of urgent transition.

With numerous studies on online learning, several predictors of student satisfaction have emerged across research studies (e.g., Alqurashi, 2019; Zeng, & Wang, 2021). For example, Asoodar et al. (2016), created a framework with six dimensions to predict student satisfaction in online learning: student, instructor, course, design, technological, and environmental dimensions. Almusharraf and Khahro (2020) used the evaluation of instructors, facility performance, and recommendations by students to evaluate student satisfaction with online learning. However, most of these studies have limitations. First, some of these studies only tested the direct effect of environmental and personal factors on student satisfaction (see, e.g., Parahoo et al., 2016). They did not demonstrate the indirect or interactive relationships of factors that predict student satisfaction with a theoretical framework. The investigation of the complicated mechanism of predictors of online learning satisfaction would help us break those barriers students have to face in online learning. Second, most previous studies are based on students from the U.S., Europe, or the Middle East (Yunusa & Umar, 2021). Few studies on student satisfaction with online learning focus on East Asian or Chinese college students, who usually prefer to learn directly from teachers, which is different from student-centered learning beliefs in Western countries (Chan, 1999; Sit, 2013). Literature in online learning regarding Western college students may not always be applicable to Chinese students considering the varied ideologies of the ideal way of learning. The factors or mechanisms that may determine student learning outcomes or satisfaction could be different among Asian students.

As a result, the current study aims to develop and test an online learning framework to examine technological, environmental, and pedagogical factors as external factors, psychological traits as internal factors, and their mechanism for predicting student satisfaction in online learning during Covid-19 with Chinese college students.

Theoretical Framework

The framework of online learning satisfaction of Chinese students in the current study was inspired by Rovai's (2003) theoretical model of online learning persistence. We adopted the concept of environmental and psychological factors in Rovai's (2003) persistence model and revised them based on Chinese students' cultural context of online learning. Researchers have extensively studied students' persistence and attrition in a face-to-face setting (Tinto, 1993; Bean & Metzner, 1985) and applied those results to the online learning context (Rovai, 2003). However, few researchers have examined student satisfaction as an online learning outcome with a systematically tested theoretical framework, especially in the Chinese context. It may be because persistence or attrition is usually considered an outcome of different levels of satisfaction in Western countries (Lakhal, Khechine, & Mukamurera, 2021; Rahim, 2020; Rovai, 2003; Park, 2007). High satisfaction is assumed to be only one of the factors that keeps students in online classes. However, if we want a better understanding of how to build up a high-

quality and large-scale online class, student satisfaction has to be one of the focuses (Zeng & Wang, 2021), and should be as important as persistence or retention.

Rovai (2003) proposes in his persistent model that two sets of prior-admission factors, including student characteristics and student skills, and another two sets of after-admission factors, internal and external factors, altogether determined students' persistence decisions. Rovai (2003) defines external and internal factors from the perspective of the class context, where external factors are factors that happened outside the classes, like family issues or financial problems, and internal factors are factors observed within the classes, like academic integration and technology issues. Park (2007) builds on Rovai's (2003) model, where he defines external factors as those that could affect inside and outside online classes. He argues that external and internal variables should interactively work together, thus in Park's model, external variables would affect students' persistence through the entire process of online learning.

Rovai's (2003) and Park's (2007) models for online learning persistence may not be applicable to Chinese college students though they were tested and expanded by numerous studies (e.g., Park, & Choi, 2009), as Chinese students have very high persistence rates and rarely drop out of college (Marioulas, 2017). Few Chinese college students are part-time or adult learners, making most external factors in Rovai's (2003) and Park's (2007) models not applicable. They mostly do not have challenges from, for example, scheduling conflicts, employment, or family responsibilities. Thus, the external and internal factors for student online satisfaction should be restructured considering cultural differences and the realistic needs of Chinese students.

The current study suggests a new theoretical framework, including student characteristics, internal, and external factors to predict Chinese student satisfaction in online learning based on Rovai's (2003) and Park's (2007) models. However, we make several revisions based on previous literature and Chinese students' characteristics (Figure 1). The current study defines external and internal factors from the perspective of individual students instead of the class setting. Technological, environmental, and pedagogical factors would be external factors as they are barriers out of students' control. In comparison, students' psychological traits, for example, attitudes and emotions, and demographic information are internal factors, as they are related to individual students within the online learning classroom. In the next four sections, we describe these external and internal factors specifically related to this study.

External: Technological and Environmental Factors

Wireless network quality is one of the most important technological factors in efficiently delivering course content and has the potential to greatly affect student satisfaction with online learning (Aguilera-Hermida, 2020; Dhawan, 2020; Putri et al., 2020; Rajabalee, & Santally, 2021; Selim, 2007; Volery & Lord, 2000). Internet difficulties may occur at home when students are not prepared to study in quarantine in an emergency (Simamora, 2020). Students from low socioeconomic status (SES) families are the most vulnerable with limited access to high-quality internet service, which is a necessity for learning online (Putri et al., 2020). Based on Akuratiya and Meddage's (2020) research with 130 students in Sri Lanka during the pandemic, 69.5% of students relied on streaming mobile data to learn online and 46.1% had a limited internet connection speed. An unstable internet connection would diminish the accessibility and quality of learning online experience. In this case, the quality of the internet technology could greatly

affect student satisfaction and make online learning quality less comparable to face-to-face learning.

The home environment is not ideal for online learning. Studying at home, which is supposed to be a place of relaxation and rest, students have to make extra effort to maintain a working status (Kay, 2020). Students feel that home is a private and comfortable space in which obligations and work should be excluded (Karim, 2021). To study productively, they have to resist distractions from family members and issues. Nambiar (2020) surveyed 412 students in Indian colleges and universities during the pandemic and found that 23.3% of students found it harder to concentrate and were more distracted when studying online at home as compared to in a face-to-face classroom. Some students reported that their home environment was not supportive and family issues made them less involved in online classes (Nambiar, 2020). Another study had a similar finding that college students reported the biggest challenge of online learning was that it was hard to concentrate at home, which usually was full of noise, family members, and housework (Aguilera-Hermida, 2020). These studies suggest that a congested and distracting living environment can be challenging for students, which may lead to diminishing their satisfaction with online learning (Aguilera-Hermida, 2020; Masha'al, Rababa, & Shahrour, 2020; Meishar-Tal, Weinblat, & Shapira, 2022).

External: Pedagogical Factors

Instructors' teaching experience and their communication with students are two main predictors of student satisfaction in online learning. Particularly during the pandemic, previous online teaching experience would help instructors quickly adapt to online teaching and increase their positive attitudes toward online learning (Ulmer, Watson, & Derby, 2007). Podolsky et al. (2019) conducted a literature review of research studies within the United States and found that the length of teaching experience is highly and positively associated with student achievement. Another study with 132 teachers in Canada found that online teaching experience was associated with instructors' self-efficacy and acceptance of technology during the transition to online learning (Dolighan & Owen, 2021). This leads to the current study assuming that previous teaching experience would associate with better teaching practices for instructors and higher student satisfaction.

Instructors' interaction and communication with students are one of the most effective teaching practices to predict student satisfaction (Gergen, 2015; Herrington & Oliver, 2000). In Vygotsky's (1978) zone of proximal development theory, instructors' facilitation and interaction would be the bridge between what students know and what they need to know and do. Instructors' availability and response are particularly important for keeping students engaged and motivated (Bolliger & Martindale, 2004). Unfortunately, students are more likely to face a loss of communication or fewer interactions with instructors due to the nature of online learning throughout the pandemic (Ives, 2021), disturbing their regular learning process. In this case, online interaction and communication would be particularly important in facilitating a virtual community and social context between instructors and students (McInnerney & Roberts, 2004). It would promote the feeling of connectedness and belonging especially during the global shutdown (Palloff & Pratt, 2001). Instructor-student communication should be a critical part of pedagogical factors associated with student satisfaction in online learning.

Internal: Psychological Traits

Students' positive psychological traits, including attitudes and emotions, play a

supporting role in online learning quality (Alavudeen, et al., 2021; Flesia et al., 2020; Wan et al., 2008). They may be the mechanism explaining the link between external environmental, technological, and pedagogical factors affecting students' satisfaction with online learning.

Attitudes Toward Online Learning

The technology acceptance model (TAM) argues that attitudes toward online learning determine online learning quality (Al-Emran, Mezhuyev, & Kamaludin, 2018; Davis, 1989; Al-hawari & Mouakket, 2010). Based on TAM, people's actual use of technology would be explained by their attitudes toward it, including perceived usefulness and perceived ease of use. Several studies have demonstrated the importance of students' attitudes toward online learning satisfaction (e.g., Han & Sa, 2022; Aguilera-Hermida, 2020; Sun et al., 2008). For example, Han and Sa, (2022) found that students' positive perceptions of the use and usefulness of online learning were significantly associated with their education satisfaction with 313 university students who took online classes. Sahin and Shelley's (2008) study with 195 undergraduate students showed that students' recognition of the flexibility of distance learning would predict their perception of the usefulness of distance learning and their learning satisfaction. Both studies suggest the significance of students' attitudes toward online learning in explaining their satisfaction.

Emotions Toward Online Learning

Another important psychological trait that should be involved when investigating student satisfaction is the emotions toward online learning. Pekrun (2006; 2011) argues in his control-value theory of achievement emotion that emotions related to learning activities or outcomes should be called achievement emotions. These emotions include both positive and negative traits, including, for example, joy, pride, hopelessness, anxiety, and boredom. Students' achievement emotions in online learning have been well studied (e.g. Daniels, & Stupnisky, 2012). For instance, a study with 730 undergraduate students found that students' emotions have a strong effect on their preference for online learning (Tempelaar et al., 2012). Negative learning emotions like boredom or hopelessness would prevent students from online learning. Artino (2009) found in his study with 481 undergraduate students that boredom and frustration were associated with lower online learning satisfaction and lower continuing motivation. During the pandemic, adapting to new learning methods and technology, distracting environments, and lack of communication could surely bring negative emotions to new online learners, resulting in low satisfaction and a poor learning experience.

Support from Learning Materials

Supplemental learning materials could be a supportive scaffold in online learning. It could motivate student-material interaction, which is associated with students' reflection, engagement, and elaboration in online learning based on the social constructive theory (Anderson, 2008). Moore et al. (1989; 1992; 2011) are some of the earliest researchers who define online interaction. They argue in their online interaction theory that there are three types of interaction: instructor-student, student-student, and student-materials interaction. Student-material/content interaction is one of the most important methods to improve online learning satisfaction. Kuo et al. (2014) surveyed 221 graduate and undergraduate students online and found that student-content interaction was the strongest predictor of student satisfaction in online learning. Sari and Oktaviani's (2021) study with 185 undergraduate students found that most

students were highly motivated by online learning materials provided by instructors. Thus, learning materials play a facilitating or scaffolding role in online learning and are associated with student satisfaction. Through the process of interacting with learning materials, students would be encouraged to integrate new ideas or knowledge obtained from online courses with the content provided by learning materials and formulate new questions and thoughts. They are expected to compensate for what students miss or misunderstand in online learning and encourage students to explore new knowledge and ideas.

Research Questions

Considering the supporting role of learning materials and the explaining mechanism of psychological traits between external factors and online learning satisfaction, a theoretical framework is presented in Figure 1. The current study aims to test the proposed student satisfaction model and explores how each factor is associated with online learning satisfaction in different directions and levels.

Figure 1
The Proposed Student Satisfaction Model in Online Learning

|-------------Outside the classroom----------| |------------Within the classroom-----------|
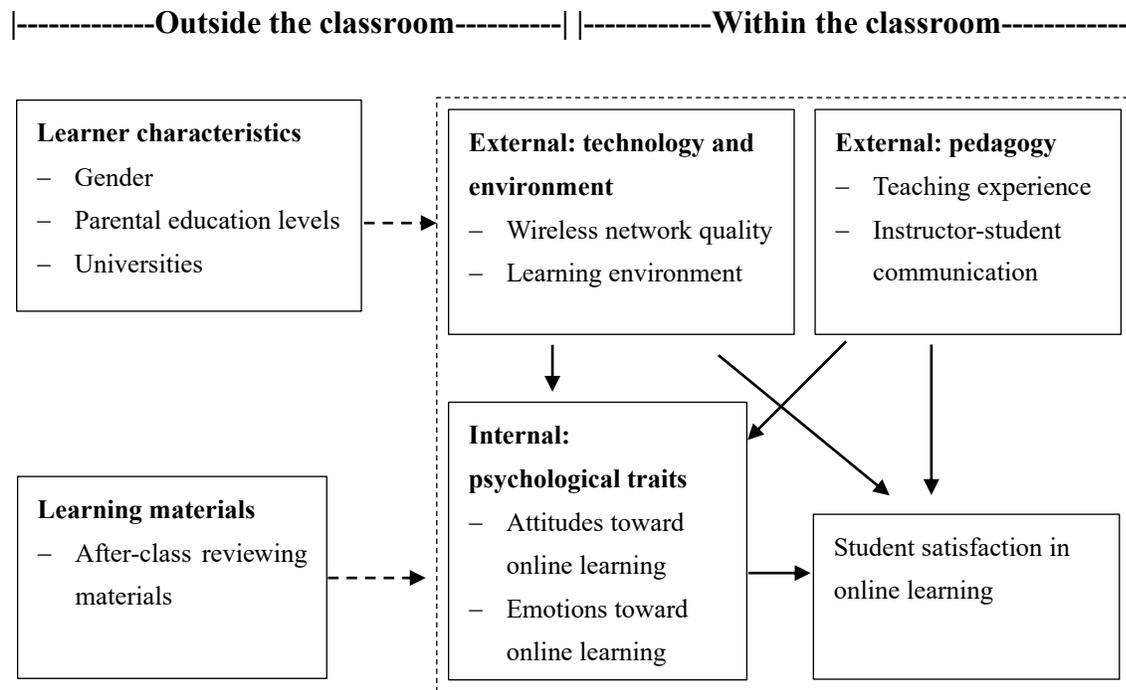
1. Are external factors, including wireless network quality, learning environment, instructors' teaching experience, and instructor-student communication associated with student satisfaction?

2. Does providing after-class reviewing materials moderate the association between external factors and student satisfaction in online learning?

3. Are internal factors, including attitudes and emotions toward online learning mediate the association between external factors and student satisfaction?

Method

Participants

The current study had a total of 5980 students who completed course evaluation surveys of general education courses from universities A and B in China. Both universities are known for their well-developed general education systems. University A is located in Wuhan, one of the biggest cities in Central China. University B is located in Beijing, which represents one of the biggest cities in Northern China. There were 2370 (40.69%) female-identifying students and 3454 (59.31%) male-identifying students. For mothers' education levels, 1286 (27.78%) students' mothers had junior high school or lower degrees; 1066 (25.57%) had high school degrees; 574 (15.30%) had associated degrees; 855 (25.81%) had Bachelor's degree, and 123 (5.55%) had Master's degree or above. Most students (2046) were engineering and technology majors (55.48%). Natural science students were 24.78%. Social science students were 15.06% and humanities students were 4.69%.

Table 1

Demographic Information of Students from Universities A and B

		University		Total	Percentage
		A	B		
Gender	Female	1695	675	2370	40.69%
	Male	2209	1245	3454	59.31%
Mother's education levels	Junior high school or lower	1286	332	1618	27.78%
	High school	1066	423	1489	25.57%
	Associated degree	574	317	891	15.30%
	Bachelor's degree	855	648	1503	25.81%
	Master's degree or above	123	200	323	5.55%
	Humanities	60	213	273	4.69%
	Social science	653	224	877	15.06%
Major	Natural sciences	1145	298	1443	24.78%
	Engineering and technology	2046	1185	3231	55.48%
Total		3904	1920	5824	100%

Procedure

Our data were collected through the Chinese University Course Evaluation (CUCE) project. The CUCE project aims to evaluate general education courses within seven top universities in China. It has been conducted for six years since 2016. The current study only adopted the data from the spring semester of 2020 from two universities, which was a remote online-learning semester due to the lockdown during the Covid-19 pandemic. All students were expected to take online courses at home during this semester as the quarantine policy was announced one day before the Spring Festival during winter break. It is the biggest holiday in China when most Chinese people would celebrate with their families at home.

The general education courses in these two universities were elective and open to all undergraduate students. Each undergraduate student had to fulfill a certain number of general education course credits to graduate. The number of credits depended on students' majors and

colleges. To achieve a higher response rate, the teaching assistants and administration office would send out several reminder emails with the survey links to students at the end of the semester until the response rate reached 50%. Participation was voluntary and anonymous.

Measures and Instruments

All the items in the CUCE were designed by the authors of current studies corresponding to the specific need of teaching and learning practices collected from the administration office, instructors, and students. As each item reflected different aspects of teaching and learning online, variables were measured on single items.

External factors

The current study took technological, environmental, and pedagogical factors as external factors, including wireless network quality, learning environment, online teaching experience, and instructor-student communication. The student-reported survey items adopted respectively were "wireless network condition is poor"; "my learning environment is distracting and not good for online learning"; "the instructor is not experienced with online teaching"; "I can't get help and guidance when I have questions." For these four items, students reported their answers with a four-point scale from one (totally disagree) to four (totally agree). Higher scores indicated inferior external conditions perceived by students while lower scores indicated good external conditions. They were treated as continuous variables.

Internal Factors

For individual-level internal factors, we examined the level of negative emotions toward online learning through the item "I feel consistently confused and hopeless on how to learn well in this class," and students' attitudes toward online learning were tested through the item "online learning makes me disengaged, distracted, and low-achieving." They were continuous variables with a four-point scale from totally agree to totally disagree. Higher scores meant more negative attitudes toward online learning, and lower scores meant fewer negative attitudes.

Moderator

The survey item used as the moderator asked students whether their instructors provide "after-class reviewing materials." The answer is 0 (no, not provided) versus 1 (yes, provided).

Student satisfaction

The outcome variable was student satisfaction with learning achievement in the online course. The answer was a five-point Likert scale from 1 = very unsatisfied to 5 = very satisfied.

Covariates

Participants' universities (university A = 0) and gender (female = 0) were treated as dummy variables (Table 1). Mothers' education levels were continuous variables (Table 1). Five majors (humanities = 0) were run as four dummy variables (Table 2). Weekly study time (almost none = 0; less than 1 hour; 1-2 hours; 2-3 hours; 3-4 hours; more than 4 hours) were nominal and taken as five dummy variables.

Data Analysis Plan

The current study had four steps of data analysis. First, we conducted descriptive statistics of student demographic information (Table 1) and external and internal variables (Table 2). Second, we ran a series of multivariate linear regression models to answer research question one to examine the direct effect of external variables on student satisfaction. Third, a series of multivariate regression models were run to examine research question two to assess the moderating effect. We first tested the effect of control variables in the first model in Table 4. In the following models, we tested the direct and interactive effect of each independent variable and moderator in models 2 and 3. In model 4, we tested all interactors all together in one model. In model 5, we put in the weekly study time to examine and control the effect of self-learning time on student satisfaction. Variables for interactions were centered to reduce multicollinearity. Fourth, two mediating effect models were tested through structural equation modeling (SEM) to answer research question three. One was for environmental and technological factors and the other was for pedagogical factors considering their different roles playing on student satisfaction in our proposed online learning theoretical models (Figure 1).

Descriptive statistics and multivariate regression models were conducted with Stata 15.1, integrated statistical software for storing, managing, and visualizing data (Stata Corp, 2017). The assumptions of multivariate regression models, including linear relationship, no multicollinearity, independence, homoscedasticity, and multivariate normality were tested. Beta is the standardized coefficient. The robust standard error was adopted for heteroskedasticity. The path analysis models through SEM were used to evaluate the best-fitting model and its structural coefficients to assess the total effect of explanatory variables on dependent variables. The model fit was based on the acceptable thresholds of indices, for example, normed fit index (NFI), comparative fit index (CFI), and root mean square error of approximation (RMSEA). The value of NFI and CFI has to range from .90 to 1 to be good. The RMSEA examines the closeness of fit with an acceptable value smaller than .08. Bootstrapping was applied to better evaluate the indirect effect of the mediating models.

Results

Descriptive Statistics

The mean and standard deviation of internal and external variables are presented in Table 2. There were 590 students, who reported that their instructors did not provide after-class reviewing materials while 5134 said their instructors did.

Table 2

Descriptive Statistics of Internal and External Variables

Variables	Mean	S.D.	95% Confidence Interval	
Wireless network quality	2.11	0.013	2.08	2.13
Learning environment	1.88	0.012	1.85	1.90
Online teaching experience	1.54	0.010	1.52	1.56
Instructor-student communication	1.71	0.011	1.69	1.73

Multivariate Regression Results

Direct Effect

Five multivariate linear regression models were conducted to examine how external factors were associated with student satisfaction (Table 3). In the first model, controlling variables were added. In the second model, poor wireless network quality (*Beta* = -.05, *p* <.01) and learning environment (*Beta* = -.09, *p* <.001) were included. Both of them were significantly and negatively associated with student satisfaction. It indicated that the worse the wireless network quality and learning environment were, the lower student satisfaction with learning achievement was. Next, the lack of online teaching experience (*Beta* =-.10, *p* <.001) and instructor-student communication (*Beta* =-.17, *p* <.001) were added to the third model and showed a significant and negative association with student satisfaction (Table 3). It meant that instructors' insufficient online teaching experience or communication with students would be correlated with low student satisfaction

In the fourth model, we put in four external variables altogether. When online teaching experience and instructor-student communication were added, wireless network quality and learning environment became nonsignificant (Table 3; Model 4). It demonstrated that online teaching experience (*Beta* =-.11, *p* <.001) and instructor-student communication (*Beta* =-.17, *p* <.001) played a bigger explanatory role in predicting student satisfaction compared to environmental or technical factors.

In the fifth model, students' weekly study times were added as five dummy variables. Results found that study time was significant and positively associated with student satisfaction (Table 3). Moreover, the beta reached the largest value (*Beta* = .22) when study time ranged from one to three hours per week, and gradually diminished when it became longer than three hours. However, after adding in weekly study time, online teaching experience (*Beta* =-.10, *p* <.001), and instructor-student communication (*Beta* =-.17, *p* <.001) were still significantly associated with student satisfaction and their coefficients barely changed (Table 3). This implies that studying after classes for a longer time predicts higher student satisfaction, but it would not prevent students from the negative effect of instructors' insufficient online teaching experience and loss of instructor-student communication.

Table 3

Multivariate Regression of External Variables on Student Satisfaction

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Beta	**S.E.**	**Beta**	**S.E.**	**Beta**	**S.E.**	**Beta**	**S.E.**	**Beta**	**S.E.**
(Constant)	4.09***	.06	4.37***	.06	4.58***	.06	4.55***	.06	4.21***	.08
University	-.06***	.02	-.07***	.02	-.08***	.02	-.08***	.02	-.07***	.02
Social science	.02	.06	.01	.06	.01	.06	.01	.06	.00	.06
Natural sciences	.00	.06	-.02	.06	-.02	.05	-.02	.05	-.03	.05
Engineering and technology	.04	.05	.02	.05	.01	.05	.01	.05	-.00	.05
Gender (female)	.02	.02	.02	.02	.04***	.02	.04***	.02	.04***	.02
Mother's education levels	.09***	.01	.07***	.01	.07***	.01	.07***	.01	.07***	.01
Wireless network quality			-.05**	.01			.01	.01	.01	.01
Learning environment			-.09***	.02			.02	.02	.01	.02
Online teaching experience					-.10***	.02	-.11***	.02	-.10***	.02
Instructor-student communication					-.17***	.02	-.17***	.02	-.17***	.02
Weekly study time： Less than 1 hour									.16***	.30
1-2 hour									.22***	.36
2-3 hour									.22***	.41
3-4 hour									.16***	.46
More than 4 hours									.11***	.44
Adjusted R^2	.01		.02		.07		.07		.08	
Error *df*	5817		5815		5815		5813		5808	

Note: *$p<0.05$; **$p<0.01$, ***$p<0.001$.

Moderating Effect

The current study conducted four multivariate linear models to examine the effect of providing after-class reviewing materials and its interaction with each external variable on student satisfaction with learning achievement (Table 4). Results showed that providing after-class reviewing materials had a significant and positive association with student satisfaction across all three models (Table 4; Model 2: *Beta* = .10, *p* < 0.01; Model 3: *Beta* = .09, *p* < 0.01; Model 4: *Beta* = .09, *p* < 0.01). However, contradicting our original hypotheses, providing after-class reviewing materials did not show a significant moderating effect on the association between each external variable and student satisfaction with learning achievement in all three moderating models in Table 4.

Table 4
The Moderating Effect of Providing After-class Reviewing Materials on Student Satisfaction with Learning Achievement

|	Model 1		Model 2		Model 3		Model 4	
	Beta	**S.E.**	**Beta**	**S.E.**	**Beta**	**S.E.**	**Beta**	**S.E.**
(Constant)	3.73***	.08	3.80***	.08	3.82***	.07	3.82***	.08
University	-.05***	.02	-.06***	.02	-.07***	.02	-.07***	.02
Social science	.01	.06	.00	.06	.00	.06	.00	.06
Natural sciences	-.01	.06	-.02	.05	-.03	.05	-.03	.05
Engineering and technology	.02	.05	.01	.05.	.00	.05	.00	.05
Gender (female)	.02	.02	.02	.02	.04**	.02	.04**	.02
Mother's education levels	.09***	.01	.07***	.01	.07***	.01	.07***	.01
Less than 1 hour	.17***	.06	.16***	.06	.15***	.06	.15***	.06
1-2 hour	.24***	.06	.23***	.06	.21***	.06	.21***	.06
2-3 hour	.24***	.06	.23***	.06	.21***	.06	.21***	.06
3-4 hour	.18***	.07	.18***	.06	.16***	.06	.16***	.06
More than 4 hours	.13***	.08	.12***	.08	.11***	.08	.11***	.08
After-class reviewing materials			.10***	.03	.09***	.03	.09***	.03
Wireless network quality			-.04*	.01			.01	.01
Interaction1			-.00	.05			.00	.04
Learning environment			-.09***	.02			.01	.02
Interaction2			-.01	.05			.00	.05
Online teaching experience					-.10***	.02	-.10***	.02
Interaction3					-01	.07	-.01	.07
Instructor-student communication					-.16***	.02	-.16***	.02
Interaction4					-.02	.06	-.02	.06
Adjusted R²	.03		.05		.09		.09	
Error *df*	5812		5807		5807		5803	

Note: *p<0.05; **p<0.01, ***p<0.001; Interaction1= After-class reviewing materials* Wireless Network quality; Interaction2= After-class reviewing materials* Learning environment; Interaction3= After-class reviewing materials* Online teaching experience; Interaction4= After-class reviewing materials* Instructor-student communication.

Mediating models

The current study conducted two path analysis models to examine the mediating effect of internal psychological traits in research question three. All estimates were standard regression coefficients. The results of the first model found that the wireless network quality and learning environment were associated with attitudes and emotions toward online learning, with the attitudes and emotions toward online learning also associated with student satisfaction (Figure 2). It demonstrated that student attitudes and emotions toward online learning mediated the links between wireless network quality, learning environment, and student satisfaction. The proposed model showed an acceptable fit to the data (RMSEA = .08, CFI = .82, NFI = .82). The total effect of wireless network quality and learning environment on student satisfaction was significant (β = -.11, p < 0.01). However, the two paths of direct effect from two external factors on student satisfaction were not significant. The indirect effect of wireless network quality (β = -.03, p < 0.01) and learning environment (β = -.05, p < 0.01) through attitudes toward online learning to student satisfaction were significant and negative. The indirect effect of wireless network quality (β = -.02, p < 0.01) and learning environment (β = -.05, p < 0.05) through emotions toward online learning to student satisfaction were significant and negative. Both negative environmental external factors were indirectly associated with lower student satisfaction through negative attitudes and emotions toward online learning.

Figure 2

The Mediating Effect of Attitudes and Emotions Toward Online Learning on the Association Between Wireless Network Quality, Learning Environment, and Student Satisfaction
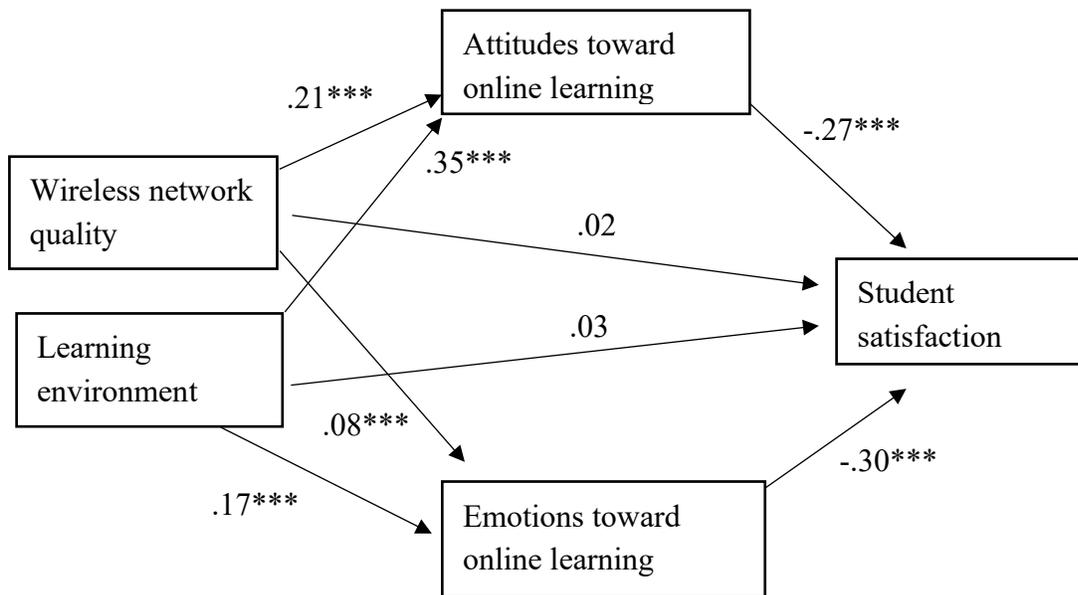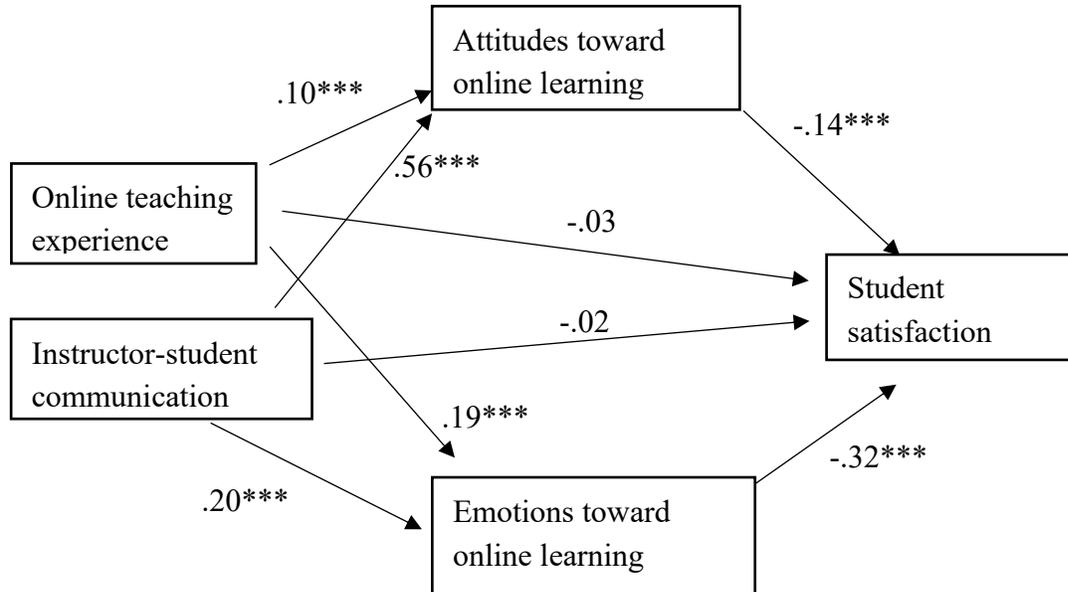

Note: **p < .01; ***p < .001.

The second path analysis model found a significant association between teaching experience, instructor-student communication, and attitudes and emotions toward online learning, and a significant association between attitudes and emotions toward online learning and student satisfaction with learning achievement (Figure 3). It demonstrated a significant mediating effect of attitudes and emotions toward online learning between online teaching experience, instructor-student communication, and student satisfaction. The model had good model fit (RMSEA = .06, CFI = .90, NFI = .90). The total effect was significant and negative (β = -.26, p < 0.01). The direct effect of teaching experience and instructor-student communication on student satisfaction was not significant. The indirect effect of teaching experience (β = -.02, p < 0.01) and instructor-student communication (β = -.07, p < 0.01) through attitudes toward online learning on student satisfaction was significantly negative. The indirect effect of teaching experience (β = -.07, p < 0.01) and instructor-student communication (β = -.06, p < 0.01) through emotions toward online learning on student satisfaction was significant and negative as well. It demonstrated that both pedagogical external factors only had an indirect effect on student satisfaction through attitudes and emotions toward online learning. Attitudes and emotions toward online learning were the mechanisms explaining the association between two negative external pedagogical factors and low student satisfaction.

Figure 3
The Mediating Effect of Attitudes and Emotions Toward Online Learning on the Association Between Online Teaching Experience, Instructor-Student Communication, and Student Satisfaction

Note: **p < .01; ***p < .001.

Discussion

Detecting factors and mechanisms that explain student satisfaction with online learning has been the focus of online education research, which is also the aim of the current study. The present study has three main findings. First, among external factors, instructors play a bigger role

than technological or environmental factors when predicting student satisfaction. Second, providing materials for learning after classes would not buffer the aversive effect of external factors in online learning. Third, our proposed student satisfaction model is supported. Inferior external factors would be internalized as negative attitudes and emotions toward online learning and indirectly relate to student satisfaction with online learning.

The Critical Role of Instructors

Our results aligned with previous theories of Rovai (2003) and Moore et al. (1989; 1992; 2011) that pedagogical factors are very important in explaining student learning outcomes, especially satisfaction. Based on our results, instructors could accumulate more online teaching experience and keep frequent communication with students to help them succeed in learning online, which is supported by previous research from Podolsky et al. (2019). These two factors have stronger predictive power on student satisfaction than wireless network quality and learning environment. This suggests that for HEIs, instructor training should be prioritized before information technology infrastructure upgrading, particularly when there is an emergency with limited resources. From another perspective, this finding is encouraging that it is easier to adjust instruction methods compared to making fundamental innovations in technical or environmental conditions within a short period. HEIs and instructors should play an active role in teacher training programs to improve online teaching practices and experience to help students succeed online.

The Challenges of Inferior Online Learning Conditions

Contrary to the researchers' hypotheses and previous study from Sari and Oktaviani's (2021), having longer study time with provided supplementary learning materials would not protect students from external challenges such as an inferior learning environment or absence of instructor-student communication. It suggested that missing content in online classes due to inferior external conditions may make self-learning at home less efficient after classes, especially with extra obstacles during the pandemic. Sufficient environmental and technological support is the precondition for a satisfactory learning experience at home alone. The results highlight the urgent necessity to improve the technological, environmental, and pedagogical support for students to succeed in learning online. Moreover, this may also explain why online learning has enlarged the educational disparities between students from different social economic statuses (SES) during the pandemic (Kuhfeld et al., 2020; Chetty et al., 2020). As students from low SES have more environmental and technological limitations at home than students from higher SES backgrounds, they might face additional challenges to success in learning online (Putri et al., 2020). Therefore, to achieve large-scale online learning while maintaining education equality, eliminating inferior environmental, technical, and pedagogy factors has to be the priority goal.

Internalization of Negative External Factors

The last finding of the current study suggests that the impact on student satisfaction brought by both internal and external factors may be larger and deeper than expected during the online learning experience. On top of previous literature on TAM (Davis, 1989) and control-value theory of achievement emotion (Pekrun, 2006; 2011) that psychological traits would affect online learning experience, we found that students would transfer external learning obstacles into negative attitudes and emotions toward online learning. Our proposed model in Figure 1 is supported. This is alerting as they are very stable and critical predictors of learning

achievements, satisfaction, and retention (Al-Hawari & Mouakket, 2010) and are hard to reverse in a short time (Lee & Stankov, 2018). The psychological intervention for students would be time-consuming and require broad and intensive collaboration and effort of educators, researchers, and parents. Thus, the negative psychological traits caused by inferior environmental, technological, and pedagogical factors may not only hurt student satisfaction but also the long-term online learning process and outcomes.

Implications and Future Research

The current study has implications for advancing online learning quality and future online program development. First, it has a theoretical contribution to previous student satisfaction or persistence models that predictors may not only have a direct effect but also an indirect effect within online learning. Determinants of student learning satisfaction and outcomes may be more complex than previous literature has suggested. Second, it has practical implications for educational resource attribution and arrangement by investing in instructor training ahead of technological upgrades. This is particularly helpful when HEIs have limited educational resources and want to improve student online learning quality within a short time. It also calls upon HEIs to enrich instructors' online teaching experience with more availability of online courses and enhance students' attitudes and experience of new technologies to motivate them to take online programs in the future. Third, due to the intensive and broad effect of poor environmental and technological factors, the public sector should enlarge the investment in information technology infrastructure to prevent the negative influence of external factors and support students from all SES to have equal opportunity and access to online learning.

Furthermore, the current study has implications for demonstrating large-scale online programs as a promising and necessary method with stable technical and environmental support, and a well-designed interactive course structure. Particularly in China, online learning is a newly emerging education method and industry. China has just entered the higher education popularization stage in 2019, which meant the higher education enrollment rate exceeded 50%. The development of online programs could speed up progress in increasing the college education enrollment rate and maintaining regular education activities during the pandemic. There is a strong practical need for the expansion of online programs in China. More research based on the Chinese population for future online program development would be valuable.

Limitations

The current study has several limitations. First, it does not have data on instructors' demographic information and their perceptions of online teaching. Having actual data from the instructors could help us better understand the influence of instructors' teaching practice on online learning outcomes. Second, our data were collected from two top-tier universities. Their results may not fully represent universities from other levels. Third, we did not have data from major required courses, in which students and instructors may put more time and effort. Student behavior in major-required courses could be different from what we observed in general education courses. Fourth, our data is cross-sectional, which limits our ability to draw causal relationships between variables.

Conclusion

To better help students across various backgrounds, future research could focus on other common teaching methods that may prevent students from experiencing inferior learning

conditions. For example, one approach is for better online course design with more types of instructor-student interactive activities. Future research in online learning could employ longitudinal studies or randomized experiments to establish causal relationships between possible mediators and moderators. For instance, researchers could use online class data with identical instructors and content to create treatment and control groups, and compare the effectiveness of different teaching practices, such as instructor-student interactions or learning materials provided. Additionally, future studies could track students who have taken online classes and subsequently returned to campus after pandemic, and compare their learning outcomes while controlling for other potential variables. These causal relationships would provide valuable evidence for identifying the most influential mechanisms that contribute to student satisfaction with online learning.

Declarations
The authors declare that they have no competing interests.

The datasets generated and/or analyzed during the current study are not publicly accessible but are available from the corresponding author on reasonable request.

The ethics board of Fudan University, China approved this research.

References

Aguilera-Hermida, A. P. (2020). College students' use and acceptance of emergency online learning due to COVID-19. *International Journal of Educational Research Open*, 1, 100011. https://doi.org/10.1016/j.ijedro.2020.100011

Akuratiya, A., & Meddage, N. (2020). Students' perception of online learning during COVID-19 pandemic: A survey study of IT students. *International Journal of Research and Innovation in Social Science*, *4*(9), 755-758. https://www.researchgate.net/publication/345140171

Alavudeen, S. S., Easwaran, V., Mir, J. I., Shahrani, S. M., Aseeri, A. A., Khan, N. A., Almodeer, A. M., & Asiri, A. A. (2021). The influence of COVID-19 -related psychological and demographic variables on the effectiveness of e-learning among health care students in the southern region of Saudi Arabia. *Saudi Pharmaceutical Journal*, *29*(7), 775–780. https://doi.org/10.1016/j.jsps.2021.05.009

Al-Emran M, Mezhuyev V, Kamaludin A. (2018).Technology acceptance model in m-learning context: A systematic review. *Computers & Education, 125*, 389-412. https://doi.org/10.1016/j.compedu.2018.06.008

Al-hawari, M. A., & Mouakket, S. (2010). The influence of technology acceptance model (TAM) factors on students' e-satisfaction and e-retention within the context of UAE e-learning. *Education, Business and Society: Contemporary Middle Eastern Issues*, *3*(4), 299-314. https://doi.org/10.1108/17537981011089596

Almusharraf, N., & Khahro, S. (2020). Students satisfaction with online learning experiences during the COVID-19 pandemic. *International Journal of Emerging Technologies in Learning , 15*(21), 246-267.   https://www.learntechlib.org/p/218355/

Alqurashi, E. (2019). Predicting student satisfaction and perceived learning within online learning environments. *Distance Education*, *40*(1), 133-148. https://doi.org/10.1080/01587919.2018.1553562

Anderson, T. (2008). Towards a theory of online learning. In T. Anderson (Ed), *The theory and practice of online learning* (pp.45-74). AU Press.

Artino, A. R. (2009). Think, feel, act: Motivational and emotional influences on military students' online academic success. *Journal of Computing in Higher Education*, *21*(2), 146-166. https://doi.org/10.1007/s12528-009-9020-9

Asoodar, M., Vaezi, S., & Izanloo, B. (2016). Framework to improve e-learner satisfaction and further strengthen e-learning implementation. *Computers in Human Behavior*, *63*, 704–716. https://doi.org/10.1016/j.chb.2016.05.060

Fang, S. X., Lu, Y., & Chen, J. (2020). The dual nature of online education quality: conflicting results between students' self-report and online-offline comparison. *Fudan Education Forum*, 18(06), 55-62. https://doi.org/10.13397/j.cnki.fef.2020.06.009

Bean, J. P., & Metzner, B. S. (1985). A conceptual model of nontraditional undergraduate student attrition. *Journal of Review of Education Research*, *55*(4), 485-540. https://doi.org/10.3102/00346543055004485

Bolliger, D. U., & Martindale, T. (2004). Key factors for determining student satisfaction in online courses. *International Journal on E-learning*, *3*(1), 61-67. https://www.learntechlib.org/p/2226/

Chan, S. (1999). The Chinese learner – a question of style. *Education + Training*, *41*(6/7), 294–305. https://doi.org/10.1108/00400919910285345

Chetty, R., Friedman, J. N., Hendren, N., & Stepner, M. (2020). Real-time economics: A new platform to track the impacts of covid-19 on people, businesses, and communities using private sector data. *NBER Working Paper, 27431.* https://opportunityinsights.org/wp-content/uploads/2020/06/Short_Covid_Paper.pdf

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Daniels, L. M., & Stupnisky, R. H. (2012). Not that different in theory: Discussing the control-value theory of emotions in online learning environments. *The Internet and Higher Education, 15*(3), 222-226. https://doi.org/10.1016/j.iheduc.2012.04.002

Dhawan, S. (2020). Online learning: A panacea in the time of COVID-19 crisis. *Journal of Educational Technology Systems*, *49*(1), 5–22. https://doi.org/10.1177/0047239520934018

Dolighan, T., & Owen, M. (2021). Teacher efficacy for online teaching during the COVID-19 pandemic. *Brock Education Journal*, *30*(1), 95–95. https://doi.org/10.26522/brocked.v30i1.851

Drennan, J., Kennedy, J., & Pisarski, A. (2005). Factors affecting student attitudes toward flexible online learning in management education. *The Journal of Educational Research*, *98*(6), 331-338. https://doi.org/10.3200/JOER.98.6.331-338

Flesia, L., Monaro, M., Mazza, C., Fietta, V., Colicino, E., Segatto, B., & Roma, P. (2020). Predicting perceived stress related to the Covid-19 outbreak through stable psychological traits and machine learning models. *Journal of clinical medicine*, *9*(10), 3350. https://doi.org/10.3390/jcm9103350

Gergen, K. J. (2015). *An invitation to social construction* (3rd ed.). London: SAGE Publications Ltd. https://dx.doi.org/10.4135/9781473921276

Han, J. H., & Sa, H. J. (2022). Acceptance of and satisfaction with online educational classes through the technology acceptance model (TAM): The COVID-19 situation in Korea. *Asia Pacific Education Review*, *23*(3), 403-415. https://doi.org/10.1007/s12564-021-09716-7

Herrington, J., & Oliver, R. (2000). An instructional design framework for authentic learning environments. *Educational Technology Research and Development*, *48*(3), 23–48. https://doi.org/10.1007/BF02319856

Ives, B. (2021). University students experience the covid-19 induced shift to remote instruction. *International Journal of Educational Technology in Higher Education*, *18*(1), 1-16. https://doi.org/10.1186/s41239-021-00296-5

Johnson, N., Veletsianos, G., & Seaman, J. (2020). U.S. faculty and administrators' experiences and approaches in the early weeks of the covid-19 pandemic. *Online Learning*, *24*(2). https://doi.org/10.24059/olj.v24i2.2285

Karim, N.S. & Alam, M. (2021). Struggling with digital pandemic: Students' narratives about adapting to online learning at home during the COVID-19 outbreak. *Southeast Asia: A Multidisciplinary Journal,21*(2),15-29. https://fass.ubd.edu.bn/SEA/vol21-2/struggling-with-digital-pandemic.pdf

Kay JB. (2020). "Stay the fuck at home!": Feminism, family and the private home in a time of coronavirus. *Feminist Media Studies, 20*(6):883-888. https://doi.org/10.1080/14680777.2020.1765293

Keengwe, J., & Kidd, T. T. (2010). Towards best practices in online learning and teaching in higher education. *MERLOT Journal of Online Learning and Teaching*, *6*(2), 533-541. https://jolt.merlot.org/vol6no2/keengwe_0610.pdf

Kuhfeld, M., Soland, J., Tarasawa, B., Johnson, A., Ruzek, E., & Liu, J. (2020). Projecting the potential impact of covid-19 school closures on academic achievement. *Educational Researcher*, *49*(8), 549–565. https://doi.org/10.3102/0013189X20965918

Kuo, Y. C., Walker, A. E., Schroder, K. E. E., & Belland, B. R. (2014). Interaction, internet self-efficacy, and self-regulated learning as predictors of student satisfaction in online education courses. *The Internet and Higher Education*, *20*, 35–50. https://doi.org/10.1016/j.iheduc.2013.10.001

Lakhal, S., Khechine, H., & Mukamurera, J. (2021). Explaining persistence in online courses in higher education: A difference-in-differences analysis. *International Journal of Educational Technology in Higher Education*, *18*(1), 1-32. https://doi.org/10.1186/s41239-021-00251-4

Lee, J., & Stankov, L. (2018). Non-cognitive predictors of academic achievement: Evidence from TIMSS and PISA. *Learning and Individual Differences*, *65*, 50–64. https://doi.org/10.1016/j.lindif.2018.05.009

Marioulas, J. (2017). China: A world leader in graduation rates. *International Higher Education*, *90*, 28–29. https://doi.org/10.6017/ihe.2017.90.10009

Masha'al, D., Rababa, M., & Shahrour, G. (2020). Distance learning–related stress among undergraduate nursing students during the COVID-19 pandemic. *Journal of Nursing Education, 59*(12), 666-674. https://doi.org/10.3928/01484834-20201118-03

McInnerney, J. M., & Roberts, T. S. (2004). Online learning: Social interaction and the creation of a sense of community. *Journal of Educational Technology & Society*, *7*(3), 73-81. https://www.jstor.org/stable/pdf/jeductechsoci.7.3.73.pdf

Meishar-Tal, H., Weinblat, A., & Shapira, N. (2022). Distractions in online learning among higher education students. *INTED2022 Proceedings,* 2723–2730. https://doi.org/10.21125/inted.2022.0795

Moore, M. G. (1989). Editorial: Three types of interaction. *The American Journal of Distance Education*, *3*(2), 1-6. https://doi.org/10.1080/08923648909526659

Moore, M. G. (1992). Distance education: The foundations of effective practice. *The Journal of Higher Education*, 63(4), 468–472. https://doi.org/10.1080/00221546.1992.11778381

Moore, M. G., & Kearsley, G. (2011). *Distance education: A systems view of online learning. Cengage Learning*. Wadsworth Cengage Learning.

Nambiar, D. (2020). The impact of online learning during covid-19: Students' and teachers' perspective. *The International Journal of Indian Psychology*, *8*(2).783-793. https://www.researchgate.net/publication/343229234

Park, J. H., & Choi, H. J. (2009). Factors influencing adult learners' decision to drop out or persist in online learning. *Journal of Educational Technology & Society, 12*(4), 207-217. https://www.jstor.org/stable/jeductechsoci.12.4.207

Palloff, R. M., Pratt, K., & Stockley, D. (2001). Building learning communities in cyberspace: Effective strategies for the online classroom. *The Canadian Journal of Higher Education, 31*(3), 175-178. https://www.academia.edu/2051324/

Parahoo, S. K., Santally, M. I., Rajabalee, Y., & Harvey, H. L. (2016). Designing a predictive model of student satisfaction in online learning. *Journal of Marketing for Higher Education*, *26*(1), 1-19. https://doi.org/10.1080/08841241.2015.1083511

Park, J. H. (2007). Factors related to learner dropout in online learning. In F. M. Nafukho, T. H. Chermack, & C. M. Graham (Eds.), *Proceedings of the 2007 Academy of Human Resource Development Annual Conference (pp. 251-258).* Academy of Human Resource Development. https://files.eric.ed.gov/fulltext/ED504556.pdf

Pekrun, R. (2006). The control-value theory of achievement emotions: Assumptions, corollaries, and implications for educational research and practice. *Educational Psychology Review*, *18*(4), 315-341. https://doi.org/10.1007/s10648-006-9029-9

Pekrun, R. (2011). Emotions as drivers of learning and cognitive development. In *New perspectives on affect and learning technologies* (pp. 23-39). Springer.

Peterson, C., & Barrett, L. C. (1987). Explanatory style and academic performance among university freshman. *Journal of Personality and Social Psychology*, *53*(3), 603–607. https://doi.org/10.1037/0022-3514.53.3.603

Podolsky, A., Kini, T., & Darling-Hammond, L. (2019). Does teaching experience increase teacher effectiveness? A review of US research. *Journal of Professional Capital and Community*, *4*(4), 286-308. https://doi.org/10.1108/JPCC-12-2018-0032

Putri, R. S., Purwanto, A., Pramono, R., Asbari, M., Wijayanti, L. M., & Hyun, C. C. (2020). Impact of the COVID-19 pandemic on online home learning: An explorative study of primary schools in Indonesia. *International Journal of Advanced Science and Technology*, *29*(5), 4809-4818. https://www.researchgate.net/publication/341194197

Rajabalee, Y. B., & Santally, M. I. (2021). Learner satisfaction, engagement and performances in an online module: Implications for institutional e-learning policy. *Education and Information Technologies*, *26*(3), 2623-2656. https://doi.org/10.1007/s10639-020-10375-1

Rahim, N. B. (2020). Improving student engagement and behavioural outcomes via persistence among distance learners. *Akademika*, *90*(2), 91-102. http://journalarticle.ukm.my/16461/1/39460-132451-1-PB.pdf

Razai, M. S., Oakeshott, P., Kankam, H., Galea, S., & Stokes-Lampard, H. (2020). Mitigating the psychological effects of social isolation during the covid-19 pandemic. *BMJ*, *369*: m1904. https://doi.org/10.1136/bmj.m1904

Rovai, A. P. (2003). In search of higher persistence rates in distance education online programs. *The Internet and Higher Education*, *6*(1), 1–16. https://doi.org/10.1016/S1096-7516(02)00158-6

Sahin, I., & Shelley, M. (2008). Considering students' perceptions: The distance education student satisfaction model. *Journal of Educational Technology & Society*, *11*(3), 216–223. https://www.researchgate.net/publication/220374226

Sari, F. M., & Oktaviani, L. (2021). Undergraduate students' views on the use of online learning platform during COVID-19 pandemic. *Teknosastik*, *19*(1), 41-47. https://doi.org/10.33365/ts.v19i1.896

Selim, H. M. (2007). Critical success factors for e-learning acceptance: Confirmatory factor models. *Computers & Education*, *49*(2), 396–413. https://doi.org/10.1016/j.compedu.2005.09.004

Simamora, R. M. (2020). The challenges of online learning during the COVID-19 pandemic: An essay analysis of performing arts education students. *Studies in Learning and Teaching*, *1*(2), 86-103. https://doi.org/10.46627/silet.v1i2.38

Sit, H. H. W. (2013). Characteristics of Chinese students' learning styles. *International Proceedings of Economics Development and Research, 62*(8), 36-39. http://www.ipedr.com/vol62/008-ICLMC2013-M10004.pdf

StataCorp. 2017. *Stata Statistical Software: Release 15*. Stata Corp LLC.

Sun, P. C., Tsai, R. J., Finger, G., Chen, Y. Y., & Yeh, D. (2008). What drives a successful e-Learning? An empirical investigation of the critical factors influencing learner satisfaction. *Computers & Education*, *50*(4), 1183-1202. https://doi.org/10.1016/j.compedu.2006.11.007

Tempelaar, D. T., Niculescu, A., Rienties, B., Gijselaers, W. H., & Giesbers, B. (2012). How achievement emotions impact students' decisions for online learning, and what precedes those emotions. *The Internet and Higher Education*, *15*(3), 161-169. https://doi.org/10.1016/j.iheduc.2011.10.003

Tinto, V. (1993). *Leaving college: rethinking the causes and cures of student attrition.* (2nd ed.). University of Chicago Press.

Ulmer, L.W., Watson, L.W., & Derby, D. (2007). Perceptions of higher education faculty members on the value of distance education. *The Quarterly Review of Distance Education, 8*(1), 59–70. https://www.learntechlib.org/p/106716/

Volery, T., & Lord, D. (2000). Critical success factors in online education. *International Journal of Educational Management*, *14*(5), 216–223. https://doi.org/10.1108/09513540010344731

Vygotsky, L.S. (1978). *Mind in Society: The Development of Higher Psychological Processes.* Harvard University Press.

Wan, Z., Wang, Y., & Haggerty, N. (2008). Why people benefit from e-learning differently: The effects of psychological processes on e-learning outcomes. *Information & management*, *45*(8), 513-521. https://doi.org/10.1016/j.im.2008.08.003

Yunusa, A. A., & Umar, I. N. (2021). A scoping review of critical predictive factors (CPFs) of satisfaction and perceived learning outcomes in e-learning environments. *Education and Information Technologies*, *26*(1), 1223–1270. https://doi.org/10.1007/s10639-020-10286-1

Zeng, X., & Wang, T. (2021). College student satisfaction with online learning during COVID-19: A review and implications. *International Journal of Multidisciplinary Perspectives in Higher Education*, 6(1), 182-195. https://www.ojed.org/index.php/jimphe/article/view/3502