

MODELING THE NEXUS BETWEEN STUDENTS' INTERACTION, SATISFACTION, AND ACCEPTANCE OF ONLINE LEARNING

Duong Minh TUAN

ORCID: 0000-0003-3011-8467
Faculty of Foreign Languages
Nam Can Tho University
Can Tho City, VIETNAM

Le Thi Diem LAN

ORCID:0009-0004-2609-396X
Faculty of Foreign Languages
Nam Can Tho University
Can Tho City, VIETNAM

Received: 02/02/2024 **Accepted:** 28/04/2024

ABSTRACT

The proliferation of communication technologies in recent years has significantly contributed to the swift transformation of education. The outbreak of the COVID-19 pandemic at the beginning of 2020 caused further drastic changes in education, making digital transformation one of its most apparent attributes. This evolution has necessitated a call for more studies delving into students' learning experiences in a fully online learning environment, especially in nations where online education is still in its nascent stage. By adopting the structural equation modeling approach, this study was intended to examine the effects of various types of interaction on student satisfaction and the impact of student satisfaction on their behavioral acceptance of online learning. The study also aimed to examine the mediating role of student satisfaction in the relationship between interaction and perceived acceptance. The participants comprised 336 students across multiple academic disciplines from a private university in the Mekong Delta of Vietnam. A questionnaire was used for data collection. The results showed that student-teacher interaction and student-student interaction were significant determinants of student satisfaction, whereas student-content interaction and student-interface interaction yielded opposite outcomes. In addition, of the four types of interaction, satisfaction only mediated the relationships of student-teacher interaction and student-student interaction with perceived acceptance. These results emphasize the importance of fostering meaningful interaction activities between teachers and students, as well as among students themselves, in enhancing student satisfaction and further boosting the prospects of online education in today's digital world.

Keywords: Online learning, relationship, student interaction, satisfaction, acceptance.

INTRODUCTION

The integration of digital platforms in the education landscape has witnessed a remarkable surge in recent times, driven by advancements in information and communication technologies (Hockly & Dudeney, 2018; Yunus, 2018). Aware of the vast potential afforded by digital media, numerous educational institutions have availed themselves of its resources to provide students with various Internet-based educational modalities, including but not limited to distance learning and blended learning. Such a propensity is particularly pertinent, given the diverse educational needs of individuals in the current epoch of life-long learning. It can be posited that the advent of technological applications has engendered a profound metamorphosis in the education milieu, thereby affording students various avenues to acquire knowledge. This transformative paradigm has not only extended the purview of learning beyond the confines of conventional educational settings but has also facilitated the dissemination of outreach education programs to home learning

environments. By harnessing the capabilities of technology-based innovations in education, many institutions have incorporated digital platforms, such as video meetings and online chatrooms, into their training curricula. This development yields enhanced convenience in educational delivery (Suvorova et al., 2021) while concurrently fostering students' learning experiences. Furthermore, the prevalence of online learning is poised to provide evidence of its myriad benefits, such as serving as a potential alternative for transcending spatial and temporal boundaries while also offering the advantages of flexibility and accessibility of quality education where it is most needed (Aydin, 2013; Wu et al., 2023). Nevertheless, the salient facets of online instruction are commensurate with its challenges, one of which pertains to optimizing student interaction in the learning process as it may affect the effectiveness of online education (Sun & Rueda, 2012).

In Vietnam, although online learning was initiated a long time ago (Tran & Nguyen, 2022), it was not until the outbreak of the COVID-19 pandemic worldwide that such a mode of education became widely adopted in response to the continuous learning needs of students during the contemporary suspension of face-to-face classes. This paradigm shift to online learning has sparked a growing interest in exploring student satisfaction with this form of education (Nguyen et al., 2022) as it serves as a barometer for gauging how students perceive their learning experiences and assessing the caliber of the course instruction (Hew et al., 2020). However, in the field of online education, Teng (2023) underpins the lack of in-depth exploration into the factors that impact student satisfaction, especially in institutions where online learning is newly executed. This work, therefore, endeavored to contribute toward expanding the existing literature investigating the determinants of satisfaction based on a comprehensive analysis of an interaction model. Besides, even though preliminary research shows that interaction has a significant role in shaping student satisfaction, there remains a dearth of works examining the relationship between students' satisfaction and their behavioral intention to accept online learning, especially in the post-pandemic "new normal." Overall, the current inquiry was undertaken to scrutinize the intricate interplay between students' interaction, satisfaction, and acceptance of online learning through the lens of tertiary students' perspectives using a structural equation modelling approach (SEM). Also, the study was intended to fill the existing gap in the relevant body of knowledge by exploring whether students' satisfaction with online learning mediates the impact of interaction on their perceived acceptance of online education. The findings of the present study are hoped to assist educators, instructional designers, and policy-makers in optimizing the design and delivery of virtual learning courses, consequently amplifying the optimal learning conditions for online students.

LITERATURE REVIEW

Student Satisfaction

Student satisfaction is widely recognized as a multifaceted construct comprising various dimensions that collectively contribute to students' reflection on their educational experiences (Amoush & Mizher, 2023; Wong & Chapman, 2022). In a parallel vein, Elliot and Healy (2001) postulate that learning satisfaction is a multidimensional concept, which is delineated by the manifestation of students' emotions and attitudes toward the learning process. Furthermore, it is contingent upon the extent to which students' learning needs and expectations are fulfilled or exceeded based on their learning encounters (Elliot & Healy, 2001; Palmer & Holt, 2009). That is, when students perceive that they have successfully attained their educational goals and procured the desired reservoir of knowledge and competencies, they are probably satisfied with their learning activities. Puzziferro and Shelton (2008) suppose that students who find online learning satisfying are more likely to succeed in their studies, whereas dissatisfied learners may encounter difficulties in their learning process (Dharmadjaja & Tiatri, 2021). Within digital education, it has been empirically established that satisfaction serves as a noteworthy determinant of academic performance and the efficacy of the execution of online learning systems (Ke & Kwak, 2013; Kuo et al., 2013; Meyer, 2014). Student satisfaction with online learning has been conceptualized as a convoluted and multifaceted concept encompassing varied factors. These include, for instance, efficient communication, participation in online discussions, flexibility, workload, technological support, instructors' teaching expertise, and feedback (Wei & Chou, 2020). Furthermore, Geary et al. (2023) underscore the significance of teachers fostering a sense

of learning community and social connection to ensure student satisfaction in virtual classes. In this study, satisfaction is characterized by the manner in which students evaluate their online learning encounters in virtual educational settings. Understanding the intricate nature of student satisfaction is, therefore, crucial for educators and institutions in enhancing the learning experiences and facilitating the academic outcomes of their students.

Interaction

Moore's (1989) Model of Interaction

The recognition that interaction is integral to the learning process is evident, be it in-person or online. Nevertheless, there is not much consensus on how it is conceptualized and what inherent characteristics it carries. Notwithstanding this, a three-type interaction model comprising student-content interaction, student-teacher interaction, and student-student interaction is widely acknowledged by scholars and researchers, as initially proposed in Moore's (1989) conceptual framework.

Student-content interaction is indispensable in pursuing educational goals since it is the process of learners' intellectual interaction with the information or knowledge intended to be acquired. This interactive process expectedly contributes to the growth in learners' understanding, perspective, and cognitive structure of the mind (Moore, 1989). This type of interaction is also very much connected to a situation in which learners "talk to themselves" about the content they are working on in a text, a lecture, a program, and the like (Holmberg, 1986). Furthermore, it can be inferred that a relationship exists between content-interactive learning and self-directed learning. Some educational programs contain student-content interaction as part of their nature. They are equivalent to one-way communications with an expert in a subject matter and a course designer at times. Learning is greatly self-directed in such a context if no other teaching expertise is involved.

Student-teacher interaction is considered vital and highly desirable by educators and students. Apart from teachers acting as instructors, others involved in the course design, such as experts preparing the learning material and those developing the content program, are likely to contribute to this sort of interaction. They aim to attract students' interest in the content of the lesson, motivate them to learn, and enhance their learning behaviors, including self-direction and self-motivation (Moore, 1989). Together with student-content interaction, student-teacher interaction corresponds with a time when teachers play a more influential role in their students' learning as opposed to student-content interaction itself. Moore also states that when student-teacher interaction is available in the learning process through correspondence or teleconference, students can be better guided under instructional influences and draw upon their teachers' experience of interacting with the content. Besides, testing and feedback are other substantial elements involved in student-teacher interaction when the role of teachers is particularly valued, especially in response to students' application of new knowledge.

Student-student interaction, or inter-student interaction, is a mutual exchange of information among class members, whether or not with the instructor's presence. This type of interaction has recognized values to some extent and is sometimes an essential resource for learning (Moore, 1989). The desirability of student-student interaction highly depends on students' circumstances and personal factors, such as age, learning experience, and level of learner autonomy. Compared with younger learners, the acts of stimulation and motivation in the teaching process are usually performed with more ease and less use of peer-group interaction when it comes to adults and advanced students, as they are likely to be self-motivated. One typical instance of student-student interaction is that of students being required to make individual or group presentations. This was followed by preliminary discussion, elaboration on critical issues in groups, exchanges of feedback, and more in-depth discussion. Researchers found that interaction among members of a crowded undergraduate class was not effectively enhanced in face-to-face classrooms, whereas students achieved higher performance in group behaviors in online classes using different teaching techniques, such as employing recorded videos and computer-mediated interaction (Phillips et al., 1988).

Student-Interface Interaction

Hillman et al. (1994) argue that Moore's (1998) three types of interaction do not encompass all facets of interaction in distance education. The distinctive technological mediation inherent in online learning environments necessitates another type of interaction - specifically, the interaction that occurs between students and the technologies, referred to as student-interface interaction. It is seen as a process of manipulating technological tools to perform a specific task. However, to this end, students must have the necessary skills and competencies to deal with the mechanisms of the delivery system. As part of these requirements, students must "understand not only the procedures of working with the interface but also the reasons why these procedures obtain results" (Hillman et al., 1994, p.34). Hillman et al., 1994 suggest that it is essential to distinguish between the manipulation of the interface as another type of interaction and the employment of the interface as an inherent facet of all interaction in technology-mediated learning settings.

Students' Acceptance of Online Learning

The concept of students' acceptance of online learning pertains to the cognitive evaluations made by students regarding the utility and simplicity of such a medium, which subsequently shape their attitudes, perceptions, and behaviors toward online learning environments (Ngampornchai & Adams, 2016). More simply, it can be construed as a gauge of their comfort level and willingness to engage in and use online learning platforms and resources for educational purposes (Rajeb et al., 2022). Recent studies have reported various components that contribute to the acceptance of students in online learning. The Technology Acceptance Model (TAM) was first coined by Davis in 1985 and has since been widely used to understand user acceptance of information technology across various fields, including online learning (Tung & Chang, 2007). In accordance with TAM, two primary factors that determine students' behavioral acceptance of online learning are perceived usefulness and ease of use (Granic & Marangunic, 2019; Venkatesh & Davis, 2000; Venkatesh et al., 2003). The concept of perceived usefulness refers to an individual's belief toward how much a specific technological system would enhance his or her work performance and productivity, while perceived ease of use is delineated as the extent to which a person believes that using a technological tool would be effortless and stress-free (Davis, 1989). In addition to the two noticeable constructing elements of TAM, online learning acceptance has also been explained through multiple components, including students' satisfaction, behavioral intention, user recommendations, and motivation to use an online learning system (Rajeb et al., 2023). In the present study, the consideration of these components culminated in the framework for measuring students' intention to accept online learning as an alternative instructional form of learning.

Theoretical Framework

Interaction and Student Satisfaction with Online Learning

Given the pivotal role of interaction in learning in the field of distance education, a growing body of studies has underscored the impact of interaction exerted on student satisfaction levels in online learning environments (e.g., Ayanbode et al., 2022; Amoush & Mizher, 2023; Dharmadjaja & Tiatri, 2021; Eom & Ashill, 2016; Kim & Kim, 2021; Li & Jhang, 2020; She et al., 2021; Tran & Nguyen, 2022; Yilmaz, 2023). The findings of these studies have also unveiled a positive correlation between these two variables. As per the findings of Kuo et al. (2014), it was observed that high interaction with the instructor, fellow students, or the course material resulted in a heightened sense of satisfaction among students, thereby indicating a significant level of involvement in online learning (Kuo et al., 2014). Analogously, using regression analysis, Amoush and Mizher (2023) examined the relationship between interaction and university students' satisfaction with online courses. The study revealed that four factors, namely student-content interaction, student-teacher interaction, student-student interaction, and student-technology interaction, had a positive influence on student satisfaction with online learning. Among these, student-technology interaction was the most influential factor, followed by student-instructor interaction. Aydin's (2021) study shared similar findings in that student-content interaction, instructor-student interaction, and student-student interaction had a significant effect on students' online education satisfaction levels. However, unlike the above study, student-content interaction was found to be the most substantial contributor to student satisfaction. This finding was

corroborated by Hettiarachchi et al.'s (2021) study, showing that student-content interaction was the most crucial factor of all forms of interaction in shaping student satisfaction in online learning settings. These studies emphasized the importance of enhancing the interaction between students and learning materials in fostering satisfaction with online education. Moreover, She et al. (2021) conducted a study that employed a serial mediation model to elucidate the connection between interaction and online learning satisfaction. The researchers found a significant relationship between these constructs, and the mediating factors of students' academic self-efficacy and engagement in online classrooms played a crucial role in the association between these two variables. Another investigation conducted by Kuo et al. (2013) focused its attention on discerning the determinants of the level of satisfaction experienced by students enrolled in online educational programs. The findings of the study obtained through regression analysis revealed that student-instructor interaction, student-content interaction, and Internet self-efficacy had a significant role to play in determining student satisfaction. Conversely, student-student interaction did not exhibit a discernible impact on the degree to which students were satisfied with online education. Another investigation by Gameel (2017) found that student-student interaction and student-instructor interaction did not affect student satisfaction with massive open online courses. Based on an appraisal of the aforementioned findings, albeit with controversies, we hypothesized that:

- H1: Student-content interaction has a significant positive effect on students' satisfaction with online learning.
- H2: Student-teacher interaction has a significant positive effect on students' satisfaction with online learning.
- H3: Student-student interaction has a significant positive effect on students' satisfaction with online learning.
- H4: Student-interface interaction has a significant positive effect on students' satisfaction with online learning.

Student Satisfaction and Online Learning Acceptance

One factor impacting students' behavioral intention to adopt online learning systems is student satisfaction with online learning outcomes (Nikou & Maslov, 2022). The relationship between student satisfaction and the acceptance of online education platforms was also denoted in a few studies (e.g., Alassaf & Szalay, 2020; Baloran et al., 2021; Daneji et al., 2019; Han & Sa, 2021; Lee & Mendlinger, 2011; Palmer & Holt, 2009; Shao, 2019; Tan et al., 2023). Lee and Mendlinger's (2011) research showed that perceived self-efficacy positively affected students' satisfaction with online learning, which in turn affected their intention regarding online learning acceptance. Likewise, another study by Baloran et al. (2021) explored student satisfaction with online learning amidst the pandemic. The study's findings revealed that satisfaction was paramount in determining students' behavioral intention to continue with online learning. This suggested that students who were satisfied with the caliber of online courses were more likely to harbor a heightened inclination to persist in adopting online learning platforms. Similarly, Palmer and Holt (2009) concluded that learner satisfaction significantly influenced students' continuance with online learning. The study highlighted the importance of satisfaction in fostering student engagement and improving retention rates in online courses. Drawing upon the presented empirical evidence of the relationship between student satisfaction and online learning acceptance, we hypothesized that:

- H5: Student satisfaction has a significant positive effect on students' online learning acceptance.

Research Model

Based on the hypotheses mentioned above, the hypothesized model of the present study is shown in Figure 1. As can be seen, the model encompasses six latent variables and illustrates the direct and indirect relationships between them. Specifically, the four types of interaction act as independent or exogenous variables, and online learning acceptance functions as a dependent or endogenous variable. In addition, student satisfaction is considered a mediator variable supposed to mediate the relationship between interaction and online

learning acceptance. It plays the role of a dependent variable, which is expected to be positively influenced by interaction. Simultaneously, it acts as an independent variable, which is assumed to significantly impact online learning acceptance.

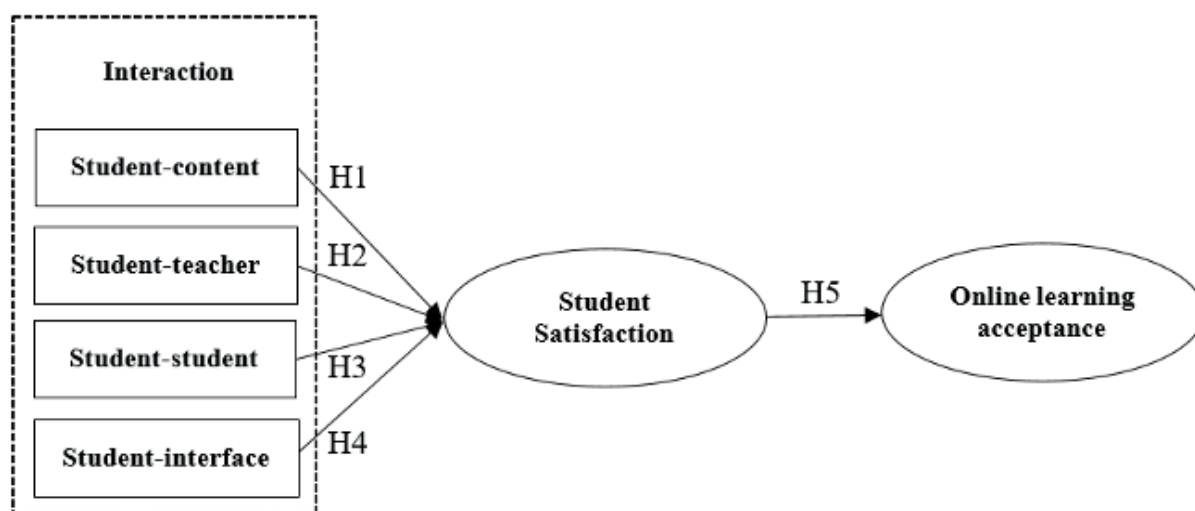


Figure 1. The hypothesized model

METHODS

Research Design

A quantitative research method was employed in this study to empirically assess the theoretical framework, specifically aiming at exploring the complex relationships between students' interaction, satisfaction, and online learning acceptance. The quantitative method is deemed sufficient to validate the theoretical framework and related hypotheses (Alarabiat et al., 2023). Such a method plays a crucial role in scientific inquiry as it offers a systematic and objective approach to studying a situation (Williams, 2011) and generalizes results (Ayanbode et al., 2022). In addition, using standardized measurement tools and statistical analysis techniques can ascertain the validity and reliability of research findings (Tirschwell & Longstreth, 2002). In the present study, SEM was employed as a multivariate statistical technique to examine the strength and direction of relationships between variables (Deng et al., 2017). It also provides a holistic framework for hypothesis testing and theoretical model evaluation (Schumacker & Lomax, 2004). Moreover, SEM is considered statistically appropriate in this study to understand the mediating role of satisfaction in explaining the nexus between interaction and online learning acceptance as it can incorporate these complex relationships and allow for the examination of mediating effects.

Participants

336 third-year and fourth-year (61.1% and 33.9%, respectively) university students from a private university in the Mekong Delta of Vietnam were invited to participate in this study. They studied at different faculties, including Foreign Languages (23.2%), Business Administration (18.5%), Pharmacy (21.7%), Law (20.2%), and Automotive Technology (16.4%). These participants were recruited through the convenience sampling method. The sample included 102 males (30.4%) and 234 females (69.6%), and their ages ranged from 19 to 22 years ($M=19.52$, $SD=0.72$). They had full-time experiences of online learning during the COVID-19 outbreak in Vietnam. They were required to take synchronous online courses lasting for 15 weeks via Zoom and Google Meet, with the support of asynchronous content, such as videos and digital documents. Thus, these participants were deemed suitable to partake in the present study. Nearly half of them spent 11 to 15 hours online every week, and the remaining participants spent between 16 and 20 hours. Table 1 summarizes the participants' demographic information.

Table 1. Demographics of the participants

Variables	Categories	Frequency	Percentage
Faculty	Foreign Languages	78	23.1
	Business Administration	62	18.5
	Pharmacy	73	21.7
	Law	68	20.2
	Automotive Technology	55	16.4
Gender	Male	102	30.4
	Female	234	69.6
Age group	19-22	336	100
Year of study	Third year	222	66.1
	Fourth year	114	33.9
Hours spent online per week	11-15 hours	208	61.9
	16-20 hours	128	38.1
Digital platform	Zoom and Google Meet	336	100
	Computer	14	4.2
Mode of online learning access	Laptop	277	82.4
	Mobile phone	45	13.4

Measures

A self-report questionnaire was employed as the primary research instrument to collect quantitative data for the study. The questionnaire included two sections. The first part was for eliciting the participants' demographic information, such as gender, age, year of study, and weekly online usage hours. The second part encompassed six measurement scales adapted from different sources aiming to assess the forms of interaction in which students typically engaged and their satisfaction with and acceptance of online learning, as shown in Table 2.

Table 2. Description of the questionnaire

Scales	Number of items	Sample items	Sources
Student interaction			
<i>Student-content interaction</i>	05	Online course materials helped me to understand the class content better.	Kuo (2010)
<i>Student-teacher interaction</i>	06	Overall, I had numerous interactions with the teacher during class.	Kuo (2010)
<i>Student-student interaction</i>	05	Overall, I had numerous interactions with fellow students during class.	Kuo (2010)
<i>Student-interface interaction</i>	05	Computers make me much more productive.	Chang (2013)
Student satisfaction	05	Overall, I was satisfied with this class.	Kuo (2010)
Student acceptance	05	In the future, I will be willing to enroll in online classes.	Rajeb (2023)

Note. Not all items are included in the table. For each measurement scale/subscale, only one item is presented for reference.

Before the administration of the instrument, it had been checked via expert review. Two senior lecturers and two experts in the field were invited to check for its validity. As a result, the questionnaire was marginally adjusted in terms of item clarity and readability based on their feedback. The questionnaire was subsequently piloted with a group of 30 students who shared the same characteristics as the target participants. All of them reported that they had no problems comprehending the questionnaire. These students were excluded from

the data collection process to maintain the independence and integrity of the data collected from the actual intended participants. Cronbach's alpha was performed to assess the reliability of the 31-item questionnaire. It was found that Cronbach's alpha of all the factors exceeded the recommended reliability coefficient threshold of 0.70 (Hair et al., 2014). The un-dimensionality of the items was also tested by computing item-total correlations. The observed items in the predetermined scales had coefficient values ranging from 0.64 to 0.85, all of which surpassed the widely agreed-upon lower limit of 0.30 (Coolidge, 2013). Thus, all items were retained for later analyses. These results collectively substantiated the internal consistency of the responses to the items in the present study. Table 3 presents the descriptive statistics of the reliability tests.

Table 3. Reliability of the questionnaire

Variables	Number of items	Cronbach's alpha	Item-total correlation range
Student-content interaction	05	0.91	0.71-0.85
Student-teacher interaction	06	0.91	0.67-0.83
Student-student interaction	05	0.92	0.74-0.82
Student-interface interaction	05	0.86	0.65-0.72
Student satisfaction	05	0.90	0.64-0.85
Student acceptance	05	0.90	0.69-0.81

Student Interaction Scale

Students' interaction in online classes was assessed using the student interaction scale adapted based on the existing literature. The scale consisted of 16 items adapted from Kuo (2010), and five items from Chang (2013). These items were selected as they were mostly relevant to the context of the present study. They were nested under four dimensions of student interaction in online classes, namely (1) student-content interaction (5 items), (2) student-teacher interaction (6 items), (3) student-student interaction (5 items), and (4) student-interface interaction (5 items). The 21 items were evaluated based on a 5-point Likert scale, ranging from (1) strongly disagree to (5) strongly agree. In combination, Kuo (2010) and Chang (2013) previously reported the scale's strong validity and demonstrated high reliability coefficients for the subscales specific to the four types of interaction.

Student Satisfaction Scale

To quantify university students' satisfaction with online learning, the study utilized the student satisfaction scale adapted from Kuo (2010) as it was appraised as appropriate for the target learning context and population. The scale constituted one latent variable with five observed items. It used a 5-point Likert rating, varying from 1 (strongly disagree) to 5 (strongly agree). Kuo (2010) proved that the scale was valid and reliable in measuring students' satisfaction with online learning.

Online Learning Acceptance Scale

The outcome variable of students' behavioral intention toward online learning acceptance was measured by the online learning acceptance scale, which was designed by Rajeb (2023). The scale consisted of one latent variable and five observed items, which were slightly modified so that they would be fully applicable to the participants. Students responded to each item using a 5-point Likert scale, ranging from (1) strongly disagree to (5) strongly agree. The validity and reliability of the scale were empirically established in Rajeb's (2023) scale development and validation study.

Data Collection Procedures

Questionnaires were initially administered to 415 students from 10 classes during their study hours with the assistance of the teachers of these classes. They were asked to fill in the questionnaire in a paper-and-pencil

format under the researchers' presence. Of 415 students, 395 completed the questionnaires with a return rate of 95.2 %. After the data screening, 336 responses were evaluated as valid and retained as the actual study sample. This number of participants was considered significant as it satisfied the sample size threshold needed for exploratory factor analysis (EFA), surpassing the requirement of being at least five times greater than the observed variables (Hair et al., 2014). Kline (2015) recommends a minimum of 100 observations for estimating SEM and 200 observations for obtaining reliable estimates. The sample size of 336 certainly met these requirements.

Data Analyses

Prior to SEM analyses, EFA was performed using IBM AMOS ver. 27, followed by confirmatory factor analysis (CFA) to evaluate the proposed model. EFA was used to investigate the correlations among the factors and their factor loadings (Hair et al., 2014), which aids in evaluating the convergent validity of scales measuring self-perceived constructs (Zhu et al., 2021). CFA is an advanced statistical method that employs the input of correlations to establish a structural model in which structural relationships between latent constructs and their observed variables are assessed (Alrabai, 2011). The theoretical model in this study was evaluated based on several types of omnibus fit indexes to determine goodness-of-fit to the sample data. These include the chi-square statistic (χ^2), degree of freedom (df), p-value, normalized χ^2 or χ^2 divided by df (χ^2/df), and other essential indices, such as the goodness-of-fit index (GFI), the comparative fit index (CFI), the normed fit index (NFI), the root mean square error of approximation (RMSEA), the standardized root mean square residual (SRMR), and the Tucker-Lewis index (TLI). It is suggested that values greater than 0.90 for GFI, CFI, NFI, and TLI are considered acceptable, and values over 0.95 indicate a good model fit (Hair et al., 2019). The acceptable values for RMSEA and SRMR are less than 0.1 and 0.05, respectively (Byrne, 2016).

Common Method Bias

Common method bias refers to measurement errors that substantially overestimate the relationship between variables measured with the same method (Kamakura, 2010; Spector, 2006). Podsakoff et al. (2003) suggest several statistical solutions to reduce bias caused by the homogeneous validity scales, one of which is Harman's single-factor test. It is known as a widely used method in this regard. Unrotated exploratory factor analysis was conducted using the 31 items loaded into one latent variable. The average variance accounted for by the single factor was only 23.8%, well below the recommended cutoff of 50%. Therefore, it could be concluded that no serious common method bias was observed in this study.

RESULTS

Exploratory Factor Analysis

An EFA was conducted on the 21 items constructing student interaction factors. First, Kaiser-Meyer-Olkin (KMO) and Barlett test of sphericity were examined for factor analysis compliance. The adequacy of the sample was measured by conducting the KMO test. A KMO value of over 0.05 is considered indicative of sufficiently high correlations among items, and therefore, they can be used to perform factor analysis (Tabachnick & Fidell, 2001). In this study, the KMO value was 0.877. Barlett's test of sphericity was then computed to assess the suitability of data for EFA (Korucu & Karakoca, 2020). A significant result of 0.000 was recorded in Barlett's test of sphericity. This means that the correlation matrix was not an identity one and was suitable for structure detection. Principal component analysis as an extraction method was employed to reflect on the data structure. The Kaiser criterion, which involves the examination of the initial eigenvalues, was applied to determine the number of factors to be extracted. In addition, Varimax rotation was adopted to ensure interrelations among factors. In this study, having the initial eigenvalues greater than 1.0, four factors underlying student interaction dimensions were ultimately extracted, which together explained 71.28% of the variance. A scree plot was used to confirm the number of suitable factors. The elbow in the scree plot suggested that four principal factors should be extracted. Hence, the remaining 28.72% of the

variance was accounted for by other possible variables which were not included in the study. Subsequently, the factor loadings and communalities of all the items were checked. Factor loadings greater than 0.4 are considered adequate for item retention in the model; likewise, communalities greater than 0.4 are deemed acceptable (Osborne et al., 2008). In the present study, the factor loadings ranged from 0.747 to 0.896, and communality values ranged from 0.582 to 0.825, as shown in Table 4. These values suggested a good fit of the items to their respective factors. As mentioned earlier, the Cronbach's coefficient alpha values for four factors were between 0.86 and 0.92, presenting sound reliability for each scale.

Table 4. Results on factor loadings and the communalities

Items	Factors				Communalities
	1	2	3	4	
STI3	.876				0.796
STI6	.861				0.778
STI5	.844				0.739
STI1	.837				0.719
STI2	.754				0.586
STI4	.752				0.582
SSI5		.881			0.801
SSI4		.873			0.794
SSI3		.860			0.792
SSI1		.840			0.723
SSI2		.821			0.691
SCI4			.896		0.825
SCI5			.868		0.786
SCI2			.845		0.760
SCI3			.821		0.707
SCI1			.793		0.660
SII5				.797	0.695
SII4				.791	0.683
SII2				.781	0.630
SII3				.773	0.624
SII1				.747	0.596

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Note. *SCI = student-content interaction, STI = student-teacher interaction, SSI = student-student interaction, SII = student-interface interaction, SAT = student satisfaction, ACC = student acceptance*

Normality Check

The normality of measurement items was examined using Mardia's skewness and kurtosis. The assumption of multivariate normality is a fundamental consideration in CFA, where the observed variables and their joint distributions are expected to adhere to a normal distribution (Dimitrov, 2010), and its violation can influence the estimation and interpretation of CFA models (Flora & Curran, 2004). For this study, skewness values ranged from -0.916 to +0.424, and kurtosis values fell between -0.380 and +2.544. All the values were within the acceptable limit, demonstrating that the data fit the normality assumption. The results of the normality assessment are illustrated in Table 5.

Table 5. Results of the normality assessment

Variables	Normality index	
	Skewness	Kurtosis
Student-content interaction	-0.289	-0.027
Student-teacher interaction	-0.578	0.213
Student-student interaction	-0.158	-0.380
Student-interface interaction	0.424	2.544
Student satisfaction	-0.916	2.145
Student acceptance	-0.344	-0.265

Convergent Validity

Convergent validity was checked based on factor loadings, composite reliability (CR), and average variance extracted (AVE) (Hair et al., 2019). In the present study, the measurement model was composed of six first-order latent constructs, namely student-content interaction, student-teacher interaction, student-student interaction, student-interface interaction, and students' online learning satisfaction and acceptance. The results indicated that the standardized factor loadings were within 0.64 to 0.88. The CR values of all factors exceeded the recommended threshold of 0.70. The AVE values for all constructs were greater than 0.5, and each construct's AVE was less than its respective CR. These results indicated that all six constructs had acceptable convergent validity. Table 6 shows the results of the convergent validity testing.

Table 6. Convergent validity measures

Variables	Factor loadings	CR	AVE
Student-content interaction	0.724-0.884	0.915	0.684
Student-teacher interaction	0.665-0.827	0.912	0.636
Student-student interaction	0.737-0.855	0.919	0.694
Student-interface interaction	0.666-0.761	0.861	0.553
Student satisfaction	0.641-0.872	0.899	0.643
Student acceptance	0.710-0.853	0.902	0.648

Discriminant Validity

The heterotrait-monotrait ratio (HTMT) of the correlations was employed as a criterion to examine the discriminant validity of the latent constructs. Henseler et al. (2015) assert that the HTMT ratio offers a more reliable and less biased evaluation of discriminant validity when compared to other widely employed methods, such as the Fornell-Larcker criterion and cross-loadings. HTMT values less than the cutoff value of 0.85 are typically regarded as satisfactory, whereas values surpassing 0.90 indicate a dearth of discriminant validity (Hair et al., 2019). In this study, all the HTMT values were far lower than 0.85, ranging from 0.082 to 0.454, as indicated in Table 7. Thus, the discriminant validity of the constructs was confirmed.

Table 7. Discriminant validity measures

	1	2	3	4	5	6
1. Student-content interaction						
2. Student-teacher interaction	0.312					
3. Student-student interaction	0.082	0.157				
4. Student-interface interaction	0.279	0.124	0.091			
5. Student satisfaction	0.454	0.385	0.086	0.273		
6. Student acceptance	0.258	0.162	0.432	0.157	0.115	

Measurement Model Assessment

As a prerequisite for SEM analyses, the entire measurement model with six first-order latent constructs was assessed using CFA to evaluate if the measurement model fits the data well. According to the CFA results, the model had a good fit, as evidenced by the following model fit indices: $\chi^2 = 585.328$; $df = 411$; $\chi^2/df = 1.420$; GFI = 0.902; CFI = 0.975; TLI = 0.972; NFI = 0.920; RMSEA = 0.035; SRMR = 0.039. Besides, the standardized estimated loadings of observed variables on latent variables were greater than 0.50, all of which were statistically significant ($p < 0.001$), demonstrating that the latent constructs were adequately operationalized by their indicators (Raykov & Marcoulides, 2008). Figure 2 depicts the six-factor measurement model based on CFA.

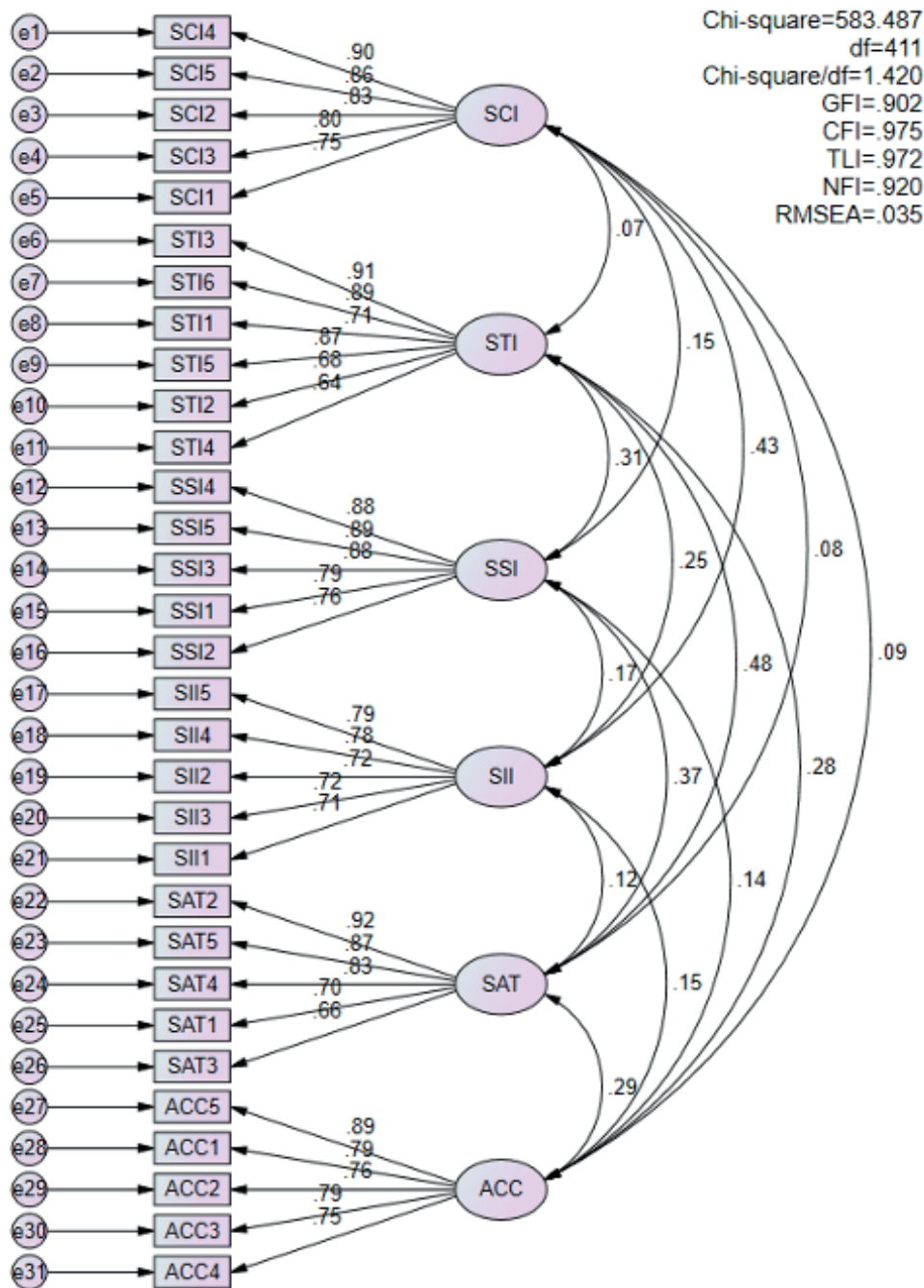


Figure 2. The six-factor measurement model based on CFA

Note. SCI = student-content interaction, STI = student-teacher interaction, SSI = student-student interaction, SII = student-interface interaction, SAT = student satisfaction, ACC = student acceptance

The Structural Model

The structural model was tested to determine the relationships between the constructs based on the hypotheses. The goodness-of-fit indices obtained from SEM showed that the proposed research model yielded a good fit to the data well ($\chi^2 = 593.355$; $df = 415$; $\chi^2/df = 1.430$; $GFI = 0.901$; $CFI = 0.974$; $TLI = 0.971$; $NFI = 0.919$; $RMSEA = 0.036$; $SRMR = 0.048$). The observed items loaded well on each of the factors, with their standardized estimated loadings both greater than 0.50 and statistically significant ($p < 0.001$). Figure 3 exposes the structural model based on SEM.

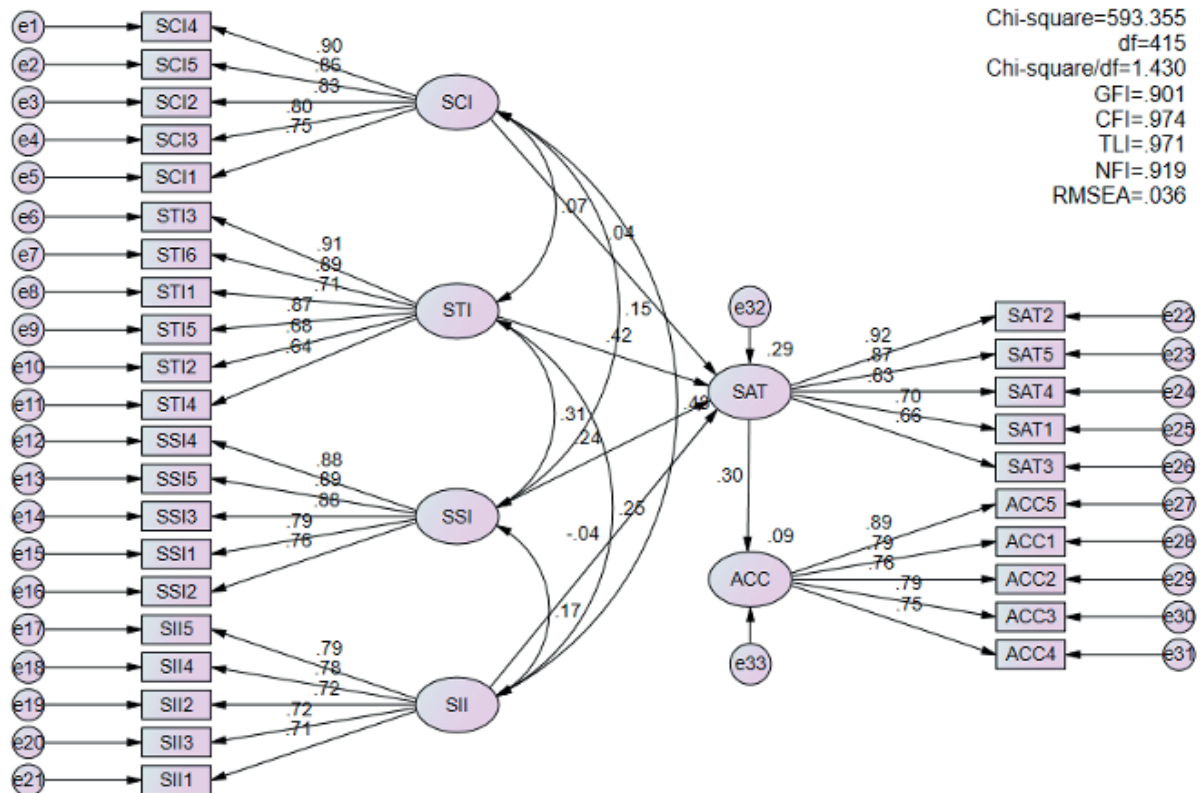


Figure 3. The structural model based on SEM

Note. *SCI* = student-content interaction, *STI* = student-teacher interaction, *SSI* = student-student interaction, *SII* = student-interface interaction, *SAT* = student satisfaction, *ACC* = student acceptance

The standardized path coefficients and p-values were utilized to test the significance of the hypotheses through the bootstrapping approach. 1000 bootstrapping samples and the 95% bias-corrected (BC) confidence intervals were executed to estimate the magnitude of the effect of each variable. The results revealed that student-teacher interaction ($\beta = 0.442$, $p = 0.000$) and student-student interaction ($\beta = 0.216$, $p = 0.000$) had a significant positive relationship with student satisfaction, with the former manifesting a stronger effect compared to the latter. Meanwhile, the opposite was true of student-content interaction ($\beta = 0.035$, $p = 0.477$) and student-interface interaction ($\beta = -0.083$, $p = 0.471$), which showed no influence on the perceived satisfaction. Furthermore, student satisfaction was found to significantly affect student's online learning acceptance ($\beta = 0.397$, $p = 0.000$). These results showed that H2, H3, and H5 were supported, while H1 and H4 were rejected, as presented in Table 8.

Table 8. Results of the hypothesis testing

Hypotheses	Hypothesized paths	SR β	SE	CR	P	Results
H1	SCI \rightarrow SAT	0.35	0.50	0.711	0.477	Rejected
H2	STI \rightarrow SAT	0.442	0.060	7.424	***	Supported
H3	SSI \rightarrow SAT	0.216	0.050	4.360	***	Supported
H4	SII \rightarrow SAT	-0.083	0.115	-0.720	0.471	Rejected
H5	SAT \rightarrow ACC	0.397	0.078	5.078	***	Supported

Note. SR β = standardized regression weights, SE = Standard errors, *** = $p < 0.001$

Note. SCI = student-content interaction, STI = student-teacher interaction, SSI = student-student interaction, SII = student-interface interaction, SAT = student satisfaction, ACC = student acceptance

Mediation Testing

By extension, this study further explored the mediating effect of satisfaction in the linkage between each interaction factor and the acceptance outcome. To this end, Preacher and Hayes' (2004) bootstrapping mediation analysis was applied. Accordingly, mediations are established if the indirect relationships exhibit statistical significance after bootstrapping ($p < 0.005$). The results revealed that the indirect effects of STI ($\beta = 0.125$, $p = 0.001 < 0.005$) and SSI ($\beta = 0.070$, $p = 0.001 < 0.005$) on students' acceptance of online learning through satisfaction were significant, proving that satisfaction mediated the relationship of student-teacher interaction and student-student interaction with acceptance. In contrast, student-content interaction and student-interface interaction had insignificant indirect effects on acceptance ($\beta = 0.012$, $p = 0.505 > 0.005$ and $\beta = -0.013$, $p = 0.400 > 0.005$, respectively), suggesting that satisfaction did not play a mediating role in the relationships between student-content interaction and acceptance as well as between student-interface interaction and acceptance. For robustness check, the indirect path coefficients from the exogenous variables and the endogenous variable or the outcome were estimated using the BC bootstrap confidence interval method, as recommended by Cheung and Lau (2017). Following this method, if the 95% BC confidence intervals do not include zero, the mediating effects are observed in the nexuses between the studied constructs. Results from Table 7 show that the confidence intervals for the mediating effects from student-teacher interaction to acceptance (lower 2.5% limit = 0.058 and upper 2.5% limit = 0.210) and student-student interaction to acceptance (lower 2.5% limit = 0.033 and upper 2.5% limit = 0.120) did not contain zero, which substantiated the mediating role of satisfaction in the links of student-teacher interaction and student-student interaction with acceptance. Nevertheless, the confidence intervals for the mediating effects from student-content interaction to acceptance (lower 2.5% limit = -0.031 and upper 2.5% limit = 0.052) and student-interface interaction to acceptance (lower 2.5% limit = -0.051 and upper 2.5% limit = 0.020) did contain zero. Thus, satisfaction did not mediate the connections between these two interaction factors and acceptance behavior. Table 9 shows the results of the mediation testing.

Table 9. Results of the mediation testing

Mediating effects	SR β	SE	P	Bootstrapping 95% BC confidence interval	
				Lower	Upper
SCI \rightarrow SAT \rightarrow ACC	0.012	0.020	0.505	-0.031	0.052
STI \rightarrow SAT \rightarrow ACC	0.125	0.041	**	0.058	0.210
SSI \rightarrow SAT \rightarrow ACC	0.070	0.022	**	0.033	0.120
SII \rightarrow SAT \rightarrow ACC	-0.013	0.017	.400	-0.051	0.020

Note. SR β = standardized regression weights, SE = Standard errors, ** = $p < 0.01$

Note. SCI = student-content interaction, STI = student-teacher interaction, SSI = student-student interaction, SII = student-interface interaction, SAT = student satisfaction, ACC = student acceptance

DISCUSSION

The overarching aim of this study was to scrutinize the interplay between students' perceptions of interaction, satisfaction, and acceptance of online learning. More precisely, it aimed to examine the effects of the four types of interaction (i.e., student-content, student-teacher, student-student, and student-interface) on student satisfaction and to illuminate the mediating role of perceived satisfaction in the nexuses between these interaction factors and student acceptance of online learning. It was found that student-teacher interaction and student-student interaction significantly impacted student satisfaction, contrasting with insignificant effects observed for student-content interaction and student-interface interaction. The results also showed that student satisfaction and online learning acceptance were significantly related. In addition, with satisfaction playing the mediating role, student-teacher interaction and student-interface interaction were found to have an indirect effect on acceptance; nevertheless, satisfaction did not mediate the relationship of student-content interaction and student-interface interaction with perceived acceptance. These results are significant as they contribute to the understanding of the mechanisms that cultivate student satisfaction in virtual learning environments through a holistic examination of the interaction model, whereby expanding upon the extant e-learning literature that has centered on the behavioral intentions of students.

The study confirmed that of the four types of interaction, student-teacher interaction was the strongest determinant of student satisfaction ($\beta = 0.442$, $p = 0.000$). This result aligns with a myriad of previous research works which showed that student-teacher interaction was a key factor in formulating students' satisfaction with their online learning experience (e.g., Ayanbode et al., 2022; Aydin, 2021; Dharmadjaja & Tiatri, 2021; Eom & Ashill, 2016; Kim & Kim, 2021; Kuo et al., 2014; Wang et al., 2022; Yilmaz, 2023). Therefore, it could be deduced that by giving ample opportunities for student-teacher interaction activities in online classrooms, teachers can elevate students' contentment with online courses. Synchronous online activities, such as video conferencing and real-time discussion, should be well designed to enhance interaction between students and teachers, further contributing to increased satisfaction levels. Notwithstanding the commonly agreed-upon magnitude of this type of interaction, Chu et al.'s (2021), Gameel's (2017), Li and Jhang's (2020), and Suat's (2021) studies yielded a divergent result, which indicated that student-teacher interaction had no impact on student satisfaction. One of the interpretations of this relationship was supposed to be due to the sudden shift to online education during the pandemic, as well as teachers' inadequate competence in teaching online and students' unreadiness for such an alternative form of learning. This explanation seems plausible, considering the intrinsically multifaced nature of online education.

The results of the study also showed that student-student interaction significantly impacted student satisfaction, albeit with a lesser degree of influence as opposed to the aforesaid factor ($\beta = 0.216$, $p = 0.471$). This result is consistent with the findings of various studies in the existing literature on online education (e.g., Ayanbode et al., 2022; Aydin, 2021; Chu et al., 2021; Dharmadjaja & Tiatri, 2021; Eom & Ashill, 2016; Kim & Kim, 2021; Li & Jhang, 2020; Yilmaz, 2023), indicating that student-student interaction and perceived satisfaction were significantly correlated. As such, it is inferred that the more teachers foster student-student interaction activities in online classes, the more students are satisfied with their online learning experience. In a similar vein, Chu et al. (2016) recommended that students should be offered room to conveniently interact with each other through collaborative tasks so that their learning outcomes could be enhanced, which in turn would contribute greatly to student satisfaction. However, contrary to common belief in this nexus, Gameel (2017) and Kuo et al. (2014) found that there was not a significant positive relationship between student-student interaction and satisfaction. One possible reason attributed to this outcome was owing to that of students' insufficient interaction in a fully online learning environment, which neither teachers nor students had experienced beforehand.

Besides, it was found in this study that there was an insignificant relationship between student-content interaction and students' perceptions of satisfaction ($\beta = 0.035$, $p = 0.477$), which is in line with Suat's (2021) study unveiling that student-content interaction exerted no influence on student satisfaction. This implies that no matter how much students interact with the course materials, their level of interaction remains unaffected. However, this finding contradicts the general pattern found in the literature showing that student-content interaction was the strongest determinant of satisfaction levels in the context of online learning environments (e.g., Ali & Mirza, 2020; Aydin, 2021; Dharmadjaja & Tiatri, 2021; Hettiarachchi et al., 2021; Kim & Kim, 2021; Kuo et al., 2014; Li & Jhang, 2020; Ngo & Ngadiman, 2021). This

discrepancy raises intriguing inquiries about the possible causes resulting in the potential variability in this connection across diverse educational settings. It is suggested that future research should delve deeper into the nuanced connections between student-content interaction and satisfaction, taking into account the potential mediating role of contextual factors, such as prior experience with online learning and learning style preferences, in determining this relationship. Variances in the characteristics of the online learning environments, including the nature of the course content, instructional design, and technological infrastructure can also influence the impact of student-content interaction on satisfaction.

An insignificant relationship between student-interface interaction and student satisfaction was observed in this study ($\beta = -0.083$, $p = 0.471$). This result was somehow supported by Suat's (2021) study, which revealed that internet self-efficacy was not an indicator of online learning satisfaction. This infers that whether the level of student-interface interaction is high or low, regardless of its inherent characteristics of computer-mediated learning, does not impact student satisfaction. Nevertheless, some past studies show a different result, concluding that this type of interaction played a significant role in formulating satisfaction (e.g., Amoush & Mizher, 2023; Kuo et al., 2014). Amoush and Mizher (2023) found that student-technology interaction was the most influential factor affecting student satisfaction with online courses. This inconsistency appears to be reasonable as Wang et al. (2013) suggest that the multifaceted nature of student-interface interaction can have varying effects on student satisfaction. In addition, the contradictory findings might be due to differences in the sample size, the analysis technique, or the specific context in which the studies were conducted. Therefore, future studies which aim to replicate these findings should use larger and more diverse samples to provide a more thorough understanding of the impact of student-interface interaction on student satisfaction in online learning environments.

Apart from the examination of the effects of interaction on satisfaction, this study sought to identify the connection between students' satisfaction and acceptance of online learning. The results showed that student satisfaction was significantly correlated with students' behavioral intention to accept this mode of education ($\beta = 0.397$, $p = 0.000$). This result is similar to studies by, for example, Daneji et al. (2019), Han and Sa (2021), and Tan et al. (2023), thus providing evidence for a positive relationship between students' satisfaction and acceptance intention. It can be implied that the more students are satisfied with online course deliveries, the more likely they are to hold positive perceptions toward online learning acceptance. This finding underscores the vitality of guaranteeing satisfying online education experiences for students, as their contentment significantly impacts their readiness to embrace this mode of learning. To date, with the proliferation of online courses, this finding offers valuable information for policy-makers, educators, and course designers to have effective strategies for promoting the prospects of online education through the enhancement of student satisfaction.

The present study distinguishes itself from other studies in that it sought to identify the mediating role of satisfaction in the link between interaction and perceived acceptance of online learning among university students. The results suggested that among the four types of interaction, learner-teacher interaction ($\beta = 0.125$, $p = 0.001 < 0.005$) and student-student interaction ($\beta = 0.070$, $p = 0.001 < 0.005$) had a positive indirect relationship with student acceptance. Despite being conducted with varying outcome constructs, various studies partly confirmed the role of satisfaction as a mediator in the context of online learning (e.g., Ayanbode et al., 2023; Tien et al., 2022). Tien et al. (2023) found that satisfaction significantly mediated the relationship between students' interaction and perceived progress. Ayanbode et al.'s (2023) study shared similar results, which resonates with the mediating role of satisfaction examined in the present study. Nonanalogously, it was established that satisfaction did not mediate the connection of student-content interaction ($\beta = 0.012$, $p = 0.505 > 0.005$) and student-interface interaction ($\beta = -0.013$, $p = 0.400 > 0.005$) with acceptance. These results indicate that satisfaction has a specific mediating role in certain aspects of online learning and may not be a universally applicable mediator. It is also inferred that students attach more importance to interpersonal interactions, herein student-teacher interaction and student-student interaction, compared to other interaction types and find them crucial for their overall satisfaction with the online learning experience. Therefore, it highlights the need for online learning platforms to prioritize and enhance features that facilitate meaningful interpersonal interactions, as these are critical drivers of student satisfaction and acceptance.

CONCLUSION

In the landscape of online education, the relationship between interaction and satisfaction has been explored in various contexts, shedding light on the intricate dynamics between these two constructs, each of which has a significant role to play in ensuring educational quality in this context and further enhancing the prospect of web-based learning. Central to this work is the examination of the interplay between students' interaction, satisfaction, and acceptance of online learning. The study revealed that student-teacher interaction emerged as the most influential determinant of student satisfaction, followed by student-student interaction, while student-content and student-interface interactions showed insignificant relationships with student satisfaction. These results add to the extant literature by shedding light on the differential impacts of various types of interaction on student satisfaction in online learning environments. Furthermore, the study confirmed a significant positive relationship between student satisfaction and acceptance of online learning, indicating that students' satisfaction with online courses influences their acceptance behavior toward online. This result emphasizes the importance of ensuring positive online education experiences for students to promote the prospects of online learning. Moreover, the study identified the mediating role of satisfaction in the link between interaction and perceived acceptance of online learning. Specifically, learner-teacher interaction and student-student interaction were found to have a significant indirect relationship with student acceptance, highlighting the significance of interpersonal interactions in shaping students' satisfaction and acceptance of online learning.

The implications of these findings for online learning practices are substantial. Educators and instructional designers should prioritize the development of strategies that promote interpersonal interaction in online learning environments. To guarantee student-teacher interaction, teachers should establish a sense of presence and accessibility in synchronous virtual classes. Research by Shea, Pickett, and Pelz (2003) stresses the value of teacher presence in online courses, emphasizing its significant role in boosting student satisfaction and promoting academic achievement. This type of interaction can be achieved through regular communication, prompt feedback, and creating opportunities for one-on-one interactions. Besides, it is the teachers' responsibility to create a supportive learning environment, as it is crucial for building a sense of teacher presence and accessibility in online learning settings. Concerning student-student interaction, this may involve the use of diverse communication tools, collaborative activities, and group projects that facilitate student-student interaction and peer-to-peer learning. By fostering a sense of community and connection among students, online learning experiences can be enhanced, leading to increased levels of student satisfaction and acceptance. Rovai (2002) suggests that a sense of community is positively associated with student satisfaction and retention in online courses. Additionally, incorporating opportunities for interaction can help alleviate feelings of isolation and promote a more engaging and interactive learning experience, ultimately improving overall learning outcomes in online education.

Limitations

Despite intriguing results, given the limited sample size of the current study, which only involved the participation of 336 students at a private university in the Mekong Delta of Vietnam, the results obtained may not be generalized to the larger population of tertiary students in the region and beyond. Therefore, future studies can be conducted with an escalated number of participants at both private and public universities to elucidate the research issue. A comparative analysis can also be performed to test whether there is a significant difference in the perception between students pursuing their learning in these educational institutions. In addition, as evidenced in the results of this study, student-content interaction and student-student interaction showed no effects on student satisfaction with online learning and acceptance, so duplicated research works can be implemented to give a common ground for the confirmation of this conclusion, or they can be done with the follow-up employment of an in-depth interview, which aims at better understanding students' perceptions of the impact of each factor in the proposed research model. Finally, the influences of contextual factors and student demographical variables, such as gender, age, and field of study, on student satisfaction with online learning can be taken into account in forthcoming investigations.

BIODATA and CONTACT ADDRESSES of AUTHORS



Duong Minh TUAN is a lecturer of English at Nam Can Tho University in the Mekong Delta of Vietnam. He holds a Master's degree in Principles and Methods in English Language Education. His research interests include English teaching methods, applied linguistics, educational psychology, and technology-enhanced teaching and learning. His professional experiences involve teaching, curriculum and syllabus design, and testing and assessment in English language instruction.

Duong Minh TUAN

Faculty of Foreign Languages

Address: Nam Can Tho University, 168 Nguyen Van Cu Street, Can Tho City, 94000, Vietnam

Phone: +84 383198558

E-mail: dmtuan@nctu.edu.vn



Le Thi Diem LAN currently works as a lecturer of English at Nam Can Tho University in the Mekong Delta of Vietnam. She obtained a Master's degree in Principles and Methods in English Language Education in 2015. She has over ten years of experience teaching English language skills to learners of different ages. Her research interests include English teaching methods, English as a medium of instruction, and technology-enhanced teaching and learning.

Le Thi Diem LAN

Faculty of Foreign Languages

Address: Nam Can Tho University, 168 Nguyen Van Cu Street, Can Tho City, 94000, Vietnam

Phone: +84 988474752

E-mail: ltdlan@nctu.edu.vn

REFERENCES

- Alarabiat, A., Hujran, O., Al-Fraihat, D., & Aljaafreh, A. (2023). Understanding students' resistance to continue using online learning. *Education and Information Technologies*, 1-26. <https://doi.org/10.1007/s10639-023-12030-x>
- Alassaf, P., & Szalay, Z. G. (2020). Transformation toward e-learning: Experience from the sudden shift to e-courses at COVID-19 time in central European countries; students' satisfaction perspective. *Studia Mundi–Economica*, 7(3), 75-85. <http://doi.org/10.18531/Studia.Mundi.2020.07.03.75-85>
- Ali, S., & Mirza, M. S. (2020). Relationship between various forms of interaction and students' satisfaction in online learning: A case of an open university of Pakistan. *Pakistan Journal of Distance and Online Learning*, 6(2). <https://files.eric.ed.gov/fulltext/EJ1321360.pdf>
- Arabai, F. (2011). Motivational instruction in practice: Do EFL instructors at King Khalid University motivate its students to learn English as a foreign language? *Arab World English Journal*, 2(4), 257-285.
- Amoush, K. H., & Mizher, R. A. (2023). Interaction as a predictor for EFL undergraduate university students' satisfaction with online English language courses. *Theory and Practice in Language Studies*, 13(4), 927-937. <https://doi.org/10.17507/tpls.1304.14>
- Ayanbode, O. F., Fagbe, A., Owolabi, R., Oladipo, S., & Ewulo, O. R. (2022). Students' interactions, satisfaction and perceived progress in an online class: Empirical evidence from Babcock University Nigeria. *Cogent Education*, 9(1), 2060783. <https://doi.org/10.1080/2331186X.2022.2060783>
- Aydin, B. (2021). Determining the effect of student-content interaction, instructor-student interaction and student-student interaction on online education satisfaction level. *University of South Florida (USF) M3 Publishing*, 3(2021), 16. <https://www.doi.org/10.5038/9781955833042>

- Aydin, H. (2013). Interaction between teachers and students in online learning. *Journal of Environmental Protection and Ecology*, 14(3A), 1335-1352.
- Baloran, E. T., & Hernan, J. T. (2021). Course satisfaction and student engagement in online learning amid COVID-19 pandemic: A structural equation model. *Turkish Online Journal of Distance Education*, 22(4), 1-12. <https://doi.org/10.17718/tojde.1002721>
- Byrne, B. M. (2016). *Structural equation modelling with AMOS: Basic concepts, applications, and programming (3rd ed.)*. New York: Routledge.
- Chang K. Y. (2013). *Factors affecting student satisfaction in different learning deliveries*. Ph.D. Dissertation, Illinois State University.
- Cheung, G. W., & Lau, R. S. (2017). Accuracy of parameter estimates and confidence intervals in moderated mediation models: A comparison of regression and latent moderated structural equations. *Organizational Research Methods*, 20(4), 746-769. <https://doi.org/10.1177/1094428115595869>
- Chu, A. M., Liu, C. K., So, M. K., & Lam, B. S. (2021). Factors for sustainable online learning in higher education during the COVID-19 pandemic. *Sustainability*, 13(9), 5038. <https://doi.org/10.3390/su13095038>
- Coolidge, F. (2013). *Statistics: A gentle introduction*. Los Angeles: Sage.
- Daneji, A. A., Ayub, A. F. M., & Khambari, M. N. M. (2019). The effects of perceived usefulness, confirmation and satisfaction on continuance intention in using massive open online course (MOOC). *Knowledge Management & E-Learning*, 11(2), 201-214. <https://doi.org/10.34105/j.kmel.2019.11.010>
- Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results*. Ph. D. dissertation, MIT Sloan School of Management, Cambridge, MA.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-339. <https://doi.org/10.2307/249008>
- Deng, L., Yang, M., & Marcoulides, K. M. (2018). Structural equation modeling with many variables: A systematic review of issues and developments. *Frontiers in Psychology*, 9, 580. <https://doi.org/10.3389/fpsyg.2018.00580>
- Dharmadjaja, P. N., & Tiatri, S. (2021). The effect of online interaction types and acceptance of technology factors on student satisfaction with online learning during the COVID-19 pandemic. In *International Conference on Economics, Business, Social, and Humanities (ICEBSH 2021)*, 570 (pp. 936-942). Atlantis Press. <https://doi.org/10.2991/assehr.k.210805.148>
- Dimitrov, D. M. (2010). Testing for factorial invariance in the context of construct validation. *Measurement and Evaluation in Counseling and Development*, 43(2), 121-149. <https://doi.org/10.1177/0748175610373459>
- Elliott, K. M., & Healy, M. A. (2001). Key factors influencing student satisfaction related to recruitment and retention. *Journal of Marketing for Higher Education*, 10(4), 1-11. https://doi.org/10.1300/J050v10n04_01
- Eom, S., & Ashill, N. J. (2023). Learning outcomes and learner satisfaction: The mediating roles of self-regulated learning and dialogues. *Journal of International Technology and Information Management*, 32(1), 1-31. <https://doi.org/10.58729/1941-6679.1557>
- Flora, D. B., & Curran, P. J. (2004). An empirical evaluation of alternative methods of estimation for confirmatory factor analysis with ordinal data. *Psychological methods*, 9(4), 466. <https://doi.org/10.1037/1082-989X.9.4.466>
- Gameel, B. G. (2017). Learner satisfaction with massive open online courses. *American Journal of Distance Education*, 31(2), 98-111. <https://doi.org/10.1080/08923647.2017.1300462>
- Geary, E., Allen, K., Gamble, N., & Pahlevansharif, S. (2023). Online learning during the COVID-19 pandemic: Does social connectedness and learning community predict self-determined needs and course satisfaction?. *Journal of University Teaching & Learning Practice*, 20(1), 13-26.

- Granic, A., & Marangunic, N. (2019). Technology acceptance model in educational context: A systematic literature review. *British Journal of Educational Technology*, 50(5), 2572-2593. <https://doi.org/10.1111/bjet.12864>
- Hair, J. F., Babin, B. J., Anderson, R. E., & Black, W. C. (2019). *Multivariate data Analysis (8th ed.)*. London, UK: Prentice Hall.
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate data analysis (7th ed.)*. London, UK: Prentice Hall.
- Han, J. H., & Sa, H. J. (2021). 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. <http://dx.doi.org/10.1007/s12564-021-09716-7>
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43, 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Hettiarachchi, S., Damayanthi, B. W. R., Heenkenda, S., Dissanayake, D. M. S. L. B., Ranagalage, M., & Ananda, L. (2021). Student satisfaction with online learning during the COVID-19 pandemic: A study at state universities in Sri Lanka. *Sustainability*, 13(21), 11749. <https://doi.org/10.3390/su132111749>
- Hew, K. F., Jia, C., Gonda, D. E., & Bai, S. (2020). Transitioning to the “new normal” of learning in unpredictable times: Pedagogical practices and learning performance in fully online flipped classrooms. *International Journal of Educational Technology in Higher Education*, 17, 1-22. <https://doi.org/10.1186/s41239-020-00234-x>
- Hillman, D. C. (1999). A new method for analyzing patterns of interaction. *American Journal of Distance Education*, 13(2), 37-47. <https://doi.org/10.1080/08923649909527023>
- Hockly, N., & Dudeney, G. (2018). Current and future digital trends in ELT. *RELC Journal*, 49(2), 164-178. <https://doi.org/10.1177/0033688218777318>
- Holmberg, B. (1986). *Growth and structure of distance education*. London: Croom-Helm.
- Kamakura, W. A. (2010). Common methods bias. *Wiley International Encyclopedia of Marketing*. <https://doi.org/10.1002/9781444316568.wiem02033>
- Ke, F., & Kwak, D. (2013). Constructs of student-centered online learning on learning satisfaction of a diverse online student body: A structural equation modeling approach. *Journal of Educational Computing Research*, 48(1), 97-122. <https://doi.org/10.2190/EC.48.1.e>
- Kim, S., & Kim, D. J. (2021). Structural relationship of key factors for student satisfaction and achievement in asynchronous online learning. *Sustainability*, 13(12), 6734. <https://doi.org/10.3390/su13126734>
- Kline, R. B. (2015). The mediation myth. *Basic and Applied Social Psychology*, 37(4), 202-213. <https://doi.org/10.1080/01973533.2015.1049349>
- Korucu, A. T., & Karakoca, A. (2020). Development and validation of the cloud technologies usage in education scale. *Bartın University Journal of Faculty of Education*, 9(1), 69-82. <https://doi.org/10.14686/buefad.623459>
- Kuo, Y. C. (2010). *Interaction, internet self-efficacy, and self-regulated learning as predictors of student satisfaction in distance education courses*. Ph.D. dissertation, Utah State University.
- Kuo, Y. C., Walker, A. E., Belland, B. R., & Schroder, K. E. (2013). A predictive study of student satisfaction in online education programs. *International Review of Research in Open and Distributed Learning*, 14(1), 16-39. <https://doi.org/10.19173/irrodl.v14i1.1338>
- Kuo, Y. C., Walker, A. E., Schroder, K. 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>

- Lee, J. W., & Mendlinger, S. (2011). Perceived self-efficacy and its effect on online learning acceptance and student satisfaction. *Journal of Service Science and Management*, 4(03), 243. <https://doi.org/10.4236/jssm.2011.43029>
- Li, F., & Jhang, F. (2020, December). The relationship between interaction and student satisfaction with online learning in social work undergraduates in China. In *2020 6th International Conference on Social Science and Higher Education (ICSSHE 2020)* (pp. 23-27). Atlantis Press. <https://doi.org/10.2991/assehr.k.201214.004>
- Martin, K. D., & Paul Hill, R. (2012). Life satisfaction, self-determination, and consumption adequacy at the bottom of the pyramid. *Journal of Consumer Research*, 38(6), 1155-1168. <https://doi.org/10.1086/661528>
- Moore, M. (1989). Three types of interaction. *The American Journal of Distance Education*, 3(2), 1-6. <https://doi.org/10.1080/08923648909526659>
- Ngampornchai, A., & Adams, J. (2016). Students' acceptance and readiness for E-learning in Northeastern Thailand. *International Journal of Educational Technology in Higher Education*, 13(1), 1-13. <https://doi.org/10.1186/s41239-016-0034-x>
- Ngo, J., & Ngadiman, A. (2021). Investigating student satisfaction in remote online learning settings during COVID-19 in Indonesia. *Journal of International and Comparative Education (JICE)*, 73-95. <http://doi.org/10.14425/jice.2021.10.2.0704>
- Nguyen, T. N. P., Nguyen, B. M., & Vo, B. T. (2022). Factors influencing student satisfaction of online learning within a Vietnamese university context during the COVID-19 pandemic. *Tra Vinh University Journal of Science*, 12(48), 11-23. <https://doi.org/10.35382/tvujs.11.48.2022.1105>
- Nikou, S., & Maslov, I. (2023). Finnish university students' satisfaction with e-learning outcomes during the COVID-19 pandemic. *International Journal of Educational Management*, 37(1), 1-21. <https://doi.org/10.1108/IJEM-04-2022-0166>
- Osborne, J. W. (2008). Creating valid prediction equations in multiple regression: Shrinkage, double cross-validation, and confidence intervals around prediction. *Best Practices in Quantitative Methods*, 299-305. <https://doi.org/10.4135/9781412995627>
- Palmer, S. R., & Holt, D. M. (2009). Examining student satisfaction with wholly online learning. *Journal of Computer Assisted Learning*, 25(2), 101-113. <https://doi.org/10.1111/j.1365-2729.2008.00294.x>
- Phillips, G. M., Santoro, G. M., & Kuehn, S. A. (1988). Computer: The use of computer-mediated communication in training students in group problem-solving and decision-making techniques. *American Journal of Distance Education*, 2(1), 38-51. <https://doi.org/10.1080/08923648809526607>
- Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879. <https://doi.org/10.1037/0021-9010.88.5.879>
- Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, & Computers*, 36, 717-731. <https://doi.org/10.3758/BF03206553>
- Puzziferro, M., & Shelton, K. (2008). A model for developing high-quality online courses: Integrating a systems approach with learning theory. *Journal of Asynchronous Learning Networks*, 12, 119-136.
- Rajeb, M., Wang, Y., Man, K., & Morett, L. M. (2023). Students' acceptance of online learning in developing nations: scale development and validation. *Educational Technology Research and Development*, 71(2), 767-792. <https://doi.org/10.1007/s11423-022-10165-1>
- Raykov, T., & Marcoulides, G. A. (2008). *An introduction to applied multivariate analysis*. New York: Taylor & Francis. <https://doi.org/10.4324/9780203809532>
- Rovai, A. P. (2002). Building sense of community at a distance. *International Review of Research in Open and Distributed Learning*, 3(1), 1-16. <https://doi.org/10.19173/irrodl.v3i1.79>

- Schumacker, R. E., & Lomax, R. G. (2004). *A beginner's guide to structural equation modeling*. Psychology Press.
- Shao, C. (2020, January). An empirical study on the identification of driving factors of satisfaction with online learning based on TAM. In *5th International Conference on Economics, Management, Law And Education (EMLE 2019)* (pp. 1067-1073). Atlantis Press. <http://doi.org/10.2991/aebmr.k.191225.205>
- She, L., Ma, L., Jan, A., Sharif Nia, H., & Rahmatpour, P. (2021). Online learning satisfaction during COVID-19 pandemic among Chinese university students: The serial mediation model. *Frontiers in Psychology, 12*, 743936. <https://doi.org/10.3389/fpsyg.2021.743936>
- Shea, P. J., Pickett, A. M., & Pelz, W. E. (2003). A follow-up investigation of “teaching presence” in the SUNY Learning Network. *Journal of Asynchronous Learning Networks, 7*(2), 61-80. <https://doi.org/10.24059/olj.v7i2.1856>
- Spector, P. E. (2006). Method variance in organizational research: Truth or urban legend?. *Organizational Research Methods, 9*(2), 221-232. <https://doi.org/10.1177/1094428105284955>
- Suat, K. A. Y. A. (2021). Predictors of online learning satisfaction of pre-service teachers in Turkey. *Research in Pedagogy, 11*(2), 586-607. <https://doi.org/10.5937/IstrPed2102586K>
- Sun, J. C. Y., & Rueda, R. (2012). Situational interest, computer self-efficacy and self-regulation: Their impact on student engagement in distance education. *British Journal of Educational Technology, 43*(2), 191-204. <https://doi.org/10.1111/j.1467-8535.2010.01157.x>
- Suvorova, S. L., Khilchenko, T. V., Olar, & Yu. V. (2021). The implementation of distance technologies of learning a foreign language as a condition of innovation of the educational strategies of a university. *Educational Sciences, 3*(13), 90-98. <https://doi.org/10.14529/ped210308>
- Tabachnick, B. G., & Fidell, L. S. (2001). *SAS for Windows workbook for Tabachnick and Fidell: Using multivariate statistics*. London, UK: Prentice Hall. <https://doi.org/10.14529/ped210308>
- Tan, J., Hendaridi, I., Micheal, M., & Jacky, J. (2023). Study Of Student Satisfaction And Acceptance In Batam City For Post-Pandemic Online Learning. *JATISI (Jurnal Teknik Informatika dan Sistem Informasi), 10*(2), 429-439. <https://doi.org/10.35957/jatisi.v10i2.5179>
- Teng, C. (2023). Using the fsQCA approach to investigate factors affecting university students' satisfaction with online learning during the COVID-19 pandemic: A case from China. *Frontiers in Psychology, 14*, 1123774. <https://doi.org/10.3389/fpsyg.2023.1123774>
- Thurmond, V., & Wambach, K. (2004). Understanding interactions in distance education: A review of the literature. *International Journal of Instructional Technology and Distance Learning, 1*(1).
- Tien, H. N., My, S. T., Duy, T. N., & Ngoc, D. N. (2022). The mediated role of satisfaction in boosting the perceived progress via interaction in online learning: empirical evidence from private universities in Vietnam. *International Journal of Learning, Teaching and Educational Research, 21*(11), 393-408. <https://doi.org/10.26803/ijlter.21.11.22>
- Tirschwell, D. L., & Longstreth, J. W. T. (2002). Validating administrative data in stroke research. *Stroke, 33*(10), 2465-2470. <https://doi.org/10.1161/01.str.0000032240.28636.bd>
- Tran, Q. H., & Nguyen, T. M. (2022). Determinants in student satisfaction with online learning: A survey study of second-year students at private universities in HCMC. *International Journal of TESOL & Education, 2*(1), 63-80. <https://doi.org/10.54855/ijte22215>
- Tung, F. C., & S. C. (2007). Exploring adolescents' intentions regarding the online learning courses in Taiwan. *Cyberpsychology & Behavior, 10*(5), 729-730. <https://doi.org/10.1089/cpb.2007.9960>
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186-204. <http://dx.doi.org/10.1287/mnsc.46.2.186.11926>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*, 425-478.

- Wang, X., Hassa, A. B., Pyn, H. S., & Ye, H. (2022). Exploring the influence of teacher-student interaction strength, interaction time, interaction distance and interaction content on international student satisfaction with online courses. *International Journal of Learning, Teaching and Educational Research*, 21(2), 380-396. <https://doi.org/10.26803/ijlter.21.2.21>
- Wei, H. C., & Chou, C. (2020). Online learning performance and satisfaction: do perceptions and readiness matter?. *Distance Education*, 41(1), 48-69. <https://doi.org/10.1080/01587919.2020.1724768>
- Williams, C. (2011). Research methods. *Journal of Business & Economics Research (JBER)*, 5(3). <https://doi.org/10.19030/jber.v5i3.2532>
- Wong, W. H., & Chapman, E. (2023). Student satisfaction and interaction in higher education. *Higher Education*, 85(5), 957-978. <https://doi.org/10.1007/s10734-022-00874-0>
- Wu, Y., Xu, X., Xue, J., & Hu, P. (2023). A cross-group comparison study of the effect of interaction on satisfaction in online learning: The parallel mediating role of academic emotions and self-regulated learning. *Computers & Education*, 199. <https://doi.org/10.1016/j.compedu.2023.104776>
- Yilmaz, A. B. (2023). The relationship between satisfaction, interaction, e-learning readiness, and academic achievement in online learning. *Open Praxis*, 15(3), 199-213. <https://doi.org/10.55982/openpraxis.15.3.578>
- Yunus, M. M. (2018). Innovation in education and language learning in 21st century. *Journal of Sustainable Development Education and Research*, 2(1), 33-34. <https://doi.org/10.17509/jsder.v2i1.12355>
- Zhang, Y. (2022). Influence of teacher-student interaction on course learning effect in distance education. *International Journal of Emerging Technologies in Learning (IJET)*, 17(10), 215-226. <https://doi.org/10.3991/ijet.v17i10.30913>
- Zhu, Y., Gao, J., Wang, J., Yu, D., Nie, X., Dai, J., & Fu, H. (2018). Association between workplace social capital and absolute presenteeism: A multilevel study in a Chinese context. *Journal of occupational and environmental medicine*, 60(10), 543-547. <https://doi.org/10.1097/JOM.0000000000001421>