



# Online learning satisfaction in higher education during the COVID-19 pandemic: A regional comparison between Eastern and Western Chinese universities

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Received: 23 December 2020 / Accepted: 22 March 2021 / Published online: 31 March 2021  
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## Abstract

Student satisfaction is of great significance in online learning, but few studies have explored its determinants in emerging countries. This study investigated the determinants of university students' satisfaction with online learning platforms in China through applying the Technology Satisfaction Model during the COVID-19 pandemic, when an unprecedented amount of learning began to take place online due to the closure of educational institutions. A total of 928 students from five universities in four Chinese provinces or municipalities were surveyed through a purposive sampling technique and analyzed through structural equation modeling and the Rasch model. Findings show that Chinese university students' satisfaction with online learning platforms is directly and indirectly impacted by their computer self-efficacy and the perceived ease of use and usefulness of the platforms. Findings also show that regional differences moderate the associations among these components. The current study adds to theoretical, methodical and practical understanding of university students' satisfaction with using online learning platforms, which have been recognized as irreplaceable emergency educational tools.

**Keywords** Online learning · Satisfaction · COVID-19 pandemic · Technology satisfaction model · Chinese higher education · Regional comparison

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Author Contribution Haozhe Jiang and A.Y.M. Atiquil Islam have equally contributed to this article, and they should be considered as first authors.

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## 1 Introduction

In an effort to mitigate the spread of the COVID-19 pandemic, most educational institutions around the world have been closed since about March 2020. This has impacted more than 90% of the world's student population (UNESCO, 2020a). In China, educational institutions were closed in late January 2020 (Zhu & Peng, 2020). The Ministry of Education of China (2020a) initiated an emergency policy called “Suspending Classes Without Stopping Learning” to make sure that students could continue their studies with online learning platforms at home on January 29. In the field of higher education, between January 29 and April 3, 1454 Chinese universities started the Spring Semester using online learning platforms nationwide. Over 950,000 university teachers offered more than 942,000 courses and 7,133,000 lectures on online learning platforms. In total, university students have attended these courses and lectures 1.18 billion times (Ministry of Education, 2020b). This online learning practice in China is unprecedented in scale, scope and depth and is considered the first exploration of its kind in the history of higher education worldwide. Moreover, helping students adapt to a new learning pattern fully integrated with information and communication technologies (ICTs) has been a very important experiment (Ministry of Education, 2020b).

In recent years, an increasing number of technology platforms have been widely adopted to support learning in higher education (de Souza Rodrigues et al., 2021; Habib et al., 2021; Mpungose, 2020; Su & Chen, 2020; Turnbull et al., 2019; Yen et al., 2018; Yunusa & Umar, 2021). For instance, learning management systems (LMSs) have been considered to be one of the most important and indispensable online learning tools and platforms (Coates et al., 2005; Turnbull et al., 2021). LMSs can be defined as “web-based software platforms that provide an interactive online learning environment and automate the administration, organization, delivery, and reporting of educational content and learner outcomes” (Turnbull et al., 2019, p. 1). LMSs have many features that support online learning, including course management, assessment, learner progress tracking, gradebook, communications, security, and smartphone access (Turnbull et al., 2019; Turnbull et al., 2021). These features can work together to provide a seamless experience for online learners (Turnbull et al., 2019). The quality of online learning is also influenced by the robustness of learning platforms (Pinho et al., 2021; Uppal et al., 2018). Furthermore, these platforms have been recognized as irreplaceable emergency educational tools in the transition to online learning during the COVID-19 pandemic (Zhu & Peng, 2020).

The success of online learning platforms (e.g., LMSs) has generally been determined by student satisfaction (Virtanen et al., 2017; Yuen et al., 2019). Dai et al. (2020) found evidence of a relationship between higher student satisfaction and more positive attitudes toward LMSs. Other studies found that student satisfaction was related to stronger intention and willingness to use (Salam & Farooq, 2020), higher long-term adoption rate (Cidral et al., 2018), better learning performance (Al-Fraihat et al., 2020; Isaac et al., 2019) and achievements (Vasileva-Stojanovska et al., 2015). Moreover, student satisfaction is also a powerful influential factor involved in a platform or system's net benefits (Martins et al., 2018; Salam

& Farooq, 2020). Although the governments, universities and service providers have made significant investments in new technologies, the full benefit and value of online learning platforms has not yet been realized (Barclay et al., 2018; Lane et al., 2015), nor have students yet been as satisfied as expected (Chingos et al., 2017; Deng et al., 2019; Jiang & Zhao, 2018). This necessitates the implementation of continuous investigations on determinants of student satisfaction (Firat et al., 2018; Herrador-Alcaide et al., 2019). On the one hand, governments, universities and service providers can target areas that need to be changed and improved based on the determinants of student satisfaction and thus enhance the online learning service quality through scientific, appropriate, effective and reliable methods (Cidral et al., 2018; Machado-Da-Silva et al., 2014). On the other hand, educators, course developers and instructional designers can also benefit from these investigations and thus provide students with better online learning environments and more suitable online learning programs (Cidral et al., 2018; Ilgaz & Gülbahar, 2015). However, prior studies on online learning were conducted mostly in developed countries, and limited effort has been made in emerging countries (Pham et al., 2019).

Motivated by these gaps, the main aim of this study was to validate the technology satisfaction model (TSM) in order to explore the determinants of university students' satisfaction with using online learning platforms in the context of Chinese higher education during the COVID-19 pandemic. Subsequently, this study validated the TSM among Eastern and Western Chinese university students and scrutinized regional differences. Governments, universities, platform service providers, educators, course developers and instructional designers can use the findings as a basis to improve the service quality of online learning, enhance university students' satisfaction, and increase contingency capacities in order to mitigate and manage risk in the future.

The remainder of the paper is organized as follows. In the next section, the background of the study is introduced, after which state-of-the-art related studies are presented. After that, the research method adopted for this study is outlined. Results follow in the subsequent section. The discussion section focuses on the contributions of this study and the theoretical and practical implications, and finally, the conclusion and limitations are outlined.

## 2 Background

Online learning platforms have played an irreplaceable role in the massive practice of online learning in China during the COVID-19 pandemic. In the early days of school closures, university students all over China faced the dilemma of “waiting to learn at home” (Zhu & Peng, 2020, p. 1). In order to deal with the dilemma swiftly and respond to the public's concerns, the Ministry of Education (2020c, d) issued a series of emergency measures which included organizing multiple platforms to support university students' online learning. By April 3, there were 37 government-backed platforms (e.g., XuetangX, Eduyun, etc.) and more than 110 social and university platforms (e.g., Daxiaxuetang, Cqooc, etc.) across the country involved in providing university students with online learning resources and services (Ministry

of Education, 2020b). Different students were required to take different courses on different platforms to avoid excessive pressure on the servers. Fortunately, these platforms could generally meet the massive online learning demands of more than 31.04 million university students in China. In view of this, more and more Chinese administrators and scholars began to shift their focus from whether students could learn to whether they could learn well and be satisfied with their learning environments (Zhu et al., 2020).

Since serving students and ensuring their satisfaction are the fundamental goals of promoting e-education in China, the Ministry of Education (2019) has launched a series of initiatives in recent years to develop and improve online learning platforms. However, students in technology-enhanced sessions have reported significantly lower satisfaction than those in traditional classrooms (Chingos et al., 2017; Deng et al., 2019), and Chinese students are no exception (Jiang & Zhao, 2018). Some studies have investigated Chinese university students' intention to use learning management systems or virtual and remote labs (Su & Chen, 2020; Zhang et al., 2020). However, as far as we know, few studies in China have explored the determinants of university students' satisfaction with using online learning platforms, let alone during the COVID-19 pandemic. As a consequence, governments, universities and platform service providers may have little strategic guidance to enhance students' satisfaction.

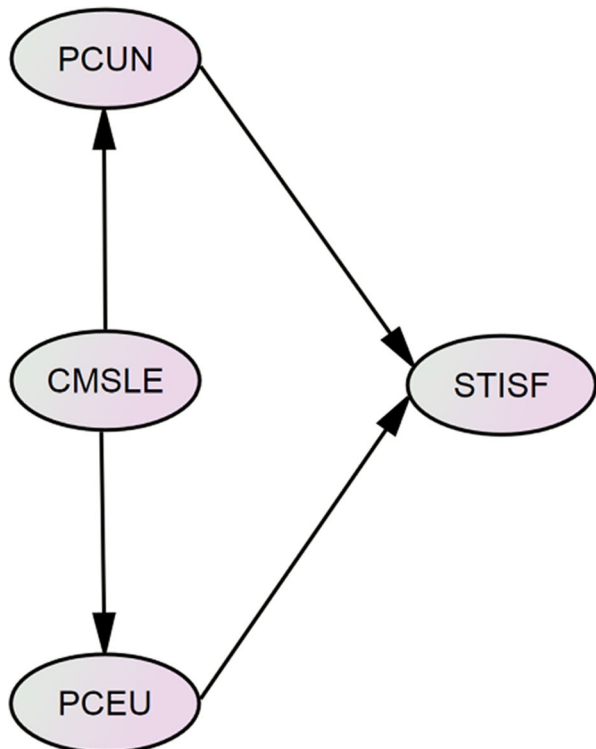
Another concern of Chinese administrators and scholars is whether online learning will exacerbate educational inequality (Hu & Xie, 2020; Yang, 2020). Previous studies in China have shown that online learning platforms expose more students to rich educational resources but do not benefit all social classes equally; disadvantaged student groups (e.g., rural students, students with low socioeconomic status) frequently benefit less from them (Xu & Yao, 2018; Xu & Ye, 2018). During the COVID-19 pandemic, these issues regarding educational equity were raised again (Kingsbury, 2021; UNESCO, 2020b). There is a huge development gap (e.g., human resources gap, financial resources gap, and material resources gap, etc.) between Eastern and Western Chinese universities (Cai et al., 2021). For instance, in 2017, Western Chinese universities' overall financial education funds were allocated about 240,763 million yuan, while Eastern Chinese universities were allocated about 612,898 million yuan (Cai et al., 2021). The latest assessment in China also illustrates the gap in development, as Western Chinese universities have 51 first-class disciplines in total while Eastern Chinese universities have 331 (Cai et al., 2021). In view of this, scrutinizing the difference between Eastern and Western Chinese university students' satisfaction with platforms may help us better understand online learning equity. However, as far as we know, very few studies have discussed these equity issues from the perspective of regional differences in developing countries.

### 3 Literature review

According to Islam et al. (2018), the present study defines student satisfaction as the degree to which “the use of technology is consistent with existing values, needs and student experiences” in the use of online learning platforms (Islam et al., 2018,

p. 4). The technology satisfaction model (TSM) is one of the most important models that has been validated as effective in explaining students' satisfaction in Asian higher educational settings. Proposed by Islam (2014), this model combines two psychological factors, namely satisfaction and computer self-efficacy (from Bandura's (1977) social cognitive theory), with two motivation variables, namely perceived ease of use and usefulness, (from Davis et al.'s (1989) technology acceptance model (TAM)). TAM has its foundation in the Theory of Reasoned Action (TRA), a general theory widely applied to predict and explain human behavior in a variety of contexts (Ajzen & Fishbein, 1980). In educational contexts, TAM has become one of the most important and popular models in understanding predictors of teachers' and students' ICT acceptance (Granić & Marangunić, 2019; Scherer et al., 2019). It asserts that perceived ease of use and usefulness are two main determinants of an individual's intention to use and attitude toward using technology (Davis et al., 1989). Despite its broad applicability and strong explanatory power, some critics have claimed that it focuses on behavioral and motivational factors while ignoring psychological factors, such as computer self-efficacy (Scherer & Teo, 2019; Yağın & Kutlu, 2019) and satisfaction (Scherer & Teo, 2019; Yuen et al., 2019). The original TSM (Islam, 2014) took these two essential psychological factors into consideration and articulated three influential determinants of technology satisfaction (STISF), namely computer self-efficacy (CMSLE), perceived ease of use (PCEU) and usefulness (PCUN) (See Fig. 1). The TSM was validated in a Malaysian

**Fig. 1** Technology satisfaction model (Islam, 2014). *Note:* satisfaction (STISF), computer self-efficacy (CMSLE), perceived ease of use (PCEU), perceived usefulness (PCUN)



university to measure students' satisfaction with using online research databases (Islam et al., 2015) and wireless internet (Islam, 2014). It was later validated in a Chinese university to measure students' satisfaction with using wireless internet in learning activities (Islam et al., 2018). In 2020, Islam and Sheikh (2020) validated the relationships within the TSM in a Pakistani university. However, the TSM has not been validated to assess online learning platform success. Nevertheless, more universities in different regions should be included to enhance the TSM's applicability (Islam et al., 2015).

## 4 Hypotheses

In this section, we present a brief but pertinent review of theoretical and empirical literature regarding the determinants of university students' satisfaction with using online learning platforms. Based on the TSM, we devised a total of seven hypotheses and thus clarified the relationships among the four latent variables of the model.

Self-efficacy, as an important component of Bandura's (1977) social cognitive theory, was defined as "people's beliefs about their capabilities to produce designated levels of performance that exercise influence over events that affect their lives" (Bandura, 1997, p. 71). Based on Bandura's (1977, 1997) theory, Venkatesh and Davis (1996) adapted the concept of computer self-efficacy to people's judgment of their capabilities to easily use information and computer technologies. Regarding educational technology, Islam et al. (2015, p. 57) referred to computer self-efficacy as "student's beliefs in their capabilities to use a computer for their learning and research". Following this definition, we posit that computer self-efficacy is associated with university students' beliefs in their capabilities to use online learning platforms for their study. Extensive studies have shown that computer self-efficacy significantly impacts learners in various ways within a technology-supported environment (Dong et al., 2020; Heckel & Ringeisen, 2019; Wang et al., 2019; Zhu & Mok, 2020). Most importantly, recent studies have found that computer self-efficacy is directly related to the two key motivation variables in the TAM, perceived ease of use and usefulness (Bin et al., 2020; Chen et al., 2019; Scherer et al., 2019; Thongsri et al., 2019; Yalçın & Kutlu, 2019). In other words, it is probable that university students with high computer self-efficacy find it easy to use online learning platforms as well as realize their value and benefits. In view of this, Islam and Sheikh (2020) suggested that more attention should be paid to the assessment of computer self-efficacy and its impact on students' perceived ease of use and usefulness. Therefore, we hypothesize the following:

- H1.** Eastern and Western Chinese students' computer self-efficacy directly impacts their perceived ease of use of online learning platforms.
- H2.** Eastern and Western Chinese students' computer self-efficacy directly impacts their perceived usefulness of online learning platforms.

Drawing from Davis et al.'s (1989) and Islam's (2011) definitions, the current study refers to perceived usefulness as university students' perception of the

benefits of using online learning platforms, and it refers to perceived ease of use as university students' perception of how easy or difficult it is to use online learning platforms. On the one hand, perceived ease of use and usefulness have frequently been considered core variables in different studies on online learning (Ameen et al., 2019; Esteban-Millat et al., 2018; Farhan et al., 2019; Scherer et al., 2019). On the other hand, technology satisfaction is also directly impacted by perceived ease of use and usefulness (Bin et al., 2020; Chen et al., 2019; Islam, 2016; Islam et al., 2018; Islam & Sheikh, 2020). However, as far as our knowledge is concerned, students' satisfaction with using online learning platforms has seldom been measured by perceived ease of use and usefulness in Chinese higher education. Thus, we have proposed the following hypotheses:

**H3.** Eastern and Western Chinese students' perceived ease of use directly impacts their satisfaction with using online learning platforms.

**H4.** Eastern and Western Chinese students' perceived usefulness directly impacts their satisfaction with using online learning platforms.

Many previous studies have validated the significant associations between computer self-efficacy, perceived ease of use and usefulness (Abdullah & Ward, 2016; Bin et al., 2020; Chen et al., 2019; Scherer et al., 2019; Thongsri et al., 2019; Yalçın & Kutlu, 2019). For instance, according to Abdullah and Ward's (2016) meta-analysis, computer self-efficacy is the greatest predictor of students' perceptions of the ease of use of online learning systems or platforms, and it is also an important predictor of students' perceived usefulness. Moreover, Chen et al. (2019), Islam et al. (2018), and Islam and Sheikh (2020) argued that learners' satisfaction can also be influenced by computer self-efficacy and mediated by perceived ease of use and usefulness. However, very few studies on online learning platforms have validated the indirect impact in China. Thus, we hypothesize that:

**H5.** Eastern and Western Chinese students' computer self-efficacy indirectly impacts their satisfaction mediated by their perceived usefulness of online learning platforms.

**H6.** Eastern and Western Chinese students' computer self-efficacy indirectly impacts their satisfaction mediated by their perceived ease of use of online learning platforms.

It is worth noting that some of the relationships and influences mentioned above may be moderated by cultural or regional factors (Huang, 2017; Islam, 2016). This has motivated some researchers to do cross-cultural or cross-regional analyses when assessing ICT acceptance, adoption, and satisfaction (Hassan & Wood, 2020; Huang, 2017; Islam, 2016; Jung & Lee, 2020). For instance, Islam (2016) found that culture did interact with computer self-efficacy, perceived ease of use, perceived usefulness and intention to use and that it influenced both Malaysian and Chinese lecturers' adoption and satisfaction with using ICT in higher education. During the COVID-19 pandemic, a large-scale survey

of 277,521 students in Hubei, China revealed that rural students' online learning satisfaction was significantly higher than city students' (Wang et al., 2020). However, despite the huge development gap between Eastern and Western China, nearly none of the research has scrutinized the regional differences in Eastern and Western Chinese university students' satisfaction with online learning platforms. Thus, our hypothesis is as follows:

**H7.** There will be a cross-regional invariant of the causal structure of the TSM between Eastern and Western Chinese university students.

## 5 Methodology

In line with Burkell (2003), we believed that it was best to employ a survey questionnaire method to collect Eastern and Western Chinese students' opinions, information, and experiences in terms of e-learning during the COVID-19 pandemic because administering surveys is the most popular method of data collection in studies related to online learning platforms in China (Turnbull et al., 2020). Islam (2011) designed the original questionnaire for the purpose of measuring online research databases in English. Recently, Chen et al. (2019) translated and validated it in the Chinese higher education context. In order to better suit our purpose of assessing university students' satisfaction with online learning platforms, both versions of the instrument were adapted and modified. Subsequently, the adapted instrument was pretested by giving the survey to a sample of 125 university students from East China Normal University and Yuxi Normal University in order to evaluate their reaction to the items and ease of answerability. Revision was undertaken after the statistical analysis which used the Rasch model. The formal questionnaire used in this current study contained 33 items, and each item was measured by a 6-point Likert scale. Table 1 shows the dimensions of the TSM model which the questionnaire measured. We had obtained ethical endorsement for this research before we distributed the questionnaires among university students.

Five universities were selected for the formal test. Among them, East China Normal University (ECNU) and Zhejiang Normal University (ZJNU) are located in eastern regions of China, while Xizang Minzu University (XZMU), Yuxi Normal University (YXNU), and Qujing Normal University (QJNU) are located

**Table 1** Dimensions of the TSM model measured by the number of items

Dimensions	Likert scale	No. of items
Perceived ease of use	1–6 (strongly disagree → strongly agree)	10
Perceived usefulness	1–6 (strongly disagree → strongly agree)	10
Computer Self-Efficacy	1–6 (strongly disagree → strongly agree)	8
Satisfaction	1–6 (very unsatisfied → very satisfied)	5
<i>Total</i>		33



in western regions. An online invitation was delivered to students of the five universities at the end of the spring semester (Semester 2, 2019–2020). During the survey, the universities' rules and regulations were followed, students' anonymity was confirmed, and all personal information was strictly protected. This study recruited a total of 936 students to participate in the survey through a purposive sampling technique. According to Etikan et al. (2016), purposive sampling, which involves deliberately choosing participants based on the qualities they possess, would facilitate a focus on the regional differences of students' universities. Summarized from a preliminary analysis report, 8 of the collected questionnaires were determined to be invalid due to incomplete responses. Next, data were analyzed using SPSS 21.0 to conduct descriptive analysis. Winsteps software version 3.94 was used to conduct Rasch analysis for validating the instrument. AMOS software version 16 was used to perform extensive analyses for three-stage structural equation modelling like confirmatory factor analysis (CFA) and a full-fledged structural model and invariance analysis for validating the measurement and structural model and cross-validating the TSM model, respectively.

The data set consisted of 33.8% male and 66.2% female university students. Of these, 52.9% came from Eastern Chinese universities, namely ECNU and ZJNU, while 47.1% came from Western Chinese universities, namely XZMU, YXNU and QJNU. 8.0% were 17–18 years of age, 47.5% were 19–20 years of age, 38.6% were 21–22 years of age, 5.1% were 23–24 years of age, and 0.9% were 25 years of age and older. Undergraduate students constituted 82.80%, and 17.20% were post-graduate students. In China, 86.14% of university students are undergraduates, and 13.86% are postgraduates (National Bureau of Statistics, 2019). This ratio is close to that in our data set.

## 6 Results

Over the last thirty years, a wide range of disciplines have gradually adopted the Rasch model (Rasch, 1960) as a theory-based method for developing measurements. A clear explanation of the factors to be estimated is an essential prerequisite for developing an assessment. In order to examine the initially predicted determinant, evaluation data are often fitted to a Rasch measurement. If the data fit the model, then the assertion can be substantiated, the existence of the initially hypothetical construct can be justified, and the construct can then be measured by the psychometric properties. Accordingly, evidence for construct and content validity is proffered. Furthermore, the Rasch model also allows for various ways to test differential item functioning or item bias, which increases the possibility of developing a fair measurement scale (Liu & Boone, 2006). As a result, the present study used Winsteps software to conduct Rasch analysis. Several outputs of the Rasch analysis explained that items' reliability and their separation are quite high, i.e., .99 and 10.31, respectively. Furthermore, Rasch person reliability and its separation are highly satisfactory, i.e., .96 and 4.95, respectively. The item polarity map of the Rasch model indicated that all the scores of point measure

correlation (PTMEA CORR.) for items were greater than .61 and that they measured in the same direction. However, item fit order found that three items out of thirty-three were outside the range of infit ( $> 0.5$ ) and outfit ( $< 1.5$ ) mean square

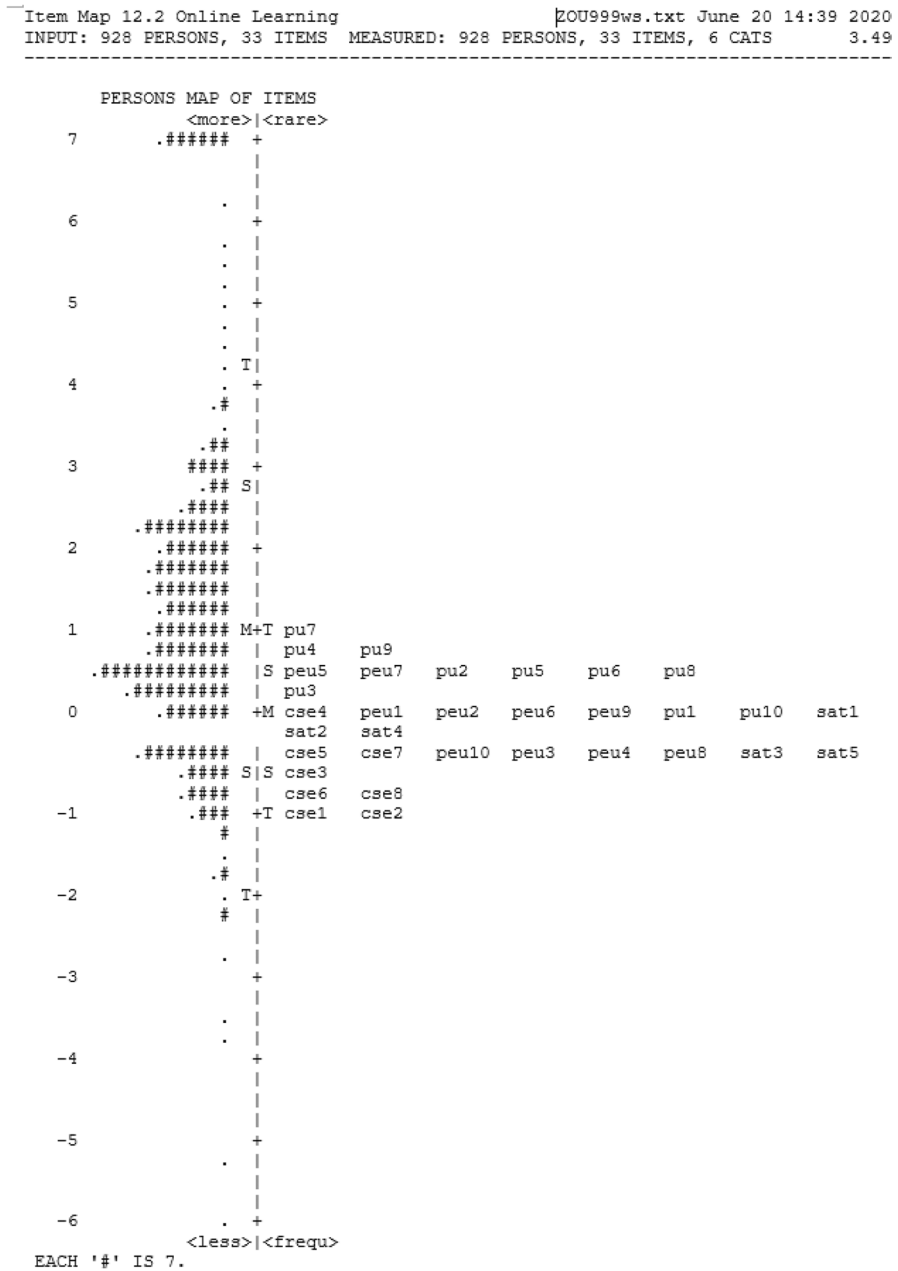


Fig. 2 Item map

(MNSQ) scores (Bond & Fox, 2001). Therefore, these three misfitting indicators (pu4, peu6 and cse5) were considered to be invalid, and they should be excluded from further estimation. According to the principal components of Rasch analysis, the remaining thirty valid items for measuring four facets empirically explained 75% of the variance and confirmed a good measurement scale. Interestingly, the item map of the Rasch model (see Fig. 2) found that the majority of Eastern and Western Chinese university students were able to respond to the items correctly, and their ability to use online learning platforms were higher than the items' difficulties. Items are located on the right-hand side of Fig. 2 while the persons are located on the left-hand side of the figure.

Firstly, we obtained a pool of 30 valid items through Rasch analysis using minimum likelihood estimation after which we ran through the confirmatory factor analysis (CFA) using maximum likelihood estimation to validate the measurement model of our study. Basically, the measurement model was designed based on the constructs of the TSM, which were interrelated to measure the convergent and discriminant validity using a few required statistical assumptions like composite reliability (CR), average variance extracted (AVE) and covariances, including square root and AVE. Hair et al. (2010) suggested that CR and AVE scores should be larger than .70 and .50, respectively. Meanwhile, Fornell and Lacker (1981) claimed that the square root of AVEs should be larger than covariances among the facets. Our measurement model was also estimated based on several recommendations (Hu & Bentler, 1999) of fit indices, like chi-square ( $\chi^2$ )/degree of freedom ( $< 5$ ) including the root mean square error of approximation (RMSEA  $< .1$ ), Tucker–Lewis Index (TLI  $> .90$ ) and comparative fit index (CFI  $> .90$ ). Based on the above assumptions, four-factor measurement model of computer self-efficacy (CMSLE), satisfaction (STISF), Perceived ease of use (PCEU) and usefulness (PCUN) adjusted the data efficaciously after isolating several items due to the multicollinearity, with  $\chi^2 = 443.609$ ;  $df = 96$ ;  $p = .000$ ; RMSEA = .062; CFI = .974; and TLI = .968. Moreover, the measurement model with the remaining 16 parameters confirmed the convergent and discriminant validity, where CR and AVE scores for all the factors are above 0.892 and 0.674 (see Table 2) including the fact that the coefficients of interrelationships among the determinants did not exceed the cut-off point of 0.85 (Fornell & Larcker, 1981) suggesting that our structure model be tested further.

In Table 3, we reported 16 valid items of our measurement model and its factor loadings including Cronbach's alpha ( $\alpha$ ), mean ( $M$ ) and standard deviation ( $SD$ ).

**Table 2** The scores of CR, AVE and square root of AVE>

Factors	CR	AVE	CMSLE	PCUN	STISF	PCEU
CMSLE	0.931	0.773	<b>0.879</b>			
PCUN	0.916	0.731	0.679	<b>0.855</b>		
STISF	0.908	0.713	0.764	0.794	<b>0.844</b>	
PCEU	0.892	0.674	0.831	0.754	0.775	<b>0.821</b>

Note: Bold numbers show the square roots of the AVEs

**Table 3** Valid parameters of the measurement model

Factors	Measurement Variables	Loadings	M	SD	$\alpha$
CMSLE	CSE1 I am able to use the online learning platforms.	.87	4.85	.984	.931
	CSE3 I can navigate my way through the online learning platforms.	.92	4.64	1.081	
	CSE6 I have the ability to communicate with teachers and classmates through online learning platforms.	.84	4.66	1.068	
	CSE8 I can access the online learning platforms from home.	.87	4.72	1.051	
PCEU	PEU2 I find it easy to access the online learning platforms.	.80	4.37	1.145	.893
	PEU3 It is easy for me to become skillful at using the online learning platforms.	.91	4.51	1.153	
	PEU4 It is easy for me to remember how to search and take courses by using the online learning platforms.	.85	4.50	1.152	
	PEU5 Interacting with the online learning platforms requires minimal mental effort.	.74	4.09	1.233	
PCUN	PU2 Using the online learning platforms helps me learn my courses.	.89	4.10	1.214	.919
	PU3 The online learning platforms address my study-related needs.	.87	4.19	1.155	
	PU6 Using the online learning platforms system allows me to accomplish more study work than would otherwise be possible.	.82	4.04	1.213	
STISF	PU8 Using the online learning platforms enhances my knowledge and learning skills.	.87	4.09	1.151	.908
	SAT1 Overall, I am satisfied with the ease of completing my tasks by using the online learning platforms.	.90	4.40	1.134	
	SAT2 The online learning platform service has greatly affected the way I learn.	.75	4.30	1.113	
	SAT3 The online learning platforms are indispensable and satisfactory services provided for Chinese university students.	.85	4.46	1.082	
SAT4 Overall, I am satisfied with the amount of time it takes to complete my study tasks by using the online learning platforms.	.85	4.29	1.176		

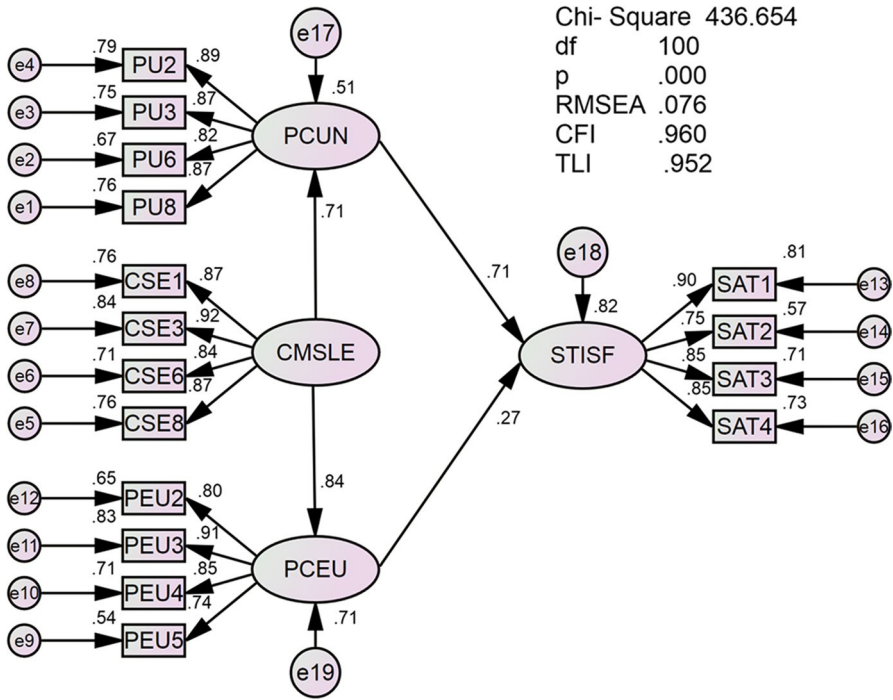


Fig. 3 The path diagram of the TSM

The TSM is the structural model of our study. We used 16 indicators of the measurement model to obtain evidence for our hypotheses. The path diagram of the TSM shows that the structural model adjusted the data satisfactorily, with  $\chi^2 = 436.654$ ;  $df = 100$ ;  $p = .000$ ;  $RMSEA = .076$ ;  $CFI = .960$ ; and  $TLI = .952$  (see Fig. 3). Six hypotheses of the TSM were tested through the path coefficients ( $\beta$ ) and critical ratios (CRs), including  $p$  values. For instance, university students’ CMSLE directly impacted their PCEU ( $\beta = .84$ ,  $CR = 22.744$ ,  $p < .000$ ) and PCUN ( $\beta = .71$ ,  $CR = 22.596$ ,  $p < .000$ ) of online learning platforms and supported the first two hypotheses (e.g.,  $H1$  &  $H2$ ). Along this line, PCEU ( $\beta = .27$ ,  $CR = 9.032$ ,  $p < .000$ ) and PCUN ( $\beta = .71$ ,  $CR = 20.730$ ,  $p < .000$ ) directly impacted STISF of online learning platforms, which supported our next two hypotheses (i.e.,  $H3$  &  $H4$ ).

We also estimated the significant indirect impacts of the exogenous variable (CMSLE) on endogenous (STISF) variable through mediating variables (PCEU and PCUN) using Sobel test (Sobel, 1982) as our indirect hypotheses supported (e.g.,  $H5$  and  $H6$ ). For example, university students’ CMSLE had an indirect impact on STISF mediated by their PCEU (Chi-square,  $\chi^2 = 15.442$ ;  $p = .000$ ) and PCUN (Chi-square,  $\chi^2 = 8.425$ ;  $p = .000$ ) of online learning platforms.

A regional comparison between Eastern and Western Chinese university students was examined using two steps of invariance analyses (i.e., configural and metric invariance analyses) to validate our last hypothesis ( $H7$ ). Before performing such

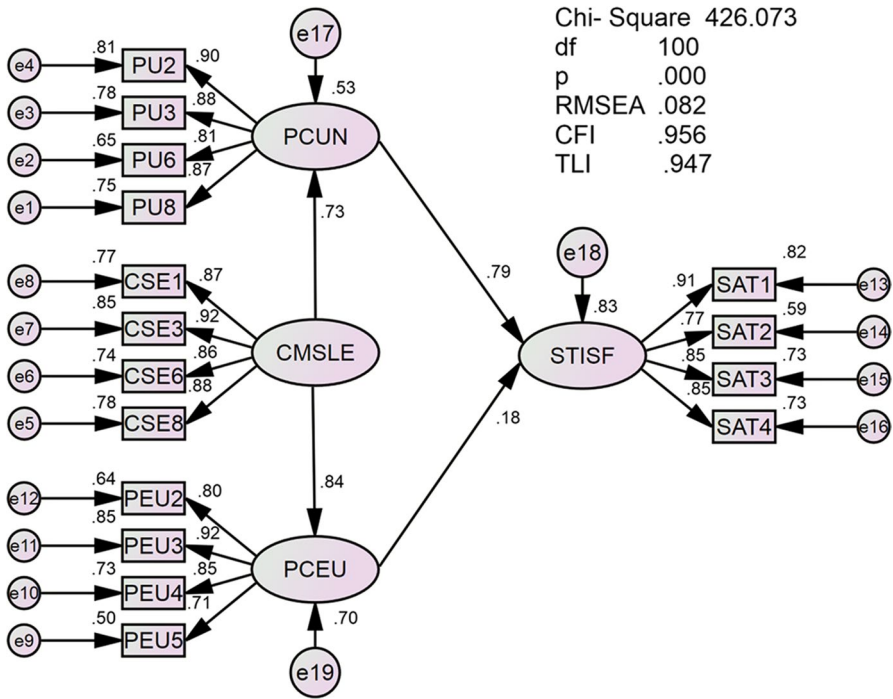


Fig. 4 The TSM for eastern Chinese universities

analyses, we cross-validated the TSM to observe the differences between Eastern ( $n_1 = 491$ ) and Western ( $n_2 = 437$ ) Chinese university students using two groups of samples. The results explained the validity of TSM for Eastern Chinese universities. For instance, the TSM for Eastern Chinese universities fitted the data satisfactorily, with  $\chi^2 = 426.073$ ;  $df = 100$ ;  $p = .000$ ;  $RMSEA = .082$ ;  $CFI = .956$ ; and  $TLI = .947$  (see Fig. 4). The first six hypotheses ( $H1-H6$ ) of the TSM were also valid for Eastern Chinese universities, where CMSLE, PCEU and PCUN explained 83% of the variability of students' satisfaction (STISF) with online learning platforms. Besides, CMSLE alone could explain 70% and 53% of the variance in PCEU and PCUN of online learning platforms, respectively.

The findings confirmed the validity of TSM for Western Chinese universities, which fitted the data satisfactorily, with  $\chi^2 = 404.744$ ;  $df = 100$ ;  $p = .000$ ;  $RMSEA = .084$ ;  $CFI = .951$ ; and  $TLI = .941$  (see Fig. 5). The proposed six hypotheses ( $H1-H6$ ) of the TSM were also found to be valid for Western Chinese universities, where exogenous (CMSLE) and mediating (PCEU and PCUN) variables together explained 83% of the variance of students' satisfaction (STISF) with online learning platforms. CMSLE alone explained 72% and 48% of the variance in PCEU and PCUN of online learning platforms, respectively. However, Figs. 4 and 5 recognize several differences between the models for Eastern and Western Chinese

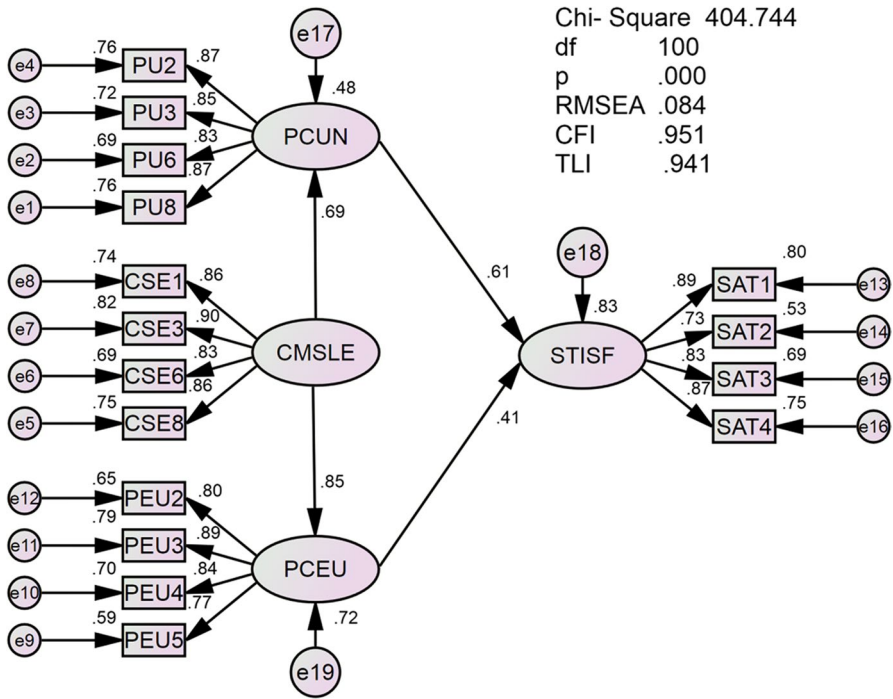


Fig. 5 The TSM for western Chinese universities

universities in terms of their fit indices, loadings, and error variances for items and variances, including path coefficients.

In doing so, we performed the invariance analyses after cross-validating the TSM to determine whether the above invariants of the causal structure of the TSM significantly moderate the relationships among the different facets. Our unconstrained models identified by TSM for Eastern Chinese universities and TSM for Western Chinese universities were grouped with the datasets ( $n_1 = 491$  and  $n_2 = 437$ ) to conduct configural analysis using unstandardized estimates. The analyses showed that both models produced similar chi-square ( $\chi^2 = 830.820$ ) and degree of freedom ( $df = 200$ ) as required for configural analysis, and then we constrained all the paths of the model to estimate the metric

Table 4 The results of regional comparison

Models		Chi- squared	df	Critical value	Chi- squared change
Eastern and Western Chinese universities invariant of the TSM	Unconstrained	830.820	200	9.49	20.246
	Constrained	851.066	204	( $p > .05$ )	

invariance. The analyses showed that both models also produced similar chi-square ( $\chi^2 = 851.066$ ) and degree of freedom ( $df = 204$ ) as required for metric invariance analysis. Next, we compared unconstrained and constrained models to compute the chi-squared differences and critical value (see Table 4). Based on these values, we concluded that there is a significant regional difference between Eastern and Western Chinese universities which moderates the relationships among the variables of TSM.

## 7 Discussion

In light of the TSM, this study tested and confirmed the first six hypotheses in the context of Chinese higher education and clarifies the relationships among the exogenous (computer self-efficacy), endogenous (satisfaction) and mediating (perceived ease of use and usefulness) variables. Furthermore, this study revealed that there was a cross-regional invariant of the causal structure of the TSM between Eastern and Western Chinese university students. The findings obtained from the TSM have broadened the existing body of knowledge and current understanding of university students' satisfaction with using online learning platforms. Our findings also have implications for both theory and practice in terms of technology-enhanced online learning, especially during the COVID-19 pandemic.

Consistent with recent studies (Bin et al., 2020; Chen et al., 2019; Scherer et al., 2019; Thongsri et al., 2019; Yalçın & Kutlu, 2019), the statistical analyses have verified that Eastern and Western Chinese university students' computer self-efficacy directly impacts their perceived ease of use and usefulness of online learning platforms. This implies that the university students' perceived ease of use and usefulness of online learning platforms depend on their beliefs in their individual capabilities to use it for study. With the enhancement of computer self-efficacy, university students are likely to gradually accept the benefits and advantages of online learning platforms. Eventually, they will likely find the use of online learning platforms to be effortless. In fact, perceived ease of use and usefulness are frequently considered to be two crucial motivation variables in numerous TAM-based models. Considering the impact of computer self-efficacy on these variables, we suggest it may be better to take such individual psychological factors into consideration when assessing new technology acceptance, adoption and satisfaction.

The direct influences of Eastern and Western Chinese university students' perceived ease of use and usefulness on their satisfaction with online learning platforms have been statistically confirmed. In fact, some up-to-date studies articulated that perceived ease of use and usefulness are associated with user satisfaction (Bin et al., 2020; Chen et al., 2019; Islam, 2016; Islam et al., 2018; Islam & Sheikh, 2020). This current study has validated such associations in measuring Chinese university students' satisfaction with online learning platforms. The findings of the TSM indicate that the easier university students find online learning platforms to use and the more benefits that online learning platforms provide, the more satisfied they will be. However, contradictory to Islam et al. (2018), this study revealed that perceived



usefulness is relatively more effective than perceived ease of use in impacting university students' satisfaction.

The mediating roles played by perceived ease of use and usefulness between computer self-efficacy and satisfaction are also substantiated. These results are consistent with recent studies on measuring user satisfaction with the wireless Internet (Islam et al., 2018), online research databases (Islam & Sheikh, 2020) and digital technologies (Bin et al., 2020) in higher and vocational and technical education. To be specific, although there are no direct relationships between computer self-efficacy and satisfaction, computer self-efficacy could improve university students' satisfaction by increasing their perception of ease of use and usefulness of online learning platforms. In this sense, computer self-efficacy is regarded as a distinct antecedent of the TSM. However, some researchers also mentioned that learners' intention to use may also multiply and mediate the relationships between satisfaction, perceived ease of use and usefulness (Bin et al., 2020; Chen et al., 2019). Further studies could also include intrinsic motivation variables, such as intention to use online learning platforms, when assessing university students' satisfaction.

As the invariance analyses exhibited, a cross-regional invariant of the causal structure of the TSM model between Eastern and Western Chinese university students do exist. This verifies that there is a significant difference between Eastern and Western Chinese university students' satisfaction with using online learning platforms. In other words, the direct influences of perceived ease of use and usefulness and the indirect influence of computer self-efficacy on university students' satisfaction with online learning platforms are moderated by regional factors. Previous studies claimed that the moderating effect of culture was significant on some paths of the TAM-based models (Jung & Lee, 2020) and user satisfaction with ICTs differed in cross-cultural or cross-regional settings (Islam, 2016). This current study also implies that the generalizability of TSM may be constrained by region or culture. Just as Scherer and Teo (2019) pointed out, testing the structural invariance is critically important in interpreting possible cultural differences or similarities meaningfully. However, such cultural comparisons are rarely conducted, and such invariance is rarely examined (Scherer & Teo, 2019). Efforts have been made to narrow the gap in this current study, and we suggest more data collection from universities in different cultures and regions. In addition, more invariance analyses in terms of cultural and regional differences should be encouraged in the future.

Based on our findings, three practical implications can be drawn. First of all, online learning platforms (e.g., LMSs) have been regarded as an integral part of the learning experience for students in many educational institutions in 2020–2021 (Turnbull et al., 2021). Considering that students have no other choice than online learning if they want to continue their studies during the COVID-19 pandemic, we cannot overemphasize the importance of online learning platforms. Against this background, online learning platforms should undertake the significant responsibilities of serving and satisfying students, which are also recognized as the fundamental goals of promoting e-education in China (Ministry of Education, 2019). The TSM proves that perceived ease of use and usefulness are two important determinants of university students' satisfaction with online learning platforms. In view of this, on

the one hand, online learning platforms need more simplified interfaces and registration and login systems to make them approachable to students. On the other hand, online learning platforms can still develop more useful features or learning support services to make them more beneficial to students. It is also necessary to publish relevant and better-designed guidebooks and manuals, with the help of which students will be able to use online learning platforms more easily and obtain more benefits from them. Course developers can also cooperate with platform designers to develop more accessible and beneficial programs that target specific teaching contents. It is also worth mentioning that governments, universities and service providers can create social media for interactive communication with users which can help improve platform services. Moreover, the TSM indicates that computer self-efficacy is an influential factor of satisfaction that cannot be ignored. University students should gradually strengthen their basic computer competence in different ways so as to enhance their computer self-efficacy. Governments, universities and service providers can also hold lectures online to help university students improve computer capabilities. More importantly, students should also be encouraged to take the initiative in learning how to use platforms for deep online learning and learning management. Last but not least, in regard to regional differences, governments, universities and service providers can improve the quality of online learning platforms by taking into account the characteristics of student groups in different regions. Personalised online learning environments can be provided to satisfy the needs of different students and promote e-education equity.

## 8 Conclusion

There is an urgent need to measure learner satisfaction with using online learning platforms as millions of Chinese university students now rely on them to continue their studies due to the COVID-19 pandemic. In response to this need, the current study successfully applied the TSM and exhibited the direct and indirect impacts of computer self-efficacy, perceived ease of use and usefulness on university students' satisfaction with online learning platforms. It was found that Chinese university students are highly satisfied and that the TSM can powerfully explain and predict Chinese university students' satisfaction with online learning platforms. In particular, a regional comparison was conducted and the moderating effect of region on the paths of the TSM was examined statistically. The results indicated that there was a cross-regional invariant of the causal structure of the TSM between Eastern and Western Chinese university students. The current study can contribute to theoretical, methodical and practical understandings of university students' satisfaction with using online learning platforms, which have been recognized as irreplaceable emergency educational tools.

Despite the aforementioned discussion and conclusion, two limitations of this study should be acknowledged. On the one hand, we selected five universities from two Eastern and Western Chinese provinces or municipalities. However, universities in other Eastern and Western Chinese provinces or municipalities were not included. Therefore, further studies can include more representative samples to validate our findings and increase the generalisability of the results. On the other hand, this was

a quantitative study which employed a modelling test while the qualitative method was ignored due to funding and time constraints. Based on our study, we call for more longitudinal studies which adopt a mixed method or triangulation method and are anchored in specific and detailed situations and contexts to explain university students' satisfaction with using online learning platforms.

**Acknowledgments** This work is supported by the Peak Discipline Construction Project of Education at East China Normal University and Fundamental Research Funds for the Central Universities (2020ECNU-HLYT035). Haozhe Jiang and A.Y.M. Atiquil Islam have equally contributed to this article, and they should be considered as first authors.

#### Declarations

**Conflict of interest** This study had obtained the ethical endorsement from the universities and Research Management Centre for Non-Clinical Faculties in the East China Normal University before we distributed the instruments among the students to collect the data. There is no conflict of interests between the authors and respondents.

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**Publisher’s note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

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