

The Impact of the Coronavirus (COVID-19) Pandemic on Education: A Model Toward Technology-Supported Synchronous Remote Learning

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ABSTRACT

During the COVID-19 pandemic, many universities have moved a large portion of their classes online. To better support students' online learning activities and to best resemble the face-to-face setting, the technology-supported, synchronous remote learning platform was adopted in most cases. In this study, the authors aim to investigate factors that could influence students' learning in this new environment during the COVID-19 pandemic. Specifically, a research model was developed and tested with 428 students. The result showed that students' IT competence had a significant impact on their learning satisfaction, while social influence had a significant impact on their intention to use the remote learning technology in future classes. As to technology-facilitating conditions, significant impacts were found from it (at both institution and student levels) to learning satisfaction. They also found that COVID-19-related mental impacts could influence student satisfaction on and intention to use the remote learning technology.

KEYWORDS

Impact of COVID-19 on Education, Learning Satisfaction and Intention, Model Development and Assessment, Synchronous Remote Learning, Technology-Supported Learning

1. INTRODUCTION

The coronavirus (COVID-19) pandemic has changed our daily lives and routines dramatically (Chen & Roldan, 2021; Majumder & Biswas, 2021; Pileggi, 2021). To better protect ourselves and the local communities, most of our daily activities have been moved online whenever possible via the use of information and communication technologies, including education (Bawa, 2020; Benhima, 2021; Shastri & Chudasma, 2021; Sun et al., 2021). Since the breakout of the COVID-19 in the US, the course content delivery model in the education system at all levels has changed significantly (Amzalag, 2021; Apak et al., 2021; Bawa, 2020; Carpenter et al., 2021; Dunaway & Kumi, 2021). For higher education, many universities have changed a significant portion of their traditional face-to-face classes to remote learning by leveraging online communication technologies and systems (such as Blackboard Collaborate Ultra, Zoom, etc.). This sudden and significant change requires faculty to devote more

DOI: 10.4018/IJICTE.292481

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time and effort to design (or re-design) their classes (Bawa, 2020; Carpenter et al., 2021; Tawafak et al., 2021). It could influence students' learning significantly (Bawa, 2020; Tawafak et al., 2021).

In general, there are two types of e-learning, including asynchronous and synchronous e-learning (Hrastinski, 2008). Until recently, the more popular type of e-learning is still asynchronous e-learning (Hrastinski, 2008). However, with the advancement of information and telecommunication technologies, synchronous e-learning has gained growing popularity. In asynchronous e-learning, students and their instructor typically interact via the use of e-mails and discussion boards, and there is no requirement for all students and the instructor to be online at the same time, which enables increased flexibility in student learning (Hrastinski, 2008). Differently, in synchronous e-learning, students and their instructor will meet online during the designated class meeting time via the use of videoconferencing tools. Students will have a higher level of involvement and feel less isolated, because synchronous e-learning provides the chance for them to interact with their instructor (such as asking questions) and classmates (such as conducting group discussions) at real time (Hrastinski, 2008).

In this study, we aim to examine factors that could possibly influence students' learning in technology-supported, synchronous remote learning environment during the COVID-19 pandemic. Potential factors from various perspectives were examined and a theoretical research model was then developed and tested. The model was tested with 428 students who took classes that adopted the technology-supported, synchronous remote learning instructional method during the COVID-19 pandemic. Overall, the results showed that task-technology fit and COVID-19 mental impacts could significantly influence both students' learning satisfaction and intention. In addition, students' IT competence had a significant impact on their learning satisfaction, while social influence had a significant impact on their intention to use the remote learning technology in future classes. As to technology facilitating conditions, significant impacts were found from it (at both the institution and student levels) to learning satisfaction. We hope findings of this research could better help educators understand factors that could influence students' learning in this new situation and bring some insights to high education under emergency situations.

The remainder of this paper is organized as follows: in Section 2 we discuss the related literature and provide the hypothesis development. Then, Section 3 provides details on the research method. Following that, data analyses and results are reported in Section 4. The paper concludes with a discussion of the research contributions and implications, and future research directions in Section 5.

2. RELATED LITERATURE AND HYPOTHESIS DEVELOPMENT

2.1 Technology-Supported Learning

The advancement, broad coverage, and rapid development of modern information and Internet technologies have been dramatically changing our lives in recent years. With their help, a lot of our daily activities could now be done very efficiently and effectively online, from working to entertaining, from selling to buying, and from information searching to knowledge sharing. This is even true as to higher education. Different types of learning management systems and communication tools have been created and adopted to support students' learning in a remote manner, either synchronously or asynchronously. With their support, new types of instructional methodologies have been developed to better fit students' learning needs, such as e-learning, blended learning, and flipped classrooms (So & Brush, 2008).

The most traditional form of technology-support learning is the e-learning (So & Brush, 2008). As a big change from the face-to-face learning that had always been utilized in the education system in the old days, e-learning has brought a significant level of flexibility in students' learning. Without the time and location constraints, e-learning has opened the door of higher education to those who could not take classes on site (Kulkarni et al., 2013; Teo et al., 2018).

However, over time, people started to notice some of the major drawbacks of e-learning. One of them is the lack of opportunity for students to physically meet and interact with their instructors and classmates (So & Brush, 2008). For those students who are socially active, e-learning may give them a feeling of coldness and separation. In addition, this learning platform seems to require a high level of students' own learning esteem. In other words, it fits better to students who are highly motivated to learn, but not to those who are less motivated.

To overcome the issues potentially associated with e-learning and to make the best use of it flexibility in the meanwhile, more recently, two new technology-supported instructional methods have been coined, namely blended learning and flipped classrooms (Hung & Chou, 2015; Padilla-Meléndez et al., 2013).

Blended learning is an instructional methodology that incorporates different teaching methods from both face-to-face instruction and e-learning, and enables students to perform both offline (i.e., in-class) and online activities (Padilla-Meléndez et al., 2013; So & Brush, 2008). It is believed to combine the advantages of both face-to-face instruction and e-learning, thus providing a better and more adaptive learning environment to students.

Defined as "*events that traditionally happen within the classroom take place during the students' own time, while work that is usually considered individual homework happens collaboratively in the classroom*" (p. 1002) (Szafir & Mutlu, 2013), flipped classrooms emphasize learner-centric activities. As an example, students will need to read book chapters and related materials on their own schedule before class, and then perform problem-solving activities during their class meeting time. The instructor will no longer take the lead of the class by lecturing, but rather facilitating students' in-class activities and providing insights and answers to questions (Rutherford & Rutherford, 2013; Szafir & Mutlu, 2013). It has been found that this instructional method could provide a better fit to personalized learning and accommodate various learning styles among different students (Rutherford & Rutherford, 2013; Szafir & Mutlu, 2013).

As of right now, the whole world is still strongly influenced by COVID-19. Considering its high level of contagiousness, many universities across the country have moved their classes online, with the support of modern information technology and learning management systems. To better assist students' learning and accommodate their social interaction needs (although via online platforms) during this difficult time, synchronous remote learning is mostly adopted and being utilized. It provides students the opportunity to interact with their instructors and classmates verbally and visually in front of their computer screens during the designated class meeting time, with the support of videoconferencing and online communication tools (such as Blackboard Collaborative Ultra and Zoom). In this study, we aim to investigate factors that could influence students' learning on the technology-supported synchronous remote learning platform during the COVID-19 pandemic.

2.2 Technology Facilitating Conditions

Facilitating conditions is defined as an individual's belief on the existence of organizational and technical support of using an information system (Venkatesh & Bala, 2008; Venkatesh et al., 2003). It is one of the influential factors stated in the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003). In existing literature on technology-supported learning, facilitating conditions has been found to be able to significantly influence students' learning acceptance (Nikou & Economides, 2017). For example, Nikou and Economides (2017) found that facilitating conditions had a significantly positive impact on students' perceived ease of use in mobile learning.

As to assessing students' online learning satisfaction during the COVID-19 pandemic, some recent research has been done by applying UTAUT to this new context (Chayomchai et al., 2020; Tiwari, 2020). For example, Tiwari (2020) found that facilitating conditions could positively influence students' intention to attend online classes during the COVID-19 pandemic.

By definition, facilitating conditions could be about both the "organizational" and "technical" support. However, in the context of remote learning during the COVID-19 pandemic, it is most likely

to be about the technical support which enables students to successfully take classes remotely. Thus, in this study, we focus on this perspective of facilitating conditions, and use the term “technology facilitating conditions” accordingly. In addition, to ensure students being able to successfully take their classes online, the technology facilitating conditions both from the institution and at students’ own places are essentially important. For students to conduct their learning activities effectively, adequate technology support from both sides is needed. Therefore, in this study, we look into these two types of technology facilitating conditions and include both of them in our proposed research model. Specifically, we hypothesize that both types of facilitating conditions can positively influence students’ satisfaction on technology-supported, synchronous remote learning during the COVID-19 pandemic, and their intention to use technology-supported, synchronous remote learning in the future.

H1a: The institution’s technology facilitating conditions can positively influence students’ satisfaction on technology-supported, synchronous remote learning during the coronavirus (COVID-19) pandemic.

H1b: The institution’s technology facilitating conditions can positively influence students’ intention to use technology-supported, synchronous remote learning in the future.

H2a: Technology facilitating conditions at students’ own places can positively influence their satisfaction on technology-supported, synchronous remote learning during the coronavirus (COVID-19) pandemic.

H2b: Technology facilitating conditions at students’ own places can positively influence their intention to use technology-supported, synchronous remote learning in the future.

2.3 Task-Technology Fit

Derived from the cognitive fit theory (Vessey, 1991), task-technology fit states that information technology is more likely to have a positive impact on an individual’s task performance if the functionality of the information technology matches the requirements of the tasks that the user needs to perform (Goodhue & Thompson, 1995). In the context of technology-supported learning, “technology” refers to the information systems or techniques that are used to support students’ learning activities, and “tasks” refer to the learning activities that students need to conduct.

Previous literature has examined and identified the impact of task-technology fit on student learning. For example, Lin (2012) found that task-technology fit could significantly influence students’ satisfaction on and their continuance intention to use virtual learning systems. In another study, Lin and Wang (2012) examined task-technology fit in the context of blended learning, and found that it had significant impacts on both students’ perceived usefulness and acceptance on an online learning system that was adopted in the blended class. In a more recent study, Cheng (2019) investigated the role of task-technology fit in cloud-based e-learning continuance. The study found out that task-technology fit had significant impacts on students’ perceived usefulness, confirmation (i.e., the degree of congruence between expectation of the information technology and its actual performance), satisfaction, and continuance intention toward the cloud-based e-learning system. It also found a significant relationship from task-technology fit to perceived impact on learning. In addition, recent research also found a significant impact of task-technology fit on students’ satisfaction in the context of the adoption of digital textbooks (Ye, 2021), as well as their perceived performance impacts in the mobile learning environment (Bere, 2018).

In this study, we expect task-technology fit to play an important role in influencing students’ learning in technology-supported, synchronous remote learning environment, during the COVID-19 pandemic. If students perceive a higher level of fit between the supporting technology/systems and their learning tasks, it would be more likely for them to become satisfied in learning, as well as become more willing to use the synchronous remote learning technology in their future classes. Therefore, we hypothesize:

H3a: Task-technology fit can positively influence students' satisfaction on technology-supported, synchronous remote learning during the coronavirus (COVID-19) pandemic.

H3b: Task-technology fit can positively influence students' intention to use technology-supported, synchronous remote learning in the future.

2.4 IT Competence

In general, IT competence is about one' ability in using and applying information technologies in problem solving. More formally, it is defined as an individual's level of proficiency in utilizing a variety of information technology related tools, resources, and systems to exchange, create, disseminate, store, and manage information (Phan et al., 2020). In technology-supported learning, students' IT competence is about their proficiency in using online course management systems and related tools to perform and complete their learning tasks (Oluwatobi & Yemisi, 2014; Phan et al., 2020).

When examining the impact of IT competence in student learning, previous research found that it could significantly influence students' perceived ease of use, usefulness, and reliability toward the e-portal that was used to support their learning activities occurred online (Oluwatobi & Yemisi, 2014). In another more recent study, Phan et al. (2020) emphasized the importance of IT competence in student learning success, and stated that a high level of IT competence would help improve students' cognitive ability and self-learning ability while conducting their learning tasks using online systems. They also developed a multi-level framework for assessing IT competence (Phan et al., 2020).

In our study, we also expect a significant impact of IT competence in student learning, especially considering that under the COVID-19 pandemic, almost all of their learning activities need to be conducted online, via the use of related information technologies and systems. Thus, we posit that students' IT competence can significantly influence their satisfaction on technology-supported, synchronous remote learning, as well as on their intention to use the remote learning technology in the future.

H4a: Students' IT competence can positively influence their satisfaction on technology-supported, synchronous remote learning during the coronavirus (COVID-19) pandemic.

H4b: Students' IT competence can positively influence their intention to use technology-supported, synchronous remote learning in the future.

2.5 Mental Impacts

During this global COVID-19 pandemic, the general public have been under intolerable psychological pressure (Cao et al., 2020). Many people (students as well) have experienced noticeable stress and anxiety. This very unpleasant, and somewhat long-lasting COVID-19 pandemic is likely to impose some level of negative mental and cognitive impacts on human beings in general. It is reported that taking care of people's mental health during the COVID-19 pandemic could help significantly improve their work-life quality (Majumder & Biswas, 2021). Therefore, in this study, we would like to examine how the potential mental impacts of the COVID-19 pandemic could influence students' learning in remote classes.

A few recent research studies have evaluated the impact of the COVID-19 pandemic on college students' psychological and mental system (Cao et al., 2020; Olmos-Gómez, 2020). For example, Cao et al. (2020) surveyed college students in China about their levels of anxiety during the COVID-19 pandemic. They found that 0.9% of the respondents were experiencing severe anxiety, 2.7% with moderate anxiety, and 21.3% with mild anxiety. In addition, living in urban areas, having stable family income, and living with parents could significantly help reduce students' level of anxiety (Cao et al., 2020). In another study, Olmos-Gómez (2020) compared the psychological impacts of the COVID-19 pandemic on students seeking different types of education degrees (including primary education, early learning, social education, and physical education and sport) in Spain. It was found that students

with the primary education and social education degrees were more psychologically negative, while those majoring in physical education and sport tended to be more positive.

In our study, we would like to examine the relationships between the COVID-19 related mental impacts and students' learning satisfaction and intention. For those who possess a stronger level of COVID-19 mental impacts might possibly value the technology-supported, synchronous learning more, and thus being more willing to use it in their future classes, compared with those who are less mentally influenced by COVID-19. Thus, we hypothesize:

H5a: High (low) levels of COVID-19 related mental impacts can lead to high (low) levels of students' satisfaction on technology-supported, synchronous remote learning during the coronavirus (COVID-19) pandemic.

H5b: High (low) levels of COVID-19 related mental impacts can lead to high (low) levels of students' intention to use technology-supported, synchronous remote learning in the future.

2.6 Social Influence

Social influence is defined as the degree to which an individual perceives that important others believe he/she should use the information technology or system (Venkatesh et al., 2003). According to UTAUT (Venkatesh et al., 2003), social influence is a significant determinant on users' behavioral intention, which in turn influences actual usage behavior. As to the context of technology-supported learning, the "important others" refer to those who could influence students learning-related activities and decision making (such as their parents, instructors, classmates, etc.).

Previous research found that social influence could significantly influence students' intention to use the e-learning system (Decman, 2015). In the context of blended learning, it was found that social influence had a significant impact on learning climate, which in turn significantly influenced students' learning satisfaction (Chen et al., 2013). In addition, recent research on student learning during the COVID-19 pandemic found that social influence could significantly influence students' intention to adopt online classes during the pandemic (Tiwari, 2020). In our study, we expect social influence to play an important role in influencing both students' satisfaction on technology-supported, synchronous remote learning during the COVID-19 pandemic, and their intention to use the remote learning platform in the future.

H6a: Social influence can positively influence students' satisfaction on technology-supported, synchronous remote learning during the coronavirus (COVID-19) pandemic.

H6b: Social influence can positively influence students' intention to use technology-supported, synchronous remote learning in the future.

2.7 Learning Satisfaction and Intention

User satisfaction and intention to use are two of the most widely adopted measures on assessing the success of adoption of information technology and systems (Venkatesh et al., 2003).

When adopted in the context of technology-supported learning, user satisfaction is mostly referred to as learning satisfaction, which is defined as the extent to which the learner is pleased with using the supporting technology and systems to perform his/her learning-related tasks. Previous research on technology-supported learning has invested factors that could influence students' learning satisfaction. For example, it was found that students' perceived usefulness of the e-learning system (Johnson et al., 2008) as well as the ease of use associated with the system (Sun et al., 2008) could significantly influence their learning satisfaction. Studies on blended learning also found that perceived usefulness (performance expectancy) and climate associated with the learning environment could significantly influence students' learning satisfaction (Chen, 2014; Wu et al., 2010). Recent research on investigating student learning during the COVID-19 pandemic found that information quality, system quality,

and service quality of the e-learning system could significantly influence users' learning satisfaction (Shahzad et al., 2021).

In the context of technology-supported learning, intention is defined as the learner's willingness to use the related technology and systems (online learning systems in most cases) to conduct their learning tasks (Cheng, 2012). Previous research on e-learning found that perceived usefulness, ease of use, and perceived enjoyment associated with the e-learning system had significant impacts on students' intention to use the system in the future (Cheng, 2012). Recent studies on investigating students learning performance during the COVID-19 pandemic also found that perceived usefulness (performance expectancy) and ease of use (effort expectancy) could significantly influence their intention to adopt the online learning format of their classes (Chayomchai et al., 2020; Tiwari, 2020). It was also found that trust could positively influence students' intention to use the online technology for their classes during the COVID-19 pandemic (Chayomchai et al., 2020).

When assessing the success of information systems adoption, it is theorized that user satisfaction has a significant impact on users' intention to use the system in the future (DeLone & McLean, 1992, 2003). Such an impact was found to be held in the context of technology-supported learning (Chiu & Tsai, 2014; Lin, 2012). For example, Lin (2012) found that student satisfaction could significantly influence their intention to continue using the virtual learning system that was adopted to assist their online learning activities. In addition, Chiu and Tsai (2014) found the significantly positive impact of satisfaction on students' intention to use the web-based learning system in the clinical nursing setting. Consistent with these studies, in this research, we also expect such an impact to be significant in the context of students' remote learning during the COVID-19 pandemic. Thus, we hypothesize:

H7: Students' learning satisfaction can positively influence their intention to use technology-supported, synchronous remote learning in the future.

The proposed research model with the above listed hypotheses is summarized in Figure 1.

3. RESEARCH METHOD

3.1 Research Process and Data Collection

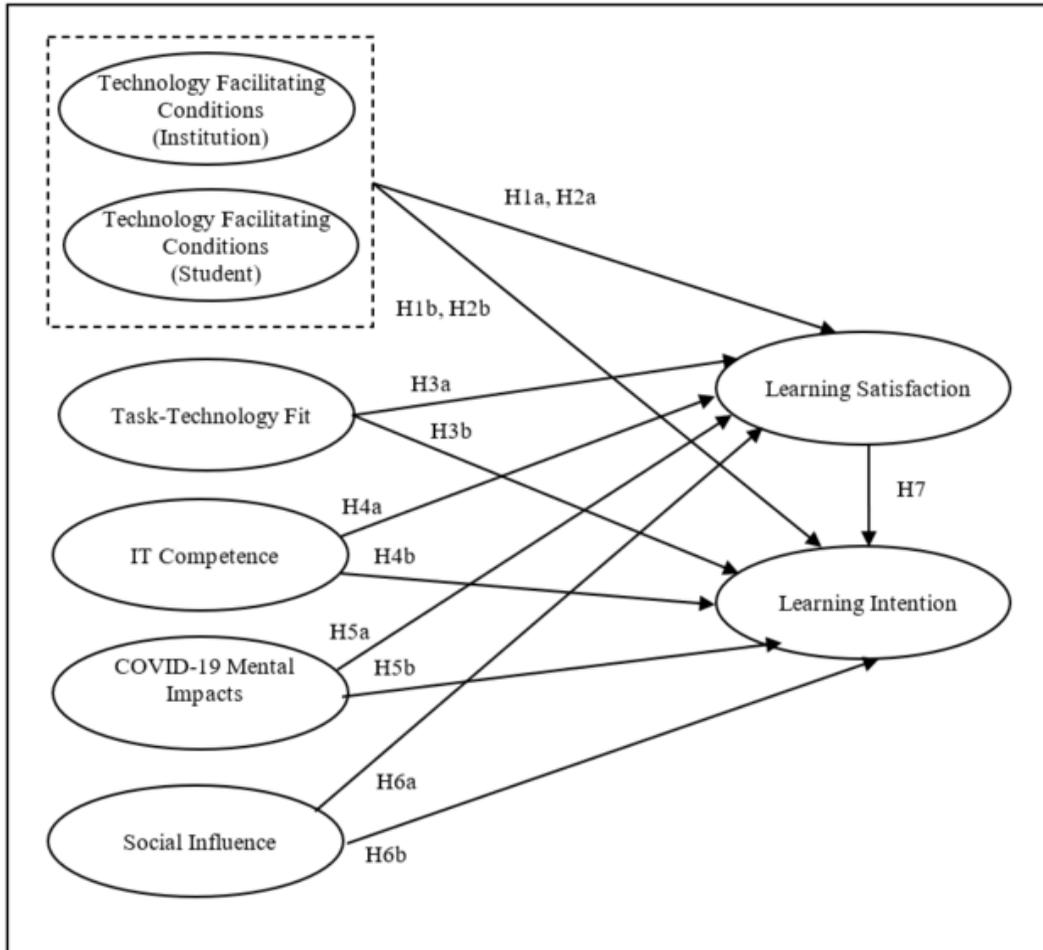
To test the proposed research model and hypotheses, we used the survey method. After receiving the IRB approval, the link of the online survey questionnaire was sent to students who attended various classes in the college of business that adopted the synchronous remote learning instructional methodology. The survey was sent out around the end of the Fall 2020 semester. We believe the timing was appropriate for our collection since by then students already had the experience with synchronous remote learning for almost an entire semester (and when COVID-19 was still an issue). Extra credit was provided as an incentive for students' voluntary participation. In total, 428 students completed the survey, with 202 being males and 226 being females. The average age of participants was 19.80. On average, they had been at college for 2.18 years.

3.2 Measures of Constructs in the Research Model

To measure technology facilitating conditions (at both the institution and student levels), we adopted the items from the original UTAUT paper (Venkatesh et al., 2003) with wording changes to fit the context of our study. Items used to measure the task-technology fit were adapted from (Cheng, 2019). To measure IT competence, we leveraged information from (Ravichandran & Lertwongsatien, 2005) and (Pérez-Aróstegui et al., 2015) with revisions and further development to better fit the context of our study.

As to measures of the COVID-19 mental impacts, to the best of our knowledge, we haven't seen it being adopted as a single theoretical construct in a nomological network in existing research about student learning during the COVID-19 pandemic. However, recent research has been done to systematically assess students' psychological responses in the e-learning environment during the

Figure 1. Research Model and Hypotheses



COVID-19 pandemic (Lan et al., 2020). Leveraging the information presented in (Lan et al., 2020), we developed the measurement items for our construct, COVID-19 mental impacts.

In addition, measures on social influence was adopted from (Tiwari, 2020), and measures on learning satisfaction was adopted from (Mohammadi, 2015). To measure learning intention, we adapted the items from the UTAUT paper (Venkatesh et al., 2003) with wording changes to fit our context of study.

All constructs in the research model were measured using the 7-Likert scale. Table 1 shows the descriptive statistics about them. Detailed measurement items are provided in Appendix A.

4. DATA ANALYSES AND RESULTS

Structural equation modeling (SEM) techniques were used to assess the research model. In particular, PLS (a component-based SEM) was utilized, which is a robust method for causal model assessment (Chin et al., 1988; Chin, 1998) and have been widely used in IS education research (Hiranrat et al., 2021). In this study, we used Smart PLS 2.0 (M3) beta (Ringle et al., 2005), a widely adopted PLS tool, for causal model analysis (Romanow et al., 2020). Findings obtained from this study are

Table 1. Descriptive Statistics

Construct	Mean	Standard Deviation
COVID-19 Mental Impacts	4.684	1.828
Learn Intention	4.245	1.946
IT Competence	5.919	1.218
Learning Satisfaction	4.833	1.672
Social Influence	4.867	1.639
Technology Facilitating Conditions (Institution)	5.061	1.400
Technology Facilitating Conditions (Student)	5.283	1.572
Task-Technology Fit	4.819	1.704

perceptions, based on students' ratings on the measurement items for each latent construct. In the following sub-sections, we present the data analysis and results for both the measurement model and structural model (hypothesis testing).

4.1 Measurement Model Assessment

To perform the measurement model assessment, we conducted the reliability and validity tests. The testing results are listed in Tables 2 and 3, respectively.

For reliability test, item loadings for all constructs were calculated. As shown in Table 2, all loadings passed the recommended threshold value of 0.7 (Au et al., 2008), and all loadings are statistically significant. The Cronbach's alpha values for the constructs were also calculated and presented in the table, all of which passed the suggested threshold value of 0.7 (Hair et al., 1998; Nunnally, 1978).

The validity test results are presented in Table 3, including values on composite reliability, average variance extracted (AVE), and the square root of AVE for each construct, as well as correlations across different constructs. For composite reliability, all constructs passed the recommended threshold of 0.7, which indicates that the measurement items used for each construct had good internal consistency (Au et al., 2008). As to the values of AVE, all of them passed the threshold of 0.5 (which is equivalent to the square root of AVE being greater than 0.707) (Gefen et al., 2000). This result indicates adequate convergent validity for each construct. In addition, for each construct, its square root of AVE value (i.e., data presented in the diagonal cells in bold case in Table 3) was greater than all correlations between it and other constructs. This means that each construct was more closely related to its own measures rather than measures for other constructs, indicating adequate discriminant validity (Chin et al., 1988; Chin, 1998). Overall, these results together suggest the model as good validity.

4.2 Structural Model Assessment

Figure 2 shows the PLS test results of the research model.

As hypothesized, both types of technology facilitating conditions (i.e., the institution's technology facilitating conditions and the technology facilitating conditions at students' own places) could significantly influence students' satisfaction on technology-supported, synchronous remote learning during the COVID-19 pandemic, with path coefficients of 0.113 and 0.129, respectively (denoted as S and I on the paths shown in Figure 2). Therefore, H1a and H2a were both supported. As to the impact of both types of technology facilitating conditions on students' intention to use technology-supported, synchronous remote learning in the future, none of them were statistically significant. Thus, H1b and H2b were not supported. This shows that the level of technical support students received, either from the institution or at their own places, did not have significant impacts on their intention to use

Table 2. Reliability Test Results

Construct	Cronbach's Alpha	Item	Loading	T-statistics
COVID-19 Mental Impacts	0.823	COVIDMI1	0.876	16.837
		COVIDMI2	0.930	50.362
		COVIDMI3	0.937	91.01
Learn Intention	0.947	INT1	0.937	154.08
		INT2	0.920	168.846
		INT3	0.924	159.992
IT Competence	0.887	ITC1	0.819	53.362
		ITC2	0.932	82.959
		ITC3	0.887	51.836
Learning Satisfaction	0.918	SAT1	0.729	125.169
		SAT2	0.819	189.711
		SAT3	0.772	100.422
Social Influence	0.780	SI1	0.872	53.373
		SI2	0.920	36.818
		SI3	0.894	16.186
Technology Facilitating Conditions (Institution)	0.924	TFCI1	0.914	53.747
		TFCI2	0.948	37.96
		TFCI3	0.898	47.183
Technology Facilitating Conditions (Student)	0.799	TFCS1	0.892	27.899
		TFCS2	0.859	46.462
		TFCS3	0.925	25.676
Task-Technology Fit	0.721	TTF1	0.892	93.639
		TTF2	0.859	169.242
		TTF3	0.925	93.888

the remote learning technology in their future classes. Such a result may indicate that when deciding whether or not to take future classes via the remote learning platform (if there is a choice), technology facilitating conditions was not a concern by students at large. Since this study was conducted at the US, where the information systems and Internet technologies are considered as very advanced and broadly covered in general, such a result is understandable. However, in less developed countries, where information systems and Internet technologies are still under development, different results might be expected (which future research could further examine).

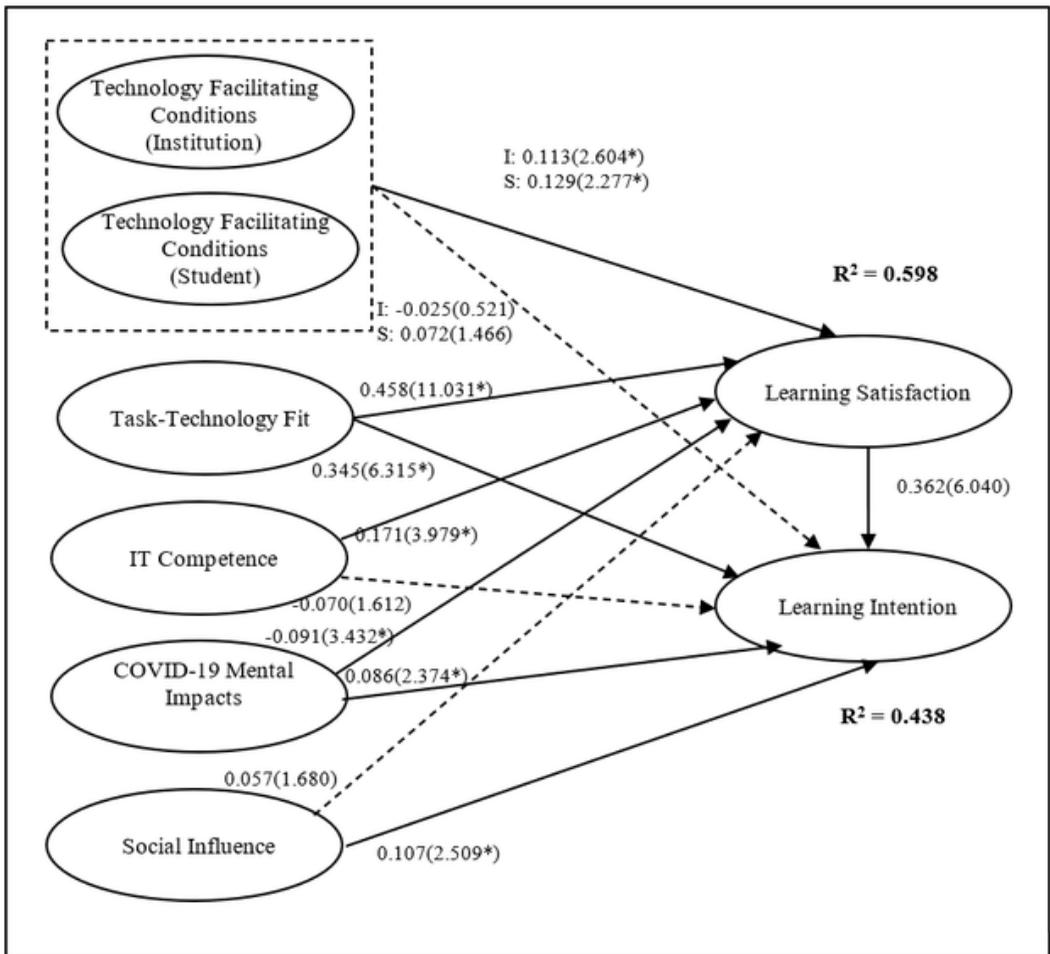
As to task-technology fit, it had significant impacts on both students' satisfaction on, and intention to use, the technology-supported, synchronous remote learning during the COVID-19 pandemic (path coefficients of 0.458 and 0.345, respectively). Thus, H3a and H3b were both supported. This shows that when students perceived a higher level of fit between their learning tasks and the synchronous remote learning platform, it would be more likely for them to be satisfied in learning and be willing to use the remote learning technology in their future classes.

Table 3. Internal Consistency and Validity Test Result

Construct	Composite Reliability	AVE	COVIDMI	INT	ITC	SAT	SI	TFCI	TFCS	TTF
COVIDMI	0.823	0.735	0.857							
INT	0.947	0.904	-0.139	0.951						
ITC	0.887	0.815	-0.142	0.358	0.903					
SAT	0.918	0.859	-0.305	0.601	0.566	0.927				
SI	0.780	0.691	-0.048	0.312	0.259	0.309	0.831			
TFCI	0.924	0.868	-0.303	0.593	0.517	0.708	0.294	0.932		
TFCS	0.799	0.712	-0.14	0.367	0.5	0.534	0.287	0.49	0.844	
TTF	0.721	0.642	-0.249	0.394	0.572	0.558	0.285	0.482	0.636	0.801

Note: Diagonal elements in bold case are the square root of average variance extracted (AVE). Off-diagonal elements are correlations across constructs.

Figure 2. Research Model and Hypotheses



As to students' IT competence, it was found that it could significantly influence students' learning satisfaction (path coefficient of 0.171), but not on learning intention. Therefore, H4a was supported, but not H4b. This result shows that when a student was more competent in using information technology, he/she would be more satisfied in using the synchronous remote learning technology to support his/her learning during the COVID-19 pandemic. However, his/her level of competence in using information technology didn't seem to be able to significantly influence his/her intention to use the remote learning technology in future classes. This may indicate that there could be other more important factors to consider when students made decisions on whether or not to use the synchronous remote learning technology in future classes.

As to the COVID-19 specific construct that we developed and utilized in this study, which is COVID-19 mental impacts, the data analysis results showed that it had statistically significant impacts on both students' learning satisfaction (H5a) and their intention to use the synchronous remote learning technology in the future (H5b). However, what we found interesting was that such an impact was positive on learning intention (with the path coefficient of 0.086), but negative on learning satisfaction (with the path coefficient of -0.091). This indicates that when a student perceived a higher level of depression and anxiety during the COVID-19 pandemic, he/she would be more willing to choose to take future classes using the remote learning technology (when there was a choice); however, he/she was less satisfied on their current remote classes. The negative relationship between COVID-19 mental impacts and learning satisfaction might be because that for students who perceived a high level of depression and anxiety during the COVID-19 pandemic, it would be more likely for them to hold negative feelings and emotions toward different things in general, including their learning in current classes. Compared with other students who were less depressed and anxious during the COVID-19 pandemic, they tended to form more negative attitudes and options. However, when making choices and decisions about how to attend future classes, those students who experienced a higher level of depression and anxiety would be more willing to take future classes by continuing using the synchronous remote learning technology. This is reasonable since they might feel classes that utilize the synchronous remote learning technology to be more mentally comfortable and could somewhat better protect their physical health at least in the near future. On the other hand, students who were less concerned about the COVID-19 pandemic would be less likely to choose to keep using the remote learning technology in future classes, since they might get bored of conducting all their learning activities online in the past semester (or academic year) and miss their personal interactions with their instructors and classmates.

For social influence, the results showed that it could significantly influence students' intention to use technology-supported, synchronous remote learning in the future (with the path coefficient of 0.107), but not on learning satisfaction. Therefore, H6a was supported, but not H6b. This result indicates that if students believed that people who were important to them (and those who could influence their learning) thought that they'd better attend classes remotely during the COVID-19 pandemic, they would be more willing to choose to use the remote learning technology even in their future classes (if there was a choice). However, the options of the influencers didn't seem to have a strong impact on their levels of satisfaction on their current classes. This seems to be reasonable, since students who were more influenced by others would be more willing to take others' options into consideration when making future decisions, but others' options might not necessarily influence their perceptions on current situation.

In addition, it was found that learning satisfaction could significantly influence learning intention (with the path coefficient of 0.362), in support of H7. Together, the significant factors – technology facilitating conditions (at both the institution and student levels), task-technology fit, IT competence, and COVID-19 mental impacts – explained 59.8% of the variance of learning satisfaction. For learning intention, the significant factors – task-technology fit, COVID-19 mental impacts, social influence, and leaning satisfaction – explained 43.8% of its variance.

5. DISCUSSION

This study examined students' learning on technology-supported, asynchronous remote learning platform during the current COVID-19 pandemic. Several research contributions are made in this study. First, we developed a research model to assess factors that could possibly influence student learning in this new situation from various perspectives, including the technology-related perspective and the social and mental related perspective. As to the technology-related perspective, specific factors that we investigated include technology facilitating conditions, task-technology fit, and students' IT competence. For the social and mental related perspective, we specifically examined COVID-19 mental impacts and social influence. A relatively large-scale empirically study, with 428 participants, was conducted to test the proposed research model. The data analysis results could potentially help us, as educators, to better understand student learning at this special moment of time.

Another contribution is the use and development of constructs technology facilitating conditions and COVID-19 mental impacts. In this study, we examined technology facilitating conditions at two levels, including: the technology facilitating conditions supported by the institution, and that at students' own places. We believe both of them could be influential on student learning in our context of study. However, to the best of our knowledge, little existing research has examined technology facilitating conditions on student learning at these two levels, and none has been seen particularly on assessing student learning during the COVID-19 pandemic.

In addition, we developed and included a COVID-19 specific factor, which is COVID-19 mental impacts, in our proposed research model. This could contribute to existing research on assessing remote learning during the COVID-19 pandemic in several ways. First, existing research models developed for examining student learning during the COVID-19 pandemic mainly adopted and applied theories and constructs related to information systems adoption and assessment. Little effort has been made on factors that are specific to the COVID-19 pandemic. We hope our study could provide an example for future research to further investigate related factors that are specific to this special situation. Second, although some research has been done to assess the psychological and mental impacts of the COVID-19 pandemic on students, little effort has been made to include those impacts into a nomological network to further investigate their causal relationships to student learning. The current study aims to address such a gap.

Some interesting results have been found in this study, which could help educators better understand influential factors related to student learning during the COVID-19 pandemic, and potentially provide some helpful insights for educators to further improve student learning during this special moment of time. First, the data analysis results showed that technology facilitating conditions (at both the institution and student levels) had a significant impact on students' learning satisfaction in their synchronous remote classes during the COVID-19 pandemic; however, it had no significant impact on students' intention to use synchronous remote learning in their future classes. Similar results were found on IT competence; that is, it could significantly influence students' learning satisfaction but not intention. These results may indicate that, in most cases, technology-related factors might be more influential on students' satisfaction toward their current remote classes during the COVID-19 pandemic, but not necessarily to be an important influential factor on students' willingness to keep using the synchronous remote learning platform in the future. Therefore, to ensure a high level of student satisfaction in learning during this special moment, the institution needs to try its best to provide highly effective technology support. In the meanwhile, it may also be important for the institution and individual educators to emphasize to students the helpfulness and importance of maintaining a good level of technology related support (such as fast Internet connections, effective computer systems, update-to-date programs, etc.) at the students' own places.

On the contrast, social influence was found to have a significant impact on intention, but not satisfaction. This may suggest that options from those who were important to, or who could affect a student's learning, could highly influence the student's decision about how he/she would like to

take future classes. But those people's options might not influence his/her level of satisfaction on current classes. Therefore, when promoting technology-supported instructional methods to be used in future classes, in addition to focus on students themselves, the institution and educators may also need to spend effort to promote them to people who are important to the students and who could influence their learning.

As to task-technology fit and COVID-19 mental impacts, both of them were found to be able to significantly influence both student satisfaction and intention, suggesting their significant influential powers on student learning during the COVID-19 pandemic. Therefore, to ensure student learning success at large, the institution needs to put special effort to make sure the systems and tools that are used to support students' synchronous learning at this special moment can highly fit students' learning activities. In the meanwhile, it would also be important for the institution and educators to be aware of their students' mental health conditions, and possibly provide additional help, advice, and services to help those in need to better cope with the pandemic.

Future research can further improve the current study in a couple of directions. First, we included on COVID-19 specific factor in this research. We hope more research effort could be put in this direction, to include more context specific factors and examine their causal relationships with students learning. Second, since this study was conducted in the US, where information and Internet technologies are considered as very advanced in general, the current results may not hold on students in other countries. Future research could apply the proposed model to other countries and cultures, and potentially perform multi-cultural comparisons.

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APPENDIX A: MEASUREMENT ITEMS

Technology Facilitating Conditions (Institution)

- TFCI1: The institution provides sufficient resources (such as instructions, tutorials, and training) on how to use the features and functions of the remote learning technology (such as Blackboard Collaborate Ultra/Zoom).
- FCIL2: The institution's information technology support team is available for assistance with technical difficulties related to the remote learning technology (such as Blackboard Collaborate Ultra/Zoom).
- FCIL3: In case the remote learning technology (such as Blackboard Collaborate Ultra/Zoom) is temporarily out of service, the institution can bring it back quickly.

Technology Facilitating Conditions (Student)

- FCSL1: I have sufficient technology infrastructure (such as computer hardware and software) at my own place to support my remote learning.
- FCSL2: The speed and quality of the Internet at my own place is effective enough to support my remote learning.
- FCSL3: When I need, I always know where and how to get the assistance with technical difficulties related to the remote learning technology (such as Blackboard Collaborate Ultra/Zoom).

Task-Technology Fit

- TTF1: Using the remote learning technology (such as Blackboard Collaborate Ultra/Zoom) fits well with my learning goals.
- TTF2: Using the remote learning technology (such as Blackboard Collaborate Ultra/Zoom) fits well with my learning needs.
- TTF3: Using the remote learning technology (such as Blackboard Collaborate Ultra/Zoom) fits well with different aspects of my learning.

IT Competence

- ITC1: In general, I am comfortable with using information technology and information systems.
- ITC2: I am confident about using the remote learning technology (such as Blackboard Collaborate Ultra/Zoom).
- ITC3: I am capable of using the remote learning technology (such as Blackboard Collaborate Ultra/Zoom).

COVID-19 Mental Impacts

- COVIDMI1: During the coronavirus (COVID-19) pandemic, I feel I am close to panic.
- COVIDMI2: During the coronavirus (COVID-19) pandemic, I have found it difficult to do things.
- COVIDMI3: During the coronavirus (COVID-19) pandemic, I have been unable to become enthusiastic about anything.

Social Influence

SI1: People who are important to me think that I should attend remote classes during the coronavirus (COVID-19) pandemic.

SI2: People who affect my learning think that I should attend remote classes during the coronavirus (COVID-19) pandemic.

SI3: I expect to attend remote classes because people around me (such as my friends) are doing so during the coronavirus (COVID-19) pandemic.

Learning Satisfaction

SAT1: Overall, I am pleased with the remote learning technology (such as Blackboard Collaborate Ultra/Zoom).

SAT2: Overall, I am satisfied with the remote learning technology (such as Blackboard Collaborate Ultra/Zoom).

SAT3: Overall, the remote learning technology (such as Blackboard Collaborate Ultra/Zoom) satisfies my learning needs.

Learning Intention

INT1: When it is offered, I intend to use the remote learning technology (such as Blackboard Collaborate Ultra/Zoom) in my future classes, regardless of whether the coronavirus (COVID-19) is still an issue or not.

INT2: When it is offered, I am willing to use the remote learning technology (such as Blackboard Collaborate Ultra/Zoom) in my future classes, regardless of whether the coronavirus (COVID-19) is still an issue or not.

INT3: When it is offered, I would like to use the remote learning technology (such as Blackboard Collaborate Ultra/Zoom) in my future classes, regardless of whether the coronavirus (COVID-19) is still an issue or not.

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