Examining the Factors Affecting Students' Switching Intention to Online Learning Systems during COVID-19 in Saudi Arabia

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Abstract

The purpose of this research is to empirically examine the factors affecting students' switching intention to online learning systems during the covid-19 in Saudi Arabia. The research utilized a quantitative research method using the Push-Pull-Mooring Theory. These factors were established from prior studies including learning convenience, service quality, perceived security risk, task-technology fit, academic performance, online learning motivation, habits, and switching cost. The survey instrument was formed based on validated items from prior research and were sent to the participants via Google Forms and received 304 completed responses. The study used SmartPLS software to test the model and analyze the data. The findings of this study revealed an overall good model. In addition, of 5 hypotheses, four hypotheses were supported. In addition, pull effect and mooring effects have a positive influence on students' switching intentions. Furthermore, the findings state that the mooring effect influences the relations with the pull and push effects. This study reveals that switching cost and task-technology fit are the primary factors of switching intention. Thus, the results indicate that offering a variety of learning tools to enable learning will make online learning systems more appealing to students.

Keywords: *Switching Intention - Online Learning Systems - Push-Pull-Mooring*

Introduction

The world was shaken due to the COVID-19 has shaken the whole world, and countries were forced to close their borders and most organizations to diminish the virus from moving to other countries (McCorkle, 2020). Thus, it has destructively impacted various aspects of our lives such as the economy, social life, and educational institutions and enterprises (Cakin, & Kulekci Akyavuz, 2021). To prevent the spread of the disease, countries around the world have momentarily closed their educational institutions which affected the education systems worldwide. Therefore, this new disease has transformed traditional learning methods (Lin, Jin, Zhao, Yu, & Su, 2021). Online learning systems are the only effective alternative approach for an academic organization to manage the learning process throughout the pandemic period. According to UNESCO,(2020) educational institutions in 180 countries were closed due to the lockdown. Furthermore, educational authorities have responded to this pandemic by reevaluating the teaching methods to cope with the challenges in the educational world (Lin et al., 2021).

In response to the lockdown, Educational authorities have urged schools and universities to train their students through virtual learning systems to support the stability of the educational learning

process. Contrasting to the traditional learning approaches that students are familiar with before the pandemic, online learning systems were enforced due to the urgent policy. Nearly all classes and programs must be switched to online learning systems in a very short time, which forced students to dedicate time and effort to accustom to themselves utilizing online learning systems. In Saudi Arabia, the Ministry of Higher Education declared virtual instruction using online learning systems. Thus, all educational institutions have been transformed into virtual educational platforms. The existence of online learning systems in most Saudi academic institutions facilitates the continuation of teaching when traditional teaching methods are impossible during the pandemic period. (Mann, Schwabe, Fraser, Fülöp, & Ansah, 2020). However, instructors and students may have to learn how to use these new systems in a short time to be able to use them effectively.

Enhancing students' intention to move to online learning systems and lowering the confusion and anxiety that they endure from experiencing new learning and teaching methods is a crucial aspect during the pandemic (Lin et al., 2021). Akhter, Abdul Rahman, Jafrin, Saif, Esha, & Mostafa (2022) investigated the obstacles that strengthen students' unwillingness to online learning during COVID-19 and indicated that legislators of higher education may plan proper initiatives to encourage students for using online learning systems. According to Jaradat and Ajlouni (2021), an academic organization may continue focusing on some short-term online learning concerns, such as teaching procedures and their long-term impacts. In contrast, Rajab, Gazal, and Alkattan (2020) stated that other scholars anticipated that it may lead to better technology acceptance in the education field. From the academic perspective, previous studies utilized the Push-Pull-Mooring theory (PPM) to explain the reasons behind the switching behavior to an online platform such as (Al-Mashraie, Chung, & Jeon, 2020; Chen & Keng, 2019; Handarkho, & Harjoseputro, 2020; Kim, 2021; Kordi, 2018). However, few studies applied the PPM framework to understand the factors behind the switching intentions to use the online learning systems (Abumalloh et al., 2021; Lisana, 2022).

Abumalloh et al. (2021) utilized the PPM theory and examined the prominent aspects that can influence the perceived positive outcomes of online courses at medical school and found that the PPM factors effect users' benefits. In addition, Lisana (2022) conducted research using the PPM theory to explore the students' switching intention to use digital devices in their learning and concluded with the same findings that PPM effects influence learners intention to switch to using digital devices. However, Xu, Wang, Tai, & Lin (2021) examined the factors that influence the students' switching behavior between different learning systems and found that push factors significantly affect user switching behavior, whereas, mooring factors negatively affect user switching behavior. In addition, Lin et al. (2021) investigated the impact of medical students' switching intention of telelearning and found that push effects have no impact on medical students' switching intention.

The research problem that this study addressed was exploring the factors that impacting the students' switching intentions. The unexpected switch from traditional classroom to online learning systems due to the pandemic would influence the global education system. However, the contrast in the findings between studies warranted further investigations using different factors that were not been used in the aforementioned studies. In addition, Chen and Keng (2019) argued

that enhancing users' switching intentions from a traditional method to an online method is a critical concern that needs to be reevaluated. Thus

The objective of this study is to further assesses the factors affecting students' switching intention to online learning using the PPM model including factors such as service quality and academic performance than not often used in previous studies. To achieve this objective, this study intends to answer the following research questions:

Q1: To what extent do push factors impact the switching intention

Q2: To what extent do pull factors impact the switching intention

Q3: To what extent do mooring factors impact the switching intention

Q4: To what extent do mooring effect impact the push effect and pull effects toward the switching intention

Literature Review & Hypothesis

The Push-Pull-Mooring Model

Lee (1966) indicated that relocation intention is determined by the influence of push and pull effects. Push effects described as the reasons that impact negatively the life standards at the home land (Chen, & Keng, 2019). Pull effects described as the reasons that impact positively the life standards at the desired land (Lisana, 2022). Mooring effects described as the individual or cultural circumstances that enable or hinder relocation intention (Xu et al., 2021). Moon (1995) extended the Push–Pull model to include the mooring effect and suggested a new version of the PPM model (PPM). The relocation decision is impacted by the effect of push, pull, and mooring effects (Lin et al., 2021). The PPM model is a useful model, which can be used to test a study empirically in the context of online switching intentions (Xu et al., 2021).

Online users' switching intentions and people migration may have similar attributes, so the PPM model will be able to identify users' switching intentions (Hou, Chern, Chen, & Chen, 2011). Previous IS literature used the model in a different context, Al-Mashraie et al. (2020) investigated user switching intention in the telecommunication business, Chen and Keng (2019) examined students' behavior to switch from traditional classroom to online platforms, Handarkho, and Harjoseputro (2020) studied the switching behavior to accept payment using digital devices in stores, Kim (2021) applied the model to study the fitness consumers' switching behavior, Kordi (2018) examined the brand switching behavior, Sun, Liu, Chen, Wu, Shen, & Zhang (2017) studied the costomers' decision to use digital instant texting applications. To better understand the students switching intentions in Saudi Arabia's from the physical room to online learning systems during the Pandemic, the PPM model will be utilized to help identify the factors using the PPM model. Therefore, nine factors were used to develop a model to understand the factors behind the switching intentions.

Push Effect

For this study push effects described as the reasons that motivate students to stop using the traditional learning methods. In other words, when the positive influences of the traditional

learning methods are greater, the push effects are reduced to influence the switching intention to online learning systems.

Learning Convenience

Convenience is described as the time and work users recognize while performing a service (Berry, Seiders, & Grewal, 2002). It has an impact on behavioral intentions when switching between offline and online (Wu, Zhao, Zhu, Tan, & Zheng, 2011). Learning convenience is characterized as the student's capability to accomplish learning activities anywhere and anytime (Lin, Chien, Hung, Chen, & Ruangkanjanases, 2021). The literature stated that learning convenience is a significant factor that impacts the students' decision to move from joining traditional classrooms to attending online learning systems (Lin et al., 2021; Chen & Keng, 2018). Furthermore, Pramana (2018) indicated that the sense of annoyance being in the traditional classroom is the key factor affecting the students' intention to switch to the mobile learning system. In addition, various studies validated the significance of convenience in users' motivation to use mobile learning systems (Qashou, 2021; Saroia and Gao, 2019). Hence, this research describes the learning convenience of switching to online learning systems as a result of the lockdown from attending to the traditional classroom. Accordingly, this research believes that learning convenience is a crucial factor influencing the push effect,

Service Quality

Service quality is an evaluation of users' prospects with real capabilities (Liao, Huang, Huang, Chen, & Wei, 2019).In the information systems domain, service quality is defined as effective services provided to the users who are using the platform (Lin et al., 2021). Service quality is a major determinant to evaluate user retaining which drives them to switch from one place to another (Chen & Keng, 2019). The literature revealed that service quality is an essential push factor that impacts switching intention. Liao et al. (2019) investigated the converting behavior of students on social networks and found that switching intention is significantly impacted by service quality. Lin et al. (2021a) examined the factors that impact learners' switching intention to use online platform and discovered that service quality significantly affected the students' switching behavior. In short, when the service quality is inadequate, it will motivate users to move to a other provider of service. In this research, service quality described as the students' opinion of the supportive service provided by the school when choosing the traditional classroom.

Perceived Security Risk

Perceived security risks are identified as negative factors that affect users' decisions about buying online (Kim, Ferrin, & Rao, 2008). Nevertheless, when an online service come to be more reliable and safe, users will move to use the service (Lai and Wang, 2015). In addition, Rahman, Thiagarajan, and Louis (2019) revealed that perceived security risk is an essential factor in decision-making. In education, students are concerned about the protection of the online learning system. Prior studies demonstrated that perceived security risk is contrarily linked with enthusiasm to use online platforms. Cheng, Lee, and Choi (2019) examined the users' converting behavior and found that perceived security risk has a major influence on switching intention. Lin et al. (2021) examined the reasons that impact learners' moving decision to online platform and found that perceived risk is a major determinant to impact moving decision. Therefore, we

anticipate that perceived security risk will decrease the students' intention to attend traditional classrooms and switch to online learning systems. Therefore, the study propose the following:

H1: The greater the push effects, the reduced the probability that students will have the switching intention to online learning systems.

Pull Effect

For this study pull effects described as the reasons motivate students to use online learning systems. In other words, when the motivation of using the online learning systems is great, the pull effects on the switching intention are great too.

Task-Technology Fit

Task-technology fit (TTF) refers to the Described as the level that technology helps a user to execute the assigned duties (Goodhue & Thompson, 1995). FTT measured the fit among technology, tasks, and users which significantly influences information technology adoption. To consider an information system as an effective and has adequate performance, it should consider whether it meets the user's demands (Lin et al. 2021). The literature indicated that FTT is an essential factor that influences students learning using the online platform. Isaac, Aldholay, Abdullah, and Ramayah (2019) evaluated online learning usage, Lin et al. (2021) investigated the impact of medical students' switching intention of telelearning, and Navarro, Prasetyo, Young, Nadlifatin, and Redi (2021) examined the usage of learning management system among engineering students and found that TTF has a positive influence on switching behavior toward the use of learning management system. During the pandemic, students were directed to use online learning systems to continue their learning. Therefore, we argue that TTF is an important factor influencing the pull effect which impacts the students' switching behavior to adopt the online learning systems.

Academic Performance

Performance refers to the extent that a system used enhances work quality to support the achievement of tasks, facilitate better work management, enhance effort performance, reduce errors, and increase work productivity (Isaac, Masoud, Samad, & Abdullah, 2016). The influence of performance is the most significant measurement of information system usage (Uddin, Isaac, Alrajawy, & Maram, 2019). Therefore, academic performance can be improved by implementing suitable online learning systems (But, Mahmood, Saleem, Murtaza, Hassan, & Molnár, 2023). Prior research has confirmed the significant correlation between learners' academic performance and their enjoyment using online platform (Hussein, 2017; Keržič et al., 2021; Uddin et al., 2019). Thus, we argue that academic performance is an important factor influencing the pull effect, which impacts the students' switching behavior to adopt online learning systems.

Online Learning Motivation

Motivation is defined as the effort or desire that occurs to execute the tasks to achieve the anticipated objectives (Mahardiana, & Thahir, 2019). Lin et al. (2021) revealed that when instructors provide various teaching tools and enhance the interaction with students, this will increase their motivation to use online learning systems effectively. Previous research has indicated the importance of online learning motivation, Nambiar (2020) investigated how Indian university students confront various challenges such as technical issues and lack of motivation,

and Ramachandran and Rodriguez (2020) described disruptions and absence of motivation as obstacles facing chemistry students. Therefore, the online learning system authorities should investigate the factors that motivate students to switch behavior and offer strategic adjustments (Xu et al., 2021). Therefore, the study proposes the following:

H2: The higher the pull effects (Task-technology fit, academic performance, and online learning motivation), the higher the probability that students have the switching intention to online learning systems.

Mooring Effect

The mooring effect described as the moderating determinant that enable or hinders the decision (Yoon & Lim, 2021). The moderating determinant are correlated to the environment and personal considerations (Kim, Choi, & Choi, 2020). These factors include switching cost and habits which has a significant impact on switching intention (Lin et al., 2021).

Switching cost

Switching costs are described as the expenses users are willing to give away to move between products or services. Using an online learning system, if students and instructors choose to switch to another learning system, the preparation and time spent to be familiar with the new system are key determinants (Chen & Keng, 2019). Therefore, high switching costs may prevent students and instructors from leaving a learning system that is less appropriate to their desires (Liao et al., 2019). Although pull and push effects have a significant influence on switching behavior, students may decide not to switch to other learning system caused by other determinant, for instance, switching costs (Lin et al., 2021a). Thus, we state that switching cost is an important factor influencing the pull-push-mooring effect which impacts the students' switching intention to use the online learning systems.

Habits

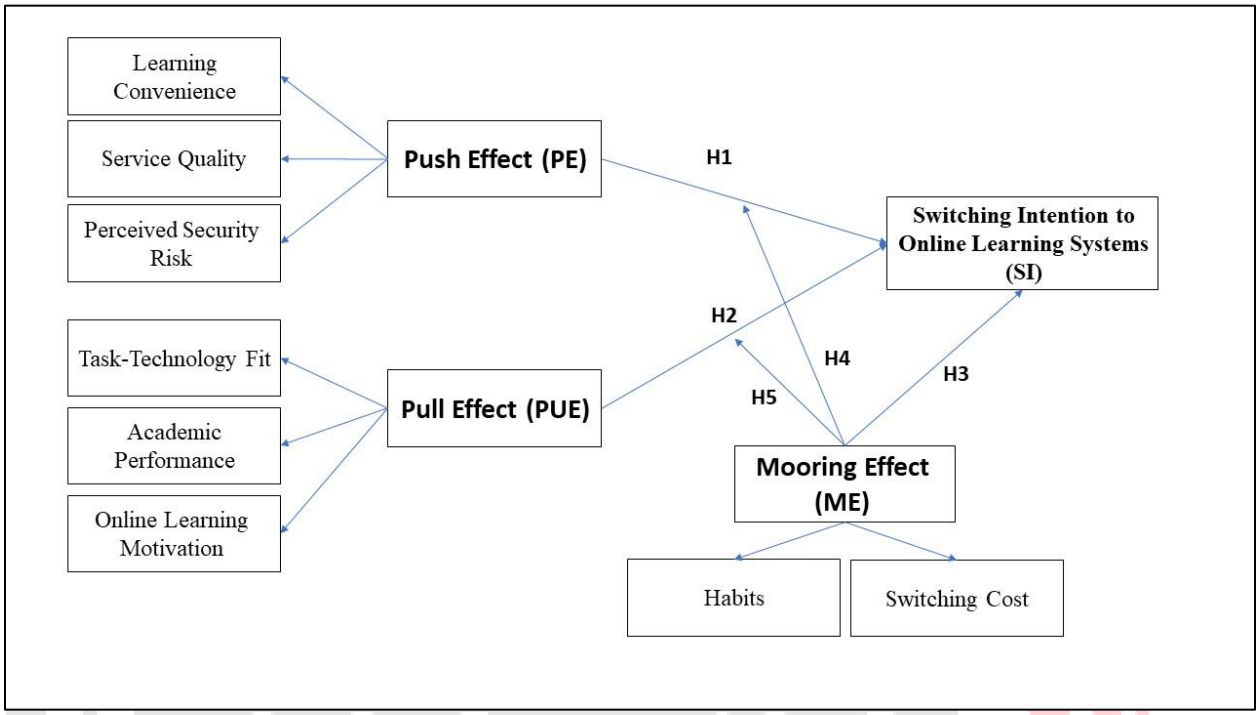
Habit is an attitude formed by past routine and practice (Li, 2018). Therefore, irrespective of the existing alternatives, prior habits encourage users to remain with their recent service providers. Users stay reluctant to move to a new platform regardless of their benefits, implying that earlier habits negatively impact switching behavior. Existing habits enforce students to maintain the current status, thus, students have weak motivation to move from traditional classrooms to online platform (Lin et al., 2021). Thus, this study states that habit is an important factor influencing the pull-push-mooring effect which impacts the students' switching intention to use online learning systems. Accordingly, three hypotheses are proposed:

H3: The greater the mooring effect, the reduced the probability that switching intention will occur

H4: The greater the mooring effect, the lower the link between the push effect and switching intentions.

H5: The greater the mooring effect, the lower the link between the pull effect and switching intentions.

Figure1: *Research Model*



Research Methodology

Research Model

The research utilized a quantitative research method and applied the PPM framework as the foundation to examine the factors affecting students' switching intention to online learning. This study applied the identified constructs push effects, pull effects, mooring effects, and switching intention to online learning that was established in prior research (Abumalloh et al. 2021; Butt et al., 2023; Chen & Keng, 2019; Isaac et al., 2019; Lisana, 2022; Mohammadi, 2015; Uddin et al., 2019; Xu et al., 2021) (see Fig. 1). The main factors identified for push effects were learning convenience, service quality, and perceived security risk. For pull effects, the main factors identified were task-technology fit, academic performance, and online learning motivation. For mooring effects, the main factors identified were habits and switching costs.

Survey Instrument

The survey instrument was formed based on validated items from prior research (Abumalloh et al. 2021; Butt et al., 2023; Chen & Keng, 2019; Isaac et al., 2019; Lisana, 2022; Mohammadi, 2015; Uddin et al., 2019; Xu et al., 2021). Without changing the original meanings, the items were adjusted to fit the context of this study. The survey instrument divided into five sections: push effects, pull effects, mooring effect, switching intention, and student demographics. The study used a seven-point Likert-type scale. While validated items from prior research were used,

an expert panel were utilized to improve the validity of the survey instrument. The SMEs were asked to provide feedback on all survey instrument items. The Cronbach's Alpha coefficient was used as a benchmark for the reliability assessment of the survey instrument.

Sampling & Data Collection

Students at Taif University were invited to participate in this study. An internet-based delivery of the instrument were used (Google Forms) to collect the data. This method deemed to be more likely to make an adequate number of unique responses and to prevent repeated respondents. The researcher sent the survey to the participants using Google Forms and received 312 answers. The study used different measures to detect missing data, biased responses, and outliers. Thus, 8 responders were removed and 304 responders remained to perform the analysis.

Data Analysis

The study used SmartPLS 4.0 to analyze the data. A partial least square is ideal for calculating latent variables. For the bootstrapping analysis, we have set the number of samples employed to 5000 as recommended by Hair, Hult, Ringle, and Sarstedt. (2016). The validity of the overall model was accessed using the confirmatory factor analysis (CFAN) in order to extract a reliable results. Moreover, for the reliability and validity of each constructs this study used Cronbach's alpha. Further, the Cronbach's alpha values was also used in assessing the overall internal reliability. The convergent validity was asses using the average variance in addition to the discriminant validity that was evaluated using the Fornell-Larcker criterion.

Table 1: *Demographics Statistics* (N = 304)

Item	Frequency	Percentage (%)
Gender		
Male	**191**	**62.8**
Female	**113**	**37.2**
Age		
Under 20	**112**	**36.9**
20 – 30	**191**	**62.8**
31 – 40	**0**	**0**
41 – 50	**1**	**0.3**
Older than 50	**0**	**0**
Education		
Diploma	**3**	**1**
Bachelor	**298**	**98**
Master	**3**	**1**
Doctorate	**0**	**0**
How many years of experience as a user of e-learning systems		
Less than a year	**41**	**13.5**
1 – 2	**149**	**49**
3 – 4	**97**	**31.9**

5 years or more	**17**	**5.6**

Result

The Measurement Model

The validity of the overall model is access by using the confirmatory factor analysis (CFA). In this regard the value of Cronbach's alpha can be used to access validity of the model in addition to the reliability of the different factors. DeVellis (2016) identified that the construct value of more then 0.7 is acceptable. In this regards by viewing the PE, PUE, ME, and SI Cronbach's alpha were 0.808, 0.951, 0.812, and 0.882, confirms the reliability as shown in Table 2. Moreover, the internal reliability is valuated by using the composite reliability (CR) which suggests that the ME, SI, and PUE coefficients exceeds from 0.70 as shown in Table 2.

Table 2: *A CFA Analysis* (N = 304)

Variables	Number of Items	Cronbach's Alpha	R^2	Composite Reliability	Average Variance Extracted (AVE)
PUSH EFFECT	11	0.808		0.769	0.267
PULL EFFECT	12	0.951		0.957	0.649
MOORING EFFECT	7	0.812		0.843	0.500
SWITCHING INTENTION	4	0.882	0.597	0.918	0738

The average variance extracted (AVE) was executed to assess convergent validity (Hair et al., 2016). AVE scores for all variables were well above 0.50, except for the push effect (PE). The Fornell-Larcker criterion was performed to evaluate the discriminant validity (Fornell & Larcker, 1981) and stated that discriminant validity was met (Table 3).

Table 3: *Discriminant Validity Results* **(**Fornell-Larcker criterion) (N = 304)

Variables	MOORING EFFECT	PULL EFFECT	PUSH EFFECT	SWITCHING INTENTION
MOORING EFFECT	**0.667**			
PULL EFFECT	-0.312	**0.805**		
PUSH EFFECT	-0.328	0.628	**0.517**	
SWITCHING INTENTION	-0.341	0.750	0.507	**0.859**

The Model Estimation

R^2 identifies the threshold value that can be used to access the overall acceptance of the constructs suggesting the quality of models (PE, PUE, and ME) combined influences on the

endogenous latent construct (SI). The R^2 of SI in Table 2 is 0.597, therefore, indicating it's more than 0.25 highlighting that that model is reliable (Hair et al., 2016).

The linkage between various constructs in the model is utilized by identifying the path coefficients (Hair et al., 2016). The finding identified four significant paths based on the coefficients of various constructs (ME -> SI, PUE -> SI, ME * PUE -> SI, and ME * PE -> SI) while one path having no significant relationship PE -> SI, (Table 4).

Table 4: *Hypothesis Test* (N = 304)

Model direction	P.C	ST.DEV	Proba.V	S.L
ME -> SI	-0.135	0.039	0.001	***
PUE -> SI	0.620	0.051	0.000	***
PE -> SI	0.066	0.051	0.201	NS
ME * PUE -> SI	0.181	0.052	0.001	***
ME * PE -> SI	-0.115	0.055	0.037	*

p < 0.05, **p < 0.01, ***p < 0.001. NS is not significant.

The significance level was determined based on the P-values. The conventional rejection of the null hypothesis was based on 5% rejection. The hypothesis is further supported with 5% significance level. In the above Table the *P*-value suggest that the respective paths are lower then 0.05 suggesting that the hypotheses H2, H3, H4 and H5 were proven correct.

Discussion and Implications

The purpose of the research is to assess the factors impacting students' switching intentions to use online learning systems during the covid-19 pandemic in Saudi Arabia. Chen and Keng (2019) argued that enhancing users' intention to switch from a traditional method to an online platform is a critical concern that needs to be reevaluated. Xu et al. (2014) indicated that The PPM model is a useful framework, which can be used to test a study empirically in the context of online switching intentions. To address this gap, this study further assesses the factors affecting students' switching intention to online learning using the PPM model**.** The results of this research showed an overall good model. In addition, of 5 hypotheses, four hypotheses were supported.

To answer the first question, we assessed the effect of push factors on the switching intention to an online learning system and uncovered that push factors have no negative effect on switching intention. This means that when traditional classroom learning doesn't cause students' rejection feelings of learning, students cannot be pushed away. This finding is inconsistent with prior studies (Lin et al., 2021; Lisana, 2022: Xu et al., 2021). Of university students in Saudi Arabia more than %50 indicated that the environment and location of the physical classroom are convenient, and the supportive services they are getting from their university are sufficient. Therefore, the convenient feeling of attending a traditional classroom harms students' switching to online learning systems. A possible explanation is that the university is providing excellent teaching tools as well as transportation and parking services to facilitate students at the university campus.

To answer the second question, we assessed the effect of pull factors on the switching intention to an online learning system and uncovered that the pull factors (task-technology fit, academic performance, and online learning motivation) have a noteworthy effect on the switching intention. The finding is in agreement with prior research (Liao et al., 2019; Lisana, 2022: Xu et al., 2021). When learning resources used in a traditional classroom cannot meet the student's needs, they will move to an online learning system. A possible explanation is that millennials are the generation who grow up surrounded by electronic devices which makes them feel convenient to use them in their learning. Chen and Keng (2019) indicated that online learning motivation can perform a crucial role in technology acceptance and usage. In addition, the feeling that online learning fits with the way students like to learn and study, which enhances their academic performance is the key attractor for them to switch intentions.

To answer the third question, we assessed the effect of mooring factors on the switching intention to an online learning system and uncovered that mooring factors have negative effect on the switching intention. The finding is in agreement with prior research (Lin et al., 2021; Xu et al., 2021). The findings demonstrated that regardless of the benefits of online learning systems students were still reluctant to switch to them. To answer the fourth question, we assessed the moderating effect of mooring factors on the push and pull effects and found that habits and switching cost mitigate the relations with the pull and push effects.

Based on the aforementioned findings, students are influenced by the factors of pull, push, and mooring when deciding between switching intentions to online learning systems or staying in a traditional classroom. These findings will help educational institutions that are planning to implement online learning systems as a main learning method in the future. Furthermore, this study reveals that switching cost and task-technology fit are the key contributing factors to switching intention. Thus, these findings indicate that offering a variety of learning tools to facilitate learning will make online learning systems more appealing to students.

Limitations and Future Research

Several limitations have been identified. First, various factors were constructed to measure the students' switching intention to online learning systems using PPM model. While there are different factors used in this study, the influence of other factors may reveal different results. Thus, future research should be consider including other factors that could influence the switching intention. Second, This study assessed the impact of moderating determinants such as habits and switching cost on the pull, push, and switching intention. However, possible research may broaden the results by investigating other factors such as gender and experience using online platforms. Third, the study population was restricted to students in Saudi Arabia regardless of their area of study. Future research may consider collecting other kinds of data covering areas of studies and technical skills, thus better explanations can be represented. Finally, to enhance the results' generalizability, future research may consider comparing the results of this study to other research findings in different countries.

Conclusions

The purpose of the research is to assess the factors impacting students' switching intention to online learning systems during the covid-19 pandemic in Saudi Arabia using the PPM model that was established from prior studies. The findings of this study revealed an overall good model. In addition, of 5 hypotheses, four hypotheses were supported. In addition, the findings showed that push factors have a weak effect on students' switching intentions to online learning systems which were inconsistent with prior findings. In addition, pull and mooring factors have a positive effect on students' switching intentions. Furthermore, the findings reveal that the mooring factors mitigate the relations with the pull and push effects. However, this study reveals that switching cost and task-technology fit are the core determining factor of switching intention. Hence, the findings stated that offering a variety of learning tools to enable learning will make online learning systems more appealing to students.

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