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# The Impact of Switching Intention of Teachers' Online Teaching in the COVID-19 Era: The Perspective of Push-Pull-Mooring

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## Abstract

In response to the COVID-19 pandemic, many educational institutions switched to online learning to maintain learning activities. With the global pandemic, the educational environment was forced to shift from traditional face-to-face teaching or blended learning to a fully online learning model. In February 2020, China took the lead in announcing the implementation of online learning, encouraging most teachers to use it. Exploring the potential of online learning to replace traditional face-to-face teaching is a topic deserving consideration. This study explored the factors that influenced teachers' intention to switch to online learning during the pandemic, using a push-pull-mooring model. The study analyzed 283 valid responses gathered through an online questionnaire and found that push effects, pull effects, and habits significantly impact teachers' intention to switch from offline to online teaching. The findings provide additional insights into the future of higher education after the pandemic.

*Keywords:* COVID-19, migration behavior, online learning, push-pull-mooring model

# Introduction

COVID-19 changed the teaching mode in many schools, especially during the first 2 years of the pandemic. To avoid interruption to university learning, educational institutions in various countries stopped face-to-face teaching and encouraged teachers and students to switch to online teaching to achieve the "study must not stop" goal (Chen et al., 2020). Before the pandemic, many countries had a certain degree of understanding and use of online learning, but some teachers may not have had much online teaching experience (Chen et al., 2020). The emergency policies adopted by various countries in response to the pandemic inevitably forced many teachers and students to start the switch. This transition from in-person to online classes caught many inexperienced teachers and students off guard (Carrillo & Flores, 2020). Most past users of online learning and teaching had positive learning or educational motivations based on their personal favorite courses and common technology (Çınar et al., 2021). However, the urgent change in learning modes during the pandemic led to a situation in which teachers experienced great risks and anxiety, as well as barriers to their teaching, all of which differed from their previous teaching habits (Liu et al., 2022). This could have caused teachers' negative emotions about online teaching, possibly turning into teaching obstacles and leading to poor teaching quality (MacIntyre et al., 2020). Many users were forced to learn how to use online teaching platforms quickly and widely, which may have affected them during the conversion process (Chen & Keng, 2019), inducing anxiety about teaching (Liu et al., 2022). Therefore, under the influence of COVID-19, the efforts teachers made to meet the educational goal of "study must not stop" became a dilemma (Lin et al., 2021).

In past research, the push-pull-mooring model (PPM) was primarily used to study behavior when changing from offline to online environments (Hou & Shiau, 2019). There were many topics covered in previous studies discussing the behavior of students switching from face-to-face to online learning (Nayak et al., 2022). Research on teachers has the same value, especially since the PPM model is a crucial theory in studying migration behavior, and its variables are not fixed in any structural framework. Researchers need to define the impact of push, pull, and mooring factors on migration behavior (Handarkho & Harjoseputro, 2020). In previous PPM studies, dissatisfaction was the main push factor (Tang & Chen, 2020), and alternative attraction was the main pull factor (Al-Mashraie et al., 2020). However, in terms of mooring factors, there are still many external factors that influence users' willingness to switch (Hou & Shiau, 2019). This study applied the PPM model to explore teachers' behaviors, identifying security risk (SR) and service quality (SQ) as push factors, and challenge motivation (CM), task-technology fit (TTF), and teaching self-efficacy (TSE) as pull factors. Habits were the main mooring factor. Analyzing 283 valid responses, the study shows how these factors influenced teachers' willingness to move to online platforms. The research integrates the stress caused by the pandemic and policy changes, providing a comprehensive understanding of the transition to online education. The findings emphasize the need to support educators through such changes to enhance the sustainability of online teaching. These findings can help policymakers and administrators develop strategies for smooth transitions to blended or fully online learning environments.

# Literature Review and Hypotheses

## Teachers' Study During the Pandemic

During the pandemic, in order to control the spread of the virus, governments around the world announced they would stop face-to-face classes, asking teachers to switch to online teaching (Cao et al., 2021). Due to the urgency of the health crisis and the fact that many countries had never had a national unified online teaching experience, many teachers needed to rapidly switch to online platforms, creating a great challenge (Carrillo & Flores, 2020). Previous studies have suggested that when teachers' emotions are affected, it will likely lead to changes in self-cognition and self-efficacy, in which stress will have a major impact (Beserra et al., 2022). The research regarding COVID-19 has mentioned that teachers may encounter facilitators or deterrents in teaching, such as stress, fatigue, support, and workplace well-being, which may affect their self-efficacy (Stang-Rabrig et al., 2022). Pressley and Ha (2021) adopted the self-efficacy theory to examine teachers' perceptions of online instruction and noted in their study of teachers' self-efficacy that even teachers with abundant face-to-face teaching experience may suffer increased stress or anxiety associated with online instruction. This may reduce their self-efficacy and thus their effectiveness. Daumiller et al. (2021) employed the achievement goal theory to discuss the research on teachers' abrupt transition to online teaching. The results indicated that achievement goals could change teachers' attitudes toward online teaching. Positive challenges that lead to good performance goals would bring more positive attitudes and less stressful rejection. MacIntyre et al. (2020) explored the influence of pressure on teachers' switching to online teaching and showed that positive versus negative emotions would affect teachers' acceptance. However, when the stress level is high, the negative effects of anxiety may be reduced by student and parental support, thereby increasing teachers' self-efficacy (Bruggeman et al., 2022). According to Wong et al. (2021), when the learning and teaching motivation of students and teachers are both positive, it will enhance positive feedback and views on online teaching from both parties, which will increase teachers' willingness to teach online.

During the pandemic, the difficulties encountered in teaching in response to the crisis catalyzed teacher innovation and development, and such changes brought innovative thinking in emergency management contexts (Moorhouse & Wong, 2022). Liu et al. (2022) noted that when teaching online courses during the pandemic, there may have been sudden interruptions from school colleagues or family members, which caused teachers to feel anxious and then affected the efficiency of online courses.

In previous studies on COVID-19, teachers' emotions, stress, self-efficacy, interaction, and anxiety during the pandemic were the main focus. However, this study argues that when using an online teaching platform during a pandemic, in addition to teachers' factors, other important factors brought about by the environment or platform services should also be considered. As discussed in previous literature, this study suggests that the PPM model is an important theory to help analyze factors affecting the transfer of in-person classes to online course platforms.

## The Push-Pull-Mooring Framework

PPM is a theoretical framework for studying people's migration behaviors. It can be traced back to a concept proposed by Lee (1966), who argued that the concept of migration should have both positive and negative factors, forming the basis of the push-pull model. Essentially, the negative concept is a push force motivating people to leave their original living environment, while the positive concept is a pull force attracting people to move to a different place. However, since the push-pull model was unable to explain the role of individual determinants in migration behavior, Moon (1995) argued that mooring factors should be introduced into migration behavior, further proposing the PPM model. Mooring is a factor that can increase or decrease push or pull, and so can further influence people's decisions. Researchers in the field of marketing and information systems have indicated that user switching behavior is similar to the concept of population migration (Fu et al., 2021; Tang & Chen, 2020). Users move from existing services (e.g., social media, information system platforms, online learning) to other services, which is the migration behavior of service platforms (Li, 2018). Similarly, migration behavior can be used to describe a transition in the classroom environment in teaching. When the PPM model was proposed, it was adopted to explain the impact of context and environment. Chen and Keng (2019) explored students' possible transfer factors for online English teaching, and Liao et al. (2019) investigated the transfer factors in social network learning. Previous studies found that when the situation in which PPM was employed differed, the conformations of push, pull, and mooring would follow. As mentioned by Xu et al. (2014), special attention must be paid to the particularity of the research background when using the PPM model to aid in understanding the possible elements of PPM in various situations. In order to fully understand teachers' willingness to switch to online teaching during the COVID-19 pandemic in China, this study adopted the PPM model to find the variables of push, pull, and mooring affecting teachers' switching behaviors.

## Push Factors

Push factors are often the negative causes that force people to leave their original place of residence and find another livable or acceptable offsite location (Lee, 1966). Push factors have been further interpreted as the cause of moving away from existing services (Tang & Chen, 2020). Lin et al. (2021) demonstrated that SR is a push factor and suggested that when users are concerned about the uncontrollable SR of the original service, they may move to avoid the problem. Liu et al. (2020) stated that when the user perceives the SR to be uncontrollable or unacceptable, they will seek out and transfer to alternative services. Chen and Keng (2019) reported that when users perceive that SQ is unsatisfactory, they are forced to shift to better services. Previous PPM studies have confirmed SQ as one of the push factors (Chen & Keng, 2019; Tang & Chen, 2020). This study argues that during the pandemic, SR should be defined as security issues related to the transmission of viruses during physical delivery, forcing teachers to move to an online platform. Similarly, for the purposes of this study, SQ should be defined as teachers being forced to move to an online platform when they experienced dissatisfaction with face-to-face instruction during the pandemic. Therefore, we considered SQ and SR as push factors and proposed the following hypothesis:

> H1: The higher the service quality and security risk, the higher the willingness of teachers to switch from face-to-face to online teaching.

## Pull Factors

Pull factors are interpreted in migration studies as the attraction of a different location when the idea of leaving one's place of residence begins (Lee, 1966). Zhang et al. (2020) explained that when students perceive that the online platform provides more satisfying results than face-to-face learning, they may be motivated to switch. TTF is considered to be the primary consideration for the functionality of an information system, which influences whether the user can successfully complete the task and continue to use it (Goodhue & Thompson, 1995). CM is composed of intrinsic and extrinsic motivation. Extrinsic motivation is interest or a sense of challenge, while intrinsic motivation is achieving a goal or desire (Amabile, 1997). TSE is defined as the teacher's ability to realize active participation and good learning outcomes for students in spite of difficulties or problems (Tschannen-Moran & Hoy, 2001). This study argues that there are three dimensions to be considered from the perspective of technology services. First, teachers should consider choosing a proper platform to fit their own pedagogy (i.e., technology fit) in order to fulfill pedagogical goals (i.e., tasks) assigned by their government's ministry of education or the school. Second, teachers face significant challenges in the urgent transition to online teaching, which can lead to a decrease in their self-efficacy. Conversely, if teachers are able to achieve the challenging goal, their self-efficacy will increase (Culp-Roche et al., 2021). Finally, TSE increases when teachers are willing to focus on their students and demonstrate good engagement and learning outcomes. In conclusion, we classified CM, TTF, and TSE as pull factors, formulating the following hypothesis:

> H2: The higher challenge motivation, TTF, and teaching self-efficacy are, the more teachers will switch from face-to-face courses to online teaching.

## Mooring Factors

Mooring may increase or decrease push and pull (Moon, 1996). In previous PPM studies, habits were defined as a form of mooring (Lin et al., 2021; Xu et al., 2017). Habits are a norm accumulated by experience, turning into laziness (Wang et al., 2019). They are difficult to change, but if there is dissatisfaction with the current situation, people often would be willing to try to change (Polites & Karahanna, 2012). When old habits are dissatisfying and there is a willingness to change, there is a high probability that new habits will be formed (Chen & Keng, 2019). This study suggests that during the pandemic, teachers relied on old habits because of great pressure. They were accustomed to their old teaching style, which may have prevented them from developing new habits, including using online platforms to teach, thus affecting their motivation to switch to online teaching. Therefore, based on past literature, we considered habits as the main mooring factor and formulated the following hypotheses.

> H3: The stronger the habit, the weaker the teachers' intentions to switch from face-to-face to online instruction.

> H3a: The stronger the past habits, the weaker the relationship between the push influence and switching intentions.

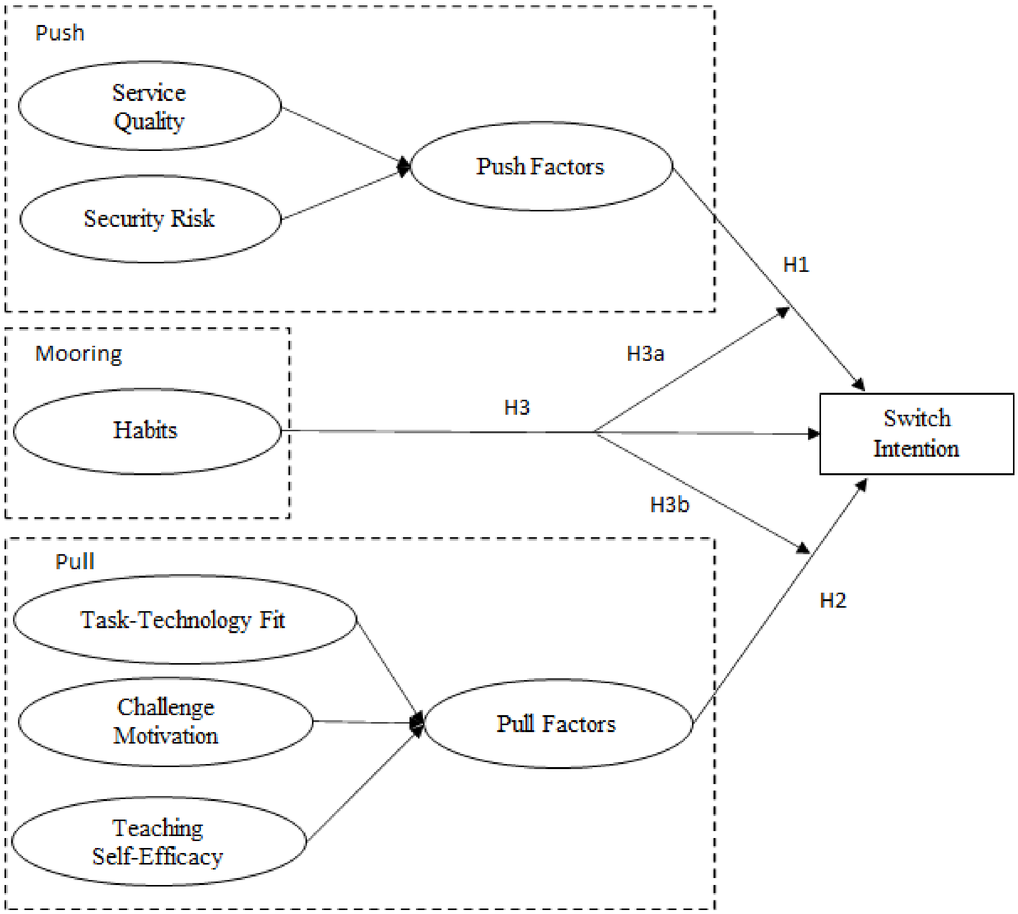
> H3b: The stronger the past habits, the weaker the relationship between the pull influence and switching intentions.

## Research Model

Based on previous literature on the PPM model, we constructed a research model of Chinese university teachers' conversion behaviors influenced by COVID-19, and defined the possible orientations of push, pull, and mooring based on the online teaching context. On the basis of the model, we identified three main orientations: push (SR and SQ), pull (TSE, TTF, and CM), and habits, as presented in Figure 1.

**Figure 1**

*Research Model and Structure*




*Note*: H = hypothesis.

## Data Collection

In this study, a pretest was conducted, following Mokkink et al.'s (2010) methodology, to ensure the validity of the questionnaire. University professors engaged in online teaching during the pandemic evaluated the initial questionnaire to verify its content and quality. Based on their feedback, necessary corrections were made before finalizing the questionnaire. The Questionnaire Star platform (https://www.wjx.cn/) was used for online distribution in the context of the COVID-19 pandemic to secure effective response collection. The study participants were university teachers in China affected by the pandemic. The survey was conducted in summer 2020, following the shift to online classes in Chinese universities.

We employed an online snowball sampling method, as our target population was university teachers using online teaching platforms. Initially, researchers sent the survey link to acquaintances who met the criteria, who then forwarded the link to others within their social and professional networks, thus increasing coverage. This method quickly gathered a large number of responses, enhancing the sample's diversity and reach (Turk et al., 2022). However, snowball sampling can introduce selection bias, as the sample is drawn from the networks of the original respondents. To mitigate these issues, the study combined convenience sampling and sought to ensure diversity in the initial pool of respondents. Indeed, many researchers in education studies also use snowball and convenience sampling methods to collect samples (Mourlam et al., 2020; Nagar & Talwar, 2023). We collected 300 questionnaires, of which 283 were deemed valid after filtering for quality and consistency. The sample size was determined based on previous studies using partial least squares structural equation modeling (PLS-SEM), supporting the robustness of our analysis given the exploratory nature of the research. To ensure the quality and validity of the collected questionnaires, we used five criteria to assess validity based on studies by Cheng et al. (2019) and Lin et al. (2021) during the pandemic:

1. We confirmed whether the teachers were using an online platform at the time of the pandemic. If not, the questionnaire was considered invalid.

2. Questionnaires in which all responses received the same score (all 1 or 7) were considered invalid.

3. A new question was added to identify respondents who completed the questionnaire in the reverse direction, in order to prevent them from completing it indiscriminately.

4. The questionnaire was only available to respondents with an account. If there was a duplicate account, the questionnaire was considered invalid.

In terms of basic demographic characteristics, 139 (49.11%) males and 144 (50.89%) females were recruited, with the same results for both genders. Regarding educational qualifications, 182 teachers had a PhD, while 101 had a master's degree, a ratio of 2:1. This indicates that a high proportion of teachers in mainland Chinese universities do not hold a PhD. In terms of the types of institutions from which these samples were drawn, 52 were from 985/211 universities, 161 were from national universities, and 70 were from private universities, reflecting the current situation of public and private universities in China. In terms of teachers' ages, 80 (28.27%) were under 35 years old, 100 (35.33%) were between 36 and 45, 51 (18.02%) were between 46 and 50, and 52 (18.37%) were over 50 years old. As for their positions, 34 (12.01%) questionnaires were returned by full professors, 128 (45.23%) by associate professors, 89 (31.45%) by assistant professors, and 32 (11.31%) by lecturers. Regarding the teacher background in China, the ratio of full/associate professors to assistant professors and below reflects the current situation in China, indicating that the sample distribution accurately reflects the actual situation. Finally, in the survey on whether they had used online teaching before the pandemic, 178 (62.9%) had never used it, while only 27 (9.54%) had used online learning platforms for more than 2 years, and 78 (27.56%) had used them for less than 2 years. The result of the basic demographic information shows that the popularity of online learning among university teachers was low before the pandemic. To ensure that there were no significant biases in the data analysis, we examined differences in teachers' intentions to switch to online teaching based on gender, education level, and age. The results of the PLS-SEM data analysis indicated that none of these factors reached statistical significance ($p > .05$). Results suggested that teachers' intentions to switch from face-to-face courses to online teaching were consistent regardless of gender, education level, or age.

# Results

The selection of PLS-SEM as the methodological approach for this study was primarily informed by its exploratory and theoretically-oriented character, necessitating subsequent analysis of potential variables (Shiau et al., 2019). Given that push and pull factors were conceptualized as second-order constructs in this investigation, traditional techniques such as analysis of moment structures (AMOS), which only support reflective indicators for the examination of second-order formation models, were deemed insufficient. On the other hand, PLS-SEM is capable of accommodating both reflective and formative indicators (Huang & Shiau, 2017), making it a more suitable method for this study. Consequently, SmartPLS (Version 3.3.4; https://www.smartpls.com/) was employed for the analysis of data and testing of hypotheses in the context of this research.

Common method variance (CMV) can cause errors if it arises from measurement methods rather than the items themselves. To reduce CMV, the survey was paginated with brief breaks between pages. Harman's one-way test showed that CMV was within acceptable limits, with a total explained variance of 41.34% and no construct exceeding 50% (Shiau et al., 2019).

Straub et al. (2004) emphasized content validity's significance in model construction. By aligning with previous operational definitions, this study ensured construct integrity, thus avoiding measurement errors (Petter et al., 2007). Consequently, second-order model constructs were defined as formative indicators, with pull factors comprising two reflective dimensions: SQ and SR, while push factors included CM, TTF, and TSE.

## Measurement Model

In the stage of evaluating reliability and validity, we needed to analyze factor loading, composite reliability (CR), average variance extracted (AVE), and discriminant validity according to the suggestions of Hair et al. (2017). Cronbach's α and factor loading were used to evaluate and analyze the reliability of each project. The factor loading in this study was based on the suggestion put forward by Shiau et al. (2019). The result values on factor loading of all facets were over .7, while α values for all facets were greater than the recommended .7 proposed by Hair et al. (2019). The CR of all facets was greater than the suggested value of .7 proposed by Hair et al. (2017). Additionally, the AVE of the construct itself was greater than the previously recommended value of > 0.5 (Shiau et al., 2019). The research results all exceeded the values suggested in the literature, indicating strong consistency and convergence of the measurement model in this study. The statistical results are shown in Table 1.

**Table 1**

*Reliability and Validity of Study Constructs*

| Construct | Factor loading | α | CR | AVE | VIF |
|---|---|---|---|---|---|
| Service quality (SQ) | .794***<br>.823***<br>.894***<br>.864***<br>.882*** | 0.905 | 0.930 | 0.726 | 1.029 |

| | | | | | |
|---|---|---|---|---|---|
| Security risk (SR) | .934***<br>.953***<br>.895*** | 0.919 | 0.949 | 0.861 | 1.029 |
| Task-technology fit (TTF) | .926***<br>.902***<br>.918***<br>.801*** | 0.910 | 0.937 | 0.789 | 2.271 |
| Challenge motivation (CM) | .820***<br>.818***<br>.725***<br>.790***<br>.759*** | 0.842 | 0.888 | 0.614 | 2.254 |
| Teaching self-efficacy (TSE) | .853***<br>.893***<br>.925***<br>.797*** | 0.890 | 0.924 | 0.753 | 2.332 |
| Habits (HA) | .887***<br>.819***<br>.706***<br>.839*** | 0.837 | 0.887 | 0.665 | 1.040 |
| Switching intention (SI) | .856***<br>.900***<br>.884***<br>.902*** | 0.908 | 0.936 | 0.785 | DV |

*Note*. CR = composite reliability; AVE = average variance extracted; VIF = Variance inflation factor.

***$p < 0.001$; DV= Dependent Variable.

The formative indicators of the second-order constructs were evaluated according to their effective significance ($p < .05$), and their contribution to the corresponding second-order constructs was indicated. As shown in Table 2, SQ, SR, TTF, CM, and TSE of the push and pull constructs all showed significant results, which had strong explanatory power even at the second level. We used the validation and testing mentioned in the previous theory in the sample; the control results fully supported the second-order concept of push and pull.

**Table 2**

*The Measurement Results of Formative Indicators*

| Construct | Sub-construct | Weight |
|---|---|---|
| Push factor | Service quality (SQ) | 0.355*** |
| | Security risk (SR) | 0.877*** |
| Pull factor | Task-technology fit (TTF) | 0.381*** |
| | Challenge motivation (CM) | 0.368*** |
| | Teaching self-efficacy (TSE) | 0.374*** |

*Note*: ***$p < .01$

Hair et al.'s (2017) approach was used to evaluate discriminant validity. It involved ensuring that the square root of the AVE for each construct surpassed the correlation coefficients between constructs, thereby confirming discriminant validity across all constructs (Table 3).

**Table 3**

*Discriminant Validity (Fornell & Larcker's Method)*

| | HA | TTF | TSE | SR | CM | SQ | SI |
|---|---|---|---|---|---|---|---|
| HA | **0.815** | | | | | | |
| TTF | -0.057 | **0.888** | | | | | |
| TSE | -0.151 | 0.694 | **0.868** | | | | |
| SR | -0.090 | -0.319 | -0.279 | **0.928** | | | |
| CM | -0.135 | 0.681 | 0.692 | -0.331 | **0.783** | | |
| SQ | 0.008 | -0.558 | -0.525 | 0.167 | -0.573 | **0.852** | |
| SI | -0.187 | 0.676 | 0.687 | -0.360 | 0.699 | -0.538 | **0.886** |

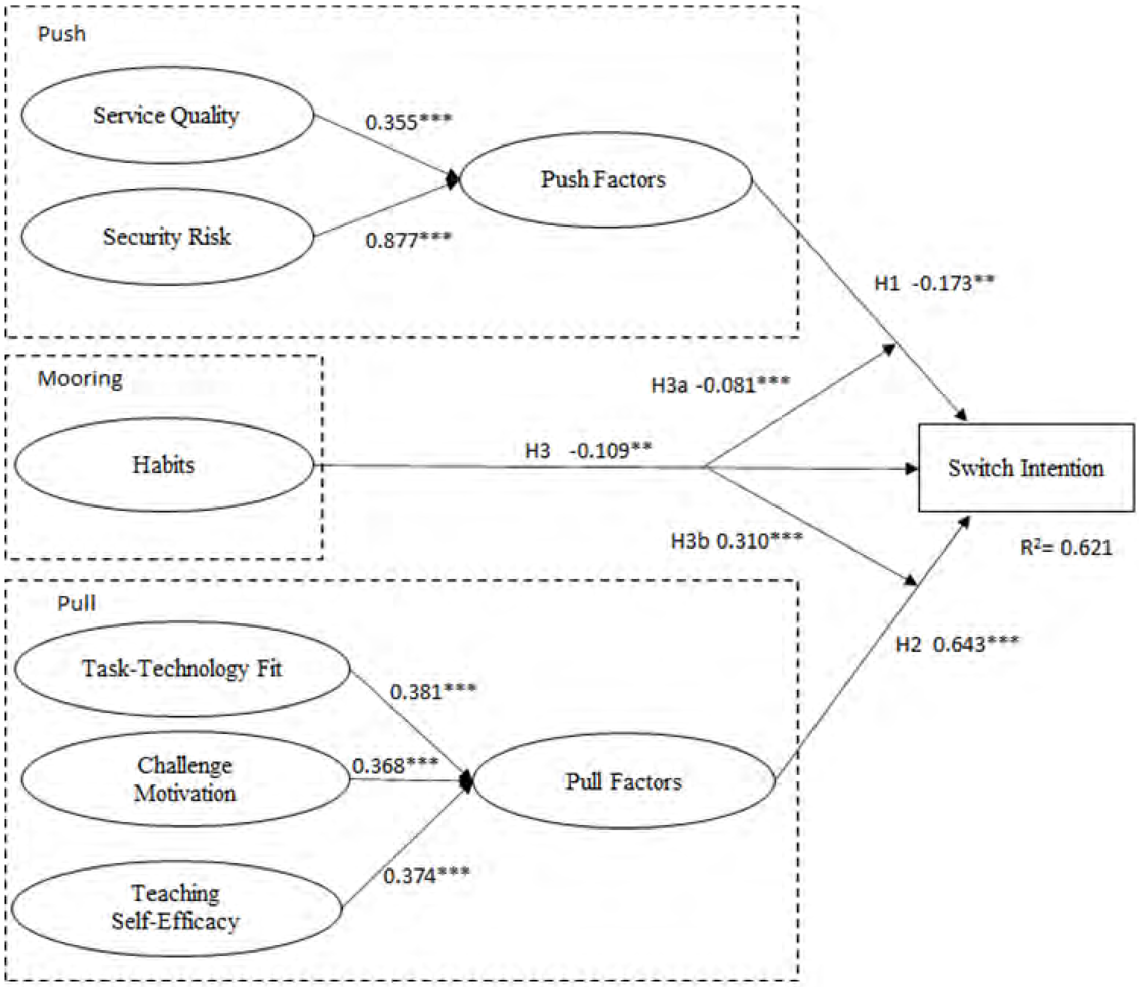
*Note*. HA = habits; TTF = task-technology fit; TSE = teaching self-efficacy; SR = security risk; CM = challenge motivation; SQ = service quality; SI = switching intention. Figures in bold represent the square root of the average variance extracted (AVE).

## Structural Model

These figures indicate that the proposed hypothesis model has good fitness. As for the analysis of the results, we tested the model using the bootstrapping resampling technique with 5,000 resamples (Hair et al., 2017). The analysis results of the structural model are shown in Figure 2. Based on the analysis results, the overall explanatory power of this study was 62.1%, showing that the model had good predictive power. In terms of the results for H1, pull factors had a negative significant influence on switching intention ($\beta = -0.173$, $p < .01$), while for H2, pull factors had a positive significant impact on switching intention ($\beta = 0.310$, $p < .001$). Subsequently, habits had a negative significant effect on switching intention ($\beta = -0.109$, $p < .01$), so H3 was supported. Finally, regarding regulatory effects, H3a exhibited a negative significant relationship ($\beta = -0.081$, $p < .001$), which is inconsistent with Li and Ku's (2018) study. However, for H3b, habits ($\beta = 0.310$, $p < .001$) had a positive regulatory effect on pull and switching intention (Chen & Keng, 2019), suggesting that prior habits could affect pull factors.

**Figure 2**

*Analysis Results of the Research Model*




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

# Conclusion

## Discussion

According to the results of testing related to H1, push factors had a significant negative influence on teachers' willingness to switch from face-to-face to online delivery. Faced with the environmental uncertainty of COVID-19, teachers refused to continue face-to-face teaching due to concerns over SQ and SR. These findings are consistent with Lee's (1966) PPM model, which suggests that negative factors lead individuals to leave existing services. Consistent with previous studies by Chen and Keng (2019) and Lin et al. (2021), our findings indicated that when teachers are dissatisfied with both SR and SQ, they are more likely to seek alternative solutions. Among the push factors, SR emerged as the most influential, followed by SQ. Security concerns, particularly in the context of a pandemic, played a critical role in prompting teachers to abandon face-to-face courses. Environmental uncertainties heightened fears about the ability of schools to effectively prevent contagion among teachers and students during face-to-face interactions. Similarly, the importance of SQ as a push factor is supported by previous research showing that inadequate SQ drives the shift from face-to-face to online learning (Chen & Keng, 2019). During the pandemic, the Ministry of Education of China's policies restricting face-to-face teaching forced teachers to switch to online teaching to meet students' educational needs. This transition highlighted the need for stable and high-quality online teaching platforms to manage emergency teaching scenarios. Future strategies should include robust real-time online emergency service mechanisms to promptly address the problems faced by teachers and students. By improving the SQ and ensuring adequate security measures, educators will be more willing to move to online platforms in times of crisis.

Regarding the results of testing related to H2, pull factors were found to have a significant positive influence on teachers' willingness to switch from face-to-face to online teaching. Pull factors, such as CM, TTF, and TSE, increased teachers' willingness to switch to online delivery. This finding is consistent with Lee's (1966) PPM model, which posits that positive attractions motivate individuals to change services. Among the pull factors, TTF emerged as the most influential, followed by TSE and CM. These findings are consistent with previous studies. For example, Wu and Chen (2017) found that TTF significantly influenced users' willingness to use online platforms. During the pandemic, meeting students' learning needs through appropriate online teaching methods became a critical task for teachers. Consequently, the willingness to switch to online teaching depends heavily on the platform's ability to meet pedagogical requirements and support students' learning needs. The influence of CM is consistent with Fulmer and Frijters' (2011) finding that positive motivation in the face of challenges enhances willingness to adopt new methods. During the pandemic, a lack of consistent online teaching experience was a significant challenge for teachers. However, those who were motivated to find suitable online platforms and pedagogies to meet students' needs were more likely to switch from face-to-face to online teaching. TSE also played a crucial role, supporting the findings of Ismayilova and Klassen (2019). The urgency of the pandemic-induced transition placed a heavy burden on teachers. However, those who focused on student engagement and learning outcomes demonstrated perseverance and increased their willingness to transition to online teaching. For future online teaching, it is important to ensure that the platform's functionality is aligned with teachers' needs. Features such as assignment grading, report grading, and evaluation comments should be linked directly to the school's teaching database to reduce administrative burden. Encouraging teachers through positive feedback and supportive comments from students can further enhance their motivation and effectiveness in online teaching.

From the results of testing connected to H3, previous habits had a negative effect on teachers' intention to switch, consistent with findings from previous PPM studies (Nayak et al., 2022). Teachers are typically accustomed to face-to-face teaching, but the pandemic caused them to reconsider these habits due to concerns about personal safety and SQ. Habit is a deeply ingrained behavior that cannot be changed immediately. However, when new habits address dissatisfaction with original practices, individuals are more willing to change (Chen & Keng, 2019; Polites & Karahanna, 2012). In our study, the pandemic created a unique context where teachers were forced to shift to online platforms. This shift was motivated by the need to ensure personal safety and maintain SQ. The negative impact of existing habits on switching intentions underlines the resistance to change that many teachers experienced. Nevertheless, the need to adapt to new conditions facilitated the formation of new teaching habits. For future emergency teaching scenarios, habits must be considered as a critical factor. While face-to-face teaching has many advantages, online platforms also offer significant benefits, especially during a pandemic. Reinforcing and promoting the advantages of online platforms can help establish new teaching habits. Encouraging teachers to embrace these new practices can facilitate a smoother transition and enhance their effectiveness in online teaching environments.

## Theoretical Implications

This study makes a unique contribution to the literature on teachers' behavior change during the pandemic by integrating the theory of self-efficacy (Pressley & Ha, 2021) and achievement goal theory (Daumiller et al., 2021; MacIntyre et al., 2020). Unlike most studies that focus on teachers' abilities, emotions, and barriers, this research adopted the push-pull-mooring (PPM) model to explain contextual change behaviors, incorporating teachers' individual competencies and integrating concepts from self-efficacy and TTF theories. This approach provides a comprehensive understanding of teachers' behavior change during emergency management in Chinese universities under the influence of the COVID-19 pandemic. Notably, no previous PPM studies have combined self-efficacy and TTF within the PPM framework, making this study a valuable addition to the transition behavior literature by applying a new perspective on PPM, self-efficacy, and TTF.

## Practical Implications

The practical implications of this study are important for guiding educational policy, practice, and future research. Educational policymakers should prioritize the development of safe and high-quality online teaching environments, implement stringent security measures, and ensure high SQ of online platforms to create a more conducive environment for online teaching. Educational institutions should provide comprehensive training and resources to enhance teachers' self-efficacy and ensure that online teaching platforms are well-aligned with teaching tasks, thus supporting teachers in effectively meeting the challenges of online education. Additionally, educational leaders should promote the advantages of online platforms to help teachers develop new teaching habits, facilitate smoother transitions, and improve the efficiency of online teaching environments. These practical insights enhance the relevance and impact of the study, providing actionable guidance for educators, policymakers, and researchers.

## Limitations and Future Research

This study integrates the theories of self-efficacy and TTF into the push-pull-mooring (PPM) model, providing a novel framework for examining behavior change in educational settings. However, the data collection methods, primarily questionnaire-based and using snowball and convenience sampling, may introduce biases such as overrepresentation of certain demographic groups. Future studies should consider a randomized sampling approach to enhance generalizability. Additionally, the study was conducted during the COVID-19 pandemic, making it difficult to determine whether teachers' behaviors changed after the pandemic. Researchers should conduct follow-up studies to assess any changes in teacher behavior. The current study's statistical results on teachers' willingness to switch from face-to-face to online teaching may not fully address all emergency-related issues. Therefore, future research should include qualitative approaches to explore additional switching factors. Longitudinal studies are recommended to assess the evolution of these factors over time and their long-term impact on teaching practices. By continuing to explore important factors from the PPM perspective when discussing emergency issues, researchers can further understand the dynamics of online teaching adoption and provide deeper insights into effective teaching practices.

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