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Push, Pull and Mooring Factors on Offline-Online Learning Switching Behavior

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Abstract: During the pandemic, many sectors, including education, were affected. The shift from traditional to online learning is an opening for students and educators to explore online learning. Students may connect from anywhere at any time through this learning mode. This sudden shift has impacted the learning behavior of students to a large extent. People can access information anytime and anywhere that is typically available only through a traditional classroom. This study adopts the Push-Pull-Mooring (PPM) theory as the theoretical framework to understand how push, pull, and mooring factors affect students' shift from offline to online learning. A survey was used as the main instrument in this study. A quantitative approach was utilized to achieve the stated research objectives. The questionnaires were distributed among undergraduate students in public and private schools in Malaysia through convenience sampling techniques. The minimal 77 sample size has been determined by utilizing G*Power software. 117 responses were collected from the questionnaires that met the minimum required sample size for this study. The findings emphasize that push and pull factors are essential to student learning. However, the mooring factor does not affect the student's switching behavior. The study sheds light on capturing more essential measures in the theoretical development of switching behavior.

Keywords: *Push Factor, Pull Factor, Mooring Factor, Push-Pull-Mooring (PPM) Theory, Switching Behavior*

1. Introduction and Background

The shift from offline to online learning has emerged as a critical research topic, especially given the global transition prompted by the COVID-19 pandemic. In reaction to the pandemic's new norm, academic institutions are attempting to implement e-learning techniques called Open and Distance Learning (ODL) practices. Universities today face significant challenges in resisting the transition from traditional teaching methods to online instruction since failing to adapt could compromise their viability in this industry (Maheshwari, 2021). In addressing this challenge, the National Fiberisation and Connectivity Plan (NFCP) 2019-2023 was launched by the Malaysian Communication and Multimedia Commission (MCMC) in September 2019. This plan targets giving an average internet speed of 30 Mbps to 98% of population regions in 2023, and fiber network passes to 70% of schools, hospitals, libraries, police stations, and post offices by 2022 (Malaysian Investment Development Authority, 2021).

Rathinam et al. (2023) reported that due to the COVID-19 outbreak in 2020, Malaysian academic institutions have been forced to embrace online learning strategies that use learning management systems to enhance students' performance. The sudden transition to online learning presented challenges in policy, pedagogy, logistics, socioeconomic factors, technology, and psychosocial (Barrot et al., 2021). Although it is impossible to ignore the challenges of online education, it is vital to acknowledge the benefits of online learning (Mozie, Jailani & Kassim, 2023). These learning methods and environments provide students with the ability to communicate with their lecturers at any location and learn at their own pace (Singh and Thurman, 2019 and offer greater flexibility, enabling students to connect from anywhere, at any time (Chen, Liu, Chang, Gui, & Na, 2020). This change has significantly impacted student learning behaviors as they can now access information previously only available through traditional classroom settings (Li, Nishimura, Yagami, & Park, 2021). Moreover, students can easily find and switch between alternative learning platforms that they prefer, and this will leverage innovative technologies, such as smart devices and online platforms, to facilitate sustainable educational practices (Mozie, Jailani & Kassim, 2023).

Online learning can be categorized into synchronous and asynchronous (Algahtani, 2011). Using tools such as videoconferences or chatrooms, synchronous online learning facilitates direct interaction between lecturers and students during class. Next, asynchronous online learning allows lecturers and students to engage in thread discussions and correspondence before or after the online class.

This online learning provides benefits in developing new skills and fostering independent learning, ultimately leading to lifelong learning (Dhawan, 2020). This is aligned with the Malaysian Ministry of Education's initiatives to incorporate online learning as a fundamental component of higher education and lifelong learning under the Malaysian Education Blueprint 2015–2025 (Higher Education). Therefore, this study is conducted to obtain a comprehensive understanding of how push (e.g., learning convenience and service quality), pull (e.g., enthusiasm, facilitating conditions, perceived ease of use, perceived usefulness/functional value, and perceived behavioral control), and mooring factors (e.g., switching cost, variety seeking, and involuntary choice) affect students to shift from offline to online learning.

2. Literature Review

Push Pull Mooring Theory

The Push Pull Mooring Theory (PPM) is a commonly used model for examining consumer switching behavior. The factors that influence people to migrate or switch can be explained by categorizing the factors into three categories: pulled (a positive factor that attracts people to the new destination), and the next is push. This negative factor encourages people to move from their origin, and lastly, are mooring, social, or interpersonal factors that might facilitate or inhibit people from switching or migrating (Lai, Debbarma, & Ulhas, 2012; Zhang et al., 2014). This theory originated from the context of human migration and is widely accepted by scholars from a variety of fields, including research that focuses on the understanding of consumer switching behavior patterns (Chang, Wong, & Li, 2017; Wang, Luo, Yang, Qiao, & Management, 2019). Chen and Keng (2019) emphasize that the transition of learners to online education service providers is a phenomenon like the "push-pull-mooring" theory, which refers to a change in behavior. This theory can be a framework for interpreting migration patterns (Chen & Keng, 2019). Therefore, the theory posits those elements from all three categories influence the offline-online learning transition among university students: push, pull, and mooring factors. This theory analyses the factors that affect student behavior by dividing them into 'push' factors, which discourage students from traditional learning environments, 'pull' factors, which attract them to online platforms, and mooring factors, which influence the decision to switch between these learning modes. It provides valuable insights into university students' behavior transitioning between offline and online learning.

Switching Behavior

Switching behavior refers to the consumer selecting an alternate seller instead of their current one (Xu et al., 2021). Switching intention relates to consumers' migration from one provider to another (Ranganathan, Seo, & Babad, 2006), which is typically related to users' discontent with the current product or service as well as evaluation of the relative benefit of a substitute (Wu, Vassileva, & Zhao, 2017). Consumers ' evaluation of switching intention is determined by their use of a product or service (Chen & Keng, 2019). The factors driving this transition may vary from individual preferences, curriculum adaptation, resource accessibility, or unexpected global transformations (Bawa, 2016). The phenomenon of university students moving from conventional offline learning to online learning has gained attention and has been the research focus in recent years. The transition from offline to online learning poses concerns and can impact the behavior of university students, affecting their readiness to transition (Lin et al., 2021). The switching intention among university students can be analyzed through the lens of push-pull migration theory, which elucidates the factors influencing students' preference for or resistance to online learning platforms (Abumalloh et al., 2021; Lin et al., 2021; Nayak, Bhattacharyya, Goswami, & Thakre, 2022; Xu et al., 2021). This theory posits that students' prior experiences, routines, and attachments to offline learning can be barriers or facilitators in their propensity to transition to online learning (Zeng et al., 2021). Consequently, it is imperative for universities and education providers to comprehend and resolve the mooring effect, in addition to the push and pull factors, to effectively support and encourage students during their transition to online learning.

The Push Factors

Hsieh et al. (2012) described this as the push effect, which happens when the consumer is not happy with the services they get from their current provider and, therefore, decides to switch to another one. This finding is

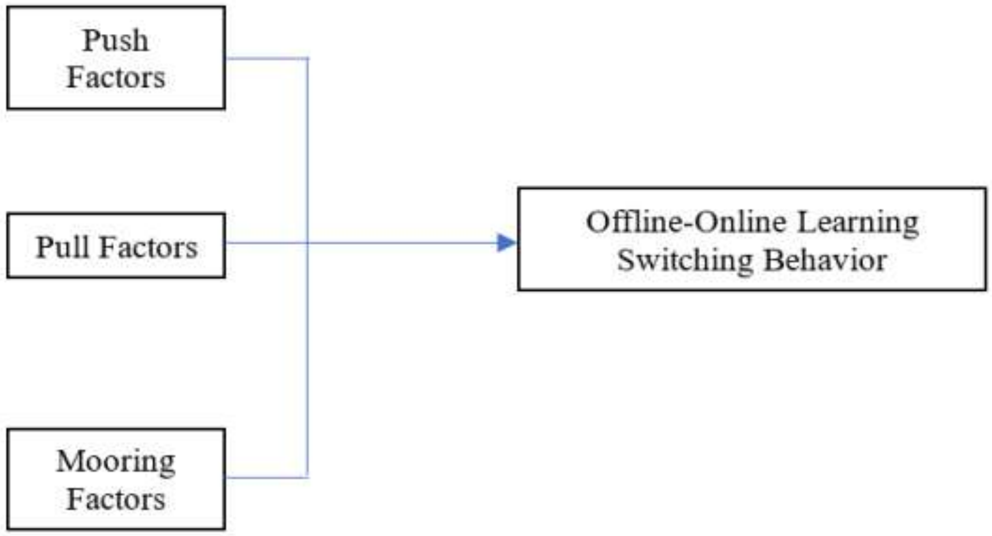
supported by Jung and Oh (2017), who argue that the push effect results from consumer dissatisfaction with existing service providers, so they desire other options in life. According to Chang, Wong & Li (2017), the push effect favors the intention to switch, leading consumers to migrate from their current service provider to a new one. Consumer switching refers to the willingness of consumers to withdraw from their current service provider and start using a different one. Astuti & Eliana (2019) asserted that the push effect influences switching intention. This demonstrates that the push effect has a pronounced inclination to impact the desire to switch. This study considers the students' switching intentions from traditional to online learning. The dimensions of push effect variables in this study include learning convenience and service quality, which will be used to analyze the influence of the push effect on switching intention. The following hypothesis is developed:
H_1: Push factors have a positive influence on the students' switching behavior.

The Pull Factors
A pull factor is a favorable aspect of alternative services that attracts consumers to switch to those services (Nurlinda & Anam, 2024). The push-pull factor theory is derived from the study of human migration (Lee, 1966), which posits that migration is the outcome of the push and pull forces that influence an individual's transition from one location to another (Chang et al., 2014). In marketing and information systems, pull primarily relies on alternative attraction to clarify the user's preference to transition from offline to online consumer behavior (Lin & Huang, 2014). The Pull Effect, as described by Sun et al. (2017), refers to the favorable aspects that pull consumers towards alternative products or services. These benefits, present in the alternative service, can bring in clients and encourage them to use the service (Guo et al., 2021). In this study, the term "pull factor" refers to the factors that inspire university students to switch between offline and online learning, including enthusiasm, facilitating conditions, perceived ease of use, perceived usefulness/functional value, and perceived behavioral control. Leong's (2022) research shows a positive correlation between customers' interest in other services and their desire to move to new services. In other words, the more interested consumers are in alternative services, the more likely they are to consider switching. A similar finding was made by Jung and Han (2017), indicating that the pull effect favors the intention to switch. This demonstrates that a service with a strong attraction will offer a superior deal, resulting in increased consumer satisfaction and influencing consumers to switch. Therefore, the following hypothesis was formulated:
H_2: Push factors have a positive influence on the students' switching behavior.

Mooring Factors
The mooring factor refers to the individual and societal influences that might encourage a potential resident to either remain or relocate from their current area of residence (Moon, 1995). The elements are linked to the switching behavior and can either restrain or assist in decision-making. In this paper, the mooring factor refers to the influence of online learning factors that motivate students to leave or remain in the physical classroom. Switching costs are a component of the anchoring factor that influences platform-switching behavior (Cheng, Lee, & Choi, 2019) and play a crucial role in determining and regulating consumer happiness (Burnham, Frels, & Mahajan, 2003). The study conducted by Chen and Keng (2019) and Liao et al. (2019) asserts that switching costs influence the mooring of learning platforms. The need for change is another mooring factor considered an involuntary choice when the users face a situation where they have no choice. As for Menon & Kahn (1995), the mooring factor refers to the tendency to select products and services that differ from one another. A past study conducted by Chen and Keng (2019) found a connection between the desire to switch from offline to online real-person English learning platforms among individuals in Taiwan. Therefore, this paper looks into the factors influencing switching behavior, such as switching cost, variety seeking, and involuntary choice. The following hypothesis was formulated:
H_3: Mooring factors have a positive influence on the students' switching behavior.

Theoretical Framework
Based on the preceding discussion, a theoretical framework was established in which push factors, pull factors, and mooring factors are posited as the key drivers prompting the transition from offline to online learning, as illustrated in Figure 1.

Figure 1: Theoretical Framework of Push, Pull, and Mooring Factors on Offline-Online Learning Switching Behavior



3. Research Methodology

A quantitative approach is utilized to achieve the stated research objectives. The research design for this study is a correlational study. The researcher tried to investigate the factors influencing students' switching behavior using the push-pull-mooring theory for this study. The population of this study is undergraduate students in a private and public university in Peninsular Malaysia. All respondents participating in this study should have experience studying online and offline.

Meanwhile, the sampling technique that is applied in this study is convenience sampling. Convenience sampling can be defined as a type of non-probability sampling, which involves the subjects being drawn from the part of the population close to hand. In determining the minimum sample size for this study, G*Power software is employed. The researcher calculates the sample size by using the G*Power 3.1.9.4. Thus, the setting measured in this study is as follows: Effect size f^2: 0.15, α=0.05, and the number of predictors=3 (push factors, pull factors, and mooring factors). The power was set at 95%. Thus, the sample size required for this study is 77. A total of 117 respondents were received from the data collection.

This research study has received ethical approval from the Faculty Research Ethics Committee under the Faculty of Business and Management. Four constructs were measured in this study: push factors, pull factors, mooring factors, and offline and online switching behavior. The constructs were measured using a five-point Likert scale ranging from 1 strongly disagree to 5 strongly agree. Appropriate item modification was performed to fit the study context and validated by experts in the study area. A reliability test was conducted before the data collection to ensure the consistency of the measure. Based on the pilot test of 30 respondents, the internal consistency value for all constructs met the minimum requirement of 0.700. Meanwhile, to collect the data, an online survey was designed using Google Forms, and the invitation to participate in the study was sent through emails and WhatsApp.

4. Results

Data were analyzed using SPSS version 28.0 and Smart PLS 4.0. Table 1 summarises the demographic profile of the respondents. Most respondents were female, between 21 and 25 years old, and had a bachelor's degree from a public university in Malaysia.

Table 1: Demographic Profile

Demographic	Frequency	Percentage
Gender		
Male	22	18.8
Female	95	81.2
Age		
< 20 years	6	5.13
21-25 years	96	82.05
25- 30 years	8	6.84
30 years	7	5.98
Education Level		
Diploma	15	12.82
Bachelor Degree	102	87.17
University		
Public	107	91.45
Private	10	8.54

The research model for this study is tested using the PLS Algorithm in SmartPLS 4.0. Table 2 shows the result summary of the measurement model. The results provide evidence for the measurement model for composite reliability, which meets the minimum requirement of 0.7 and above to achieve internal consistency reliability (Ramayah et al.,2018). Moreover, all indicator loadings reached the minimum requirement of 0.4, with the average variance extracted (AVE) establishing more than 0.5 to accomplish the convergence validity requirement. Next, a discriminant validity procedure was conducted to observe how a particular construct differed from the other construct in the study (Lowry & Gaskin,2014).

Table 2: Measurement Model

Constructs	**Items**	**Indicator Reliability Outer Loadings > 0.6**	**Convergent Validity AVE > 0.5**	**Internal Consistency Reliability Composite Reliability > 0.7**	**Cronbach's Alpha > 0.7**
Push Factor	C1	0.879	0.798	0.956	0.949
	C2	0.920			
	C3	0.913			
	C4	0.888			
	C5	0.913			
	C6	0.846			

Constructs	Items	Indicator Reliability Outer Loadings > 0.6	Convergent Validity AVE > 0.5	Internal Consistency Reliability Composite Reliability > 0.7	Cronbach's Alpha > 0.7
Pull Factor	ENT11	0.722			
	ENT2	0.705			
	ENT3	0.758			
	ENT4	0.807			
	FC1	0.728			
	FC2	0.739			
	FC3	0.808			
	FC4	0.875			
	PBC1	0.792			
	PBC2	0.745			
	PBC3	0.839	0.634	0.974	0.971
	PEOU1	0.778			
	PEOU2	0.839			
	PEOU3	0.864			
	PEOU4	0.739			
	PEOU5	0.824			
	PEOU6	0.742			
	PU1	0.866			
	PU2	0.799			
	PU3	0.854			
	PU4	0.859			
Mooring Factor	IC1	0.940	0.784	0.918	0.901
	IC2	0.941			
	IC3	0.952			
Switching Behavior	SB2	0.787			
	SB3	0.927			
	SB4	0.901	0.763	0.874	0.845

Using the heterotrait-monotrait ratio (HTMT) techniques, the results shown in Table 3 indicate that all values fulfilled the criterion of HTMT 0.85, as suggested by Kline (2015), which established discriminant validity. Furthermore, the result of HTMT inference also revealed that the confidence interval did not show a one on any of the constructs, which further confirmed discriminant validity (Henseler et al.,2015; Ramayah et al.,2018). In addition, based on the Confidence Interval Bias value, the columns labelled 2.5% and 97.5% showed that the lower and upper bounds of the 95% (bias-corrected and accelerated) confidence interval did not include the value of 1. In conclusion, the measurement model has established its discriminant validity. Before the structural model development, a procedure to address the issue of collinearity was conducted, as the existence of multicollinearity does not contribute to a good regression model.

Table 3: HTMT 0.85

	Mooring Factor	**Pull Factor**	**Push Factor**	**Switching Behavior**
Mooring Factor				
Pull Factor	0.291			
Push Factor	0.305	0.213		
Switching Behaviour	0.357	0.713	0.342	

Finally, the structural model analysis was performed through several steps. As illustrated in Table 4, values for all constructs met the requirement of VIF below 5.00 (Hair, Hult, Ringle, & Sarstedt, 2016; Wong,2013), thus confirming the absence of multicollinearity. This was preceded by the structural model and followed by the PLS algorithm to test the hypotheses. A bootstrapping technique with 5000 subsamples was performed to ensure the accuracy of PLS estimates, and the results are presented in Table 5. The relationship was found to have a t value ≥ 1.645, thus significant at 0.01 for the pull factor (β= 0.617, t value = 9.599) and push factor (β= 0.150, t value = 2.095).

The r^2 value of 0.491 suggests that pull and push factors explained 49.1% of the variation in switching behavior among undergraduate students. Next, the blindfolding procedure was conducted to obtain the model's predictive capability using Q^2 (Hair et al., 2016). According to Hair et al. (2016) and Ramayah, Cheah, Chuah, Ting, and Memon (2016), if the Q^2 value is more than 0, the model has predictive relevance for a specific endogenous construct. Based on predictive analytics, the predictive relevance for Q2 values for mooring, pull and push factor are 0.201, 0.343 and 0.456, respectively, indicating that the model has a predictive relevance because the Q^2 values are considerably above zero, as Hair et al. (2016) outlined. The f^2 values represent the effect size of a specific exogenous construct on the endogenous construct (Hair et al.,2016). The effect size of the mooring factor → switching behavior was 0.016 (small), the pull factor → switching behavior was 0.683 (medium), and the push factor → switching behavior was 0.040 (small) based on the guidelines provided by Cohen (1988).

Table 4: Structural Model

	Path Coefficient (β)	Std. Error	T statistics	P values	f^2	Effect Size	VIF	Q^2
Mooring Factor -> Switching Behavior	0.097	0.101	1.251	0.211	0.016	Small	1.136	0.201
Pull factor -> Switching Behavior	0.617	0.622	9.599	0.000	0.683	Mediu m	1.094	0.343
Push factor -> Switching Behavior	0.150	0.155	2.095	0.036	0.040	Small	1.109	0.456

Table 5: Summary of Hypotheses Result

No	Hypotheses	Result
H_1	Push factors have a positive influence on the students' switching behavior.	Supported
H_2	Pull factors have a positive influence on the students' switching behavior.	Supported
H_3	Mooring factors have a positive influence on the students' switching behavior.	Not Supported

Discussion

This study examined the relationship between offline-online learning switching behavior (dependent variable) and push, pull and mooring factors (independent variables). Online learning platforms are essential for giving students all the resources they need to gain information and skills and the opportunity to continue studying throughout their lives. Encouraging lifelong learning is critical for improving people's skill sets and the economy's overall well-being. The research findings provide fresh perspectives and valuable ramifications for the long-term growth of online learning environments. It is clear from Table 5 that two of the three hypotheses (the push and pull factors) are supported. Concurrently, the hypothesis between the mooring factor and switching behavior needs to be supported. According to Hsu (2014), Push factors will influence users to stay away from current technology. Meanwhile, pull factors will attract users to newer technologies. Furthermore, the mooring factor is a variable that facilitates or limits the intention to switch users towards technology adoption (Cheng et al., 2019).

The hypothesis clearly shows that the push factor significantly influences the students to switch behavior. With the p-value smaller than the significant level value, the results support H1's assertion that there is a meaningful relationship between push factors and switching behavior. This study aligns with earlier research by Lisana (2023), which emphasizes that push factors significantly influence young people's intention to change their behavior as H_1 is accepted. Moreover, a study by Handarkho (2020) and Chao et al. (2020) stated that push factors are a potential factor that triggers people to switch behaviors in fulfilling their social needs. Due to the push factor during the COVID-19 pandemic, many young people developed depressive emotional states as they were forced to spend most of their time at home, limiting their ability to interact physically with friends. As a result, information and communication technology tools like the Internet of Things and smart devices play a crucial role in analyzing the real-time environment, which allows people to respond effectively if any problems arise (Handarkho, Khaerunnisa, & Michelle, 2023). The other study by Lisana (2023) mentions that the discomfort of attending physical classes had become a significant reason for students to switch to mobile learning. This type of learning offers a more convenient platform that isn't restricted by time or place, making it more likely that students will switch. Furthermore, push factors directly relate to why individuals seek better education, such as building connections (Brandt & Hagge, 2020) and better job opportunities (Alexander, 2021). On the other hand, push factors also can lead people to choose an alternative way, as stated in a study by Monoarfa, Sumarwan, Suroso, and Wulandari (2023) that the pandemic is a push factor for customers to shop from alternative places and media. However, this does not mean that customers will quickly accept the consequences of switching from the old habit of shopping for groceries in physical markets to e-grocery services. In future investigations, it might be possible to use a different motive variable, which can be done differently to help shed more light on this topic.

A strong correlation has also been found between the pull factor and switching behavior. The result of p-values smaller than significant value indicates that H_2 also has been supported for this study. Moreover, these findings are consistent with the outcomes of prior research by Abbas et al. (2021), Do and Le (2020), and Pratama, Aditya, Putra, and Hendriana (2024), which found that the positive influence of pull factors on decisions that made by students when to study abroad. Meanwhile, the attractiveness of e-grocery shopping as the pull factor has a binding effect on the switching cost and intention to switch to e-grocery shopping (Monoarfa, Sumarwan, Suroso, & Wulandari, 2023). In addition, it has been found to have a pull effect on the intention to switch from traditional methods to distance learning methods (Lin, Chien, Hung, Chen, & Ruangkanjanases, 2021). Pull factors also affect the intention to switch to digital application services (Zhang, Oh, & Lee, 2021), as reflected in the consistency and quality of Peer-to-Peer accommodation services.

Lastly, the result indicates the analysis between mooring factors and switching behavior. The findings of this analysis, which provide different perspectives in this study $H_{3,}$ are not supported. The mooring factor that has been used for this study is Involuntary Choice. This study indicates that students did not connect emotionally to their type of study in determining their switching behavior. This result is consistent with Lisana (2023), who indicates that students did not connect emotionally to their network when developing their switching intention to use mobile learning. This result is consistent with the investigation study of mobile payment adoption by Lisana (2021). Moreover, a study by Zhou (2016) also determines that mooring factors, which are switching costs, hurt switch intention.

5. Managerial Implications and Recommendations

There are various ways to look at the implications. The educational institution should list the drawbacks of traditional learning environments, such as strict timetables, and a restricted selection of courses. By considering these drawbacks in consideration, educators may create more adaptable and easily accessible online learning. Furthermore, institutions should invest in technological innovations, such as interactive content, adaptive learning technologies, and immersive virtual environments, to create a compelling and differentiated online learning experience. These enhancements can significantly increase the appeal of online learning and encourage switching behavior. To increase the legitimacy of online education and reduce institutional resistance, institutions should collaborate closely with accreditation and regulatory bodies to include online learning in the broader educational system. It is anticipated that the findings of this study shall provide a deep insight into students' perspectives on how they feel about online and offline learning. This study may also contribute to a better alliance of formal and informal support systems in the education field. Moreover, the research output will contribute significantly not only to the corpus of knowledge but also to understanding the importance of comprehensive context towards determining the best factor in online and offline study.

The recommendations to be developed at the end of the research will be a list of factors the government can consider in developing comprehensive strategies for applying the best practices for Malaysian education. This will also allow for policy advice and reform suggestions to strengthen Malaysian education further. Originality/value: The research on university students' offline-to-online learning switching behavior utilizing the push-pull-mooring theory holds significant originality and value in education and behavioral psychology. The research offers a unique cultural perspective by focusing on Malaysian Public University students, potentially uncovering nuances in switching behavior that may differ from other regions. Overall, this research adds valuable knowledge to the ongoing discourse on educational adaptability and enhances learning environments in the digital age.

Conclusion

The offline-online learning switch among university students has dramatically altered the educational landscape. Grasping the dynamics behind this transition is fundamental to optimizing students' experiences and outcomes in the new learning frontier. Push factors are factors that encourage learners to switch to online learning environments, including the constraints and challenges encountered with traditional offline learning platforms. On the other hand, learners who are searching for flexibility, accessibility, and a wider variety of educational options are primarily motivated by pull factors, which are defined as the intrinsic benefits and alluring features of online learning. Mooring factors, which include both individual and contextual elements, can help or interfere with learners in this transition by addressing the challenges they may encounter from their personal, technological, and institutional environments. With a deeper understanding of the factors fueling offline-online learning switching behavior among university students, educators can tailor their teaching methods to meet the learners' evolving needs. The Push-Pull-Mooring theory acts as a solid framework for analyzing these factors. The results demonstrate that push and pull variables influence students' decision to switch behaviors. In contrast, the mooring elements do not play a significant role in influencing students' decisions.

Meanwhile, policymakers can make informed decisions to build a flexible, inclusive education system that embraces the digital age. Based on the Push Pull Mooring Theory, this paper has provided a comprehensive overview of the factors determining offline-online learning switching behavior among university students. Through deeper understanding, educational institutions and policymakers can gear up to effectively provide a blended learning environment that meets the evolving needs of their students. To better understand the factors influencing students' switching behavior. University students of this digital age stand at the forefront of this radical shift in learning models, presenting a new wave in education.

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