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Do you want to Learn? The Motivating Reasons behind Individual Switching Behavior on Nonformal Education Platforms based on Push-Pull-Mooring Framework

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DO YOU REALLY WANT TO LEARN? THE MOTIVATING REASONS BEHIND INDIVIDUAL'S SWITCHING BEHAVIOUR ON NONFORMAL EDUCATION PLATFORM BASED ON PUSH-PULL-MOORING FRAMEWORK

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ABSTRACT

While the online learning industry has a positive growth rate, the completion rate has remained low in recent years. Previous studies have examined the influence of the push-pull-mooring effect on individuals' intentions to switch to non-formal educational platforms. Since financial and usability factors had been overlooked, this study added perceived price and perceived usefulness factors. Based on the push-pull-mooring framework, the study aimed to explore the drivers of users' intentions to switch for performance on non-formal education platforms. Data were gathered through an online survey of 370 respondents. Covariance-based structural equation modeling (CB-SEM) was used to analyze the data. The study's results showed an indirect influence of perceived price and perceived usefulness factors on individuals' switching intentions. By understanding the driving reasons behind the intention to switch to non-formal education platforms, the research was expected to assist education platform providers in developing platform services aligned with user needs.

Keywords: non-formal education, learning platform, switching behavior, online education, platform switching

Introduction

Online education platforms are becoming increasingly popular in Indonesian society. In 2022, the online education industry in Indonesia recorded revenue from in-app purchases of $4.87 million. This figure increased to $5.27 million in 2023 and is projected to reach $5.67 million in 2024. In terms of total downloads of education platforms, there were 125.2 million downloads in 2023, and it is estimated to increase to 137.9 million downloads in 2024 (Statista, 2022). The continuous increase in demand each year reflects the population's preference for digital learning methods. This trend is also supported by the push for professional skills development, leading to an increase in language learning and professional and vocational education platforms.

In the Statista report (2022), online education in Indonesia indicates that a total of 81.58 million hours were spent on learning management, 38.49 million hours on language learning platforms, and 12.19 million hours on professional education platforms. The i360 Report (2020) found that the most extensive segmentation in the online education industry in Indonesia is the MOOC (Massive Open Online Course) segment and the marketplace segment. The MOOC segment provides courses that offer learning services accessible to many students simultaneously. MOOCs use learning management systems (LMS) to distribute learning materials. Some well-known LMS platforms are EdX, Canvas, Coursera, and Udacity.

Meanwhile, the marketplace segment, similar to the concept of e-commerce, bridges educators and students. The marketplace segment provides services such as tutoring centers, language schools, and private tutors. One example of a marketplace segment platform is Ruang Guru and Cakap. These two segments are the largest in Indonesia because they can meet students' specific needs and preferences. An example of the Ruang Guru platform is that it allows students to find teachers who suit their learning needs.

Despite the significant potential indicated by the increasing market size of the online education industry and the government's support through the integration of the two tracks, there does not seem to be an increase in the desire to learn. Research conducted by Hollands et al. (2018) at Columbia University, studying the EdX and Coursera platforms, shows a completion rate of only 15% of the courses followed. This figure has remained low for the past 4 years. Research by Reich (2014) at Harvard University states that only 22% of students intend to complete courses and obtain certificates. Considering the very low completion rate of education platforms, an interesting phenomenon occurs where the revenue obtained by the online education industry comes from students who do not complete the courses they purchase.

This phenomenon has drawn the attention of researchers, as the low completion rate contrasts with the increasing performance of the online education industry year after year. Researchers employed the Push-Pull Mooring Framework to understand the phenomenon of high switching intention to online platforms despite the low completion rate. The intention to switch or switch behavior can be explained through the Push-Pull Mooring Framework (Lin et al., 2021). This framework was first proposed by Everett Lee in 1966 in migration theory and further developed by Rogers in 1983 in the diffusion of innovation theory (DOI). The Push-Pull-Mooring theory provides a robust foundation for understanding the dynamics of individual decisions in transitioning to online education (Chen & Keng, 2019). It emerges as a relevant conceptual framework for understanding the dynamics behind learners' decisions to switch to educational platforms (Lin et al., 2021). Push, pull, and mooring factors are interrelated and can provide deep insights into learners' choices regarding non-formal education platforms. The behavior of online user switching and population migration share similar characteristics, involving movement from one place to another. Therefore, the Push-Pull-Mooring (PPM) theory can be used to understand better user switching behavior (Hou et al., 2011).

Previous research conducted by Nayak et al. (2022) used DOI theory as a basis to explain why students switch to online education. This study used a combination of extended TAM and DOI theory. This is based on research conducted by Al-Rahmi et al. (2019), which also explains behavioral intention (BI) in online education using extended TAM and DOI theory. However, in this study that uses extended TAM, the perceived usefulness variable, which is the main component of TAM, was not included. This study also did not include economic factors in the PPM framework. Economic factors such as perceived price are important variables that can motivate students to switch. Offline course students have experienced physical learning. Suppose the learning level is not adjusted, and the quality remains constant or similar to that of other courses. In that case, students will be more inclined to focus on minimizing price (Garbarino & Maxwell, 2010), which will motivate them to seek better course prices. Research conducted by Chen and Keng (2019) showed that perceived price and usefulness play a significant role in motivating students to switch. Considering this, the researcher tried to provide a new understanding by adding two variables: perceived price and perceived usefulness to the PPM framework.

Aims

This study aimed to understand the factors contributing to the low completion rates of online courses in Indonesia despite the substantial growth in user engagement and industry revenue. It sought to uncover the reasons behind the discrepancy between the high number of enrollments and the relatively low percentage of students who finish their courses. By exploring both the motivations and barriers faced by users, the study aspired to provide a deeper understanding of user behavior within the context of online education. Ultimately, the research aimed to generate actionable insights that can improve course design, delivery, and support mechanisms, enhancing the effectiveness and appeal of online education platforms in Indonesia.

Purpose

This study aimed to analyze why users switch to online education platforms and identify the factors contributing to low course completion rates. By employing the push-pull-mooring (PPM) framework, the study systematically investigated the elements that influence users' decisions to engage with and persist in online learning environments. It sought to understand the motivations that drive individuals toward online education as well as the specific challenges they face that hinder course completion. The findings informed the development of user-centered strategies that enhance the online learning experience and improve outcomes for users in Indonesia.

Objectives

The study's objectives were threefold. First, it aimed to identify the push factors that drive users to transition to online education platforms, revealing the reasons that compel individuals to engage with these learning environments. Second, it sought to evaluate the pull factors that make online platforms attractive, highlighting the features and benefits that encourage users to choose and remain on these platforms. Third, the study investigated the mooring factors that influence users' decisions to complete or abandon their courses, examining social support, intrinsic motivation, and external commitments. By addressing these objectives, the research aimed to provide insights that can help online education providers better support their users and achieve higher completion rates.

Literature review

Push, pull, and mooring framework

The Push-Pull-Mooring (PPM) framework, stemming from migration theory pioneered by Everett Lee in 1966, elucidates individual adoption decisions concerning innovations, services, or products. Lee introduced the concept to explain migration patterns, defining migration as a change of residence driven by push, pull, and mooring factors. Push factors impel individuals to leave their origin, pull factors attract them to a destination, and mooring factors anchor them despite push-pull dynamics. Rogers (1983) further developed the framework within the Diffusion of Innovation theory, categorizing factors into push (motivations for change), pull (advantages of the innovation), and mooring (emotional ties to the origin). This framework offers insights into understanding user switching behavior online, akin to population migration, emphasizing the interplay of motivations, benefits, and emotional connections in decision-making (Hou et al., 2011). User switching behavior online and population migration share similar characteristics, involving movement from one place to another. Therefore, the Push-Pull-Mooring (PPM) framework can be used to understand better user switching behavior (Hou et al., 2011).

Push factors

In the context of the push-pull mooring framework, "push" refers to external factors that drive or influence an individual or organization to behave or take certain actions (Rogers, 1983). The push effect pertains to negative factors that urge people to leave their origin (Coast et al., 1998).

Platform knowledge scope

Platform knowledge scope (PKS) is crucial for understanding the effectiveness and efficiency of learning in online courses (Cheng et al., 2019). PKS encompasses three variables: the effectiveness and efficiency of learning, the development of new teaching models, and individuals' progress and personal development (Alhumaid et al., 2020; Crawford et al., n.d.; Teräs et al., 2020). Nayak et al. (2022) define these three components as platform knowledge scope.

Experts and educators have leveraged online education platforms extensively as a teaching medium (Deming et al., n.d.). Technological advancements in educational platforms facilitate user transition between products with similar functions (Xu et al., 2021). Consequently, online education platforms provide the technological framework for conducting online courses and support educational institutions in designing, producing, and delivering these courses (Chirikov et al., 2020). These platforms are promising for individuals looking to enhance their skills and performance (Nayak et al., 2022). Nayak et al. (2022) argue that online education boosts individuals' decision-making confidence by aiding their learning process.

The flexibility in developing new learning models and relevant materials is a key strength of online platforms (Nayak et al., 2022). Online education platforms offer opportunities for individuals to improve their skills and performance. Schunk and Zimmerman (1994) state that individuals motivated by relevant learning materials are more driven to learn. Research by Xu et al. (2021) indicates that individuals are inclined to switch to and commit to online education that enhances their knowledge, skills, and performance. The development of materials and learning models is thus a significant factor for such a transition and commitment to online education. Therefore, it can be assumed:

- H1: Platform knowledge scope (PKS) positively influences decision self-efficacy (DSE)
- H2: Platform knowledge scope (PKS) positively influences motivation & intention for switching (MIS)
- H3: Platform knowledge scope (PKS) positively influences switching behavior for performance (SBP)

Perceived price

Perceived price (PP) is a crucial concept in consumer behavior, referring to individuals' perception of the value or sacrifice associated with a product or service rather than the actual listed price (Phan Tan & Le, 2023). Beneke and Zimmerman (2014) distinguish between the actual product price and the price perceived by buyers, emphasizing that consumers tend to interpret prices in personally meaningful ways. This subjective perception often holds more weight than the actual price, as consumers can perceive the same price differently depending on their unique contexts and experiences.

In this study, price perception encompasses monetary costs and perceived sacrifices such as time, effort, search, or psychic costs. Consumers who value their time and effort are susceptible to these sacrifices, significantly influencing their price perception (Yu et al., 2011). For individuals accustomed to physical learning in offline courses, maintaining similar quality levels while minimizing perceived sacrifices can motivate them to seek better-priced courses (Garbarino & Maxwell, 2010). Moreover, high perceived prices can lead customers to switch to other service providers that better align with their quality and price expectations (Xu et al., 2021). Thus, understanding perceived price is essential for anticipating consumer behavior and switching intentions in the context of online education. Considering this, it can be assumed:

- H4: Perceived price (PP) negatively influences motivation & intention for switching (MIS)
- H5: Perceived price (PP) negatively influences switching behavior for performance (SBP)

Pull factors

The primary pull factor involves influencing individuals to switch from one place to another (Lee, 1966). It drives the intention to switch, emerging when the provided platform or service is more satisfying (Tang & Chen, 2020; Xu et al., 2021). Similarly, from a service perspective, higher service quality generates a stronger pull effect, urging consumers to switch to new services (Keaveney, 1995).

Alternate media attractiveness

Nayak et al. (2022) define alternate media attractiveness (AMA) as the increasing interest of individuals in switching to educational platforms, driven by their preference for online education as a tool to enhance career opportunities. Factors driving AMA include the relevance of course materials to job market needs, the quality of online learning, and the flexibility offered by online programs. The positive attributes of an alternative service provider characterize attractiveness. According to Kim and Yoon (2004), the attractiveness of an alternative encompasses the quality of service, image, and reputation, suggesting that a substitute provider is expected to offer more suitable or superior services than the current one.

In the context of online learning, the functional value is a key determinant in consumer decision-making, reflecting a rational evaluation of the product (Chen & Keng, 2019). Individuals' decisions are influenced by the comparative ease provided by one platform over another, encompassing aspects such as usability, features, location, time, and training methods. The provision of superior learning resources, activities, instructor quality, and facilities can enhance users' skills and competitiveness, making the platform more attractive (Al-Kumaim et al., 2021). In competitive markets, platforms that offer advanced features like artificial intelligence and the Internet of Things can stimulate switching behavior (Fang et al., 2019). Conversely, users tend to remain with their current provider if they are unaware of more attractive alternatives. Online courses are perceived as opportunities to gain valuable experience and knowledge applicable to future work (Crawford et al., 2020), supported by robust IT infrastructure and expert-driven quality materials (Chirikov et al., 2020). The ease and freedom provided by online education platforms enhance the likelihood of individuals switching to online education (Knightley, 2007). Considering this, it can be assumed that:

- H6: Alternate media attractiveness (AMA) positively influences decision self-efficacy (DSE)

- H7: alternate media attractiveness (AMA) positively influences motivation & intention for switching (MIS)
- H8: Alternate Media Attractiveness (AMA) positively influences switching behavior for performance (SBP)

Perceived usefulness

Perceived usefulness (PU), also known as utility, is a key factor in the Technology Acceptance Model (TAM) proposed by Fred D. Davis (1989). TAM explains how individuals adopt and use new technology, with perceived usefulness defined as the extent to which an individual believes that using a particular technology will enhance their performance (Davis et al., 1989). Common dimensions of perceived usefulness measured in TAM research include increased productivity, job effectiveness, job quality, goal achievement, and the acquisition of knowledge and skills. Perceived usefulness strongly influences users' attitudes and intentions to use technology. The higher an individual's perceived usefulness, the more positive their attitude toward the technology and the greater their likelihood of using it (Venkatesh et al., 2003).

The Technology Acceptance Model (TAM) has been utilized in numerous studies to explain and predict user acceptance of specific types of systems (Davis et al., 1989). When users recognize a new technology product's usefulness and ease of use, they exhibit a positive attitude toward that technology, influencing their intention and behavior. Additionally, individuals who believe that using an educational platform can enhance their learning performance tend to be more motivated towards that platform (Chen & Keng, 2019). Consequently, when individuals find online education beneficial, they are more likely to switch to using that platform (Liu et al., 2010). Given that perceived usefulness is related to the improvement of learning performance resulting from the educational platform, this study defines the perceived usefulness of the learning platform as a perceived usefulness effect. When the perceived usefulness of the learning platform is more significant than traditional classroom learning, their intention to switch from physical learning to the learning platform will be higher. Considering this, it can be assumed:

- H9: Perceived usefulness (PU) positively influences motivation & intention for switching (MIS)
- H10: Perceived usefulness (PU) positively influences switching behavior for performance (SBP)

Normative environmental pressure

Normative pressure, the urges or demands of social norms, rules, or group expectations, plays a powerful role in shaping individuals' decisions to stay or leave (Ramesh & Gelfand, 2010). It can impose demands and expectations, but it also empowers individuals to make choices that align with their goals. Normative environmental pressure, stemming from network effects (Cheng et al., 2019), is a force for positive change. In this study, NEP is based on several factors, including the influence of friends and relatives encouraging individuals to switch to online courses.

Normative pressure refers to the influences or demands from social norms, rules, or group expectations that affect individuals. These influences or demands shape an individual's decision to stay or switch (Ramesh & Gelfand, 2010). In the theory proposed by Bandura (1977) through Social Learning Theory, four main sources are mentioned that can enhance self-efficacy: mastery experiences (successfully completing tasks), vicarious experiences (observing others' successes), social persuasion (receiving support and encouragement), and physiological states (managing stress and emotions). Considering that vicarious experiences and social support and encouragement are key factors that shape self-efficacy, it can be assumed:

- H11: Normative Environmental Pressure (NEP) positively influences Decision Self-Efficacy (DSE)

Peer influence is a significant motivator for individuals to try new online courses (Alhumaid et al., 2020) and to complete those courses (Hodges et al., 2020). This social dynamic is a key consideration in this study.

- H12: Normative Environmental Pressure (NEP) positively influences Motivation and Intention for Switching (MIS)

Individuals are more likely to have the intention to switch to an online course or platform if they have peer companions. Some individuals prefer online courses or platforms if encouraged or accompanied by peers, despite differences in price, features, and other factors (Xu et al., 2021). Considering this, it can be assumed:

- H13: Normative Environmental Pressure (NEP) positively influences Switching Behaviour for Performance (SBP)

Mooring factors

Mooring factors refer to the personal and social impacts that can either encourage or deter an individual from leaving or staying in their residence (Moon, 1995).

Decision self-efficacy

Albert Bandura first developed the concept of self-efficacy in 1977 as part of the Social Learning Theory. Self-efficacy is defined as an individual's belief in their ability to succeed in specific situations, drawing from personal experience, vicarious experiences (observing others), social persuasion (encouragement from others), and physiological states (Bandura, 1977). Self-efficacy is crucial in motivation, behavioral choices, and individual achievements. Individuals with high self-efficacy are more likely to set challenging goals, persevere in the face of difficulties, and remain resilient. Conversely, those with low self-efficacy risk avoiding challenges, giving up quickly, and achieving less (Bandura, 1977).

Further research has explored factors influencing self-efficacy. Bandura (1977) identified four main sources that enhance self-efficacy: mastery experiences (successfully completing tasks), vicarious experiences (observing others' successes), social persuasion (receiving support and encouragement), and physiological states (managing stress and emotions). Additionally, studies have found that self-efficacy can be influenced by personal factors such as self-confidence and optimism and environmental factors like social support and cultural influences. Previous research by Nayak et al. (2022) defines decision self-efficacy as individuals' choice to opt for online education to enhance or support their learning. Nayak et al. (2022) suggest that the availability of features and the ease of use of learning platforms can influence individuals' decision-making, affecting their self-efficacy.

Individuals also view online education as a substitute for classroom learning (Senthamarai, 2018). Those who see digital educational platforms as value-adding are motivated to choose and use them in online courses (Hodges et al., 2020). This indicates a tendency for individuals to adapt to online platforms to enhance their skills and knowledge (Teräs et al., 2020). In e-learning systems, learning motivation includes intrinsic, extrinsic, self-efficacy, and learning experience (Chang et al., 2015). Self-efficacy is an important factor that motivates individuals to use online education. Considering this, it can be assumed:

- H14: Decision self-efficacy (DSE) positively influences Motivation & Intention for Switching (MIS)
- H15: Decision self-efficacy (DSE) positively influences Intention to Adapt for Knowledge (IAK)

Motivation and intention for switching

Nayak et al. (2022) posit that motivation and intention are pivotal for switching. Motivation, defined as internal forces propelling individuals to act and achieve goals (Eccles & Wigfield, 2002), is crucial in online education, representing the desire and determination to learn and complete programs (Chen & Keng, 2019). Factors like interest, relevance, beliefs, and values play significant roles in fostering motivation for online learning (Schunk & Zimmerman, 1994; Bandura, 1977; Eccles & Wigfield, 2002). Intention, conversely, refers to an individual's commitment to specific actions (Ajzen, 1991) concerning online education, denoting students' dedication to completing programs and achieving learning objectives (Nayak et al., 2022). Perceived usefulness and support, including encouragement from family, friends, and instructors, influence individuals' intentions toward online learning (Ajzen, 1991; Alhumaid et al., 2020). Technology integration has also become an integral part of the academic environment. Although technology has merged into everyday life, some individuals are more adept at using technology than others. For some, mastering new technological skills is significant (McCoy, 2010). It has been observed that there is a relationship between the need to use new learning technologies for educational purposes and the ability to adopt these technologies to drive changes in how individuals want and are willing to learn (Nayak et al., 2022). There is also a correlation between the level of learning completion in courses driven by individual motivation (Anyatasia et al., 2020). Considering this, it can be assumed:

- H16: Motivation and intention for Switching (MIS) positively influence Intention to Adapt for Knowledge (IAK)

Intention to adopt knowledge

Nayak et al. (2022) define Intention to adapt for knowledge (IAK) as depicting students' desire and motivation to utilize online learning opportunities to expand their knowledge base. This concept emerged during the COVID-19 pandemic, where prolonged lockdowns necessitated a shift to online education. IAK is influenced by several factors, including active information seeking, focus on knowledge development, and learning motivation (Nayak et al., 2022). Individuals with high IAK actively search for information and reviews of online courses to identify the most relevant and valuable learning opportunities (Willging & Johnson, 2009). They use their spare time to explore online resources, driven by a desire to expand their knowledge base (Grouws & Cebulla, 2000). IAK represents a strong motivation for lifelong learning, as individuals with high IAK recognize the importance of broad knowledge for future success. Individuals who push themselves to adapt to using online education platforms can improve their learning performance (Alhumaid et al., 2020; Hodges et al., 2020). Nayak et al. (2022) mention that the intention to adapt for knowledge (IAK) is based on active information seeking, focus on knowledge development and learning motivation. Individuals with high IAK actively seek information and reviews of online courses to identify the most relevant and valuable learning opportunities (Willging & Johnson, 2009). Those with IAK use their free time to explore online resources, driven by a desire to expand their knowledge base (Grouws & Cebulla, 2000). IAK is a strong motivator for acquiring knowledge and lifelong learning. Individuals with high IAK recognize the importance of broad knowledge for future success. Researchers assume that individuals with high IAK will have a solid intention to switch to online education. Considering this, it can be assumed:

- H17: Intention to adapt for knowledge (IAK) positively influences Switching behavior for performance (SBP)

Switching behavior for performance

Switching behavior for performance (SBP) refers to consumers' tendency to move from familiar brands, products, or services to those of competitors (Oliver, 1997). Zeithaml et al. (1988) argue that SBP is not just about switching but also involves evaluation and consideration before making the decision. In the educational context, individuals' transition to online learning platforms from traditional offline classes can be called switching behavior (Chen & Keng, 2019). Nayak et al. (2022) define switching behavior for performance as individuals' intent to switch to online learning platforms and courses more seriously, indicating the intention to switch and the time, effort, and attention individuals dedicate to online course learning.

Methodology

Research model

The model employed in this study builds upon the research by Nayak et al. (2022). This research utilizes several PPM (Push-Pull-Mooring) factors influencing the transition to educational platforms. The study elucidates the adoption process undertaken by individuals towards educational platforms. The PPM framework is used as the theoretical model. Unlike other studies employing the PPM framework, this research integrates self-efficacy, motivation, and intention as mediators between the PPM factors and the intention to switch to educational platforms. Nayak et al. (2022) argue that individuals who perceive online education as a means to enhance their skills demonstrate greater efficiency, effectiveness, and a stronger desire to engage in online learning, leading to their decision to transition to online education. Nayak et al. (2022) study utilized PPM variables as follows: the push variable consisted of platform knowledge scope (PKS), the pull variables included alternative media attractiveness (AMA) and normative environmental pressure (NEP), and the mooring variables, which also served as mediating variables, comprised decision self-efficacy (DSE), motivation, and intention for switching (MIS). The intention to re-adapt for knowledge (IAK) was also a mediating variable but was not part of the mooring variables. As a result, all direct effects from PKS, AMA, and NEP towards SBP were insignificant. Furthermore, economic factors and perceived usefulness were also incorporated as PPM factors. However, the results did not demonstrate significant support for a change in switching behavior for performance.

To address this, the researchers revisited the topic with additional studies. Chen and Keng (2019) examined the push, pull, and mooring factors influencing individuals' intentions to switch from offline English language learning to using educational platforms for English learning. This study posited that perceived price and perceived usefulness are significant factors driving individuals to transition to online education. These two variables are crucial in determining individuals' intentions to switch. Individuals' perceptions of the cost of online education influence their motivation and intention to switch. The lower the perceived cost of online education, the more motivated individuals are to switch. Similarly, perceived usefulness plays a role; when individuals perceive online education as beneficial for their learning process, they become more motivated to switch to online education (Chen & Keng, 2019). To address the gaps identified in Nayak et al.'s (2022) research, the current study incorporated these variables, perceived price, and usefulness, into the analysis.

Chen & Keng's (2019) study included other variables: push factors like learning convenience and service quality, pull factors like e-learning motivation, and mooring factors like social presence, switching cost, and learning engagement. This study showed that the pull effect was the most significant switching force. The push and mooring effect had a negative influence on switching intention. The variable learning convenience is a push factor, represented by the variable alternative media attractiveness, a pull factor. Alternative media attractiveness discusses how educational platforms compete to attract individuals through features such as social interaction, ease of learning, and service quality (Nayak et al., 2022). Hsieh et al. (2012) also used convenience as a pull factor. The switching cost variable is represented by perceived price because perceived price encompasses not only monetary cost but also the time and effort involved (Beneke & Zimmerman, 2014). Social presence and learning engagement, mooring variables, represented by normative environmental pressure, a pull variable. Li & Ku (2018) used social factors, including the presence of others and social interaction, as pull factors.

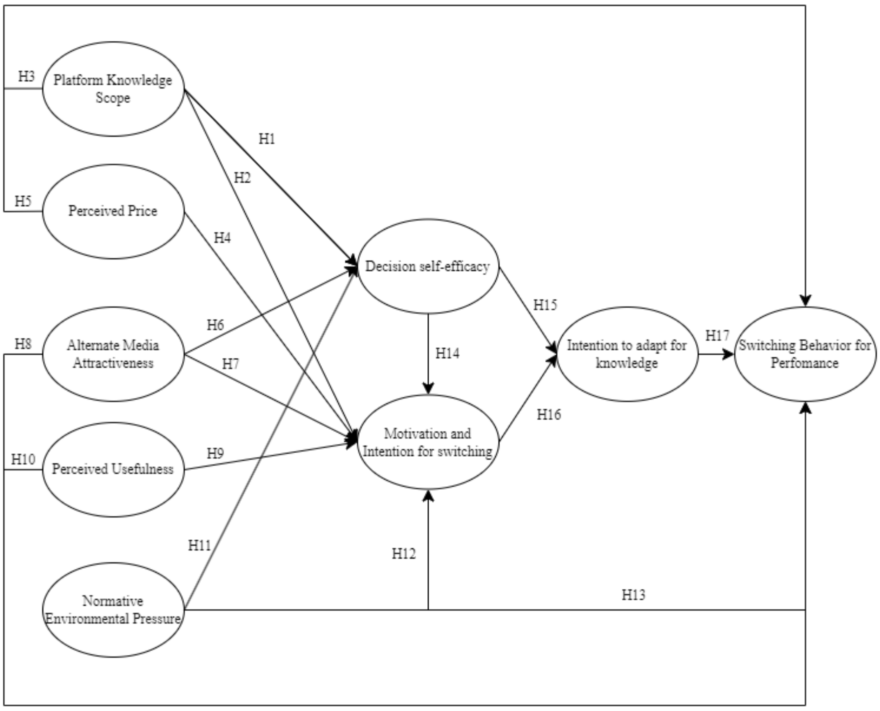

Figure 1: Conceptual framework

This study's push factors include platform knowledge scope and perceived price. Hsu (2014) identified push factors as those driving individuals to switch to another product. Platform knowledge scope compares offline and online learning. If individuals perceive online courses as superior, they will be motivated to switch to online courses (Nayak et al., 2022). Similarly, when individuals perceive that the cost of offline courses is not commensurate with their value, they will be driven to switch to online courses (Chen & Keng, 2019). Thus, this study's platform knowledge scope and perceived price are push factors. The pull factors in this study are alternate media attractiveness, perceived usefulness, and normative environmental pressure. Hsu (2014) identified pull factors as those attracting individuals to a product. Alternate media attractiveness pertains to features that capture individuals' attention (Nayak et al., 2022; Sun et al., 2017). Supported by perceived usefulness, when individuals find the provided features useful and beneficial for their development, they are more inclined to use the product (Chen & Keng, 2019; Kang et al., 2021). Normative environmental pressure involves the influence of social expectations and pressures. When individuals see that their environment suggests and uses a product, they are likelier to use it (Nayak et al., 2022; Sprague & IEEE Computer Society, 2009). Thus, alternate media attractiveness, perceived usefulness, and normative environmental pressure are pull factors in this study. The variable normative environmental pressure was modified to show a relationship between decision self-efficacy and switching behavior for performance.

The mooring factors, decision self-efficacy, motivation, and intention for switching also serve as mediators. This follows previous research by Nayak et al. (2022). According to the PPM framework, mooring factors do not directly influence switching intention; some may act as mediators or moderators affecting switching intention (Lee, 1966). When push and pull factors are strong, but mooring is weak, individuals are inclined to stay with the previous product

(Bansal et al., 2005). For instance, Nayak et al. (2022) used mooring variables as mediators between push and pull factors and switching behavior for performance. Monoarfa et al. (2023) found that switching cost mediated the relationship between push and pull factors and individuals' intention to switch to E-grocery. Thus, the mooring variables in this study also functioned as mediators for push and pull factors. Finally, the intention to re-adapt to knowledge will be a mediator, consistent with previous research (Nayak et al., 2022).

Instrument

Respondents answered 29 questions related to the research variables, including platform knowledge scope (4 items) (Nayak et al., 2022), perceived price (3 items) (Chen & Keng, 2019), alternate media attractiveness (3 items) (Nayak et al., 2022), perceived usefulness (3 items) (Chen & Keng, 2019), normative environmental pressure (3 items) (Nayak et al., 2022), decision self-efficacy (3 items) (Nayak et al., 2022), motivation and intention for switching (4 items) (Nayak et al., 2022), intention to adapt for knowledge (3 items) (Nayak et al., 2022), and switching behavior for performance (3 items) (Nayak et al., 2022). The scale in this study was measured using a 5-point Likert scale. According to Arikunto (2016), the Likert scale measures individuals' or groups' attitudes, perceptions, and opinions.

Table 1: Operational Variable

Constructs	Measure	
Platform knowledge scope (Nayak et al., 2022)	PKS1	Online learning platforms contribute a lot to my personal development
	PKS2	Online learning platforms help improve my performance in comparison to classroom teaching.
	PKS3	Online learning platforms help improve my effectiveness in comparison to classroom teaching.
	PKS4	Online learning platforms help me manage my learning efficiency compared to classroom teaching.
Perceived price (Chen & Keng, 2019)	PP1	The price of physical learning is lower than online courses
	PP2	The price of physical learning is more reasonable than online courses.
	PP3	The price of physical learning is more approachable than online courses.
Alternate media attractiveness (Nayak et al., 2022)	AMA1	Online courses should have content that meets industry requirements
	AMA2	Online courses should provide better learning value, considering the price charged.
	AMA3	Online courses should help me become better skilled in the field of my study.
Perceived usefulness (Chen & Keng, 2019)	PU1	Online courses should be convenient
	PU2	Online courses are helpful for my learning.
	PU3	Online courses save me time.
Normative environmental pressure (Nayak et al., 2022)	NEP1	I get influenced to study a particular course or certification online when my friends think it is appropriate to undertake.
	NEP2	I get influenced to study a particular course or certification online when my friends consider it necessary to do it.
	NEP3	I get influenced to study a particular course or certification online when my friends have already completed it.
Decision self-efficacy (Nayak et al., 2022)	DSE1	I can motivate and change myself to experience a suitable online platform with ease.
	DSE2	I can motivate and change myself to learn to use the features offered by online platforms.
	DSE3	I can motivate and change myself to streamline my learning efforts with an online platform methodology.

Constructs	Measure	
Motivation intention for switching (Nayak et al., 2022)	MIS1	In the future, when I study online courses, I would like to increase the time I devote
	MIS2	In the future, when I study online courses, I would like to be determined to take up the course/ certification options.
	MIS3	In the future, when I study online courses, I would like to have more focus while choosing the online courses/certifications.
	MIS4	In the future, when I study online courses, I would like to increase my level of effort to learn from the online course/certification.
Intention to adopt for knowledge (Nayak et al., 2022)	IAK1	In the next few months, I intend to invest time in online courses to increase my knowledge base
	IAK2	In the next few months, I intend to invest effort in online courses to improve my knowledge base.
	IAK3	In the next few months, I intend to search for different online sources of courses to improve my current knowledge base.
Switching behavior for performance (Nayak et al., 2022)	SBP1	In the future, I will prefer to consider online courses/certifications as a substitute for classroom teaching.
	SBP2	In the future, I would prefer to increase the time I devote to online courses relative to the time I devote to classroom teaching.
	SBP3	In the future, I will prefer to believe that I will be able to switch to online learning mode substantially.

Data collection

A definitive and illustrative research design was utilized to examine the research hypothesis and obtain a thorough understanding of the target demographic. Information was gathered via a cross-sectional approach using an online survey from January to March 2024. Only individuals who meet the criteria will be selected to participate in this survey. The required criteria are individuals who have taken an online course, obtained certification, and fall within the age range of Gen Z and Gen Y (12-39 years old).

The determination of the minimum sample size for SEM, according to Hair et al. (2019), is (Number of items) x (5 to 10 times). Since the number of measurement items in this study is 29 items, the sample size for this research would be 145-290 respondents. The survey gathered 410 questionnaires, and 370 valid questionnaires were returned. Table 2 shows the demographic distribution of the sample. Among these valid respondents, males account for 59%, and females account for 41%. 80% of respondents were between the ages of 20 and 29. Most respondents get a bachelor's degree or higher for education background demographics. Most respondents (69%) used professional and vocational as their course type, and 44% chose low course prices (<Rp 500.000).

Table 2: Respondent profile

Variable	Levels	Frequency	Percentage (%)
Age	15-19	9	2
	20-29	294	80
	30-39	67	18
Gender	Male	217	59
	Female	153	41
Education	High school or below	31	8
	Bachelor's degree	279	77
	Master's degree or higher	54	15
Course type	Language	50	14
	Tutor	65	17
	Professional and vocational	255	69
Course price	< Rp 500.000	162	44
	Rp 500.000 - Rp 999.900	69	19
	Rp 1.000.000 - Rp 1.999.900	40	11
	Rp 2.000.000 - Rp 2.999.900	27	7
	Rp 3.000.000 - Rp 4.999.900	24	6
	Rp 5.000.000 - Rp 9.999.900	24	6
	> Rp 10.000.000	24	7

Data analysis

Common method bias

Common Method Bias (CMB) analysis is conducted to detect potential bias arising from responses collected using the same type of scale. This study examined variance inflation factors using Harman's test. The guideline for using Harman's test is that the variance of the first component should be less than 50%, and more than one component should be generated. If the variance of the first component is greater than 50%, it indicates collinearity or redundancy in the responses. Additionally, if only one component is generated, it also indicates collinearity (Hair et al., 2019).

Measurement model

According to the rule of thumb (Hair et al., 2019), Standardized loading estimates should be 0.5 or higher. Ideally, 0.7 or higher, and the Average Variance Extracted (AVE) value should be 0.5 or higher to suggest adequate convergent validity. Furthermore, items are considered reliable if Composite Reliability (C.R) and Cronbach's Alpha ≥ 0,70.

Covariance-based structural equation modeling (CB-SEM)

According to Hair et al. (2021), CB-SEM is considered more suitable for analysis when the research objective entails testing and confirming the theory along with its underlying hypotheses. The present study encountered this scenario, where the research aims to validate hypotheses derived from observed variables within the frameworks of push-pull mooring.

Structural model

After the absence of multicollinearity is verified, the next stage involves evaluating the model's capacity to anticipate internal constructs and/or measurable variables. According to Hair et al. (2019), the significance and relevance of the structural model relationships are evaluated by examining path coefficients (β), T values, and P values. P values, path coefficients (β), and T values with results ≤ 0.05 indicate a significant relationship between the observed variables.

Results and Discussion

CB (Covariance based) was adopted in this study to test both the measurement model (i.e., measures underlying each construct) and structural model (i.e., relationships among the conceptual of interest) simultaneously (Gefen & Straub, 2005). CB-SEM is well suited for testing theoretical models. It explicitly accounts for measurement error, which improves the reliability and validity of the relationships between constructs (Hair et al., 2019). In addition, 370 respondents were enough to use CB-SEM analysis. SmartPLS4 was used as the main analysis technique in this study.

Measurement model

Before model measurement, we evaluated the collinearity variance of the construct measures first. A collinearity variance test was conducted to detect potential bias originating from responses collected using the type of scale (Hair et al., 2019). Collinearity variance was examined using Harman's test. The critical value for the first component is 50%, and the number of components generated is more than one. Table 3 shows that the first component value is 22.668%, and 9 components were generated using Harman's test, suggesting that there are no potential biases from the data collected in this study.

Table 3: Harman's test for assessment of collinearity variance of constructs

Total	% of Variance	Cumulative %
6.266	22.668	22.668
2.266	9.077	31.745
2.111	8.421	40.167
1.963	7.695	47.862
1.513	6.573	54.434
1.348	6.070	60.504
1.080	4.789	65.293
0.959	4.583	69.876
0.886	4.150	74.026

Before testing hypotheses, we evaluated the reliability and validity of the construct measures first. The reliability of the measurement was examined using average variance extracted (AVE), composite reliability (CR), and Cronbach's Alpha. The critical values for AVE CR are 0.5 and 0.7, respectively, and the recommended value for Cronbach's Alpha is 0.7 (Fornell & Larcker, 1981). Table 4 shows that the minimum values of AVE, CR, and Cronbach's alpha were 0.529, 0.768, and 0.767, respectively. Each value was higher than the recommended value, suggesting that all constructs were reliable.

Table 4: Assessment reliability of constructs

Variables	Cronbach's Alpha (CA)	Composite Reliability (CR)	AVE
Platform knowledge scope (PKS)	0.815	0.816	0.530
Perceived price (PP)	0.791	0.777	0.561
Alternate media attractiveness (AMA)	0.795	0.795	0.564
Perceived usefulness (PU)	0.767	0.768	0.529
Normative Environmental Pressure (NEP)	0.882	0.882	0.714
Decision self-efficacy	0.866	0.865	0.685
Motivation and intention for switching (MIS)	0.817	0.819	0.531
Intention to adapt for knowledge (IAK)	0.885	0.887	0.720
Switching behavior for performance (SBP)	0.891	0.890	0.734

Structural model

Since the measurement model evaluation provides evidence of validity and reliability, the structural model was examined to evaluate the hypothesized relationships among the constructs in the research model (Hair et al., 2019). A range of indices was used to asses the model fit. Table 7 demonstrated broadly satisfactory levels of fit. The model fit indices, mainly the absolute fit indices, did not differ significantly from the measurement model, suggesting strong model validity.

Table 7: Model fit indices

Fit indices	Value	Desired value
Absolute fit indices		
ChiSqr/df	1.667	< 3
Goodness-of-fit Index (GFI)	0.907	≥ 0.90
Root Mean Square Residual (RMR)	0.051	≤ 0.6
Root Mean Square Error of Approximation (RMSEA)	0.042	< 0.05
Incremental fit indices		
Tucker-Lewis Index (TLI)	0.945	≥ 0.90
Comparative Fit Index (CFI)	0.953	≥ 0.90
Adjusted Goodness of Fit Index (AGFI)	0.884	≥ 0.90
Normed Fit Index (NFI)	0.891	≥ 0.90

Figure 2 presents the results of the CB analysis of the structural model. As expected, platform knowledge scope had significant positive effects on decision self-efficacy ($\beta = 0.196$, $t = 2.854$, $p < 0.01$) and switching behavior for performance ($\beta = 0.309$, $t = 4.521$, $p < 0.01$). This result indicates that the higher the knowledge scope of an online education platform, the more likely a person is to choose online education, accepting H1 and H3. Contrary to our expectation, the impact of platform knowledge scope had a significant negative effect ($\beta = -0.141$, $t = 1.903$, $p < 0.01$), indicating that the higher the platform knowledge scope of an online education platform, the lower a person's motivation and intention to switch to online education tends to be, rejecting H2. Perceived price had a significant negative effect on motivation and intention for switching ($\beta = -0.181$, $t = 2.702$, $p < 0.01$) but only modest on switching behavior for performance ($\beta = -0.043$, $t = 0.750$, $p > 0.01$), validating H4 and rejecting H5. This result indicates that a higher perceived price will lower a person's motivation to choose online education. There has been no research showing a relationship between perceived price and switching behavior for performance. However, the study by Kwarteng et al. (2020) indicates a negative relationship between perceived price and switching behavior in the context of online switching behavior. The path coefficient also shows a negative relationship between these two variables. However, the insignificant t-stat and p-value suggest that this relationship can be re-tested by changing the sample and increasing the sample size.

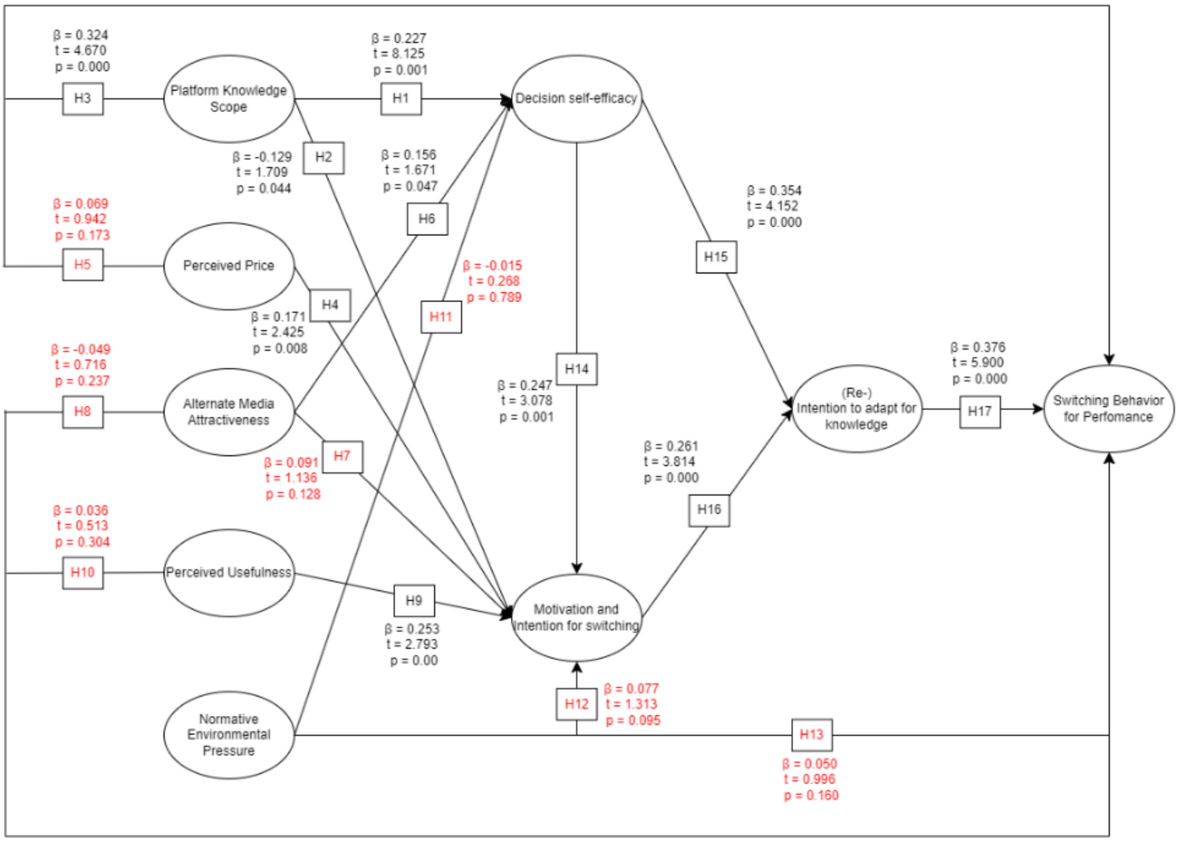

Figure 2: Results of the structural model

Alternate media attractiveness had significant positive effects on decision self-efficacy ($\beta = 0.169$, $t = 2.816$, $p < 0.01$), validating H6. On the contrary, the impacts of alternate media attractiveness towards motivation and intention for switching ($\beta = 0.095$, $t = 1.475$, $p > 0.01$) and switching behavior for performance ($\beta = -0.011$, $t = 0.190$, $p > 0.01$) were only modest, rejecting H7 and H8. This result indicates that a higher appeal of an online education platform does not necessarily increase an individual's motivation and intention to choose online education. Perceived usefulness had a significant positive effect on motivation and intention for switching ($\beta = 0.239$, $t = 3.220$, $p < 0.01$) but only modest for switching behavior for performance ($\beta = 0.108$, $t = 0.839$, $p < 0.01$), validating H9 and rejecting H10. This result indicates that the higher an individual's perception of the usefulness of an online education platform, the greater their motivation and intention to switch to online education tends to be. There has been no research showing a relationship between perceived usefulness and switching behavior for performance. However, the study by Kwarteng et al. (2020) indicates a positive relationship between perceived usefulness and switching behavior in the context of online switching behavior. This difference in context suggests that the relationship between perceived price and switching behavior for performance needs to be re-examined. The path coefficient shows a negative relationship between these two variables. However, the insignificant t-stat and p-value suggest that this relationship can be tested again by changing the sample and increasing the sample size. Lastly, for the pull effect, normative environmental pressure had no significant effect on decision self-efficacy ($\beta = -0.021$, $t = 0.399$, $p > 0.01$), motivation and intention for switching ($\beta = 0.047$, $t = 1.454$, $p > 0.01$) and switching behavior for performance ($\beta = 0.244$, $t = 0.953$, $p > 0.01$), rejecting H11, H12, and H13. As expected with our mooring factors, decision self-efficacy had a significant positive effect on motivation and intention for switching ($\beta = 0.241$, $t = 3.392$, $p < 0.01$) and intention to adapt for knowledge ($\beta = 0.354$, $t = 5.865$, $p < 0.01$), validating H14 and H15. Motivation and intention for switching had a significant positive effect on the intention to adapt for knowledge ($\beta = 0.262$, $t = 4.190$, $p < 0.01$) as well, validating H16. This result indicates that the higher an individual's motivation and decision to choose an online education platform, the greater their intention to adapt to learning and their motivation to switch to online education tends to be. Lastly, the intention to adapt to knowledge had a significant positive effect on switching behavior for performance ($\beta = 0.367$, $t = 6.396$, $p < 0.01$), validating H17, indicates that the higher an individual's intention to adapt to learning, the greater their likelihood of transitioning to online education tends to be.

Table 8: Hypotheses testing results

	Path	Path coefficients	Standard errors	T statistics	P-values	Result
H1	PKS→DSE	0.196	0.085	2.854	0.005	Supported
H2	PKS→MIS	-0.141	0.054	1.903	0.040	Not supported
H3	PKS→SBP	0.309	0.104	4.521	0.000	Supported
H4	PP→MIS	-0.181	0.039	2.702	0.007	Supported
H5	PP→SBP	-0.043	0.069	0.750	0.454	Not supported
H6	AMA→DSE	0.169	0.066	2.816	0.005	Supported
H7	AMA→MIS	0.095	0.042	1.475	0.141	Not supported
H8	AMA→SBP	-0.011	0.078	0.190	0.850	Not supported
H9	PU→MIS	0.239	0.074	3.220	0.001	Supported
H10	PU→SBP	0.108	0.129	0.839	0.611	Not supported
H11	NEP→DSE	-0.021	0.051	0.399	0.801	Not supported
H12	NEP→MIS	0.047	0.032	1.454	0.149	Not supported
H13	NEP→SBP	0.244	0.085	0.953	0.341	Not supported
H14	DSE→MIS	0.241	0.042	3.392	0.001	Supported
H15	DSE→IAK	0.354	0.071	5.865	0.000	Supported
H16	MIS→IAK	0.262	0.125	4.190	0.000	Supported
H17	IAK→SBP	0.367	0.060	6.396	0.000	Supported

Table 9 shows the results of the analysis of 13 mediation effects (indirect effects) based on the structural model. In the PKS→SBP path, significant mediation occurs through DSE→IAK→SBP and DSE→MIS→IAK→SBP, whereas MIS→IAK→SBP was not significant, with a p-value above 0.05. Given the significant mediation effects, it can be stated that DSE, MIS, and IAK mediate the relationship between PKS and SBP. This aligns with the hypothesis that PKS positively affects SBP, consistent with previous research by Nayak et al. (2022). In the PP→SBP path, the mediation path through MIS→IAK→SBP was significant, indicating that MIS and IAK mediate the relationship between PP and SBP.

In the AMA→SBP path, all mediation paths were not significant, supporting the hypothesis that AMA does not positively affect SBP. Since no significant mediation effects were found, DSE, MIS, and IAK were not mediators in the AMA→SBP relationship, differing from Nayak et al. (2022), where DSE, MIS, and IAK were mediators for AMA→SBP. This discrepancy may be due to geographical and national differences in sampling and respondent characteristics. In the PU→SBP path, the mediation path through MIS→IAK→SBP was significant, suggesting that MIS and IAK mediate the relationship between PU and SBP.

In the NEP→SBP path, no significant mediation effects were found through DSE, MIS, and IAK, supporting the hypothesis that NEP did not positively affect SBP. This differs from Nayak et al. (2022), where MIS and IAK were mediators for NEP→SBP, possibly due to different sampling and respondent characteristics.

Table 9: Mediator testing results

Path	Path coefficient	Confidence interval 95%		T statistics	P value	Result
		Lower Bound	Upper Bound			
PKS→DSE→IAK→SBP	0.046	0.016	0.087	2.050	0.020	Significant
PKS→MIS→IAK→SBP	-0.019	-0.043	-0.000	1.453	0.073	Not significant
PKS→DSE→MIS→IAK→SBP	0.008	0.002	0.017	1.788	0.037	Significant
PP→MIS→IAK→SBP	-0.017	-0.033	-0.006	2.104	0.018	Significant
AMA→DSE→IAK→SBP	0.029	-0.001	0.069	1.327	0.092	Not significant
AMA→MIS→IAK→SBP	0.012	-0.003	0.035	1.049	0.147	Not significant
AMA→DSE→MIS→IAK→SBP	0.005	-0.000	0.012	1.407	0.080	Not significant
PU→MIS→IAK→SBP	0.020	0.006	0.040	2.171	0.015	Significant
PU→DSE→MIS→IAK→SBP	0.010	0.002	0.021	1.639	0.051	Not significant
NEP→DSE→IAK→SBP	-0.002	-0.015	0.010	0.242	0.404	Not significant
NEP→DSE→MIS→IAK→SBP	-0.000	-0.003	0.002	0.239	0.406	Not significant
NEP→MIS→IAK→SBP	0.009	-0.002	0.023	1.182	0.119	Not significant

Conclusion

This study built on previous research by Nayak et al. (2022) and Chen & Keng (2019), exploring how push-pull-mooring effects influence switching behavior towards online education. Nayak et al. (2022) conducted their study among Indian students, enhancing the push-pull-mooring framework by incorporating mediation variables, which provided a nuanced understanding of the factors driving students to switch to online education. On the other hand, Chen & Keng (2019) focused on Taiwanese students, investigating their switching intentions specifically towards online English education without including mediation variables. Their study emphasized the direct influences on switching behavior, such as the appeal of learning English online.

In the context of Indonesian individuals engaging in nonformal online education, this study expands on these foundations by testing 17 hypotheses to understand the dynamics of switching behavior. Out of these, 10 hypotheses were accepted, and 8 were rejected, offering a detailed view of the factors at play.

The findings of this study highlight several key points. Firstly, the scope of platform knowledge (PKS) emerged as a significant determinant of switching behavior for performance, underscoring the importance of technological innovations and the dissemination of shared knowledge within online education platforms. This indicates that platforms with a broad and accessible knowledge base are more likely to attract and retain users.

Secondly, the perceived price was found to have an indirect influence on switching behavior through its effects on motivation and intention. Lower prices were shown to enhance individual motivation to switch, suggesting that affordability is a critical factor in attracting users to online education platforms. Interestingly, the attractiveness of alternative media did not significantly affect switching behavior in this study.

Perceived usefulness also played an indirect role in influencing switching behavior, aligning with findings from previous studies that emphasize the importance of the perceived value of the platform's offerings. Conversely, normative environmental pressure did not have a direct impact on switching behavior, indicating that social expectations and pressures may be less critical in the decision to switch to online education in this context.

Regarding mooring factors, the intention to adapt to knowledge was identified as the second most influential factor in switching behavior. This highlights the crucial role of learners' intrinsic intentions and desires to gain knowledge. Additionally, decision self-efficacy and motivation for switching were found to be pivotal, influenced by factors such as platform knowledge scope and perceived price.

These findings reveal the complexity of factors influencing switching behavior in online education, providing valuable insights for both future research and strategic planning in the industry. They suggest that online education platforms should focus on enhancing their knowledge scope, maintaining affordable pricing, and fostering intrinsic motivation among users to improve engagement and completion rates.

Theoretical implications

This study provides a significant theoretical contribution by extending the existing body of knowledge on switching behavior in the context of online education, specifically within the Indonesian market. The study integrates new variables such as perceived price and perceived usefulness into the push-pull-mooring framework, offering fresh insights into the indirect mechanisms that influence switching behavior for performance. In doing so, it highlights the importance of decision self-efficacy, motivation and intention for switching, and intention to adapt for knowledge as mediating factors.

Firstly, this research addresses a gap in the literature by identifying the indirect relationship between perceived price and perceived usefulness with switching behavior for performance. Previous studies, such as those by Nayak et al. (2022), did not find a relationship between perceived price and perceived usefulness. Chen & Keng (2019) observed that these factors influence intentions but do not change behavior. In contrast, Kwarteng et al. (2020) identified a positive relationship between these variables and switching behavior, but no studies have explored their link to switching behavior for performance. By establishing an indirect relationship through mediating factors, this study adds a new theoretical layer, showing that while the perceived price and perceived usefulness do not directly trigger switching behavior for performance, they shape the broader motivational and decision-making processes that drive individuals to engage in online education.

Secondly, the findings suggest that while alternate media attractiveness and normative environmental pressure are often theorized to influence behavior, these variables do not consistently affect all aspects of switching behavior, as seen in Nayak et al. (2022). This study provides empirical evidence that these factors have limited influence on switching behavior for performance. Specifically, alternate media attractiveness did not significantly impact switching behavior, indicating that the perceived value of the current platform may be more important than the allure of alternatives in driving switching behavior in online education.

Thirdly, the research confirms the pivotal role of mediating variables, such as decision self-efficacy, motivation, and intention to switch, in influencing switching behavior for performance. By demonstrating that these mediators have a substantial effect on the switching process, the study underscores their importance in shaping individuals' willingness and readiness to transition to online education platforms. These findings advance the literature by clarifying how psychological readiness and self-belief in decision-making play critical roles in users' adoption of new educational platforms.

Lastly, this study's focus on the Indonesian market adds to the body of research on consumer behavior in emerging markets. It offers specific insights into how cultural and economic contexts shape the relationships between perceived price, usefulness, and switching behavior. The findings suggest that affordability and perceived value are significant drivers in an emerging market like Indonesia, where economic considerations may play a more substantial role in shaping consumer decisions than in more developed markets. This research offers an enhanced understanding of switching behavior for performance by integrating perceived price and usefulness into the push-pull-mooring framework and exploring their indirect influence. This theoretical expansion has implications for future studies on consumer behavior, especially in the rapidly evolving field of online education. It highlights the need for marketing and product development strategies that address these mediating factors to improve user retention and performance outcomes.

Limitations and recommendations

Based on the analysis and implementation of this study, the researchers acknowledge several limitations and challenges. Firstly, the research was conducted with respondents residing in Indonesia, which means the results may not be generalizable to other contexts or countries with different socio-economic dynamics and cultures without proper adaptation. Future research could compare respondents from various countries to explore broader findings and enhance the generalizability of the results.

Secondly, this study involved respondents from diverse backgrounds, including different types of online courses, education levels, and occupations. The study by Nayak et al. (2022) focused solely on individuals, while the research by Chen & Keng (2019) targeted workers in the service industry. The diverse respondent pool in this study led to more general conclusions. Future research could specify respondent criteria more narrowly to achieve more precise results. The variables of perceived price, perceived usefulness, and alternate media attractiveness showed different outcomes compared to previous studies, suggesting that these variables could be further investigated in subsequent research.

Lastly, this study did not focus on specific types of online education, resulting in general conclusions. Non-formal online education types, such as community learning centers and religious study groups, were not analyzed. Future research could sample these specific types of online education to provide deeper insights into individuals' switching intentions towards online learning. By addressing these limitations, future studies can offer more targeted and applicable insights for the online education sector.

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