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**Author(s):** Ye, Dingyu; Liu, Fufan; Cho, Dongmin; Jia, Zhengzhi

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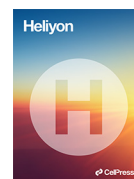
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## Research article

## Investigating switching intention of e-commerce live streaming users

Dingyu Ye<sup>a,\*</sup>, Fufan Liu<sup>b</sup>, Dongmin Cho<sup>c</sup>, Zhengzhi Jia<sup>d</sup><sup>a</sup> Department of Design and Manufacturing Engineering, Jeonbuk National University, Jeollabuk-do, Republic of Korea<sup>b</sup> Faculty of Information Technology, University of Jyväskylä, Finland<sup>c</sup> Department of Industrial Design, Jeonbuk National University, Jeollabuk-do, Republic of Korea<sup>d</sup> Department of International Communication, Birmingham City University, Birmingham, UK

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## ABSTRACT

As a new way of shopping, e-commerce live streaming (ELS) has gained unprecedented growth and popularity in the past years, especially in China. Because of the considerable rivalry in the ELS market, users frequently switch between ELS platforms. However, the switching intention of ELS users is yet to be explored for gaining new knowledge and practical insights. This study aims to improve the understanding of ELS users' switching intentions by developing an extended Push-Pull-Mooring (PPM) model. Using structural equation modeling, the study model was examined based on 443 valid responses from an online survey questionnaire. SmartPLS 3.3.2 was used to validate the causal model, and most of the study hypotheses were supported. According to the results, push effects (dissatisfaction, privacy concern, and negativity perceived value), pull effects (attractiveness of alternatives, perceived usefulness, perceived ease of use, and knowledge-based trust), and mooring effects (switching cost, social influence, and inertia) significantly influence ELS users' switching intentions. Furthermore, we found that mooring effects had a moderating role on the link between push effects and ELS user switching intention. However, the link between pull effects and ELS user switching intention was not found. The findings should aid ELS providers in deciphering ELS users' intentions in switching to other platforms and developing relevant theories, services, and regulations. The present study expands on previous research by introducing the PPM as a general model and demonstrating its effectiveness in explaining user switching intentions.

## 1. Introduction

Recently, the rapid rise of the e-commerce business has spawned a new online shopping form named e-commerce live streaming (ELS, [Hu and Chaudhry, 2020](#)), which is a marketing strategy developed by the e-commerce platform to sell goods in live streaming. A high level of interactivity, entertainment, authenticity, and visibility is usually present to accompany the user's shopping experience ([Ma and Mei, 2019](#)). In terms of product presentation, social attributes, and shopping experience, ELS outperforms traditional e-commerce platforms. Its purpose is to drive traffic via live streaming, thereby increasing e-commerce sales ([Luo et al., 2021](#)). To understand the ELS industry, the first place to look may be China, where a two trillion yuan (\$313.36 billion) market is expected to form soon ([iiMedia, 2021](#)). According to CNNIC's "Statistical Report on Internet Development in China," China's live streaming user base hit 638 million in June 2021, which increased by 21.75 million compared to December 2020. The total number of ELS users is 388 million, with users who have purchased goods on the platform accounting for 60.8 percent

of all ELS users ([CNNIC, 2021](#)). Because of its distinct advantages over traditional text-to-image shopping, ELS has gained much popularity among Chinese users ([Li et al., 2021](#)).

Since 2016, China's ELS industry has been developing rapidly, with a large influx of capital, companies forming, and users rushing to it ([Lu and Chen, 2021](#); [Zhou et al., 2021](#)). The ELS in 2019 has become the fastest-growing form of e-commerce in the world in the past three years. Live streaming booths cover factories, fields, shopping malls, streets, and farmers' markets, creating rich webcast of content and scenarios ([Zhang et al., 2022](#); [Zhou et al., 2021](#)). In 2020, people's offline social distance was encouraged even more because of the epidemic, as the online live sales model has further accelerated development ([Lu and Chen, 2021](#); [Zhou et al., 2021](#)). Over time, the competition in the industry has intensified, resulting in the situation of "too many live streams and not enough viewers", as teased by netizens. Due to the increasing number of platforms with ELS features and users' increasingly complex social interactions, certain functional needs of the platform may be sometimes not met and users' negative emotions may arise. This could lead to the

\* Corresponding author.

E-mail address: [yedingyu@buu.edu.kg](mailto:yedingyu@buu.edu.kg) (D. Ye).<https://doi.org/10.1016/j.heliyon.2022.e11145>

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switching behavior of ELS users, resulting in losses for the platforms. With difficulty of acquiring new users and gradual decrease in user activity, the critical thing is to solve the problem of user retention while improving user loyalty, promoting user activity, and avoiding user loss (Lin et al., 2021). Despite the growing need to comprehend ELS users' switching intentions deeper, prior studies in this field are still limited. Our analysis found that only a few studies have analyzed users' switching intentions with social media platforms in general (Bhattacharjee et al., 2012; Bhattacharjee and Park, 2017; Han et al., 2015; Hsieh et al., 2012; Polites and Karahanna, 2012; Wu et al., 2017), with even fewer study in the setting of two or more homogeneous ELS platforms (Chang et al., 2014; Fang and Tang, 2017; Lai et al., 2012; Peng et al., 2016), and further none on ELS users' switching intentions. Additionally, an overview of the prior study on "ELS" reveals that the current research on ELS mainly focuses on the status quo and definition of ELS (Kang et al., 2021; Lv et al., 2021; O'Leary, 2022a). Prior focus was mainly in the direction of studying the continued willingness of ELS users' platform usage (Singh et al., 2021) and few scholars have researched ELS users' switching intentions. Secondly, prior research on the negative aspects of social media platforms is mainly based on overload factors, such as system function overload, information overload, and social overload (Fu et al., 2020; Whelan et al., 2020; Yu et al., 2018). Such negative factors related to social media platforms that are rather one-sided. At the same time, studies on user behavioral intentions have mainly used the Technology Acceptance Model (TAM) as the theoretical framework (Assaker, 2019; Baby and Kannammal, 2020; Thong et al., 2002). However, TAM theory only considers the acceptance and use of ELS users. Users' switching intention is a behavioral strategy beyond using and accepting ELS. Thus, the theory does not explain the potential process of user's switching intention. This study aims to fill the gap in the research on social media switches regarding the switching intention of ELS users while promoting the academic community in developing research perspectives on ELS and diversifying meaningful research results.

This study aims to design and validate an extended PPM paradigm for analyzing ELS users' switching intentions. The PPM model, derived from migration theory, explains why people move from one place to another for a specified amount of time (Bansal, 2005; Boyle et al., 1998; Moon, 1995). The PPM model has been extensively utilized to explain and forecast user switching intention and behavior in varieties of social media, including mobile map services (Liu et al., 2021), instant messaging (Yin et al., 2021), mobile payment (Fan et al., 2021), online real-person English learning platforms (Chen and Keng, 2019), cloud storage services (Bhattacharjee and Park, 2017; Wu et al., 2017), etc. On the other hand, no prior studies have attempted to apply the PPM model in ELS. Furthermore, even though the user's attitude and psychological qualities are major predictors of user behavior (Qahri-Saremi et al., 2021; Wei et al., 2021), these aspects attracted less attention in prior studies on social media switching intentions. The source of the user's switching intention is considered as negative factors (push effects) experienced while using the current e-commerce live streaming platform. Moreover, the destination of the user's switching intention is considered as positive factors (pull effects) of the new e-commerce live streaming platform, which contributes to the users' switching intention. As a result, this study combines the characteristics of ELS itself, building a model based on the PPM and investigating the factors influencing the switching intention of Chinese ELS users in three aspects: push, pull, and mooring effects, to address the post-adoption behavior in the ELS social environment. Specifically, this study focuses on the following two research questions (RQs):

**RQ1.** which factors have a significant causal influence on the ELS user's switching intention.

**RQ2.** which factors have a moderating effect on ELS users' switching intention.

Furthermore, our findings are intended to provide recommendations for ELS suppliers as well as other interested parties for developing adoption plans.

## 2. Theoretical background

### 2.1. E-commerce live streaming

E-commerce live streaming has both attributes of e-commerce and streaming media (Xie et al., 2022), which connect potential consumers and goods with the "what you see is what you get" business model (Wang et al., 2021). Specifically, e-commerce live streaming platforms can be divided into two main categories (Xu et al., 2021). In one, live streaming is implemented as one of the merchandise promotion channels, such as in Taobao, Jingdong, and Pinduoduo. The other category is in the direction of content platforms, which integrates third-party e-commerce information into live streaming media and realizes the commercial value of consumable content, such as TikTok (O'Leary, 2022b) and Xiaohongshu (Zhang and Ma, 2021). Live e-commerce can use streaming technology to imitate offline shopping experiences to a great extent in that it promotes users' shopping in groups, such as in the same virtual live streaming room. Rooted in the user's post-adoption behavior, this study focuses on the switch intention of users in the context of e-commerce live streaming (Zhou et al., 2021). Overall, we define e-commerce live streaming as e-commerce platforms embedded with streaming media technology.

### 2.2. The push-pull-mooring (PPM) framework

The push-pull-mooring (PPM) theory of migration was first proposed as the "Law of Population Migration" by the British scholar Ravenstein (1885). Heberle (1938) further expanded on his research and created the push-pull model of population migration, where push has a negative effect and pull has a positive effect. Over time, the push-pull theory's flaws become apparent – it is overbroad as it ignores the role of individuals in decision-making. Numerous researchers' arguments incorporated mooring effects into the push-pull theory in response to the erroneous hypothesis (Cheng et al., 2019; Tang and Chen, 2020; Xie and Luo, 2021; Zeng et al., 2021). Individual- and social-level variables can be introduced and integrated into the PPM model to describe the population movement phenomenon thoroughly. Since then, PPM theory has developed into a formalized theoretical model with a broad range of applications.

Although the PPM theory originated in the population migration problem, it has been applied to social media users' switching intentions and behaviors. Zengyan et al. (2009) analyzed the factors influencing users' switching intention on social networking sites and categorized dissatisfaction with information, technical quality, among others, as the push effect. Hou et al. (2011) investigated the intention of online game service users to switch providers and they emphasized the importance of entertainment experience and social interactions. Sun et al. (2017) examined the switching behavior of instant messaging software users. They discovered that emotional identity, switching cost, and habit played a role in switching intention.

No previous research has examined user switching intentions in the context of ELS using the PPM model. This study contributes to the body of knowledge for social media switch research by analyzing the PPM model and listing relevant variables regarding Chinese users' use of ELS. For that, this study defines the push, pull, and mooring effects within our context. The push effects refer to the various factors that drive e-commerce live streaming users away from the platform they initially used, including dissatisfaction, privacy concern, and negativity perceived value. The pull effects refer to the various factors that pull e-commerce live streaming users to use a new platform, including attractiveness of alternatives, perceived usefulness, Perceived ease of use, and knowledge-based trust. The mooring effects in this study are described as the various factors that make e-commerce live streaming users dependent on the platform they initially used, including switching cost, social influence, and inertia that can impact users' switching intention.

### 2.3. Personal innovativeness

Personal innovativeness is considered to be an essential personal factor influencing technology adoption, reflecting stable and continuous psychological characteristics of the user. Rogers (2010) argues that differences in individual innovativeness will lead to differences in their attitudes toward adopting innovative technologies. The study classifies individuals into five categories (from earliest to last adopters): Innovators, Early Adopters, Early Majority, Late Majority, and Laggards. Flynn and Goldsmith (1999) argue that there are problems judging individual innovations based on time. For example, it is difficult to compare different studies as there is a lack of appropriate scales.

Based on prior research, Agarwal and Prasad (1998) proposed the concept of Personal Innovativeness Information Technology (PIIT), which refers to the extent to which individuals are willing to try new information technologies. Lewis et al. (2003) also examined the indirect effect of PIIT on adoption intention through perceived usefulness and perceived ease of use. Their study showed that PIIT significantly and positively influenced perceived usefulness and perceived ease of use, which in turn influenced adoption intentions.

Later, scholars have conducted studies in related information system areas. For example, Yang (2005) added the external variable of individual innovation to TAM theory in a mobile commerce study. The results showed that personal innovativeness positively affects both perceived usefulness and perceived ease of use. Xiang et al. (2008) empirically found that personal innovativeness affects perceived usefulness, perceived ease of use, perceived risk, etc. Kuo and Yen (2009) have used personal innovativeness as an external variable in their study on users' behavioral intention to adopt 3G mobile services. The empirical results show that personal innovativeness significantly affects perceived ease of use and has a non-significant effect on perceived usefulness.

With above studies, it is evident that personal innovativeness occupies a vital position in IT adoption. Therefore, we add it as an individual characteristic to the conceptual model to study the switching intention of e-commerce live streaming users.

### 2.4. Switching intention

The concept of “user migration” first originated from the “migration theory” in population geography (Boyle and Keith, 2014). It was used to study the permanent or semi-permanent migration of populations over two geographic spaces (Keaveney, 2018). Subsequently, it was introduced by scholars in marketing to study the behavior of consumers' replacing service providers (Ghufran et al., 2022; Iranmanesh et al., 2022; Mu and Lee, 2022). Currently, user migration is receiving much attention in information systems research and e-commerce. It discusses the phenomenon of the inter-network switch of information system users from using the original system to using the new system (Zengyan et al., 2009). Ye and Potter (2011) define users' switching intention as a partial reduction or complete termination of users' use of a particular information technology product. At the same time, the user switches intention to other alternative products that can satisfy their specific needs better. Based on prior research, this study characterizes “switching intention” as the user's increased usage of the new e-commerce live streaming platform and gradual to complete discontinuation of the current platform over a period of time.

## 3. Research model and research hypothesis

### 3.1. Research model

Switching behavior refers to the act of switching from one service provider to another (Bansal, 2005; Jung et al., 2017; Keaveney and Parthasarathy, 2001). However, social media switching generally refers to users who partially replace current services rather than completely abandoning them (Keaveney and Parthasarathy, 2001). This means that

users utilize both services concurrently but rely increasingly on one of them. As a result, like prior studies, we do not strictly characterize user switching as fully leaving current services (Peng et al., 2016; Wu et al., 2017).

ELS users are gradually reducing or discontinuing their use of one platform while steadily increasing their use of other platforms. The PPM theory can better explain users' switching intention by combining discrete factors that influence users' switching intention into a cohesive framework model—these aid researchers in explaining the phenomenon of ELS users switching. The impact of crucial constructs in ELS users' switching intention is investigated in this study. The push, pull, and mooring effects of the PPM model are incorporated. As shown in Figure 1, we specified the overall model as first-order formative and second-order reflective based on causal priority (Nimako and Ntim, 2013). That is, push, mooring, and pull effects are forces that give rise to or cause switching intention (as the original model suggests). The base level indicators (e.g., dissatisfaction) which compose into PPM effects are specified as reflective (Nimako and Ntim, 2013, p88) as they are variables we choose to measure that reflect those PPM effects in our research context. This is in line with previous studies on platform switching intention (Chen and Keng, 2019; Isibor and Odia, 2020).

#### 3.1.1. Push effects

The push effect explains why individuals switch locations due to certain qualities of the existing location that may have a detrimental effect on the existing location's quality of life (Lee, 1966; Moon, 1995). This study employs push effects as negative variables to explain why users generate switching intentions about the existing ELS platform. The push effects in this study refer to the various factors that drive e-commerce live streaming users away from the platform they originally used, including dissatisfaction, privacy concern, and negativity perceived value.

**3.1.1.1. Dissatisfaction.** Many scholars have found that user satisfaction is crucial (Jarman et al., 2021; Pang, 2021; Pozón-López et al., 2020; Xu et al., 2020). User satisfaction is positively correlated with user intention to utilize. The higher the user satisfaction, the stronger the intention to utilize. Satisfaction is considered in marketing as the primary determinant of consumers' repeat purchase decisions (Meilatinova, 2021). In business research, Bansal (2005) found a negative effect of satisfaction on the intention to change service providers. Zhang et al. (2008) concluded that satisfaction is negatively related to users' switching intention to a blogging service provider. In addition, dissatisfaction is often the first-factor influencing users' switching intention, compared with satisfaction and continued use concerns. Numerous studies show that when users are dissatisfied with the product or service they are currently using, their dissatisfaction affects the generation of their switching intention. Bhattacharjee et al. (2012) found that social media switching was driven by user dissatisfaction with existing products or services and user awareness of the availability of potentially superior products or services. In studying the switch behavior of users of social networking sites, Xu et al. (2014b) explored the factors influencing users' switching intention and found that if users are dissatisfied with a social networking site, it increases their desire to switch to other social networking sites.

**3.1.1.2. Privacy concern.** Privacy concerns about user information stem from the privacy risks associated with social platforms themselves, including the inability of users to effectively control the information posted by others about themselves and the possibility that user identity information may be stolen. In recent years, research on privacy concerns has focused on influencing user privacy perceptions in social networks. Sung et al. (2016) point to privacy concerns as a fundamental reason when exploring what factors are essential to users' intent to switch platforms. Xu et al. (2014a) suggests that when users are aware of personal information leakage, they will reject the social platform and move on to another social platform. Bright et al. (2015) cite privacy concerns as

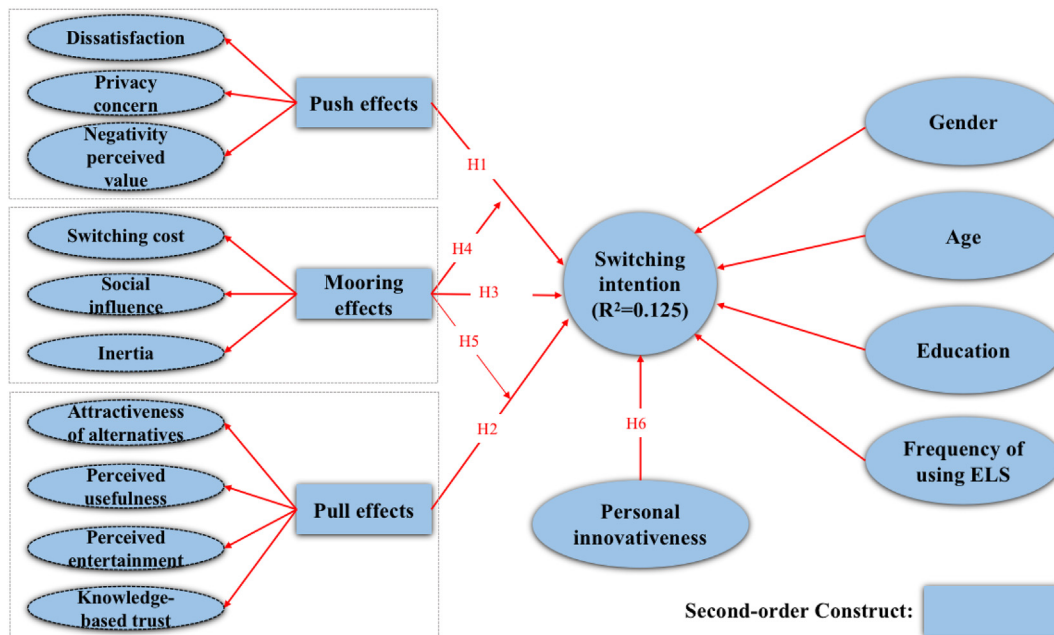


Figure 1. Research model.

a factor influencing the continued use of social networks. Too many privacy breaches can lead to user fatigue with social networks. Based on this, the user is not likely to keep using the ELS platform if the platform cannot guarantee the safety of the user's privacy or use user data for profit. In other words, it is likely to lead to increased willingness to leave the ELS platform.

**3.1.1.3. Negativity perceived value.** When social media users are faced with viable alternatives, the high perceived benefits of these alternatives may lead to higher likelihood of switching intentions. Sweeney and Soutar (2001) argue that users' perceived value is influenced by perceived emotional value, social value, economic value, and functional value, supporting that users' high perceived value positively affects behavior. Bhattacharjee et al. (2012) show that the perceived value of the relative advantage of using new information technology is positively related to shifters' switching intention to the latest information technology. When the perceived value of the original product is low, it leads users to switch to other alternatives. Perceived value has been proposed as the third push effect in the switch decision. Bansal (2005) considers low perceived value as a direct determinant of user switch. In this study, the perceived value factor is used as a push effect. It is believed that users have the switching intention because of the negative perceived value of the ELS platform.

In summary, dissatisfaction, privacy concern, and negativity perceived value are the push effects associated with the platform currently used by ELS users. These push effects produce a negative relationship that results in user switching intentions. As a result, the following hypothesis may be formed:

**H1.** Push effects (dissatisfaction, privacy concern, and negative perceived value) towards the platform currently used by ELS users are positively linked with the user switching intention.

**3.1.2. Pull effects**

The PPM model's pull effects initially referred to the reasons that compel people to leave their original domicile and relocate to their final location (Lee, 1966; Moon, 1995). These determinants will have a beneficial effect on people's lives. In the context of ELS, pull effects relate to the favorable characteristics that encourage users to utilize ELS. These variables all contribute to the benefits of employing ELS. The pull effects

in this study refer to the various factors that pull e-commerce live streaming users to use a new platform, including into attractiveness of alternatives, perceived usefulness, perceived entertainment, and knowledge-based trust.

**3.1.1.4. Attractiveness of alternatives.** The attractiveness of alternatives is typically measured by the degree to which users intend to abandon the original social media platform in favor of another (Pham and Ho, 2015). Kim et al. (2006) argue that alternative service providers' perceived attractiveness can be modified through various information sources, including anecdotal evidence, word-of-mouth, advertising, and the media. Users' switching intention services is positively related to the attractiveness of alternative options. The attractiveness of alternatives has also been identified as a significant pull effect in studies of PPM-related users' switching intention. Users may choose to switch to an alternative platform if they provide superior services that are more appealing.

**3.1.1.5. Perceived usefulness.** Perceived usefulness shows how users perceive the performance of social media platforms. Numerous types of research have found the major effect of perceived usefulness on the adoption behavior of information system users (Davis, 1989; Shin, 2009). As an information system, the perceived usefulness of ELSs will also significantly affect user switching intention. That is, satisfying the ELS platform should be simple and assist users in efficiently building relationships and sharing information with other users.

**3.1.1.6. Perceived ease of use.** Perceived ease of use refers to the enjoyment and pleasure that individuals derive from using social media. According to research, there is a considerable correlation between Perceived ease of use and users' use of information systems (Shin, 2009; van der, 2004). Humans are emotional creatures, and any time a decision is made, it is an emotional decision. Positive emotions can be addictive to users (Gao et al., 2017). Today's ELS platforms are increasingly focused on the user's entertainment experience while using them. Because users use ELS, consumption is only one aspect of demand. They expect more to get a good experience in the live room, such as a sense of entertainment.

**3.1.1.7. Knowledge-based trust.** In the social network-based theory of human migration, Curran and Saguy (2001) argued that trust can help



the migration process. Since there is no release of a more trustworthy system in social media, this paper will explore the effect of trust on users' switching intention from knowledge-based trust. Gefen et al. (2003) argue that knowledge-based trust refers to the extent to which people trust a specific kind of thing or organization about how much they have known about it in the past. Hsieh et al. (2012) found that a lack of experience and understanding of IT migration would inhibit users' switching intention. It can be postulated that users' knowledge about their switching intention and whether they have had similar switching experiences in the past may influence their switching intention.

This study, in accordance with related research, develops the pull effects generated by ELS attraction. It consists of four variables: attractiveness of alternatives, perceived usefulness, Perceived ease of use, and knowledge-based trust. As a result, the second hypothesis proposed in this study is:

**H2.** Pull effects (attractiveness of alternatives, perceived usefulness, Perceived ease of use, and knowledge-based trust) are positively associated with the user switching intention to an alternative ELS platform.

### 3.1.3. Mooring effects

Even though the push and pull forces significantly affect migrants, they may not migrate to other places when mooring effects exist (Lee et al., 2016). Hsieh et al. (2012) postulated that, similar to human migration, mooring effects could inhibit or facilitate user switching intention between online services. Mooring variables are identified as migratory facilitators in this study and it is described as various factors that make e-commerce live streaming users dependent on the platform they originally used, including switching cost, social influence, and inertia that can impact users' switching intentions.

**3.1.1.8. Switching cost.** Switching cost is an economic term that refers to users' one-time cost when switching from one product or service to another (Burnham et al., 2003). Dick and Basu (1994) defined switching cost as the monetary value, time, and effort incurred by users during the early stages of switching. They viewed switching costs as a significant indicator of users' reliance on a certain switch path. As various social media switching studies demonstrate, this component has developed into a significant mooring impact in the PPM model (Bhattacharjee and Park, 2017; Hou et al., 2011; Xu et al., 2014b). The organization of prior studies demonstrates that scholars have widely divergent conceptions of switching costs. The narrow definition of switching cost focuses exclusively on the economic and psychological costs associated with switching. The broad meaning of switching cost includes financial, time, and energy costs as perceived by users. However, the narrow definition is more limited in scope. Given the context of our research, this paper uses a broad definition of switching cost as a variable for analysis. When Hsieh et al. (2012) examined the migration of blog users to SNS, they discovered that a higher switching cost makes users feel "locked-in" by their current service provider. Zhang et al. (2009) investigated the factors influencing users' switching intentions using PPM theory and implemented switching costs as a mooring effect to discourage users from switching. Switching costs are certain to produce as ELS users migrate from their current platform to another platform. Users will almost certainly spend time and effort learning how to use new platforms. In summary, this study considers the characteristics of ELS. It defines switching costs as the cost of time and effort required by users to complete their shopping when using other ELS platforms. This study argues that users perceive that switching to a new ELS platform will incur switching costs, which will hinder their switching intention.

**3.1.1.9. Social influence.** Social influence reflects users' influences from friends, family, peers, and others (Campbell and Russo, 2003). Social influence operates as a mooring effect, assisting users in making switch decisions (Chang et al., 2014). According to previous research, social influence plays a critical role in users' adoption and use of social media

products (Kulviwat et al., 2009). Social influence is used in this study to refer to the influence of relatives or friends who have relocated to another ELS platform or have been using another ELS platform when they invite users to utilize the ELS platform they are now using. Watjatrakul (2013) proved that social influence affects individuals' perceptions and perceptions of products (perceived usefulness, perceived ease of use, and Perceived ease of use). Li et al. (2010) propose that employees' subjective views and social effects positively affect their adherence to internet policies when they use the Internet. Their study of user usage of instant messaging discovered that, in addition to subjective norms, group norms and social identity substantially impact users' intention to use (Li et al., 2010; Shen et al., 2009). Most platforms offer users some functions, such as automatic invitations and friend suggestions, etc., by associating them with their mobile address book. Users are more likely to send invitations to their friends and relatives when they receive a prompt from the platform. This will influence the behavioral decisions of the invited users. Therefore, the social influence may have a strong mooring effect on ELS users' switching intention.

**3.1.1.10. Inertia.** Samuelson defines inertia as the preference for the status quo when individuals are presented with better alternatives yet choose to maintain their current behavior based on prior experience (Samuelson and Zeckhauser, 1988). Existing research has introduced inertia into the sphere of information systems (Alos-Ferrer et al., 2016; Polites and Karahanna, 2012; Tripsas and Gavetti, 2000). They describe inertia as users who always utilize the same social media service (Polites and Karahanna, 2012). Sun et al. (2017), for example, claim that user inertia towards instant messaging services reduces users' switching intention to other services with new options. Users reject new technologies and services, obstructing their switching from traditional to new platforms. ELS users must experience great stress as they switch from the platform they are presently using to a completely new platform. In contrast, comfort will keep them on the platform they are already using. ELS users devote their emotions and energy to the platform that they are currently using. When ELS users want to step outside their psychological comfort zone and begin experimenting with new platforms, they face a significant challenge. This will significantly impact their switching intention.

Aside from reasons relating to the current platform push effects and the new platform pull effects, switching cost, social influence, and inertia are projected to directly and positively impact ELS users' switching intention. As a result, the hypothesis is advanced:

**H3.** Mooring effects (switching cost, social influence, and inertia) are positively associated with ELS users' switching intention to a new platform.

According to migration theory, the mooring variable acts as a moderator by mediating between push-pull variables and actual migratory choice (Lee, 1966). Much research on social media switching has also confirmed the moderating effect (Bhattacharjee and Park, 2017; Hsieh et al., 2012; Wu et al., 2017). According to Jung et al. (2017), even though the push-pull variables strongly influence ELS users' switching intention, if the mooring variable has a strong influence on the user, they will also want to switch service providers. Therefore, this study argues that mooring factors will reinforce the role of push and pull factors in promote users' switching intentions. Specifically, the more users are influenced by mooring factors (switching cost, social influence, and inertia), the stronger the role of push factors (dissatisfaction, privacy concern, negativity perceived value) and pull factors (attractiveness of alternatives, perceived usefulness, Perceived ease of use, and knowledge-based trust) on switching intention, and vice versa. Consequently, this study proposes the following hypothesis:

**H4.** Mooring factors positively moderate the role of push effects on switching intention.

**H5.** Mooring factors positively moderate the role of pull effects on switching intention.

### 3.2. Personal innovativeness

Individual differences are constantly emphasized in studies related to users' switching intentions, with personal innovativeness being the most frequently cited factor in the research (Bhattacharjee et al., 2012; Handarkho and Harjoseputro, 2019; Peng et al., 2016). Many studies have found the influence of demographic characteristics factors on social media acceptance (Chen et al., 2019; Dumpit and Fernandez, 2017; Naqvi et al., 2019; Zhang et al., 2021). As discussed before, we implement personal innovativeness as an dispositional factor embodying key individual difference potentially interacting with other demographic variables. For example, people of different ages and genders may differ in their innovativeness, which affects their acceptance of switching to a new ELS platform. We hypothesize that personal innovativeness impacts the intention of ELS platform users to switch. Users with high personal innovativeness may have higher standards for ELS platforms. Once the platform fails to meet their usage habits, it is easy for them to switch to another platform. Users with low personal innovativeness may prefer to continue using the ELS platform they are currently using, even if they feel problematic.

We make the following hypotheses about the impact of personal innovativeness:

**H6.** Personal innovativeness has a positive impact on ELS users' switching intentions.

## 4. Study design

### 4.1. Measurements and quasi-experimental design

The questionnaire is used to collect data for this investigation. In empirical research, the questionnaire method is one of the most commonly utilized data collection methods (Flynn et al., 1990). The researcher uses a uniformly constructed questionnaire to understand the issue better or request opinions from selected respondents to collect accurate and detailed primary data, which serves as the foundation for performing empirical research. Strict controls were implemented in this study to ensure the accuracy of the returned data, including the design of the scale, distribution of the questionnaire, and collection of the returned data.

In this study, the scale's question content was designed utilizing correlation theories and a conceptual model. The questionnaire is divided into three sections: basic information about the subjects, experience with ELS, and feelings about ELS. To meet this study's ELS research setting, the relevant scales in this research were all fine-tuned using mature scales or based on mature scales. The push effects were measured using the variables of dissatisfaction (three items), privacy concern (three items), and negativity perceived value (three items), which were adapted from Cao and Sun (2018), Chang et al. (2014), Bhattacharjee (2001), Sung et al. (2016), and Lin (2008). The pull effects were measured using the variables of the attractiveness of alternatives (three items), perceived usefulness (three items), Perceived ease of use (three items), and knowledge-based trust (three items), adopted from Chuang (2011), Xu et al. (2014b), Chang et al. (2014), Chen et al. (2013), and Fei and Bo (2013). The mooring effects were measured using three variables. The variables of switching cost (three items), social influence (three items), inertia (three items) were derived from Wu et al. (2014), Sun et al. (2017), Lee (2014), and Polites and Karahanna (2012). In addition, the variables of Personal Innovativeness (three items) were derived from Bhattacharjee et al. (2012). Finally, switching intention was measured using three items derived from Fang and Tang (2017) and Jung et al. (2017), as shown in Table 1. A two-way translation method was used for the scale translation to ensure the Chinese translation's consistency and the original text's semantics. All English items were first translated into Chinese. Then international students (three Ph.D. students, all native English speakers) from the research team were invited to back-translate the Chinese scale into English, adjusting the items with obvious differences and disagreements.

All items were measured on a 5-point Likert scale. Subjects were asked to rate the items in the order of "1 strongly disagree; 2 not quite agree; 3 not sure; 4 somewhat agree; 5 strongly agree".

The study used gender, education, age, and the frequency of using ELS as control variables. To demonstrate the demographic generalizability of findings, gender, age, and education are typically employed as major demographic characteristics (Liu et al., 2018, 2020; Zhang et al., 2012). These factors have also been discovered to affect how users utilize the internet (Venkatesh et al., 2003). The frequency of using ELS was also included because various research on social media has shown that the frequency of using social media products has a significant effect on user behavior (Wu et al., 2017).

The resulting translated scale was given to nine users with experience using ELSs and five Ph.D. students to strengthen the scale's content validity even more. They were asked to evaluate each of the measurements separately to determine whether they corresponded to their subjective judgments of this construct. The contentious question items were addressed and revised based on their feedback to improve clarity and comprehensibility. Before finishing the questionnaire, we did a pretest using Wen Juan Xing (<https://www.wjx.cn/>) to distribute and collect questionnaires. The scale's reliability and validity were initially determined using the 68 valid questionnaires that we collected. The relevant questions were eliminated and changed, and a formal questionnaire for this study was produced.

### 4.2. Data collection

This study aims to examine the psychological processes and behavioral intents of ELS users. The data for this study were gathered using an online questionnaire survey conducted on the Wen Juan Xing ([www.wjx.cn](http://www.wjx.cn)). The Wen Juan Xing website is a popular professional research outlet for Chinese academic researchers (Lin, 2008; Wang et al., 2015). Although this method does not provide a high degree of control over the subjects and the situations in which they complete the questionnaires, it enables a much broader survey. Therefore, based on the existing literature (Liu et al., 2016; Zheng et al., 2018), this study collected data via an online questionnaire to examine the theoretical hypotheses. Additionally, the Wen Juan Xing website's sample service function ensures that subjects are randomly selected from various populations, resulting in more representative statistics. All subjects who completed the questionnaire were rewarded with an e-red packet of two to five RMB to encourage active participation.

In this study, 499 questionnaires were distributed between June 1 and October 1, 2021. The research team received 499 responses to the questionnaire with a full response rate of 100%. Prior to answering the questionnaires, all participants signed a written informed consent. The consent and questionnaire were designed and implemented with the approval of the Ethics Committee of the Jeonbuk National University. After removing 56 invalid surveys due to incomplete responses, excessive repetition, or inadequate time to complete, 443 valid questionnaires were retrieved, producing an effective rate of 88.78 percent. The research team examined the online research process to test whether the problem of no-response bias occurred. This study compared the means of all variables and demographic information for the earlier 25% of respondents and the later 25% of respondents. Calculations showed no significant differences between these two samples. Therefore, there was no significant problem of non-response bias in this study. In terms of geographical affiliation, subjects were from more than 20 provinces in China. Among all subjects, 42.9% were male, and 57.1% were female. In addition, about 38% of the subjects had more than 100 purchase records in the e-commerce live streaming room. About 46% of the subjects used e-commerce live streaming once every three days.

### 4.3. Descriptive analysis of demographic characteristics

SPSS 25.0 software package was used to implement descriptive statistical analysis on the demographic characteristics of the 443 sample

Table 1. Scale items.

Construct	Number	Items
Dissatisfaction (D)	D1	Currently, I have difficulty seeing helpful information on my usual e-commerce live streaming platforms.
	D2	I think the features and services of the commonly used e-commerce live streaming platforms do not meet my expectations.
	D3	I think the commonly used e-commerce live streaming platforms do not meet my needs.
Privacy concern (PC)	PC1	I am concerned that the e-commerce live streaming platform I am currently using may collect my personal information without telling me about it.
	PC2	I am concerned that personal information submitted to the e-commerce live streaming platform I am currently using may be misused.
	PC3	I am concerned that other people may find my private information from the e-commerce live streaming platform I am currently using.
Negativity perceived value (NPV)	NPV1	The price of goods on the e-commerce live streaming platform is unreasonable.
	NPV2	The prices of goods in the e-commerce live streaming platform are high.
	NPV3	I am not satisfied with the prices of the goods sold on the e-commerce live streaming platform.
Switching cost (SC)	SC1	Learning to use a new e-commerce live streaming platform can be a bit tricky.
	SC2	Getting familiar with using a new e-commerce live streaming platform requires time and effort.
	SC3	Stopping using a commonly used e-commerce live streaming platform will lose the number of followers and attention you have accumulated.
Social influence (SI)	SI1	My friends around me are not very happy with the current e-commerce live streaming platform.
	SI2	My friends strongly recommended the new e-commerce live streaming platform to me.
	SI3	My friends invited me to sign up for the new e-commerce live streaming platform.
Inertia (I)	I1	Using e-commerce live streaming platforms is a spontaneous act for me.
	I2	Using other e-commerce live streaming platforms is part of my daily routine.
	I3	Using other e-commerce live streaming platforms makes me feel dependent.
Attractiveness of alternatives (AOA)	AOA 1	If I need to change apps, there are other and better e-commerce live streaming platforms that offer a high-quality service.
	AOA 2	I find other e-commerce live streaming platforms more attractive than the one I'm using.
	AOA 3	Other e-commerce live streaming platforms would benefit me compared to the one I'm using now.
Perceived usefulness (PU)	PU1	I think other e-commerce live streaming platforms have filters and effects that are more responsive to my creative needs.
	PU2	The quality of the videos I create is higher on other e-commerce live streaming platforms.
	PU3	I can learn more valuable things from other e-commerce live streaming platforms.
	PU4	Other e-commerce live streaming platforms push more precise content, which I am concerned about.
Perceived ease of use (PE)	PE1	I think other e-commerce live streaming platforms are faster and smoother to use.
	PE2	I think the interface of other e-commerce live streaming platforms is well designed and easy to understand.
	PE3	It is easier for me to find the features or services I want on other e-commerce live streaming platforms.
Knowledge-based trust (KT)	KT1	Based on my experience with e-commerce live streaming, I don't think it is trustworthy.
	KT2	Based on my experience with e-commerce live streaming, I don't think it cares about its users.
	KT3	Based on my experience with e-commerce live streaming, I don't think the good or bad of the item after the purchase is unknown.
Switching intention (SWI)	SWI1	I plan to use the new e-commerce live streaming platform more in the future.
	SWI2	I plan to devote more time and energy to new e-commerce live streaming platforms.
	SWI3	I plan to move from the e-commerce live streaming platform to a new e-commerce live streaming platform.
Personal innovativeness (PI)	PI1	I like to try out new e-commerce live streaming platforms.
	PI2	I am one of the first to try new e-commerce live streaming platforms among my friends.
	PI3	If I hear about a new e-commerce live streaming platform, I will try to use it.

data to explore the distribution of the sample data. The results of the descriptive analysis in Table 2 show that there are more female users than male users, with a male to female ratio of 42.9% and 57.1%. In terms of the age distribution, the users group of 18–25 years old account for the 32.1% of the sample, followed by users younger than 18 years old with a percentage of 27.5%. In terms of education level, the most users were undergraduates (43.3%), followed by college education (40.6%). As for the frequency of using ELS, most users use the platform once a day, accounting for 37.0%, followed by users who use it once a half month, which accounts for 23.3%. These data indicate that the sample data collected in the questionnaire survey of this study covers a wide range, which is consistent with the situation of Chinese ELS users.

#### 4.4. Measurement model analysis

##### 4.4.1. Software setting

The research tool in this study employed SmartPLS 3.3.2 to analyze the data and test the hypotheses. The PLS (Partial Least Squares) approach was chosen because it allows us to assess both the measurement model and the structural model. Furthermore, PLS is better suited for exploratory analyses and applications to studies focusing on theory

development (Cheung and Lee, 2012; Chin et al., 2003). Another argument for utilizing PLS-SEM is the model's complexity. In comparison to covariance-based structural equation modeling (SEM), this method necessitates a smaller sample size. It imposes no constraints on the distribution of variables (Wang et al., 2013). As a result, PLS is better suited for data analysis for this study. We analyzed the measurement model and structural model individually using a two-step methodology (Anderson and Gerbing, 1988).

Thus, structural equation modeling was performed on 443 samples using SmartPLS 3.3.2. Some specific key software settings were: "weighting scheme" using "path weighting scheme", "maximum number of iterations" = 300, and end criterion =  $1 \times 10^{-7}$ . The "maximum number of iterations" = 300 and the end criterion =  $1 \times 10^{-7}$ . In the Bootstrapping test, the significance of each indicator was determined as follows. In terms of the significance of each indicator of Bootstrapping test: subsample = 5000, confidence interval method using Bias-Corrected and Accelerated (BCA) Bootstrap, test type using the two-tailed test, significance level = 0.05.

##### 4.4.2. Common method variance

Prior to the reliability and validity analysis, the data were tested for common method variance (CMV). The common method variance



**Table 2.** Descriptive statistics of sociodemographic variables (N = 443).

Measure	Category	Frequency	Percentage (%)
Gender	Male	190	42.9
	Female	253	57.1
Age	<18	122	27.5
	18–25	142	32.1
	26–34	88	19.9
	35–45	81	18.3
	>45	10	2.3
Education	Junior college	180	40.6
	Bachelor	192	43.3
	Master	33	7.4
	Doctor	38	8.6
Frequency of using ELS	Very rarely	101	22.8
	Once every half month	103	23.3
	About three days once	75	16.9
	Once a day	164	37.0
	Very frequently	101	22.8

problem should have been avoided by disrupting the order of measurement items at different times and places, hiding variables and measurement items. In terms of means of the CMV detection, we used Harman’s one-way test. The results of unrotated factor analysis showed 11 factors with characteristic roots greater than 1, explaining a total of 70.2% of the variance. The first factor explained 26.87% of the method variance. Thus, there should be no significant common method bias in the sample data of this study.

**4.4.3. Results of the reliability and validity test**

The reliability results in Table 3 show that the range of  $\alpha$  is 0.707–0.909, both of which are higher than the reference value of 0.7 (Fornell and Larcker, 2018). The range of CR is 0.700–0.989, both of which are higher than the reference value of 0.7 (Hair et al., 2017). Therefore, the measurement model of the study has a good reliability level. The convergent validity results in Table 4 show that for the factor loadings of the measurement items, except for SI1 and SI3, where the factor loadings are less than 0.5, the factor loadings of all the measurement items are greater than the critical value of 0.5 (Hair, 2009), ranging from 0.712 to 0.952; the Average Variance Extracted (AVE), all variables had AVEs greater than the critical value of 0.5 (Hair et al., 2017), ranging from 0.524 to 0.596. Thus, the measurement models studied had a good convergent validity level. Finally, the discriminant validity results of the measurement model in Table 3 show that the square root of the AVE of each variable is greater than the correlation coefficient of that variable with any other variable. The measurement model has good discriminant validity.

**4.5. Measurement model analysis**

**4.5.1. Collinearity diagnostics**

Prior to the path analysis, the collinearity of the structural model was examined by the VIF (Variance Inflation Factor) criterion of (Hair et al., 2021). The results showed that the VIF of both the external and internal models were less than 5, 1.856 to 4.511 and 2.562 to 4.127, respectively, which were lower than the standard reference value of 5. Therefore, the structural model should not have serious multicollinearity problems.

**4.5.2. Path analysis**

The results of the path analysis in Figure 2 and Table 5 show that Push and Pull both have a significant positive effect on SWI with path coefficients of 0.031 ( $p < 0.05$ ) and 0.022 ( $p < 0.05$ ), respectively, and hypotheses H1 and H2 are supported; Mooring also has a positive and significant effect on SWI with a path coefficient of 0.018 ( $p < 0.05$ ) and hypothesis H3 was supported; PI had a positive and significant effect on

**Table 3.** Reliability and convergent validity analysis (N = 443).

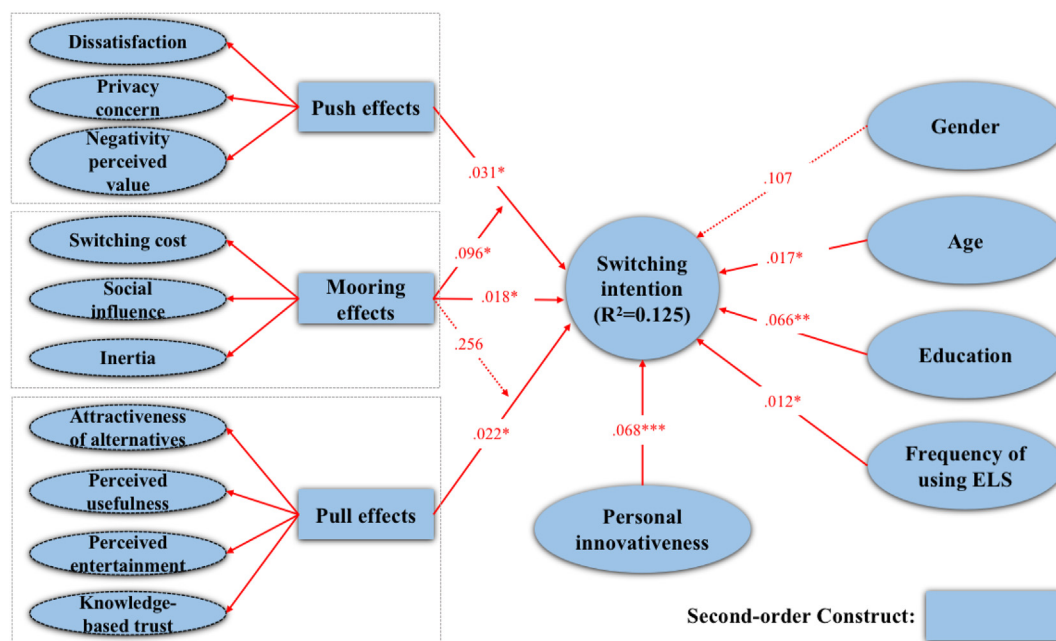
Construct and Items	Factor Loadings	Cronbach’s $\alpha$	CR	AVE
Dissatisfaction (D)		0.762	0.700	0.535
D1	0.823			
D2	0.855			
D3	0.806			
Privacy concern (PC)		0.744	0.901	0.550
PC1	0.756			
PC2	0.824			
PC3	0.821			
Negativity perceived value (NPV)		0.909	0.928	0.585
NPV1	0.719			
NPV2	0.811			
NPV3	0.833			
Switching cost (SC)		0.707	0.778	0.554
SC1	0.767			
SC2	0.765			
SC3	0.843			
Social influence (SI)		0.758	0.948	0.553
SI1	0.448			
SI2	0.807			
SI3	0.455			
Inertia (I)		0.906	0.702	0.558
I1	0.734			
I2	0.754			
I3	0.817			
Attractiveness of alternatives (AOA)		0.815	0.987	0.553
AOA1	0.731			
AOA2	0.758			
AOA3	0.762			
Perceived usefulness (PU)		0.719	0.980	0.579
PU1	0.840			
PU2	0.952			
PU3	0.712			
PU4	0.824			
Perceived ease of use (PE)		0.952	0.919	0.596
PE1	0.721			
PE2	0.868			
PE3	0.862			
Knowledge-based trust (KT)		0.778	0.918	0.551
KT1	0.805			
KT2	0.914			
KT3	0.723			
Personal innovativeness (PI)		0.754	0.752	0.524
PI1	0.830			
PI2	0.853			
PI3	0.735			
Switching intention (SWI)		0.776	0.989	0.542
SWI1	0.767			
SWI2	0.765			
SWI3	0.843			

SWI with a path coefficient of 0.068 ( $p < 0.001$ ). The results of the moderating effect showed that Push  $\times$  Mooring had a positive and significant effect on SWI, with a path coefficient of 0.096 ( $p < 0.05$ ), and Mooring played a positive moderating role in the relationship between Push and SWI; Pull  $\times$  Mooring had no effect on SWI, and Mooring did not play a moderating role in the relationship between Pull and SWI. Hypothesis H4 was supported, and hypothesis H5 was rejected. In order to visualize the moderating effect of the mooring effects on the relationship

**Table 4.** Discriminant validity analysis (N = 443).

	D	PI	AOA	KT	I	NPV	PE	PU	SI	SC	SWI	PC
D	<b>0.732</b>											
PI	0.473	<b>0.724</b>										
AOA	0.628	0.540	<b>0.743</b>									
KT	0.653	0.598	0.534	<b>0.742</b>								
I	0.591	0.569	0.451	0.663	<b>0.747</b>							
NPV	0.573	0.635	0.690	0.532	0.711	<b>0.765</b>						
PE	0.681	0.589	0.647	0.674	0.674	0.412	<b>0.772</b>					
PU	0.435	0.405	0.438	0.533	0.531	0.472	0.475	<b>0.761</b>				
SI	0.655	0.477	0.579	0.432	0.591	0.585	0.492	0.487	<b>0.744</b>			
SC	0.685	0.452	0.672	0.412	0.400	0.685	0.705	0.438	0.631	<b>0.745</b>		
SWI	0.532	0.573	0.545	0.566	0.545	0.640	0.607	0.710	0.563	0.681	<b>0.736</b>	
PC	0.695	0.508	0.468	0.636	0.579	0.611	0.659	0.460	0.568	0.553	0.429	<b>0.742</b>

Note: The diagonal elements (in bold) are the square root of variance shared between the AVEs, whereas the off-diagonal elements are correlations among constructs.



**Figure 2.** PLS results of the structural model. Note: The dotted line indicates that the relationship is not valid. \*\*p < 0.01; \*p < 0.05.

**Table 5.** Path coefficients and research hypothesis testing results.

Research hypothesis	Path coefficients	Mean	T	P	95% Confidence interval		f²	Results
H6: PI → SWI	0.068	0.041	3.587	0.000	0.091	0.652	0.107	Supported
H2: Pull → SWI	0.022	0.002	2.406	0.017	0.107	0.545	0.066	Supported
H1: Push → SWI	0.031	0.010	2.506	0.013	0.483	0.770	0.092	Supported
H5: Pull × Mooring → SWI	0.256	0.145	0.774	0.439	0.001	0.094	0.004	Rejected
H4: Push × Mooring → SWI	0.096	0.041	2.432	0.015	0.151	0.257	0.087	Supported
H3: Mooring → SWI	0.018	0.007	2.166	0.031	0.054	0.472	0.062	Supported
Gender → SWI	0.107	0.062	1.268	0.205	-0.134	0.004	0.002	/
Age → SWI	0.017	0.010	2.200	0.028	-0.035	-0.010	0.058	/
Education → SWI	0.066	0.021	2.747	0.006	-0.026	-0.020	0.098	/
Frequency of using ELSP → SWI	0.012	0.024	2.128	0.034	-0.001	-0.100	0.052	/

between push effects and switching intention, and that between pull effects and switching intention, we plot the moderating effect following the method of Dawson (2013), as shown in Figures 3 and 4. In terms of the control variables, age, education, and frequency of using ELS significantly affect SWI, and gender did not affect SWI.

**4.5.3. Predictive power assessment**

The predictive power assessment showed R² = 0.125 for SWI. Based on Blindfolding, Q² was calculated, and Q² > 0 indicates that the structural model has predictive relevance for the endogenous variables and vice versa (Hair et al., 2017). The calculated Q² = 0.938 for SWI, which

was greater than 0. This indicates that the structural model has predictive relevance for SWI.

## 5. Discussion and conclusions

### 5.1. Results and discussion

We have used the PPM model to investigate the variables that influence ELS users' switching intentions. The findings and implications are outlined below.

The overall results show that each of the three factors – push, pull, and mooring – directly influences ELS users' switching intentions. Dissatisfaction, privacy concern, and negativity perceived value are all factors that push ELS users to abandon their existing platform. In contrast, the attractiveness of alternatives, perceived usefulness, perceived ease of use, and knowledge-based trust can pull users towards a new ELS. Additionally, variables relating to contextual and social factors, such as switching cost, social influence, and inertia, show mooring effect. The pull and push effect had greater effects on the switching intention of ELS users than the mooring effect. Such findings corroborate those of previous studies. Hou et al. (2011) found that the push-pull-mooring model could explain the switching intention of online gamers. Hsieh et al. (2012) found positive effect of push and pull effects, negative effect of mooring effects, and the interaction effect between push and mooring on switching intentions for online service substitutes. Jung et al. (2017) demonstrated that all PPM categories directly affected switching intention in airline travelers' switching behavior. Regarding our current study, while users may use ELS to watch live streaming and buy products, the ELS may improve user experience by delivering value goods and pleasant entertainment experience, as well as accumulating confidence and loyalty to the platform when they purchase goods. With this, users may utilize the ELS for a long period. Second, if negative emotions (e.g., dissatisfaction with the platform) emerge during the use of ELS, privacy concerns generate, or if the user feels that the product purchased in the ELS does not meet the expected value, they may abandon the current ELS platform.

Furthermore, we revealed that mooring variables moderated the association between push effects and switching intentions but not the relationship between pull effects and switching intentions. Different previous studies on the moderating effect of parking factors on social media users' switching intention have reached different conclusions. Although with some previous studies, mooring effects may only have a

subtle moderating effect (Kim et al., 2006; Xu et al., 2014b), our study has found a significant effect, which is also in line with certain prior studies, such as the study where Chang et al. (2014) discovered substantial effects on the moderating effect of mooring variables. Hou et al. (2011) discovered substantial interaction between the push and mooring effect on switching intention, but not between pull and mooring effect. This difference may be related to the questionnaire respondents of this study. The mooring effect had a significant moderating effect on the relationship between the push factors and switching intention. The possible reason is that the questionnaire respondents of this study have rich experience in using ELS. As soon as they found a slight disadvantage of the ELS, they were highly prone to the switching intention. In other words, the more experienced users are with ELS, the more sensitive they may be to the shortcomings of the current ELS. The mooring effect has no moderating effect on the relationship between pull factors and switching intention. Therefore, users who are more influenced by the mooring factors do not show switching intention to other ELS platforms when the level of influence of the pull factor is similar. This may be because ELS development is matured and convergent at this point. While users are well aware of the advantages and disadvantages of each ELS platform, they would not generate switching intention solely because they have discovered the advantages of other ELS platforms.

Prior studies found personal innovativeness to be a significant positive effect on continued intention (Singh et al., 2021), discontinuous usage intention (Avornyo et al., 2019), purchase intention (Li et al., 2021), etc. With our findings, personal innovativeness greatly influences ELS users' switching intentions. In our context, we view personal innovativeness as a critical dispositional characteristic that approximates users' perspectives on social media goods and services, which can vary substantially among individuals. Certain groups of users who enjoy experimenting with new social media products or services are more inclined to switch to another platform given the same level of other factors. The findings of this inquiry corroborated those of previous studies. When Park and Ryoo (2013) examined end-user behavior in terms of cloud computing platform switching, they observed that personal innovativeness had a beneficial effect on users' switching intention. Meanwhile, scholars have discovered that personal innovativeness has a significant moderating effect on other aspects influencing users' switching intentions, such as contentment with the original social media and the relative advantages of alternatives (Bhattacharjee et al., 2012).

Concerning control variables, people who used ELS more frequently were older or had more educational experience were more likely to

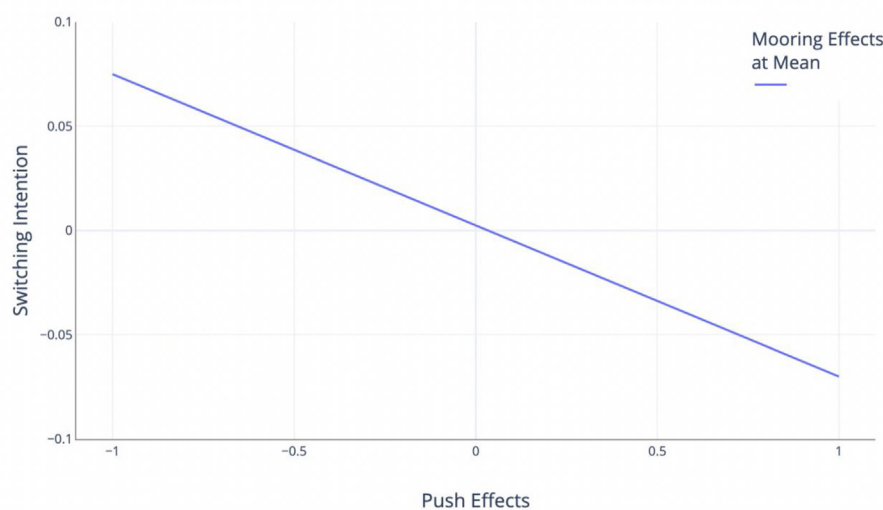


Figure 3. Moderating effect of mooring effects on the relationship between push effects and switching intention.

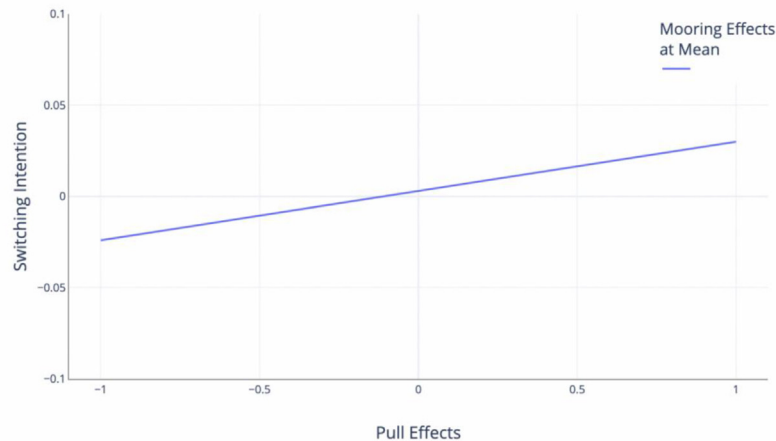


Figure 4. Moderating effect of mooring effects on the relationship between pull effects and switching intention.

generate switch intention. This contradicts the findings of Xu et al. (2014b), which observed that no control variable significantly influenced switch intention. In our view, this may be explained by the user demographics that older users have more opportunities to utilize ELS than younger users. They will be more concerned with the technical quality and satisfaction associated with ELS use. As a result, they are more apt to switching intentions at any moment if they are dissatisfied with the current ELS platform's performance. Similarly, people who use ELS regularly understand the ELS platform accessible on the market more than users who use ELS seldom. As a result, those individuals are more likely to switch to another platform if they are dissatisfied with the ELS they are presently using. Finally, highly educated users are better capable of self-learning (Adams and Demaiter, 2008). They are therefore more likely to master a completely new platform. As a result, if they are unsatisfied with the ELS they are using, switching intention may be generated.

### 5.2. Theoretical implications

This study's theoretical contributions are divided into three categories.

Firstly, while there is growing interest among researchers in the issue of social media switch, there is not nearly enough research on users' switching intention between various products and services, such as online documentation, online games, knowledge-sharing platform, ELS, etc. Our research is an early effort to explain ELS users' switching intentions. Moreover, this study applies the PPM model, an anthropological study of human migration, to online social media users' switching intentions. As we show that the PPM model may be used to investigate the switching intention to social media, this study can be considered a research paradigm that uses theories from other research fields to analyze the switching intention of social media users on the Internet. Future research on relevant concerns can also be preceded by referring to the theoretical framework of this study.

Secondly, the prior study chose only low service satisfaction (Liu et al., 2021), low enjoyment (Liu et al., 2021), inconvenience (Lai et al., 2012), etc., for the pull effect, and alternative attractiveness (Lai et al., 2012), peer influence (Lai et al., 2012), etc., for the push effect. This research proposed new pull and push effect variables, such as perceived ease of use, knowledge-based trust, negativity perceived value, etc., that substantially influence users' switching intentions in the framework of ELS. Some of these factors (i.e., knowledge-based trust and negativity perceived value) have seldom been examined previously. Our findings may help guide future research on the topic of social media users' switching intentions.

Thirdly, this study found inertia as a mooring factor impacting users' switching intention, which is unusual in the study of ELS. Inertia is

determined by cognitive, affective, and subconscious antecedents (Sun et al., 2017). Because of the individual differences of user groups, the role of inertia on individual switching intentions cannot be overlooked. Recognizing the role of inertia hindrance enables us to grasp the fundamental process by which mooring variables influence the creation of individuals' intentions to switch to other platforms.

### 5.3. Practical implications

First and foremost, the platform operator should elicit the satisfaction of ELS users. The platform's primary purpose is to identify user satisfaction factors and enhance the user experience based on demands to minimize users' discontent with the platform, thus retaining existing users. According to the findings of this study, dissatisfaction directly impacts the push effect of ELS users' switching intention, therefore indirectly impacting ELS users' switching intention. Platform operators may improve user satisfaction and retention by assisting users in resolving issues that arise when utilizing ELS. First, making it simpler for users to discover the information they need necessitates that the platform party improves four aspects: platform network information architecture, platform content search system, platform navigation design, and relevant content recommendation mechanism. Second, privacy concerns directly impact the push effect of ELS users' switching intention and indirectly impact ELS users' switching intention. Users are always concerned about the stuff they browse or purchase being permanently recorded on the internet when utilizing an ELS platform. As a result, from the standpoint of user experience, the platform side can cut in three ways to ease users' privacy concerns: Incognito mode, reduced permanence, and reduced publicness. Specifically, Incognito Mode is for the operator to anonymize all user interactions on the platform. Reduced permanence allows operators to set a time limit on all comments or items shared by users on the platform, allowing users to feel more comfortable. Reduced publicness allows the operator to provide multiple privacy settings such as friends only, self only, etc. Secondly, the negative perceived value directly affects the pull effect of ELS users' switching intention, thus indirectly affecting ELS users' switching intention. Users purchase goods in the live streaming, and if these goods have no context of use, there is no way to make the user feel like using them. Therefore, the host should create a context for the goods sold to help the user imagine and let the user experience the positive perceived value of the goods (Rungruangjit, 2022).

Then, platform operators should make ELS more appealing. The platform's prime target is to find active users. Commonly used ELS platforms attract users by differentiating from competitors. As a result, the platform operator should do the following to attract more users to the



platform. First, the platform should speed up platform iteration and improve the platform's perceived usefulness. User needs are always changing, and platform designers must build relevant functions to meet users' needs at various periods. Second, the platform operator can integrate live streaming and short videos while carrying out new information flow revision design from the platform mechanism. By interspersing live streamings and short videos, the swipe screen design is carried out. Third, ELS is, in some ways, a form of trust in e-commerce. The user pays for the hosts based on trust. The user's previous trust and understanding of the brand transferred to a specific host. Unlike the Western marketing system of the brand is king methodology, the channel is the focus of the Chinese marketing system. As a result, the platform operator should start from this point, reconstruct the user's consumption decision, and turn the traditional single price advantage strategy of the live streaming room into the emotional support of improving the IP endorsement of the host. Fourth, Highlight the personalized features of the platform. Platforms should find their positioning and design personalized features that meet the users' habits. Let users have patience with the platform and avoid the situation of malicious imitation between platforms.

Finally, platform operators should improve the retention rate of users. Switch costs, social influence, and inertia all negatively affect the mooring effects of ELS users' switching intentions. Therefore, to improve user loyalty, the platform should strengthen the switching cost of ELS users in three aspects: money, social relations, and inertia. Relating to money, operators can implement membership systems that give more preferential benefits to the user as the user sticks over time. Such benefits serve as switching cost as once users stop using the current ELS platform, they are lost. From the relationship point of view, ELS is at advantage compared to traditional online shopping, since ELS hosts can start live streams and interact with users at any time, strengthening user loyalty and developing weak social relations. Despite that the new online shopping platform may be well-designed in features and interactions, increased switching cost and social influence shall counter that. Finally, many of the decisions made by users rely on inertia. Once a platform makes users change their habits and shopping style, other platforms may be hardly any threat, as leaving the platform they are currently using is difficult.

#### 5.4. Limitations and future research

This study has numerous shortcomings as well. First, rather than investigating users' actual switching behavior, this study studies the switching intention of ELS users. If the current findings could be repeated in studies that evaluate actual switching behavior, they would be enhanced. Second, the data we collect comes from Chinese ELS users. China's high collectivism, high policy control, and relational culture (Zhao et al., 2008) may exert extra ramifications for interpersonal relationships and social interactions. Perceptions of ELS may differ greatly between countries and cultures. This disparity in views due to cultural differences is especially noticeable in organizational contexts. Given this, future research should include people from different countries and cultures, and comparison studies might be undertaken to improve the study's generalizability. Finally, the research model needs further improvement. This study relies on PPM theory and adopts a second-order model to study the switching intention of ELS users, which has achieved good empirical results. However, the variables proposed in this model have certain limitations and the variables within the push, pull, and mooring effects can be enriched in future studies. Moderators, such as users' experience and technology self-efficacy, can be further incorporated into the model.

#### Declarations

##### Author contribution statement

Dingyu Ye; Fufan Liu; Dongmin Cho; Zhengzhi Jia: Conceived and designed the experiments; Performed the experiments; Analyzed and

interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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The authors do not have permission to share data.

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