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Examining user switching intention between generative AI platforms: A push-pull-mooring perspective

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Abstract

Due to the intense competition among generative AI platforms, users may switch from a platform to an alternative one. This may lead to user attrition and undermine the competitive advantage. The purpose of this research is to examine user switching intention between generative AI platforms based on the push-pull-mooring (PPM). Push factors include information hallucination, privacy risk, and dissatisfaction, while pull factors include perceived interactivity, perceived anthropomorphism, perceived personalization, and user experience. Mooring factor is switching costs. Both structural equation modeling (SEM) and fuzzy-set qualitative comparative analysis (fsQCA) were used to conduct data analysis. The results validate the hypotheses. The fsQCA found that dissatisfaction is a common core condition triggering switching intention.

Keywords

generative AI, switching intention, PPM, privacy risk, perceived interactivity

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Introduction

Generative AI has rapidly gained prominence in 2023. Representative platforms such as ChatGPT have attracted hundreds of millions of registered users and received wide attention from both industries and academia. Encouraged by the success of ChatGPT, generative AI platforms are emerging one after another in the world. Well-known generative AI platforms include ChatGPT, Stable Diffusion, Midjourney, Baidu ERNIE Bot, and Alibaba Qianwen. Multiple generative AI platforms have similar functions, such as chat, questions & answers (Q&A), coding, and text generating images. There is intense competition among these platforms and they try to attract users and retain them. However, users may switch from a platform to an alternative one due to various reasons such as dissatisfaction and better experience. This may lead to user attrition and undermine the competitive advantage of the platform. Thus, it is necessary to examine users' switching between generative AI platforms in order to retain them.

As an emerging application, generative AI has received significant attention from researchers. They have examined generative AI user adoption (Faruk et al., 2023; Ma and Huo, 2023; Polyportis and Pahos, 2024), and continuance intention (Baek and Kim, 2023; Kim et al., 2024). Various factors such as performance expectancy, effort expectancy, trust and perceived enjoyment are found to affect user adoption and continuance of generative AI. However, previous studies have seldom explored user switching between generative AI platforms, which is crucial to user retention and the platform competitiveness. This research tries to fill the gap. Drawing on the push-pull-mooring (PPM), this research intends to investigate user switching intention between generative AI platforms. The PPM argues that user switch is influenced by three types of factors: push, pull and mooring factors. Among them, push factors are those driving users away from

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the original platform. Pull factors are those attracting users to a new platform. Mooring factors may hinder or promote user switching. In this research, based on the context of generative AI, we include information hallucination, privacy risk, and dissatisfaction as the push factors. Perceived interactivity, perceived anthropomorphism, perceived personalization, and user experience are the pull factors, and switching costs are the mooring factor. The results will uncover the mechanism underlying the formation of generative AI user switching intention and provide insights for generative AI platforms to curb user switching and retain users.

Literature review

Generative AI user behavior

Based on large language models, generative AI can interact with users using natural language in a way similar to human thinking. As a hot application, generative AI user behavior such as adoption and continuance usage has received increasing attention from researchers. User adoption reflects initial use, whereas continuance usage reflects a post-adoption behavior. With respect to user adoption, previous research has focused on ChatGPT adoption. Factors such as perceived anthropomorphism, perceived usefulness, trust and novelty are found to affect college students' adoption of ChatGPT (Faruk et al., 2023; Polyportis and Pahos, 2024). Besides these cognitive factors, affective attitude also affects user intention to adopt ChatGPT (Ma and Huo, 2023). Zhang et al. (2023) conducted a review and argued that subject factors, technical factors, information factors and social environmental factors affect ChatGPT use. With respect to continuance usage, previous research has noted the effect of trust on continuance intention of ChatGPT (Baek and Kim, 2023) and food-ordering chatbots (Hsiao and Chen, 2022). In addition, user satisfaction is another factor affecting continuance intention with generative AI (Kim et al., 2024).

From these literatures, it can be found that extant research has focused on user adoption and continuance use of generative AI. However, it has paid little attention to user switching between different generative AI platforms, which is crucial to user retention. This research tries to fill the gap and identify the determinants of user switching between generative AI platforms.

Push-pull-mooring (PPM)

The PPM was originally developed to describe people's migration behavior due to customs and geographic mobility (Ravenstein, 1885). Lee (1966) argued that human migration behavior is influenced by both push and pull factors, and proposed the push-pull model. Moon (1995) added mooring factors to further enrich the PPM model. Push factors are those that motivate people to abandon their current choices, whereas pull factors reflect the attractiveness of new choices. Mooring factors are those that would facilitate or hinder migration.

PPM has been widely used to examine user switching in the information systems research, such as cross-channel switch from offline to online services (Lee and Wang, 2023), and user switch between cloud storage services (Mohd-Any et al., 2024; Wu et al., 2017). Satisfaction, alternative attractiveness and switching costs are found to affect user switch between cloud storage services. PPM has also been used to explore user switching between social networking services (Chang et al., 2014; Hsieh et al., 2012; Xu et al., 2014). Push factors consist of dissatisfaction and regret, whereas pull factors consist of alternative attractiveness, usefulness and ease of use. Switching costs are the mooring factor. In addition, subjective norm, user experience and emotional commitment are also found to affect user switching between instant messaging products (Sun et al., 2017; Yin et al., 2023).

In summary, PPM provides a useful lens to disclose the process of user switching between information systems. As noted in the above literatures, PPM has been used to explain user switching in the contexts of instant messaging, cloud storage services and social networking. Consistent with these literatures, this research will generalize the PPM to the emerging context of generative AI. Compared to traditional technologies such as social networking, generative AI has a few new features such as human-like interactions and information hallucination, which may affect user switching intention. Thus, this research involved these features into the research model. The results will uncover the mechanism underlying user switching between generative AI platforms and provide guidance for platforms to prevent users' switching and retain them.

Research model and hypotheses

The research model is shown in Figure 1.

Push factors

Information hallucination means that generative AI may produce the contents that seem reasonable but are actually wrong or fabricated (Rawte et al., 2023). Since generative AI models may be trained based on incomplete or biased data, the generated contents may be inaccurate or illogical. Van Dis et al. (2023) found that using conversational AI for scientific research can lead to inaccuracies, bias, and plagiarism. Tan et al. (2023) found that ChatGPT is inaccurate in answering questions about math and time or other logical questions, and Bang et al. (2023) noted that ChatGPT will produce hallucinations due to its inability to access external knowledge bases. This exists not only in the text output of large language models, but also in contents such as images, videos, and audio (Rawte et al., 2023). Information hallucination may lead to user doubts and mistrust in the generated contents and reduce user satisfaction. Thus, we suggest,

H1a. Information hallucination leads to user dissatisfaction with generative AI.

Privacy risk reflects the potential losses derived from privacy misuse and leakage (Featherman et al., 2010). Existing research has shown that the higher the users' perceived privacy risk, the lower their usage intention (Featherman et al., 2010). A report released by Microsoft on voice AI shows that 41% of its respondents are worried about privacy and eavesdropping issues (Olson, 2019). Generative AI entails collecting large amount of data including user data for training. Users may also need to provide certain personal information in order to obtain accurate answers while using it. If these data are not properly processed and used, users may have privacy concern, which leads to negative attitudes such as dissatisfaction. Gurung and Raja (2016) stated that privacy risk concern affects consumer attitudes and the use intention. Sekarputri et al. (2024) found that privacy risk affects dissatisfaction, which further affects user intention to switch between instant messaging programs. Cheng and Jiang (2020) noted that privacy risk reduces user satisfaction with using AI chatbots. Thus, we propose,

H1b. Privacy risk leads to user dissatisfaction with generative AI.

Dissatisfaction has been found to be a crucial factor affecting user switching in information systems research (Jang et al., 2013; Xu et al., 2021; Yoon and Lim, 2021). If users are dissatisfied with the performance, content quality, or interaction experience of the current generative AI platform, they may switch to an alternative one for better services. Dai and Deng (2018) found that dissatisfaction will prompt users to abandon the current social networking platform and use alternatives. Fan and Suh (2014) argued that

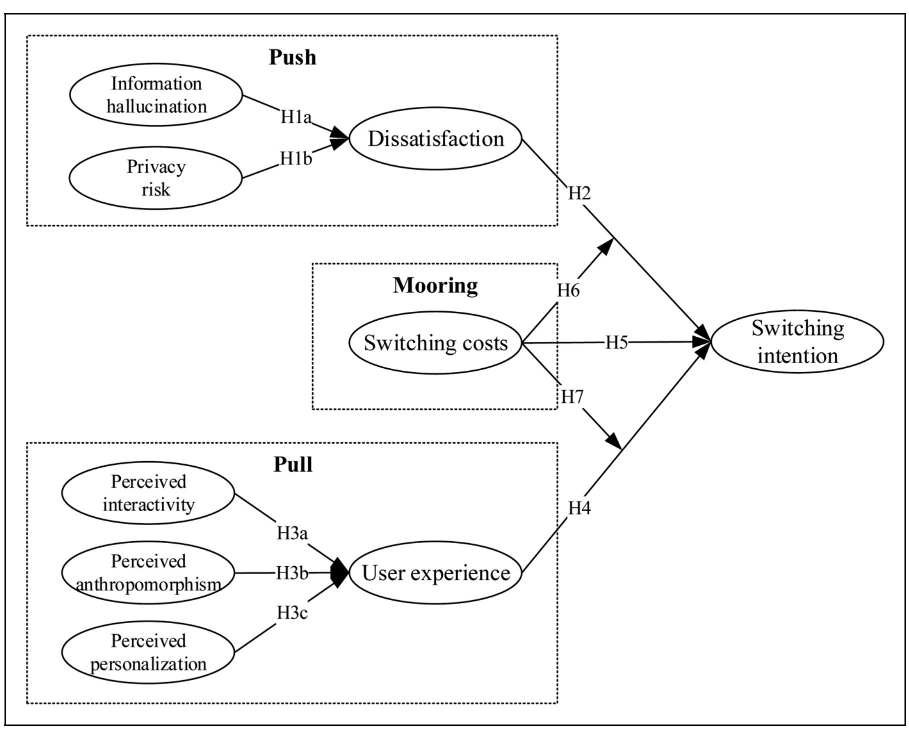

Figure 1. Research model.

dissatisfaction affects users' intention to switch to breakthrough technologies. Monoarfa et al. (2023) reported that dissatisfaction affects online shopping users' switching intention. Sekarputri et al. (2024) noted that dissatisfaction affects instant messaging user switching. In line with these studies, we state,

H2. User dissatisfaction with generative AI affects switching intention.

Pull factors

In the fields of information systems and human-computer interaction, interactivity is often considered as an important factor affecting user experience. Perceived interactivity reflects the response speed and professionalism of generative AI. When using generative AI during work or learning, good interactivity such as prompt responses and professional and accurate answers can provide an enjoyable user experience, which further improves user satisfaction and the usage intention. Zhou and Lu (2011) found that interactivity has a significant impact on the flow experience of mobile commerce users. Similarly, Guertin-Lahoud et al. (2023) found that interactivity affects a user's immersive experience. Mende et al. (2019) noted that interactivity influences users' intention to purchase products. Zhou et al. (2023) stated that the interactivity of online health communities affects user engagement. Compared to traditional human-computer interaction methods, the natural language interaction capabilities of generative AI will significantly improve user experience. Users can present more open-ended questions, and generative AI systems can respond in a more flexible and intelligent manner. Therefore, we suggest,

H3a. Perceived interactivity of generative AI affects user experience.

Perceived anthropomorphism refers to endow generative AI with human characteristics (Baek et al., 2022). Perceived anthropomorphism has been recognized as an important factor affecting chatbots user behavior (Balakrishnan et al., 2022). It can improve users' attitudes toward products in human-computer interaction (Li and Sung, 2021; Polyportis and Pahos, 2024). Calahorra-Candao and Martín-de Hoyos (2024) found that anthropomorphic features of intelligent voice assistants reduce the perceived risk and improve the overall acceptance of the product. Baek et al. (2022) found that anthropomorphic AI assistants can increase users' psychological closeness and participation intention. Blut et al. (2021) showed that the anthropomorphism of chatbots can increase users' intention to use them. Li et al. (2024) found that anthropomorphic features can improve users' human-computer interaction experience. The anthropomorphic features of generative AI such as anthropomorphic texts and emotional expressions will increase users' familiarity and intimacy, and create a compelling experience for them. Thus, we posit,

H3b. Perceived anthropomorphism of generative AI affects user experience.

Perceived personalization means providing customized contents, suggestions or services based on the user's preferences, interests, and historical behaviors (Kang et al., 2016). Personalization allows users to access more relevant and useful information, which may improve their interaction experience. Research has found that personalized marketing messages were more appealing to users than non-personalized contents (Howard and Kerin, 2004). Kang et al. (2016) found that personalized contents enhanced user engagement in online communities. Zhang et al. (2019) found that the personalization of mobile reading services has a significant effect on users' continuance intention. Research shows that perceived personalization positively affects employee attitudes and intention to use chatbots (Gkinko and Elbanna, 2022; Pillai et al., 2023). When users interact with generative AI, personalized features can not only make users feel understood and valued but also improve the efficiency by helping them find the information or complete tasks more quickly. For example, ChatGPT can personalize generated contents based on conversation history, and provide responses that are better aligned with user needs. Therefore, we propose,

H3c. Perceived personalization of generative AI affects user experience.

User experience reflects a user's subjective feelings such as enjoyment and immersion (Meng and Zhu, 2021). A positive user experience typically increases user satisfaction with a system or service. If users obtain a pleasant experience when trying generative AI, they may develop the attachment and loyalty towards the platform. Users will be inclined to continue using it, which may lead to their switching intention. Previous research has found that a positive experience with a mobile application promotes users' continuous intention (Hong and Xu, 2017; Xiang et al., 2022). Zhou and Mi (2024) found that user experience will affect social Q&A users' switching intention. Thus, we argue,

H4. User experience of generative AI affects switching intention.

Mooring factor

Switching costs refer to the various costs associated with switching from a service to another one, such as learning costs and sunk costs (Chang et al., 2017). In the PPM, switching costs are often deemed as a mooring factor that hinders users from switching (Liu et al., 2021; Sun et al., 2017). Cheng (2024) examined users' switching between intelligent personal assistant devices and found that inconvenience and switching costs affect switch intention. When users switch from a generative AI platform to another one, users may need to invest time on registration and learning the operation process, while giving up the convenience of using the original AI platform as well as the accumulated experience. When users feel the costs of switching between generative AI platforms to be high, they may abandon the switch and continue to use the original platform.

In addition, research has shown that mooring factors have a moderating effect on switching intention (Chang et al., 2017). Specifically, switching costs will negatively moderate the effect of dissatisfaction and user experience on switching intention. That is, switching costs will weaken the effects of dissatisfaction as a push factor and user experience as a pull factor on switching intention. Therefore, we propose,

H5. Switching costs affect generative AI user switching intention.

H6. Switching costs negatively moderate the relationship between dissatisfaction and switching intention.

H7. Switching costs negatively moderate the relationship between user experience and switching intention.

Method

The research model includes nine constructs, and the measurement items of these constructs were adapted from the existing literature and revised based on the context of generative AI to improve the content validity. A pretest was conducted among fifteen users that had experience using generative AI. Based on their comments, a few items were revised to improve the clarity and understandability. Table 1 lists the final items and their sources. We selected these nine constructs based on the extant literature and generative AI context. As noted in the literature review, dissatisfaction, user experience and switching costs are often found to be the significant factors affecting user switching in previous studies. Thus, these three factors were included into the research model. In addition, information hallucination, privacy risk, perceived interactivity, perceived anthropomorphism, and perceived personalization reflect the technical features of generative AI. They were also included into the model to highlight the generative AI context.

Three items of information hallucination were adapted from Zha et al. (2018) to reflect the false and fabricated information output by the generative AI. Four items of privacy risk were adapted from Hong and Thong (2013) to measure the potential loss and uncertainty derived from information disclosure. Items of dissatisfaction were adapted from Bhattacherjee (2001) to reflect the poor experience and dissatisfaction with using generative AI. Items of switching costs were adapted from Chen and Keng (2019) to measure the costs such as effort and time associated with switching from a generative AI platform to an alternative one. Items of perceived interactivity were adapted from Kim et al. (2022) to reflect the prompt and professional response. Items of perceived anthropomorphism were adapted from Haridasan et al. (2021) to reflect the human-like interactions between generative AI and users. Items of perceived personalization were adapted from Kang et al. (2016) to measure the personalized concerns and attention by generative AI. Items of user experience were adapted from Zhou and Mi (2024) to reflect the immersion and enjoyment. Items of switching intention were adapted from Chen and Keng (2019) to measure a user's intention to switch between generative AI platforms.

We used an online survey platform to develop the questionnaire and invited those users that had experience using generative AI to participate in the survey. We adopted snow balling sampling to collect data. Participants were encouraged to forward the questionnaire to their friends in order to expedite data collection. Data collection lasted for two weeks. We scrutinized all responses and dropped those that had

Table 1. Measurement items and their sources.

Constructs	Items	Contents	Source
Information hallucination (II)	II1	The information output by the current generative AI platform may be false.	Zha et al. (2018)
	II2	The information output by the current generative AI platform is not very reliable.	
	II3	The information output by the current generative AI platform may be untrue.	
Privacy risk (PR)	PR1	Providing my personal information to the current generative AI platform may bring risk.	Hong and Thong (2013)
	PR2	Providing my personal information to the current generative AI platform could potentially lead to significant losses.	
	PR3	Providing my personal information to the current generative AI platform would bring too much uncertainty.	
	PR4	Providing my personal information to the current generative AI platform could bring many unexpected problems.	
Dissatisfaction (DIS)	DIS1	I am dissatisfied with the services of the current generative AI platform.	Bhattacherjee (2001)
	DIS2	I have a poor experience with using the current generative AI platform.	
	DIS3	The services of the current generative AI platform are awkward.	
Switching costs (SC)	SC1	Replacing the current generative AI platform with a new one would be troublesome.	Chen and Keng (2019)
	SC2	Switching from the current generative AI platform to a new one could cost much time and effort for me.	
	SC3	The costs of replacing the current generative AI platform with a new one are high for me.	
Perceived interactivity (PI)	PI1	The new generative AI platform responses promptly.	Kim et al. (2022)
	PI2	The new generative AI platform responses professionally.	
	PI3	The new generative AI platform keeps me focused.	
Perceived anthropomorphism (PA)	PA1	The new generative AI platform interacts in a very natural way.	Haridasan et al. (2021)
	PA2	The new generative AI platform can think like a human.	
	PA3	The new generative AI platform has some degree of consciousness.	
Perceived personalization (PP)	PP1	The new generative AI platform understands my needs.	Kang et al. (2016)
	PP2	The new generative AI platform knows what I want.	
	PP3	The new generative AI platform can provide personalized contents based on my preferences.	
User experience (UE)	UE1	Using the new generative AI platform let me feel immersed.	Zhou and Mi (2024)
	UE2	Using the new generative AI platform brings pleasure to me.	
	UE3	Using the new generative AI platform brings enjoyment to me.	
Switching intention (SI)	SI1	I would consider using the new generative AI platform.	Chen and Keng (2019)
	SI2	I would recommend others to replace the current generative AI platform with the new one.	
	SI3	I will switch from the current generative AI platform to the new one soon.	

no experience using generative AI, and those that replied the same answer to all questions. As a result, 376 valid responses were obtained. Among them, 46.81% were male and 53.19% were female, showing a gender balance. 80.32% of them were between twenty and forty years old. A report also indicates that those users below thirty-five years old are the core users of generative AI (iResearch, 2024).

89.89% had received college or higher education. 71.28% of the respondents have used text-based generative AI (such as ChatGPT, Baidu ERNIE Bot, and Ali Qianwen), 44.15% have used image-based generative AI (such as Midjourney and Stable Diffusion), and 25.27% have used video-based generative AI (such as Runaway and Stable Audio). Over half of them (65.43%) used generative AI at least once a week.

Results

Structural equation modeling (SEM)

Measurement model. First, the reliability and validity were examined. As listed in Table 2, each alpha coefficient is larger than the threshold value of 0.7, showing good reliability. Each factor loading exceeds 0.7, composite reliability (CR) exceeds 0.7, and the average variance extracted (AVE) value exceeds 0.5. These results demonstrate good convergent validity. Meanwhile, as shown in Table 3, the square root of each AVE is larger than the correlation coefficients between variables, indicating good discriminant validity.

Structural model. Second, AMOS 26 was adopted for hypotheses testing. The model fit indices are shown in Table 4. The actual values of all indices are better than the recommended values, showing a good fit. Figure 2 presents the estimation results. Except H3b, other hypotheses were supported. The explained variance of dissatisfaction, user experience and switching intention is 33.4%, 43.3%, and 55.7%, respectively.

Fuzzy-set qualitative comparative analysis (fsQCA)

Model construction. According to the research model, this research selected information hallucination, privacy risk, dissatisfaction, switching costs, perceived interactivity, perceived anthropomorphism, perceived personalization, and user experience as the antecedent variables. Switching intention is the outcome variable. According to the standards of 5%, 95% and 50% of the intersection (Ragin, 2008), fsQCA 4.0 was used to calibrate the data. The results showed that the consistency of all antecedent variables was lower than 0.9, showing that each antecedent variable is not a necessary condition for the outcome variable. Then we proceeded to the configuration analysis.

Configuration analysis. A truth table of 256 (2^8) rows was first constructed, with each row representing a possible combination of the antecedent conditions. The frequency threshold was set to 7, the consistency threshold was set to 0.8, and the PRI threshold was set to 0.75 (Pappas and Woodside, 2021). The results are shown in Table 5. ● indicates that the core condition exists, ● indicates that the peripheral condition exists, ⊗ indicates that the peripheral condition is absent, and "blank" indicates that the condition is optional.

As shown in Table 5, there are three configurations that lead to switching intention. S1 suggests that "information hallucination*privacy risk*dissatisfaction*∼switching costs* perceived interactivity*perceived anthropomorphism*perceived personalization" will trigger switching intention. This path means that when the push and pull factors (except user experience) are at high level and the switching costs are low, users are not concerned with their experience when determining their switching intention.

S2 suggests that "privacy risk*dissatisfaction*∼switching costs*perceived interactivity*perceived anthropomorphism*perceived personalization*user experience" will trigger switching intention. This path is similar to S1 except that user experience substitutes information hallucination as a peripheral condition. This indicates that these users pay more attention to their experience rather than information hallucination when deciding switching.

S3 suggests that "information hallucination*privacy risk*dissatisfaction*perceived interactivity*perceived anthropomorphism*perceived personalization*user experience" will trigger switching intention. This path shows that when the push and pull factors are at high level, users will have an intention to switch, regardless of switching costs. Comparing S3 with S1 and S2, we can find that S3 highlights the role of both push and pull factors rather than the mooring factor.

Comparing three paths, we can find that user experience, information hallucination and switching costs are the optional condition of S1, S2 and S3, respectively. In comparison, dissatisfaction is the common core condition of three paths, indicating that it is a crucial factor leading to switching intention. Privacy risk, perceived interactivity, perceived anthropomorphism, and perceived personalization are the common peripheral conditions, indicating that they are also the indispensable factors that trigger user switch.

Table 2. Reliability and validity.

Constructs	Items	Loading	CR	AVE	Alpha
Information hallucination (II)	II1	0.768	0.804	0.577	0.807
	II2	0.789			
	II3	0.721			
Privacy risk (PR)	PR1	0.741	0.844	0.575	0.847
	PR2	0.784			
	PR3	0.755			
	PR4	0.753			
Dissatisfaction (DIS)	DIS1	0.734	0.809	0.585	0.811
	DIS2	0.786			
	DIS3	0.774			
Switching costs (SC)	SC1	0.783	0.827	0.615	0.831
	SC2	0.785			
	SC3	0.784			
Perceived interactivity (PI)	PI1	0.739	0.807	0.583	0.809
	PI2	0.750			
	PI3	0.800			
Perceived anthropomorphism (PA)	PA1	0.793	0.830	0.619	0.831
	PA2	0.773			
	PA3	0.795			
Perceived personalization (PP)	PP1	0.768	0.837	0.631	0.837
	PP2	0.834			
	PP3	0.780			
User experience (UE)	UE1	0.757	0.816	0.597	0.818
	UE2	0.783			
	UE3	0.777			
Switching intention (SI)	SI1	0.803	0.811	0.589	0.819
	SI2	0.755			
	SI3	0.744			

Table 3. Correlation coefficients and the square root of AVE.

	II	PR	DIS	SC	PI	PA	PP	UE	SI
II	**0.760**								
PR	0.487	**0.758**							
DIS	0.471	0.522	**0.765**						
SC	−0.482	−0.502	−0.330	**0.784**					
PI	0.542	0.531	0.358	−0.615	**0.763**				
PA	0.544	0.583	0.378	−0.525	0.577	**0.787**			
PP	0.508	0.518	0.343	−0.571	0.540	0.574	**0.795**		
UE	0.414	0.421	0.279	−0.449	0.567	0.534	0.557	**0.772**	
SI	0.449	0.474	0.502	−0.614	0.515	0.477	0.491	0.569	**0.768**

Discussions

As shown in Figure 2, except the path from perceived anthropomorphism to user experience, other hypotheses are supported. Table 5 shows that there are three configurations leading to switching intention. SEM results indicate that dissatisfaction and user experience positively affect switching intention, whereas switching costs negatively affect switching intention. fsQCA results indicate that dissatisfaction is a common core condition of three paths, whereas user experience and ~switching costs are the common peripheral conditions of two paths. This indicates that the results of SEM are roughly consistent with those of fsQCA.

Table 4. The fit indices.

Fit index	χ^2/df	GFI	AGFI	CFI	NFI	RMSEA
The recommended value	<3	>0.9	>0.8	>0.9	>0.9	<0.08
The actual value	1.782	0.904	0.881	0.950	0.894	0.046

With respect to the push factors, information hallucination and privacy risk significantly affect users' dissatisfaction with generative AI, which in turn affects their switching intention. Compared to information hallucination (β=0.284, $p<0.001$), privacy risk has a larger impact (β=0.384, $p<0.001$) on dissatisfaction, suggesting that users are much concerned with privacy risk when using generative AI. Users always expect to obtain reliable and credible answers from generative AI, which may generate responses that seem reasonable but actually contain incorrect or fabricated contents due to the information hallucination (Bang et al., 2023). This can make users dissatisfied. In addition, privacy risk may occur in the model training stage (generative AI usually requires a large amount of data to train the model, which may contain the user's personal privacy information), the usage stage (generative AI may generate contents containing the user's personal privacy information) and the post-usage stage (generative AI may collect prompt words entered by users to improve the model). Privacy risk increases the perceived uncertainty and incurs user dissatisfaction. Therefore, generative AI needs to reduce information hallucination and privacy risk in order to alleviate user dissatisfaction and prevent user switch.

With respect to the pull factors, perceived interactivity and perceived personalization affect user experience, which in turn affects switching intention. Prompt and professional responses of generative AI will improve users' interaction experience and increase their learning and working efficiency. Similarly, personalized contents can make users feel that their individual needs are addressed, which may meet their performance expectation toward generative AI platforms. For example, when students use a generative AI platform to assist their learning, the personalized functions can generate customized learning paths and contents based on students' learning history, preferences, and knowledge level. This personalized service may reduce user effort and time spent on information seeking and increase user satisfaction, which further promotes user switching to the platform. We did not find the effect of perceived anthropomorphism on user experience. This is inconsistent with existing research (Balakrishnan and Dwivedi, 2024; Cheng et al., 2022; Li and Sung, 2021). This may be for the reason that users are much concerned with the responsiveness and personalized contents when using generative AI, and have paid little attention to the anthropomorphic features, which reflect emotional factors. Further, the anthropomorphic features may create an uncanny valley that makes users feel uncomfortable (Baek and Kim, 2023). This may lead to the insignificant effect of perceived anthropomorphism on user experience.

As a mooring factor, switching costs negatively affect switching intention. When users switch from a generative AI platform to another one, due to the differences in interfaces, functions, and services, users may need to spend certain time and effort learning to adapt, which will inhibit their switching intention. In addition, we also found that switching costs negatively moderate the impact of dissatisfaction and user experience on switching intention. The higher the switching costs, the lower the effects of dissatisfaction and user experience on switching intention. This is in line with existing research (Cheng, 2024), and suggests the attenuating effect of switching costs on the relationship between both push and pull factors and switching intention.

Theoretical and managerial implications

From a theoretical perspective, this research makes three contributions. First, existing research has focused on user adoption and continuance use of generative AI, and has seldom examined generative AI user switch, which may lead to user attrition and undermine the competitive advantage. This research examined user switching intention between generative AI platforms from a PPM perspective. The results enrich extant research on generative AI user behavior. Second, we found that generative AI user switching intention is affected by push factors (information hallucination, privacy risk, and dissatisfaction), pull factors (perceived interactivity, perceived anthropomorphism, perceived personalization, and user

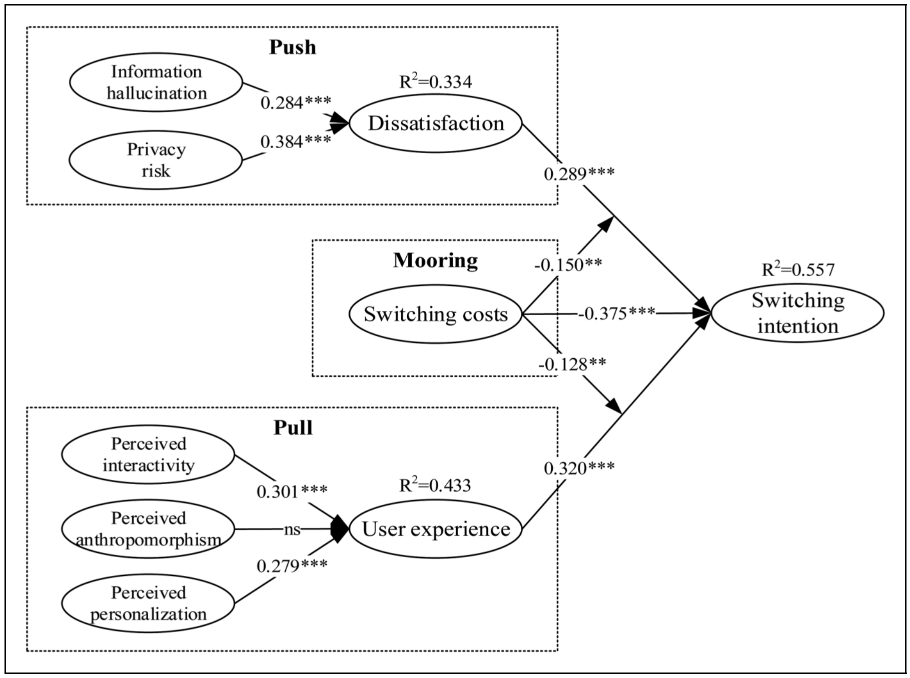

Figure 2. Path coefficients and significance.

Table 5. FsQCA results.

	Switching intention		
Conditions	S1	S2	S3
Information hallucination	●		●
Privacy risk	●	●	●
Dissatisfaction	●	●	●
Switching costs	⊗	⊗	
Perceived interactivity	●	●	●
Perceived anthropomorphism	●	●	●
Perceived personalization	●	●	●
User experience		●	●
Raw coverage	0.393	0.393	0.388
Unique coverage	0.020	0.021	0.016
Consistency	0.973	0.966	0.972
Solution coverage	0.429		
Solution consistency	0.955		

experience), and mooring factor (switching costs). The results disclose the formation mechanism of generative AI user switching intention. Third, the results indicated that generative AI user experience is mainly influenced by perceived interactivity and personalization rather than perceived anthropomorphism. This suggests that users weigh the utilitarian factors (interactivity and personalization) over the emotional factor (anthropomorphism) when evaluating their experience using generative AI. This result also increases the understanding of generative AI user experience.

This research has a few implications for generative AI platforms. On one hand, they need to reduce information hallucination and privacy risk in order to mitigate user dissatisfaction. They can improve algorithms and adopt review mechanisms to alleviate information hallucination. They also should properly collect and use personal information to decrease user privacy concern. On the other hand, generative AI platforms need to enhance the interactivity and personalization features in order to improve user experience. They can optimize the user interface, improve the responsiveness, and provide personalized and customized features and services to attract users. In addition, switching costs are also an important factor affecting switching intention. Generative AI platforms can develop relationship connections with users to increase switching costs and prevent their switch.

Conclusion

Based on the PPM, this research examined user switching intention between generative AI platforms. The results indicated that information hallucination and privacy risk lead to dissatisfaction, while perceived interactivity and personalization affect user experience. Dissatisfaction, user experience, and switching cost determine switching intention. The fsQCA identified three configurations leading to switching intentions. The results suggest that generative AI platforms need to be concerned with push, pull and mooring factors in order to prevent user switch.

This research has a few limitations. First, generative AI user switching may be affected by multiple factors. In addition to the factors identified in this research, other factors such as trust and identification may also affect switching intention. Future research may examine their effects. Second, generative AI is developing rapidly and it may evolve from general AI to professional AI. Future research may examine user switching between professional AI platforms. Third, we mainly conducted a cross-sectional study. Future research may collect longitudinal data to examine the dynamic development of user switching. Fourth, we collected 376 valid responses in this research. Future research may obtain a larger sample to improve the reliability and validity of the results.

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References

Baek TH, Bakpayev M, Yoon S, et al. (2022) Smiling AI agents: How anthropomorphism and broad smiles increase charitable giving. *International Journal of Advertising* 41(5): 850–867.

Baek TH and Kim M (2023) Is ChatGPT scary good? How user motivations affect creepiness and trust in generative artificial intelligence. *Telematics and Informatics* 83: 102030.

Balakrishnan J, Abed SS and Jones P (2022) The role of meta-UTAUT factors, perceived anthropomorphism, perceived intelligence, and social self-efficacy in chatbot-based services? *Technological Forecasting and Social Change* 180: 121692.

Balakrishnan J and Dwivedi YK (2024) Conversational commerce: Entering the next stage of AI-powered digital assistants. *Annals of Operations Research* 333: 653–687.

Bang Y, Cahyawijaya S, Lee N, et al. (2023) A multitask, multilingual, multimodal evaluation of ChatGPT on reasoning, hallucination, and interactivity. In: Proceedings of the 13th International Joint Conference on Natural Language Processing, pp.675–718.

Bhattacherjee A (2001) Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly* 25(3): 351–370.

Blut M, Wang C, Wünderlich NV, et al. (2021) Understanding anthropomorphism in service provision: A meta-analysis of physical robots, chatbots, and other AI. *Journal of the Academy of Marketing Science* 49: 632–658.

Calahorra-Candao G and Martín-de Hoyos MJ (2024) The effect of anthropomorphism of virtual voice assistants on perceived safety as an antecedent to voice shopping. *Computers in Human Behavior* 153: 108124.

Chang HH, Li SY and Wong KH (2017) Applying push-pull-mooring to investigate channel switching behaviors: M-shopping self-efficacy and switching costs as moderators. *Electronic Commerce Research and Applications* 24: 50–67.

Chang I-C, Liu C-C and Chen K (2014) The push, pull and mooring effects in virtual migration for social networking sites. *Information Systems Journal* 24(4): 323–346.

Chen Y-H and Keng C-J (2019) Utilizing the push-pull-mooring-habit framework to explore users' intention to switch from offline to online real-person English learning platform. *Internet Research* 29(1): 167–193.

Cheng S (2024) Understanding users' voluntary switching behavior for user interfaces of intelligent personal assistant devices. *Information Systems Frontiers*: 1–24.

Cheng X, Zhang X, Cohen J, et al. (2022) Human vs. AI: Understanding the impact of anthropomorphism on consumer response to chatbots from the perspective of trust and relationship norms. *Information Processing & Management* 59(3): 102940.

Cheng Y and Jiang H (2020) How do AI-driven chatbots impact user experience? Examining gratifications, perceived privacy risk, satisfaction, loyalty, and continued use. *Journal of Broadcasting & Electronic Media* 64(4): 592–614.

Dai B and Deng A (2018) Analysis on the influencing factors of social media discontinuance and switching behaviors. *Information Science* 36(5): 64–70.

Fan L and Suh Y-H (2014) Why do users switch to a disruptive technology? An empirical study based on expectation-disconfirmation theory. *Information & Management* 51(2): 240–248.

Faruk LID, Rohan R, Ninrutsirikun U, et al. (2023) University students' acceptance and usage of generative

AI (ChatGPT) from a psycho-technical perspective. In: Proceedings of the 13th International Conference on Advances in Information Technology, pp.1–8.

Featherman MS, Miyazaki AD and Sprott DE (2010) Reducing online privacy risk to facilitate e-service adoption: The influence of perceived ease of use and corporate credibility. *Journal of Services Marketing* 24(3): 219–229.

Gkinko L and Elbanna A (2022) Hope, tolerance and empathy: Employees' emotions when using an AI-enabled chatbot in a digitalised workplace. *Information Technology & People* 35(6): 1714–1743.

Guertin-Lahoud S, Coursaris CK, Sénécal S, et al. (2023) User experience evaluation in shared interactive virtual reality. *Cyberpsychology, Behavior, and Social Networking* 26(4): 263–272.

Gurung A and Raja MK (2016) Online privacy and security concerns of consumers. *Information & Computer Security* 24(4): 348–371.

Haridasan AC, Fernando AG and Balakrishnan S (2021) Investigation of consumers' cross-channel switching intentions: A push-pull-mooring approach. *Journal of Consumer Behaviour* 20(5): 1092–1112.

Hong H and Xu D (2017) An empirical study of mobile social app continuance intention: Integrating flow experience and switching costs. *International Journal of Networking and Virtual Organisations* 17(4): 410–424.

Hong W and Thong JYL (2013) Internet privacy concerns: An integrated conceptualization and four empirical studies. *MIS Quarterly* 37(1): 275–298.

Howard DJ and Kerin RA (2004) The effects of personalized product recommendations on advertisement response rates: The "try this. It works!" technique. *Journal of Consumer Psychology* 14(3): 271–279.

Hsiao K-L and Chen C-C (2022) What drives continuance intention to use a food-ordering chatbot? An examination of trust and satisfaction. *Library Hi Tech* 40(4): 929–946.

Hsieh J-K, Hsieh Y-C, Chiu H-C, et al. (2012) Post-adoption switching behavior for online service substitutes: A perspective of the push-pull-mooring framework. *Computers in Human Behavior* 28(5): 1912–1920.

iResearch (2024). China mobile Internet AIGC track traffic report. https://www.iresearch.com.cn/Detail/report?id=4393&isfree=0.

Jang YJ, Cho S-B and Kim WG (2013) Effect of restaurant patrons' regret and disappointment on dissatisfaction and behavioral intention. *Journal of Travel & Tourism Marketing* 30(5): 431–444.

Kang M, Shin D-H and Gong T (2016) The role of personalization, engagement, and trust in online communities. *Information Technology & People* 29(3): 580–596.

Kim J, Kang S and Bae J (2022) Human likeness and attachment effect on the perceived interactivity of AI speakers. *Journal of Business Research* 144: 797–804.

Kim JS, Kim M and Baek TH (2024) Enhancing user experience with a generative AI chatbot. *International Journal of Human–Computer Interaction*: 1–13.

Lee ES (1966) A theory of migration. *Demography* 3(1): 47–57.

Lee J-C and Wang J (2023) From offline to online: Understanding users' switching intentions from traditional wealth management services to mobile wealth management applications. *International Journal of Bank Marketing* 41(2): 369–394.

Li X, Lee GJX and Yuen KF (2024) Consumer acceptance of urban drone delivery: The role of perceived anthropomorphic characteristics. *Cities* 148: 104867.

Li X and Sung Y (2021) Anthropomorphism brings us closer: The mediating role of psychological distance in user-AI assistant interactions. *Computers in Human Behavior* 118: 106680.

Liu Z, Zhao Y, Chen S, et al. (2021) Exploring askers' switching from free to paid social Q&A services: A perspective on the push-pull-mooring framework. *Information Processing & Management* 58(1): 102396.

Ma X and Huo Y (2023) Are users willing to embrace ChatGPT? Exploring the factors on the acceptance of chatbots from the perspective of AIDUA framework. *Technology in Society* 75: 102362.

Mende M, Scott ML, van Doorn J, et al. (2019) Service robots rising: How humanoid robots influence service experiences and elicit compensatory consumer responses. *Journal of Marketing Research* 56(4): 535–556.

Meng M and Zhu Q (2021) A review of research on user experience at home and abroad. *Research on Library Science* 9: 9–19.

Mohd-Any AA, Sarker M and Hui FLZ (2024) Understanding users' switching intention of cloud storage services: A push-pull-mooring framework. *Journal of Consumer Behaviour* 23(2): 748–768.

Monoarfa TA, Sumarwan U, Suroso AI, et al. (2023) Switch or stay? Applying a push-pull-mooring framework to evaluate behavior in e-grocery shopping. *Sustainability* 15(7): 6018.

Moon B (1995) Paradigms in migration research: Exploring "moorings" as a schema. *Progress in Human Geography* 19(4): 504–524.

Olson C (2019). New report tackles tough questions on voice and AI. https://about.ads.microsoft.com/en-us/blog/post/april-2019/new-report-tackles-tough-questions-on-voice-and-ai.

Pappas IO and Woodside AG (2021) Fuzzy-set qualitative comparative analysis (fsQCA): Guidelines for research practice in information systems and marketing. *International Journal of Information Management* 58: 102310.

Pillai R, Ghanghorkar Y, Sivathanu B, et al. (2023) Adoption of artificial intelligence (AI) based employee experience (EEX) chatbots. *Information Technology & People* 37(1): 449–478.

Polyportis A and Pahos N (2024) Understanding students' adoption of the ChatGPT chatbot in higher education: The role of anthropomorphism, trust, design novelty and institutional policy. *Behaviour & Information Technology*: 1–22.

Ragin C (2008) *Redesigning Social Inquiry: Fuzzy Sets and Beyond*. Chicago, IL: University of Chicago Press.

Ravenstein EG (1885) The laws of migration. *Journal of the Statistical Society* 48(2): 167–227.

Rawte V, Sheth A and Das A (2023) A Survey of Hallucination in Large Foundation Models. https://arxiv.org/abs/2309.05922.

Sekarputri JA, Fitriani WR, Hidayanto AN, et al. (2024) The roles of privacy, security, and dissatisfaction in affecting switching intention on messenger applications. *Multimedia Tools and Applications* 83: 45625–45651.

Sun Y, Liu D, Chen S, et al. (2017) Understanding users' switching behavior of mobile instant messaging applications: An empirical study from the perspective of push-pull-mooring framework. *Computers in Human Behavior* 75: 727–738.

Tan Y, Min D, Li Y, et al. (2023) Can ChatGPT replace traditional KBQA models? An in-depth analysis of the question answering performance of the GPT LLM family. *Lecture Notes in Computer Science* 14265: 348–367.

Van Dis EA, Bollen J, Zuidema W, et al. (2023) ChatGPT: Five priorities for research. *Nature* 614(7947): 224–226.

Wu K, Vassileva J and Zhao Y (2017) Understanding users' intention to switch personal cloud storage services: Evidence from the Chinese market. *Computers in Human Behavior* 68: 300–314.

Xiang G, Chen Q and Li Q (2022) How attachment affects users' continued use intention of tourism mobile platform: A user experience perspective. *Frontiers in Psychology* 13: 995384.

Xu H, Wang J, Tai Z, et al. (2021) Empirical study on the factors affecting user switching behavior of online learning platform based on push-pull-mooring theory. *Sustainability* 13(13): 7087.

Xu Y, Yang Y, Cheng Z, et al. (2014) Retaining and attracting users in social networking services: An empirical investigation of cyber migration. *The Journal of Strategic Information Systems* 23(3): 239–253.

Yin C, Zhou Y, He P, et al. (2023) Research on the influencing factors of the switching behavior of Chinese social media users: QQ transfer to WeChat. *Library Hi Tech* 41(3): 771–787.

Yoon C and Lim D (2021) Customers' intentions to switch to internet-only banks: Perspective of the push-pull-mooring model. *Sustainability* 13(14): 8062.

Zha X, Yang H, Yan Y, et al. (2018) Exploring the effect of social media information quality, source credibility and reputation on informational fit-to-task: Moderating role of focused immersion. *Computers in Human Behavior* 79: 227–237.

Zhang H, Liu C, Wang D, et al. (2023) Research on the influencing factors of ChatGPT users' intention. *Information Studies: Theory & Application* 46(4): 15–22.

Zhang Z, He H and Cao G (2019) The influence of perception characteristics and personalization on the willingness to use mobile phone Reading continuously. *Library and Information Service* 63(7): 80–85.

Zhou P, Zhao S, Ma Y, et al. (2023) What influences user participation in an online health community? *The Stimulus-Organism-Response Model Perspective. Aslib Journal of Information Management* 75(2): 364–389.

Zhou T and Lu Y (2011) The effect of interactivity on the flow experience of mobile commerce user. *International Journal of Mobile Communications* 9(3): 225–242.

Zhou T and Mi Q (2024) Examining user switching between social Q&A platforms: A push–pull-mooring perspective. *Universal Access in the Information Society* 23: 1333–1342.

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