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Examining user migration intention from social Q&A communities to generative AI

Tao Zhou[1]✉ & Xiaoying Wu[1]

As an emerging application, generative AI has attracted many users to conduct question and answer (Q&A), which may lead to their defection from social Q&A communities. Based on the push-pull-mooring (PPM) model, this research examined user migration intention from social Q&A communities to generative AI. Data were analyzed using a mixed method of SEM and fsQCA. The results revealed that migration intention is influenced by a combination of push factors (information overload and community fatigue), pull factors (perceived anthropomorphism, perceived accuracy, perceived trustworthiness, and flow experience), and mooring factor (social influence). The fsQCA results identified three main paths leading to migration intention. These results imply that Q&A communities need to reduce information overload and mitigate users' fatigue in order to retain them and achieve a sustainable development.

[1] School of Management, Hangzhou Dianzi University, Hangzhou 310018, P.R. China. ✉email: zhoutao@hdu.edu.cn

Introduction

With the increasing abundance of information and the accelerated pace of life, people tend to actively seek knowledge to solve problems in different scenarios. Social question and answer (Q&A) communities such as Quora and Zhihu provide a platform for users to share and exchange knowledge, which include user-generated content (UGC) and professional-generated content (PGC). Platform users consist of ordinary users and expert users. Ordinary users have a low threshold for content creation, but they lack sufficient motivation to create contents and may produce a lot of knowledge noise. In contrast, expert users generate high-quality contents, but the creation period is long and some knowledge requires users' payment for access. Under this circumstance, generative AI has expanded the way of content generation. Generative AI such as ChatGPT can generate texts or codes and conduct real-time Q&A with users. It has been applied in many fields such as education, healthcare, and e-commerce. In the field of knowledge Q&A, AI-generated content (AIGC) may have an impact on traditional social Q&A communities by diversifying the way that users access knowledge contents. Users may reduce or abandon the use of social Q&A communities in favor of generative AI for knowledge Q&A, which will lead to their defection from social Q&A communities. Therefore, it is necessary to study users' migration from social Q&A communities to generative AI in order to prevent users' migration and retain them.

Previous studies have explored generative AI in various fields, such as school education (Lim et al., 2023), academic ecology (Lund et al., 2023), and managerial work (Korzynski et al., 2023). However, few studies have examined the effect of generative AI on knowledge Q&A user behavior, more specifically, users' migration from social Q&A communities to generative AI. Compared with traditional Q&A communities, generative AI has significant advantages, such as providing real-time, accurate, and free answers and engendering better interaction experience, which may lead to users' migration intention. On the other hand, users' negative feelings of social Q&A communities such as low quality, information overload, and fatigue may also influence users' migration intention. In addition, environmental factors such as social influence may contribute to users' migration. Therefore, drawing on the push-pull-mooring (PPM) model, this research will examine users' migration intention from social Q&A communities to generative AI. We employed a mixed method of structural equation modeling (SEM) and fuzzy-set qualitative comparative analysis (fsQCA). The results will help understand the effect of generative AI on users' knowledge Q&A migration intention.

Literature review

User migration. Sociology proposes that migration behavior reflects human migration in physical space (Boyle et al., 2014). In the field of information systems, it has been used to describe users' migration in cyberspace, such as users' migration in social networks (Cheng et al., 2009). This process may be slow and gradual, i.e., users do not completely abandon the use of the original media when they start using a new media, but gradually reduce their use. Thus, users' migration means that users decrease their use of the original system and increase their use of the new system. The emergence of generative AI may substitute social Q&A communities. When users need knowledge, they can choose between asking people and asking AI, and this decision may be affected by multiple factors such as platform content characteristics, users' knowledge needs and social influence.

Users' migration includes three categories. (1) Users' migration between different media, such as migration from offline to online. Li et al. (2019) examined patients' switch from offline to online medical services. Kim and Han (2023) explored consumers' shift from online to offline shopping. (2) Users' migration in the same medium, such as migration between the platforms providing similar services. Hwang et al. (2019) identified the factors affecting user switching between social networking sites. (3) Users' migration in the same medium that has different characteristics. Hsieh et al. (2012) studied users' migration from blogs to micro-blogs. Users migrate between knowledge Q&A communities based on their own needs and the platform's features such as functionality and interactivity. A few users who expect to acquire knowledge efficiently and try new technologies may turn to generative AI for services. Thus, this research focuses on users' migration intention from traditional social Q&A communities to generative AI. This migration belongs to the third category.

PPM. The PPM argues that migration is influenced by three types of factors: push, pull, and mooring (Moon, 1995). The model was introduced as the dominant paradigm to study population migration (Bansal et al., 2005), and was later widely applied to examine users' migration on information systems (Lai et al., 2012).

Among three types of factors, push factors are those that push users away from their original platform, such as dissatisfaction with the original platform. Chen et al. (2023) reported that low enjoyment and low satisfaction are the push factors affecting user switching between fitness wearable devices. Hwang et al. (2019) argued that interaction overload and unwanted relationships lead to users' switching of social networking sites. Pull factors are the factors that pull users toward a new platform, such as the attractiveness. Ye and Potter (2011) noted that ease of use and security influence users' migration. Mooring factors are those that prevent or facilitate users' migration between platforms. Social influence is a common mooring factor. Cheng et al. (2009) argued that social influence such as peer influence will affect users' migration. Cao et al. (2020) found that users' migration from blogs to micro-blogs is influenced by the inertia effect. In addition, mooring factors include sunk costs (Fei and Bo, 2014), continuance costs (Chang et al., 2014), and switching costs (Cao et al., 2020). Consistent with these studies, this research will adopt the PPM to study users' migration intention from social Q&A communities to generative AI.

Research model and hypotheses

Push factors

Low content quality. Low content quality refers to users' low perceptions of content usefulness, sufficiency, and timeliness (Rieh, 2002). Knowledge contribution has a higher threshold than the information sharing in social media. Users often lack the motivation to create contents in knowledge communities. Most of them seek answers but few answer questions, leading to the phenomenon of only reading but not speaking. This will cause a "tragedy of the commons" and affect the overall quality of platform contents in the long term. Information quality is a key factor affecting users' expectations and satisfaction (Lin and Wu, 2002). When users perceive low content quality, they feel that their time and effort are exhausted, eventually causing the negative emotion of fatigue (Han, 2018). If users cannot find satisfactory answers or usually take a long time to meet their needs in Q&A communities, they may perceive inefficiency and feel fatigue. Therefore, we propose,

H1. Low content quality significantly affects community fatigue.

Information overload. Information overload means that the overwhelming information exceeds what users' own information processing capacity can process (Soto-Acosta et al., 2014). The massive amount of information generated in knowledge Q&A communities, such as advertisements, personalized recommendations, and user-generated contents, lowers users' information processing efficiency and even makes them feel overloaded. Users need to invest much effort and time on information scrutinizing, which may lead to their exhaustion and fatigue. Dai et al. (2020) reported that perceived information overload induces negative emotional experiences, such as fatigue and frustration, which in turn trigger negative behaviors. Lee et al. (2016) argued that information overload affects social network fatigue. Thus,

H2. Information overload significantly affects community fatigue.

Community fatigue. As users become more active in the community, they may also feel community fatigue. As an emotional factor, community fatigue has a negative impact on users' psychology and behavior. The psychological aspects include emotions such as anxiety and disappointment, as well as reactions such as low motivation and loss of interest (Ravindran et al., 2013). These negative emotions may lead to users' discontinuance of the current service and their switch to an alternative one. Users may decide to migrate from social Q&A communities to generative AI in order to alleviate the fatigue feelings accumulated in the social Q&A communities. Thus, we suggest,

H3. Community fatigue significantly affects users' migration intention.

Pull factors

Perceived anthropomorphism. Perceived anthropomorphism means that non-human subjects are endowed with human qualities such as traits, motivations, and mental states (Epley et al., 2007). Generative AI is not only instrumental but also endowed with certain social functions. It can express cognitive empathy or show verbal humor catering to users' needs during Q&A interactions with users, especially in contexts where they have emotional appeals (e.g., consulting on emotional issues). Spatola and Wudarczyk (2021) found that users' emotions toward AI are related to the perceived degree of anthropomorphism. The anthropomorphism such as conversational patterns and personality play will engender users' positive emotions and good experience when they seek knowledge from generative AI. Prior studies have found that for AI assistants with high anthropomorphic tendencies, users usually have more positive evaluations (Graaf and Allouch, 2014), and enjoy more fun (Mishra et al., 2022). Based on these results, we state,

H4. Perceived anthropomorphism significantly affects flow experience.

Perceived accuracy. The content accuracy includes recognition (how well the answers match the expectations of the questioner), consistency (comprehensive judgment of the relevance between all answers), and expertise (the degree of expertise in the field related to the question) (Frické and Fallis, 2004). Generative AI generates contents based on large data sets and complex mathematical algorithms. The accuracy of these contents is critical to the user experience. The perceived accuracy of replies is a determinant of information value, especially for knowledge-based Q&A, where users expect to obtain accurate and useful answers. In other words, if users perceive the contents to be inaccurate, they may need to take much time and effort to screen the contents, thus leading to a poor experience. Nadarzynski et al. (2019) found the relationship between information accuracy and patients' perceptions of AI diagnostic expertise. Yin and Qiu (2021) noted that the accuracy of AI technology has a positive effect on both utilitarian value and hedonic value. Thus, we suggest,

H5. Perceived accuracy significantly affects flow experience.

Perceived trustworthiness. In the field of information systems, trustworthiness is a very important factor when generative AI is used to assist users' decision making (Fogg and Tseng, 1999). Users may develop trust in texts that are reliable, fair (Schoeffer et al., 2022), and free from bias when using generative AI. Jakesch et al. (2019) noted that users' trust in Airbnb host profiles are correlated with whether they are written by AI. Li and Peng (2021) found that the trustworthiness of live streaming hosts can stimulate users' emotional attachment, which in turn promotes their gift giving. With the continuous improvement of AI language processing, the public gradually agree with the trustworthiness of its content generation. When users' trust in generative AI increases, they are more likely to feel immersion and enjoyment during the Q&A process, thus leading to flow experience.

H6. Perceived trustworthiness significantly affects flow experience.

Flow experience. Flow experience reflects a positive emotional experience that a user is fully engaged in an activity and enjoys pleasure and enjoyment from it (Csikszentmihalyi, 1975). Numerous studies have confirmed that flow experience is a factor influencing users' continuance intention (Guo et al., 2016a; Guo et al., 2016b). Lin et al. (2019) found that flow affects brand identification and loyalty. Chen et al. (2023) noted that perceived enjoyment affects user switching of fitness wearable devices. As an optimal experience, flow may facilitate user migration intention as the user expects to obtain this experience again in future. Users who obtain an immersive experience will feel controlled, focused, and interested during the knowledge Q&A process, and choose generative AI when they have knowledge needs, thus promoting their intention to migrate from social Q&A communities to generative AI.

H7. Flow experience significantly affects users' migration intention.

Mooring factor. According to the social network theory (Adams, 1967), when users engage in social activities, the information, resources, and opportunities they receive are influenced by the social networks such as family, friends, and online related users. Group beliefs are considered to be a reliable information source for evaluating applications when users are not familiar with new applications such as generative AI products (Althuizen, 2018). Social influence has been found to affect consumers' intention to interact with AI (Gursoy et al., 2019) and facilitate social network users' migration (Xu et al., 2014). Thus, if a user's social circle recommends generative AI to the user, he or she may adopt it and migrate from traditional social Q&A platforms to generative AI.

H8. Social influence significantly affects users' migration intention.

The model is shown in Fig. 1.

Methodology

Instrument development. The research model contains nine variables, and each variable includes three to four indicators. To ensure the validity of the scale, all indicators were adapted from the extant literature, and modified based on the research context. A pretest was conducted among twenty users who had experience using generative AI and social Q&A communities. Then, the

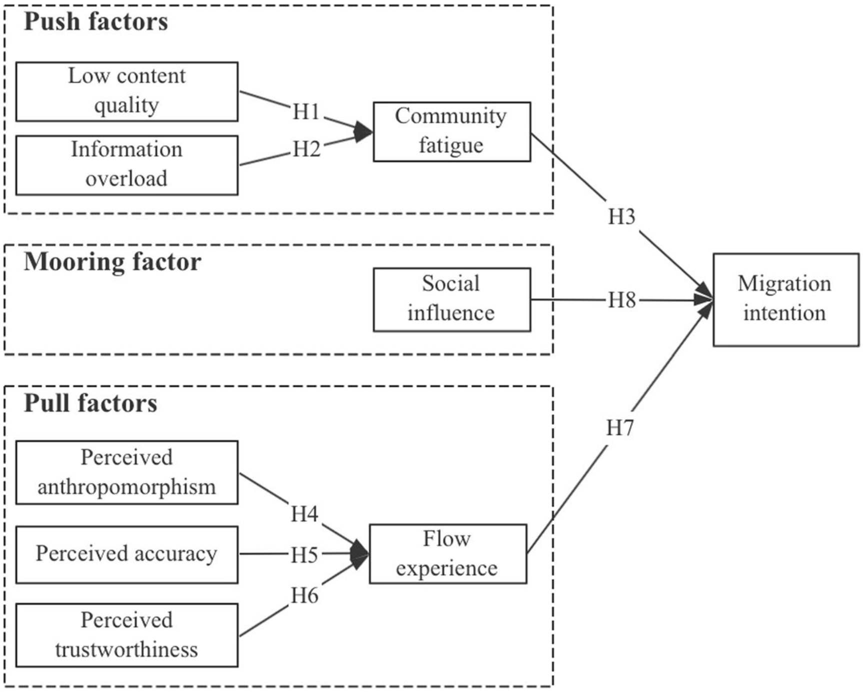

Fig. 1 Research model. The rectangular boxs represent variables. H1-H8 are hypotheses.

measurement items were modified based on their feedback. Table 1 lists the measurement indicators, which were measured using a five-point Likert scale.

Procedures. The questionnaire was developed on the Credamo and the linkage to the questionnaire was posted on a few popular social media such as WeChat and Weibo. We invited those users that had experience using both social Q&A communities and generative AI to participate in the survey. We also encouraged the subjects to forward the linkage to their social circle in order to expedite data collection. Data collection lasted for two weeks and a total of 532 questionnaires were collected. The following criteria were used to screen out invalid questionnaires. First, the overall response time was less than one minute. Second, the answers did not pass the attention test. Third, all questions had the same options. As a result, 483 valid questionnaires were obtained.

Sample demographics. In terms of gender, 44.7% were male and 55.3% were female. Most of them (92.8%) were between 20 and 29 years old. In terms of education, 63.8% held bachelor's degree and 32.5% held master and higher degree. A report shows that young users with high education are the major group of knowledge Q&A users (iResearch, 2020). Our sample is consistent with the report. The frequently-used social Q&A communities include Zhihu (91.3%), Baidu Knows (82.0%), social media-related Q&A communities such as Xiaohongshu/Weibo/Douban (82.0%), education-related Q&A communities such as Yuansouti/Zuoyebang (65.8%), and technology-related Q&A communities such as CSDN community (37.5%). The frequently-used generative AI includes ChatGPT (66.9%), Baidu ERNIE Bot (24.6%), and New Bing (24.2%).

Analysis methods. In this research, we adopted a mixed method of SEM and fsQCA to conduct data analysis. SEM is based on a single linear relationship and it aims to study the marginal "net effect" of each independent variable on the dependent variable. However, there is a multiple concurrent causal relationship between variables (Pappas and Woodside, 2021). FsQCA treats the combinations of variables as configurations and test their effect on the outcome variable. Therefore, fsQCA is used to investigate the configurations triggering users' migration intention.

Results

Structural equation modeling

Reliability and validity. We adopted SPSS 26 to obtain the Alpha value of each variable. All Alpha values were greater than 0.8, indicating the good internal consistency. In the confirmation factor analysis, most of the factor loadings exceeded 0.7, all composite reliability (CR) values were greater than 0.8, and all average variance extracted (AVE) values were greater than 0.5, showing good convergent validity (Anderson and Gerbing, 1988). The results are listed in Table 2. SD means the standard deviation. The tolerance and variance inflation factor (VIF) values indicated that multicollinearity is not a significant problem in this research. In addition, as shown in Table 3, the square root of the AVE is larger than the correlation coefficients between factors, indicating the good discriminant validity.

Hypotheses testing. AMOS 28 was adopted to test the research hypotheses. The fit indices were listed in Table 4. Path coefficients and their significance were shown in Fig. 2. The results show that among the push factors, low content quality has no effect on community fatigue, which does not support H1. Information overload has a significant effect on community fatigue, which supports H2. Community fatigue leads to migration intention, which supports H3. Among the pull factors, perceived anthropomorphism, perceived accuracy, and perceived trustworthiness significantly affect flow experience, which supports H4, H5, and H6. Flow experience affects migration intention, supporting H7. For mooring factors, social influence has a significant effect on migration intention, supporting H8. The model explains 69% of the variance of migration intention, suggesting good explanatory power.

Fuzzy-set qualitative comparative analysis

Table 1 The indicators and sources.

Variable	Item	Content	Source
Low content quality (CQ)	LCQ1	Information on the Q&A community is biased.	Zheng et al. (2013)
	LCQ2	Information on the Q&A community is not sufficient.	
	LCQ3	Information on the Q&A community is presented in an inconsistent form.	
	LCQ4	Information on the Q&A community is out-of-date.	
Information overload (IO)	IO1	I am often distracted by the excessive amount of information available to me on the Q&A community.	Zhang et al. (2016)
	IO2	I find that I am overwhelmed by the amount of information I have to process on a daily basis on the Q&A community.	
	IO3	There is too much information about my friends on the Q&A community so I find it a burden to handle.	
	IO4	I find that only a small part of the information on the Q&A community is relevant to my needs.	
Community fatigue (CF)	CF1	Sometimes I feel tired when using the Q&A community.	Zhang et al. (2016)
	CF2	Sometimes I feel bored when using the Q&A community.	
	CF3	I have no interest with the reminders or alerts of new things on the Q&A community.	
Perceived anthropomorphism (PAN)	PAN1	Generative AI can express emotions.	Lu et al. (2019); Mishra et al. (2022)
	PAN2	Generative AI has a mind of its own.	
	PAN3	Generative AI interacts like a person.	
Perceived accuracy (PAC)	PAC1	Information provided by generative AI is free of errors.	Zheng et al. (2013); Nadarzynski et al. (2019)
	PAC2	Information provided by generative AI comes from reputable sources.	
	PAC3	Generative AI would not intentionally give me false information.	
Perceived trustworthiness (PT)	PT1	If problems arise, one can expect to be treated fairly by generative AI.	Büttner and Göritz (2008)
	PT2	I would rely on advice from generative AI.	
	PT3	One can expect good advice from generative AI.	
Flow experience (FE)	FE1	Generative AI allowed me to control the interaction.	Webster et al. (1993)
	FE2	When using generative AI, I was totally absorbed in the activity.	
	FE3	Using generative AI aroused my curiosity.	
	FE4	Using generative AI was intrinsically interesting.	
Social influence (SI)	SI1	I would use generative AI if most of my friends use it.	Lu et al. (2019)
	SI2	People who influence my behavior recommend me to use generative AI.	
	SI3	People who are important to me encourage me to use generative AI.	
Migration intention (MI)	MI1	I intend to increase my use of generative AI in future.	Fang and Tang (2017)
	MI2	I intend to invest my time and effort on generative AI.	
	MI3	I intend to migrate from the Q&A community to generative AI.	

Data calibration. According to the research model, low content quality, information overload, perceived anthropomorphism, perceived accuracy, perceived trustworthiness, community fatigue, flow experience, and social influence were selected as the antecedent variables. The indicators of each antecedent variable were first averaged. Then the data were calibrated based on the criteria of 5%, 95%, and 50% of the cross-point to improve the interpretability (Ragin, 2009). Necessity analysis was then performed, and the consistency threshold for the necessary condition is set to 0.9 (Schneider and Wagemann, 2012). The results showed that the consistency values for all antecedent variables were lower than 0.9, indicating that no single antecedent variable constitutes a necessary condition of migration intention.

Configuration analysis. The truth table was first constructed using fsQCA, and a case frequency threshold of 3 or higher was set for large sample data (e.g., more than 150 cases) (Pappas and Woodside, 2021). In this research, the frequency threshold was set to 5, the consistency threshold was set to 0.8, and the PRI (Proportional Reduction in Inconsistency) threshold was set to 0.7. The results are shown in Table 5. ● indicates the presence of the core condition, • indicates the presence of the peripheral condition, ⊗ indicates the absence of the peripheral condition, and "blank" indicates that the condition is optional.

As listed in Table 5, flow experience appears as a core condition for five paths, indicating that it is a critical factor influencing users' migration intention. Both information overload and perceived accuracy exist as important core conditions. This is consistent with SEM results, which reported that both factors have strong effects on emotional factors, which further lead to migration intention. Community fatigue and perceived anthropomorphism are the peripheral conditions for five paths. This suggests that both factors are indispensable for users' migration intention. Similarly, perceived trustworthiness and social influence are the peripheral conditions in the first three paths. In addition, low content quality is an optional condition in the first three paths. This is consistent with its insignificant effect in SEM.

By examining these six paths, it can be found that the raw coverage of S1–3 exceeds 0.3, and that of S4–6 is below 0.3. Therefore, this research mainly analyzes the first three paths. S1 is "Information overload*community fatigue*perceived accuracy*perceived trustworthiness*flow experience*social influence", where information overload, perceived accuracy, and flow experience are core conditions, and community fatigue, perceived trustworthiness, and social influence are peripheral conditions. Thus, when users perceive the information overload brought by traditional Q&A communities and feel community fatigue as a result, at the same time perceive accuracy and trustworthiness

Table 2 Reliability and validity.

Factor	Item	Loadings	Mean	SD	Alpha	AVE	CR	Tolerance	VIF
Low content quality (LCQ)	LCQ1	0.732	3.798	0.572	0.824	0.547	0.828	0.832	1.201
	LCQ2	0.748							
	LCQ3	0.808							
	LCQ4	0.664							
Information overload (IO)	IO1	0.728	3.713	0.680	0.834	0.558	0.835	0.693	1.443
	IO2	0.794							
	IO3	0.770							
	IO4	0.693							
Community fatigue (CF)	CF1	0.859	3.654	0.726	0.851	0.655	0.851	0.712	1.404
	CF2	0.794							
	CF3	0.773							
Perceived Anthropomorphism (PAN)	PAN1	0.764	3.344	0.762	0.837	0.633	0.838	0.758	1.320
	PAN2	0.817							
	PAN3	0.805							
Perceived accuracy (PAC)	PAC1	0.759	3.698	0.653	0.815	0.591	0.813	0.599	1.670
	PAC2	0.778							
	PAC3	0.769							
Perceived trustworthiness (PT)	PT1	0.793	3.546	0.644	0.818	0.606	0.821	0.589	1.697
	PT2	0.825							
	PT3	0.713							
Flow experience (FE)	FE1	0.646	3.791	0.596	0.820	0.531	0.819	0.528	1.895
	FE2	0.775							
	FE3	0.754							
	FE4	0.734							
Social influence (SI)	SI1	0.703	3.689	0.642	0.849	0.664	0.854	0.574	1.744
	SI2	0.850							
	SI3	0.880							
Migration intention (MI)	MI1	0.787	3.698	0.650	0.832	0.611	0.825	-	-
	MI2	0.757							
	MI3	0.800							

Table 3 Correlation matrix of variables.

	LCQ	IO	CF	PAN	PAC	PT	FE	SI	MI
LCQ	**0.740**								
IO	0.428	**0.747**							
CF	0.323	0.594	**0.810**						
PAN	0.210	0.244	0.154	**0.796**					
PAC	0.231	0.315	0.195	0.452	**0.769**				
PT	0.206	0.209	0.134	0.482	0.630	**0.778**			
FE	0.193	0.232	0.146	0.491	0.679	0.665	**0.729**		
SI	0.190	0.290	0.178	0.425	0.589	0.619	0.504	**0.815**	
MI	0.216	0.316	0.274	0.436	0.597	0.604	0.688	0.732	**0.782**

Bold values are the square root of AVE.

Table 4 Model fit index.

Fit indices	*Chi*^{2}/df	GFI	AGFI	NFI	IFI	CFI	RMSEA
Threshold value	<3	>0.90	>0.80	>0.90	>0.90	>0.90	<0.08
Actual value	1.951	0.904	0.883	0.902	0.950	0.949	0.044

Chi^2*/df* ratio between chi-square value and degrees of freedom, *GFI* Goodness of Fit Index, *AGFI* Adjusted Goodness of Fit Index, *NFI* Normed Fit Index, *IFI* Incremental Fit Index, *CFI* Comparative Fit Index, *RMSEA* Root Mean Square Error of Approximation.

and obtain flow experience using generative AI, and receive social influence, they may engender the migration intention.

S2 is "Information overload*perceived anthropomorphism*perceived accuracy*perceived trustworthiness*flow experience*social influence", where core conditions are the same as those of S1, and perceived anthropomorphism, perceived trustworthiness, and social influence are peripheral conditions. Thus, information overload, perceived accuracy, and flow experience are the key factors affecting users' migration intention. In addition, if users perceive high anthropomorphism, accuracy, trustworthiness, and flow experience using generative AI, and receive social influence, they may still migrate to generative AI even if they do not perceive community fatigue in traditional Q&A communities.

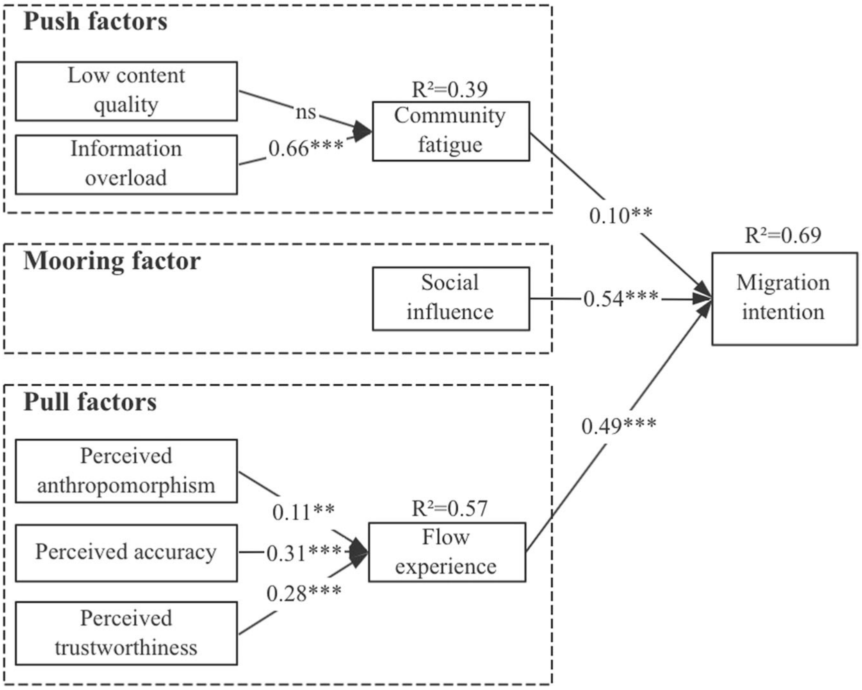

Fig. 2 Path coefficients and significance. (note: ns, not significant; $^{**}P < 0.01$; $^{***}P < 0.001$; R^2 is the explained variance).

Table 5 Configurations that produce migration intention.

Conditional variables	Migration intention					
	S1	S2	S3	S4	S5	S6
Low content quality				•	•	•
Information overload	●	●		●	●	•
Community fatigue	•		•	•	•	•
Perceived anthropomorphism		•	•	•	•	•
Perceived accuracy	●	●	•	●	●	
Perceived trustworthiness	•	•	•	•	⊗	⊗
Flow experience	●	●	●	⊗	●	●
Social influence	•	•	•			•
Consistency	0.964	0.964	0.963	0.942	0.953	0.974
Raw coverage	0.352	0.351	0.366	0.240	0.239	0.236
Unique coverage	0.026	0.025	0.040	0.027	0.008	0.018
Overall consistency	0.935					
Overall coverage	0.493					

S3 is "Community fatigue*perceived anthropomorphism*perceived accuracy*perceived trustworthiness*flow experience*social influence", where flow experience is the core condition and the remaining antecedent variables are peripheral conditions. Thus, when users perceive community fatigue in Q&A communities and anthropomorphism, accuracy, trustworthiness and flow experience using generative AI, and receive social influence, they may migrate from social Q&A communities to generative AI.

Discussion

Among the push factors, information overload has a significant impact on community fatigue. This is consistent with existing studies (Lee et al., 2016; Dai et al., 2020), which have reported the effect of information overload on social media users' fatigue. This suggests that the excessive information may exhaust users' effort and lead to negative emotions such as tiredness and fatigue. Advertisement push and commercial information on traditional Q&A communities are interspersed within Q&A contents, and it is difficult to discern the authenticity of some promotions. In addition, when the personalized algorithm pushes many similar topics and invited answers based on users' search records, it will lead to the saturation of users' information reception, reduce their efficiency, and increase information overload. The results also show that the community fatigue caused by information overload will lead to users' migration intention. Q&A communities need to control the push frequency and give users the option to receive information, thus creating a friendly interaction environment.

The results indicated that low content quality has no effect on community fatigue. This is inconsistent with previous research (Han, 2018). This may be due to two reasons. First, compared to entertainment social media, Q&A community users often purposefully seek answers to solve the problems. They may filter out irrelevant contents in order to obtain satisfactory answers more efficiently, rather than spend much time on arbitrary browsing. Thus, users may not be exposed to a lot of low-quality contents such as controversial topics, invalid answers, or outdated information in Q&A communities. In contrast, they focus on selected answers, hot reviews with more likes and expert answers. Second, as information overload strongly affects community fatigue, this suggests that information quantity rather than quality leads to users' fatigue feelings. The excessive information may cause users to spend considerable effort and time on information scrutinizing, which leads to their exhaustion and fatigue (Hwang et al., 2019). This highlights the necessity to reduce information overload in order to mitigate user fatigue in social Q&A communities.

Among the pull factors, perceived anthropomorphism, perceived accuracy, and perceived trustworthiness have significant effects on the flow experience. Among them, perceived accuracy and perceived trustworthiness have relatively larger effects ($\beta = 0.31$ and 0.28, respectively), whereas perceived anthropomorphism has a lower effect on flow experience ($\beta = 0.11$). This suggests that users are utilitarian rather than hedonic when assessing their experience using generative AI. Perceived accuracy acts as a core condition in the fsQCA results, showing that users focus on solving problem and pay much attention to the accuracy of answers. It is also necessary to offer the information source below answers and improve the ability to provide quality answers through big data training. Generative AI also needs to avoid information hallucination that output fake or fabricated contents, which may undermine user trust. At the same time, it is important to optimize anthropomorphic details centering on users' needs to increase intimacy. The human-like interactions may further develop emotional connections between users and generative AI (Spatola and Wudarczyk, 2021; Mishra et al., 2022) and create an engaging experience. In addition, flow experience has a significant impact on migration intention and it is a core condition of three main paths of fsQCA. Thus, generative AI needs to engender an enjoyable experience in order to promote user migration intention.

For the mooring factors, social influence has a significant effect on migration intention. Social influence has been found to affect social network users' migration (Xu et al., 2014). As an emerging application, generative AI has received great attention from the public. An individual user's behavior may be influenced by the people around him or her and the key opinion leaders (KOLs). It is worth noting that although the SEM results show a strong effect of social influence on migration intention ($\beta = 0.54$), the fsQCA results indicate that social influence is a peripheral condition for three main paths. This may be because SEM examines the single effect of social influence on migration intention, whereas fsQCA examines the effect of variables combinations (configurations). Thus, the effect of social influence on migration intention is diminished by other variables.

Among the three factors affecting migration intention, both social influence and flow experience have strong effects on migration intention, whereas community fatigue has a relatively low effect. This suggests that user migration is mainly influenced by both the pull and mooring factors. In other words, the attractiveness of generative AI and social circle influence determine users' migration from social Q&A communities to generative AI. In contrast, they do not pay much attention to the fatigue feelings associated with using social Q&A communities. This result highlights the need to improve user experience and leverage social influence in order to facilitate user migration intention.

Implications and limitations

From a theoretical perspective, this research makes three contributions. First, existing studies have focused on user behavioral intention such as continuance intention and knowledge payment intention in Q&A communities (Shi et al., 2020; Sun et al., 2022; Zeng and Bao, 2023), and have seldom examined user migration between different channels. Our results suggest that user migration intention from social Q&A communities to generative AI is influenced by content features, emotional experience, and social influence. These results enrich the research on social Q&A user behavior. Second, as an emerging application, generative AI user behavior has received little attention in the knowledge Q&A field. Our results indicated that the features of generative AI such as perceived anthropomorphism, perceived accuracy, and perceived trustworthiness, influence users' flow experience, which further promotes their migration intention. The results help improve the understanding of generative AI user behavior. Third, this research integrated both cognitive and affective factors to examine their effects on migration intention. Cognitive factors include low content quality, information overload, perceived anthropomorphism, perceived accuracy, and perceived trustworthiness, whereas affective factors include community fatigue and flow experience. The results indicate that cognitive factors influence migration intention through affective factors. These results disclose the underlying mechanism of users' migration intention from traditional social Q&A communities to generative AI.

The results imply that Q&A communities need to reduce users' fatigue in order to prevent their migration. Although personalized recommendations can better meet users' needs, an excessive amount of similar information not only puts users in an information cocoon, but also makes them perceive information overload. The platform can let users option the push quantity and frequency. Second, generative AI should create an engaging experience to attract users' migration. They need to increase the accuracy and credibility of contents by improving data sources and algorithms. In addition, the AI expression should be optimized, such as showing emotional communication to offer an enjoyable experience to users. Third, the role of social influence cannot be neglected. Generative AI can increase the popularity through social media and encourage existing users to recommend the platform to their social circle.

This research has a few limitations, which also offer directions for future research. First, this research mainly investigated a few popular generative AI such as ChatGPT and ERNIE Bot. However, generative AI is developing rapidly. Smarter and more anthropomorphic AI may emerge in the future. Future research needs to generalize our results to these new AI. Second, there are many factors that affect migration intention. Future research may examine the possible effects of privacy risk, dissatisfaction and habit on user migration intention. Third, we measured migration intention in this research. Future research may examine the actual behavior of migration, which may provide a rich understanding of user migration.

Data availability

The dataset analyzed during the current study was available in the supplementary file.

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Author contributions
Tao Zhou developed the research model and revised the manuscript. Xiaoying Wu collected data, conducted data analysis and completed the draft.

Competing interests
The authors declare no competing interests.

Ethical approval
This study has been performed in accordance with the Declaration of Helsinki. Approval was granted by the Academic Committee of School of Management at Hangzhou Dianzi University (No. SM20230201).

Informed consent
Informed consent was obtained from all participants. Data were recorded in Arabic numerals, which did not include participants' names.

Additional information
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Correspondence and requests for materials should be addressed to Tao Zhou.