Research on the Influencing Factors of Behavioral Intention to Use Generative AI in Search Engines

Xi Chen

School of Journalism and Communication, Wuhan University, Wuhan, Hubei, 430000, China

2023301031022@whu.edu.cn

Abstract. As generative AI technology becomes more widely used in search engines, users' acceptance of it shows significant differences. This study explores the core factors that influence consumers' propensity to utilize it the Technology Acceptance Model (TAM) states. The findings indicate that technical task fit and perceived ease of use drive behavioral intention through the mediating variable (perceived benefits), while privacy concerns only have a significant negative impact on the highly sensitive user group (β=-0.18, $p<0.05$); information overload's inhibitory effect was not statistically significant ($p=0.12$). The conclusion shows that search engine companies need to prioritize the optimization of the accuracy and interactive friendliness of generative AI, and reduce user risk perception through a transparent information processing mechanism, providing empirical evidence for technology iteration and policy supervision. At the same time, search engine companies also need to optimize the quality of generated results, improve user retrieval efficiency, and enhance user satisfaction.

Keywords: Generative AI in Search Engines, Behavioral Intention, Perceived Benefits, Perceived Risk

1 Introduction

1.1 Background

The rapid development of AI is reshaping the way search engines operate, moving from traditional keyword matching to a deeper understanding of user intent and delivering personalized, accurate search results.

Generative AI in search engines utilizes cutting-edge technologies, artificial intelligence algorithms, neural networks, and natural language processing (NLP). These generative AIs are able to understand user queries, interpret context, personalize search results, and create immersive experiences, and effectively use convolutional (CNN), recursive (RNN), and generative neural networks (GANs) to solve small-scale retrieval challenges [1]. This change has not only improved the user experience, but has also changed users' search habits, making them more inclined to use generative AI in search engines that can provide answers directly rather than just returning to a list of links. Although generative AI in search engines brings many advantages, it is also prone to

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risks such as information overload and privacy leakage due to the limitations of technological development.

1.2 Literature Review

There is abundant evidence in existing research that perceived ease of use has an advantageous influence on user acceptance of new technologies or services. For instance, a study that looked at how perceived ease of use affected the adoption of AI chatbots discovered that one of the main reasons why people embrace and keep using AI chatbots is perceived ease of use. The higher perceived ease of use of AI chatbots, the stronger their willingness to use them [2]. Similarly, in the application of AI large model search engines, if users find it easy to understand and use, the ease of use evaluation will be higher, and their acceptance and willingness to continue using it may increase.

Although generative AI in search engines brings many advantages, it is also prone to risks such as information overload and privacy leakage due to the limitations of technological development. On the one hand, in the era of big data, AI can collect a lot of relevant information, but overly complex and comprehensive information can mislead users and be easily distracted [3]. On the other hand, the privacy information collected by generative AI in search engines, including AI-based human-computer interaction behavior trajectory information, such as browsing information and transaction information, is easily exposed to risks such as leakage, misuse, and theft during the platform's acquisition, use, transmission, and storage [4].Although there has been a lot of literature on the use of AI, there is little research on inclination to employ generative AI in search engines.

1.3 Research Theme

Based on this real-world scenario, this paper will study the elements that influence social platform behavioral intention to use generative AI in search engines. Taking perceived benefits and perceived risk as mediating variables, combined with the TAM model, this paper takes information overload, privacy concerns, ease of use and technical task adaptability into account to study the elements that influence social platform behavioral intention to use generative AI in search engines.

2 Research Methodology

2.1 Subjects

This study adopts the questionnaire survey method, one of which is that in the narrative space of social media, the diversity of the survey object structure is one of the foundations of the scientific research, and the questionnaire survey method can include social media users with different basic characteristics such as age, education, gender, etc., and enrich the survey subjects; Second, the empirical research on user behavior attitudes of

generative AI in search engines in the existing literature mostly adopts the survey method, and the research group is limited to the young group, which aims to fill the gap in the age structure of the research subjects and enrich the research methods in the field [3].

Specifically, the questionnaire method of this study was to recruit eligible research subjects through the online platform in the form of online questionnaire survey. Due to the anonymity of the network, the online questionnaire distribution is a sample collection in the form of a survey, which can fully reflect the real thoughts and wishes of netizens, which is in line with the focus of this study, that is, the perspective of users. In addition, the advantages of network surveys are that they are simple to organize, inexpensive, and free from time, space and geography, which are strongly related to the use of generative AI in search engines by mainstream browser users in this study, and the research targets can be found from the network. However, it is difficult to limit the number of people who can be interviewed on the Internet.

2.2 Questionnaire Design

The questionnaire used to measure information overload was adapted from the Ae Ri Lee et al. investigation, as indicated in Table 1 [5]. The questionnaire scale used for privacy concerns refers to the research of Chantal, Mutimukwe et al, in which "what others might do with it" has a similar meaning to "it could be used in a way I did not foresee", so it is combined into one question, as shown in Table 1 [6]. The usefulness questionnaire is predicated on the study of BALAKRISHNAN J Aand adapted from it [7]. The questionnaire scale on the suitability of technical tasks is based on the study of GOODHUE, D. L., as shown in table 1 [8]. The questionnaire for perceived benefits and perceived risk was adapted from Nadia Said's study and combined into a single question from the expressions "how beneficial would the consequences be for you" and "how likely is it that you would benefit", as shown in Table 1 [9]. The questionnaire scale on user willingness to use is adapted from the study of Shu-Mei Wang, as shown in Table 1 [10].

Table 1. Scale

Variables	Items	Sources
Information Overload	I am frequently sidetracked by the abundance of content in search engine generation formula AI.	Information and communication technology overload and social networking service fatigue: a stress perspective [3]
	The quantity of information I process every day leaves me feeling overloaded search engine generation formula AI.	
Privacy Concern	I'm worried that someone could discover personal information about me from search engine generation formula AI.	Information privacy in e-service: Effect of organizational privacy assurances on individual privacy concerns, perceptions, trust and self-disclosure behavior [6]
	I'm hesitant to give personal information to search engine generative AI in search engines	

	because it could be used in a way I did not foresee.	
Perceived Ease of Use	I feel engine generative AI in search engines is easy to use I feel learning to operate engine generative AI in search engines is easy	Conversational commerce: entering the next stage of AI-powered digital assistants [7]
Task-Technology Fit	Search engine generative AI in search engines is highly relevant to my needs. Using search engine generative AI in search engines helps me efficiently complete tasks. Search engine generative AI in search engines provides functions that match my task requirements.	Task-technology fit and individual performance [8]
Perceived Risk	To what extent, if at all, are you worried about using generative AI in search engines? Should you encounter this application of generative AI in search engines in your environment, what is the likelihood that you would suffer?	An artificial intelligence perspective: How knowledge and confidence shape risk and benefit perception [9]
Perceived Benefits	To what degree do you feel reassured by this application of generative AI in search engines? If you were to see this use of generative AI in search engines in your environment, how likely is it that you would benefit?	An artificial intelligence perspective: How knowledge and confidence shape risk and benefit perception [9]
Behavior Intention	I will to use search engine generation formula AI. I will to recommend others to use search engine generation formula AI.	A Model of Consumer Perception and Behavioral Intention for AI Service [10]

2.3 Sampling Methods

The current survey primarily employs a volunteer sampling method on internet social media, sampling based on the activity levels of users in different age groups and the usage of generative AI in search engines. Data is collected through an online questionnaire, distributed via platforms such as WeChat Moments, Xiaohongshu, and community forums. The questionnaire distribution lasted for three weeks, resulting in 408 valid responses. Of the participants, 79.2% were under 40, 67.2% held at least a bachelor's degree, and 44.61% of the respondents were men and 55.39% were women.

The random sampling method used in this study is due to the more proactive nature of volunteer samples in surveys. Additionally, the sample size of internet users is more diverse and abundant, which can essentially cover most demographic characteristics, thereby compensating for the shortcomings in age and gender structure of previous studies. From specific investigations, it was found that there are relevant tags and questions on platforms like Xiaohongshu and Zhihu. This study will start from posts that align with the research objectives and expand the sample in the comment sections.

Through this method, it is more likely to reach users who have a strong interest in AI large model search engines, thus gaining a better understanding of their usage intentions and influencing factors.

2.4 Variable Description

Referring to the TAM theory, this study chose the concept of ease of use, considering that both traditional search engines and generative AI in search engines can provide the information that users need, so the usefulness in this study is not obvious. At the same time, this study also considers the perceived risk perspective on the basis of TAM, and considers the resistance elements that influence consumers' propensity to use, including privacy concerns and information overload.

Since there is a lot of overlap between the functions of traditional search engines and generative AI in search engines, compared with traditional search engines, the outstanding feature of generative AI is that it summarizes and filters the searched information and generates outlining results. Therefore, the selection of independent this study's factors concentrate on the traits of "generative" rather than the characteristics of search engines. Based on various researches, this study analyzes the factors of push and pull force, and concludes that compared with agility and other factors, the adaptability and ease of use of technical tasks have a greater impact on behavioral intention from the perspective of benefits. At the same time, due to the convenience of generative AI reading retrieval, from the perspective of risk, this study did not consider factors such as dyslexia, but considered privacy concerns and information overload as independent variables.

Considering a number of factors, the independent variables of this study were privacy concerns, information overload, Task-Technology Fit, and perceived ease of use. Privacy concerns refer to the fact that when users use generative AI in search engines, personal information is illegally collected, used, or disclosed to third parties without their consent, causing users to worry about their privacy and security. Information overload means that when generative AI search results are large and of low quality, users may find it difficult to sift through and identify the most valuable information. Perceived ease of use is derived from the TAM theory, which in this study refers to the convenience and simplicity of operation that users experience when using generative AI in search engines. Task-Technology Fit refers to the efficiency and accuracy of the application of generative AI in search engines, as well as the task matching degree felt by users in the process of use.

The mediating variables in this study were perceived risk and perceived benefits. A user's subjective evaluation of the potential negative outcomes is known as perceived risk or uncertainties they may encounter when using generative AI in search engines. Perceived risk is an important factor influencing behavioral intention, and it involves users' awareness and concerns about the potential threats that may be brought about by the use of new technologies. perceived benefits refers to the user's personal perception of the positive results or benefits that generative AI in the search engine may bring, which is an important factor affecting behavioral intention, which is directly related to the user's assessment of the technology's worth.

The study's dependent variable (behavioral intention) is the users' readiness to use generative AI in search engines.

2.5 Data Analysis

SPSS25.0 was used to organize the data acquired from the questionnaire survey, and the data were subjected to descriptive statistics, Pearson correlation analysis, reliability and validity test, and model fitting test. In this study, the Bootstrap method was used for mediation analysis, and the process of SPSS25.0 software was used to test the mediation effect.

2.6 Hypothesis

Jillian Carmody et al. proposed that AI can analyze and match large amounts of consumer information, and may illegally identify information to generate user portraits [11]. According to D. Supriyadi, data analysis within the legal framework might even turn what is typically regarded as "non-personal data" into personal information. [12]. Although it is not directly leaked, it poses a threat to user privacy. In this study, generative AI in search engines also has the risk of illegally "profiling" individual users by analyzing their search history, thus causing privacy concerns for users. These direct or indirect privacy breaches will cause users to be concerned about the safety of their sensitive data, which will result in a notable rise in the perceived risk of generative AI in search engines. In light of this, this paper puts up the following theories:

H1: Privacy concerns brought about by generative AI in search engines positively affect users' perceived risk of generative AI in search engines.

The problem of information overload is especially obvious in the era of big data. Chaouali found that when users use social media, information overload affects efficiency, which in turn produces negative emotions such as anxiety, which in turn affects users' willingness to use [13]. K. Koroleva et al. argue that Facebook users find it difficult to complete tasks due to information overload [14]. In this study, the synthetic results generated by generative AI in search engines are characterized by a surge in the amount of information compared with a single web page in traditional search engines, but on the other hand, the quality of such information is uneven, which may produce information noise, blur cognition, and mislead information. The resulting information overload increases the user's workload, which in turn significantly increases the user's perceived risk to generative AI in search engines. In light of this, this paper puts up the following theories:

H2: The information overload brought by generative AI in search engines positively affects users' perceived risk of generative AI in search engines.

In the search for traditional search engines, users often find it difficult to find truly effective information due to the large number of web pages, thus reducing the search efficiency. Generative AI in search engines can accurately identify user needs and organize and aggregate the results of searched web pages. Generative AI in search engines can effectively screen messy web page information and summarize it for users, with strong accuracy and timeliness, which can better meet users' search needs and

improve users' perceived benefits than traditional search engines. In light of this, this paper puts up the following theories:

H3: The Task-Technology Fit of generative AI in search engines positively affects users' perceived benefits of generative AI in search engines.

With the continuous development of artificial intelligence in the big data era, generative AI has greatly reduced the difficulty of user learning. For example, Maruf Fatima Sadriwala et al. discovered that AI's usability drives user learning techniques and marketing innovation [15].

Compared with generative AI in the form of apps or web pages, such as "Zhipu Qingyan" and "deepseek", generative AI in search engines appears directly in traditional search engines, without the need to download another APP or open a web page, and the threshold for use is low. In general, generative AI in search engines is more convenient, easy to learn, and optimizes search results to enhance users' perceived benefits.In light of this, this paper puts up the following theories:

H4: Perceived ease of use generative AI in search engines has a positive impact on users' perceived benefits of generative AI in search engines.

Nadia Said believes that the ambiguous nature of AI brings both risks and benefits. Although AI has a lasting effect on society that is both beneficial and detrimental, it will continue to exist for a long time [16]. See Figure 1, This study examines the perceived benefits and perceived risk of generative AI in search engines affect users' user experience, and then positively or negatively affect behavioral intention to use generative AI in search engines. In light of this, this paper puts up the following theories:

H5: The perceived benefits of generative AI in search engines positively affect behavioral intention to use generative AI in search engines.

H6: The perceived risk of generative AI in search engines negatively affects behavioral intention to use generative AI in search engines.

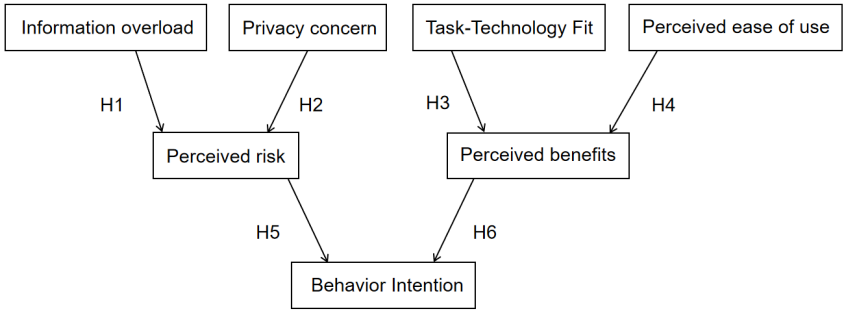

Fig. 1. Model theory

3 Result

Drawing from the Technology Acceptance Model (TAM), this research explores the influencing factors of behavioral intention to use generative AI in search engines. Through the analysis of 408 valid questionnaires, the following conclusions were drawn:

First, SPSS25.0 was used for reliability and validity. The α coefficient was 0.774, which exceeded the recommended cutoff point of 0.7, signifying a high degree of internal consistency.

SPSS25.0 was used to analyze the KMO value and Bartley's test. The data fully satisfied the requirements of factor analysis, as demonstrated by the extraordinarily high KMO value (0.915) and the significant Bartlett test (p=0.000).

The model fit test of the data showed that the R value was 0.725, the Adjusted R Square was 0.520, and the R Square was 0.525, demonstrating the model's good fit.

Table 2. Correlations

		Information overload	Privacy concern	Perceived ease of use	Perceived risk	perceived benefits	behavioral intention
Information overload	Pearson Correlation	1	.523**	-.087	.531**	-.096	-.112*
	Sig. (2-tailed)		.000	.081	.000	.053	.024
Privacy concern	Pearson Correlation	.523**	1	-.140**	.539**	-.139**	-.172**
	Sig. (2-tailed)	.000		.005	.000	.005	.000
Perceived ease of use	Pearson Correlation	-.087	-.140**	1	-.193**	.634**	.611**
	Sig. (2-tailed)	.081	.005		.000	.000	.000
Task-Technology Fit	Pearson Correlation	-.121*	-.153**	.761**	-.186**	.699**	.715**
	Sig. (2-tailed)	.014	.002	.000	.000	.000	.000
Perceived risk	Pearson Correlation	.531**	.539**	-.193**	1	-.169**	-.230**
	Sig. (2-tailed)	.000	.000	.000		.001	.000
perceived benefits	Pearson Correlation	-.096	-.139**	.634**	-.169**	1	.714**
	Sig. (2-tailed)	.053	.005	.000	.001		.000
behavioral intention	Pearson Correlation	-.112*	-.172**	.611**	-.230**	.714**	1
	Sig. (2-tailed)	.024	.000	.000	.000	.000	

This study uses SPS25.0 to analyze the data. As Table 2 shows, information overload is significantly positively correlated with perceived risk, with a correlation coefficient of 0.531 ($p<0.01$), and H2 is established. Privacy concerns are significantly positively correlated with perceived risk, with a correlation coefficient of 0.539 ($p<0.01$), and H1 is established. behavioral intention is substantially inversely connected with perceived risk, with a correlation coefficient of -0.230 ($p<0.01$), and H5 is established. Perceived ease of use is highly significantly positively correlated with perceived benefits, with a correlation coefficient of 0.634 (significant level: p=0.000), and H3 is established. There is a significant positive correlation between Task-Technology Fit and perceived benefits, with a correlation coefficient of 0.699 (significant level: p=0.000), and perceived benefits and behavioral intention show, H4

is established. perceived benefits and behavioral intention had a 0.714 association coefficient ($p < 0.01$), which is highly positively correlated, and H6 is established.

The correlation coefficient between perceived risk and perceived benefits is -0.169, which is a moderate negative correlation, indicating that the perceived risk and perceived benefits are traded off. The correlation coefficients between information overload and behavioral intention is -0.112, the correlation coefficients between privacy concerns and behavioral intention is -0.172, which are negatively correlated, indicating that these two variables inhibit behavioral intention. The correlation coefficients between perceived ease of use and behavioral intention is 0.611, the correlation coefficients between behavioral intention and Task-Technology Fit is 0.715, which are positively correlated, indicating that these two variables increase behavioral intention.

In addition, the process of SPSS25.0 software was used to test the mediating effect of SPSS25.0 software, both the mediating effect of perceived benefits and perceived risk of search engines was investigated. The confidence interval for each mediating effect size does not involve zero, suggesting a large mediating effect, so it is appropriate to use perceived benefits and perceived risk as mediating variables.

Table 3. Mediator effect test 1

Total effect of X on Y						
Effect	se	t	p	LLCI	ULCI	c_cs
-.116	.051	-2.270	.024	-.217	-.016	-.112
Direct effect of X on Y						
Effect	se	t	p	LLCI	ULCI	c'_cs
.015	.059	.249	.803	-.102	.131	.014
Indirect effect(s) of X on Y:						
Perceived risk	Effect	BootSE	BootLLCI	BootULCI		
	-.131	.036	-.206	-.063		

Perceived risk's mediation role in the link between behavioral intention and information overload, it was found that the total effect was significant: effect = -0.116, p = 0.024, see Table 3, showing that information overload, an independent variable, significantly impacted the behavioral intention. However, there was no discernible direct effect: Effect = 0.015, p = 0.803, proving that the independent effect of information overload on the willingness to use disappeared after the control mediator variable perceived risk. Indirect effects were significant: Effect = -0.131, 95% Bootstrap CI [-0.206 to -0.063], indicating that the mediating variables fully explained the influence path of the independent variable Dowdependent variable, and the directional consistency indicated that the indirect effect and the total effect were negative, and the direct effect was not significant and the direction was opposite, which may be statistical fluctuation or inhibition. So H1 was established.

Table 4. Mediator effect test 2

Total effect of X on Y						
Effect	se	t	p	LLCI	ULCI	c_cs
-.175	.050	-3.510	.000	-.272	-.077	-.172
Direct effect of X on Y						
Effect	se	t	p	LLCI	ULCI	c'_cs
-.068	.058	-1.171	.242	-.183	.046	-.067
Indirect effect(s) of X on Y:						
Perceived risk	Effect	BootSE	BootLLCI	BootULCI		
	.106	.034	-.177	-.042		

Privacy concerns' effects on behavioral intention is determined by testing the mediating role of perceived risk discusses the connection of privacy concern and behavioral intention is completely transmitted through the mediating variable perception risk, and there is no direct path independent of perceived risk, see Table 4. So H2 was established.

Table 5. Mediator effect test 3

Total effect of X on Y						
Effect	se	t	p	LLCI	ULCI	c_cs
.539	.035	15.543	.000	.471	.608	.611
Direct effect of X on Y						
Effect	se	t	p	LLCI	ULCI	c'_cs
.234	.038	6.148	.000	.159	.308	.265
Indirect effect(s) of X on Y:						
Perceived risk	Effect	BootSE	BootLLCI	BootULCI		
	.306	.033	.244	.371		
Completely standardized indirect effect(s) of X on Y:						
Perceived risk	Effect	BootSE	BootLLCI	BootULCI		
	.346	.034	.279	.415		

Perceived advantages' moderating role in the link between behavioral intention and perceived ease of use, it was found that the total effect was effect = 0.539, $p < .001$, indicating that Behavioral intention was significantly positively impacted by perceived ease of use. As Table 5 shows, the direct effect was significant: Effect = 0.234, $p < .00$, indicating that even after controlling for the mediating variables, ease of use still had an independent effect on behavioral intention (43.4% of the direct effect was attributable to the direct effect.). Perceived benefits act as a mediator in the relationship between perceived ease of use and behavioral intention. So H3 was established.

Table 6. Mediator effect test 4

Total effect of X on Y						
Effect	se	t	p	LLCI	ULCI	c_cs
.671	.033	20.597	.000	.607	.735	.715

Direct effect of X on Y						
Effect	se	t	p	LLCI	ULCI	c'_cs
.396	.041	9.610	.000	.315	.477	.422
Indirect effect(s) of X on Y:						
Perceived risk	Effect	BootSE	BootLLCI	BootULCI		
	.275	.032	.214	.340		
Completely standardized indirect effect(s) of X on Y:						
Perceived risk	Effect	BootSE	BootLLCI	BootULCI		
	.293	.032	.230	.359		

The investigation of the mediating role of perceived advantages on the relationship between behavioral intention and Task-Technology Fit indicates that the degree of Task-Technology Fit considerably increases behavioral intention. The confidence interval does not contain 0, and the results are robust. As Table 6 shows, the direct effect was significant: Effect = 0.396, $p < 0.001$, indicating that even after adjusting for perceived benefits, the mediating variable, the adaptability of technical tasks still had an independent positive influence in behavioral intention, and the direct effect constituted 59.0% of the overall impact. The indirect effect is significant. The mediating variable explained 41.0% of the total effect, with the path being consistent (positive). It is concluded that perceived benefits serve as a mediator in the partnership between behavioral intention and Task-Technology Fit.

Perceived ease of use (β=0.611, $p<0.001$) and Task-Technology Fit (β=0.715, $p<0.001$) significantly favorably influenced behavioral intention, indicating that functional matching and perceived ease of use could best improve user acceptance. Privacy concerns (β=-0.172, $p<0.01$) and information overload (β=-0.112, $p<0.05$) showed a minor inhibitory influence in behavioral intention.

Perceived benefits and perceived risk play some mediating roles between independent variables and willingness to use, wherein:
Task-Technology Fit indirectly promoted the intention to use by increasing the perceived benefits (β=0.275, 95% CI [0.214 to 0.340]).

Privacy concerns indirectly inhibited behavioral intention by exacerbating perceived risk (β=-0.131, 95% CI [-0.206 to -0.063]). There was a significant trade-off between risk and return (r=-0.169, $p<0.01$), and reducing perceived risk was more effective in enhancing the willingness to use than increasing return.

4 Discussion

4.1 Ethical Controversy and Social Responsibility of Generative AI in Search Engines

This study found that privacy concerns have a rise in perceived risk, while perceived risk has an adverse effect on behavioral intention. AI training relies on massive amounts of user data, which may leak sensitive content such as search records and location information. User profiles are used for targeted advertising or political manipulation, and may even be subject to data blackmail. Technology developers should

seek a balance in the ethical demand triangle of technology design (user rights, technical reliability, and social welfare), and avoid ignoring the social responsibility of algorithms in order to increase short-term acceptance [17].

Generative AI in search engines is both an efficiency tool and an amplifier of social risks. Enterprises need to go beyond the bottom line of "compliance" and take the initiative to assume social responsibility. Through technical self-reflection, user co-governance, and industry collaboration, they can find a balance between information freedom and ethical constraints. Only in this way can AI truly become a force for the advancement of knowledge, rather than a hidden danger that divides society. Today, the development of technology has made it possible to protect user privacy. For example, Li, T. explored how federated learning can reduce the risk of privacy leakage through distributed data training [18].

4.2 A "Dual-Track Intervention" Strategy Based on the Balance Between Perceived Benefits and Perceived Risk

This study found that perceived benefits favorably impact behavioral intention, while perceived risk negatively affect user willingness to use. If the perceived benefits are increased by 1 standard deviation (SD=0.82), the willingness to use is expected to increase by 0.293 SD ($p<0.001$), which is equivalent to the user's willingness to recommend from "neutral" to "likely to recommend" (+0.6 points on a 5-level scale). For technology developers, designing simple and clear output templates, such as the "quick overview of key points" mode, is the key to improving AI retrieval efficiency and meeting user search needs. In addition, by displaying value visualization feedback such as "the time saved by this AI search", the user's perceived benefits can be enhanced. In order to reduce the cognitive burden of privacy, progressive transparency design can be adopted, such as displaying data usage details after the user clicks. At the same time, implementing a risk compensation mechanism, such as providing a privacy protection certification badge, can transform users' perception of risk into trust in technology.

5 Conclusion

Based on TAM theory, this study found that ease of use and Task-Technology Fit positively affect behavioral intention, while privacy concerns and information overload adversely affect behavioral intention.

However, this study still has limitations. For example, although the sample size (N=408) meets the statistical requirements, the sample is concentrated in a specific region (such as mainland China), lacks cross-cultural comparison, and the generalizability of the conclusion is limited. At the same time, the participants are mainly young users (such as students/white-collar workers), and the elderly or low-educated groups are not fully covered, which may underestimate the barriers to technology acceptance. In the research method, it can be found that there are collinearity problems between variables (such as technical task fit and perceived ease of use, $r=0.761$), which may overestimate the independent effects of individual variables. Using cross-sectional

data, it is impossible to verify the temporal nature of the causal relationship between variables (such as willingness to use may reversely affect perceived benefits).

This study also has strong practical significance. To increase behavioral intention to use, developers can optimize the interaction design of generative AI (such as providing personalized options) to enhance technical task fit and ease of use. At the same time, privacy concerns can be reduced through transparent data usage policies, and perceived risk can be reduced through functional value promotion.

In future research, researchers need to go beyond the static "technology acceptance" perspective and start from interdisciplinary frameworks such as human-AI co-evolution and social-technical systems to reveal the two-way shaping mechanism of generative AI and user behavior. At the same time, we should strengthen the collaboration between academia and industry to ensure the synchronous iteration of theoretical exploration, technology implementation, and policy governance, and promote generative AI to truly become a "people-centered" inclusive technology.

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