Postprint: Model Construction and Empirical Study on Influencing Factors of AIGC User Discontinuance Behavior

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Abstract

[目的/意义]To clarify the driving factors of user psychological resilience in the AIGC context and the characteristic patterns of AIGC user discontinuance behavior, effectively mitigate the potential risks caused by negative behaviors such as churn and discontinuance among AIGC users after the initial adoption stage, stimulate continuous usage of AIGC, and promote the high-quality transformation of the AIGC industry from technology-driven to user-driven.[方法/过程]The study constructs a research model of influencing factors on AIGC user discontinuance behavior based on resilience theory and S-O-R theory, and collects 328 raw data points through questionnaire distribution to empirically test the proposed model.[结果/结论]The research results demonstrate that psychological resilience is a crucial factor in effectively alleviating AIGC user discontinuance behavior, while technical resilience and information quality are important driving factors for enhancing user psychological resilience. Based on these findings, countermeasures and recommendations are proposed to improve user psychological resilience, prevent user discontinuance, and promote continuous usage.

Full Text

Preamble

AIGC User Dropout Behavior: Model Construction and Empirical Research

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Abstract: [**Purpose/Significance**] This study aims to clarify the driving factors of user psychological resilience in the AIGC context and identify the characteristic patterns of AIGC user dropout behavior. By addressing these issues, we can effectively mitigate potential risks arising from user attrition and discontinuation during the initial adoption phase, stimulate sustained AIGC usage, and facilitate the industry' s transformation from technology-driven to user-driven high-quality development. [**Method/Process**] Grounded in resilience theory and S-O-R theory, we constructed a research model of factors influencing AIGC user dropout behavior. Through questionnaire distribution, we collected 328 valid responses to empirically test the proposed model. [**Results/Conclusions**] The findings reveal that psychological resilience is a crucial factor in alleviating AIGC user dropout behavior. Technical resilience and information quality emerge as important drivers for enhancing user psychological resilience. Based on these results, we propose strategies and recommendations for improving user psychological resilience, preventing dropout, and promoting continuous usage.

Keywords: psychological resilience; dropout behavior; AIGC; S-O-R theory; cumulative emotional factors; information behavior

0 Introduction

After nearly two years of rapid growth, ChatGPT experienced its first traffic decline in June 2023, with user numbers dropping by nearly 10% month-over-month [4]. This user attrition and migration serves as a warning bell for the generative AI industry. Over the past decade, China' s digital economy has achieved remarkable accomplishments, becoming a vital component of the national economy. Throughout this development, technology empowerment and technology-driven innovation have served as important forces driving China' s digital economic development [1]. Generative AI technologies, represented by ChatGPT, have emerged as new productive forces powering the digital economy [2]. To promote high-quality development of generative AI, China has introduced corresponding policies and interim measures to guide industrial innovation [3].

Simultaneously, as a barometer of generative AI industry development, ChatGPT' s user decline signals a critical transition. According to a Sequoia Capital research report, the first development phase of generative AI—driven by technology—has concluded, and 2024 will usher in a second phase dominated by users [5]. In this user-dominated stage, user loyalty and stickiness will largely determine the survival of generative AI enterprises. Domestic academia has also recognized the significant impact of user behavior on the generative AI industry, conducting research on user adoption and usage intentions. However, studies of negative behaviors often better reflect actual usage characteristics and patterns than research on positive behaviors. User negative behaviors generally fall

into three categories: severe, moderate, and mild [6]. During the early stages of technological innovation and diffusion, severe negative behaviors rarely occur, while mild negative behaviors offer limited intervention value. Moderate negative behaviors, represented by user attrition and dropout, likely reflect the actual usage state of generative AI users following initial adoption. Therefore, considering the technological development reality and actual usage patterns of generative AI, this study selects generative AI user dropout behavior as its research focus to explore the formation mechanisms and development patterns of moderate negative usage behaviors, providing necessary insights for promoting sustained usage and high-quality development of domestic generative AI.

1 Literature Review

1.1 Overview of Generative AI

Artificial Intelligence Generated Content (AIGC) constructs large language models through AI and natural language processing, relying on deep learning technologies to generate intelligent information that conforms to human reading habits [7]. Although AIGC remains in its initial development stage without a unified definition, both academia and industry have developed broad and narrow conceptualizations. Broadly, AIGC is considered an AI technology with human-like generative and creative capabilities [8], while narrowly, it refers to content production methods that automatically generate content using AI technology [9]. Despite these definitional differences, both conceptualizations involve two dimensions: technology and information.

The information innovation dimension primarily manifests in content generation, positioning AIGC as a content generation model corresponding to Professionally-Generated Content (PGC) and User-Generated Content (UGC). PGC and UGC represent information generation models from the Web 2.0 era, relying primarily on users and communities to create content. However, as information technology has advanced, user needs have become increasingly personalized and differentiated, making it difficult for user- and individual-based generation models to satisfy these demands. In the Web 3.0 era, the role of information technology has become increasingly prominent, and AI-driven content generation has proven more effective in meeting personalized user needs. The technological dimension involves AIGC' s foundation on the Transformer architecture, leveraging massive datasets and large language model processing technologies to generate personalized content according to user needs. AIGC profoundly embodies Shannon' s information theory, predicting text content probabilistically to reduce user uncertainty and satisfy personalized information needs [10]. Compared to UGC, AIGC relies on deep human-computer interaction, where both model fine-tuning capabilities and user questioning abilities profoundly influence AIGC user information behavior and information acquisition patterns.

1.2 Research on Dropout Behavior

Dropout behavior represents a precursor to non-continuous usage behaviors such as user attrition and migration [11]. As user information behavior research has become more granular, the focus has shifted from coarse-grained behaviors like initial adoption and continuous usage to non-continuous usage behaviors with typical characteristics, such as user attrition and dropout. Although academia has not yet formed a unified definition of dropout behavior, most scholars agree that temporary cessation behavior occurring after initial adoption, lasting from several days or weeks to less than six months, can be identified as dropout behavior [12]. Based on occurrence characteristics and patterns, dropout behavior mainly includes abstinent dropout, suspended dropout, and intermittent dropout [13]; it can also be categorized according to timing into intermittent dropout and recurrent dropout [14].

Regarding causal factors, early research attributed dropout behavior primarily to individual factors [6]. Literature review reveals that many scholars focused on user cognitive factors, with rational cognitive factors such as self-efficacy [15], perceived behavioral control [16], and social media confidence [17] considered important causes of dropout behavior. As cognitive factor research matured, scholars like Zhang Min [18] and Gan Chunmei [19] discovered that emotional factors also represent significant, non-negligible causes of user dropout. Immediate emotional factors such as anxiety, fear, distress, and tension entered researchers' field of vision, forming a series of important research findings that fundamentally clarified user dropout behavior formation mechanisms and characteristic patterns. However, regarding dropout behavior formation mechanisms, existing research has largely established a research system centered on cognitive factors and immediate emotional factors like panic and anxiety [20]. According to emotional cause classification, emotional factors include both immediate and cumulative emotional factors [21]. Compared to immediate emotional factors, cumulative emotional factors have often been neglected by researchers. Therefore, this study attempts to introduce psychological resilience as a cumulative emotional factor, focusing on analyzing its driving factors, constructing a research model of AIGC user dropout behavior influencing factors around psychological resilience, conducting empirical research, and exploring in detail the significance of cumulative emotional factors like psychological resilience in continuously improving AIGC user dropout behavior.

1.3 Resilience Theory

The term "resilience"originates from the Latin "Resilio,"containing the metaphor of "rebounding" [22]. It first appeared in physics and mathematics to describe a material' s ability to absorb impact energy when subjected to external shocks and threats—the better the resilience, the greater the energy absorption capacity and the lower the likelihood of brittle failure [23]. In the interdisciplinary development process, resilience theory has been borrowed and absorbed by multiple disciplines, forming discipline-specific resilience research. Ecologists borrowed

the concept from physics, proposing that resilience theory can explain ecosystems' ability to automatically adjust and adapt to external environments while maintaining normal operations when facing threats and impacts [24]. This formulation laid the theoretical foundation for deepening and developing the resilience concept.

Although resilience theory has not yet formed a complete and applicable theoretical system, different disciplines have derived discipline-specific resilience theories and concepts by borrowing existing resilience theory and combining it with disciplinary development realities and external social environments. For example, in psychology, American scholar Masten proposed the concept of psychological resilience, defining it as an individual' s capacity to remain strong in the face of risks and trauma amid pressure, challenges, adversity, and difficulties —a mental elasticity and psychological fortitude that overcomes adversity [25]. In economics, scholars have proposed the concept of economic resilience, referring to the ability to effectively restructure the economy and achieve sustainable development when facing major external threats, including industrial resilience, institutional resilience, and enterprise resilience [26]. In sociology, scholars have proposed the concept of technical resilience, arguing that it facilitates organic coordination among society, organizations, and resources, serving as a key technical resource for achieving technology empowerment and effective connection across various levels [27].

Although information resource management has not yet formed relevant descriptions and positioning regarding resilience theory, scholars have attempted to introduce it into the field to enrich its theoretical and academic systems. Luan Yu et al. introduced resilience theory into intelligence decision-making research, refining its connotation into five capabilities including maintenance capacity and absorption capacity, thereby constructing an emergency event intelligence decision-making system [28]. Bao Xin et al. introduced the sociological concept of community resilience, analyzing and discussing foreign development experiences to explore possibilities and pathways for libraries to empower social resilience, providing theoretical and practical guidance for libraries to realize their value in public safety [29]. Given resilience theory' s good adaptability and explanatory power across disciplines, this study introduces it into AIGC user dropout behavior research. Compared to other information service platforms, deep human-computer interaction represents a typical feature of AIGC application platforms. Therefore, during model construction, we introduce the psychological resilience concept from psychology to analyze how cumulative emotional factors like psychological resilience affect AIGC user dropout behavior, and introduce the technical resilience concept from a technological perspective to analyze the interactive influence between technical factors and AIGC user dropout behavior. Resilience theory can not only enrich the theoretical system of user information behavior but also provide necessary reference for subsequent research.

1.4 S-O-R Theory

The S-O-R (Stimuli-Organism-Response) theory evolved from S-R theory, where S represents external stimuli and R represents individual behaviors under external stimuli [30]. Holistic behaviorist scholar Tolman argued that while S-R theory could adequately explain the relationship between external stimuli and individual behavior, S and R should not be directly linked, proposing the O concept—organism changes—thus forming S-O-R theory [31]. The introduction of O, representing organism changes, incorporates user cognitive and emotional changes into behavioral research, greatly enhancing S-O-R theory' s explanatory power and applicability.

In information resource management, some scholars have attempted to introduce S-O-R theory into user information behavior research to better explain how external environments and emotional factors significantly influence user behavior. Xu Xiaojuan et al. explored social networking site user attrition based on S-O-R theory, finding that factors like satisfaction and perceived privacy risk play important roles in mitigating user attrition [32]. Zhang Hai et al. investigated the formation mechanisms and operational patterns of online user information cocoons using S-O-R theory, with results showing that under external environmental stimuli, emotional factors such as user interests and preferences change significantly, leading to information cocoons [33]. These studies confirm S-O-R theory' s good applicability and explanatory power in exploring user information behavior. Considering this study' s focus on psychological resilience driving factors and the high similarity between AIGC user dropout behavior influencing factors and S-O-R theory' s user behavior logic, this study adopts S-O-R theory to explore how external stimulus factors like technological changes and information service model changes affect users' cumulative and immediate emotional factors, ultimately leading to dropout responses.

2 Model Construction and Research Hypotheses

In model construction, this study borrows the S-O-R theoretical framework to build a research model of factors influencing AIGC user dropout behavior. In the stimulus dimension, we selected technical resilience, technical personification, and information quality to represent AIGC service platform characteristics; in the organism change dimension, we selected psychological resilience and satisfaction to represent changes in cumulative and immediate emotional factors; in the response dimension, we proposed dropout behavior as the dependent variable closely related to our research theme. The final theoretical model framework is shown in Figure 1 [Figure 1: see original paper].

Psychological Resilience originates from psychology and represents a conceptual system integrating resilience theory with psychological research, reflecting individual personality qualities. Resilience theory refers to an individual's ability to maintain relatively stable and healthy psychological states when encountering setbacks and difficulties, and to remain confident and optimistic during adversity

[34]. Existing literature shows that psychological resilience mainly includes user individual psychological adaptability, recovery ability when facing difficulties, and the ability to overcome adverse environments while still developing positively. Compared to emotions like pleasure and anxiety, psychological resilience represents a more stable emotional state belonging to the cumulative emotional factors category. Domestic research has found that psychological resilience can effectively enhance entrepreneurs' entrepreneurial resilience, representing an important factor for entrepreneurial success [35]; it also belongs to the important theoretical foundation of positive psychology, can improve nurses'job satisfaction and work efficiency, and serves as an important influencing factor in effectively alleviating nurses' job burnout [36].

Specifically in the AIGC domain, AIGC platforms like ChatGPT represent entirely new technology service systems that inevitably face various unknown risks and challenges during development. Particularly, current AIGC technology remains imperfect, even criticized as "seriously talking nonsense."Only AIGC users with higher psychological resilience can maintain optimistic attitudes toward AIGC technology when encountering usage difficulties and challenges, quickly adjust in difficult situations, and effectively avoid user attrition and dropout caused by difficulties and challenges. Therefore, this study proposes that psychological resilience is an important influencing factor in preventing AIGC user dropout and promoting sustained usage, leading to the following hypothesis:

H1: Psychological resilience has a negative effect on AIGC user dropout behavior.

Satisfaction is an important variable in satisfaction models, referring to users' subjective evaluation of information systems and reflecting their pleasure level after using information system services. When users' pre-use expectations better match their actual experience with information system services, satisfaction increases. In essence, satisfaction belongs to the important component of immediate emotional factors. In user information behavior research, many studies have confirmed satisfaction as an important factor influencing user adoption intention and continuous usage behavior. Xu Xiaojuan et al. confirmed that satisfaction is a key driver in effectively mitigating social networking site user attrition and stimulating continuous usage [37]; Li Juanjuan found through inductive analysis that satisfaction is an important emotional factor promoting positive adoption in social Q&A communities [38]. Regarding this study's theme, when using AIGC platforms, users typically have strong usage purposes and expectations. When AIGC' s actual service level and capacity effectively match user expectations and satisfy their purposes and needs, AIGC user satisfaction increases, continuous usage intention strengthens, and dropout behavior likelihood decreases. Based on this analysis, this study proposes that satisfaction can effectively stimulate AIGC users' continuous usage intention and prevent dropout behavior, leading to:

H2: Satisfaction has a negative effect on AIGC user dropout behavior.

Technical Resilience is an important variable reflecting technology evolution characteristics from the resilience theory perspective. It represents information technology' s adaptability and resistance when encountering external threats and development bottlenecks. Fu Liping et al. argued that technical resilience is inseparable from data resource governance [27]. Technical resilience includes both temporal adaptation to social productivity development and spatial coverage of social production relations, proposing that its key lies in organic integration among technology, society, organizations, and resources. From a temporal perspective, AIGC technology is new and requires continuous iteration and updating according to social development. From a spatial perspective, AIGC technology has not yet fully integrated with social production relations, social organizations, and data resources, requiring self-improvement and organic renewal. Therefore, during AIGC development, besides emphasizing technological intelligence and novelty, technical resilience should be enhanced. When AIGC technical resilience significantly improves, the relationship between AIGC technology and social relations/resources becomes more harmonious, helping to increase user satisfaction. When AIGC' s self-adaptability and resistance significantly improve, it also contributes to enhancing user psychological resilience. This study proposes that technical resilience can significantly improve user satisfaction and psychological resilience, leading to:

H3: Technical resilience positively affects user psychological resilience. H4: Technical resilience positively affects user satisfaction.

Technical Personification is a relatively cutting-edge concept in the AIGC domain, originating from the anthropomorphism concept in human-computer interaction and serving as an important indicator for measuring AI technology' s friendliness and intelligence level [39]. Technical personification refers to the approach of attributing human characteristics, motivations, intentions, or emotions to non-human entities through technical means and methods, thereby enhancing human-computer interaction experiences. Technical personification degree can be measured and explained through two dimensions: warmth and competence. The warmth dimension primarily examines AI technology's friendliness toward humans and the ethical relationship between humans and machines, while the competence dimension mainly examines AI technology' s advancement and ability to understand human intentions. Compared to other information technologies and services, technical personification represents AIGC application platforms' technological advantage and typical characteristic. AIGC application platforms can better understand user needs and information intentions during information processing, emphasize integrating human emotional factors in human-computer interaction, build good human-computer relationships, and ensure continuously enhanced user pleasure, activity, and usage frequency. During usage, AIGC application platforms can effectively understand users' search intentions and information needs, reduce usage burden, and thereby enhance user satisfaction and confidence in AIGC technology development. Based on this analysis, this study proposes that technical personification can effectively improve user satisfaction and psychological resilience, leading to:

H5: Technical personification positively affects user psychological resilience. H6: Technical personification positively affects user satisfaction.

Information Quality is an important variable in information system success models, reflecting information systems' accuracy, timeliness, and usefulness in information content dimensions. According to information system success model descriptions, information quality is considered an important factor affecting information system success. Existing research has also confirmed information quality as a key factor affecting information system success and user acceptance and satisfaction. Wang Xiwei et al. confirmed that in smart library contexts, information quality is an important factor affecting user satisfaction with intelligent robot chat services [40]; Zhang Hai et al. also found that in mobile government usage contexts, information quality is an important factor affecting user usage intention [41]. Compared to UGC, AIGC platforms' information is entirely AI-generated, better meeting users' personalized information needs, thus relatively higher in information quality from the user needs perspective. Although some deficiencies exist in information accuracy, with users even describing it as a "stochastic parrot," these characteristics also reflect that information quality is a highly concerned content and indicator during AIGC usage. Improving AIGC platform information quality can effectively enhance user satisfaction and usage experience. Overall, this study argues that improving AIGC platform information quality is important for effectively enhancing user psychological resilience and satisfaction. Based on this analysis, we propose:

H7: Information quality positively affects user psychological resilience. H8: Information quality positively affects user satisfaction.

3 Research Design

3.1 Questionnaire Design

This study focuses on exploring the driving factors of psychological resilience and constructs an AIGC user dropout behavior influencing factor research model based on S-O-R theory. To verify the model' s scientificity and reliability, the research team decided to use the questionnaire survey method to obtain AIGC user data for empirical testing. Based on domestic and international research findings, an initial questionnaire was developed. When determining measurement items, variables like satisfaction, information quality, and dropout behavior are relatively mature with complete observation scales. The research team appropriately adjusted mature scales according to AIGC user characteristics to form initial scales. Variables like technical resilience, technical personification, and psychological resilience are relatively novel without complete scale systems. The team subdivided relevant variable dimensions based on existing literature, combined with AIGC development realities, and initially formed observation scales. Considering the initial questionnaire' s complexity, the team first conducted a pilot survey, randomly selecting 135 users for pre-testing. Based on

respondent feedback and questionnaire reliability and validity results, the psychological resilience observation scale was simplified from 5 to 3 items, and technical resilience from 4 to 3 items, forming the final questionnaire (see Appendix for details).

3.2 Data Collection

According to the "2024 Top 10 AIGC Application Layer Trends" white paper jointly released by Alibaba DingTalk and an international data company, AIGC users show a trend toward younger demographics, with bachelor's degree holders comprising the largest proportion. To ensure data collection representativeness and reliability, the formal survey targeted younger users with bachelor' s degrees. Formal respondents were required to have at least three months of AIGC platform usage experience. Table 1 presents respondent demographics. The formal survey was conducted through both online and offline channels over 53 days, collecting 386 questionnaires. After eliminating invalid responses (those completed in less than 3 minutes, with contradictory answers, or showing obvious response patterns), 328 valid questionnaires remained, yielding an effective response rate of 84.97%.

Table 1 Interviewee Statistics

Demographic	Category	Percentage
Education	Bachelor' s/Associate	71.3%
	Master' s	24.1%
	Doctorate	4.6%
Age	Under 25	38.7%
	26-36	45.1%
	37-47	12.5%
	48 and above	3.7%
Primary AIGC Platform	ChatGPT	68.9%
	Others	31.1%

3.3 Reliability and Validity Testing

To verify questionnaire data reliability and consistency, this study used SPSS 20.0 for reliability and validity analysis. For reliability verification, we calculated Cronbach' s α coefficients for each measurement item and the Cronbach' s α if item deleted. Results showed each observed variable' s Cronbach' s α coefficient exceeded 0.80, with overall scale reliability significantly decreasing when any specific item was deleted, indicating good internal consistency and overall reliability.

For validity testing, we calculated factor loadings, composite reliability, and average variance extracted (AVE). Results showed composite reliability for all

variables exceeded 0.60, factor loadings exceeded 0.70, and AVE values were above 0.60, demonstrating good convergent validity (see Table 2).

For discriminant validity, we compared the square root of each latent variable' s AVE value with inter-variable correlation coefficients. Results showed all latent variables' AVE square roots exceeded their correlation coefficients with any other latent variable (see Table 3), indicating good discriminant validity.

Table 2 Reliability and Validity Analysis of the Questionnaire

Variable	Cronbach' s α	α if Item Deleted	Factor Loading	Composite Reliability	AVE
Technical Resilience (TRE)	0.852	0.801-0.823	0.823-0.867	0.854	0.662
Technical Personification (TEP)	0.841	0.792-0.814	0.812-0.854	0.843	0.641
Information Quality (INQ)	0.876	0.831-0.859	0.845-0.881	0.879	0.708
Psychological Resilience (PYR)	0.835	0.784-0.806	0.805-0.847	0.838	0.632
Satisfaction (SAT)	0.863	0.819-0.842	0.834-0.872	0.865	0.683
Dropout Behavior (DPB)	0.891	0.851-0.874	0.867-0.895	0.893	0.735

Table 3 Variable Correlation Coefficient Matrix

Note: Diagonal values represent the square root of each latent variable' s AVE; off-diagonal values represent correlation coefficients between latent variables.

	TRE	TEP	INQ	PYR	SAT	DPB
TRE	0.814					
TEP	0.423	0.801				
INQ	0.512	0.456	0.842			
PYR	0.605	0.387	0.589	0.795		

	TRE	TEP	INQ	PYR	SAT	DPB
SAT	0.398	0.512	0.634	0.523	0.826	
DPB	-0.423	-0.298	-0.456	-0.587	-0.412	0.857

3.4 Hypothesis and Model Testing

This study used AMOS 28 software to verify research hypotheses and model fit. For model fit, all indicators met critical threshold requirements (see Table 4). The research model explained 64.80% of AIGC user dropout behavior variance.

Table 4 Model Fit Index Values

Index	^{2}/df	GFI	AGFI	NFI	IFI	CFI	RMSEA
Threshold	<3.0	>0.90	>0.80	>0.90	>0.90	>0.90	<0.08
Actual Value	2.342	0.923	0.851	0.912	0.934	0.933	0.072

Based on resilience theory and S-O-R theory, this study constructed an AIGC user dropout behavior influencing factor research model with eight hypotheses. Empirical testing using questionnaire data revealed that five hypotheses were supported and three were not supported (see Figure 2 [Figure 2: see original paper]).

Figure 2 Verification Results of the Research Model on Influencing Factors of AIGC User Dropout Behavior

Note: **: P<0.001;** : P<0.01; *: P<0.05*

4 Results Analysis

4.1 Psychological Factor Analysis

Results show that cumulative emotional factors like psychological resilience can effectively alleviate AIGC user dropout behavior (coefficient = -0.487, P<0.001), while immediate emotional factors like satisfaction have less significant impact on dropout behavior (coefficient = -0.328, P=ns). Building on research by Wang Xiwei [40] and Yuan et al. [21], satisfaction is an important factor stimulating initial adoption intention. The non-significant result may occur because while satisfaction can enhance user experience and stimulate positive adoption, in the AIGC context, immediate emotional factors like satisfaction primarily influence adoption intention. In subsequent stages, once users exhibit dropout behavior, immediate emotional factors struggle to prevent user attrition and migration. In contrast, cumulative emotional factors like psychological resilience can effectively improve users' psychological adaptability and recovery, pulling them back from the brink of attrition and encouraging continued usage.

AIGC technology holds significant advantages and appeal, with many users recognizing it as representing future technological development directions. Cumulative emotional factors like psychological resilience can resolve frustrations and difficulties during usage, motivating sustained usage. Compared to cumulative emotional factors, immediate emotional factors like satisfaction have limited sustainability and effectiveness, particularly in addressing usage frustrations, preventing user attrition, and motivating continuous usage. Therefore, academic research should emphasize cumulative emotional factors like psychological resilience, developing AIGC-specific psychological resilience measurement scales and refining the psychological resilience variable according to AIGC contexts. In practice, information service centers like libraries should optimize and improve user information literacy education around AIGC technology, adding resilience education modules to enhance users' psychological adaptability, recovery, and immunity when encountering major setbacks and difficulties in information service contexts. AIGC service platforms should focus on cultivating users' cumulative emotional factors, strengthening psychological resilience-related perceptions alongside satisfaction improvement to genuinely enhance continuous usage.

4.2 Technical Factor Analysis

This study finds that technical personification significantly impacts immediate emotional factors (coefficient = 0.328, P<0.01), effectively improving user satisfaction, but does not significantly affect cumulative emotional factors (coefficient = 0.376, P=ns). AIGC technology needs to adapt to social productivity and relations development, continuously iterating and innovating according to societal progress to maintain user confidence. Additionally, Ni Shiguang et al. noted that technical resilience promotes science and technology for social good [43]; Chen Zhi also proposed that technical resilience facilitates technology self-improvement and adjustment, holding important significance for resilience governance and harmonious human-machine relationships [44]. This study similarly views technical resilience as a key factor maintaining benign human-computer interaction, further demonstrating that technical resilience positively and significantly impacts cumulative emotional factors, effectively enhancing user psychological resilience (coefficient = 0.367, P<0.001), while having less significant impact on satisfaction (coefficient = 0.286, P=ns).

Technical personification represents AIGC' s technological advantage and characteristic, effectively enhancing user satisfaction and bringing novel usage experiences that stimulate positive adoption and improve initial adoption intention. After initial adoption, some users may attrite or temporarily discontinue usage due to technology-related fear and anxiety. On the other hand, AIGC technology is a double-edged sword: while providing personalized information, it also raises technological ethics and risks that cannot be ignored. When immediate positive emotional factors are depleted, negative factors like technology costs, burdens, and risks affect user perceptions and cognition of AIGC technology. Once emotional fluctuations occur, users' continuous usage decisions and behav-

iors may be affected, potentially leading to dropout behavior. To prevent user dropout and migration and enhance continuous usage intention, AIGC technical resilience must be improved to enhance technological risk resistance and social adaptability. Future research could focus on technical resilience: clarifying its characteristics and states to provide theoretical foundations for AIGC development, and conducting empirical research to identify its antecedents and consequences, providing practical guidance for subsequent applied research and AIGC technology development.

4.3 Information Factor Analysis

Compared to technical factors, information quality can both positively and significantly affect satisfaction (coefficient = 0.415, P<0.001) and effectively enhance user psychological resilience (coefficient = 0.158, P<0.01). AIGC service platforms leverage technological advantages to provide efficient personalized information, including text, images, and videos. Multi-modal information forms and personalized information models can quickly attract user attention, with most users actively using AIGC service platforms during initial adoption. After this phase, information service models and multi-modal information can no longer fully satisfy user needs. To effectively avoid user dropout and stimulate continuous usage, merely relying on information carrier forms is insufficient—information quality must be improved to enhance knowledge content, including information accuracy, richness, and usefulness.

According to AIGC development stages and usage patterns, AIGC users have generally adopted and recognized AIGC service models and forms. To further enhance user loyalty and stickiness, cumulative emotional factors must be cultivated and psychological resilience optimized and improved, actively compensating for information quality deficiencies. Relevant measures for information resource management disciplines mainly include: improving raw data quality, as AIGC operations rely on massive datasets for deep learning analysis and probabilistic text prediction to complete information output, making raw data quality crucial for AIGC service platform information quality. AIGC service platforms can collaborate with information service centers like libraries to organize and describe raw data, improving its quality. During operation, human intervention modes can be added to effectively screen output information quality through expert verification, ensuring effective and accurate information delivery. Additionally, AIGC platform information quality is closely related to user questioning methods. In the UGC era, users primarily obtained useful information through search; in the AIGC era, information acquisition has undergone disruptive changes, mainly through questioning and multi-round interaction. Therefore, future information literacy education should adapt to this shift by appropriately adding "questioning quotient" (问商) elements to suit human-computer interaction information acquisition modes. "Questioning quotient" includes not only users' ability to accurately express information needs and guide AIGC platforms to provide precise information but also the ability

to construct questioning strategies based on AIGC service platforms to enhance human-computer interaction. Cultivating AIGC users' questioning quotient can effectively tap information potential value, improving user information quality perception through feedback and learning in human-computer interaction, thereby promoting continuous usage.

5 Conclusion

Represented by AIGC, artificial intelligence is in a critical period of technological iteration and renewal. The vigorous development of AIGC, exemplified by ChatGPT, represents the development direction of new productive forces. To better promote AIGC' s orderly development from technology-driven to user-driven approaches and deeply explore the characteristics and patterns of AIGC users' continuous usage behavior, this study selected AIGC user dropout behavior influencing factors as its research object, focusing on how immediate and cumulative emotional factors affect AIGC user dropout behavior. During the research process, the team introduced psychological resilience as a cumulative emotional factor based on resilience theory, clarified its antecedents, constructed an AIGC user dropout behavior influencing factor research model based on S-O-R theory, and conducted empirical testing. Results show that compared to immediate emotional factors, cumulative emotional factors like psychological resilience can effectively alleviate AIGC user dropout behavior and promote continuous usage. Additionally, technical resilience and information quality emerge as important antecedents for enhancing user psychological resilience.

These conclusions provide theoretical and practical guidance for improving user psychological resilience, addressing user attrition and migration after initial adoption, and preventing non-continuous usage behaviors. However, this study has several limitations: First, although it clarified AIGC user psychological resilience driving factors, it did not develop an AIGC-specific psychological resilience scale due to space constraints. Second, although the model was constructed and empirically tested, the study relied primarily on questionnaire data, which may involve subjective factors and cannot objectively and scientifically present the complete picture of AIGC user dropout behavior formation mechanisms. Future research should incorporate secondary data like user logs to improve data quality. Finally, temporally, this study represents static cross-sectional research, while AIGC user dropout behavior changes over time. Future research could introduce temporal studies through dynamic comparative approaches to more accurately capture the changing processes and characteristic patterns of AIGC user dropout behavior.

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Appendix: Questionnaire Items and Sources

Construct	Item	Statement	Source
Technical Resilience (TRE)	TRE_1	I believe AIGC technology represents future development trends	Adapted from [27]
	TRE_2	I believe AIGC technology can adapt to social development and continuously update	
	TRE_3	I believe AIGC technology can overcome technical bottlenecks and continuously evolve	
Technical Personification (TEP)	TEP_1	I feel AIGC information content fits my reading habits	Adapted from [39]
	TEP_2	I feel AIGC services understand my information needs	
	TEP_3	I feel AIGC technology is relatively intelligent with high personification degree	
Information Quality (INQ)	INQ_1	I believe AIGC provides reliable information	Adapted from [40]
	INQ_2	AIGC provides me with accurate information	
	INQ_3	I have obtained sufficient information from AIGC	
Psychological Resilience (PYR)	PYR_1	When facing difficulties, I can concentrate all my energy	Adapted from [34]
	PYR_2	When facing difficulties, I can control my emotions well	

Construct	Item	Statement	Source
	PYR_3	After experiencing setbacks, I generally become more mature and experienced	
Satisfaction (SAT)	SAT_1	The AIGC service platform has generally met my expectations	Adapted from [37]
	SAT_2	The AIGC service platform has generally satisfied my needs	
	SAT_3	I am satisfied with the interaction experience of the AIGC service platform	
Dropout Behavior (DPB)	DPB_1	After using for a period, I will use the AIGC service platform less or not at all	Adapted from [12]
	DPB_2	I currently won' t use it anymore; I' ll use it again when technology makes breakthroughs	
	DPB_3	I often use it for work but rarely use it in daily life	

Note: Figure translations are in progress. See original paper for figures.