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Factors Influencing the Usage Behavior of Generative AI Among Shanghai Residents

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Abstract. This study explores the influencing factors of generative AI usage behavior among residents in Shanghai. Based on 208 questionnaire responses and analyzed using SPSS, the findings reveal that users can be categorized into three types: technology-dependent, ethics-sensitive, and function-oriented. High-frequency users (80.19%) exhibit weaker awareness of privacy risks, while low-frequency users (19.8%) pay more attention to technological transparency. Age and education level significantly influence usage intention in specific scenarios. Recommendations are provided to optimize technology design and policy regulation for different user groups.

Keywords: Generative Artificial Intelligence;Usage Behavior;Technology Acceptance

1. Introduction

With the rapid development of generative AI technology, China has been actively promoting AI innovation and industrial integration under policies such as the New Generation Artificial Intelligence Development Plan [1]. While this technology enhances efficiency in fields like education and healthcare, it also poses risks such as privacy breaches [2]. Domestic scholars have conducted research based on the Technology Acceptance Model (TAM). For instance, Wang Ru and Yu Fei (2024) found that perceived interactivity influences usage attitudes through ease of use and usefulness [3], while Zhang Chi (2023) introduced variables like perceived risk to refine the model [4]. Southwest University (2024) proposed a "three-level, ten-dimensional" framework for AI applications in higher education [5]. However, existing studies primarily focus on technical aspects, with insufficient research on the adaptive strategies, risk perceptions, and ethical considerations of megacity residents in AI applications [6]. This study takes Shanghai residents as the research subjects, analyzing their usage habits and potential concerns, aiming to provide a Chinese case for smart city development and global AI governance in megacities.

2. Questionnaire Analysis and Research

2.1 Questionnaire Design

This study collected 208 valid responses through an online questionnaire, which consisted of three parts: basic information, branch questions based on usage frequency (high-frequency users answered questions about usage scenarios, while low-frequency users explained reasons for non-use) [7], and development perspective questions answered by all participants [8,9]. Using a Likert scale, the study constructed a usage intention model based on the Technology Acceptance Model (TAM), incorporating variables such as perceived risk and technology anxiety . It investigated the frequency and scenarios of generative AI usage, analyzed influencing factors, and examined user concerns regarding privacy protection and technological trust. The findings provide a basis for optimizing AI technology, establishing ethical guidelines, and informing policy-making.

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2.2 Reliability and Validity Tests

The study employed Cronbach's alpha coefficient for reliability testing, with all scales demonstrating α values above 0.7 (ranging from 0.807 to 0.928), indicating good data reliability. Validity tests showed that the KMO values for all three sections of the data exceeded 0.8 (ranging from 0.819 to 0.879), and Bartlett's test significance levels were all below 0.001, confirming the questionnaire's strong construct validity .

3. Factors Influencing Generative AI Usage Behavior

3.1 Nonparametric Tests

This study examined the relationship between demographic variables and AI usage behaviors through non-parametric tests. Tables 1 to 3 revealed that region (p=0.005) and age (p=0.03) significantly influenced usage frequency, with urban residents and the 18-30 age group exhibiting higher adoption rates, while education level was not significant (p=0.690). Spearman analysis (Table 4) indicated that older adults held reserved attitudes toward AI in emotional interaction scenarios (AV3, p=0.044). The Kruskal-Wallis test (Table 5) found that highly educated groups were more concerned about AI's impact on independent thinking (RA1, χ^2=9.034, p=0.029) and copyright issues (RA3, χ^2=9.677, p=0.022).

Table 1. Kruskal-Wallis H Test for Generative AI Usage Across Different Regions

	H	df	Asymp. Sig.
Kruskal-Wallis H	14.915	4	.005

Table 2. Kruskal-Wallis H Test for Generative AI Usage Across Different Age Groups

	H	df	Asymp. Sig.
Kruskal-Wallis H	10.699	4	.030

Table 3. Kruskal-Wallis H Test for Generative AI Usage Across Different Education Levels

	H	df	Asymp. Sig.
Kruskal-Wallis H	1.468	3	.690

Table 4. Analysis of the Relationship Between Age and Scenario Ratings (Spearman Rank Correlation)

Correlation Coefficient							
			age	AV1	AV2	AV3	AV4
Spearman's rho	age	Correlation Coefficient	1.000	.040	-.015	.130*	.077
		Sig. (1-tailed)	.	.298	.422	.044	.156
		N	217	174	174	174	174
	AV1_Scenarios requiring truthful and accurate answers	Correlation Coefficient	.040	1.000	.628**	.567**	.595**
		Sig. (1-tailed)	.298	.	.000	.000	.000
		N	174	174	174	174	174
	AV2_Aspects involving personal privacy and information security	Correlation Coefficient	-.015	.628**	1.000	.498**	.445**
		Sig. (1-tailed)	.422	.000	.	.000	.000
		N	174	174	174	174	174
	AV3_Issues requiring emotional resonance and psychological care	Correlation Coefficient	.130*	.567**	.498**	1.000	.475**
		Sig. (1-tailed)	.044	.000	.000	.	.000
		N	174	174	174	174	174
	AV4_Creative and original work	Correlation Coefficient	.077	.595**	.445**	.475**	1.000
		Sig. (1-tailed)	.156	.000	.000	.000	.
		N	174	174	174	174	174

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*. Correlation is significant at the 0.05 level (1-tailed).
**. Correlation is significant at the 0.01 level (1-tailed).

Table 5. Differences in AI Rejection Scenarios Across Education Levels (Kruskal-Wallis Test)

Test Statistic[a,b]							
	RA1	RA2	RA3	RA4	RA5	RA6	RA7
Chi-Square	9.034	2.877	9.677	4.054	4.676	6.641	.981
df	3	3	3	3	3	3	3
Asymp. Sig.	.029	.411	.022	.256	.197	.084	.806

RA1: AI may create dependency and impair independent thinking ability; RA2: I'm concerned about privacy data collection or misuse; RA3: I believe AI uses unauthorized works, violating copyright; RA4: Using AI is too difficult for me; RA5: I distrust the results generated by AI; RA6: I believe AI diminishes human uniqueness; RA7: I'm concerned about risks of algorithmic bias in AI

a.Kruskal-Wallis Test

b.Grouping Variable: education

3.2 Correlation Analysis

This study employed Pearson correlation analysis to explore the relationship between AI debugging behaviors and usage frequency, educational background, and age. Tables 6 to 8 reveal that users' AI usage frequency showed significant negative correlations with debugging behaviors such as privacy protection (r = -0.342) and information verification (r = -0.205), indicating that frequent users tend to reduce proactive interventions. Additionally, strong positive correlations were observed among various debugging behaviors (r = 0.427–0.657), reflecting the systematic nature of user intervention behaviors.

Table 6. Relationship Between Participants' AI Debugging Behaviors and Usage Frequency

Correlations						
		AD1	AD2	AD3	AD4	frequency
AD1_I limit AI's data collection permissions to protect privacy	Pearson Correlation	1	.627**	.630**	.657**	-.342**
	Sig. (2-tailed)		.000	.000	.000	.000
	N	174	174	174	174	174
AD2_I train AI to learn my schedule preferences for reminders	Pearson Correlation	.627**	1	.428**	.485**	-.158*
	Sig. (2-tailed)	.000		.000	.000	.037
	N	174	174	174	174	174
AD3_I simultaneously query multiple AIs to compare answers	Pearson Correlation	.630**	.428**	1	.500**	-.095
	Sig. (2-tailed)	.000	.000		.000	.214
	N	174	174	174	174	174
AD4_I cross-validate the authenticity of information provided by AI	Pearson Correlation	.657**	.485**	.500**	1	-.205**
	Sig. (2-tailed)	.000	.000	.000		.007
	N	174	174	174	174	174
frequency	Pearson Correlation	-.342**	-.158*	-.095	-.205**	1
	Sig. (2-tailed)	.000	.037	.214	.007	
	N	174	174	174	174	217

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

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Table 7. Relationship Between Participants' AI Debugging Behaviors and Education Background

Correlations						
		AD1	AD2	AD3	AD4	education
AD1_I limit AI's data collection permissions to protect privacy	Pearson Correlation	1	.627**	.630**	.657**	-.043
	Sig. (2-tailed)		.000	.000	.000	.571
	N	174	174	174	174	174
AD2_I train AI to learn my schedule preferences for reminders	Pearson Correlation	.627**	1	.428**	.485**	-.078
	Sig. (2-tailed)	.000		.000	.000	.306
	N	174	174	174	174	174
AD3_I simultaneously query multiple AIs to compare answers	Pearson Correlation	.630**	.428**	1	.500**	-.006
	Sig. (2-tailed)	.000	.000		.000	.933
	N	174	174	174	174	174
AD4_I cross-validate the authenticity of information provided by AI	Pearson Correlation	.657**	.485**	.500**	1	-.037
	Sig. (2-tailed)	.000	.000	.000		.630
	N	174	174	174	174	174
education	Pearson Correlation	-.043	-.078	-.006	-.037	1
	Sig. (2-tailed)	.571	.306	.933	.630	
	N	174	174	174	174	217

**. Correlation is significant at the 0.01 level (2-tailed).

Table 8. Relationship Between Participants' AI Adoption Level and Age

Correlations						
		AD1	AD2	AD3	AD4	age
AD1	Pearson Correlation	1	.627**	.630**	.657**	.032
	Sig. (2-tailed)		.000	.000	.000	.671
	N	174	174	174	174	174
AD2	Pearson Correlation	.627**	1	.428**	.485**	.140
	Sig. (2-tailed)	.000		.000	.000	.065
	N	174	174	174	174	174
AD3	Pearson Correlation	.630**	.428**	1	.500**	-.072
	Sig. (2-tailed)	.000	.000		.000	.344
	N	174	174	174	174	174
AD4	Pearson Correlation	.657**	.485**	.500**	1	.003
	Sig. (2-tailed)	.000	.000	.000		.967
	N	174	174	174	174	174
age	Pearson Correlation	.032	.140	-.072	.003	1
	Sig. (2-tailed)	.671	.065	.344	.967	
	N	174	174	174	174	217

3.3 Analysis of AI Usage Scenarios

The Kruskal-Wallis non-parametric tests in Tables 9 and 10 revealed that regional factors significantly influenced AI usage in work settings ($\chi^2 = 16.251$, $p = 0.003$), while educational background selectively affected its application in social scenarios ($\chi^2 = 8.052$, $p = 0.045$).

Table 9. Test Statistics[a]

	SC1_Using AI for learning assistance	SC2_Using AI for work tasks	SC3_Using AI to optimize social interactions	SC4_Using AI for creative design	SC5_Using AI for non-professional domain consultations
Chi-Square	9.236	16.251	5.100	3.660	8.981
df	4	4	4	4	4
Asymp. Sig.	.055	.003	.277	.454	.062
a. Grouping Variable: Q1_Which region do you belong to?					

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Table 10 Test Statisticsa

	SC1_Using AI for learning assistance	SC2_Using AI for work tasks	SC3_Using AI to optimize social interactions	SC4_Using AI for creative design	SC5_Using AI for non-professional domain consultations
Chi-Square	1.580	1.593	8.052	4.750	2.350
df	3	3	3	3	3
Asymp. Sig.	.664	.661	.045	.191	.503
a. Grouping Variable: Q3_What is your highest education level?					

4. Research Findings and Recommendations

Research findings indicate that user groups can be divided into three categories: technology-dependent (high-frequency users accounting for 80.19%, with weaker privacy risk awareness), ethics-sensitive (low-frequency users accounting for 19.8%, more concerned about technological transparency), and function-oriented (usage willingness in specific scenarios significantly influenced by age and education level). Below, targeted recommendations are proposed based on specific data.

4.1 Optimization of Technological Transparency and Privacy Protection

High-frequency users (AD1-AD4) show a negative correlation between debugging and usage frequency ($r = -0.342$ to -0.205, $p < 0.05$), suggesting reduced proactive intervention with higher usage, increasing trust but lowering risk vigilance. Highly educated users are more sensitive to copyright (RA3, $\chi^2 = 9.677$, $p = 0.022$) and independent thinking impacts (RA1, $\chi^2 = 9.034$, $p = 0.029$). Recommendations include embedding dynamic privacy protections (e.g., default data restrictions (AD1) and transparency prompts for high-frequency use) and auto-attaching copyright disclaimers (RA3) for educated users to address ethical concerns.

4.2 Improvement of Ethical Norm Systems

Older users show more reservation toward AI in emotional interactions (AV3, Spearman $r = 0.130$, $p = 0.044$), while highly educated groups better understand AI's ethical risks (RA1-RA7). Recommendations include: labeling emotional AI (e.g., "non-human service" (AV3)) and adding an "independent thinking assistance" mode (RA1) in education. No link was found between transparency demand and education level ($p > 0.05$), suggesting a need for AI ethics education, especially for low-frequency users.

4.3 Strengthening of Policy Regulatory Frameworks

Regional disparities analysis indicates that AI usage rates are significantly higher among urban residents ($H = 14.915$, $p = 0.005$), and workplace acceptance is significantly influenced by region ($\chi^2 = 16.251$, $p = 0.003$). This necessitates differentiated regulatory approaches: in regions with high technology penetration (e.g., urban centers), focus on regulating data monopolies and algorithmic biases (RA7); in low-penetration regions, prioritize technology popularization and equitable access. Furthermore, the high positive correlation in debugging behaviors ($r = 0.427 - 0.657$) reflects the systematic nature of user interventions. It is recommended to incorporate "active verification mechanisms" (AD4) into national standards for AI products and require companies to provide multi-model comparison tools (AD3) to safeguard user right to know.

In summary, this study reveals the layered characteristics underlying user behavior through quantitative analysis, providing data-driven support for technological optimization and governance.

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