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# **Factors affecting users' behaviour with task-driven Chatbots : an empirical study based on the TTF and UTAUT models**

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**Abstract:**In the digital age, users in China are increasingly inclined to adopt task-oriented chatbots for task-driven work. This study, based on the Task Technology Fit model combined with the UTAUT model, collected 700 valid questionnaires. It employed Amos 24.0 for descriptive statistical analysis, reliability and validity testing, and correlation analysis of the collected data. The Harman single-factor test method was used to examine common method bias, and the Bootstrap method and simple slope analysis method were applied to verify hypotheses. SPSS 28.0 was used for multiple linear regression analysis and mediation effect analysis to test hypotheses. The study empirically investigated the factors influencing users' behavior in using task-oriented chatbots in China, focusing on seven impact factors: two dependent variables of AI communication anthropomorphism and interactivity, one independent variable of behavior, two mediating variables of performance expectancy and usage intention, and three moderating variables of task characteristics, technology characteristics, and task-technology fit. The results indicate that the factors of AI anthropomorphism and interactivity have a significant impact on the residents of the Yangtze River Delta region using task-driven Chatbots for task-driven work. Moreover, through the mediating effects and moderating roles of other variables, a complex networked structure is formed. The adaptability of technology and the individual's willingness to use it in varying scenarios together constitute the influencing factors of behavior.

**Keywords:**Task-Driven chatbots;User Behavior; Influencing Factors;TTF Model;UTAUT Model

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## 1. Introduction

Task-oriented chatbot technology has made significant advancements in recent years. These bots are not only capable of understanding and generating natural language, but they also assist in specific tasks such as bookings, inquiries, customer service, etc. Utilizing machine learning, deep learning, and natural language processing technologies, these robots have become more accurate in understanding complex queries and maintaining contextual coherence. With the improvement of user experience, consumer acceptance of task-oriented chatbots continues to rise. Many users are now more inclined to use chatbots to obtain information or complete specific tasks, especially in situations where a quick response is needed.

In the 1950s and 1960s, with the rise of the field of artificial intelligence, early chatbots began to emerge. For example, the Turing Test proposed by Alan Turing during this period laid the theoretical foundation for the later development of chatbots. In 1966, Joseph Weizenbaum developed ELIZA, one of the earliest chatbots in history. From the 1990s to the early 21st century, chatbots gradually evolved from simple conversational systems to systems capable of performing specific tasks.

Against this backdrop, task-oriented chatbots, as a novel user interaction tool, have gained widespread application in multiple sectors such as service, finance, education, etc., fulfilling the needs for efficient and collaborative work. This study aims to apply and validate the applicability of Task Technology Fit (TTF) theory and the Unified Theory of Acceptance and Use of Technology (UTAUT) in the research domain of task-driven chatbots. By analyzing the usage behavior of Chinese users towards task-oriented chatbots, this study intends to provide new perspectives and data support for theoretical research in the field of information technology acceptance and usage.

A total of 2078 papers on "chatbots" were retrieved from 2020 to 2023 in the SSCI and CSSCI databases.

For policymakers and corporate decision-makers, the insights offered by this study can be used to guide the formulation of IT-related policies in China, promoting

the synergistic development of regional economy and technology. Additionally, this study also holds significant practical value in promoting the widespread adoption and application of information technology in the region, enhancing service quality and efficiency.

In recent years, research in China on the use of task-driven chatbots has gradually gained momentum. Scholars have explored the interactive relationship between humans and chatbots, including aspects of trust, role positioning, and user engagement. As discussed, artificial intelligence chatbots in mental health counseling can effectively express emotions. This emotional expression significantly improves user satisfaction and their willingness to reuse the service. The study highlights the positive impact of emotion-expressing chatbots on user experience in psychological consultations.goo suggested that the domain features used by chatbots are strong predictors of user preference, and that machines with appropriate domain features need to be designed to improve user acceptance and perception of chatbot interactions(goo & Cha, 2020).Park, Chung believe that anthropomorphism, interactivity, functional value judgments, and attachment relationships all influence and deepen user engagement(Park, Chung, & Lee, 2022) .

From a practical perspective, some scholars focus on the functionality of task-driven chatbots in business and service sectors, scientific research and medical fields, and in areas of journalism and public administration. Factors influencing chatbot interaction design and the service impact of anthropomorphism are widely discussed. For instance, Lee and Yoon's study showed that chatbot's etiquette, entertainment, curiosity and empathy are key determinants in predicting user acceptance, and that the ability of a chatbot to respond naturally and appropriately to a user's expression of sensibility with appropriate etiquette styles is determinative of the ability of an open-domain chatbot to conform to user expectations.(Lee & Yoon, 2022).Loureiro suggested that chatbots' human-like characteristics, empathy and social presence, have a positive impact on whether chatbots are able to gain customers' trust, whereas perceptual anthropomorphism has a negative impact on trust, and that customers' trust significantly affects the willingness to use this new technology(Loureiro, Ali, & Ali,

2024). Santos discovered that task-driven chatbots in the medical consultation field possess highly human-like communication abilities, potentially making them effective tools for communication between healthcare providers and patients. Participants expressed a mild trust in the responses of chatbots, with trust varying across different types of questions. The study highlights the potential application value of chatbots in the medical field but also emphasizes the need for awareness of the limitations and potential biases of AI models (Santos et al., 2022). Suh indicated that the outputs of chatbots and other artificial text generators should be meaningless. They aren't produced with communicative intentions and the systems producing them are not following linguistic conventions. Nevertheless, chatbots have assumed roles in customer service and healthcare, they are spreading information and disinformation and, in some cases, it may be more rational to trust the outputs of bots than those of our fellow human beings (Suh & Ok, 2019). And also, Kuhail, Thomas found that compared to non-adopters, adopters were more trusting of chatbots, were willing to reveal more information, perceived security and privacy risks to be less likely, and took fewer precautions (Kuhail, Thomas, Alramlawi, Shah, & Thornquist, 2022). El Hefny studied the role of chatbots in student teaching and noted that chatbots provide students with learning tools that are of higher quality and suited to the learner's mindset (El Hefny, Sabry, Sewelam, & El Nokrashy, 2022). Etikala advocated the use of DMN decision-making models to provide customers with more transparency and trust in decision-making (Etikala & Vanthienen, 2021). Kaushal discussed the nature of chatbot's services for enterprise successful implementation in enterprises (Kaushal & Khanna, 2024).

Malik et al. examined the effects of chatbot identity disclosure on consumer trust, customer loyalty, and customer attrition under different service scenarios and outcomes. The study found that identity disclosure does not reduce user trust when chatbots handle routine tasks; trust loss due to identity disclosure only occurs in critical tasks (Malik et al., 2022).

Balcombe, L concluded that AI chatbots hold promise in transforming digital mental health but must navigate complex ethical and practical challenges. The

integration of HAI principles, responsible regulation and scoping reviews are crucial to maximizing their benefits while minimizing potential risks. Collaborative approaches and modern educational solutions may enhance responsible use and mitigate biases in AI applications, ensuring a more inclusive and effective digital mental health landscape(Balcombe, 2023).

Based on the literature, global research on "chatbots" began in the last century, reaching a peak from 2018 to the present, and continues to grow. In 2023, scholars focused on topics such as "human-computer interaction" and "interpersonal relationships." In China, research on local "chatbots" started in 2002, heated up in 2016, and concentrated from 2017 to 2024, with a surge in 2023. Due to the early invention of chatbots but technological stagnation, they didn't spark much interest in the early 21st century. The leap in AI in 2023, amidst the fourth technological revolution, led scholars to discuss interactions between humans and chatbots, the practical service areas and capabilities of chatbots, and issues of law, governance, and order arising from chatbot development. There were frequent mentions of the impact of technology and tasks, user behavior, and feedback, suggesting that empirical studies on factors affecting user behavior with task-oriented chatbots can guide the direction of chatbot technology enhancement, increase user frequency, and inform government AI governance trends. It's also apparent that while Chinese academia has a trend in studying user behavior, there's less empirical research on micro-factors affecting user behavior, overlooking studies deeply experienced from the user's perspective.

## **2.Theoretical Foundation and Hypothesis Formulation**

### **2.1Theoretical Foundation**

#### **2.1.1Task-oriented chatbot**

Task-oriented chatbots are artificial intelligence systems designed primarily to accomplish specific tasks. They interact with users through Natural Language Processing (NLP) technology to understand user needs and provide relevant assistance or solutions. Unlike chatbots that focus on casual conversations or

providing general information, task-oriented chatbots are more concentrated on completing specific, predefined tasks such as service bookings, user support, and transaction execution. These are highly focused and purpose-driven applications of AI. They interact with users in text or voice format by simulating human conversation, understanding the user's language and intent to perform specific tasks. Typically, these robots are designed to handle problems or needs in specific domains, like hotel reservations, customer service inquiries, and banking transaction processing.

Task-oriented chatbots enhance efficiency and automation, improve the user experience, save on customer service costs, assist in data collection and analysis, and offer personalized services based on machine learning and user interaction history. They also provide integrated cross-channel services. The current trend in the development of task-oriented chatbots leans towards more advanced natural language understanding, multi-tasking capabilities, improved emotional intelligence, enhanced security and privacy protection, and industry-specific solutions.

### **2.1.2 Task Technology Fit Model (TTF Model)**

The Task Technology Fit Model (TTF) is a significant theoretical framework in the field of information systems, originating in the early 1990s. This model was proposed by Goodhue and Thompson in 1995, aiming to explain and predict the effectiveness of technology in organizational settings. The core idea of the model is that the effectiveness of information technology depends on the degree of fit between the technology's characteristics and the characteristics of the tasks it is meant to support. That is, the best outcomes of technology use are achieved when the attributes of the technology match the requirements of the task. The Task Technology Fit Model emphasizes that assessing the success of information technology should not solely be based on the technology's performance or features but should also consider the degree of fit between the technology and task requirements. The model is widely applied in research areas such as organizational information systems, e-commerce, education, and communication. With the rise of mobile technologies and cloud computing, researchers have begun exploring how these emerging technologies can better support specific tasks. Furthermore, with the development of artificial intelligence and big

data technologies, the application of this model in intelligent decision support systems and big data analytics is increasingly gaining attention.

### **2.1.3 Unified Theory of Acceptance and Use of Technology (UTAUT Model)**

The Technology Acceptance Model (commonly referred to as "TAM") is primarily used to explain how intermediary factors affect users' acceptance of technology during the process of technology dissemination. This model was proposed by Davis in 1989, based on the Theory of Reasoned Action (TRA) to analyze user acceptance behavior for information systems. Davis, in summarizing his research, found that users' perceived usefulness and ease of use of technology play a decisive role in accepting new technology, which led him to propose the TAM model. In 2000, Venkatesh, while using the TAM model in empirical research, pointed out that the mediating role of usage attitude was not prominent, and the effect of perceived usefulness on usage attitude was not significant. Based on this, he proposed an extended version of TAM, namely TAM2, which laid the foundation for the later Unified Theory of Acceptance and Use of Technology (abbreviated as "UTAUT").

The UTAUT model comprehensively considers eight different models, including TRA theory, the Theory of Planned Behavior (TPB), TAM, the Motivation Model, models combining TAM and TPB, the Personal Computer Utilization Model, the Diffusion of Innovations Theory, and Social Cognitive Theory. By re-selecting and integrating variable elements, UTAUT identifies four core variables: performance expectancy, effort expectancy, facilitating conditions, and social influence, as well as four moderating variables: gender, age, experience, and voluntariness of use.

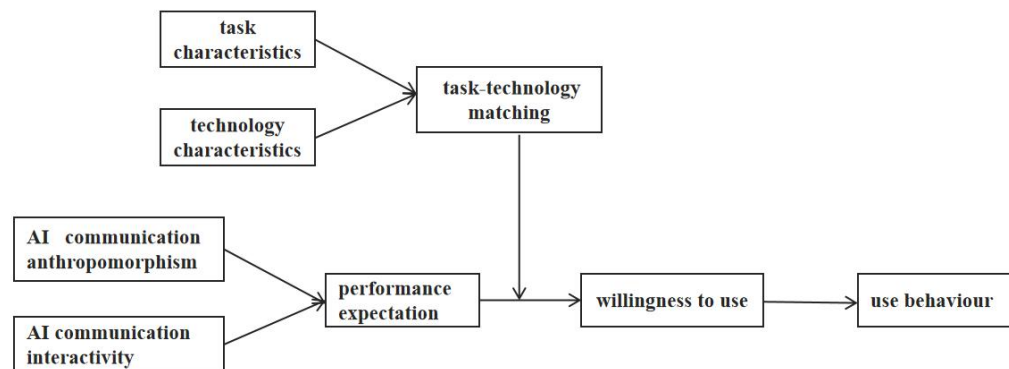
## **2.2 Research design**

### **2.2.1 Research model**

Based on the previous discussion of the Task Technology Fit Model, the UTAUT model, and an introduction to the research on task-oriented chatbots in China, this paper distills 8 research variables from the existing mature models: AI communication anthropomorphism, AI communication interactivity, performance expectancy, usage intention, usage behavior, task characteristics, technology characteristics, and task-technology fit. AI communication anthropomorphism and AI communication



interactivity are used as independent variables, and usage behavior as the dependent variable. Performance expectancy and usage intention are considered as mediating variables, with a chain mediation relationship established between them. Task characteristics, technology characteristics, and task-technology fit are treated as moderating variables. The research model is illustrated in Figure 3-1:



**Figure 3-1 Research Model of Factors Influencing the Usage Behavior of Task-Oriented Chatbots among Users in the Yangtze River Delta**

## 2.2.2 Variable Definitions and Research Hypotheses

Based on the hypotheses proposed by the Task Technology Fit Model and the Unified Theory of Acceptance and Use of Technology Model

AI Communication Personification (ACP) is a multi-faceted concept primarily involving the design of artificial intelligence system communication to closely resemble or mimic human interaction. It is a quantifiable comparative indicator. Currently, the academic community defines AI Communication Personification as AI simulating human-to-human communication patterns to interact with users, characterized by empathetic ability in the communication process. This concept has been investigated with questionnaires by scholars like Waytz et al. in 2010. In this study, the AI communication personification of task-oriented chatbots is defined as: compared to the traditional task completion process, the anthropomorphic characteristics possessed by task-oriented chatbots are specifically unfolded in six

aspects: representation, interaction effects, feedback mechanisms, personality traits, interpersonal interactions, and legal normative tendencies. These include the five aspects explored in the empirical research by Waytz and others in 2010, namely, the concrete extensions of intent, emotion, consciousness, free will, and thought.

Therefore, this paper proposes the hypotheses:

H1a: AI Communication Personification positively influences performance expectancy.

H1b: AI Communication Personification positively influences usage intention.

AI Communication Interactivity (ACI) in this study is defined as the dynamic interaction capability between task-oriented chatbots and users in terms of communication and exchange when performing specific tasks. This includes the chatbot's ability to respond to user inputs, proactively ask questions, give suggestions, guide the conversation, and adjust its responses to adapt to user needs and context changes. The research variable scale for this study refers to the mature interactivity scale validated in Liu's (2002) research. The questionnaire scale draws from Liu's (2002) interactivity scale, comprising 5 items. Therefore, this paper proposes the hypotheses:

H2a: AI Communication Interactivity positively influences performance expectancy

H2b: AI Communication Interactivity positively influences usage intention

Technology Characteristics (TeC) in the Task Technology Fit Model refer to the specific functions and characteristics of information technology and how these characteristics adapt or support users in performing specific tasks. This paper defines it as the specific functions and characteristics of task-oriented chatbots, acting as a moderating variable in this research.

Task Characteristics (TaC) in the Task Technology Fit Model involve evaluating the characteristics of specific tasks, such as complexity, variability, interdependence, etc., and how these characteristics affect technology choice and usage. This paper defines it as the evaluation of task characteristics by task-oriented chatbots, serving as a moderating variable in this research.

Task Characteristics Fit (TCF) in the Task Technology Fit Model refers to how the characteristics of specific tasks match the used technology characteristics. This paper defines it as how the characteristics of specific tasks of task-oriented chatbots match with the used technology characteristics, acting as a moderating variable.

Based on the above three variables, the following hypotheses are proposed:

H3a: Task Characteristics positively influence Task Technology Fit

H3b: Technology Characteristics positively influence Task Technology Fit

H9: Technology Characteristics and Task Characteristics respectively moderate the relationship between AI Communication Personification/Interactivity

H10: Technology Characteristics and Task Characteristics respectively moderate the relationship between AI Communication Personification/Interactivity and Usage Intention

Performance Expectancy (PE) is the user's perceived effectiveness of using emerging technology to meet specific task needs, encompassing technology difficulty and user perceived capability. This paper defines it as the perceived effectiveness of using task-oriented chatbots to meet specific task needs, serving as a mediating variable. Therefore, this paper proposes the hypotheses:

H4: Performance Expectancy positively influences usage behavior

H6: Performance Expectancy mediates the relationship between AI Communication Personification/Interactivity and usage behavior

Behavioral Intention (BI) is used to predict the extent to which an individual is willing to implement a certain behavior and is willing to exert effort for it. This paper follows Venkatesh et al.'s setting in validating the UTAUT2 model to measure Behavioral Intention. Therefore, this paper proposes the hypotheses:

H7: Behavioral Intention mediates the relationship between AI Communication Personification/Interactivity and usage behavior

H8: There is a positive relationship between Performance Expectancy and Behavioral Intention.

Usage Behavior (Social Influence, SI) is mainly derived from the subjective norm in the Theory of Reasoned Action and the social system concept in Diffusion

of Innovations Theory, as well as the UTAUT model. This paper continues Venkatesh et al.'s setting in validating the UTAUT2 model to measure Usage Behavior. Therefore, this paper proposes the hypotheses:

H5: Behavioral Intention positively influences usage behavior

H11: Task Technology Fit moderates the relationship between Performance Expectancy and Behavioral Intention

H12: Performance Expectancy and Behavioral Intention play a chain mediation role between AI Communication Personification, AI Communication Interactivity, and usage behavior

### Summary of Research Hypotheses

This paper, drawing upon the Task Technology Fit Model and the Unified Theory of Acceptance and Use of Technology Model, combined with the current status of users in the Yangtze River Delta region using task-oriented chatbots, infers research hypotheses summarized as shown in Table 3-2

**Table 3-2 Summary of Research Hypotheses**

serial number	research hypothesis
H1a	AI Communication Personification positively influences performance expectancy
H1b	AI Communication Interactivity positively influences usage intention
H2a	AI Communication Interactivity positively influences performance expectancy
H2b	AI Communication Interactivity positively influences usage intention
H3a	Task Characteristics positively influence Task Technology Fit
H3b	Technology Characteristics positively influence Task Technology Fit
H4	Performance Expectancy positively influences usage behavior

H5	Behavioral Intention positively influences usage behavior
H6	Performance Expectancy mediates the relationship between AI Communication Personification/Interactivity and usage behavior
H7	Behavioral Intention mediates the relationship between AI Communication Personification/Interactivity and usage behavior
H8	There is a positive relationship between Performance Expectancy and Behavioral Intention
H9	Technology Characteristics and Task Characteristics respectively moderate the relationship between AI Communication Personification/Interactivity
H10	Technology Characteristics and Task Characteristics respectively moderate the relationship between AI Communication Personification/Interactivity
H11	Task Technology Fit moderates the relationship between Performance Expectancy and Behavioral Intention
H12	Performance Expectancy and Behavioral Intention play a chain mediation role between AI Communication Personification, AI Communication Interactivity, and usage behavior

## 2.3 Variable Measurement

### 2.3.1 AI Communication Anthropomorphism

**Table 3-1 Measurement Dimensions of AI Communication Anthropomorphism**

Number	Survey item	References
ACP1	Behavior seems to be determined by humans	Waytz (2010)
ACP2	Communication is natural, like	

	interacting with a real person	
ACP3	Able to understand and respond to my task requirements	
ACP4	Seems to have its own personality and characteristics	
ACP5	Can establish social relationships like with a real person	
ACP6	Seems to understand and adhere to social norms	

### 2.3.2AI Communication Interactivity

**Table 3-2 Dimensions of AI Communication Interactivity**

Number	Survey item	References
ACI1	Responds quickly to requests or questions	Liu (2002)
ACI2	Adjusts its responses based on needs and preferences	
ACI3	Can accurately understand my queries and statements	
ACI4	The provided information and suggestions seem to be tailored	
ACI5	Can understand the context of the conversation	

### 2.3.3 Technological Characteristics

**Table 3-3 Measurement Dimensions of Technological Characteristics**

Number	Survey item	References
TeC1	Thoroughly understands various functions and purposes	Good Hue、

TeC2	Performs reliably and consistently during use	Thompson(1995)
TeC3	Does not require extensive technical knowledge for everyday use	
TeC4	Can integrate well with other systems or tools	

#### 2.3.4Task Characteristics

**Table 3-4 Measurement Dimensions of Task Characteristics**

Number	Survey item	References
TaC1	Trusts in security and confidentiality	Good Hue、 Thompson(1995)
TaC2	Involves multiple steps and processes in its usage	
TaC3	Frequently performs the same or similar tasks	

### 2.3.5 Task-Technology Fit

**Table 3-5 Measurement Dimensions of Task-Technology Fit**

Number	Survey item	References
TCF1	Relies on it to complete my daily tasks	Good Hue、 Thompson(1995)
TCF2	Has a high degree of autonomy in decision-making	
TCF3	Processing and interpreting information is crucial	
TCF4	Provides the necessary functions and support for me	
TCF5	Makes task processing faster	
TCF6	The provided information is very useful for completing tasks	

### 2.3.6 Performance Expectations

**Table 3-6 Measurement Dimensions of Performance Expectations**

Number	Survey item	References
PE1	Responds quickly to requests or questions	Venkatesh (2012)
PE2	Adjusts its responses based on needs and preferences	
PE3	Can accurately understand my queries and statements	
PE4	The provided information and suggestions seem to be tailored	
PE5	Can understand the context of the conversation	



### 2.3.7 Usage Intentions

**Table 3-7 Measurement Dimensions of Usage Intentions**

Number	Survey item	References
BI1	Plan to use it when needed	Venkatesh (2012)
BI2	Would recommend it to others	

### 2.3.8 Usage Behavior

**Table 3-8 Measurement Dimensions of Usage Behavior**

Number	Survey item	References
SI1	Interested in future updates and improvements	Venkatesh (2012)
SI2	Rely on it to complete my daily tasks	
SI3	I use it frequently	
SI4	Use multiple features of it	

## 3. Empirical Analysis

### 3.1 Descriptive Statistical Analysis

#### 3.1.1 Descriptive Analysis of Sample Basic Information

This survey research primarily unfolds through data collection and analysis; hence, the sample for data collection needs to have sufficient cognizance of the theme of this study – the factors influencing users' behavior in using task-oriented chatbots. In October 2023, the People's Daily Research Institute released the "Intelligent Internet Development Report," indicating that the emergence and widespread application of general artificial intelligence platforms mark the advent of the intelligent internet era. The development of intelligent interconnectivity is "deepening

and becoming more practical," moving towards "broad scenarios," thus forming a new "orderly pattern." Particularly in economically developed regions, task-oriented chatbots, as representatives of AI, are embedding into people's daily life and workspaces.

The selection of survey samples needs to satisfy three conditions to provide scientific inductivity to the research conclusions and establish a mathematical model for sufficient mathematical rationale. First, the choice of sample size needs to reflect the total social status under a certain time and area. The sample size should be determined based on the overall level, confidence interval, confidence level, and expected response amount. The size of the sample directly affects the accuracy and feasibility of the survey results. Second, whether the sample structure aligns with objective reality. If the sample structure deviates from the objective reality, it can lead to perspective fallacies and fail to reflect the true situation. Third, whether the sample pattern aligns with the research objective and can fully display the data required by the research objective within limited data, which relies on the scientific division and identification of the sample population.

After reading, comparing, and analyzing related literature, considering the national regional economic and technological development, national policy orientation, AI technology user groups, and cultural demand orientation, the data collection region was determined to be the Yangtze River Delta area. Finally, 400 valid questionnaires were obtained through methods such as snowballing and mutual recommendation, with 356 effective samples. These 356 samples all have varying degrees of understanding of the topic, meeting the prerequisites for conducting this research.

**Table 4-1 Basic Statistical Information of the Sample**

<b>Valid Data</b>	<b>Program</b>	<b>Frequency</b>	<b>percentage</b>	<b>effective percentage</b>	<b>cumulative percentage</b>
	male	185	52.0	52.0	52.0
	female	171	48.0	48.0	100.0
	sum	356	100.0	100.0	
	aged 18-25	71	3.4	3.4	3.4
	aged 26-35	108	5.1	5.1	8.4
	aged 36-45	87	3.1	3.1	11.5
	aged 46-55	45	2.0	2.0	13.5
	56 years and above	44	86.5	86.5	100.0
	sum	356	100.0	100.0	
	high school and below	61	17.1	17.1	17.1
	undergraduate and associate degree	193	54.2	54.2	71.3
	graduate and above	102	28.7	28.7	100.0
	sum	356	100.0	100.0	

According to Table 4-1, there were a total of 356 valid responses to the survey, including 185 males and 171 females, accounting for 52% and 48% respectively. According to the seventh national population census, the gender ratio in China is 104.69 (with females as 100). This indicates that the gender ratio of the survey respondents is roughly in line with the national gender ratio, effectively ensuring the sample's gender consistency with objective reality and avoiding gender bias issues.

In terms of age distribution, the survey primarily targeted individuals aged 56 and above. This aligns with the research focus of the survey.

Regarding the educational background of the sample, individuals with college degrees and above accounted for 82.9% of the total sample. This is inherently compatible with the research objective of this survey. Task-oriented chatbots have not yet achieved nationwide popularity, and their users are mostly concentrated among highly educated intellectuals. Influenced by educational background and technical ability, this group can not only reflect the degree of technology popularization but also ensure a certain level of forward-looking nature in the sample data. Additionally, to avoid bias due to educational perspective, a certain amount of data was also collected from respondents with high school education or below, thus ensuring the diversity and comprehensive representativeness of the sample.

Overall, the survey sample, in terms of structure and data distribution, aligns with the research objective and conforms to the objective reality, fully meeting the prerequisites for conducting this data analysis.

### **3.2 Reliability and Validity Testing**

Before further analyzing the questionnaire data, it is necessary to test the reliability and validity of the formal questionnaire scale. This is an important safeguard for the reliability of the questionnaire data source and the effectiveness of the questionnaire structure. This paper uses SPSS software to process the questionnaire data, mainly employing the Cronbach Alpha coefficient to test the reliability of the questionnaire. Hotelling's T-square test is used to demonstrate the reliability of the internal consistency of the questionnaire, and Bartlett's test of

sphericity is applied to verify the validity of the questionnaire structure.

**Table 4-2 Reliability Statistics**

<b>Reliability Statistics</b>		
<b>Cronbach's Alpha</b>	<b>Cronbach's Alpha based on standardized items</b>	<b>number of items</b>
.935	.934	33

The Cronbach Alpha coefficient refers to the average of all possible item-splitting methods of the scale's split-half reliability coefficients and can be used to test item reliability. According to Table 4-2, the reliability value (i.e., Cronbach's Alpha coefficient) of the data from the formal questionnaire sample in this paper is 0.935, which is greater than 0.8. This indicates that the questionnaire data has high credibility, reflecting the true situation of the sample to a large extent, and meets the requirements for conducting further data analysis.

**Table 4-3 Hotelling's T-square test**

<b>Hotelling's T-square test</b>				
<b>Hotelling's T-square</b>	<b>F</b>	<b>df1</b>	<b>df2</b>	<b>Sig</b>
67.452	1.924	32	324	.003

The Hotelling's  $T^2$  test is a commonly used multivariate testing method, often employed for comparing two group mean vectors. It is a classical tool for testing whether the mean of a multivariate normal distribution is a specified value or whether the means of two multivariate normal distributions are equal. This test becomes inapplicable if the dimensionality of the population is higher than the sample size. According to Table 4-3, conducting Hotelling's T-square test on the data from the formal questionnaire sample of this paper results in an F-value of 1.924 and a sig

value of 0.003, which is less than 0.05, indicating high significance. This meets the conditions for conducting further data analysis.

**Table 4-4 KMO and Bartlett's Test**

<b>KMO and Bartlett's test</b>		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO)		.924
Bartlett's test	approximated chi-square	10867.658
	df	528
	Sig.	0.000

The Kaiser-Meyer-Olkin (KMO) coefficient is used to compare the simple correlations and partial correlations between variables. The closer the KMO value is to 1, the stronger the correlation between variables, providing a basic condition for factor analysis. Similarly, Bartlett's test of sphericity is an important index for estimating the correlation of original variables. Factor analysis can only be further conducted if there is significant evidence, indicating that the original variable data is effective and operable. According to Table 4-4, the questionnaire scale's KMO value is 0.924, greater than 0.8, and the sig value for Bartlett's test of sphericity is 0.000, less than 0.005, indicating that the questionnaire has high validity.

In summary, the formally collected questionnaire data in this study shows good significance in both reliability and validity, proving that the questionnaire data has a considerable degree of reliability and structural effectiveness, providing a premise for further data analysis.

### **3.3 Correlation analysis**

Correlation analysis is a method for further judging the relationships between phenomena, serving as a key basis for determining whether there is a dependency relationship between phenomena and the degree of this dependency. This also constitutes the main core of quantitative research in social science studies. Through

correlation analysis, one can clearly determine whether there is a correlation between two phenomena, that is, whether a change in one phenomenon will cause a change in another. If it does, the analysis assesses whether this change is of a generally significant degree. This paper employs inter-subject effect tests to explore the inherent relationships between different variables through multivariate analysis. If the sig value is less than 0.005, it indicates a significant correlation between variables. Given the numerous data variables studied in this paper, not all are listed here. Instead, only representative results of the data analysis are presented.

**Table 4-5 Communication Anthropomorphism Positively Affects  
Performance Expectations and Usage Intentions**

<b>Hypothesis 1 &amp; 2: Testing the Between-Subject Effects</b>						
source		Type III sum of squares	df	mean square	F	Sig.
corrected model	performance expectations	2353.927 <sup>a</sup>	27	87.182	4.203	.000
	willingness to use	590.459 <sup>b</sup>	27	21.869	3.865	.000
AI communication anthropomorphism	performance expectations	2354	27	87.18248331	4	.000
	willingness to use	590	27	21.86884365	4	.000
a. R-squared = .257 (Adjusted R-squared = .196)						
b. R-squared = .241 (Adjusted R-squared = .179)						

According to Table 4-5, it is evident that AI Communication Personification significantly impacts users' performance expectancy and usage intention. The higher the level of AI Communication Personification, the greater the users' performance expectancy and the stronger their usage intention.

**Table 4-6 AI Communication Interactivity Positively Influences Performance Expectations and Usage Intentions**

<b>Hypotheses 3 &amp; 4: Testing Between-Subject Effects</b>						
source		Type III sum of squares	df	mean square	F	Sig.
corrected model	performance expectations	5132.826 <sup>a</sup>	23	223.166	18.409	.000
	willingness to use	1105.859 <sup>b</sup>	23	48.081	11.908	.000
AI communication interactivity	performance expectations	5132.826	23	223.166	18.409	.000
	willingness to use	1105.859	23	48.081	11.908	.000
a. R-squared = .561 (Adjusted R-squared = .530)						
b. R-squared = .452 (Adjusted R-squared = .414)						

Based on Table 4-6, it can be observed that AI Communication Interactivity, as an independent variable, has significant correlation with users' performance expectancy and usage intention. This holds statistical model significance and meets the conditions necessary for conducting further regression analysis.

**Table 4-7 Task Characteristics Positively Impact Task-Technology Fit**

<b>Hypotheses 5 &amp; 6: Testing Between-Subject Effects</b>					
dependent variable:	task-feature matching				
source	Type III sum of squares	df	mean square	F	Sig.
corrected model	15733.360 <sup>a</sup>	127	123.885	1.789	.000
task characteristics	2693.418	17	158.436	2.288	.003
a. R-squared = .499 (Adjusted R-squared = .220)					

According to Table 4-7, it can be seen that task characteristics, as a part of the intrinsic components of task-technology fit, have a significant impact on task-



technology fit. Changes in task characteristics will directly lead to changes in task-technology fit.

**Table 4-8 Performance Expectations and Usage Intentions Positively Impact Usage Behavior**

<b>Hypotheses 7 &amp; 8: Testing Between-Subject Effects</b>					
dependent variable:	usage intention				
source	Type III sum of squares	df	mean square	F	Sig.
corrected model	10389.718 <sup>a</sup>	90	115.441	13.607	.000
performance expectations	1610.654	16	100.666	11.865	.000
willingness to use	3758.804	11	341.709	40.277	.000
performance expectations * willingness to use	1757.363	63	27.895	3.288	.000
a. R-squared = .822 (Adjusted R-squared = .762)					

As shown in Table 4-8, both performance expectancy and usage intention significantly impact usage behavior. Furthermore, the combined effect of performance expectancy and usage intention also has a significant correlation with usage behavior, indicating a meaningful construction in the data model and fulfilling the requirement for further data analysis.

In summary, both AI communication personification and interactivity significantly affect users' performance expectancy, usage intention, and usage behavior. Simultaneously, there is a significant correlation between performance expectancy and usage intention themselves with usage behavior, indicating the presence of a mediating effect. Additionally, task characteristics significantly influence task-technology fit, suggesting that moderating variables have a potential

impact on usage behavior.

**Table 4-9 Performance Expectations Mediate the Relationship Between AI Communication Anthropomorphism/Interactivity and Usage Behavior**

Model : 4										
Y : Behavior										
X : Interaction										
M1 : Performance										
M2 : Intention										
Sample										
Size: 356										
*****										
*****										
OUTCOME VARIABLE:										
performance										
Model Summary										
R	R-sq	MSE	F	df1						
df2	p									
.4956	.2457	19.5135	115.2893							
1.0000	354.0000	.0000								
Model										
coeff	se	t	p	LLCI						
ULCI										
constant	4.6696	.9701	4.8134	.0000						
2.7617	6.5775									
Interaction	.3890	.0362								
10.7373	.0000	.3178	.4603							
Standardized coefficients										
coeff										
Interaction .4956										
*****										
*****										
OUTCOME VARIABLE:										
Intention										
Model Summary										
R	R-sq	MSE	F	df1						
df2	p									
.4298	.1847	5.6340	80.2080							
1.0000	354.0000	.0000								
Model										
coeff	se	t	p	LLCI						
ULCI										
constant	5.7532	.5213	11.0369	.0000						
4.7280	6.7784									
Interaction	.1744	.0195								
8.9559	.0000	.1361	.2127							

Standardized coefficients										
coeff										
Interaction .4298										
*****										
*****										
OUTCOME VARIABLE:										
Behavior										
Model Summary										
R	R-sq	MSE	F	df1						
df2	p									
.7133	.5089	17.6333	121.5702							
3.0000	352.0000	.0000								
Model										
coeff	se	t	p	LLCI						
ULCI										
constant	5.2823	1.0812	4.8855	.0000						
3.1559	7.4087									
Interaction	.0092	.0399	.2315	.8171						
-.0693	.0877									
Performance	-.4192	.0672	-							
6.2342	.0000	-.5514	-.2869							
Intention	2.1085	.1251								
16.8501	.0000	1.8624	2.3546							
Standardized coefficients										
coeff										
Interaction .0100										
Performance -.3568										
Intention .9277										
***** TOTAL										
EFFECT MODEL										
*****										
OUTCOME VARIABLE:										
Behavior										
***** TOTAL, DIRECT, AND										
INDIRECT EFFECTS OF X ON Y										
*****										
Total effect of X on Y										
Effect	se	t	p	LLCI						
ULCI										
	c_cs									
.2138	.0477									
4.4850	.0000	.1201	.3076	.2319						
Direct effect of X on Y										
Effect	se	t	p	LLCI						
ULCI										
	c'_cs									
.0092	.0399	.2315	.8171	-						
.0693	.0877	.0100								
Indirect effect(s) of X on Y:										
Effect	BootSE	BootLLCI	BootULCI							

TOTAL	.2046	.0371	.1324	.2783
Performance	-.1631	.0304	-.2256	-.1073
Intention	.3676	.0421	.2876	.4530
(C1)	-.5307	.0634	-.6578	-.4113
Specific indirect effect contrast definition(s):				
(C1)	Performance	minus	Intention	

The multivariate collinearity test can determine the degree of influence different factors have on the dependent variable, thereby providing further analytical perspectives for the study. It also allows for the iteration of collinearity factors between different elements, avoiding potential cross-influences. Generally, in the academic community, it is considered that a Variance Inflation Factor (VIF) of less than 10 indicates the absence of collinearity impact.

According to Table 4-9: Mediation effects refer to the interrelationships between variables. The relationship between independent and dependent variables is not formed through a single channel, but through the progressive or entangled relationships among other variables, forming a more complex network of interactions. As seen in Table 4-9, the Bootstrap method testing conducted with the SPSS process plugin reveals that the p-value for the Outcome Variable is less than 0.05. This indicates that AI interactivity has a significant impact on performance expectancy, usage intention, and usage behavior, and performance expectancy and usage intention also significantly influence usage behavior, thus exhibiting partial mediating effects. The LLCI and ULCI values being partially positive or negative indicate significant indirect mediation effects, and the mediating effect of performance expectancy is less impactful than that of usage intention.

## AI Communication Anthropomorphism/Interactivity and Usage Behavior

Model : 4												
Y : Behavior												
X : Anthropomorphism												
M1 :Performance												
M2 : Intentions												
Sample												
Size: 356												
*****												
*****												
OUTCOME VARIABLE:												
Performance												
Model Summary												
R	R-sq	MSE	F	df1								
df2	p											
.3088	.0954	23.4016	37.3184									
1.0000	354.0000	.0000										
Model												
	coeff	se	t	p	LLCI							
ULCI												
constant	9.4761	.9050	10.4709	.0000								
7.6963	11.2559											
Anthropomorphism		.1760	.0288									
6.1089	.0000	.1193	.2327									
Standardized coefficients												
coeff												
Anthropomorphism .3088												
*****												
*****												
OUTCOME VARIABLE:												
Intentions												
Model Summary												
R	R-sq	MSE	F	df1								
df2	p											
.2885	.0832	6.3355	32.1300									
1.0000	354.0000	.0000										
Model												
	coeff	se	t	p	LLCI							
ULCI												
constant	7.7239	.4709	16.4030	.0000								
6.7978	8.6500											
Anthropomorphism		.0850	.0150									
5.6683	.0000	.0555	.1145									
Standardized coefficients												
coeff												

Anthropomorphism .2885									
*****									
*****									
OUTCOME VARIABLE:									
Behavior									
Model Summary									
R	R-sq	MSE	F	df1					
df2	p								
.7163	.5131	17.4821	123.6359						
3.0000	352.0000	.0000							
Model									
coeff	se	t	p	LLCI					
ULCI									
constant	4.4963	1.0397	4.3248	.0000					
2.4516	6.5410								
Anthropomorphism	.0463	.0263							
1.7600	.0793	-.0054	.0980						
Performance	-.4317	.0647	-						
6.6710	.0000	-.5589	-.3044						
Intentions	2.0906	.1244							
16.8105	.0000	1.8460	2.3352						
Standardized coefficients									
coeff									
Anthropomorphism .0691									
Performance -.3675									
Intentions .9198									
***** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y *****									
Total effect of X on Y									
Effect	se	t	p	LLCI					
ULCI	c_cs								
.1480	.0347								
4.2636	.0000	.0797	.2162	.2210					
Direct effect of X on Y									
Effect	se	t	p	LLCI					
ULCI	c'_cs								
.0463	.0263	1.7600	.0793	-					
.0054	.0980	.0691							
Indirect effect(s) of X on Y:									
Effect	BootSE	BootLLCI	BootULCI						
TOTAL	.1017	.0241	.0552	.1502					
Performance	-.0760	.0165	-.1105	-.0459					
Intentions	.1777	.0307	.1186	.2405					
(C1)	-.2536	.0431	-.3426	-.1731					
Specific indirect effect contrast definition(s):									
(C1)	Performance	minus	Intentions						

As shown in Table 4-10, the p-values for the Outcome Variable are all less than 0.05. This indicates that AI personification significantly influences performance expectancy, usage intention, and usage behavior, and that performance expectancy and usage intention also significantly impact usage behavior, thereby exhibiting partial mediating effects. The LLCI and ULCI values are partially positive or negative, indicating significant indirect mediation effects. Furthermore, the mediating effect of performance expectancy is less impactful than that of usage intention.

**Table 4-11 There is a Positive Relationship Between Performance Expectations and Usage Intentions**

<b>Hypothesis 11: Testing Between-Subject Effects</b>					
dependent variable:	Intentions				
source	Type III sum of squares	df	mean square	F	Sig.
corrected model	1394.869 <sup>a</sup>	16	87.179	28.107	.000
performance	1394.869	16	87.179	28.107	.000
a. R-squared = 0.570 (Adjusted R-squared = 0.550)					

According to Table 4-11, it is evident that the performance expectancy of users significantly affects their intention to use chatbots. The higher the performance expectancy, the stronger the usage intention, indicating a significant positive relationship between the two.

**Table 4-12 Technical Characteristics and Task Characteristics Moderately Regulate the Relationships Between AI Communication Anthropomorphism and AI Communication Interactivity with Usage Intentions**



Data centering is a process employed to ensure that variable data are not affected by multicollinearity, thereby achieving effective data processing through normalization. Data processed through centering are better suited for analyses related to mediating effects. Interaction terms, produced by multiplying the centered independent variables with the moderating variables, directly reflect the strength of the moderating effects, thus indicating the independence of the moderating variables.

Moderating variables are directional and can affect or change the strength and direction (positive or negative) of the relationship between other independent and dependent variables. Technology characteristics and task characteristics, as moderating variables, influence the relationships between other variables. According to Table 4-12, the regression analysis results of the two interaction items with usage intention show that the sig values are all  $<0.05$ , indicating that technology characteristics and task characteristics significantly moderate the impact relationship between AI communication personification and interactivity, and usage intention. Specifically, if task characteristics indicate that a task is highly complex and diverse, then personified AI can provide more humanized services, thereby increasing the users' willingness to use.

**Table 4-13 Task-Technology Fit Moderates the Relationship Between  
Performance Expectations and Usage Intentions**

Coefficient <sup>a</sup>						
Model		unstandardized coefficient		standardized coefficient	t	Sig.
		B	standard error	trial version		
1	(constant)	10.284	.095		108.077	.000
	performance (centralization)	.378	.019	.730	20.124	.000
2	(constant)	10.284	.094		109.313	.000
	performance (centralization)	.356	.020	.688	17.865	.000
	task-technology fit (centralization)	.032	.011	.116	3.024	.003
3	(constant)	10.230	.100		101.867	.000
	performance (centralization)	.357	.020	.691	17.946	.000
	task-technology fit (centralization)	.036	.011	.128	3.272	.001
	interaction term (task-technology fit 与 performance expectations)	.003	.002	.056	1.512	.023
a. dependent variable: Intentions						

According to Table 4-13, the regression analysis of the interaction item between task-technology fit and performance expectancy with usage intention shows a sig value of 0.023, which is less than 0.05. This indicates a significant correlation, meaning that task-technology fit, as a moderating variable, has a significant moderating effect between performance expectancy and usage intention.

## **5. Discussion and conclusion**

### **5.1 Research Findings**

#### **5.1.1 The anthropomorphism and interactivity of AI communication significantly impact usage behavior**

According to the inter-subject effects test of regression analysis, a sig value less than 0.05 indicates a significant impact relationship between related variables. This means that the anthropomorphism and interactivity of AI communication significantly influence users' behavior in using chatbots for task-oriented work, and can be considered as primary factors. Task-oriented chatbots, as the latest advancement in artificial intelligence technology, fully represent the scientific concept of cutting-edge technology embedded in human society. However, due to the high complexity of the technology, the embedding process often needs to be gradually realized through technological packaging and integration with social life. AI communication anthropomorphism reduces the social members' resistance by humanizing artificial intelligence, while interactivity enhances the user experience and can provide unique social services. These factors significantly impact whether social members decide to use them or not.

#### **5.1.2 Performance expectation and usage intention have a partial indirect mediating effect**

According to the Bootstrap method test conducted by SPSS's process program model 4, the p-values of the mediating variables were all less than 0.05. The LLCI and ULCI values of 'indirect' under the same variable were either both positive or both negative, with performance expectation minus usage intention. This indicates that performance expectation and usage intention have a significant partial mediating effect on usage behavior, forming a chain mediating relationship with the independent variable, where the impact of performance expectation is less than that of usage intention. Performance expectation represents the functional-economic category that users consider when choosing technology, based on work demands and technology's ability to meet these demands and offer relative superiority; usage intention is the

user's subjective, personalized choice, forming a broader user group through social interaction. Both factors have a partial indirect mediating effect on usage behavior, meaning although AI communication anthropomorphism and interactivity independently influence usage behavior, some of their aspects still impact usage behavior through interference with users' performance expectations and usage intentions.

### **5.1.3 The moderating effect of technology characteristics, task characteristics, and task-technology fit on performance expectation and usage intention is significant**

Moderating variables uniquely adjust the relationship between independent and dependent variables. Under different moderating variable conditions, the relationship between independent and dependent variables changes to varying degrees, with different positive and negative tendencies and effects. After digital centralization processing, regression analysis found that the sig values of all three interaction items were less than 0.05, indicating that technology characteristics, task characteristics, and task-technology fit significantly moderate the relationship between performance expectation and usage intention. The degree of technology characteristics, task characteristics, and task-technology fit are all factors that users need to consider when facing technology choices, representing the correspondence between objective task demands and subjective capability performance. Only when chatbots' technology has superior aggregation and collective effects to meet diversified, programmed task demands can it significantly positively modulate users' performance expectations and usage intentions. Otherwise, it would reduce users' related demands, leading to ineffective improvements in AI technology and standardized usage behavior.

## **5.2 Research Suggestions**

### **5.2.1 Enhance the interactivity and personalization features of task-oriented chatbots**

Given the significant impact of AI communication interactivity and anthropomorphism on user behavior, future research should focus more on optimizing these two aspects. It is suggested to explore how to enhance chatbots' interactivity

through technological innovation, such as improving natural language processing (NLP) technology, enhancing emotion recognition and response capabilities, and designing personalized user experiences to increase user participation and satisfaction. Simultaneously, research should consider different user groups' preferences for chatbots' interactivity and anthropomorphism levels to better meet diverse needs.

### **5.2.2 Promote the role of chatbot technology in digital inclusion**

In today's digital age, task-oriented chatbot technology has become an important tool for promoting socio-economic development. The core of this technology lies in its interaction with task elements and its potential to regulate user behavior and intentions. It is this regulatory role that gives chatbots significant potential in achieving digital inclusion, becoming a key link in serving the socio-economy. The development and popularization of chatbot technology can not only improve the efficiency and quality of public services but also promote the development of emerging markets.

This technology can provide instant information queries and data processing and offer customized solutions based on the complexity and specificity of tasks. The combination of this technology and task elements can improve the efficiency and quality of task execution, thereby directly affecting users' behavior and intentions.

Economically, chatbots can serve as a bridge between businesses and consumers, providing personalized customer services, enhancing user experience, and thus promoting business growth. Socially, they can supplement public services, especially in fields like education, health, and social welfare, helping to improve the overall social welfare level. Chatbots can promote digital inclusion by providing basic education, financial literacy, and health consulting services, accelerating the process of societal informatization and addressing regional development imbalances, positively impacting overall social welfare. Economically, this can help develop new market areas and promote broader economic participation and growth.

### **5.2.3 Feature analysis and a cycle of performance and intention feedback mechanisms**

Task-oriented chatbots should build a cross-departmental collaboration platform

aimed at optimizing the efficiency and effectiveness of various tasks. This platform should gather experts from government, education, medical, commercial, and other fields to jointly research how to match the latest technological solutions with specific task demands in their respective fields. The platform should have strong data analysis capabilities to deeply understand the task characteristics of various departments or industries, such as task frequency, complexity, urgency, etc. This analysis will help the platform identify and understand different tasks' specific needs for technological support. Establish a feedback mechanism to monitor and evaluate the impact of technology applications on task performance and user intentions. This feedback can help the platform continuously optimize technological solutions, ensuring they meet evolving task demands and user expectations.

### **5.3 Research Limitations**

This study focuses on the Yangtze River Delta region. To understand and apply research findings more comprehensively, subsequent cross-regional comparative studies will be conducted. By comparing data from the Yangtze River Delta region with other regions (such as other economically developed or developing areas), regional differences in task-oriented chatbot usage behavior can be revealed, as well as differences in user needs and behavior patterns across different regions. This not only enriches the theoretical framework but also provides guidance for regional market strategies for chatbots.

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