International Journal of Multiphysics
Volume 18, No. 3, 2024
ISSN: 1750-9548

Research on Behavioral Intention and Use Behavior of Youth Group Concerning "AI Partner" Based on UTAUT

Ning Lou#, Mingxi Li#, Yangbin Ye, Yunqian Zhou*
School of Journalism and Communication, Nanchang University, Nanchang, 330031, Jiangxi, China
#NL and ML contributed equally to this study.
*Corresponding Author.

Abstract

“AI partner”, a chatbot, has a significantly increasing impact on society and relationship. Given limited research, the user group, the use behavior and the behavioral intention regarding “AI partner” are studied in this paper. 571 valid questionnaires in total are collected. On the basis of UTAUT, the research hypotheses are developed from the perspective of HCR theory. The influencing factors are included in seven specific indicators, such as Performance Expectancy (PE), Effort Expectancy (EE), social influence (SI), privacy risk perception, self-disclosure, loneliness and boredom tendency. And a structural equation model is constructed. Except privacy risk perception, the other variables have positive correlation with the behavioral intention. The higher the privacy risk perception, the lower the behavioral intention. And the behavioral intention, loneliness and boredom are positively correlated with the use behavior. In addition, it is found that marital status and educational background have a great influence on use behavior. For example, the divorced, single people with no partner and users with primary school degree, master degree and junior high school degree have better use behavior. The new theoretical integration model provides guidance for privacy protection, reference for legislation, and data support for debugging chatbots. However, the dimensions of the selected influencing factors are small, which can be further expanded to enrich the related research.

Keywords: AI partner, Human-chatbot, youth group, UTAUT.

1. Introduction

The youth are defined as people aged between 14 and 35 in *The Medium and Long-term Youth Development Plan* (2016-2025). In the social and media context of the new era, they are defined as the generation of "group loneliness". The loneliness caused by the relative absence of peer groups in real life, making them eager to make more friends online to realize image recognition, congenial interests, enhanced aspirations and emotional belonging, manifesting their own personality and value.

As AI services are increasingly reaching millions of households, a large number of "AI companions" (e.g., social chatbots Xiao Ice and Replika) gain increasing popularity among youth groups, especially those aged between 18 and 25. For example, since its release in 2014, Xiao Ice has interacted with more than 0.66 billion active subscribers. Replika, a chatbot on the market in 2017 as a social companion, has reached over 6 million users. In 2020, Xiao Ice and Huawei Mobile jointly launched a seven-day customized "virtual boyfriend" activity and 1.18 million "virtual boyfriends" were created by users in 7 days. On March 9, 2022, as the *Daily Star* reported, a programmer from Cleveland, Ohio, saved his marriage after he fell in love with an "AI companion". In 2022, the documentary "My AI Lover" documented the impact of the AI on three women's life. Social chatbots, managing to get into people's lives, are becoming an indispensable part of human society.

Therefore, it is very vital to comprehend the users of "AI companion" and the behavioral intention. As Følstad, A. [1] and others put forward, it is necessary to shift the research on general chatbot users to the research on social chatbot users and use behaviors with specific demographic variables and fields. However, the relevant literature is mostly about the elderly and users with special needs. The research on the behavioral intention and use behavior among the youth is sorely lacking, a gap that this paper bridges.

2. Literature Review

The use behavior of the "AI partner" belongs to the research area related to social chatbots. Chatbots, as software agents, interact with users' daily language through text or voice, presenting services and information. Social chatbots are a subgroup of chat robots to play social roles, in which users may develop socio-emotional relationships. These chatbots are able to talk with users, in an empathetic way, and even connect with them. The human-like behavior makes them perfect for companions, friends and even romantic partners.

2.1 Research on human-chatbot relationships (HCR)

At present, most of the researches related to social chatbots focus on the research of human-chatbot relationship (HCR), i.e. the research on the relationship between human beings and social chatbots with social properties and influence. Generally speaking, Computers-Are-Social-Actors (CASA) Paradigm is adopted to apply some rules in interpersonal communication to human-chatbot relationship. According to the framework, people unconsciously respond to chatbots with the same steps as those in human-to-human interactions [2]. Under the guidance of social penetration theory, the development of HCR is studied. It is found that it is usually driven by users' curiosity at the beginning. And with the growing users' convincement and involvement in self-disclosure, substantive emotional exploration is carried out. As the relationship stabilizes with significant emotional and social values, the frequency of interactions may decrease. Acceptance, understanding and non-judgment of social chatbots are seen as key to facilitating relationship development. Another example is a survey on the friendship between human beings and social chatbots. On the basis of the artificial nature of social chatbots, the concept of friendship has been changed in many ways, such as tailoring more personalized friendship to users' needs. Among the common research objectives of the current scientific community, it is possible to establish a well-developed technical system, which takes into account the needs and characteristics of users (i.e. users' personalities) and do great help in the interaction process between human beings and chatbots. The study of HCR provides a theoretical perspective for this paper, that is, it draws on the interpersonal relationship variables (socio-personal temperaments such as loneliness and boredom affecting interpersonal communication) [3], to enquire into the behavioral intention and use behavior about social chatbots.

2.2 Research on the use behavior of social chatbots

Entertainment, socialization and relationship are the main motivations for some users to use social chatbots. Social chatbots are an interesting or entertaining means of passing time, which can help reduce loneliness or realize social interaction to meet people's relational needs. However, some users have some negative attitudes towards social chatbots. For example, when investigating people's thoughts about future home robots, most people were attracted to the idea of robots as assistants to do a variety of chores, and few people showed interest in having a robot friend [4]. Judging from the users of social chatbots, most of the research focuses on the elderly and vulnerable groups. For example, social chatbots can help improve the social communication, interactive skills, activity participation and loneliness among the elderly in nursing institutions, and may improve residential care. However, there exists a scarcity of research on the use behavior and behavioral intention about social chatbots in other groups. This paper attempts to supplement the research on the use of social chatbots among youth.

2.3 UTAUT & acceptance and use of social chatbots

The Unified Theory of Acceptance and Use of Technology (UTAUT) was made by Viswanath and others in 2003. It is considered as the most reliable framework for cross-context extensive verification, adaptable to novel technology, accounting for 70% of the divergences in behavioral intention and 48% of the differences in use behavior [5]. At present, UTAUT is widely used in functional chatbots, such as health chatbots, consultation chatbots, chatbots for assisted learning, and chatbots for serving consumers. The most commonly used theoretical model for the relevant research on the acceptance and use of social chatbot is the technology acceptance model (TAM), while in this paper UTAUT model is used.

3. Research Hypotheses and Theoretical Model Construction

3.1 Research hypotheses

Base on UTAUT model, there are three independent variables directly affecting the behavioral intention: PE, EE and SI. In addition, the independent variable Facilitating Conditions directly affects the Use Behavior, and the behavioral intention as an intermediary variable affects the use behavior. Meanwhile, these four cores influencing factors are also influenced by control variables such as Gender, Age, Experience and Voluntariness of Use. The related model diagram is demonstrated in Figure 1.

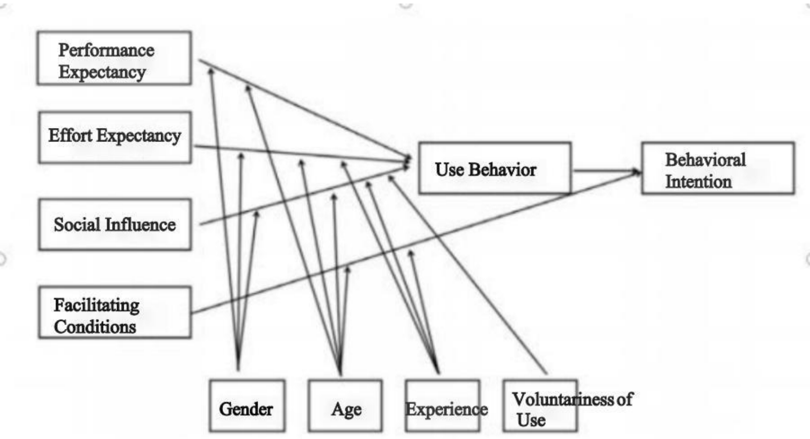

Figure 1 Integrated Technology Acceptance and Use Model (UTAUT)

PE, the most important factor affecting behavioral intention, is the degree to which the use of technology will do great gains in consumers in the performance of certain activities. As shown in many studies, PE is positively correlated with the behavioral intention about chatbots [6]. PE is related to perceived utility and extrinsic motivation. Entertainment or social and relationship are the main motivations of some users to use social chatbots. For example, some users report that chatbots are an interesting or entertaining means of passing time, which can help reduce loneliness or achieve social interaction, while others emphasize their interest in trying new technologies. One user of social chatbot Xiao Ice mentioned that she recently broke up with her boyfriend and asked Xiao Ice for companionship and comfort. Thus, the following assumption is made.

H1: There exists a positive correlation between the PE of the youth and their behavioral intention.

EE is identified as "the ease with which a consumer can use a technology", related to perceptual usability. Social chatbots use language models such as GPT2 and GPT3 for deep learning to generate human-like texts, making complex communication skills possible. Users can customize the social chatbots in a variety of aspects, such as determining the gender, birthday, name and appearance of the social chatbot Replika, establishing a relationship they would like to have. Personalization is key to interacting with artificial intelligence, especially for youth groups who like customized services. By activating the settings, the social chatbot will actively contact the users. The easy accessibility and time flexibility of the social chatbots facilitate the fulfillment of human relationship [7], satisfying the needs of the youth. So the following hypotheses are proposed.

H2: There is a positive correlation between the EE and behavioral intention.

SI refers to the influence of people who mean a great deal to decision makers (such as family members and friends) on their technology use, which can significantly establish positive behavioral intentions for specific technologies.

As shown in previous studies, SI is a significant predictor of the use of artificial intelligence [8], making a driven attitude on chatbot services. Therefore, we assume this.

H3: The SI of "AI partner" in youth group has a positive correlation with their behavioral intentions.

Privacy risk perception is the most important dimension of risk perception by artificial intelligence. Designers of social chatbot Xiao Ice believe that Xiao Ice can obtain users' highly personal and private information. Privacy risk is one of the major risks when Xiao Ice is used. In Douban's "Man-Chatbot Love" group, some critics think that "AI partner" will invade privacy, use cameras to obtain information, and it may be alternating roles between humans and chatbots. The effect of privacy risk perception on the behavioral intention has been validated in the adoption and use contexts of chatbots. For instance, in the adoption of health chatbots, the privacy risk perception of the younger generation is defined as a determining factor. Research on acceptance of chatbots in customer communications at retailers found that privacy concerns have a negative impact on behavioral intention and use frequency [9]. Therefore, we assume this.

H4: The privacy risk perception of youth group and behavioral intention are negatively correlated.

Loneliness refers to the subjective discomfort we experience when our social relationship lacks some important features. Personality, coping style and social support are the important factors affecting loneliness. Previous experiments have shown that lonely participants are significantly more likely to consider the robot a social companion, even with lower levels of third order subjective symmetry in the HRI condition. The main function is to act as social partners, helping people participate in interactions and do with loneliness. However, the existing research basically takes loneliness as a dependent variable to explore its relationship with the use of social chatbots. For example, the higher the degree of para-social interaction between users and social chatbots, the more media dependency on social chatbots, thus deepening the users' sense of loneliness. Some researches have also found that social chatbots can potentially alleviate depression and loneliness [10]. However, the empirical research on whether loneliness, as an independent variable, affects the use of social chatbots is very limited. Therefore, here are two assumptions.

H5: There exists a positive correlation between the loneliness degree of the youth group and the behavioral intention.

H6: There is a positive correlation between the loneliness extent of youth groups and the use behavior.

Self-disclosure is the course of sharing his or her personal and private thoughts and feelings with others honestly. At present, Computers-Are-Social-Actors (CASA) Paradigm has been introduced into the study of human-chatbot relationship, stating that people's interactions with social chatbots are the same as human-to-human interactions. It is safer for people to use chatbots to engage in self-disclosure. Chatting with chatbots is such a comfort as chatting with human companions. Users will disclose intimate details of their lives to them, which is beneficial to self-disclosure. Therefore, here is an assumption.

H7: Self-disclosure and behavioral intention are positively correlated in the youth group.

Boredom is a state of unease due to lack of interests and various negative states, such as depression, anxiety and stress. For the youth group, boredom is a universal emotional experience. In order to reduce and eliminate these negative conditions relevant to boredom, bored people usually need more amusement and recreation. The existing researches have mostly focused on boredom tendency, new media use and social media use. For example, boredom is positively correlated with Internet addiction and mobile phone dependence behavior. Therefore, this paper holds that boredom tendency may affect the use of AI partners. Therefore, here are another two assumptions.

H8: There is a positive correlation between the boredom tendency of the youth group and the behavioral intention.

H9: Boredom and use behavior in youth groups are positively correlated.

A number of technology acceptance and use models have built a positive relationship between behavioral intention and use behavior, such as TAM, UTAUT, etc. This relationship has also been validated in the contexts of AI adoption and use [11]. The acceptance of chatbots in the context of hotel and tourism [12] has been verified. Thus, we assume this.

H10: The behavioral intention in youth group has a positive correlation with its use behavior.

3.2 Construction of structural equation model

Because of a relatively large number of variables studied in this paper, multiple dependent variables could not be dealt with simultaneously in the general linear correlation and linear regression analyses, while that could in the Structural Equation Model (SEM). SEM is a model for developing, estimating and testing the causal relationships between model variables. The model includes observable explicit variables and unobservable implicit variables. Multiple dependent variables can be processed at the same time and the theoretical models and their relationships can be compared and evaluated. In addition to traditional multiple regression, path analysis, factor analysis and covariance analysis, the structural equation model can also be analyzed to derive the interaction among individual indicators and the effect of single indexes on the whole. Unlike the traditional exploratory factor analysis, the structural equation model has a specific structure for the factors and tests its compatibility with the data. Multiple structural equation analyses provide insights into whether the relationships between variables remain constant across groups and whether the average value of each factor varies tremendously.

Among the variables involved in this paper, the independent variables are seven latent variables such as PE, EE, SI, privacy risk perception, loneliness, self-disclosure, and boredom tendency. The intermediary variable is behavioral intention; the dependent variable is the use behavior; and the control variables add the marital status variable on top of the age and gender variables. Some studies have shown that convenience has no great effect on intention to use chatbots, because most people have rich experience in using smartphones and convenience may not be important to them, so convenience is not considered. According to the research hypotheses, the specific relationship between various variables is clarified in Figure 2.

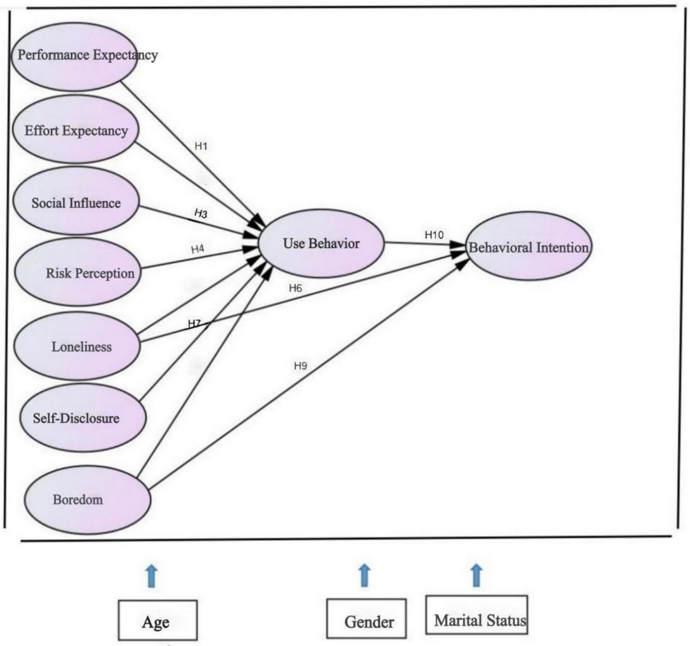

Figure 2 Behavior Model of "AI companion" (UTAUT) use among youth groups

4. Materials and Methods

4.1 Participants

In this paper, Douban's "Man-Chat Love" group was recruited as the investigation object, and the investigation was conducted in the form of questionnaires and snowballing. 590 questionnaires in total were distributed, and 571 valid questionnaires were collected. The efficacy rate is 96.8%, and the demographic characteristics of the sample are shown in Table 1. This study has been approved by the Ethics Committee of our university, and participants are asked to read and confirm the informed consent form.

Table 1 Descriptive statistics of survey sample

Name	Option	Frequency	Percentage (%)	Cumulative percentage (%)
Gender	Male	462	80.911	80.911
	Female	109	19.089	100
Age	Under 18 years old	49	8.58	8.58
	18-25 years old	161	28.2	36.78
	26-30 years old	157	27.5	64.27
	31-35 years old	204	35.73	100
Marital Status	Single in a relationship	243	42.557	42.557
	Single without a date	195	34.151	76.708
	Married	106	18.564	95.271
	Divorced	24	4.203	99.475
	Widowed	3	0.525	100
Academic Degree	Associate Degree	199	34.851	34.851
	Bachelor Degree	179	31.349	66.2
	High Middle School Degree/Technical Secondary School Degree	70	12.259	78.459
	Junior High School Degree	54	9.457	87.916
	Primary School Degree	47	8.231	96.147
	Master Degree	14	2.452	98.599
	Doctoral Degree	8	1.401	100
Total		571	100	100

4.2 Tools and measures

With reference to the dimensions and measurement criteria of new media acceptance and use proposed by previous researchers, the main measurement items of this questionnaire are revealed in Table 2.

Seven latent variables, such as PE, EE, SI, privacy risk perception, self-disclosure, behavioral intention, and use behavior, are differentiated by a five-point Likert scale, from disagreement to agreement, with the numbers "from 1 to 5" used to represent five different degrees respectively. The number "1" stands for "deep disagreement", which means that the participants of the questionnaire least agree with the situation described in the question. By analogy, "5" stands for "strong agreement". The higher the privacy risk perception score, the stronger the user's perception of privacy risk. And the more the self-disclosure score, the higher the user's self-disclosure. Loneliness is measured by four scales, where "1" stands for "never" and "5" stands for "often". The more the score, the higher the loneliness of users. Boredom tendency is measured by a 7-point scale in which "1" stands for "total disagreement" and "7" stands for "complete agreement". The more the score, the higher the boredom tendency of users. The specific measurement items for latent variables are shown in Table 2.

The data analyses of this paper are divided into two parts. On the one hand, the reliability and validity of the questionnaire are analyzed by SPSS22.0, and the correlation analysis among various latent variables, social demography and other variables is conducted. The one-way ANOVA analysis is carried out on the sociodemographic characteristics and the use behavior of the youth. On the other hand, the model is tested for goodness of fit and calibrated by AMOS24.0.

Table 2 Specific measurement questions for latent variables

Latent variable	Questions	Source
PE	AI partner can provide recreation, game entertainment and amusement when I am bored.	Venkatesh, 2003
	AI partner can be caring and attentive, bringing me emotional value and comfort.	
	I think the AI partner knows me very well and understands me with high EQ.	
	AI partner can listen to me and interact with me.	
	AI partner can solve my troubles and miseries.	
	AI partner can relieve my own emotions and stress.	
	AI partner can establish companionship, thus effectively alleviating loneliness.	
EE	AI partner is simple to operate.	Venkatesh, 2003
	AI partner can quickly grasp what I mean and respond accurately.	
	AI partner can be personalized (e.g. AI partner's hobbies, temperament, expression and other conditions can be changed to meet the player's needs)	
	AI partner is free to use.	
	I can interact with my AI partner in real time.	
	AI partner will initiate a conversation to establish a connection with me.	
SI	Classmates, colleagues or friends around me all use AI partner.	Venkatesh, 2003
	The extent to which my classmates, coworkers, or friends recommend an AI companion will affect my choice	
	I use AI partner to better communicate with my classmates, coworkers, or friends, to have something in common, and to gain acceptance.	
Privacy Risk Perception	I think "AI partner" will collect my personal information without my consent.	Dinev & Hart,(2006)
	I believe that my personal information may be used without my consent.	
	I think my operations on "AI partner" will be tracked and monitored.	
	I am concerned about that the private information uploaded to "AI partner" will be illegally used.	
	I am worried that "AI partner" will give away my personal information.	
Self-disclosure	Every time I enter the "AI partner", I begin to release my personal information and feelings comprehensively and deeply.	Leung(2001)Fogel &Nehmad,(2009)
	I talk about a wide range of topics in the "AI partner".	
	I don't intentionally control the number of topics talked about, nor do I limit myself to a limited number of topics.	
	I'm always posting my personal updates to "AI partner".	
	Once I started expressing myself on "AI partner", I was immersed in it for a long time.	
Loneliness	I'm always in a lack of companionship.	Russell, Peplau & Cutrona 1980[13]
	It often strikes me that nobody can count on.	
	Loneliness usually comes to my mind.	
	It appears that others turn a deaf ear to me.	
	It seems that no one cares about me.	
Behavioral intention	I'll try the AI partner.	Kang et al., 2015
	I'll keep using "AI partner".	
	I would recommend "AI partner" to others.	
Use Behavior	I use "AI partner" almost every day.	
	I often use "AI partner".	
	I will keep using "AI partner".	
Boredom Tendency	I'm often at loose ends, occupied with nothing.	J. Isacescu, J. Danckert,2018[14]
	It is difficult to entertain myself.	
	A lot of what I have to do is repetitive.	
	Only more stimulation can keep me going.	
	There is no motivation for most things I do.	
	In most cases, I find it difficult to find something that interests me.	
	Most of the time, I just sit around and do nothing.	
	Except something thrilling, or even dangerous, I will feel bored.	

5. Data Analysis and Theoretical Model Test

5.1 Data quality analysis

Reliability analysis assesses the stability, consistency, and dependability of measurement results to ensure their accuracy. Currently, Cronbach’s alpha coefficient is commonly used for this purpose. Generally, a reliability coefficient above 0.9 indicates excellent reliability. Coefficients between 0.8 and 0.9 are considered very good, while those between 0.7 and 0.8 are deemed good. A range of 0.6 to 0.7 is acceptable, but coefficients below 0.6 suggest that revisions are necessary. As shown in the table below (Table 3), all reliability coefficient values exceed 0.7, indicating a high level of reliability.

Table 3 Cronbach's alpha coefficient test

Dimension	Item Count	Cronbach's Alpha Coefficient
PE	7	0.886
EE	6	0.870
SI	3	0.762
Privacy Risk Perception	5	0.834
Self-disclosure	5	0.848
Loneliness	5	0.869
Boredom Tendency	8	0.923
Behavioral Intention	3	0.740
Use Behavior	3	0.780
Total	45	0.924

Validity refers to the degree to which psychological and behavioral characteristics can be accurately measured by tests or scale instruments, reflecting the precision and reliability of the test results. Generally, a lower Bartlett’s test of sphericity value ($P<0.05$) indicates a higher likelihood of a meaningful relationship among the original variables. The KMO values are used to assess the adequacy of factor analysis by comparing the simple and partial correlation coefficients among items, with values ranging from 0 to 1. The suitability criteria for factor analysis are as follows: values above 0.9 are considered excellent; 0.7 to 0.9 is considered good; 0.6 to 0.7 is acceptable; 0.5 to 0.6 is considered questionable; and below 0.5 is unacceptable. Bartlett’s test of sphericity is used to determine whether there are significant correlations among items. A significance level less than 0.05 indicates that the items are suitable for factor analysis. As shown in the following table, the KMO value is 0.955, which is favorable for information extraction and reflects good validity. The data results are presented in Table 4.

Table 4 KMO Sample Measures and Bartlett's Spherical Tests

KMO Quantity of Sample Suitability		0.955
Bartlett’s Test of Sphericity	Approximate chi-square	13661.129
	Freedom	990
	Significance	0

5.2 Correlation analysis of latent variables in structural equation model

Correlation analysis involves describing and analyzing the interrelationship among multiple variables. The correlation coefficient is marked with a * sign in the upper right corner, indicating a relationship, whereas it does not. When the correlation coefficient is more than 0, there is a positive correlation between the two variables; while it is less than 0, the two variables are negatively correlated. For instance, the correlation coefficient between PE and EE is 0.557***, indicating a significant positive relationship. The results of the data are presented in Table 5.

Table 5 Correlation analysis of research hypotheses among latent variables (R)

	PE	EE	SI	Privacy Risk Perception	Self-disclosure	Loneliness	Boredom Tendency	Behavioral Intention	Use behavior
PE	1								
EE	0.557***	1							
SI	0.465***	0.532***	1						
Privacy Risk Perception	-0.485***	-0.535***	-0.488***	1					
Self-disclosure	0.358***	0.449***	0.353***	-0.417***	1				
Loneliness	0.465***	0.449***	0.423***	-0.48***	0.317***	1			
Boredom Tendency	0.544***	0.525***	0.526***	-0.524***	0.345***	0.494***	1		
Behavioral Intention	0.541***	0.534***	0.483***	-0.518***	0.367***	0.491***	0.548***	1	
Use behavior	0.479***	0.524***	0.47***	-0.528***	0.407***	0.508***	0.532***	0.54***	1
Note: * * *, * *, * stand for the significance level of 1%, 5% and 10% respectively.									

From Table 6, the relationships between the latent variables in the main analytic model and behavioral intention are as follows. PE is significantly positively correlated with behavioral intention (H1). EE is significantly positively correlated with behavioral intention (H2). SI is significantly positively correlated with behavioral intention (H3). Privacy Risk Perception is significantly negatively correlated with behavioral intention (H4). Loneliness has an evident positive correlation with behavioral intention (H5) and use behavior (H6). Self-disclosure is positively correlated with behavioral intention (H7). Boredom tendency has a distinct positive correlation with behavioral intention (H8) and use behavior (H9). There is a visible positive correlation between behavioral intention and use behavior (H10).

5.3 Structural equation model test and correction

5.3.1 Model fit test

The results of structural equation model obtained by maximum likelihood method of AMOS24.0 are shown in table 5, and most of the model fit indexes meet the standard with good adaptability.

Table 6 Model fit indexes

Common Indicators	X^2	DF	P	RMSEA	SRMR	CFI	TLI
Criterion	-	-	>0.05	<0.10	<0.05	>0.9	>0.9
Value	1432.1	914	0	0.032	0.033	0.96	0.957

5.3.2 Analyses of latent variable effects

Based on the analysis, the effect relationship among latent variables is demonstrated in Table 7. Among the latent variables affecting the behavioral intention, the latent variables with the highest total effect are, in order, privacy risk perception, PE, loneliness, SI, EE, boredom tendency and self-disclosure, among which privacy risk perception and behavioral intention have negative effects. The higher privacy risk perception is, the lower behavioral intention is, in conformity with the psychological concerns of AI partner's use groups.

Among the latent variables affecting the use behavior, loneliness and boredom tendency can affect the use behavior in addition to the behavioral intention. Behavioral intention plays an intermediary role in loneliness, boredom tendency and use behavior respectively. The finding that loneliness influences use behavior accords with the result of a study on social loneliness and the use of artificial intelligence loudspeakers. In this study, consumers are more likely to use artificial intelligence loudspeakers when they feel socially lonely [15]. Previous studies have mostly focused on boredom and new media use, and social media use, however, there is a lack of relevant literature on boredom tendency towards social chatbots. This paper makes up for this deficiency.

The influence of privacy risk perception on behavioral intention, and the key role of loneliness and boredom tendency in "AI partner" use behavior are the important findings and innovations in this paper.

Table7 Latent variable effects of structural equation model

Trails	Direct Effect	Indirect effect	Aggregate Effect	Order
PE →Behavioral Intention (BI)	0.192***	-	0.192***	1
Loneliness→BI	0.142**	-	0.142**	2
SI→BI	0.131*	-	0.131*	3
EE→BI	0.13*	-	0.13*	4
Boredom Tendency→BI	0.094**	-	0.094**	5
Self-disclosure→BI	0.071	-	0.071	6
Privacy Risk Perception→BI	-0.193**	-	-0.193**	7
Behavioral Intention→Use Behavior (UB)	0.578***	-	0.578***	1
Loneliness→UB	0.227***	0.082*	0.309***	2
Boredom Tendency→UB	0.109**	0.054*	0.163***	3

5.3.3 Model modification

Based on the above data analysis results, the structural equation model is further modified and improved according to the research assumptions and research models mentioned above. The relevant results can be seen in Figure 3.

With the results of the whole model, recalculate after removing one insignificant path at a time, check the model significance again based on the calculation results, repeat this process until all paths are significant, and finally delete the path of "self-disclosure → behavioral intention". That is, the research hypothesis H7 is rejected, which shows that the impact of self-disclosure on behavioral intention is untenable. Studies have shown that users' self-disclosure will be affected by the conversation style of chatbots, and it may be dependent on the conversation expectation. For example, when the chatbot does not give them any response and the conversation topics are similar from day to day, users feel like they are talking to a stranger. Or when the chatbot mostly keeps stimulating the users to answer questions, not particularly interactive, without understanding what the users are talking about, users may feel unable to establish a relationship with the chatbot, and it has also been found that when users interact with chatbots, the novelty effect kicks in during the first interaction, after which self-disclosure and interaction quality may decrease over time. In terms of social penetration theory, the initial stages of relationship development, interactions with others are usually characterized by exchanging superficial information, only to move to the level of self-representation as the relationship progresses. All the above may explain the untenable impact of self-disclosure on behavioral intention. In addition, the negative effect of "privacy risk perception → behavioral intention" and the direct and indirect effects of "loneliness → use behavior" and "boredom tendency → use behavior" are both true, so they are partially mediated effects. The results of the data are presented in Figure 3.

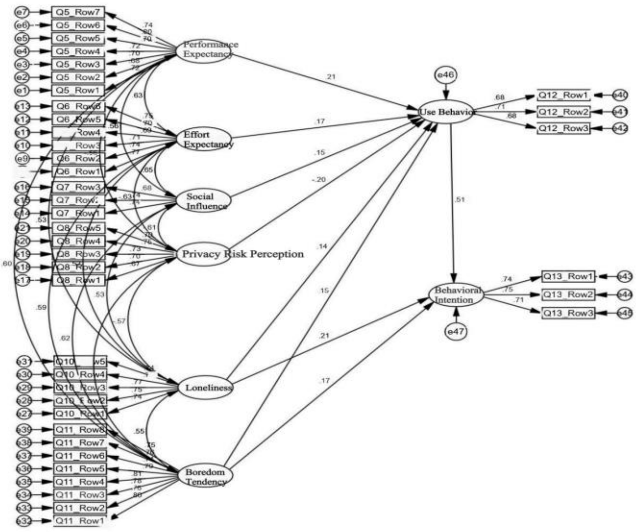

Figure 3 Coefficient estimation of the structural equation model for the use of "AI partners" by the youth group.

5.4 Impact of demographic variables on use behavior

In addition to the latent variables in the model, this paper also explores the influence of demographic variables on the use behavior in youth groups through one-way ANOVA. In Table 8, there is a marked difference between marital status and education on the use behavior among youth groups. Looking at the average values, we can see that the divorced and single with no partner have higher use behavior scores. In terms of academic qualifications, people with primary school degree, master degree and bachelor degree have higher scores in use behavior.

Table 8 Analyses of differences in demographic variables

variable name	variable value	Sample	average value	standard deviation	T/F	P
Gender	Female	109	3.413	0.797	-0.971	0.332
	Male	462	3.51	0.973		
Age	Under 18	49	3.668	0.88	0.91	0.436
	18-25 Years Old	161	3.42	0.87		
	26-30 Years Old	157	3.53	0.86		
	31-35 Years Old	204	3.47	1.06		
Marital Status	Divorced	24	3.681	0.732	5.119	0.000**
	Single Without A Date	195	3.704	0.884		
	Married	106	3.311	0.842		
	Single In A Relationship	243	3.391	1.015		
	Widowed	3	2.667	0.335		
Academic Degree	Associate Degree	199	3.39	1.008	2.761	0.012*
	Junior High School Degree	54	3.636	0.869		
	High Middle School Degree/Technical Secondary School Degree	70	3.319	0.83		
	Bachelor Degree	179	3.533	0.923		
	Primary School Degree	47	3.865	0.864		
	Master Degree	14	3.714	0.985		
	Doctoral Degree	8	3.041	0.764		
Note: * *, * act for the significance level of 1% and 5% respectively.						

6. Research Conclusions and Suggestions

In conclusion, based on UTAUT, research hypotheses are developed from the perspective of HCR theory. The influencing factors are included in seven specific indicators, such as PE, EE, SI, privacy risk perception, self-disclosure, loneliness and boredom tendency. It is found that privacy risk perception is negatively correlated with the "AI partner" behavioral intention, and the other variables are positively correlated with the behavioral intention. The behavioral intention, loneliness and boredom tendency are positively correlated with the use behavior. However, the influence path of "self-disclosure" is rejected, which may be related to the conversational style of "AI partner" and the user's expectation of the type of dialogue. In response to the research on chatbots proposed by Eysseltt and Friederike, it is possible to establish a technical system taking into account the needs and characteristics of users (i.e. the users' personalities), which can do great help in the interaction process between human beings and chatbots.

What's more, among the latent variables affecting the "AI partners" behavioral intention, the latent variables with the highest total effect are, in order, privacy risk perception, PE, loneliness, SI, EE, boredom tendency and self-disclosure, in which privacy risk perception and behavioral intention have negative effects. The higher privacy risk perception is, the lower behavioral intention is, which is in line with the psychological concerns of the "AI partner" users. As The Survey Report on the Protection of the Rights and Interests of Chinese Internet Users (2016) shows, personal information protection is the most concerned problem for netizens. As for 54% of netizens, personal data disclosure is serious, and 84% of netizens feel the adverse effects brought by personal information leakage. This research provides directions for the developers and operators of AI-related products and chatbots to improve their privacy protection, and provides research references for the legislature to improve the privacy protection law.

Last but not least, among the latent variables affecting the use behavior, loneliness and boredom tendency can affect the use behavior. The behavioral intention can also indirectly have an effect on the "AI partner" use behavior. The behavioral intention plays an intermediary role in loneliness and use behavior, boredom and use behavior respectively. Loneliness and boredom are undesirable psychological states. Scholars have studied human loneliness and other symptoms in the media society. For example, Japanese communication scholar Makoto Nakano mentioned the concept of "container people" in his book Information Behavior of Modern People. In his opinion, the inner world in the media environment is like a closed "pot". To get rid of loneliness, it is also desirable to keep in touch with the outside. With the rapid development of AI, the emergence and popularity of "AI partner" reflects the existence of a lot of lonely individuals in the real society. They feel stressed and mistrustful in the real society, and are willing to withdraw to the virtual space, preferring to work with strangers or virtual friends rather than with the people around them. Therefore, the phenomenon of youth "group loneliness" needs to be paid attention to and adjusted to provide data support for the debugging of the social chatbots and "group loneliness" among youth groups nowadays. At the same time, this paper bridges the previous research limitation, that is, by analyzing lonely people, we will make certain the category profiting from chatbot communication, and find out some personality traits affecting the connections people make with social chatbots.

Acknowledgments

This paper is supported by two funding projects. The first is the Key Research Project of the Philosophy and Social Sciences Research Base in Jiangxi Province titled "Research on the Mechanism of Public Opinion Evolution and Good Governance from the Perspective of Complexity," project number 21SKJD01. The second is the Jiangxi Province 2023 Graduate Innovation Special Fund Project titled "The Mechanism and Intervention Strategies of Mindfulness on Adolescent Short Video Addiction," project number YC2023-B009.

References

[1] Følstad, A., Araujo, T., Law, E. L.-C., Brandtzaeg, P. B., Papadopoulos, S., Reis, L., Baez, M., Laban, G., McAllister, P., Ischen, C., Wald, R., Catania, F., Meyer Von Wolff, R., Hobert, S., & Luger, E. (2021). Future directions for chatbot research: An interdisciplinary research agenda. Computing, 103(12), 2915–2942. https://doi.org/10.1007/s00607-021-01016-7

[2] Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. Journal of Social Issues, 56, 81–103. https://doi.org/10.1111/0022-4537.00153.

[3] EDITEDBYGERDANTOSANDEIJAVENTOLA, & INCOOPERA. (2008). HANDBOOK OF INTERPERSONAL COMMUNICATION. MOUTON DE GRUYTER.

[4] Deloitte, 2017. How much time and money can AI save government? Retrieved from https://www2.deloitte.com/content/dam/insights/us/articles/3834_How-muchtime-and-money-can-AI-save-government/DUP_How-much-time-and-money-can-AI-save-government.pdf.

[5] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unifed view. MIS Quarterly, 27(3), 425–478.

[6] Mesbah, N., & Pumplun, L. (2020). "Hello, I'm here to help you" – Medical care where it is needed most: Seniors' acceptance of health chatbots. European Conference on Information Systems (ECIS).

[7] Bae, B. P., Marita, S. & Asbjrn, F. (2022). My ai friend: how users of a social chatbot understand their human–ai friendship. Human Communication Research (3), 3.

[8] Juan-Pedro Cabrera-Sánchez, Villarejo-Ramos, N. F., Francisco Liébana-Cabanillas, &Shaikh, A. A.. (2021). Identifying relevant segments of ai applications adopters - expanding the utaut2's variables. Telematics and Informatics, 58(2), 101529.

[9] Rese, A., Ganster, L., &Baier, D.. (2020). Chatbots in retailers' customer communication: how to measure their acceptance?. Journal of Retailing and Consumer Services, 56, 102176.

[10] Chen, S. C., Moyle, W., Jones, C, & Petsky, H.. (2020). A social robot intervention on depression, loneliness, and quality of life for taiwanese older adults in long-term care. International Psychogeriatrics, 32(8), 1-11.

[11] Andrews, J. E., Ward, H., & Yoon, J. W.. (2021). Utaut as a model for understanding intention to adopt ai and related technologies among librarians. The Journal of Academic Librarianship, 47(6), 102437.

[12] Pillai, R., & Sivathanu, B.. (2020). Adoption of ai-based chatbots for hospitality and tourism. International Journal of Contemporary Hospitality Management, 32(10), 3199-3226.

[13] Russell, L A, Peplau, C E, & Cutrona. (1980). The revised ucla loneliness scale: concurrent and discriminant validity evidence. Journal of personality and social psychology.

[14] J. Isacescu, J. Danckert, Exploring the relationship between boredom proneness and self-control in traumatic brain injury (TBI), Exp. Brain Res. 236 (9) (2018) 2493–2505, https://doi.org/10.1007/s00221-016-4674-9.

[15] Ryan, T., & Xenos, S. (2011). Who uses Facebook? An investigation into the relationship between the Big Five, shyness, narcissism, loneliness, and Facebook usage. Computers in Human Behavior, 27(5), 1658–1664. doi:10.1016/j.chb.2011.02.004