How does the degree of anthropomorphism of health chatbots affect the public's willingness to seek help from them? Empirical research using HBM

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Abstract Currently, health chatbots have a wide range of applications in the medical field. However, most of the related research centers around self-diagnosis at the user's physical level, while the psychological level is rarely discussed. Unlike real doctors, health chatbots are more accessible, more convenient and less stigmatizing. Consequently, this study develops a structural equation model on the degree of anthropomorphism of chatbots and willingness to ask for help from them based on the health belief model, the technology acceptance model, and the privacy computing theory. It contributes to complementing the lack of research on human-robot communication in health communication. The results show that an increase in the degree of chatbot anthropomorphism significantly increases users' perceived benefits and reduces privacy concerns, thus increasing their willingness to seek help from it. Interestingly, increased anthropomorphism enhances users' perceived severity and perceived susceptibility, which may be due to the specificity of mental health problems, where the more the chatbot resembles a real person, the more likely it is to aggravate users' tension and anxiety. This study also found that Chinese users generally have a low level of acceptance of psychological counseling chatbots, and chatbots are not their first choice for help when experiencing psychological problems. In the future, the professionalism of the psychological counseling function of health chatbots can be further improved, and at the same time well publicized for the benefit of more people troubled by psychological problems.

Keywords: chatbot anthropomorphism; health beliefs; depression; health chatbot

1.Introduction

Depression is a public health problem of great importance worldwide, often presenting with other chronic conditions and potentially worsening other health outcomes. According to the Institute for Health Metrics and Evaluation (IHME) at the University of Washington, the prevalence of depressive disorders in China has increased by about 22 percent over the 30-year period from 1990 to 2019, getting closer to the global average. In other words, for every 100 people, there are 3.5 people with depression. However, the current rate of depression patients seeking medical treatment in China is low. A study published in 2019 by Peking University Sixth Hospital showed that only 0.5 percent of patients diagnosed with depressive disorders in the past 12 months were adequately treated.

The development of big language modeling technology has accelerated the application of chatbots in healthcare.2023 In May 2023, MedLINK launched MedGPT, the first medical big language model in China, which is based on deep learning of 2 billion real doctor-patient conversations, as well as reinforcement learning using feedback from real doctors, and can achieve multimodal and uninterrupted output, realizing a comprehensive range of prevention, diagnosis, treatment, and rehabilitation from prevention to Intelligent. In addition to these “specialized” medical models, ChatGPT, Copilot and other “all-around” large language models can also answer users' health inquiries. Patients don't need to travel to hospitals to communicate with doctors face-to-face, and they don't need to worry about their privacy being known by real doctors. Low-cost, high-efficiency, accessible human-computer communication is playing an increasingly important role in health communication.

Past research on health communication mostly focused on exploring the impact of communication channels on health communication, while a few have been done to explore the role played by artificial intelligence, especially chatbots based on large language modeling technology, in the process of health communication. Unlike online consultations with real doctors, does the “machine-inspired” effect of chatbots interfere with the adoption of health advice by users? Meanwhile, the discussion of human-machine communication （HMC） is mostly in the fields of marketing, management and psychology, neglecting the application of chatbots in healthcare. This study enriches the new application of the health belief model in human-machine communication by introducing new variables (chatbot anthropomorphism, privacy concerns), which provides new insights for the future development of human-machine health communication.

2.Literature review

2.1. Human-machine communication (HMC)

Some scholars have done research on the perception of human influence by robot doctors and real doctors through a mixed method, where subjects in the experimental group and the control group were first placed in the scenarios of robot doctors and real doctors respectively, and then were interviewed in depth separately. It was found that human trust towards real doctors was generated based on emotion, and trust towards robot doctors was generated based on cognition, and that the robot's ability to communicate was more important than its ability to empathize (Seitz et al., 2022). Chatbots contributed to disease prevention surveillance and health protection outreach in the just-passed New Crown Pneumonia outbreak, and a scholar identified 61 chatbots deployed in 30 countries or regions through a literature search of 61 articles selected from 3,334 articles. It was found that chatbots are mainly used for six basic functions: risk assessment, disease surveillance, information dissemination, post outbreak eligibility, distributed coordination, and vaccine scheduling procedures, and that the scalability, accessibility, ease of use, and rapid dissemination of chatbots can enhance the ability of the relevant departments and agencies to respond to public health matters (Amiri & Karahanna, 2022).

2.2. Health Belief Model (HBM)

The Health Belief Model (HBM) was first proposed in the 1950s to describe in general terms the preventive health behaviors of individuals (Hochbaum, 1958). The model includes Perceived Susceptibility, Perceived Severity, Perceived Benefits, Perceived Barriers, Self- Efficency, Cues to Action, and other variables. Currently, the Health Belief Model has been widely used in health prevention behavior studies of chronic diseases, including type 2 diabetes, hypertension, HPV, and mental illness.

2.3. Privacy Computing Theory

In 1999, Culnan and other scholars proposed the privacy computation theory (Culnan & Armstrong, 1999). The theory suggests that individuals are rational in most situations, and that privacy decisions are made by individuals based on weighing perceived benefits against perceived risks. When the perceived benefits outweigh the risks, individuals are willing to disclose some of their privacy in exchange for services. This theory can be used to explain the game psychology of individuals in industrialized societies when they use information systems, mobile commerce, and social media platforms to display their personal images.

3. Hypotheses development

3.1. Chatbot anthropormorphism and health belief

The degree of anthropomorphism has been an important variable in chatbot-related research since the Turing test (Sheehan et al., 2020). Differences in the degree of anthropomorphization of chatbots lead to different levels of willingness to disclose by users (Liu, 2019). Self-disclosure is crucial for psychological problem solving, which makes chatbots in the field of mental health care possible. Previous research has shown that the degree of anthropomorphism affects users' perceived warmth and perceived competence of chatbots (Cheng et al., 2022). This would enhance the placebo effect in patients, thus affecting their health beliefs(Howe et al, 2019). Therefore, we hypothesize the following:

H1a: Chatbot anthropomorphism is positively related to perceived severity.

H1b: Chatbot anthropomorphism is positively related to perceived vulnerability.

H1c: Chatbot anthropomorphism is negatively related to perceived barriers.

H1d: Chatbot anthropomorphism is positively related to perceived benefits.

3.2. Chatbot anthropormorphism and privacy concerns

Research has shown that human-like chatbots lead to higher perceptions of anthropomorphism compared to machine-like chatbots, which in turn leads to lower privacy concerns for users（Ischen, 2020）. Therefore, users are willing to disclose more information to human-like chatbots than machine-like chatbots. Based on this, we propose the following hypothesis:

H2: Chatbot anthropomorphism is negatively related to privacy concerns.

3.3. Health belief and intention to obtain health information

The health belief model suggests that health beliefs motivate individuals to adopt positive health-related behaviors(Hochbaum, 1958). The emergence of health chatbots has motivated users to use them for self-diagnosis and counseling on health-related issues (Shahsavar & Choudhury，2023). Thus, we propose the following hypothesis:

H3a: Perceived severity is positively related to intention to obtain health information.

H3b: Perceived vulnerability is positively related to intention to obtain health information.

H3c: Perceived barriers are negatively related to intention to obtain health information**.**

H3d: Perceived benefits are positively related to intention to obtain health information**.**

3.4. Privacy concerns and intention to obtain health information

Privacy concerns have long been an important factor in whether people adopt new applications. Research has shown that privacy concerns can negatively affect users' trust in new technology products（Zhang et al., 2022）. Therefore, we argue the following:

H4: Privacy concerns are negatively related to intention to obtain health information**.**

Our research model is presented in Figure 1 [Figure 1 near here].

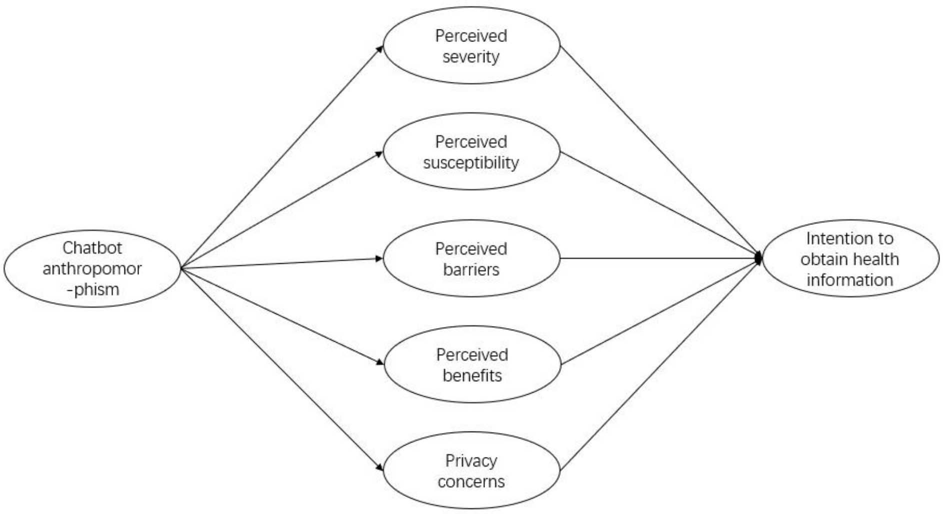

Figure 1. The research model in this study

4. Study methods

4.1. Data collection procedures and participant

This study used the Credamo (a large Chinese sampling website) platform for data collection. Participants were first asked to read a long conversation screenshot. They were told to assume that they had depression-related symptomsand were seeking health suggestions from a health chatbot. Next, after reading the instruction and the experimental steps, participants need to finish the following test. A total of 300 users were invited to the survey. Among those participants, 268 were qualified. In order to ensure the quality of questionnaire recovery, quota sampling was conducted according to the ratio of the 7th China Population Census (East: Central: West: Northeast = 40%: 26%: 27%: 7%) and the ratio of gender (male: female = 51%: 49%) at the time of releasing the questionnaires. There was no significant difference between the valid sample and the total sample in terms of demographic variables.

4.2. Measurement

Items of our study were adapted from previous literature. Specifically, items for chatbot anthropomorphism were adapted from Crolic et al. (2022); items for perceived severity, perceived vulnerability, perceived barriers were based on Nobiling et al. (2017); items for perceived benefits were adapted from Liu et al. (2022); items for privacy concerns were adapted from Xu et al.(2011); items for intention to obtain health information were based on Li et al. (2018). Each question was measured on a 5-point, Likert type scale. Items for credibility were anchored on 1 = not at all to 5 extremely, while the rest were anchored on 1 = strongly disagree to 5 = strongly agree.

The final items used are shown in the table 1 [Table 1 near here].

Table 1. Variables and Cronbach's α

Variable	Items	Cronbach's α
chatbot	It has some human-like qualities.	0.866

anthropomorphism	It seems to have a personality of its own. It seems to have its own agenda. It seems to have free will. It seems to be conscious.	
perceived severity	Being diagnosed with a mental illness would affect my health. Being diagnosed with a mental illness would affect my social life. People diagnosed with mental illness experience a lower quality of life.	0.702
perceived vulnerability	My family history puts me at risk for mental illness. My lifestyle puts me at risk for mental illness. The amount of stress in my life puts me at risk for mental illness.	0.741
perceived barriers	Paying for services can be a barrier to utilizing mental health services. Fear of possible mental illness diagnoses can be a barrier to utilizing mental health services. Stigma/negative beliefs attached to possible mental illness diagnoses can be a barrier to utilizing mental health services.	0.748
perceived benefits	I can obtain better knowledge about curing depression. I can better know how to improve my depression symptoms. It helps answer my questions about depression. This chatbot's careful work will not complicate things.	0.700
privacy concerns	It bothers me when it asks me for more personal information to make a diagnosis. When it asks me for more personal information to diagnose, I worry that it would leak our chat logs to others. When it asks me for more personal information to make a diagnosis, I worry that it may use my personal information in ways I didn't foresee.	0.898
intention to obtain health information	I intend to keep obtaining health related information on such robots in the future. I am willing to obtain health related information on such robots. I will obtain related health information on such robots when I need to. I will consider health advice from such robots before I make a decision regarding health.	0.781

4.3. Analysis and results

Table 2. Goodness of Fit Index

X^2/df	RMSEA	GFI	AGFI	CFI

1.573	0.046	0.891	0.866	0.942

Table 3. Items and descriptive statistics

latent vairables	observed variables	std.	Unstd.	S.E.	t-value	P	SMC	CR	AVE
PSE	CA	0.172	0.086	0.038	2.256	0.024			
PSU	CA	0.19	0.08	0.03	2.659	0.008			
PBA	CA	0.097	0.046	0.034	1.338	0.181			
PBE	CA	0.461	0.155	0.028	5.559	***			
PC	CA	-0.207	-0.164	0.053	-3.115	0.002			
IOHI	PSE	0.118	0.132	0.076	1.733	0.083			
IOHI	PSU	0.086	0.114	0.08	1.433	0.152			
IOHI	PBA	0.075	0.088	0.076	1.167	0.243			
IOHI	PBE	0.75	1.239	0.181	6.848	***			
IOHI	PC	-0.138	-0.097	0.041	-2.37	0.018			
PSE1	PSE	0.715	1				0.511		
PSE2	PSE	0.663	0.924	0.129	7.17	***	0.440	0.711	0.451
PSE3	PSE	0.634	1.086	0.154	7.032	***	0.402		
PSU1	PSU	0.421	1				0.177		
PSU2	PSU	0.963	2.744	0.475	5.779	***	0.927	0.772	0.553
PSU3	PSU	0.745	2.019	0.299	6.75	***	0.555		
PBA1	PBA	0.469	1				0.220		
PBA2	PBA	0.837	2.063	0.299	6.912	***	0.701	0.764	0.533
PBA3	PBA	0.824	2.041	0.312	6.545	***	0.679		
PBE1	PBE	0.553	1				0.306		
PBE2	PBE	0.529	1.194	0.181	6.603	***	0.280	0.700	0.371
PBE3	PBE	0.69	1.354	0.184	7.359	***	0.476		
PBE4	PBE	0.651	1.347	0.189	7.118	***	0.424		
PC1	PC	0.756	1				0.572		
PC2	PC	0.954	1.585	0.1	15.863	***	0.910	0.903	0.759
PC3	PC	0.891	1.37	0.088	15.498	***	0.794		
CA5	CA	0.873	1				0.762		
CA4	CA	0.892	0.959	0.049	19.394	***	0.796		
CA3	CA	0.765	0.795	0.054	14.857	***	0.585	0.870	0.582
CA2	CA	0.724	0.711	0.052	13.678	***	0.524		
CA1	CA	0.493	0.315	0.038	8.337	***	0.243		
IOHI1	IOHI	0.777	1				0.604		
IOHI2	IOHI	0.739	0.935	0.084	11.191	***	0.546	0.780	0.473
IOHI3	IOHI	0.661	0.85	0.084	10.152	***	0.437		
IOHI4	IOHI	0.554	0.669	0.077	8.686	***	0.307		

Table 4. Correlation between constructs and square-root of AVEs

	AVE	CA	PC	PBE	PBA	PSU
CA	0.582	**0.763**				
PC	0.759	-0.207	**0.871**			
PBE	0.371	0.461	-0.095	**0.609**		
PBA	0.533	0.097	-0.020	0.045	**0.730**	
PSU	0.553	0.190	-0.039	0.088	0.018	**0.744**
PSE	0.451	0.172	-0.036	0.079	0.017	0.033
IOHI	0.473	0.418	-0.219	0.783	0.115	0.162

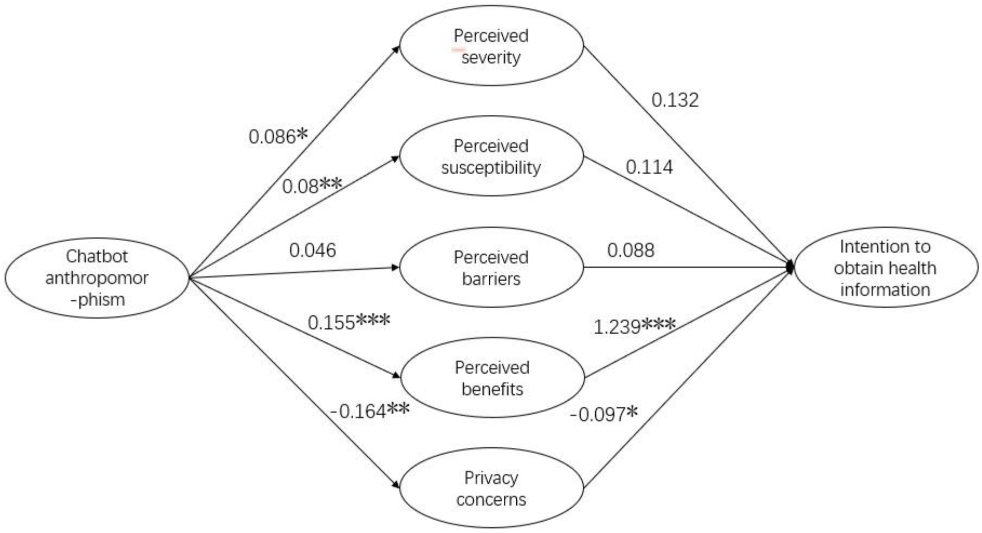

Figure 2. Model Results with Chinese Sample

Table 5. Summary of Hypotheses Testing

Hypothesis	Supported?
H1a: Chatbot anthropomorphism is positively related to perceived severity.	Yes
H1b: Chatbot anthropomorphism is positively related to perceived vulnerability.	Yes

H1c: Chatbot anthropomorphism is negatively related to perceived barriers.	No
H1d: Chatbot anthropomorphism is positively related to perceived benefits.	Yes
H2: Chatbot anthropomorphism is negatively related to privacy concerns.	Yes
H3a: Perceived severity is positively related to intention to obtain health information.	No
H3b: Perceived vulnerability is positively related to intention to obtain health information.	No
H3c: Perceived barriers are negatively related to intention to obtain health information.	No
H3d: Perceived benefits are positively related to intention to obtain health information.	Yes
H4: Privacy concerns are negatively related to intention to obtain health information.	Yes

The data analysis was conducted in two phases: measurement and structural evaluation. Convergent validity was established by ensuring significant item loadings (>0.50), composite reliability (CR) above 0.70, and average variance extracted (AVE) exceeding 0.36 (Gefen & Straub, 2005; Hulland, 1999).Most values satisfied standards, although only one square root of AVE are lower than the interconstruct correlation coefficients. As stated by Hair et al. (2013), it is acceptable for a few individual indicators to be slightly below the criteria, provided that the majority of factors meet the standards.The structural model was appraised via R2 values and path coefficients, delineating the significance of construct relationships (Gefen et al., 2005).

H1a, stating that chatbot anthropomorphism positively associated with perceived severity, was supported ($b=0.086$, $p<0.05$). H1b argues that chatbot anthropomorphism is positively associated with perceived vulnerability. This hypothesis was supported ($b=0.08$, $p<0.01$). H1c posits that chatbot anthropomorphism is negatively related to perceived barriers. This hypothesis was not supported($b=0.046$, $p>0.05$). H1d states that chatbot anthropomorphism is positively associated with perceived benefits. This hypothesis was supported($b=0.155$, $p<0.001$). H2 states that chatbot anthropomorphism is negatively associated with privacy concerns. This hypothesis was supported($b=-0.164$, $p<0.01$). H3a, stating that perceived severity are positively associated with intention to obtain health information, was not supported ($b=0.132$, $p>0.05$). H3b argues that perceived benefits are positively related to intention to obtain health information. This hypothesis was not supported($b=0.114$, $p>0.05$). H3c posits that perceived barriers is negatively related to intention to obtain health information. This hypothesis was not supported($b=0.088$, $p>0.05$). H3d states that perceived benefits is positively associated with intention to obtain health information. This hypothesis was supported($b=1.239$, $p<0.001$). H4 posits that privacy concerns is negatively related to intention to obtain health information**.** This hypothesis was supported ($b=-0.097$, $p <0.05$).

6. Discussions

The SEM results showed that the higher degree of health chatbot anthropomorphism, the higher degree of perceived vulnerability and perceived severity of psychological problems of the individuals. This finding may seem counterintuitive, but can be verified from previous interviews. That is, the more a chatbot resembles a real person in terms of visual cues and conversational cues, the more it can put psychological pressure on the user to talk to a real doctor, thus exacerbating psychological panic.

The results of the study also show that the increase in the degree of chatbot anthropomorphism does not have a significant effect on users' perceived barriers, which may be due to the fact that users' perceptions of economic stress and mental illness stigmatization are the result of long-term formation, and short-term encounters with chatbots do not change users' long-term impressions. However, changes in perceived severity, perceived susceptibility, and perceived barriers did not significantly affect users' willingness to seek help from chatbots, echoing the research of Patil & Kulkarni in 2022, who similarly confirmed that perceived severity and perceived susceptibility had no significant effect on the adoption of health chatbots. This suggests that current users in China are skeptical about the expertise of bots in psychological healing, and because the technology is not yet in its infancy, chatbots are not the first choice for users when they are experiencing real psychological disorders such as depression.

Higher anthropomorphism of health chatbots would significantly increase the perceived benefits to users and decrease their privacy concerns, which would improve their willingness to seek help from chatbots. This study reveals that in the future, we can further promote the function of the psychological healing of chatbots, and improve the anthropomorphism and privacy protection, which will bring benefits to a large number of users who have psychological disturbances. Through the encouragement and guidance of health chatbots, they are more likely to open their minds and seek more correct curing opportunities positively in real life.

7. Conclusion

This study was based on users' assumptions about disease conditions, regardless of whether or not they suffered from such conditions, which, while it may reduce the impact of uncontrollable factors in the experiment, would reduce ecological validity. Considering that our study only shot a sample size of 268, the sample data could be expanded in the future to improve the generalizability of the results. Future research could be devoted to exploring self-disclosure of chatbots, level of personalization, and level of empathy on the perceived trust of humans.

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