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Empowering users with medical artificial intelligence technologies

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EMPOWERING USERS WITH MEDICAL ARTIFICIAL INTELLIGENCE TECHNOLOGIES

Research Paper

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Abstract

Medical AI technologies promise to empower their users in managing their health. We develop a research model aiming to explain the role of user empowerment and resistance on users' continuous use intention of medical AI technologies. The model was tested with data from 306 users of the Left-Hand Doctor self-diagnosis chatbot in China. The analyses indicate that users value the emotional support, responsiveness and accessibility of the chatbot. These features provide a strong explanation of user empowerment which in turn supports continuous use intention. While resistance to medical AI technologies negatively affects continuous use intention, it does not weaken the positive effects of empowerment. The research contributes to our knowledge of what user empowerment means and how it can support sustainable engagement with medical AI technologies. It further guides developers to more comprehensively consider similar user experience elements and positive outcomes of AI technologies in other application areas.

Keywords: chatbots, user empowerment, digital health, continuous use intention.

1 Introduction

Facing a shortage of medical professionals, artificial intelligence (AI) and other healthcare information technologies are becoming one of the frontlines to renovating healthcare services (Bardhan et al., 2020; Sipior, 2020; Zhao et al., 2018). For example, rather than visiting a doctor in person, alternative routes include online consultations and social support groups (Sharma and Khadka, 2019). Medical chatbots constitute a major implementation of conversational AI technologies in healthcare (Miller et al., 2020; Nadarzynski et al., 2019). Chatbots hold tremendous potential to reshape how individuals obtain medical support without traditional constraints of time and space (Xiao and Kumar 2021). Users can commonly perform a preliminary symptom assessment and obtain prompt advice on the type and amount of further care they might need to seek. Chatbots also simplify the information searching process compared to online patient platforms or the 'Google' doctor, with more relevant results through conversations that mimic the ones with human doctors (Laumer et al., 2019; Valtolina et al., 2020).

Research has investigated the interaction dynamics and performance expectations of conversational AI chatbots for customer service and workplace assistants (Elshan et al., Zierau, 2022; Gkinko and Elbanna, 2022; Schanke et al., 2021; Schuetzler et al., 2020; Vassilakopoulou et al., 2022). In the context of healthcare, although chatbots can be integrated into a powerful spectrum of tools to facilitate self-care management, our understanding of the potential impact is limited from the user perspective. In theory, medical AI technologies like chatbots can empower users to manage their own health with an additional, immediately available tool for self-diagnosis and advice. Besides, prior literature reveals that empowered users of medical technologies position themselves as active participants in their health management and there is a strong positive association between information support and positive outcomes for users (Brady et al., 2017; Johnston et al., 2013). However, few studies have examined the features that contribute to the development of user-perceived empowerment.

Despite the strong potential for empowering users, our knowledge of the long-term use of chatbots and similar medical AI technologies remains in preliminary stages. Users might be reluctant to engage with medical AI chatbots due to concerns about chatbots' performance risk and communication efficacy (Lai et al., 2021; Nadarzynski et al., 2019; Schuetzler et al., 2020; Valtolina et al., 2020). Other users might be attracted to the immediately available information that chatbots can provide while their degree of confidence on how to act on this information is still evolving (Fan et al., 2021; You, et al., 2021). These observations highlight the importance of investigating how users can engage sustainably with medical AI technologies with regard to the elements and outcomes of empowerment.

Considering the above research gaps, this study deployes the psychological empowerment theory and adaptes it to the medical AI context. The aim is to illustrate how AI chatbots enable individuals to achieve positive outcomes through the creation of motivating conditions for health management and the enhancement of personal efficacy (Conger and Kanungo, 1988). In particular, this study aims to address the research question *(1) what are the antecedents of user empowerment in relation to the features of medical AI chatbots, and how does user empowerment affect users' continuous use intention?*

Furthermore, past research has shown that medical AI technologies like chatbots might form an unclear proposition to users due to a limited understanding of their advanced algorithmic features and the extent to which they can exert medical authority on critical healthcare issues (Palanica et al., 2019; You et al., 2021), resulting in users' resistance to medical AI (Longhi et al. 2020). Taking into account user resistance, this study also aims to address the question (*2) how does medical AI resistance alter the role of user empowerment on continuous engagement?*

After introducing psychological empowerment in the context of healthcare technologies, we present our conceptual framework and hypotheses in the following section. To empirically test the hypotheses, we collected data from 306 users of the Left-Hand Doctor app which is a popular medical chatbot in China. The survey findings inform on the experience of repeated users, their perceptions of empowerment as an outcome of using the Left-Hand Doctor chatbot and its relationship with continuous use intention. We find that users value the emotional support, responsiveness and accessibility of the chatbot while information support was not found to be significant. These features provide a strong explanation of user empowerment which in turn explains continuous use intention. We also find that resistance to medical AI technologies negatively affects continuous use intention without however moderating the relationship between user empowerment and continuous use intention. We discuss our theoretical and practical contributions along the lines of improving user engagement with medical AI technologies. We further discuss how user empowerment can enhance the potential and positive outcomes of AI technologies in other application areas.

2 Theoretical Background and Hypotheses

Thomas and Velthouse (1990) define psychological empowerment as increased intrinsic task motivation. Their multifaceted approach to empowerment entails four cognitions – further illustrated by Spreitzer (1995, p. 1443) as: (1) *meaning* that represents "the value of a work goal or purpose, judged in relation to an individual's own ideals or standards"; (2) *competence* as "an individual's belief in his or her capability to perform activities with skill", analogous to self-efficacy and effort-performance expectancy; (3) *self-determination* that indicates "an individual's autonomy in the initiation and continuation of work behaviours and processes"; (4) *impact* that stands for "the degree to which an individual can influence strategic, administrative, or operating outcomes at work".

Originating from the organizational context, psychological empowerment has been applied in areas like consumer empowerment (Davies and Elliott, 2006) and empowerment through value co-creation in online brand community (Hsieh et al., 2022). In healthcare, the concept of patient empowerment has been introduced to "allow patients to shed their passive role and play an active part in the decision-making process about their health and quality of life" (Castro et al., 2016, p. 1924). It refers to "the educational process designed to help patients develop the knowledge, skills, attitudes, and degree of self-awareness necessary to effectively assume responsibility for their health-related decisions" (Feste and Anderson 1995, p. 139). Empowered patients represent those who have mastered knowledge about their health condition and believe in their ability to influence their health positively with self-management skills (Aujoulat et al., 2007).

Digital health technologies like mobile apps and forums empower their users through self-monitoring tools, peer support systems and relevant health education (Kuijpers et al., 2013; Lober and Flowers, 2011; Nelson, et al, 2016; Petrič, et al., 2017; Sharma and Khadka, 2019). For example, participants in online health communities were found to display higher self-esteem, self-efficacy and improved confidence alongside services offered in formal healthcare settings (Atanasova and Petric, 2019). Equally, users of devices like activity trackers reported increased empowerment via health management using goal-setting and feedback mechanisms (Nelson et al., 2016).

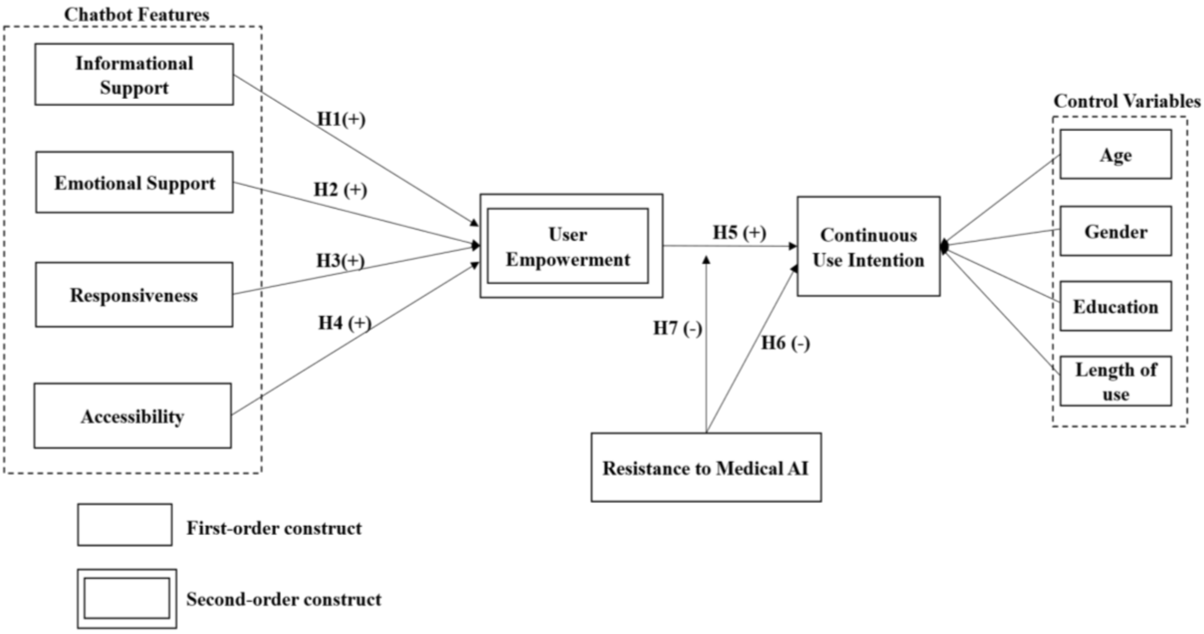

Figure 1. Research model.

Our approach aims to explain user empowerment with medical AI technologies via the underlying interaction elements that define the active motivational orientation for health self-management. For example, applications like chatbots enable users to immediately receive medical advice and support in ways that are potentially transformational compared to human doctors or other digital health technologies. We present the model shown in Figure 1 to associate the interaction elements of chatbots with their effects on user empowerment. In line with our research questions, after attempting to explain user empowerment, we focus on its relationship with continuous use intention and the moderating role of resistance to medical AI technologies.

2.1 Antecedents of user empowerment

Informational support in this study refers to providing advice on health issues requested by the user. Information is one of the most fundamental ingredients of empowerment (Kanter, 1989). Patients become empowered when their competencies to understand health conditions and their belief in their ability to effectively manage personal health are significantly increased (Aujoulat et al., 2007). Critical to the establishment of such ability is the useful information and feedback obtained through a variety of channels including online communities (Barak et al., 2008; Johnston et al., 2013) and wearable devices (Nelson et al., 2016). The array of online information can facilitate empowerment by fuelling users' medical competence perception and their intention to take a proactive role in their medical decision (Brady et al., 2017).

Based on existing evidence about the relationship between information and empowerment, we contend that the information support a user gets from a medical AI chatbot can be transferred to a greater understanding and ability to make informed decisions (Johnston et al., 2013), which are essential elements of user empowerment. Following this line of reasoning, we hypothesise:

***H1:** Higher perceptions of informational support offered by chatbots will be associated with higher user empowerment.*

Emotional support in this context refers to the psychosocial support users received from interacting with medical AI technologies to reduce fear and anxiety. The main purpose for people seeking healthcare services is to receive proper treatment for their health conditions. However, the diagnosis and treatment of a health problem will often cause significant emotional trauma including feelings of vulnerability, depression, loss of control, anxiety and uncertainty (Huang et al., 2019). In most cases, the lack of medical knowledge and feelings of being emotionally vulnerable caused by loss of control will impose major challenges on individuals to overcome a health problem (Johnston et al., 2013). Over time, people tend to have an increasing need of obtaining support from healthcare providers (Zhou et al., 2017).

To cope with these issues, patients have gradually turned to online health communities where they can obtain peer support and insights from the experiences of people with similar conditions. These communities have been identified as an effective way to complement healthcare services (Huang et al., 2019). Research shows that social support seeking is related to the alleviation of perceived uncertainty about disease diagnosis and treatment (Liu et al., 2020). Traditionally, emotional support is delivered through face-to-face interaction with healthcare providers (Zhou et al., 2017). In the chatbot use scenario, we presume that reassurance could help restore users' emotional stability, which will be translated to higher levels of perceived empowerment. Therefore, we hypothesise:

***H2:** Higher perceptions of emotional support offered by chatbots will be associated with higher user empowerment.*

A critical feature of mobile health applications is their immediate availability and responsiveness to user requests in contrast to services that require human presence. Responsiveness is an established dimension of service quality in information system success (Delone & Mclean, 2003). Nordheim et al. (2019) indicate that quick responses can lead to stronger consumer trust in customer service chatbots – an association that has also been identified in online health communities (Mpinganjira, 2018). Hsieh et al. (2022) show that user-perceived responsiveness in online brand communities can facilitate the formation of psychological empowerment because an encouraging environment characterised by responsive interactions stimulates user confidence. Essentially, responsiveness denotes a caring and supportive attitude which can help increase trust and reduce risk perception (Mpinganjira, 2018). Thereby, if a chatbot displays higher levels of responsiveness, users will feel supported whenever they need help, thus developing higher confidence in their capability to handle health issues. Accordingly, we hypothesise:

***H3**: Higher perceptions of chatbot responsiveness will be associated with higher user empowerment.*

Hsieh et al. (2022) identify that system quality can improve consumers' psychological empowerment and satisfaction. Closely linked to responsiveness, accessibility is a strong antecedent of system quality and, in our study, refers to the ease with which information can be accessed or extracted from chatbot applications (Wixom and Todd, 2005). Accessibility can reduce the perceived risks of using the health information available online (Liang and Xue, 2013). With automated, ubiquitous services provided by chatbots, individuals can easily acquire some level of health advice and support without the presence of human doctors. The accessibility of chatbots is an important feature as their implementation can be achieved in a standalone format as mobile applications or integrated into multiple channels like websites and social media like Facebook Messenger or WeChat. Accessibility aligns with the core proposition to support users most conveniently according to their digital experiences and preferences. In particular, multi-channel accessible chatbots empower users by enabling them to impact their health condition in a way that is compatible with modern digital lifestyles, which differs from the traditional way of obtaining assistance from healthcare professionals in person (Brady et al., 2017). Thus, we hypothesise:

H4: *Higher perceptions of chatbot accessibility will be associated with higher user empowerment.*

2.2 Sustained use as an outcome of user empowerment

Previous research has confirmed that empowerment reflected in the increased self-determination and efficacy can determine the initiation of activity and persistent task involvement (Füller et al., 2009). Self-management and participation in decision-making processes are recognised as important outcomes of empowerment in healthcare (Aujoulat et al., 2007). The sense of empowerment also leads to inner strength (Castro et al., 2016) and positively relates to the psychological attachment to self-made health goals (Nelson et al., 2016), which drives sustained engagement with health technologies. Furthermore, prior study shows that patient empowerment is positively associated with the continuous intention of using online social support groups for chronic disease management (Sharma and Khadka, 2019).

Therefore, we assume that empowered users of medical chatbots develop a high sense of self-efficacy and a strong sense of ownership for their own health conditions (Feste and Anderson, 1995), which in turn leads to active healthcare engagement (Sak et al., 2017; Sharma and Khadka, 2019). It is plausible to contend that in order to main the empowerment perception, users will tend to continue using medical chatbots. Likewise, we have:

H5: *User empowerment has a positive impact on users' continuous use intention of chatbots.*

2.3 The moderating role of resistance to medical AI

Resistance to change is a common dynamic occurring when new technologies are introduced to establish a new normal for performing a task (Valtolina et al., 2020). It happens due to the uncertainty and sunk costs incurred by implementing the new technology (Kim, 2011). Consumer research has shown that loss of control and individuality induce negative feelings about employing autonomous shopping systems (de Bellis et al., 2020). This is consistent with the concern that healthcare services deploying AI features are less able to account for users' unique characteristics and circumstances, which results in consumers' resistance to medical AI (Longoni et al., 2019). Negative attitudes towards AI technologies were similarly detected in interactions with fully autonomous vehicles (Hengstler et al., 2016). Due to low familiarity with AI-enabled services, users might be hesitant to build a clear case for their confidence in chatbots' medical authority despite valuing their experience (You et al., 2021).

User resistance often becomes a significant factor in information systems implementation because resisting users may spend little time and effort with a new system and such resistance may persist after initial use (Hsieh and Lin, 2018). Following this line of reasoning, we point to the potentially critical role of resistance to medical AI services that will hinder users' sustained use of chatbot services even after having experienced potential psychological benefits from initial use. We further identify a potential moderating relationship between user empowerment and continuous use intention as:

H6: *Higher medical AI resistance will be associated with lower continuous use intention of chatbots.*

H7: *Higher medical AI resistance will negatively moderate the relationship between user empowerment and the continuous use intention of chatbots.*

3 Methodology

To empirically validate the research model, we collaborated with a leading healthcare AI company that operates a widely deployed self-diagnosis chatbot called Left-Hand Doctor (LHD) in China (Fan et al., 2021). The LHD incorporates techniques like knowledge graphs, deep learning and natural language processing to build interactive dialogue with users. The latest version of the LHD contains features of symptom assessment, medicine instructions and Covid-19 support. Users can use text or voice to input their symptoms and, following rounds of conversation, they obtain a report that explains potential conditions and treatment suggestions. The application has been adopted by hospitals as well as individual users.

The questionnaire was designed around each latent construct of our research interest. Three items measuring informational support and four items measuring emotional support were developed based on Lin et al. (2015), Zhou (2018) and Johnson and Lowe (2015). Four items from Lai and Wang (2015) were deployed to measure responsiveness. Three items adapted from Liang and Xue (2013) were used to measure accessibility. Continuous use intention was measured using items adapted from Venkatesh and Davis (2000). The items for medical AI resistance were adopted from Ye et al. (2019). The four dimensions of empowerment (meaning, impact, self-determination, competence) were measured with multiple items (Spreitzer, 1995). Three items per dimension were utilized as this three-item measure has been proven to be stable and reliable (Spreitzer et al., 1997). Because of the non-interchangeability among the four dimensions and the different significance magnitude of the path coefficients, we treated user empowerment as a first-order reflective second-order formative construct as per Hsieh et al. (2022). Participants were asked to evaluate each statement in the questionnaire based on their use experience with LHD. Seven-point Likert response scales anchoring from 1 (strongly disagree) to 7 (strongly agree) were used to measure all items of the major latent constructs. Further questions collected information about the demographic background and length of use of the application. The questions were first developed in English and then translated into Chinese with the help of a researcher who is fluent in both languages. Another researcher was invited to translate the Chinese questionnaire back into English. The two versions of the English questionnaire were compared and no significant differences were observed.

The survey design and data collection were independently completed by the team of authors. The company made available a randomly selected sample of 2,000 registered users as potential study participants. Users were invited via the WeChat account linked to their mobile number and received a small monetary reward (£3) for completing the questionnaire. Data collection lasted four months from September 2021 to December 2021. We only considered completed questionnaires from participants who had used the chatbot at least twice and those who provided relevant answers for the last open-ended question (Which aspects do you think the LHD should improve?), leaving us a total of 306 valid questionnaires out of the 345 responses we received, with a survey response rate of 15.3%. Table 1 shows the demographics of participants.

We first examined potential biases associated with the survey data. We assessed nonresponse bias by comparing the demographic variables between the first 100 respondents and the last 100 respondents (Liang et al. 2019). The T-test showed that the two groups do not differ in age (p = 0.471). Chi-square tests showed that these two groups do not differ in gender (p = 0.659) and education (p = 0.274) as well, indicating that nonresponse bias is not a likely issue in the dataset.

Subsequently, we took several steps to detect common method bias (CMB) that our dataset might suffer from. Instrumental design and data collection procedures were used to create a psychological separation between dependent variables and independent variables. In addition, Harman’s one-factor test was conducted and the result showed that the first factor extracted accounted for 36.93% of the total variance in the items – less than 50% indicates that common method variance is not severe (Podsakoff and Organ, 1986). Furthermore, before collecting the data, we adopted three questions from the Social Desirability Scale (Fischer and Fick, 1993) (*SDS1: I have never intensely disliked anyone; SDS2: When I don’t know something I don’t at all mind admitting it; SDS3: I am always courteous, even to people who are disagreeable.*) to work as a measured latent marker variable. In SmartPLS, we pointed the marker variable to both independent and dependent variables and then compared the new R^2 values (0.632 for user empowerment and 0.461 for continuous intention) of the two endogenous variables with the ones without the marker variable (Rönkkö and Ylitalo, 2011). Since the change is less than 10%, we confirm the observation that common method variance is not an issue. Considering the exploratory objectives of this research together with the formative operationalisation of user empowerment and non-normality of the multivariate dataset, SmartPLS 3.0 was used as an appropriate tool for data analysis.

Demographics		**Frequency**	**Percentage**
Gender	Male	175	57.2
	Female	131	42.8
Age	20 or below	35	11.4
	21-30	186	60.8
	31-40	59	19.3
	41-50	18	5.9
	51 or above	8	2.6
Education	High school or below	44	14.4
	College	57	18.6
	Bachelor’s degree	139	45.4
	Master’s degree	54	17.6
	PhD.	12	3.9
Length of use	Less than 1 month	112	36.6
	1 month – 3 months	65	21.2
	3 months – 6 months	57	18.6
	More than 6 months	72	23.5

Table 1. Descriptive statistics of respondents (N=306).

Item	**Loadings**	**AVE**	**rho_A**
Informational support (Mean = 5.301, S.D. = 1.213, α = 0.854, CR = 0.911, VIF = 2.026)		0.774	0.855
IS1: The Left-Hand Doctor (LHD) can give me preliminary diagnoses and explanations before I rush to a doctor.	0.903		
IS2: LHD can offer me tentative treatment suggestions to cope with my conditions.	0.892		
IS3: LHD can help me understand symptoms and guide me towards what I need to say to a doctor.	0.844		
Emotional support (Mean = 4.957, S.D. =1.314, α = 0.892, CR = 0.925, VIF = 2.400)		0.756	0.897
ES1: LHD makes me feel more at ease.	0.890		
ES2: LHD can reassure me about my health conditions.	0.904		
ES3: LHD can alleviate my fears about my symptoms.	0.839		
ES4: LHD makes me feel supported.	0.843		
Responsiveness (Mean = 5.681, S.D. =1.177, α = 0.863, CR = 0.907, VIF = 2.674)		0.708	0.863
RES1: LHD can provide trusted health information very quickly.	0.849		
RES2: I can use LHD to assess my symptoms anytime from anywhere.	0.855		
RES3: LHD can respond to my requests in time.	0.838		
RES4: LHD is always available when I need medical advice.	0.824		
Accessibility (Mean= 5.726, S.D. =1.175, α = 0.782 , CR = 0.872, VIF = 1.580)		0.695	0.785
AC1: I find LHD easily accessible and portable on my phone.	0.795		

AC2: LHD can be easily accessed through multi-channels like WeChat, App, website, etc.	0.881		
AC3: I have many different ways to use the service provided by LHD.	0.822		
Competence (Mean = 5.157, S.D.=1.228, α = 0.843, CR = 0.905, weight = 0.342***, VIF = 2.674): After using LHD,		0.761	0.844
COM1: I am more confident about my ability to manage my personal healthcare.	0.884		
COM2: I have mastered the medical knowledge necessary to manage my personal healthcare.	0.843		
COM3: I am self-assured about my capabilities to perform personal healthcare management.	0.891		
Self-determination (Mean= 5.390, S.D.=1.157, α = 0.839, CR = 0.903, weight = 0.341***, VIF = 2.741): After using LHD, I think		0.756	0.839
SD1: I have significant autonomy in determining how I manage my personal healthcare.	0.877		
SD2: I can make better decisions on whether or when to consult a doctor.	0.860		
SD3: I can decide on my own how to go about managing my health.	0.872		
Impact (Mean= 4.991, S.D.=1.230, α = 0.824, CR = 0.895, weight = 0.253***, VIF = 1.539) : After using LHD, I think		0.739	0.826
IMP1: I have a great deal of influence on what happens with my health.	0.844		
IMP2: I have a great deal of control over what happens with my health.	0.842		
IMP3: My impact on my personal health is large.	0.893		
Meaning (Mean = 5.846, S.D.=1.008, α = 0.775, CR = 0.868, weight = 0.270***, VIF = 2.093) : After using LHD,		0.688	0.780
MN1: I feel personal healthcare management is very important to me.	0.853		
MN2: I consider the activities I do for my health to be meaningful to me.	0.829		
MN3: I feel that the use of AI doctors for managing my health is meaningful.	0.805		
Resistance to Medical AI (Mean= 4.930, S.D.= 1.345, α = 0.851, CR = 0.894, VIF = 1.061)		0.680	0.879
RMAI1: I would choose to rely more on humans rather than on AI.	0.726		
RMAI2: I prefer to communicate with humans rather than AI.	0.882		
RMAI3: I trust advice from human doctors more rather than AI.	0.867		
RMAI4: I don’t want AI to change how I obtain healthcare services because it is unfamiliar to me.	0.814		
Continuous use intention (Mean= 5.543, S.D.=1.241, α = 0.896, CR = 0.935)		0.828	0.898
CI1: I intend to continue using LHD in the near future.	0.918		
CI2: I expect to continue using LHD in the near future.	0.914		
CI3: I would like to continue using LHD in the near future.	0.898		
Note: S.D. (standard deviation), AVE (Average Variance Extracted); CR (Composite Reliability); α (Cronbach’s alpha); rho_A (Dijkstra-Henseler’s ρA); VIF is inner VIF value.			

Table 2. Measurement model assessment

4 Results

4.1 Measurement model and structural model estimation

All item loadings are significant ($p<0.05$) and greater than 0.708 (Chin, 1998). The indicator reliability for all items is above 0.6 except MAIRB1 (0.53), showing that good indicator reliability is supported (Hulland, 1999). Cronbach's alpha (α), composite reliability (CR) and Dijkstra-Henseler's ρA (rho_A) were used to assess internal consistency reliability. As shown in Table 2, the value of Cronbach's alpha for all constructs is within 0.7 - 0.9 while CR values and rho_A are all above 0.7 (Bagozzi and Yi, 1988; Dijkstra and Henseler, 2015), therefore indicating high levels of internal consistency reliability for all reflective variables.

Each latent variable's Average Variance Extracted (AVE) was evaluated to check for convergent validity. As shown in Table 2, all of the AVE values are greater than the required threshold of 0.5 (Bagozzi and Yi, 1988), establishing convergent validity. We examined constructs' discriminant validity in two ways. We first obtained the loadings and cross-loadings of all items, which shows every indicator's outer loading on the associated construct is greater than all of its loadings on other constructs. Second, the square root of AVE in each latent variable is larger than other correlation values among the latent variables, so the Fornell-Larcker Criterion is satisfied (Fornell and Larcker, 1981).

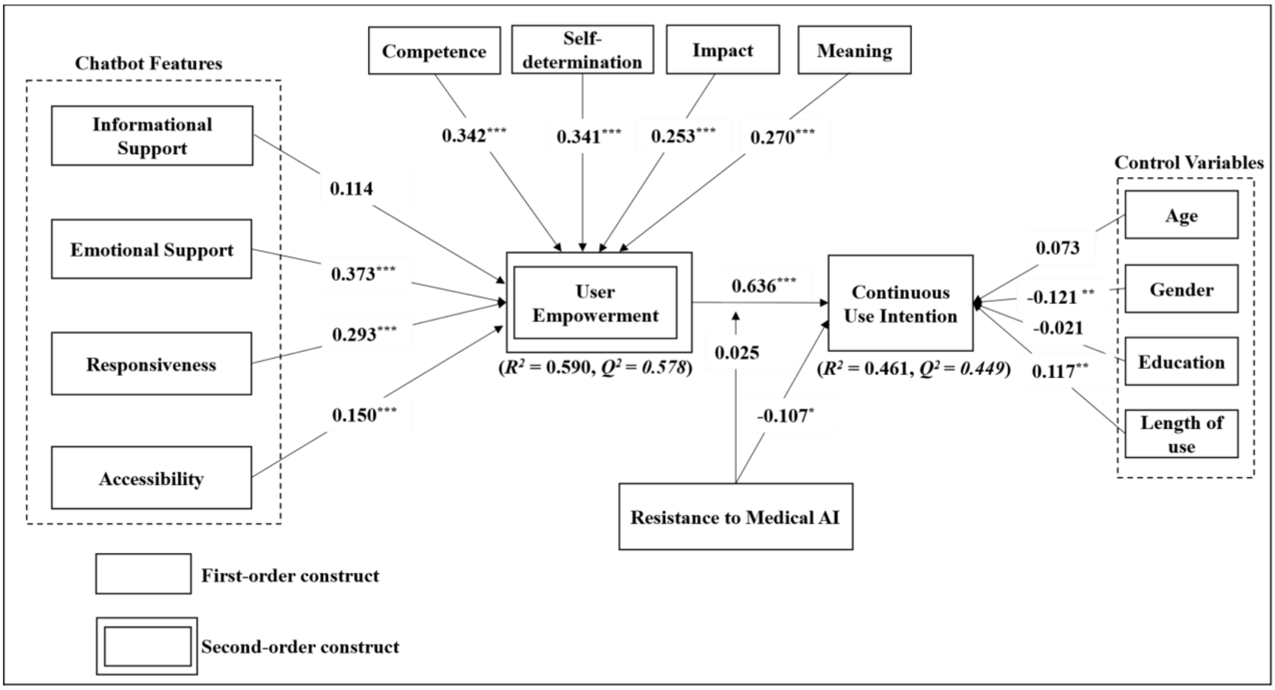

Figure 2. Research model results.
*(note: * p <0.05, * *p <0.01, ***p <0.001, Q^2 is the Stone-Geisser's predictive relevance)*

The structural model performs assessments for path coefficients, the significance of the coefficients, the coefficient of determination (R^2), and the effect size (f^2) of predictors (Benitez et al., 2020; Hsieh et al., 2022). In SmartPLS, the path coefficients and related t-statistics are calculated via the bootstrapping procedure. To ensure the stability of the results, we used 5,000 bootstrap subsamples. We first checked the potential collinearity issue of the inner model via the VIF values. All latent variables' VIF values are below 3.3 (Kock and Lynn, 2012), suggesting that there is no indication of collinearity between each set of predictors. For path coefficients, from Figure 2, it is clear that the chatbot's features except for informational support all have a significant positive impact on the user's empowerment development, thus supporting H2, H3, and H4. User empowerment is positively related to the user's intention to continue using the chatbot (H5 supported). Medical AI resistance is negatively associated with continuous use intention (H6 supported), but the moderation effect (H7) is not supported. As for the control variables, only gender and length of use have significant effects on continuous use intention.

The R^2 values of the two endogenous constructs are 0.590 and 0.461, suggesting that emotional support, responsiveness, and accessibility can jointly explain 59% of the variance of user empowerment, and that user empowerment, resistance to medical AI, and controls explain 46.1% of the variance of continuous use intention. A substantive, moderate, and weak predictive power correspond to the R^2 threshold of 0.67, 0.33, and 0.19, respectively (Chin, 1998). According to this rule, the predictive power of our model for both user empowerment and continuous use intention locates somewhere between moderate and substantive. We also examined Stone-Geisser's predictive relevance (Q^2) for user empowerment (0.578) and continuous use intention (0.449), both much larger than zero (Chin, 1998). Hence, the proposed model has good predictive relevance for all endogenous variables.

Finally, we checked the f^2 and q^2 effect sizes derived from R^2 and Q^2 respectively to assess the effect of a specific exogenous construct on the endogenous construct if deleted from the model. As shown in Table 3, following Cohen's (1992) guidelines, emotional support has a medium to large effect size on user empowerment; responsiveness and accessibility both have a small to medium effect size on user empowerment.

4.2 Mediation analysis

The potential mediating effect of user empowerment on the linkage between the antecedents and continuous use intention was examined with the Preacher and Hayes (2008) two-step procedure. We used this procedure instead of Sobel's test because it does not have strict distributional assumptions (Hair et al., 2021). The analysis shows that no mediation exists for informational support and accessibility. For emotional support and responsiveness, the indirect effect is significant.

Hypothesis	**Path coefficient**	**p-value**	**t-value**	**Decision**	**95%CI LL**	**95%CI UL**	**f^2**	**q^2**
H1: IS → Empowerment	0.114	0.066	1.839	Not Supported	-0.013	0.227	0.016	0.005
H2: ES → Empowerment	0.373***	0.000	6.914	Supported	0.263	0.477	0.179	0.171
H3: RES→ Empowerment	0.293***	0.000	5.433	Supported	0.189	0.396	0.100	0.092
H4: AC→ Empowerment	0.15***	0.000	3.573	Supported	0.064	0.23	0.038	0.019
H5: Empowerment → CI	0.636***	0.000	15.25	Supported	0.554	0.715	n/a	n/a
H6: RMAI → CI	-0.107*	0.02	2.322	Supported	-0.207	-0.02	0.023	0.005
H7: RMAI * Empowerment → CI	0.025	0.602	0.521	Not supported	-0.076	0.112	0	0

Note: $f^2 = (R^2 \text{ included} - R^2 \text{ excluded}) / (1 - R^2 \text{ included})$; $q^2 = (Q^2\text{included} - Q^2\text{excluded}) / (1 - Q^2\text{included})$; Q^2 is the Stone-Geisser's predictive relevance. According to Cohen (1992), f^2 values of 0.02, 0.15, and 0.35 are interpreted as small, medium, and large effect sizes. $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 3. Hypothesis testing results.

We further examined the magnitude of mediation through the use of total effect and variance account for (VAF). A 26.5% of emotional support's effect on continuous use intention can be explained via the user empowerment mediator. Since the VAF is greater than the 20% threshold level but below 80% (Hair et al., 2021), user empowerment is argued to have a partial mediation effect on the emotional support → continuous use intention linkage. Moreover, 28.6% of responsiveness's effect on continuous use intention can be explained via the user empowerment mediator and the magnitude is partial as well.

5 Discussion

5.1 Key findings

The findings offer a positive case and supportive explanation of empowerment as a pathway to sustain users' engagement with healthcare chatbots like the Left-Hand Doctor. Consequently, increased levels of psychological empowerment provide an important factor that reinforces intentions to continue using such a chatbot. User empowerment is strongly explained by emotional support, responsiveness and accessibility. Despite the lack of human interaction, responsive delivery and easily accessible information made users feel reassured and reduced stress levels eventually resulting in a sense of support. Such functional and system features work all together to create a sense of support that users can get at any time from anywhere. When researchers studied empowerment in online health communities, they did not find a significant association between the emotional elements of the social support users obtained and their individual empowerment levels (Johnston et al., 2013).

In contrast, the relationship between informational support and user empowerment lacks significance in this study. While it is common for people to use the internet to search for health-related information (e.g. Atanasova and Petric, 2019; Johnston et al., 2013; Sharma and Khadka, 2019), potential lack of trust, limited added value or other factors affected the perceived informational support received from the Left-Hand Doctor chatbot. One possible explanation lies in the fact that chatbots perfprming the role of preliminary symptom assessments are not currently regarded as a major source of medical information. Digital and mobile health technologies already offer several sources of health information and advice through online communities, forums and medical websites (Brady et al., 2017). Such information comes from human providers with relatively clear accountability, in contrast to chatbots whose medical authority is not yet equally established (You et al., 2021). More studies can investigate how chatbots can become a critical additional source of information beyond emotional support.

Alternatively, the information users obtained through a specific symptom-checking process may be useful but not sufficient to confidently lead to a sense of empowerment. In a study by Fan et al. (2021), over half of the users of the same chatbot (Left-Hand Doctor) interacted with the application only once in a half-year period. Even though our respondents were selected because they had used the application at least twice, it is likely that more sustained engagement is required for users to acquire wider knowledge and skills. The development of empowerment may also relate to whether the experience confirmed user expectations. Research has shown that expectations prior to interacting with conversational AI technologies and feedback loops matter significantly (Grimes et al., 2021; Schuetzler et al., 2020). For example, if the diagnosis outputs confirm the ones provided by human doctors repeatedly, users will feel more confident and therefore empowered in their subsequent interactions.

As expected, resistance remains a significant source of lower continuous use intention even with experienced chatbot users. Our major finding informs that medical AI resistance does not affect the relationship between user empowerment and continuous use intention. This indicates that users do maintain scepticism about how novel AI technologies like chatbots will disrupt traditional healthcare services. However, this scepticism does not directly weaken our respondents' perceived empowerment or the effect that empowerment has on motivation to carry on using the chatbot. This encouraging finding suggests that, despite their early stages and inherent limitations like outcome uncertainty (Lai et al., 2021), medical AI technologies like chatbots can be assessed by users on their own merits. Current research has raised concerns about user resistance to medical services provided by AI (Longoni et al., 2019). Our findings suggest that positive user outcomes can come from system quality characteristics other than direct comparisons with human doctors. We propose that, instead of human replacement through automation, studies of user resistance to medical AI technologies should focus more on how technologies deliver on their own premise within the spectrum of options available to users.

5.2 Contributions and implications

The study contributes to an emerging stream of information systems research in human-AI interactions (e.g. Elshan et al., 2022; Gkinko and Elbanna, 2022; Schanke et al., 2021; Schuetzler et al., 2020; Vassilakopoulou et al., 2022), with a particular contribution to understanding how users benefit from conversational agents. We present a new theoretical perspective and empirical findings from users of an existing chatbot pplication in a real-world context. The findings show that chatbots like the Left-Hand Doctor have the potential to enhance the psychological empowerment of their users, despite scepticism surrounding AI for healthcare (Longoni et al., 2019). Empowerment stems from users' perceived emotional support as well as the characteristics of these new technologies in responsiveness and multi-platform accessibility. This reinforces the proposition of medical AI technologies like chatbots as tools that can be integrated with current healthcare systems to empower individuals with prompt support through preliminary symptom checking.

The study demonstrates the significance of system design characteristics as empowering features that play a crucial role in motivating sustained use intention (Elshan et al., 2022). The development of psychological empowerment as a theoretical lens to understand user outcomes in relation to the chatbot's features lead to expected (emotional support, responsiveness, accessibility) and less expected results (informational support). These features offer a strong predictive power of empowerment and, subsequently, the intention to keep using the chatbot. The contribution to users' continuous use intention with AI applications provides a new perspective as previous studies have primarily focused on the design characteristics, ethical concerns, acceptability, and early adoption (Laumer et al. 2019; Nadarzynski et al. 2019; Valtolina et al. 2020). In line with Vassilakopoulou et al. (2022), we show critical differences in the intended and actual impact of conversational agents, which in our study translated into users' focus on emotional rather than informational support as a pathway to empowerment.

Our further contribution lies in examining elements of psychological empowerment in relation to medical AI resistance. Although users' motivations to engage with chatbots and other intelligent agents do vary (Elshan et al., 2022; Gkinko and Elbanna, 2022), resistance remains a prominent underlying factor with even stronger effects in the medical AI context (Lai et al., 2021; Longoni et al., 2019). We found that hesitancy towards medical AI technologies may operate in isolation from user empowerment, at least in terms of explaining continuous use intention. This finding opens further opportunities to explore whether psychological and other positive outcomes can be achieved irrespective of users' expected sources of resistance and cognitive biases towards medical AI technologies.

In its practical implications, the study supports chatbot developers to better design and engage with users. In addition to clearly and transparently communicating the relative advantages of chatbots compared with other digital health solutions such as search engines (Laumer et al., 2019), developers should also cultivate user empowerment as a means of sustaining user attention and promoting features of chatbots that users value and motivate them the most. For instance, to improve the informational support conveyed in the form of symptom checking, developers could add features so that chatbots can deliver more personalised content based on users' unique circumstances and interactive learning. So far, the interaction between chatbots and users is always initiated by users with potentially urgent health needs. Developers could consider allowing chatbots to send notifications or other proactive educational materials to help users build their medical knowledge when possible. Developers should also continue their work to improve chatbots' ability to deliver emotional support, given that emotional support is an important antecedent of user empowerment and may not be acquired through healthcare technologies like online communities (Johnston et al., 2013). Non-verbal, social cues like emojis embedded in the interaction dynamics can enable chatbots to show greater empathy for users' health conditions.

6 Conclusion

The paper developed a conceptual model of user empowerment in relation to its antecedents and moderating relationship with user resistance in the medical AI context. The 306 experienced users of the Left-Hand Doctor chatbot helped us test the model and generate novel insights based on a real-word application. The findings support the proposition that medical AI technologies like chatbots can play a positive role in empowering users to manage their health. Although resistance to algorithmic and AI-based features remains a negative factor, the study showed that such resistance does not limit users' positive assessment of empowerment. Contrary to our expectations, support via information was not found to develop user empowerment; instead, we found a strong positive role of features like emotional support, responsiveness, and accessibility.

Limitations in the scope of the study and data collection need to be noted. The Left-Hand Doctor chatbot functions mainly as a self-diagnosis, symptom-checker, or general triage tool. Its potential to empower users may therefore differ considerably compared to more specialist AI applications that serve a specific population or condition (e.g. mental health support chatbots). Although self-diagnosis represents the most common scenario of medical AI chatbots, the findings remain bound to the characteristics and experiences of Left-Hand Doctor users. Studies with chatbots in more demographically diverse samples and use scenarios may provide different results. For instance, as highlighted by Brady et al. (2017), individuals at different points of their illness trajectory may have different support needs. It is worth exploring when and under what circumstances chatbots can bring the highest benefits of user empowerment. In addition, the predominance of young users of the Left-Hand Doctor may limit the generalisability of the findings. Future research focusing on more diverse user samples will provide further insights. Due to the high stakes of medical applications, more longitudinal studies and field experiments can identify the benefits and potential risks from using AI technologies.

Despite the use of control variables to capture these variations in the sample of respondents, it is possible that significant factors remain that may determine which users experience a sense of empowerment and when as part of their interaction with the Left-Hand Doctor. As Thomas and Velthouse (1990) note, context and personality traits collectively shape empowerment cognitions. Future research could delve into how user characteristics impact the level of psychological empowerment, which was beyond the scope of this study. Additional personal variables could include innovativeness, uncertainty avoidance, and user expectations of algorithmic services like explainability and trustworthiness.

We believe that insights from the study and further development of the empowerment theory can provide a useful basis for other consumer-facing AI applications. Future research can provide more links to show how sustained user engagement leads to stronger outcomes like empowerment and reduces the effects of resistance with AI applications. For example, while emotional support empowers users in the medical context, functional benefits like responsiveness and information quality might be more prominent in applications like customer service agents or smart home assistants.

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References

Atanasova, S., & Petric, G. (2019). Collective Empowerment in Online Health Communities: Scale Development and Empirical Validation. *Journal of Medical Internet Research*, *21*(11), e14392.

Aujoulat, I., d'Hoore, W., & Deccache, A. (2007). Patient empowerment in theory and practice: Polysemy or cacophony? *Patient Education and Counseling*, *66*(1), 13–20.

Bagozzi, R., & Yi, Y. (1988). On the evaluation of structure equation models. *Journal of the Academy of Marketing Science*, *16*(1), 74–94.

Barak, A., Boniel-Nissim, M., & Suler, J. (2008). Fostering empowerment in online support groups. *Computers in Human Behavior*, *24*(5), 1867–1883.

Bardhan, I., Chen, H., & Karahanna, E. (2020). Connecting Systems, Data, and People: A Multidisciplinary Research Roadmap for Chronic Disease Management. *Management Information Systems Quarterly*, *44*(1).

Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information & Management*, *57*(2), 103168.

Brady, E., Segar, J., & Sanders, C. (2017). Accessing support and empowerment online: The experiences of individuals with diabetes. *Health Expectations*, *20*(5), 1088–1095.

Castro, E. M., Van Regenmortel, T., Vanhaecht, K., Sermeus, W., & Van Hecke, A. (2016). Patient empowerment, patient participation and patient-centeredness in hospital care: A concept analysis based on a literature review. *Patient Education and Counseling*, *99*(12), 1923–1939.

Chin, W. W. (1998). The partial least squares approach to structural equation modelling. *Modern Methods for Business Research*, *295*(2), 295–336.

Cohen, J. (1992). Quantitative methods in psychology: A power primer. *Psychological Bulletin*, *112*(1), 155–159.

Conger, J. A., & Kanungo, R. N. (1988). The Empowerment Process: Integrating Theory and Practice. *The Academy of Management Review*, *13*(3), 471.

Davies, A., & Elliott, R. (2006). The evolution of the empowered consumer. *European Journal of Marketing*, *40*(9), 1106–1121.

de Bellis, E., & Venkataramani Johar, G. (2020). Autonomous Shopping Systems: Identifying and Overcoming Barriers to Consumer Adoption. *Journal of Retailing*, *96*(1), 74–87.

Delone, W. H., & Mclean, E. R. (2003). The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. *Journal of Management Information Systems*, *19*(4), 9–30.

Dijkstra, T. K., & Henseler, J. (2015). Consistent partial least squares path modeling. *MIS Quarterly*, *39*(2), 297–316.

Elshan, E., Zierau, N., Engel, C., Janson, A., & Leimeister, J. M. (2022). Understanding the Design Elements Affecting User Acceptance of Intelligent Agents: Past, Present and Future. *Information Systems Frontiers*, *24*(3), 699–730.

Fan, X., Chao, D., Zhang, Z., Wang, D., Li, ; Xiaohua, & Tian, F. (2021). Utilization of Self-Diagnosis Health Chatbots in Real-World Settings: Case Study. *Journal of Medical Internet Research*, *23*(1).

Feste, C., & Anderson, R. M. (1995). Empowerment: from philosophy to practice. *Patient Education and Counseling*, *26*, 139–144.

Fischer, D. G., & Fick, C. (1993). Measuring social desirability: Short forms of the Marlowe-Crowne social desirability scale. Educational and Psychological measurement, 53(2), 417-424.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50.

Füller, J., Mühlbacher, H., Matzler, K., & Jawecki, G. (2009). Consumer empowerment through internet-based co-creation. *Journal of Management Information Systems*, *26*(3), 71–102.

Gkinko, L., & Elbanna, A. (2022). The appropriation of conversational AI in the workplace: A taxonomy of AI chatbot users. *International Journal of Information Management*, 102568.

Grimes, G. M., Schuetzler, R. M., & Giboney, J. S. (2021). Mental models and expectation violations in conversational AI interactions. *Decision Support Systems*, *144*, 113515.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Sage publications.

Hengstler, M., Enkel, E., & Duelli, S. (2016). Applied artificial intelligence and trust-The case of autonomous vehicles and medical assistance devices. *Technological Forecasting and Social Change*, *105*, 105–120.

Hsieh, P. J., & Lin, W. Sen. (2018). Explaining resistance to system usage in the PharmaCloud: A view of the dual-factor model. *Information & Management*, *55*(1), 51–63.

Hsieh, S. H., Lee, C. T., & Tseng, T. H. (2022). Psychological empowerment and user satisfaction: Investigating the influences of online brand community participation. *Information and Management*, *59*(1), 103570.

Huang, K. Y., Chengalur-Smith, I. S., & Pinsonneault, A. (2019). Sharing is caring: Social support provision and companionship activities in healthcare virtual support communities. *MIS Quarterly*, *43*(2), 395–423.

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: a review of four recent studies. *Strategic Management Journal*, *20*, 195–204.

Johnson, D. S., & Lowe, B. (2015). Emotional Support, Perceived Corporate Ownership and Skepticism toward Out-groups in Virtual Communities. *Journal of Interactive Marketing*, *29*(C), 1–10.

Johnston, A. C., Worrell, J. L., Gangi, P. M. D., & Wasko, M. (2013). Online health communities: An assessment of the influence of participation on patient empowerment outcomes. *Information Technology and People*, *26*(2), 213–235.

Kanter, R. M. (1989). The new managerial work. *Harvard Business Review*, *89*(6), 85–92.

Kim, H. W. (2011). The effects of switching costs on user resistance to enterprise systems implementation. *IEEE Transactions on Engineering Management*, *58*(3), 471–482.

Kock, N., & Lynn, G. S. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for Information Systems*, *13*(7), 546–580.

Kuijpers, W., Groen, W. G., Aaronson, N. K., & Van Harten, W. H. (2013). A Systematic Review of Web-Based Interventions for Patient Empowerment and Physical Activity in Chronic Diseases: Relevance for Cancer Survivors. *Journal of Medical Internet Research*, *15*(2).

Lai, J. Y., & Wang, J. (2015). Switching attitudes of Taiwanese middle-aged and elderly patients toward cloud healthcare services: an exploratory study. *Technological Forecasting and Social Change*, *92*, 155–167.

Lai, Y., Lioliou, E., & Panagiotopoulos, P. (2021). Understanding Users' Switching Intention to AI-powered Healthcare Chatbots. In *European Conference on Information Systems*. Research Papers 51.

Laumer, S., Maier, C., Tobias Gubler, F., & Tobias, F. (2019). Chatbot acceptance in healthcare: explaining user adoption of conversational agents for disease diagnosis. In *Proceedings of the 27th European Conference on Information Systems,* Stockholm & Uppsala, Sweden, June 8-14, 2019.

Liang, H., & Xue, Y. (2013). Online health information use by disabled people: The moderating role of disability. In *Thirty Fourth International Conference on Information Systems, Milan 2013* (pp. 1–16).

Liang, H., Xue, Y., Pinsonneault, A., & Wu, Y. A. (2019). What users do besides problem-focused coping when facing IT security threats: An emotion-focused coping perspective. MIS quarterly, 43(2), 373-394.

Lin, T. C., Hsu, J. S. C., Cheng, H. L., & Chiu, C. M. (2015). Exploring the relationship between receiving and offering online social support: A dual social support model. *Information and Management*, *52*(3), 371–383.

Liu, N., Tong, Y., & Chan, H. C. (2020). Dual effects of social support seeking in patient-centric online healthcare communities: A longitudinal study. *Information and Management*, *57*(8), 103270.

Lober, W. B., & Flowers, J. L. (2011). Consumer empowerment in health care amid the internet and social media. *Seminars in Oncology Nursing*, *27*(3), 169–182.

Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to Medical Artificial Intelligence. *Journal of Consumer Research*, *46*(4), 629–650.

Miller, S., Gilbert, S., Virani, V., & Wicks, P. (2020). Patients' utilization and perception of an artificial intelligence-based symptom assessment and advice technology in a British primary care waiting room: exploratory pilot study. *Journal of Medical Internet Research*, *7*(3), e19713.

Mpinganjira, M. (2018). Precursors of trust in virtual health communities: a hierarchical investigation. *Information and Management*, *55*(6), 686–694.

Nadarzynski, T., Miles, O., Cowie, A., & Ridge, D. (2019a). Acceptability of artificial intelligence (AI)-led chatbot services in healthcare: a mixed-methods study. *Digital Health*, *5*, 1–12.

Nelson, E. C., Verhagen, T., & Noordzij, M. L. (2016). Health empowerment through activity trackers: An empirical smart wristband study. *Computers in Human Behavior*, *62*, 364–374.

Nordheim, C. B., Følstad, A., & Bjørkli, C. A. (2019). An Initial Model of Trust in Chatbots for Customer Service—Findings from a Questionnaire Study. *Interacting with Computers, 31*(3), 317–335.

Palanica, A., Flaschner, P., Thommandram, A., Li, M., & Fossat, Y. (2019). Physicians' perceptions of chatbots in health care: Cross-sectional web-based survey. *Journal of Medical Internet Research, 21*(4), 1–10.

Petrič, G., Atanasova, S., & Kamin, T. (2017). Impact of social processes in online health communities on patient empowerment in relationship with the physician: Emergence of functional and dysfunctional empowerment. *Journal of Medical Internet Research*, *19*(3), 1–17.

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: problems and prospects. *Journal of Management*, *12*(4), 531–544.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, *40*(3), 879–891.

Rönkkö, M., & Ylitalo, J. (2011). PLS marker variable approach to diagnosing and controlling for method variance. In *International Conference on Information Systems (ICIS) 2011 Proceedings* (pp. 1–16).

Sak, G., Rothenfluh, F., & Schulz, P. J. (2017). Assessing the predictive power of psychological empowerment and health literacy for older patients' participation in health care: a cross-sectional population-based study. *BMC Geriatrics*, *17*(1), 1–15.

Schanke, S., Burtch, G., & Ray, G. (2021). Estimating the Impact of "Humanizing" Customer Service Chatbots. *Information Systems Research*, *32*(3), 736–751.

Schuetzler, R. M., Grimes, G. M., & Scott Giboney, J. (2020). The impact of chatbot conversational skill on engagement and perceived humanness. *Journal of Management Information Systems*, *37*(3), 875–900.

Sharma, S., & Khadka, A. (2019a). Role of empowerment and sense of community on online social health support group. *Information Technology and People*, *32*(6), 1564–1590.

Sipior, J. C. (2020). Considerations for development and use of AI in response to COVID-19. *International Journal of Information Management*, *55*, 102170.

Spreitzer, G. M. (1995). Psychological empowerment in the workplace: dimensions, measurement, and validation. *Academy of Management Journal*, *38*(5), 1442–1465.

Spreitzer, G. M., Kizilos, M. A., Nason, S. W., & Kong, H. (1997). A Dimensional Analysis of the Relationship between Psychological Empowerment and Effectiveness, Satisfaction, and Strain. *Journal of Management*, *23*(5), 679–704.

Thomas, K. W., & Velthouse, B. A. (1990). Cognitive Elements of Empowerment: An "Interpretive" Model of Intrinsic Task Motivation. *Academy of Management Review*, *15*(4), 666–681.

Valtolina, S., Barricelli, B. R., & Di Gaetano, S. (2020a). Communicability of traditional interfaces VS chatbots in healthcare and smart home domains. *Behaviour & Information Technology*, *39*(1), 108–132.

Vassilakopoulou, P., Haug, A., Salvesen, L. M., & O. Pappas, I. (2022). Developing human/AI interactions for chat-based customer services: lessons learned from the Norwegian government, *European Journal of Information Systems*, (advanced online publication).

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, *46*(2), 186–204.

Wixom, B. H., & Todd, P. A. (2005). A theoretical integration of user satisfaction and technology acceptance. *Information Systems Research*, *16*(1), 85–102.

Ye, T., Xue, J., He, M., Gu, J., Lin, H., Xu, B., & Cheng, Y. (2019). Psychosocial factors affecting artificial intelligence adoption in health care in China: cross-sectional study. *Journal of medical Internet Research*, *21*(10), e14316.

You, Y., Kou, Y., Ding, X., & Gui, X. (2021). The medical authority of AI: a study of AI-enabled consumer-facing health technology. *arXiv preprint arXiv:2101.04794*.

Zhao, Y., Ni, Q., & Zhou, R. (2018). What factors influence the mobile health service adoption? A meta-analysis and the moderating role of age. *International Journal of Information Management*, *43*, 342–350.

Zhou, J. (2018). Factors Influencing People's Personal Information Disclosure Behaviors in Online Health Communities: A Pilot Study. *Asia-Pacific Journal of Public Health*, *30*(3), 286–295.

Zhou, Y., Kankanhalli, A., Yang, Z., & Lei, J. (2017). Expectations of patient-centred care: Investigating IS-related and other antecedents. *Information & Management*, *54*(5), 583–598.