ORIGINAL PAPER

doi: 10.5455/medarh.2021.75.50-55
MED ARCH. 2021 FEB; 75(1): 50-55
RECEIVED: DEC 22, 2020
ACCEPTED: JAN 25, 2021

Exploring the Influential Factors of Consumers' Willingness Toward Using COVID-19 Related Chatbots: An Empirical Study

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ABSTRACT

Background: Consumers' willingness to use health chatbots can eventually determine if the adoption of health chatbots will succeed in delivering healthcare services for combating COVID-19. However, little research to date has empirically explored influential factors of consumer willingness toward using these novel technologies, and the effect of individual differences in predicting this willingness. **Objectives:** This study aims to explore (a) the influential factors of consumers' willingness to use health chatbots related to COVID-19, (b) the effect of individual differences in predicting willingness, and (c) the likelihood of using health chatbots in the near future as well as the challenges/barriers that could hinder peoples' motivations. **Methods:** An online survey was conducted which comprised of two sections. Section one measured participants' willingness by evaluating the following six factors: performance efficacy, intrinsic motivation, anthropomorphism, social influence, facilitating conditions, and emotions. Section two included questions on demographics, the likelihood of using health chatbots in the future, and concerns that could impede such motivation. **Results:** A total of 166 individuals provided complete responses. Although 40% were aware of health chatbots and only 24% had used them before, about 84% wanted to use health chatbots in the future. The strongest predictors of willingness to use health chatbots came from the intrinsic motivation factor whereas the next strongest predictors came from the performance efficacy factor. Nearly 39.5% of participants perceived health chatbots to have human-like features such as consciousness and free will, but no emotions. About 38.4% were uncertain about the ease of using health chatbots. **Conclusion:** This study contributes toward theoretically understanding factors influencing peoples' willingness to use COVID-19-related health chatbots. The findings also show that the perception of chatbots' benefits outweigh the challenges.

Keywords: health chatbots; apps, COVID-19; willingness; perception; health informatics.

1. INTRODUCTION

As COVID-19 has become widespread across the world, health chatbots have been introduced as an innovative digital intervention to combat this disease [1]. Health chatbots are systems that implement artificial intelligence (AI) techniques to respond in a way that seems like a conversation with an actual agent or health specialist [2,3]. Health chatbots can be deployed from diverse types of platforms such as messaging apps (e.g., WhatsApp and Telegram), social networks (e.g., Facebook and Twitter), emails, and websites. This makes them accessible, affordable and potentially sustainable in the digital world [3,4].

These emerging technologies have been adopted by many health organizations and authorities such as World Health Organization (WHO) [5], the Saudi Ministry of Health [6], the U.K. government [7], and the U.S. Department of Veterans Affairs [8]. Furthermore, these technologies are becoming common in performing health-related activities in daily life [9], medical care such as pediatric care [10], geriatric care [11], orthopaedics [12], virtual medical consultations [2], public health and surveillance [13], large scale monitoring systems [14], supporting healthcare personnel (e.g., automate tasks like filling forms and scheduling appointments) [15], and self-triage and personal risk assessment [16].

The expansion of health chatbots can eventually improve healthcare [17-19]. For healthcare providers and organizations hoping to invest in health chatbots, it is imperative they gain insight into the consumers' intentions toward using these novel technologies [18-20]. The consumers' willingness to use health chatbots can eventually determine if the adoption of health chatbots will succeed in delivering healthcare services. [20-22].

However, few researchers to date have empirically explored the influential factors of willingness toward using these novel technologies, and the effect of individual differences in predicting their willingness [17-20]. Therefore, this study aims to explore (a) the influential factors of consumers' willingness to use health chatbots related to COVID-19, (b) the effect of individual differences in predicting their willingness, and (c) the likelihood of using those health chatbots in the near future as well as challenges/barriers that could hinder their motivations.

2. OBJECTIVES

This study aims to explore (a) the influential factors of consumers' willingness to use health chatbots related to COVID-19, (b) the effect of individual differences in predicting willingness, and (c) the likelihood of using health chatbots in the near future as well as the challenges/barriers that could hinder peoples' motivations.

3. METHODS

Measures and theoretical model

Previous research has identified two theoretical models that explain the acceptance of chatbots [23-25]. The first theoretical model was developed by Melián-González [23] and the second was developed by Lu [22] that is entitled the Service Robots Integration Willingness (SRIW) model. However, in comparison with the SRIW, the first model does not include constructs pertaining to offering support by the service providers (e.g., facilitating conditions). This construct, which is concerned with the resources and assistance available for facilitating the use of technology, is necessary to minimize any barriers of usage (e.g., poor recognition of emotions during interactions) and maintain long-term adoption of these novel technologies (e.g., technical support for upgrading the services) [22]. As this construct is included in the SRIW model, it was adopted in this study.

The SRIW model has 6 factors and a set of 37 items that end-users deem important to measure whether participants would support or reject new AI-based technologies as follows:

- Performance efficacy (F1) refers to the degree to which AI-based systems can provide consistent and dependable service to consumers, and has 8 items.
- Intrinsic motivation (F2) refers to the pleasure received while interacting with AI-based agents, and has 6 items.
- Anthropomorphism (F3) refers to the fact that a product bears a human appearance which includes psychological features (emotions, gestures, etc.) and non-psychological features such as the presence of physical resemblance to human bodies (e.g., head, eyes, etc.), and has 7 items.
- Social influence (F4) refers to the reference group may influence consumers' perceptions toward AI-based agents and play a role in developing decisions to support or refuse such new technology, and has 7 items.
- Facilitating condition (F5) refers to the resources and assistance available that would facilitate the use of AI-based technology, and has 4 items.
- Emotions (F6) include positive emotions such as the fun and excitement of interacting with these AI-based technologies as well as negative emotions such as hostility and cold-heartedness, and has 5 items.

Recruitment and data collection procedures

Participants were recruited via social networks (i.e., Twitter and Facebook) and messaging apps (i.e., WhatsApp and Telegram) [26]. Recruitment was undertaken in the period between 17 June 2020 and 15 July 2020. People were eligible for participation if their ages were above 18 years old, and had a smartphone that supported 3G network or above. Other characteristics such as gender, nationality, language, and occupation were not restricted.

An online survey was conducted which comprised of two sections. Section one had 37 items to measure the participants' willingness toward using COVID-19-related health chatbots based on the SRIW scale [22]. Section two included two parts. Part one had 11 questions on the participants' demographics and general information. Part two involved 8 questions that looked at the participants' likelihood of using health chatbots within 12 months and concerns that could hinder such motivations.

Data analysis procedures

Data were firstly cleansed and prepared for statistical analysis. The demographic variables were checked and converted into variables with binary values for easier and informative interpretation. Descriptive statistics was then performed to identify the characteristics of our sample. Findings are presented in Table 1 in the Results section.

Next, to accomplish the objective (a) of this study, the items in the SRIW scale were read and checked for fitting this study context. Few issues were found with the original items' wordings, but small changes were made. For example, the words "artificially intelligent devices such as robots" replaced with "artificially intelligent systems such as chatbots" when it occurred in all related items. Then, exploratory factor analysis and Principal Components Analysis (PCA) were used to extract meaningful factors and associated key items that can predict at least 60% of the total variance in the measured outcome [22,27,28]. This was achieved through feeding the PCA statistical model with all items from the online survey and checking the eigenvalue of the factor (i.e., the amount of variance that was accounted for by a given factor, which had to be greater than 1 in order to retain the factor). Next, the rotated solution was then used to identify items with trivial loadings on each retained factor and exclude them from the analysis. This step also helped in testing the compliance of our extracted list of factors and items with the corresponding factors in the original SRIW scale developed by Lu [22].

After completing this step, the participants' perception of each of these items was assessed by using the 5-points Likert scale. The midpoint of the scale (3) was used to split the sample into three groups (i.e., agree, neutral, disagree) in order to achieve good model fit across those splits [27,28]. Findings are presented in Table 2 in the Results section.

To accomplish the objective (b) of this study, we conducted inferential statistics by using an independent samples t-test to find the statistically significant effect of the individual characteristics on their willingness to use health chatbots. This statistical model was fed with the participants' demographics as control variables and the six factors as outcome variables (Appendix 1). This step was also useful in revealing the attributes of the groups who were more willing to use these technologies.

Finally, to accomplish the objective (c) of this study, descriptive statistics (i.e., frequency) was performed to determine the participants' likelihood of using health chatbot in the near future and the perceived challenges/barriers for using health chatbots. Findings are presented in Table 3 in the Results section.

4. RESULTS

Characteristics of the participants

A total of 166 out of 173 individuals provided complete responses. Table 1 summarizes the characteristics of the participants. Nearly 40% were aware of health chatbots but only 24% had used chatbots before. The majority were Saudi with no medically diagnosed conditions. More than half were male and had at least a university undergraduate degree. Two-thirds were aged 30 years and above. Nearly 57.8% did not provide any healthcare-related services (e.g., in healthcare facilities, quarantine or isolation centers or check-up points; or home-based care for a family member, relative or friend). About 64.5% of participants reported having high to a very high level of information technology (IT) skills. Almost 70% searched frequently for health information on the Internet.

Willingness to use health chatbots related to COVID-19

The PCA analysis retained (6 out 6, 100%) factors and (28 out of 37, 75.7%) items of the original SRIW scale (Table 2). There were strong correlations between F1 and six items, F2 and five items, F3 and four items, F4 and four items, F5 and four items, and F6 and five items as shown in Table 2. All item-to-factor loadings surpassed the 0.60 level. The items with the highest loadings on each factor were identified as follows: the item number 1, 7, 12, 16, 20, and 24 had the highest correlation with F1, F2, F3, F4, F5, and F6 respectively. Furthermore, the extracted 28 items explained about 75% of the total variance of the measured outcome (i.e., willingness to use health chatbots). This is regarded as being significant loadings and higher than what is usually achieved in factors analysis (i.e., 50-60%) [22,27,28].

Variable	Value	N (166)	%
Gender	Female	79	47.6
	Male	87	52.4
Age	Under 30	53	31.9
	30 and above	113	68.1
Nationality	Saudi	149	89.8
	Non-Saudi	17	10.2
Highest level of education	Undergraduate degree	95	57.2
	Postgraduate degree	71	42.8
Current occupation	Unemployed	52	31.3
	Employed	114	68.7
Provided healthcare related services	No	96	57.8
	Yes	70	42.2
Med. diagnosed cond.	No	136	81.9
	Yes	30	18.1
Perceived IT skills	Low or medium	59	35.5
	High or very high	107	64.5
Searched health info	Less frequent	50	30.1
	Frequent	116	69.9
Health chatbot awareness	No	99	59.6
	Yes	67	40.4
Past health chatbot use	No	126	75.9
	Yes	40	24.1

Table 1. Characteristics of the participants

In addition, at this stage, the participants' perceptions about each of these items were examined within three categories (i.e., agree, neutral, disagree) for each factor. In F1, the overall average of participants who agreed to all items related to this factor showed that 56.9% had positive perceptions about health chatbots' performance efficacy to provide consistent and dependable service. In this part of the scale, almost two-third of participants perceived that they would be able to avoid inefficient personal contacts if they used AI systems such as chatbots.

In F2, the overall average of participants who agreed to all items related to this factor also revealed that 64.5% had high intrinsic motivation toward using health chatbots. In this part of the scale, the majority of participants 69.9% agreed that interacting with AI systems like chatbots would be fun.

Similarly, in F3, the overall average of participants who agreed to all items related to this factor found that 39.5% perceived AI-based technologies to have human-like psychological features. For example, about 45.2% of participants perceived that AI systems such as chatbots would have a mind of their own; however, 42.7% disagreed that AI systems such as chatbots would experience emotions.

In this same vein, in F4, the overall average of participants who agreed to all items related to this factor indicated that 43.9% of subjects would change their decisions to accept or reject using these health technologies based on the social influence of people they know. For example, 47.6% of participants would utilize AI systems such as chatbots in seeking health information or tips if people whose opinions deemed valued by those subjects did so.

The overall average of participants who agreed to all items related to F5 revealed that 38.4% were uncertain about the ease of using health chatbots. In this part of the scale, 41.6% participants were also unsure if health chatbots would be intimidating to them.

Finally, the overall average of participants who agreed to all items related to F6 showed that over half of respondents had positive emotions about using health chatbots. For example, 54.3% of participants perceived that they would be both relaxed as well as satisfied if they used these AI-based technologies.

The effect of individual differences in predicting their willingness

The statistical comparison performed with the independent samples t-test revealed no statistically significant differences at the 5% level between the two groups in the following variables: gender (male or female), current occupation (employed or unemployed), provided healthcare related services (yes or no), health status (medically diagnosed conditions or not), perceived IT skills (low-medium or high-very high), and health chatbot awareness (yes or no), see Appendix 1. On the other hand, it revealed statistically significant differences between the two groups in the following variables: age, nationality, highest level of education, searched health information, and past health chatbot use.

The statistically significant difference between the participants whose age under 30 years old (n=53) and those 30 years old and above (n=113) in the score of intrinsic motivation (F2) indicates that the participants whose ages were under 30 years old tended to perceive having more pleasure when interacting with the health chatbots more in comparison to older group, t(164)=-2.28, P = 0.024.

The statistically significant difference between Saudi (n=149) and non-Saudi (n=17) groups in the score of anthropomorphism (F3) indicates that the Saudi group tended to perceive that health chatbots can bear a human-like appearance more than the other group, t(164)=2.82, P = 0.005. This.

Willingness Analysis: All Factors (N=6)	Item-to-factor loadings	Agree %	Neutral %	Disagree %
Performance efficacy	**F1**	**56.9**	**29.5**	**13.6**
1. Health information and tips provided by artificially intelligent (AI) systems such as chatbots are more accurate with less human errors	0.726	58.5	28.3	13.2
2. AI systems such as chatbots are more dependable than human beings	0.700	42.8	32.5	24.7
3. Health information and tips provided by AI systems such as chatbots are more consistent than health information provided by human beings	0.668	54.8	30.1	15.1
4. I am able to avoid inefficient personal contacts if I use AI systems such as chatbots	0.658	65.1	27.1	07.8
5. Health information and tips provided by AI systems such as chatbots is more predictable than what can be provided by human beings	0.616	55.5	32.5	12.0
6. Using AI systems such as chatbots would enhance my effectiveness for seeking health information or tips	0.588	64.5	26.5	09.0
Intrinsic motivation	**F2**	**64.5**	**28.4**	**07.1**
7. Interacting with AI systems like chatbots is fun	0.872	69.9	25.3	04.8
8. Interacting with AI systems like chatbots is entertaining	0.812	60.9	28.3	10.8
9. I would have fun interacting with AI systems such as chatbots	0.779	69.3	25.3	05.4
10. I would find the interaction with AI systems like chatbots to be enjoyable	0.737	60.9	30.1	09.0
11. The actual process of interacting with AI systems like chatbots would be pleasant	0.644	61.5	33.1	5.4
Anthropomorphism	**F3**	**39.5**	**32.4**	**28.1**
12. AI systems such as chatbots will have consciousness	0.814	43.4	33.7	22.9
13. AI systems such as chatbots will have their own free will	0.791	40.3	30.7	29.0
14. AI systems such as chatbots will have a mind of their own	0.782	45.2	36.7	18.1
15. AI systems such as chatbots will experience emotions	0.613	29.0	28.3	42.7
Social influence	**F4**	**43.9**	**40.5**	**15.6**
16. People who are important to me would encourage me to utilize AI systems such as chatbots in seeking health information or tips	0.798	45.8	38.0	16.2
17. People whose opinions that I value would prefer that I utilize AI systems such as chatbots in seeking health information or tips	0.723	47.6	42.8	09.6
18. People in my social networks (e.g., friends, family and co-workers) who would utilize AI systems such as chatbots have a high profile	0.618	41.5	44.0	14.5
19. People in my social networks (e.g., friends, family and co-workers) who would utilize AI systems such as chatbots have more prestige than those who don't	0.615	40.9	37.3	21.8
Facilitating conditions	**F5**	**30.7**	**38.4**	**30.9**
20. AI systems such as chatbots are intimidating to me	0.851	22.9	41.6	35.5
21. It takes me too long to learn how to interact with AI systems such as chatbots	0.837	28.9	38.0	33.1
22. Working with AI systems such as chatbots is so difficult to understand and use	0.778	32.5	37.3	30.2
23. Interactions with AI systems such as chatbots take too much of my time	0.632	38.6	36.7	24.7
Emotions/affects	**F6**	**52.12**	**38.0**	**11.64**
24. If I use AI systems such as chatbots, I will feel satisfied	0.744	54.3	34.9	10.8
25. If I use AI systems such as chatbots, I will feel pleased	0.718	53.1	34.3	12.6
26. If I use AI systems such as chatbots, I will feel contented	0.656	50.1	36.7	13.2
27. If I use AI systems such as chatbots, I will feel relaxed	0.622	54.3	43.9	10.8
28. If I use AI systems such as chatbots, I will feel hopeful	0.574	48.8	40.4	10.8

Table 2. Summary of willingness analysis

Additionally, applying the independent samples t-test to compare the participants who had undergraduate degrees (n=95) with those with postgraduate degrees (n=71) showed a statistically significant difference between the two groups for all of the six factors, indicating that the participants who had undergraduate degrees have more scoring tendency for each of these willingness factors in comparison to those with postgraduate degrees as follows: F1 t(164)=-2.58, P = 0.011; F2 t(164)=-2.52, P = 0.013; F3 t(164)=-3.30, P = 0.001; F4 t(164)=-3.29, P = 0.001; F5 t(164)=-2.61, P = 0.010; and F6 t(164)=-2.62, P = 0.010.

There was a statistically significant difference between the participants who frequently searched for health information on the Internet (n=116) and those who were less frequent searchers (n=50) in the score of perfor-

Likelihood of using health chatbot within 12 months	N (166)	%
Yes	140	84.3
No	26	15.7
Perceived challenges/barriers	N (26)	%
Prefer to talk face to face with a doctor about health	16	61.5
I do not like talking to computers/ chatbots	11	42.3
I do not trust advice from a health chatbot	7	26.9
Worried about privacy using a health chatbot	4	15.4
Confident in finding accurate health information and tips online	4	15.4
Worried about the security of information using a health chatbot	3	11.5
It would be strange to talk to a chatbot about health	3	11.5

Table 3. Likelihood of using health chatbot within 12 months and perceived challenges/barriers

mance efficacy (F1) which indicates that this group tended to perceive that health chatbots were able to provide consistent and dependable service to consumers more than the other compared group, t(164)=3.89, P = 0.001.

Similar results were obtained for the factor intrinsic motivation (F2) and emotions (F6) for subjects who frequently searched health information in this study, F2 t(131)=2.49, P = 0.014; and F6 t(164)=2.079, P = 0.040, respectively. This indicates that this group tended to perceive having more pleasure and fun when interacting with health chatbots than the other compared group.

Lastly, the independent samples t-test also revealed a statistically significant difference in the score of intrinsic motivation (F2) between participants who had used health chatbots before and who had not. Participants who had used health chatbots (n=67) scored higher than the other group (n=99), t(164)=2.06, P = 0.044. Likewise, participants who were previously aware of health chatbots scored higher than the other group in their score of anthropomorphism F3 t(164)=2.06, P = 0.041.

Likelihood of using health chatbots in the near future

About 84% of the participants answered 'yes' to using health chatbots that provide health information or tips within 12 months. On the other hand, only 16% answered with 'no', which indicates that they had no interest in using these emerging technologies for the reasons presented in Table 3. This finding reveals that consumers appreciate the benefits that these novel technologies offer more than the unfavorable impacts that health chatbots may introduce such as limiting face-to-face interaction with doctors, privacy concerns, and security issues.

5. DISCUSSION

Findings of the current study confirm the importance of the included 6 factors from SRIW model for measuring whether participants would accept or reject using health chatbots to combat or mitigate the effects of COVID-19. This finding also supports the validity and generalizability of this model for explaining consumers' willingness toward using software-based AI technologies (health chatbots) in the healthcare field.

Generally, the statistical analysis revealed that the participants had positive perceptions about health chatbots and were willing to use these novel technologies. The strongest predictors of willingness to use health chatbots came from the intrinsic motivation factor (F2) whereas the next strongest predictors came from the performance efficacy factor (F1), as shown in Table 2. Prior studies have confirmed that the enjoyment of the chats have made these technologies more acceptable to consumers (3). Some studies have prioritized the intrinsic values associated with chatbots over functional benefits when assessing long-term acceptance by consumers (22). Our findings are in alignment with this finding from relevant studies. Therefore, the consumers' intrinsic values can create new interaction requirements, which must be integrated into the chatbot's design in order to increase its success in healthcare.

Regarding the chatbots' emotion sensitivity as measured by the anthropomorphism factor, the statistical analysis showed that the participants in this study perceived health chatbots to have no emotions. This perceived lack of empathy may hinder the acceptance of AI-based technologies in healthcare (29). Prior studies have found that when using chatbots consumers perceive that they are interacting with a human entity who is providing services. This perception, in turn, amplifies their emotional attachment to the chatbot (30). They were also seen as a convenient and anonymous way for sharing health concerns that may be embarrassing or carry a level of stigma (e.g., stigma of having COVID-19 infection) (20). Therefore, chatbots have to be equipped with empathy features in order to enhance consumers' engagement and acceptance (30). User-centered approaches can be used to inform the technical structure of health chatbots and in turn overcome these potential barriers to engagement (29).

Another key insight gained from this research pertains to the importance of the social acceptance of using health chatbots. Our statistical analysis found that many participants tend to comply with others' views on health chatbots, given the limited knowledge about these novel technologies (22). However, for long-term adoption, raising peoples' awareness about health chatbots' integrity, benevolence, their ability to provide accurate information and their diverse applications in healthcare is required. Health mass media campaigns, social role models' endorsements, or adaption of health chatbots by national healthcare providers may help in this regard (13,16).

6. CONCLUSION

The willingness to use COVID-19-related health chatbots can be measured by SRIW model. The findings also show that the perception of chatbots' benefits outweigh the challenges. Intervention developers need to employ theory-based and user-centered approaches to determine the consumers' values and interaction requirements in order to achieve the best utilization of health chatbots for delivering healthcare services during pandemics.

- **Acknowledgments**: The authors are grateful to the Deanship of Scientific Research at Jazan University for funding this study (Cov19-12). We also would like to thank Dr Mohammed Zain, the statistical consultant, for his advice during data analysis.
- **Author's contribution**: Author was involved in all steps for preparation this article, including final proofreading.
- **Conflicts of Interest**: None declared.
- **Financial support and sponsorship**: Nil.

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