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
challenges/barriers that could hinder their motivations. 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.

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” 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 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)=2.81, P = 0.005. This.

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)=2.61, 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-

| Willingness Analysis: All Factors (N=6) | Item-to-factor loadings | Agree % | Neutral % | Disagree % |
|---------------------------------------|------------------------|---------|-----------|-----------|
| Performance efficacy | F1 | 0.726 | 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 | | 58.5 | 23.2 | 18.3 |
| 2. AI systems such as chatbots are more dependable than human beings | | 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 | | 54.8 | 30.1 | 15.1 |
| 4. I am able to avoid inefficient personal contacts if I use AI systems such as chatbots | | 65.1 | 27.1 | 7.8 |
| 5. Health information and tips provided by AI systems such as chatbots is more predictable than what can be provided by human beings | | 55.5 | 32.5 | 12.0 |
| 6. Using AI systems such as chatbots would enhance my effectiveness for seeking health information or tips | | 64.5 | 26.5 | 9.0 |

Table 2. Summary of willingness analysis
Table 3. Likelihood of using health chatbot within 12 months and perceived challenges/barriers

| Likelihood of using health chatbot within 12 months | N (166) | %    |
|-----------------------------------------------|-------|------|
| Yes                                          | 140   | 84.3 |
| No                                           | 26    | 15.7 |
| Perceived challenges/barriers                 |       |      |
| 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

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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 deter-
mine the consumers’ values and interaction requirements in order to achieve the best utilization of health chatbots for delivering healthcare services during pandemics.

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**REFERENCES**

1. Miner AS, Laranjo L, Kocaballi AB. Chatbots in the fight against the COVID-19 pandemic. NPJ digital medicine. 2020; 3(1): 65.
2. Battineni G, Chintalapudi N, Amenta F. AI chatbot design during an epidemic like the novel coronavirus. Healthcare. 2020; 8: 154.
3. Montenegro JLZ, da Costa CA, da Rosa Righi R. Survey of conversational agents in health. Expert Systems with Applications. 2019; 129: 56-67.
4. Espinoza J, Crown K, Kulkarni O. A guide to chatbots for COVID-19 screening at pediatric health care facilities. JMIR Public Health Surveill. 2020; 6(2): e18808-e.
5. Walwema J. The WHO health alert: Communicating a global pandemic with WhatsApp. JBTC. 0(0):1050651920958507.
6. MoH: https://www.moh.gov.sa/en/Ministry/MediaCenter/Ads/Pages/Ads-2020-02-19-001.aspx
7. Techcrunch: https://techcrunch.com/2020/03/25/uk-whatsapp-coronavirus-information/
8. US Department of Veterans Affairs coronavirus chatbot: https://www.va.gov/coronavirus-chatbot/
9. Zhang J, Oh YJ, Lange P, Yu Z, Fukuoka Y. Artificial intelligence chatbot behavior model for designing artificial intelligence chatbots to promote physical activity and a healthy diet: Viewpoint. JMIR. 2020; 22(6): e19284.
10. Espinoza J, Crown K, Kulkarni O. A guide to chatbots for COVID-19 screening at pediatric health care facilities. JMIR Public Health Surveill. 2020; 6(2): e18808-e.
11. Meinert E, Milne-Ives M, Surodinia S, Lam C. Agile requirements engineering and software planning for a digital health platform to engage the effects of isolation caused by social distancing: Case study. JMIR Public Health Surveill. 2020; 6(2): e19297-e.
12. Bini SA, Schilling PL, Patel SP, Kalore NV, Ast MP, Maratt JD, et al. Digital orthopaedics: A glimpse into the future in the midst of a pandemic. The Journal of Arthroplasty. 2020; 35(7): S68-S73.
13. Rodsawang C, Thongkliang P, Intawong T, Sonong A, Thitithwathana Y, Chottanapund S. Designing a competent chatbot to counter the COVID-19 pandemic and empower risk communication in an emergency response system. OSIR Journal. 2020; 13(2).
14. Yoneoka D, Kawashima T, Tanoue Y, Nomura S, Ejima K, Shi S, et al. Early SNS-based monitoring system for the covid-19 outbreak in Japan: A population-level observational study. J Epidemiol. 2020; 30(8): 362-370.
15. Bharti U, Bajaj D, Batra H, Lalit S, Lalit S, Gangwani A, editors. Medbot: Conversational artificial intelligence powered chatbot for delivering tele-health after COVID-19. 2020 5th International Conference on Communication and Electronics Systems (ICCES); 2020 10-12 June 2020.
16. Judson T, Odisho A, Young J, Bigazzi O, Steuer D, Gonzales R, et al. Case report: Implementation of a digital chatbot to screen health system employees during the COVID-19 pandemic. JAMIA. 2020.
17. Almalki M, Azeez F. Health chatbots for fighting covid-19: A scoping review. Acta Inform Med. 2020; 28(4): 242-248. doi: 10.5455/aim.2020.28.242-248.
18. Fagherazzi G, Goetzinger C, Rashid MA, Aguayo GA, Huirart L. Digital health strategies to fight covid-19 worldwide: Challenges, recommendations, and a call for papers. JMIR. 2020; 22(6): e19284.
19. Tudor Car L, Dhinagarana DA, Kyaw BM, Kowatsch T, Joty S, Theng Y-L, et al. Conversational agents in health care: Scoping review and conceptual analysis. JMIR. 2020; 22(8): e17158.
20. Dennis AR, Kim A, Rahimi M, Ayabakan S. User reactions to COVID-19 screening chatbots from reputable providers. JAMIA. 2020.
21. Esmaeilzadeh P. Use of AI-based tools for healthcare purposes: a survey study from consumers’ perspectives. BMC Medical Informatics and Decision Making. 2020; 20(1): 170.
22. Lu L, Cai R, Gursoy D. Developing and validating a service robot integration willingness scale. IJHM. 2019; 80: 36-51.
23. Melián-González S, Taño D, Bulchand-Gidumal J. Predicting the intentions to use chatbots for travel and tourism. Current Issues in Tourism. 2019: 1-19.
24. Chi OH, Denton G, Dogan G. Artificially intelligent device use in service delivery: a systematic review, synthesis, and research agenda. IJHM. 2020: 1-30.
25. Belanche D, Casaló Ariño L, Flavian C, Schepers J. Service robot implementation: a theoretical framework and research agenda. Service Industries Journal. 2020: 40: 203-225.
26. Creswell J. W. Research design: Qualitative, quantitative, and mixed method approaches (4th ed.). Thousand Oaks, California: SAGE Publications; 2014.
27. O’Rourke N, Hatcher L. A step-by-step approach to using SAS system for factor analysis and structural equation modelling. 2nd ed: SAS Institute; 2013.
28. Stevens J. Applied multivariate statistics for the social sciences. Routledge; 2012.
29. Nadarzynski T, Miles O, Cowie A, Ridge D. Acceptability of artificial intelligence (AI)-led chatbot services in healthcare: a mixed-methods study. Digital Health. 2019: 5.