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Individual differences in views toward healthcare conversational agents: A cross-sectional survey study

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Abstract

Background and Objective: To date, there has been limited research on people's attitudes and design preferences with respect to conversational agents (CAs) that are used for healthcare. Individual differences in attitudes and design preferences have received particularly little attention. The purpose of this study was to gain greater insight into this topic.

Methods: We recruited American and Canadian residents through the online research platform Prolific. Participants completed a cross-sectional survey assessing demographic, personality, and health factors, as well as attitudes and design preferences with respect to healthcare CAs. Hierarchical regressions were used to determine demographic, personality, and health predictors of attitudes and design preferences.

Results: A total of 227 participants (116 women; M age = 39.92 years, SD = 12.94) were included in the analysis. Participants tended to report slightly positive attitudes toward healthcare CAs, with more positive attitudes among American residents and people with lower income, lower education levels, and higher levels of the personality factor conscientiousness. In general, participants preferred CAs that use text communication, have unrestricted language input, are disembodied, and simulate health professionals in their presentation. CAs that use text communication were preferred to a greater degree among people with higher levels of digital health literacy, and disembodied CAs were preferred to a greater degree among people with lower levels of conscientiousness.

Conclusion: The results of this study provide insight into people's attitudes and design preferences with respect to healthcare CAs. This information will help guide developers on how to better design and market CAs for the health sector, which may increase people's adoption and use of these programs.

Keywords

Conversational agents, chatbots, attitudes, design preferences, individual differences, health, demographics, personality

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Introduction

Digital technologies are providing the public with new and innovative ways to access healthcare. Conversational agents (CAs) are one digital technology showing great potential in this area. CAs are automated software programs that are designed to engage in humanlike conversation with people.[1–3] They come in many forms, such as text-based chatbots,[4] voice-activated virtual assistants,[5] and "embodied" CAs with computer-generated bodies.[6] Over the past several years, researchers and companies have developed a wide variety of CAs for use in the health sector.[3,7–9] Research on these programs is ongoing, but current evidence suggests that they are capable of performing a range of healthcare tasks. For instance, they have been used to provide patient education

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and treatment support, foster healthy lifestyle habits (e.g. physical activity), and address mental health issues.[10–13]

Despite their promising capabilities, healthcare CAs appear to lack widespread public acceptance. Past studies have shown that people tend to have mixed or neutral attitudes toward these programs, with a greater willingness to use CAs for health management or routine healthcare versus more serious health issues.[14,15] This finding suggests that the public is somewhat cautious or hesitant toward healthcare CAs, and that uptake of these programs may be limited. However, it is possible that there are individual differences in people's attitudes toward this technology. In other words, certain types of individuals may be more receptive to healthcare CAs than others. It would be beneficial to identify individual differences in people's attitudes toward these programs, as researchers and companies could leverage this information to ensure that their CAs are directed to those audiences that are most likely to accept and use them. There has been little research on this specific topic to date, although Nadarzynski et al.[15] did present some evidence that these programs have greater appeal for people with better technological skills.

People's design preferences for healthcare CAs also warrant some consideration. CAs can vary according to several characteristics, such as their communication modality (text vs. speech),[9,16] their embodiment (the presence vs. the absence of a computer-generated body),[9,16] and their depicted role (a peer vs. a professional).[17] Information on people's design preferences for healthcare CAs would be useful from a development standpoint, as it would help guide researchers and companies as they try to improve the appeal of their programs. Insight into individual differences in design preferences would be especially useful. It is possible that certain design characteristics appeal to some types of individuals more than others, and developers that understand these preferences would be able to tailor their programs to specific audiences. To our knowledge, this particular topic has received no attention in the literature to date.

The purpose of the current study was to gain a better understanding of people's attitudes and design preferences with respect to healthcare CAs. We were particularly interested in individual differences in their attitudes and design preferences. We considered a wide range of individual difference factors for the study, looking to the broader literature on digital health for guidance. Past research has linked the use of digital health to a number of individual difference factors, including demographics,[18,19] personality traits,[20,21] and health characteristics such as health status[19,22] and digital health literacy (i.e. the ability to find, evaluate, and apply online health information and use digital health applications).[23,24] We expected that these same individual difference factors would be useful for exploring other aspects of digital health that are closely related to usage, such as attitudes and design preferences. In the current study, we drew on these various factors to learn more about people's attitudes toward healthcare CAs, as well as their design preferences for these programs.

Materials and methods

Design

This study was an exploratory observational study with a cross-sectional survey design. The study survey captured information on demographic, personality, and health factors, as well as attitudes and design preferences with respect to healthcare CAs. It was administered to an online sample of participants. The study protocol and related materials were approved by the research ethics board at the University of New Brunswick (REB #2023-082). The study is reported according to STROBE cross-sectional reporting guidelines.[25]

Participants

Participants were recruited through Prolific (Prolific, London, UK), an online research platform that connects researchers to a diverse pool of participants for research studies. A power analysis conducted using G*Power version 3.1.9.7 (Heinrich-Heine-Universität, Düsseldorf, Germany) indicated that 123 participants would be required for the statistical analysis, assuming .80 power, an alpha level of .05, and a moderate effect size of $f^2 = .15$ (corresponding to an $R^2 = .13$; see Cohen[26] for more details). However, a larger number of participants ($N > 200$) was targeted to provide a more robust sample for the analysis. Participation was open to residents of Canada or the United States aged 19 years and older. Individuals needed to have a successful completion rate of 97% or above on their Prolific tasks to participate. Filters were used within the Prolific platform to ensure that a similar number of Canadian and American residents were recruited, as well as a similar number of men and women. Participants were provided with $3.00 (US) for their participation. Recruitment occurred from 13 to 19 July 2023.

Measures

A short series of demographic questions captured information about participant age, gender, annual household income, education, and country of residence. These questions were accompanied by a health-related question asking whether participants had a primary care provider. This question was included based on the idea that individuals without a primary care provider may be more receptive to alternative sources of healthcare, such as CAs. Other measures are described in detail below.[a]

Personality factors. Personality factors were assessed with items from the Mini International Personality Item Pool (Mini-IPIP) Scales from Donnellan and colleagues.[27] We focused on two specific personality factors that have been linked to digital health use in past research: *conscientiousness*, which reflects responsibility, planfulness, and organization; and *neuroticism*, which reflects anxiety, nervousness, and general emotional instability.[20,21,28] Each item on the measure asks how accurately a specific personality-related quality or behavior describes the individual. Conscientiousness and neuroticism are assessed with four items each. Items are rated on a five-point scale, with responses ranging from 1 (*very inaccurate*) to 5 (*very accurate*). Responses to certain items are reverse scored, such that higher ratings reflect higher levels of a personality factor. Responses to the items were averaged within each of the two personality factors to obtain composite scores for each participant. The conscientiousness items demonstrated acceptable internal consistency, with a Cronbach's α of .77. The neuroticism items demonstrated good internal consistency, with a Cronbach's α of .86.

Health status. Health status was assessed with the 12-item Short-Form Health Survey (SF-12) from Ware and colleagues.[29] Each item on the measure asks about a specific aspect of a person's health and wellbeing. Items are rated on a scale with two to six response options, depending on the item. A scoring algorithm is applied to participant responses to generate two summary scores, one for physical health and one for mental health.[30] In both cases, higher scores indicate better health. A score of 50 represents average health.

Digital health literacy. Digital health literacy was assessed with the 21-item Digital Health Literacy Instrument (DHLI) from van der Vaart and Drossaert.[24] Each item on the measure asks about the difficulty or frequency of performing certain tasks related to digital health use. Items are rated on a four-point scale, with responses ranging from 1 (*very easy / never*) to 4 (*very difficult / often*). Responses are reverse scored such that higher scores represent higher levels of digital health literacy. Responses to the items were averaged to obtain a composite score for each participant. Items on the DHLI demonstrated good internal consistency, with a Cronbach's α of .89.

Attitudes. Attitudes toward healthcare CAs were assessed with the 10-item Emerging Technologies Semantic Differential Scale (ETSDS) from Ajani and Stork.[31,32] Each item on the measure is a semantic differential item that asks participants to rate a technology according to two polar adjectives (e.g. *Bad* vs. *Good*; *Useless* vs. *Useful*). Items are rated on a seven-point scale, with responses ranging from 1 (*more like the adjective to the left*) to 7 (*more like the adjective to the right*). In this study, the adjectives were arranged such that higher ratings indicate more positive attitudes toward healthcare CAs. Responses to the items were averaged to obtain a composite score for each participant. Items on the ETSDS demonstrated excellent internal consistency, with a Cronbach's α of .93.

Although the ETSDS was designed to measure attitudes toward emerging information and communication technologies, it was developed within the context of sensor technologies specifically. Therefore, prior to computing the composite score, a principal component analysis (PCA) was conducted on the 10 ETSDS items to explore the structure of the scale for healthcare CAs. The Kaiser–Meyer–Olkin measure of sampling adequacy (KMO = .93) and Bartlett's test of sphericity ($p < .001$) both indicated that a PCA was appropriate. Results showed one eigenvalue greater than 1.00 (eigenvalue = 6.17), which suggested a single-component solution. The Scree plot and a parallel analysis also indicated a single-component solution. This component explained 61.66% of the variance in the data. The factor loadings were above .60 for all 10 items. Forcing additional components created several cross-loadings and did not produce components that made conceptual sense. Therefore, the single-component 10-item solution was retained.

Design preferences. Design preferences were assessed with five items created for this study. Each item asked participants to consider which of two design characteristics they would prefer in healthcare CAs. The first item addressed *input modality*, reflecting a preference for CAs with text input versus voice input. The second item addressed *output modality*, reflecting a preference for CAs with text output versus voice output. There was a strong correlation between these two items in the study data ($r = .75$), and so they were averaged to create a general *communication modality* variable reflecting a preference for CAs with text versus voice communication. The remaining three items addressed *input flexibility*, reflecting a preference for CAs with restricted input (input limited to predefined response buttons or voice commands) versus unrestricted input (say or write whatever you want); *embodiment*, reflecting a preference for disembodied CAs (text- or voice-only) versus embodied CAs; and *depicted role*, reflecting a preference for CAs that simulate a peer versus a health professional. Items were rated on a seven-point scale, with responses ranging from 1 (*prefer the first option*) to 7 (*prefer the second option*).

Procedure

Participants were redirected from Prolific to the online survey platform Qualtrics (Qualtrics, Provo, USA), which hosted the study materials. They began by completing an informed consent form and the demographic, personality, and health measures. Next, they were shown a slideshow with background information on healthcare CAs. The slideshow included several screenshots of healthcare CAs, all of which demonstrated CA/user interaction. These screenshots were drawn from past articles in this area.[33–39] In some cases, article images were replaced with higher-quality versions of the same or similar images from web sources (e.g. researcher websites). The purpose of the slideshow was simply to ensure that all participants had an adequate understanding of these programs. After reviewing this material, participants filled out the measure assessing their attitudes toward healthcare CAs. They also completed the items assessing their design preferences.

Data analysis

Data were entered into SPSS version 29 (IBM Corp., Armonk, USA) for statistical analysis. The analysis consisted of five separate hierarchical (i.e. sequential) regressions. Each regression had a different outcome variable. The outcome for the first regression was ETSDS score, which reflects attitudes toward healthcare CAs. The outcomes for the four remaining regressions were ratings for the four design preference variables. The predictors were identical for each regression. Demographic variables (age, gender, annual household income, education, and country of residence) were entered as predictors on the first step of the regression. A median split was performed on household income due to heavy skew, and the various education categories were grouped into postsecondary degree/diploma versus no postsecondary degree/diploma. The personality variables (conscientiousness and neuroticism) were added as predictors on the second step of the regression to see if they had predictive value over and above the demographic variables. Finally, the health variables (physical health status, mental health status, digital health literacy, and primary care provider) were added as predictors on the final step of the regression to see if they had predictive value over and above the demographic and personality variables. Due to the exploratory nature of the study, no adjustments were made to the .05 alpha level.[40,41]

Table 1. Descriptive statistics for the demographic, personality, and health variables.

Variable	Statistic
Age in years, *M* (*SD*)	39.92 (12.94)
Gender, *N*	
Men	111
Women	116
Household income, *N*	
$65,000 (US) or less	115
Over $65,000 (US)	112
Education, *N*	
No postsecondary degree/diploma	63
Postsecondary degree/diploma	164
Country, *N*	
Canada	117
United States	110
Mini-IPIP conscientiousness, *M* (*SD*)	3.61 (0.86)
Mini-IPIP neuroticism, *M* (*SD*)	2.85 (1.06)
SF-12 physical health, *M* (*SD*)	50.49 (8.37)
SF-12 mental health, *M* (*SD*)	43.03 (12.32)
DHLI digital health literacy, *M* (*SD*)	3.38 (0.35)
Primary care provider, *N*	
Yes	173
No	54

Note. DHLI: Digital Health Literacy Instrument; Mini-IPIP: Mini International Personality Item Pool Scales; SF-12: Short-Form Health Survey.

Results

Participants

A total of 253 participants were recruited for the study. Twenty-six of these participants were excluded from the analysis: five participants completed the survey in an implausible time frame (<5 minutes), four participants failed quality control questions, two participants left the survey before completion and had large amounts of missing data, one participant exhibited monotonic responding, one participant was identified as a bot via Qualtrics' reCAPTCHA score, and 13 participants were categorical (e.g. gender) or statistical outliers. Following these exclusions, 227 participants remained for the analysis. Descriptive statistics for the demographic, personality, and health variables are presented in Table 1.

Attitudes

Participants in this study tended to report slightly positive attitudes toward healthcare CAs ($M = 4.41$, $SD = 1.16$). The regression analysis indicated that there were individual differences in their attitudes. The initial regression model containing the demographic variables was significant, $R^2 = .11$, F $(5, 221) = 5.29$, $p < .001$. This result was largely driven by income, education, and country: individuals with lower income reported more positive attitudes than those with higher income; individuals with lower education levels reported more positive attitudes than those with higher education levels; and American residents reported more positive attitudes than Canadian residents. Personality variables showed a unique contribution to the prediction of attitudes over and above demographic variables, $\Delta R^2 = .05$, ΔF (2, 219) = 6.15, $p = .003$. This result was largely driven by conscientiousness, such that people with higher levels of conscientiousness reported more positive attitudes than those with lower levels of conscientiousness. Health variables failed to show a unique contribution to the prediction of attitudes over demographic and personality variables, $\Delta R^2 = .00$, ΔF (4, 215) = 0.31, $p = .872$. Overall, the full regression model was significant, $R^2 = .16$, F (11, 215) = 3.70, $p < .001$. Regression coefficients for this and subsequent regressions are presented in Table 2. Zero-order correlations are presented in the Supplemental materials.

Design preferences

Communication modality. When asked to indicate their preference for CAs that use text communication (lower scores) versus voice communication (higher scores; neutral = 4), participants tended to report a preference for CAs that use text communication ($M = 2.78$, $SD = 1.67$). The regression analysis indicated that there were individual differences in their preferences. The initial regression model containing the demographic variables was not significant, $R^2 = .03$, F (5, 221) = 1.36, $p = .240$. Personality variables failed to show a unique contribution to the prediction of participant preferences over and above demographic variables, $\Delta R^2 = .01$, ΔF (2, 219) = 1.30, $p = .275$. However, health variables did show a unique contribution to the prediction of preferences over demographic and personality variables, $\Delta R^2 = .07$, ΔF (4, 215) = 4.19, $p = .003$. This result was largely driven by digital health literacy, such that people with higher levels of digital health literacy reported a greater preference for CAs that use text communication than those with lower levels of digital health literacy. Overall, the full regression model was significant, $R^2 = .11$, F (11, 215) = 2.43, $p = .007$.

Input flexibility. When asked to indicate their preference for CAs that have restricted input (lower scores) versus unrestricted input (higher scores; neutral = 4), participants tended to report a preference for CAs that have unrestricted input ($M = 5.46$, $SD = 1.60$). The regression analysis failed to uncover individual differences in their preferences. The initial regression model containing the demographic variables was not significant, $R^2 = .04$, F (5, 221) = 1.67, $p = .144$. Personality variables failed to show a unique contribution to the prediction of participant preferences over and above demographic variables, $\Delta R^2 = .02$, ΔF (2, 219) = 1.83, $p = .163$. Similarly, health variables failed to show a unique contribution to the prediction of preferences over demographic and personality variables, $\Delta R^2 = .00$, ΔF (4, 215) = 0.23, $p = .923$. Overall, the full regression model did not reach the threshold for significance, $R^2 = .06$, F (11, 215) = 1.16, $p = .315$.

Embodiment. When asked to indicate their preference for disembodied CAs (lower scores) versus embodied CAs (higher scores; neutral = 4), participants tended to report a preference for disembodied CAs ($M = 3.26$, $SD = 1.91$). The regression analysis indicated that there were individual differences in their preferences. The initial regression model containing the demographic variables was not significant, $R^2 = .05$, F (5, 221) = 2.24, $p = .051$. Personality variables showed a unique contribution to the prediction of participant preferences over and above demographic variables, $\Delta R^2 = .04$, ΔF (2, 219) = 4.37, $p = .014$. This result was largely driven by conscientiousness, such that people with lower levels of conscientiousness reported a greater preference for disembodied CAs than those with higher levels of conscientiousness. Health variables failed to show a unique contribution to the prediction of preferences over demographic and personality variables, $\Delta R^2 = .02$, ΔF (4, 215) = 0.99, $p = .412$. Overall, the full regression model was significant, $R^2 = .10$, F (11, 215) = 2.21, $p = .015$.

Depicted role. When asked to indicate their preference for CAs that simulate peers (lower scores) versus health professionals (higher scores; neutral = 4), participants tended to report a preference for CAs that simulate health professionals ($M = 5.57$, $SD = 1.20$). The regression analysis failed to uncover individual differences in their preferences. The initial regression model containing the demographic variables was not significant, $R^2 = .05$, F (5, 221) = 2.14, $p = .062$. Personality variables failed to show a unique contribution to the prediction of participant preferences over and above demographic variables, $\Delta R^2 = .02$, ΔF (2, 219) = 1.87, $p = .157$. Similarly, health variables failed to show a unique contribution to the prediction of preferences over demographic and personality variables, $\Delta R^2 = .00$, ΔF (4, 215) = 0.15, $p = .963$. Overall, the full regression model did not reach the threshold for significance, $R^2 = .06$, F (11, 215) = 1.35, $p = .197$.

Discussion

The results of this study provide insight into people's attitudes toward healthcare CAs, as well as their design preferences for these programs. Participants tended to report slightly positive attitudes toward healthcare CAs, with more positive attitudes among American residents and people with lower income, lower education levels, and higher levels of conscientiousness. Generally speaking, participants preferred CAs that use text communication, have unrestricted language input, are disembodied, and simulate health professionals in their presentation. CAs that use text communication were preferred to a greater degree among people with higher levels of digital health literacy, and

Table 2. Summary of regression results.

	ETSDS attitudes		Communication modality		Input flexibility		Embodiment		Depicted role	
	ΔR^2	β	ΔR^2	β	ΔR^2	β	ΔR^2	β	ΔR^2	β
Step 1	.11***		.03		.04		.05		.05	
Age		0.02		0.07		−0.04		0.08		−0.15
Gender		0.04		−0.08		0.11		−0.12		0.16
Household income		−0.16*		−0.02		0.07		−0.08		0.03
Education		−0.18**		−0.01		−0.18		−0.04		−0.02
Country		0.15*		0.13		0.02		0.11		0.01
Step 2	.05**		.01		.02		.04*		.02	
Mini-IPIP conscientiousness		0.21**		0.02		0.15		0.19*		0.14
Mini-IPIP neuroticism		−0.04		−0.10		0.09		−0.01		0.02
Step 3	.00		.07**		.00		.02		.00	
SF-12 physical health		−0.03		−0.14		0.05		−0.08		0.00
SF-12 mental health		−0.09		−0.09		−0.02		−0.14		0.01
DHLI digital health literacy		0.04		-0.22**		−0.03		−0.06		0.05
Primary care provider		0.01		−0.01		0.03		0.05		0.01

Note. *$p < .05$; **$p < .01$; ***$p < .001$. Coefficients are not interpreted unless they contribute to a significant ΔR^2. DHLI: Digital Health Literacy Instrument; ETSDS: Emerging Technologies Semantic Differential Scale; Mini-IPIP: Mini International Personality Item Pool Scales; SF-12: Short-Form Health Survey.

disembodied CAs were preferred to a greater degree among people with lower levels of conscientiousness. In the following sections, we discuss these results in greater detail and draw from past research to provide some context and interpretation for our findings.

Attitudes

In general, participants in this study reported slightly positive attitudes toward healthcare CAs. They seemed to be open to the use of these programs, but their ratings indicate a certain amount of cautiousness or hesitancy. This finding is consistent with past research on people's attitudes toward healthcare CAs, which also showed somewhat mixed attitudes among study participants.[14,15] Although the availability and sophistication of healthcare CAs has increased in recent years, it appears that many people are not overly receptive to these programs. Previous research suggests that their hesitancy is due, at least in part, to concerns over the accuracy and security of this technology.[15]

The individual difference results provide some nuance to participants' attitudinal ratings. For instance, participants with lower income and education levels tended to report more positive attitudes toward healthcare CAs than others. People in these demographic groups often experience socioeconomic barriers to conventional forms of healthcare (e.g. securing reliable transportation to appointments), and so it makes sense that they would be open to alternative sources of health support. However, it is worth noting that CAs are typically delivered through technologies that may not be readily accessible to these demographics, which might limit their use of these programs. Consistent with this idea, past research has shown that people with lower income and education levels are less likely to engage in digital health use than their counterparts with higher income and education levels,[18,19,42,43] due in part to poorer access to digital technologies.[44] It may be necessary to improve technological infrastructure, technology literacy, and similar supports if individuals with a lower socioeconomic status are to benefit from healthcare CAs.[45,46]

In general, American residents reported more positive attitudes toward healthcare CAs than Canadian residents. There are several social and cultural differences between Canada and the United States that might have contributed to this result, although it seems likely that differences in their healthcare systems played an important role. Canada has a universal healthcare system that is funded chiefly through government taxation.[47] Provincial and territorial governments cover essential medical services for their residents, and patients do not have to pay directly for most medical procedures. By comparison, the United States has a complex mix of private and public health insurance options that can be difficult to navigate and access.[48] Tens of millions of Americans are uninsured and must pay for health services out of pocket or forgo medical care altogether. Many insured Americans also face out of pocket medical costs, and these costs can dissuade them from seeking care as well.[49,50] Predictably, research has shown that the American healthcare system performs more poorly than the Canadian system in areas such as administrative efficiency and access to care.[51] These challenges may encourage a greater willingness among Americans to try accessible and relatively inexpensive alternatives to conventional health services, such as CAs.

Conscientiousness was the only personality factor to predict participants' attitudes toward healthcare CAs. Participants tended to report more positive attitudes toward these programs if they had higher versus lower levels of conscientiousness. This finding supports past research showing that conscientious individuals are more receptive to digital health applications than others.[20,21] This receptiveness might be explained by the way in which conscientious individuals approach the management of their health. Conscientiousness reflects a characteristic tendency to be responsible, planful, and organized,[28] all of which are qualities that would facilitate health management. Consistent with this idea, past research has shown that conscientious individuals engage in more preventive health behaviors than their peers, which may in turn lead to better health outcomes.[52,53] Conscientious individuals may see CAs and other digital health applications as useful tools that they can use to proactively manage and maintain their health.

Design preferences

In addition to the attitudinal findings, this study provides insight into people's design preferences for healthcare CAs. Participants in our sample reported a preference for CAs that use text versus speech communication, have unrestricted versus restricted language input, are disembodied versus embodied, and simulate health professionals versus peers. Some of these design preferences are likely rooted in practical or pragmatic considerations. For instance, text interfaces offer users more privacy and discretion than speech interfaces, which might be particularly appealing when one is discussing potentially sensitive health issues.[54,55] In addition, unrestricted language input provides greater flexibility than restricted input and gives users more control over the focus and direction of the conversation.[56] It is less clear why individuals prefer disembodied over embodied CAs, although it should be mentioned that embodied CAs are not widely available to the public and are probably less familiar to individuals than disembodied CAs.[9] Finally, a preference for CAs that simulate health professionals is consistent with past research suggesting that these depictions elicit feelings of confidence and trust in users.[57,58]

Two individual differences in participants' design preferences were identified during the analysis. People with higher levels of digital health literacy tended to prefer CAs that use text communication to a greater extent than people with lower levels of digital health literacy. This finding is not particularly surprising, as digital health literacy is partly contingent on a person's reading and writing skills.[24] People with higher levels of digital health literacy may be more likely than others to seek out or use text-based interfaces due to their comfort with this form of communication. Meanwhile, people with lower levels of conscientiousness preferred disembodied CAs to a greater extent than those with higher levels of conscientiousness. People who are low in conscientiousness tend to have poorer nonverbal communication skills than others (e.g. trouble maintaining eye contact), which may be linked to lower levels of attentiveness and self-control in these individuals.[59,60] It makes sense that they would prefer CAs that lack an embodied component, as the use of these programs would be less reliant on a person's nonverbal communication skills.

Practical implications

The results of this study offer useful information to researchers and companies that develop healthcare CAs, particularly those that are looking to increase public uptake of their programs. Based on our results, people tend to have mild interest in healthcare CAs, although these programs seem to appeal to some groups of individuals more than others. For instance, people who have fewer socioeconomic resources, people who face inaccessible or costly healthcare (e.g. many Americans), and people who are conscientious and keenly motivated to manage their health appear to be particularly receptive to this technology. Developers may be able to increase adoption and use of their CAs by targeting these specific groups. This in turn could have benefits in terms of improving public health outcomes and reducing health system use. However, the extent of these benefits should not be overstated. Healthcare CAs can provide individuals with some health support, but their assistance is limited and they are not a replacement for real health professionals.[3,61] It is also worth noting that many people are not overly receptive to healthcare CAs, and it will be important for developers to consider how to improve adoption and use in these individuals if this technology is to establish a more prominent role in healthcare in the coming years.

One way that developers might improve the public's receptivity to healthcare CAs is by accommodating people's design preferences for these programs. Our results suggest that developers should focus their efforts on CAs that are disembodied and use text communication, although these design characteristics may be more important for individuals who have lower levels of conscientiousness and higher levels of digital health literacy, respectively. Developers may also want to offer CAs that have unrestricted language input and that simulate health professionals from a presentation standpoint, as these characteristics would appeal to a broad range of individuals. Some of these characteristics are widely used in healthcare CAs, which suggests that developers may be capitalizing on people's preferences already. For instance, recent scoping reviews indicate that most CAs in this domain are text-based and disembodied.[9,16,62] However, CAs that accept unrestricted language input are less common than CAs with restricted input,[9,62] likely due to concerns that limited or inaccurate user input could result in inappropriate health advice and negative health outcomes.[54,63] CAs that simulate health professionals are also relatively uncommon, even though these depictions would be fairly easy to implement in practice.[17] There are potential ethical and legal issues surrounding the depiction of CAs as health professionals (e.g. users could be misled about the quality of health advice), and concern over these issues might be deterring developers from using these depictions. Developers will need to weigh user preferences against these and similar concerns when designing healthcare CAs, seeking a reasonable balance so that these programs are both attractive to users and safe and appropriate for use.

Limitations and future directions

In this study, we identified several individual difference factors that predict people's attitudes and design preferences with respect to healthcare CAs. However, the total variance explained by the regression models was somewhat low ($R^2 = .06–.16$), which suggests that there are many other factors related to attitudes and design preferences in this domain. The Technology Acceptance Model[64] and the Unified Theory of Acceptance and Use of Technology[65] are two well-known models of technology use that emphasize alternate (i.e. nonindividual difference) factors such as user expectations and social influence. In the future, researchers may want to combine a broad and comprehensive individual differences approach with these and similar models to obtain a better understanding of people's views toward healthcare CAs. Future research could expand on the outcome variables as well. Although we included a number of outcomes in this study, there were certain opinions and beliefs (e.g. the safety of healthcare CAs) and design preferences (e.g. the use of relational cues) that were not considered. Exploring these outcomes would provide further insight into people's views toward this technology.

Participants in this study were asked to share their views on CAs that are used for healthcare. Healthcare is an admittedly broad concept, and results might have differed had participants been asked about CAs that are used in narrow or specific healthcare contexts. For instance, past studies have distinguished between CAs that are used for health management or routine healthcare versus more serious health issues.[14,15] In a similar manner, researchers could ask about CAs that are used in certain health service areas (e.g. CAs for preconception care or mental health support). It is possible that people's attitudes and design preferences vary based on the healthcare context, and that individual differences in attitudes and design preferences manifest differently as well. In the future, researchers may want to focus on how contextual factors affect attitudes and design preferences to gain a finer understanding of this topic.

The results of this study provide useful information on people's general or overarching views toward healthcare CAs. These views may not apply to specific healthcare CAs, which vary in terms of the nature and quality of their implementation. For instance, our results suggest that individuals have a general preference for CAs that use text versus speech communication. However, people may report a strong dislike or aversion toward a particular CA that engages in low-quality text communication. Similarly, the individual differences that we uncovered in our study may be contingent on the execution of a CA and its design features. Researchers should attempt to replicate our results with a variety of real CAs to test the robustness of our findings. Evaluating actual CAs would also allow researchers to assess how nuances and variations in people's views relate to certain practical or real-use outcomes, such as user engagement[66,67] and the strength of the working alliance that develops between a user and a CA.[68–70]

There were some limitations concerning the study sample as well. The participants in our study were recruited through the online research platform Prolific. Individuals on this platform tend to supply higher quality survey data than those on other online research platforms.[71,72] However, the fact that our participants were accessed through an online platform suggests that they may be more familiar and comfortable with digital technologies than the public at large. Some of the demographic data reinforce the notion that our participants were well acquainted with digital technologies. More specifically, our sample was relatively young and highly educated, two demographic characteristics that have been linked to higher levels of digital technology use.[73] Due to the nature of our sample, it is possible that participants' views on digital technologies that are used for healthcare (including healthcare CAs) are not representative of the public as a whole. In future studies, researchers may want to use other recruitment methods to ensure that they capture individuals with a wide range of experience with digital technologies.

Conclusions

The current study offers insight into people's attitudes and design preferences with respect to healthcare CAs. It provides particularly useful information on individual differences in their attitudes and design preferences. This collective information will help guide developers on how to better design and market healthcare CAs, which may increase people's adoption and use of these programs. In the future, it will be important to consider individual differences alongside other potential predictors of attitudes and design preferences (e.g. user expectations) to gain a broader understanding of people's views toward this technology.

Author contributions: ALM was responsible for study design and administration, including data collection and formal analysis. He also wrote the original draft of the manuscript. All authors contributed to the study's conceptualization and manuscript editing and revision.

Consent to participate: Respondents were presented with an online consent form before starting the study. They provided informed consent by clicking an acknowledgment box at the end of the form.

Data availability: The dataset generated during and/or analyzed during the current study is available in the Open Science Framework repository.[74]

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Notes

a. In addition to the listed measures, participants were asked whether they had previously used a CA, and whether they had previously used a CA for healthcare specifically. We captured this information as we considered adding past experience with CAs and/or healthcare CAs as predictors in the analysis. Ultimately, they were not added due to the skewed nature of the results: most of the participants in the study (89%) had previously used a CA, whereas only a handful (9%) had used a CA for healthcare specifically.

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