Digital Doctors and Robot Receptionists: User Attributes that Predict Acceptance of Automation in Healthcare Facilities

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ABSTRACT

Advances in artificial intelligence offer the promise of accessibility, precision, and personalized care in health settings. However, growth in technology has not translated to commensurate growth in automation of healthcare facilities. To gain a better understanding of user psychology behind the acceptance of automation in clinics, a 3 (Role: Receptionist, Nurse, Doctor) x 3 (Digital Agent Representation: Human, Avatar, Robot) factorial experiment (N = 283) was conducted. Results suggest that the digital nature of the interaction overpowers any individual role effects, with acceptance depending upon individual traits (belief in machine heuristic; power usage). Implications for theory and the design of digital healthcare facilities are discussed.

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Table 1: Hypotheses & Research Questions

RQ1: Will users prefer a human, machine, or avatar automated agent in an automated healthcare facility?
H1: Belief in the machine heuristic will positively predict attitudes towards the automated agent, chat service, and behavioral intentions towards the chat service.
H2: Power usage will positively predict attitudes towards the automated agent, chat service, and behavioral intentions towards the chat service.
RQ2: Will the effect of any one IV (source type, source role, belief in the machine heuristic, power usage, and privacy concern) have an influence on the effect of a separate IV (i.e., interaction / moderation) on attitudes towards automated agent, attitudes towards chat service, behavioral intentions towards chat service, and self-disclosure?

KEYWORDS

Automation, Artificial Intelligence, Health Information Systems, Cognitive Heuristics, Self-disclosure

1 INTRODUCTION

Primary care clinicians face an extremely heavy workload, with very high demand for service [17]. Much of this workload consists of relatively menial tasks, such as acquiring symptom and patient background information, which could potentially be handled by an artificial-intelligence (AI) powered-agent. However, advances in AI systems have not simply translated to the domain of health care, despite the great potential. Simply put, automation in healthcare facilities might not be preferred by patients. Research has shown that individuals are less comfortable with automation when it takes on a personal role [11], and the doctor-patient relationship may fall within this category. If general acceptance of automated health services is low, it behooves researchers and designers to explore the individual traits that predict acceptance within the specific context of health care, given its societal-level potential.

Digital media afford interactions with both human and machine sources. Their respective representations can be equated to computer-mediated communication (Human as source), human-computer interaction (Machine as source), and avatar-based communication (Human representative as source). These three approaches represent potential design strategies for implementing automation in healthcare facilities. General attitudes towards robots and automation have been shown to predict perceptions of specific machine agents [12]. These attitudes make up the machine heuristic [15], which is a rule of thumb that machines are more objective and trustworthy than humans. Further, research has found that the machine heuristic can predict source credibility in experimental settings [2]. Although research suggests that in personal roles, a human agent will be preferred, increasing diffusion of machine agents into everyday life may make it more desirable to disclose to a machine healthcare agent than a human.

When individuals process information, they often rely on heuristics, or mental shortcuts to preserve cognitive resources [3]. Often, this research has been conducted by designing the heuristic into the interface e.g., star ratings to represent mass opinion or the "bandwagon heuristic"), however this approach may yield alternative explanations (e.g., was this specific heuristic used?). To gain a more robust understanding of user psychology, researchers have begun measuring an individual's belief in a given heuristic [1]. For example, in terms of privacy attitudes and behaviors, an experiment showed that a user's belief in the community-building heuristic predicted their attitudes toward community-related cues on the interface of an online forum site, and moderated the effect of the manipulated conditions [16]. Similarly, a user's attitude toward an autonomous healthcare facility is likely to be influenced by the machine heuristic ("Machines are more objective and trustworthy than humans"). Altogether, we find support for the notion that user attitudes and behavioral intentions will be influenced by the user's belief in the machine heuristic.

Figure 1: Experimental Stimuli: Receptionist Human (top); Doctor Avatar (middle); Nurse Bot (bottom)

In general, individuals who are both efficacious and competent with technology are considered power users. For example, power users are known to enjoy more control over their technology, whereas non-power users prefer the technology to cater to them [16]. Further, power users prefer to explore diverse, novel features of new technology, rather than sticking to the default options [14]. It can be expected that power users are more open to new technology, or in this case, technology in a new context. As power usage is conceptualized as an individual difference variable, comprised additionally of an individual's readiness and willingness to productively use technology, we hypothesize that it will be central to the level of acceptance of our autonomous healthcare facility [16, 18].

2 METHOD

In order to test the proposed hypotheses and research questions (See Table 1), a 3 (avatar type: human, machine, avatar) x 3 (role: receptionist, nurse, doctor) between-subjects factorial online experiment was conducted. An online chat interaction was used in order to test for the effects of source and user attributes in the context of autonomous healthcare facilities. Nine versions of the website prototype were designed, based on the two source factors. Participants (N = 283) were tasked with interacting and disclosing information to one of the 9 sources (See Figure 1). The interaction was framed to the participants as an annual physical, in order to properly assess how users would respond to patient intake (the information-disclosing portion of a doctor's office visit) being conducted by an automated agent. Further, at the beginning of the interaction, participants were told that their "information will be used to make some recommendations for good future health practices." The interaction continued on in a traditional chat-like manner, with participants answering "yes," "no," or "I do not wish to answer," through the 21 health related questions. The questions ranged from common health disclosures (e.g., Do you have any pre-existing medical conditions?) to potentially private (e.g., Do you occasionally eat the excess nasal matter that you have picked?). Once the online chat interaction was completed, participants answered a series of questions related to their experience (i.e., user attitude and behavioral intention towards the automated agent and chat service; See Table 2).

Participants were recruited via the Turk Prime Panel service through which study invitations were sent. In order to improve external validity of our findings, participants' demographics were matched to those of the US Census Bureau's 2017 American Community Survey (ACS) in terms of gender (49% males; 51% females), age (18-29: 22%, 30-39: 17%, 40-49: 16%, 50-59: 18%, 60-69:14%, and 70-99:13%), annual household income (median = $60,000), and race (white: 79%, black or African American: 13%, American Indian or Alaska Native: 1%, Asian: 5%, and Others: 2%).

3 RESULTS

The regression analyses revealed belief in the machine heuristic, power usage, and privacy concern to be significant predictors of all three user experience variables: 1) attitude towards the chat agent, 2) attitude towards the chat service, and 3) behavioral intention towards the chat service

Table 2: Measures

Participants' **belief in the machine heuristic** was measured by six, five-point Likert-items (1 = Strongly disagree, 5 = Strongly agree) adapted from the measure used by Kim et al. [9]. Participants were tasked with indicating their level of agreement with the statements such as: "When machines, rather than humans, complete a task, the results are more accurate."
Participant's **power usage** was measured by a 12, five-point Likert-items (1 = Strongly disagree, 5 = Strongly agree), from Sundar and Marathe [16]. The measure for power usage identifies users who are expert users, and users who both prefer options and make use of them.
Attitude toward the automated agent was measured using 17, 5-point, adjective based, Likert-type items adapted from Flanagin and Metzger [4]. Each question used a stem base of: Keeping in mind the online chat agent, how well does the following adjective describe the online chat agent that you interacted with today? Adjectives used included: Believable, trustworthy, interesting, sophisticated, (1 = Not at all, 5 = Extremely).
Attitude toward the chat service was measured using 16, 5-point, adjective based, Likert-type items adapted from Kalyanaraman and Sundar [10]. Adjectives used included: Valuable, informative, professional, useful, entertaining (1 = Not at al, 5 = Extremely).
Behavioral intention toward the chat service was measured using four, five-point, Likert-items (1 = Strongly disagree, 5 = Strongly agree) from Kim and Gambino [7]. Participants indicated their level of agreement with statements pertaining to their likeliness to reuse the service.

Further, the interaction effect between a user's belief in the machine heuristic and their power usage was significant for attitude toward the automated agent, attitude toward the chat service, and behavioral intention towards the chat service (Figure 2). Probing the interaction effect shows that when power usage is higher, the effect of a user's belief in the machine heuristic is greater. Thus, individuals who are both power users and have a high belief in the machine heuristic had the most positive attitudes and the highest behavioral intentions to use the automated healthcare facilities again.

The MANOVA did not suggest that source type (Wilk's $\lambda = .98$, $F(8, 273) = 0.60$, $p = .78$.) or source role (Wilk's $\lambda = .98$, $F(8, 273) = 0.76$, $p = .64$) had any significant effects on attitude towards the automated agent, attitude towards the chat service, behavioral intention towards the chat service, or self-disclosure.

In summary, an individual's belief in the machine heuristic and their power usage both significantly predicted user experience, specifically their attitude towards the automated agent, chat service, and behavioral intention. Further, these relationships between machine heuristic and the three outcomes were moderated by power usage, resulting in an additive effect, whereby power users are more affected by their belief in the machine heuristic than non-power users.

4 DISCUSSION

Our results suggest that a user's espousal of the machine heuristic positively predicts attitude towards the automated agent, chat service, and behavioral intentions. Thus, acceptance of automated healthcare facilities may be based on user attributes, as the digital nature of the service may have already given individuals a sense of machine-ness in the interaction. The degree of perceived humanness being similar across all experimental conditions supports this contention. This combination of findings is especially important for design initiatives of automated healthcare facilities. Further implications for theory and design are discussed in the following section.

The results also show that an individual's degree of power usage is influential in predicting user attitudes and intentions. Further, power users are more influenced by their belief in the machine heuristic, which presents opportunities and challenges for design. Power users are typically technology-efficacious, and while they are more open to novel technological uses, they are also generally high in income. One of the most appealing aspects of automation in healthcare facilities is that it would be cost efficient for the user, and allow access to better health care for disadvantaged populations, especially displaced, rural populations that otherwise would have to spend significant amounts of time and resources to get to a primary care clinician. While the general population has become more connected and technologically efficacious with the proliferation of mobile phones, power users may be a minority amongst these displaced populations. Putting these findings in context, they may explain why automated or tele-health services have not risen to mass adoption, despite the obvious economic and social benefits.

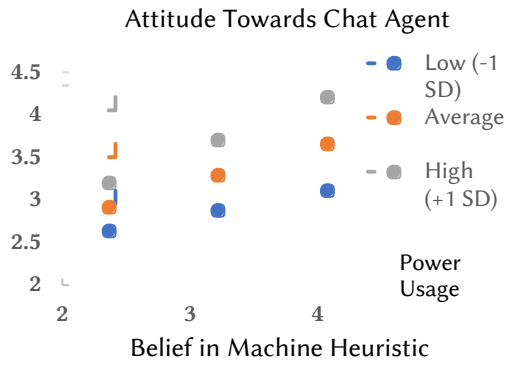

Figure 2: Moderation graph: X Axis – User's belief in the Machine Heuristic, Y Axis – Attitude Towards the Automated agent, Separate Lines: Power Usage Level

The finding that the machine heuristic plays a key role in driving positive attitudes supports the application of social cognition principles to HCI [3, 15]. The finding adds to a growing body of literature which suggests that cognitive heuristics, or psychological nudges, are of particular importance in digital interfaces with regard to a user's private information [6]. Specifically, the results suggest the importance of measuring belief in heuristics as individual difference variables. Although the identification and verification of particular heuristics may be challenging, through triangulation of research methods such as interviews [13], focus groups [5], and experiments [8], the process can lead to the systematic identification of specific cognitive heuristics that can be tracked and analyzed. While there may have been some concerns regarding the integration of AI into such a personal role, it appears that the visual reminder that the health agent has machine characteristics does not have a negative effect on user perceptions of the source, and the digital setting may allow for even more personal care through information gathering. Given the potentially transformative impact of AI-based agents to aid primary care clinicians with information gathering and simple diagnosis, our results suggest designers to be transparent with their representation of the agent [17]. Improving the reputation of AI-based services in general may positively aid in user belief in the machine heuristic over time.

In conclusion, the key to implementing automation in healthcare facilities may lie in designing the interface in such a way that it appeals to expert users who have a high belief in machine abilities. Instead of expending design resources on anthropomorphizing healthcare bots, they can be directed towards features such as chat functionality, and advanced features. As suggested by our results, increasing the number of power users and the general belief that machines are trustworthy may increase the adoption of futuristic, automated services. As designers look for solutions, they are likely to find that the answers lie in addressing the audience: growing a user base by increasing trust in machines, and then adding functionality to retain that trust.

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