Do You Feel Special When an AI Doctor Remembers You? Individuation Effects of AI vs. Human Doctors on User Experience

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ABSTRACT

You may feel special and believe that you are getting personalized care when your doctor remembers your name and your unique medical history. But, what if it is an AI doctor and not human? Since AI systems are driven by personalization algorithms, it is possible to design AI doctors that can individuate patients with great precision. Is this appreciated or perceived as eerie and intrusive, thereby negatively affecting doctor-patient interaction? We decided to find out by designing a healthcare chatbot that identified itself as AI, Human, or Human assisted by AI. In a user study assessing Covid-19 risk, participants interacted twice, 10 days apart, with a bot that either individuated them or not. Data show that individuation by an AI doctor lowers patient compliance. Surprisingly, a majority of participants in the human doctor condition thought that they chatted with an AI doctor. Findings provide implications for design of healthcare chat applications.

CCS CONCEPTS

• **Human-centered computing** → Human computer interaction (HCI); Empirical studies in HCI.

KEYWORDS

Artificial intelligence, Healthcare chatbot, AI resistance, Individuation

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1 INTRODUCTION

Advances in artificial intelligence (AI) hold the promise of transforming healthcare. The market size for medical AI is expected to reach $19.25 billion by 2026 [32]. The availability of abundant medical data and the need for data analytics made the healthcare industry more amenable to AI technologies [35, 46]. In recent years, a growing number of medical AI systems have demonstrated superior performance compared to human experts [9, 18]. The use of medical AI can reduce administrative burden on doctors, prevent human errors, and ultimately improve the quality of healthcare [33, 36]. With AI handling repetitive and tedious medical tasks like data entry and medical coding, doctors can have more time to focus on patients' needs and improve the doctor-patient relationship [1, 21, 22]. Countries have begun to invest in medical AI technologies to improve efficiency and increase access to medical services [38]. On the other hand, the surge of medical AI raises concerns about data privacy, safety and transparency, as well as algorithmic biases [13, 23, 34, 37].

Against this backdrop, patients have been reluctant to embrace AI systems for their healthcare [27, 44]. This poses a major challenge to the wide adoption of medical AI because patients are the ultimate users and the "last mile" of the healthcare system [6]. Thus, it is important to explore and address patients' concerns about AI. In general, patients prefer human to AI health providers because they believe medical AI cannot consider their unique characteristics [27] nor interact with them socially [8]. Research on online discussions about medical AI shows that the lack of humanistic care in AI and distrust are primary reasons for negative attitudes toward medical AI [12]. In response, we propose infusing individuation into healthcare chatbots as a solution to meet patients' emotional needs.

In patient counseling, individuation is a process where information unique to a patient is recognized as differentiating him or her from other patients [28]. Psychologically, individuals have the need to be viewed as unique and to maintain self-identity [39, 41]. The satisfaction of this need is likely to trigger positive psychological and behavioral outcomes. Therefore, doctors who tailor health advice to patients' unique medical conditions can not only provide better treatment but also improve patients' experience, which in turn encourages patients' adherence to their medical advice. This leads to the question of whether automated individuation can address patients' concerns and increase their adoption of medical AI. To answer this question, we tested the distinct and combined effects of doctor identity and individuation in online health counselling on patients' experience.

2 RELATED WORK

2.1 Computers are Social Actors (CASA)

As CASA studies have long shown, individuals have a natural tendency to apply social rules when interacting with machines [29]. Such social responses tend to be enhanced when these machines exhibit humanlike traits or behaviors [25]. Individuation is desirable in human-human interactions because it demonstrates that one acquires the interpersonal knowledge to respond uniquely to the other person, which is essential for building interpersonal trust and affect [45]. Based on this logic, if patients perceive individuation as a desirable attribute associated with human doctors, infusing individuation into AI doctors (e.g., healthcare chatbots) is likely to induce similarly favorable perceptions from patients, thus leading to positive outcomes, even though users of information technology are generally quite leery about intrusiveness of personalization systems [4]. That is, the positive effect of individuating patients is likely to overcome the negativity of potential privacy violation. Therefore, individuation from AI doctors and AI-assisted human doctors will be favored by patients and result in positive outcomes, such as lower perceived intrusiveness and higher patient compliance (Hypothesis 1).

2.2 Uncanny Valley of Mind

On the other hand, the uncanny valley phenomenon would suggest that machines are unnerving when individuals perceive a humanlike mind in machines [17, 41]. Humans tend to attribute mind to others along two independent dimensions: agency (the capacity to act) and experience (the capacity to feel) [16, 17]. Studies have found that the feeling of uncanniness is particularly tied to the perception of experience, which is seen as being exclusive to humans and fundamentally lacking in machines [2, 17]. In other words, embedding machines with characteristics that are distinctively human is likely to result in negative responses because it blurs the boundary between humans and non-humans, and thereby threatens human identity and distinctiveness [10, 26]. One previous study [27] suggests that the resistance to medical AI partly derives from the belief that AI doctors are unable to consider patients' unique characteristics. Participants were less likely to follow recommendations from an AI health provider compared to a human provider, an effect that was mediated by their perception of AI's inability for personalized care. It appears that individuation is viewed as being unique to human doctors.

2.3 Personalization Privacy Paradox

Receiving unsolicited personalized information from machines often raises users' concerns about their privacy, leading to greater perceived intrusiveness [24], a phenomenon known as personalization privacy paradox [4]. Prior studies show that privacy concerns over the use of personal data negatively influence users' satisfaction and adoption of e-health services, as well as their willingness to share personal information [5, 19, 48]. Since individuation involves knowing and using patients' unique information, AI-initiated individuation may cause patients to feel greater intrusion into their privacy (Hypothesis 2). The perceived intrusiveness triggered by AI individuation may undermine their evaluation of the tailored medical suggestions, leading to lower compliance (Hypothesis 3), but the opposite would be true if the individuation was done by a human doctor, leading us to predict a moderated mediation effect (Hypothesis 4; see Figure 1).

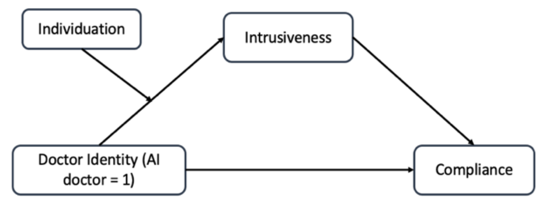

Figure 1: Moderated Mediation Model

3 METHOD

3.1 Chatbot Prototype and Procedure

In order to test the effects of doctor identity (human, human assisted by AI, AI) and individuation (present, absent) in the context of online healthcare, we designed five versions of a chatbot prototype using the platform Flow XO (https://flowxo.com/) and tested them with users. Participants were told to join a two-phase study on online patient-doctor communication. Three chatbots were programmed to simulate the first visit to a doctor online while two were programmed for the second visit. Participants were informed that they would be compensated $1 in total if they completed the entire study—$0.10 for Phase 1 and $0.90 for Phase 2.

The first study was framed as seeing a doctor for the first time on an e-health platform, a web interface of the chat. Participants were randomly assigned to interact with one of the three chatbots. In the chat, participants were first welcomed and then directed to a separate webpage where they filled out a health form ("Please complete this form so that our online doctors can provide better health advice for you!"). Upon completion, they returned to the chat interface and continued the interaction. Participants were asked to read a description of the doctor that they were going to meet (see Table 1) before the doctor entered the chat. The doctor-patient interaction began after 5 seconds and was devoted to the topic of Covid-19 ("How are you handling the Covid-19 situation") after greetings and small talk. The chatbots were programmed to ask eight questions concerning Covid-19 symptoms and behaviors. Six of the questions were set to be answered with "yes," "no," or "hard to say" (e.g., "Do you have a fever or are you feeling feverish?") while two questions allowed text input (e.g., "How often do you wash your hands in a day?"). At the end of the chat, participants were offered a Covid-19 diagnosis and recommendations, modeled after the CDC Coronavirus Self-Checker (https://www.cdc.gov/coronavirus/2019-ncov/symptoms-testing/coronavirus-self-checker.html).

About ten days after the first interaction, participants were notified using the Notify Workers Feature of Turk Prime ("You are

Table 1: Doctor introductions

Human doctor	Dr. Alex received a medical degree from the University of Pittsburgh School of Medicine in 2005, and he is board certified in pulmonary (lung) medicine. His area of focus includes cough, obstructive lung disease, and respiratory problems. Dr. Alex says, "I strive to provide accurate diagnosis and treatment for the patients."
AI doctor	AI Dr. Alex is a deep learning-based AI algorithm for detection of influenza, lung disease, and respiratory problems. The algorithm was developed by several research groups at the University of Pittsburgh School of Medicine with a massive real-world dataset. In practice, AI Dr. Alex has achieved high accuracy in diagnosis and treatment.
AI-assisted human doctor	Dr. Alex is a board-certified pulmonary specialist who received a medical degree from the University of Pittsburgh School of Medicine in 2005. The AI medical system assisting Dr. Alex is based on deep learning algorithms for the detection of influenza, lung disease, and respiratory problems.

Table 2: Individuation manipulation

	Individuation	Non-individuation
Preferred name	-Welcome, Lisa	-How would you like to be addressed? Please type in your preferred name
Heart disease	-I recall that you don't have heart disease, is that correct?	-Do you have heart disease?
	-Well, unlike people with heart disease, you are at a lower risk from Covid-19 and you don't have to worry about stocking medicines.	-Well, people with heart disease are at higher risk of Covid-19. You don't have to worry about stocking medicines.
Hand washing	-Also, last time you mentioned you washed hands as many times as possible every day. How about now?	-Also, how often do you wash hands in a day?

invited to participate in the second session of our doctor-patient online communication study. You will be rewarded $0.9 upon completion"). Participants were assigned to interact with the doctor of the same identity that they interacted with previously. And they were randomly assigned to the individuation or non-individuation condition using two chatbots. The dialogue was similar to the phase one chat, but without the administration of the intake health form. Individuation from the doctor was manipulated with chats referring to three pieces of patients' information obtained from their first interaction (see examples in Table 2). After the second chat, participants were directed to a Qualtrics questionnaire where they evaluated the doctor and their interaction. In the end, participants were debriefed that the doctors they interacted with during the experiment were all bots, regardless of the claimed identity.

3.2 Participants

The two-phase study was launched on Turk Prime from September 10-22, 2020. A total of 295 MTukers participated in the first phase of our study, and 223 of them participated in the second phase, thus yielding a retention rate of 75.59%. Among the 223 respondents, 11 failed at least one attention check question. After excluding them, we were left with 212 participants. There were 145 women (68.4%) and 67 men (31.6%) in this sample, and their ages ranged from 19 to 76 years (M = 39.22, SD = 12.38). Demographically, 72.2% of participants self-identified as White, and 42.9% reported having a four-year bachelor's degree.

3.3 Measures

Perceived individuation was assessed with 4 items, including "This doctor differentiated me from other patients" and "This doctor was familiar with my medical record". *Patient compliance* was measured with 4 items adapted from [7], for example, "I am committed to follow this doctor's health advice" and "I intend to follow this doctor's health suggestions". *Privacy Intrusiveness* was assessed via 6 items adapted from [47] (e.g., "I feel that as a result of this interaction, information about me is out there that, if used, will invade my privacy").

3.4 Construct Validity and Reliability

Based on the criteria proposed by [11], convergent validity is established if the average variance extracted (AVE) is higher than .50 and the composite reliability is greater than .70, and discriminant validity is achieved if the square root of the AVE for each construct is greater than the correlation coefficients involving that construct. As shown in Table 3, all constructs were reliable and valid.

4 RESULTS

4.1 Manipulation Checks

After the second chatbot interaction, participants were asked "which type of doctor did you just chat with?" with the following five response options: (a) a human doctor, (b) a human doctor assisted by an AI medical system, (c) an AI doctor (i.e., an AI medical

Table 3: Construct Validity of Study Variables

Variable	M	SD	1	2	3	AVE (> .50)	CR (> .70)	Cronbach's α(> .70)
1.Perceived Individuation	4.71	1.48	**.82**			.67	.89	.83
2.Perceived Intrusiveness	3.24	1.62	.01	**.84**		.71	.98	.97
3.Patient Compliance	5.11	1.26	.32***	-.35***	**.83**	.69.83	.90	.85

Note. ***p < .001, N = 212. CR = composite reliability; AVE = average variance extracted. Diagonal elements (bold) are the square root of AVE. Off-diagonal elements are correlations between constructs.

system), (d) others, and (e) I don't remember. A chi-square analysis showed that most participants correctly identified the doctor they interacted with: χ^2 (6, N = 212) = 110.16, V^* = .72, p < .001. But surprisingly, 54 out of 69 participants (78.26%) in the human doctor condition thought they had interacted with an AI doctor. Thus, our manipulation of doctor identity was not successful. The failure of manipulation check on doctor identity may be attributable to a variety of causes, which will be discussed later. To solve this problem, we decided to run two separate analyses based on the suggestions made by [30]. If the ontological manipulation of doctor identity is of interest, we should use manipulated doctor identity as independent variable (IV) in further analysis. By contrast, if the perceptions created by exposure to different message conditions is of greater interest, we should use perceived doctor identity as IV. Given the exploratory nature of the study, we examined the effects of both on persuasive outcomes such as perceived intrusiveness and patient compliance.

In addition, we also examined the manipulation effectiveness of individuation by running an independent sample t test with the manipulated individuation as IV and perceived individuation as dependent variable (DV). Results indicated that participants in the individuation condition (M = 5.59, SD = .97) perceived the level of individuation to be significantly higher than those who were in the non-individuation condition (M = 3.83, SD = 1.36). Therefore, our manipulation of individuation was successful.

4.2 Hypotheses Testing

As indicated above, we decided to test all the hypotheses with two separate analyses. First, we present the results using manipulated doctor identity as IV. Second, we present the results of the analyses we ran by using perceived doctor identity as IV.

Manipulated Doctor Identity as IV. We performed two-way ANOVAs to test the competing hypotheses (H1-H3) given that both manipulated IVs (i.e., doctor identity and individuation) are categorical and the two DVs are continuous. Results showed an interaction effect between doctor identity and individuation on patient compliance: F(2, 206) = 2.49, p = .09, partial η^2 = .02 as well as on perceived intrusiveness: F(2, 206) = 2.49, p = .09, partial η^2 = .02. As presented in Figure 2, patient compliance was higher when human doctors and AI-assisted human doctors differentiated the patient from others, but was lower when AI doctors did the same. The reverse pattern was found for perceived intrusiveness. Participants perceived a greater level of intrusiveness when AI doctor differentiated the patient from others, but lesser intrusiveness when human doctor or AI-assisted human doctor did so. Therefore, our results supported H2 and H3 but rejected H1.

H4 proposed a moderated mediation effect, that is the indirect effect of doctor identity on patient compliance via perceived intrusiveness would be conditioned upon individuation. We tested this with the Model 7 in PROCESS Macro (see the appendix of Hayes [20]), using 5,000 bootstrapping samples and 95% bias-corrected and bias-accelerated confidence interval (CI) estimates [20]. The index of moderated mediation was significant (inferred from the absence of zero between the lower and upper CI) for the comparison between AI-assisted human doctor and AI doctor: Index = .2998, SE = .1694, 95% CI: .0208, .6760. That is, when the AI doctor individuated patients, the perceived intrusiveness was higher and patient compliance lower compared to the AI-assisted human doctor. However, the moderated mediation model was not significant for the comparison between human doctor and AI doctor, probably because of the failure of manipulation check on human doctor identity: Index = .2596, SE = .1609, 95% CI: -.0287, .6022.

Perceived Doctor Identity as IV. When using perceived doctor identity as IV, we excluded one participant who chose "I don't remember" as a response to our manipulation check question, leaving us with 211 valid responses for this analysis. Similar to previous results, we found an interaction effect of doctor identity and individuation on patient compliance, F(2, 205) = 3.38, p = .036, η^2 = .03. As shown in Figure 3, individuation resulted in more patient compliance if it came from a human doctor or an AI-assisted human doctor, but participants were less likely to comply when the AI doctor differentiated the patient from others. However, there was no significant interaction effect of doctor identity and individuation on perceived intrusiveness, F(2, 205) = 1.25, p = .29, η^2 = .01. Further, we found that individuation moderated the indirect effect of perceived doctor identity on patient compliance via perceived intrusiveness (AI vs. human doctor: Index = -.6166, SE = .2451, 90% CI: [-1.1520, -.1775] and AI-assisted human vs human doctor: Index = -.7240, SE = .2544, 90% CI: [-1.2820, -.2805]). That is, compared to the AI doctor and the AI-assisted human doctor, when the human doctor did not differentiate the patient from others, study participants perceived greater intrusiveness, which in turn resulted in lower compliance (see Figure 3).

5 DISCUSSION

This study designed chat interfaces for online patient counseling and tested user responses (perceived intrusiveness and patient compliance) to individuation from doctors with different identities. The

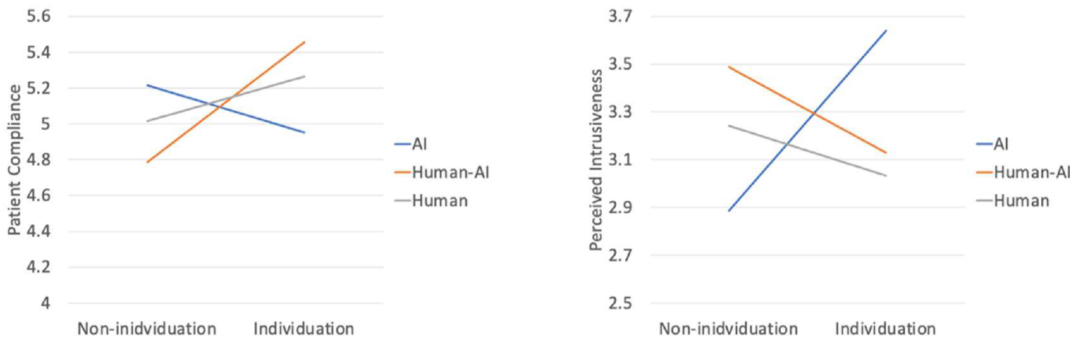

Figure 2: Interaction between Doctor Identity and Individuation on Patient Compliance (left) and Perceived Intrusiveness (right).

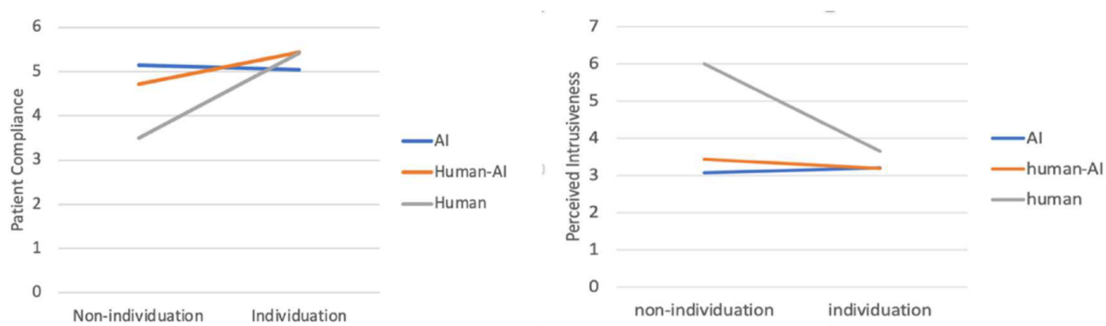

Figure 3: Interaction of Perceived Doctor Identity and Individuation on Patient Compliance (left) and Perceived Intrusiveness (right).

following section will discuss our two major findings and design implications for chat interfaces in health settings.

5.1 Summary of Findings and Future Studies

First, data showed that the majority of participants (78.26%) in the human doctor condition thought that they had interacted with an AI doctor. The reason for this finding was possibly due to our chatbot design. All chatbots were designed to send responses to participants with a 2-second delay. This turnaround time could have made the responses appear mechanical and may have led participants in the human doctor condition to think that they had encountered an AI doctor, as humans typically need more time to construct and send long messages. Also, the medical advice provided by the doctors at the end of the chat was very similar in both phases. Participants may have associated such repetitive messaging as more indicative of a machine than a human. Perhaps they expected less rigid advice from a human doctor. Also, suggestions of human presence on the interface (e.g., profile photo) were somewhat limited in our human-doctor condition, probably insufficient to imbue strong perceptions of "humanness" [3, 15].

In addition, participants in this study were fairly familiar with doctors online, scoring 4.47 on average on a 7-point scale of familiarity. This is not surprising given that the experiment was conducted during the Covid-19 pandemic, when many had turned to online medical services to avoid physical contact. In this regard, our participants may have already formed certain expectations of virtual doctor visits based on previous experiences. For example, many health apps allow not only text messaging as we did in this study but also audio messaging or live video sessions [31]. Individuals may have come to prefer to use Zoom or other video platforms for their online doctor visits. The lack of these modalities may reduce the perceived realism of our online health consultation, which may have lowered the credibility of the experimental manipulation of our human doctor condition [42].

Furthermore, the social isolation caused by the pandemic may lead to even greater need for connection with humans and interpersonal warmth, which is difficult to realize through scripted text messages. Similar to human-like machines, robotic humans are also disturbing to users and can cause cognitive dissonance [17, 40], which in turn may result in denial of the identity information. When participants were told that they would be chatting with a human doctor, their expectations were likely to be shaped by previous human-human interactions (e.g., proper response time; flexible responses). When the interaction did not align with their expectations, they probably experienced dissonance and were therefore motivated to resolve it. It appears that our manipulation-check item provided the opportunity to resolve this dissonance by affirming that the doctor was indeed a machine, not a human.

Our second major finding is the interaction effect, such that individuation coming from a human doctor is appreciated whereas that coming from an AI doctor is perceived as too intrusive and therefore unappreciated. Although previous research suggests that user resistance to medical AI systems is driven by a belief that they lack individuation [27], our attempt at infusing individuation in healthcare chatbots did not produce desired outcomes. In line with the uncanny valley theory of mind, it could be that individuation is viewed as being unique to human-human interaction. Individuation from AI is probably viewed as a pretense, i.e., a disingenuous attempt at caring and closeness. On the other hand, when a human doctor does not individuate and repeatedly asks patients' name, medical history, and behavior, individuals tend to perceive greater intrusiveness which leads to less patient compliance. Future research could measure perceived authenticity of AI individuation and use open-ended questions to further explore how individuals perceive individuation from different entities.

5.2 Design Implications

The two findings of our study have design implications. In terms of healthcare chatbots, designers could implement stronger visual cues on the interface to convey the humanness of the doctor, e.g., include avatars to help users better perceive and remember the doctors' identity. Especially in the bot-human hybrid design, when the human doctor takes over the chat from the bot assistant, the avatar should change accordingly to help clarify the source of the messages. Furthermore, human doctors using medical chat interfaces should make an effort to include socioemotional cues to show they are human, including proper delays in responding. We should note however that static response delays in chatbots have been known to backfire if the complexity of the previous response and other features of the interaction are not taken into consideration [14, 43]. Additionally, a human doctor who sends rigid and repetitive responses via a chat interface is in danger of being mistaken for an AI doctor, which could undermine efforts to individuate care to their patients. Thus, doctors who communicate with patients via online chat should avoid the tendency to cut and paste stock responses to routine questions. Although individuation can be easily built into chat dialogue systems by mentioning the name of the patients or retrieving patients' previous responses, it seems to be premature for digital individuation to scale now. However, such digital individuation systems could be built into the chat interface controlled by human doctors and utilized by them in online consultations, which could improve user experience and increase their compliance to medical advice.

5.3 Limitations

The study also has several limitations. The Mturk sample may limit the generalizability of the findings because Mturkers tend to be more tech savvy. The use of disembodied and text-based conversational bots limits generalizability to voice-based and embodied agents. Also, the online nature of the study may have introduced noise and undermined experimental control. The lack of open-ended questions relating to users' attitudes limit our ability to verify our explanations for the findings (e.g., why the manipulation check failed).

6 CONCLUSION

In conclusion, the current study contributes to our knowledge of individuation effects of AI and human doctors on user experience using a two-phase online experiment and self-developed text-based chatbots. This study found that individuation by an AI doctor lowers patient compliance while individuation coming from a human doctor is appreciated. When a human doctor does not individuate however, and repeatedly attempts to elicit patient information, patients perceive greater intrusiveness, leading to lower compliance. Interestingly, a majority of participants in the human doctor condition of our study thought that they chatted with an AI doctor, which has implications for use and design of chat interfaces for delivering health care.

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