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Human vs. machine-like representation in chatbot mental health counseling: the serial mediation of psychological distance and trust on compliance intention

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Abstract
This study examined a serial mediation mechanism to test the effect of chatbots' human representation on the intention to comply with health recommendations through psychological distance and trust towards the chatbot counselor. The sample of the study comprised 385 adults from the USA. Two artificial intelligence chatbots either with human or machine-like representation were developed. Participants had a short conversation with either of the chatbots to simulate an online mental health counseling session and reported their experience in an online survey. The results showed that participants in the human representation condition reported a higher intention to comply with chatbot-generated mental health recommendations than those in the machine-like representation condition. Furthermore, the results supported that both psychological distance and perceived trust towards the chatbot mediated the relationship between human representation and compliance intention, respectively. The serial mediation through psychological distance and trust in the relationship between human representation and compliance intention was also supported. These findings provide practical guidance for healthcare chatbot developers and theoretical implications for human-computer interaction research.

Keywords Chatbot · Emotional disclosure · Mental health · Intimacy · User satisfaction · Intention to reuse

Introduction

According to the world mental health report (World Health Organization, WHO, 2021), during the first year of the COVID-19 pandemic, patients with major depressive disorder increased by 28%. Moreover, the Centers for Disease Control and Prevention (CDC, 2022) reported that more than 44% of high school students persistently felt sad or hopeless during the pandemic. Studies point out that mental healthcare providers' stress and burnout are also critical issues (van Dam, 2021; Weiner, 2022); half a population is living in areas where one mental healthcare provider is responsible for 200,000 people's mental health (WHO, 2021). Such an increased demand for mental health services and the labor shortage in the mental healthcare field caused by the COVID-19 pandemic have drawn more attention to artificial intelligence (AI) chatbot counselors.

Studies have demonstrated various merits of using chatbot agents in mental health services (Lattie et al., 2022; Miner et al., 2020; Zhu et al., 2022). For example, studies have found that the mental health chatbots such as Woebot,

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IntelliCare, SuperBetter, and WebMAP mobile have positive effects on mental health (Lattie et al., 2022). To be more specific, a mental health chatbot, Woebot, exchanges millions of messages every week in more than 130 countries and demonstrated efficacy in alleviating mental health symptoms in both college students and adults (Woebot Health, 2018). Moreover, the growing preference toward human-machine interactions over in-person counseling, especially among youth will lead to further expansion of chatbot use, not only for a simple information delivery function but for conversations that require more complex social interactions (Lattie et al., 2022; Miner et al., 2017). To serve the high demand for mental health chatbots that can replace human presence, mental health chatbot designers have employed humanlike designs such as visual human representations for chatbots, however, the understanding of the psychological mechanism behind the effects is still limited. There is still room for improvement in the chatbot design to address the challenges of users' perception and acceptability (Almalki & Azeez, 2020).

To add to the understanding of the mechanisms underlying human-chatbot interactions and provide practical suggestions on the physical attributes of chatbot agents in the context of mental health counseling, this study focused on the human representation of chatbots, which is a compelling component that induces immediate effects in a conversation with a stranger (Nowak & Rauh, 2006; Walker et al., 1994). Moreover, this study employed the elaboration likelihood model (Petty & Cacioppo, 1984), the folk theory (Jung et al., 2022), the theory of anthropomorphism (Epley et al., 2008), the construal level theory (Trope & Liberman, 2010), the computers are social actors (CASA) paradigm (Reeves & Nass, 1996; Nass & Moon, 2000), and the uncertainty reduction theory (Berger & Calabrese, 1975) to unravel the determinants of intention to comply with chatbots' health recommendations.

Thus, we developed two AI-powered chatbot agents with human vs. machine-like face representations and conducted a quasi-experiment to test the effect of a human representation of a chatbot on the intention to comply with health recommendations. Furthermore, we tested the independent and serial mediating roles of psychological distance and trust in the proposed main effect. Theoretical relationships between human representation, psychological distance, trust, and compliance intention are discussed in the following section.

Theoretical premises

Human representation and compliance intention

The CASA paradigm suggests that individuals use social norms and show social responses when interacting with computers (Reeves & Nass, 1996; Nass & Moon, 2000). The theory of anthropomorphism indicates that individuals tend to perceive human-like characteristics in nonhuman agents and the level of perceived humanness affects psychological, attitudinal, and behavioral outcomes resulting from human-computer interactions (Epley et al., 2008; Go & Sundar, 2019). Studies supporting this line of thought found that anthropomorphic agents are perceived to be more responsive (Gong, 2008), attractive, and credible, (Nowak & Rauh, 2006), evaluated more positively (Li & Sung, 2021), and increase social presence, perceived similarity, dialogue, attitude, and behavioral intentions (Go & Sundar, 2019).

Based on such findings, computer interface design has evolved to be more human-like. The three most common types of humanness cues for chatbot agents include visual, identity, and conversational cues (Go & Sundar, 2019). The current study focuses on visual cues (i.e., human vs. machine-like face representations) of chatbots, a compelling component that induces immediate effects, especially in a short conversation with a stranger such as a chatbot agent where there is often a high level of uncertainty (Nowak & Rauh, 2006; Walker et al., 1994). According to uncertainty reduction theory (Berger & Calabrese, 1975), the primary goal of an unfamiliar interaction is to reduce uncertainty, and individuals rely heavily on physical cues such as avatars or human images to have better control over uncertain situations (Epley et al., 2008; Nowak & Rauh, 2006; Stinnett et al., 2013). Moreover, studies have suggested that visual heuristic cues (e.g., human representation) are processed unconsciously and automatically, and deliver most of the necessary information required for users to deal with unfamiliar situations (Mousavi & Gigerenzer, 2014; Pettitt et al., 2020). The folk theory also highlights that individuals use intuitive and informal information to process interaction with technology such as AIs (Jung et al., 2022). The elaboration likelihood model further suggests that when individuals are less motivated or involved in a topic, they tend to use peripheral cues such as simple source cues (i.e., intuitive evaluation of the source) to determine their outcome attitudes and behaviors (Petty & Cacioppo, 1984). We developed our study on these theories that consistently highlighted the importance of heuristic cues and suggested the persuasive effects of visual human representations of virtual agents (Gong, 2008; Go & Sundar, 2019; Li & Sung, 2021; Nowak & Biocca, 2003; Nowak & Rauh, 2006).

Despite the extant literature, we argue that there remains much room to improve the understanding of the human-like design of chatbots due to the complex psychological mechanisms behind the effects. For example, in the context of mental health counseling, higher perceived humanness may negatively affect counseling effectiveness due to privacy concerns (Miner et al., 2017). Moreover, Go and Sundar (2019) highlighted that humanlike cues may increase users' expectations of human-chatbot interaction, which may lead to negative outcomes if the interaction quality is below their expectations. Walker and colleagues (1994) also suggest that increased humanness and interactivity do not always lead to other interaction outcomes. To add to the clarification of the conflicting results (e.g., Go & Sundar 2019; Miner et al., 2017; Nowak & Biocca, 2003; Walker et al., 1994), we propose the following hypothesis and examine the effect of representation on compliance intention.

H1 Human representation increases the intention to comply with health recommendations: A chatbot with a human representation yields a higher intention to comply with health recommendations than one with a machine-like representation.

Mediation of psychological distance

According to construal level theory, psychological distance refers to the subjective perception of social, spatial, and temporal distances from a target (e.g., person, place, time, etc.), which have various cognitive and psychological effects on judgment (Liberman & Trope, 1998), evaluation, prediction, choice (Park & Park, 2016; Trope & Liberman, 2003), behavior, (Trope & Liberman, 2010) and so on. This study explores the social distance dimension, the most relevant psychological distance dimension in the context of human-chatbot interaction, and examines the mediating role of psychological distance between anthropomorphism and compliance intention. In the present study, psychological distance (i.e., social distance) is defined as a subjective perception of closeness (Magee & Smith, 2013), familiarity, similarity (Li & Sung, 2021), and group identity (Buchan et al., 2006) from another individual or an AI.

Visual cues of humanlike characters and mascots are one of the most commonly used strategies to anthropomorphize nonhuman agents (Ali et al., 2021), which help individuals reduce perceived risk and better manage uncertain situations by familiarizing the target (Epley et al., 2008, Guthrie, 1997; Stinnett et al., 2013). Extant studies suggest that humanlike designs bring individuals psychologically closer to AIs because human likeness increases perceived similarity (Chung & Han, 2022; Guido & Peluso, 2015; Li & Sung, 2021) and makes them accept a nonhuman agent as an in-group member (Puzakova et al., 2009). For example, Guido and Peluso (2015) found that anthropomorphized products with humanlike bodies and faces increased consumers' perceived similarity and self-brand congruency. Chung and Han (2022) also tested the effect of human representation in the context of chatbot conversation and found that the use of emojis to represent chatbots significantly reduced perceived psychological distance.

Reduced psychological distance affects several interaction outcomes such as general positivity (Trope & Liberman, 2010), attitudes (Li & Sung, 2021), attractiveness (Nowak & Rauh, 2006), judgmental confidence (Goethals & Nelson, 1973), and complacence with chatbot recommendations (Ahn et al., 2021). Moreover, studies have found that information provided by psychologically proximal others is considered more credible and reliable and therefore more influential and persuasive (Ahn et al., 2021; Bakshy et al., 2012; Rogers & Bhowmik, 1970). This indicates the important role of psychological distance between a user and a chatbot counselor in persuading an individual to comply with mental health recommendations. Li and Sung (2021) further found that perceived humanness positively affects attitudes toward AI chatbots through psychological distance indicating the mediating role of psychological distance between humanness designs and interaction outcomes. The effect of psychological distance has also been tested in the context of health counseling since it is an important factor in building a therapeutic relationship and increasing patient satisfaction, reuse intention, and compliance with health recommendations (Burgoon et al., 1987; Dehlendorf et al., 2014; Spake & Bishop, 2009).

Based on these findings, we propose that perceived psychological distance is an important variable in mental health counseling and a mediator in the relationship between chatbots' human representation and compliance intentions toward mental health recommendations.

H2 Psychological distance mediates the effect of human representation on the intention to comply with health recommendations.

Mediation of trust

Trust is an essential factor of successful human-computer interaction, and individuals require trust before they can comply with others' recommendations (Liu, 2021; Przegalinska et al., 2019). This is especially true in the context of health-related recommendations where trust in health information providers is crucial to enhancing compliance (Gaston & Alleyne-Green, 2013; Holroyd et al., 2020; Whetten et al., 2006). However, developing trust can be challenging, especially in an initial state of interaction between strangers, and it becomes even more challenging if one knows the partner is an AI, which significantly increases users' level of uncertainty about the interaction (Liu, 2021). Individuals tend to raise the bar for trust when experiencing such high uncertainty (Jian et al., 2000; Liu 2021). Therefore, it has been a long-standing challenge for both healthcare practitioners and medical chatbot developers to increase trust. In this study, we define trust as an individual's belief in a chatbot agent to help them achieve specific goals (Lee & See, 2004; Yagoda & Gillan, 2012).

Previous studies of human-computer interaction have highlighted the role of embodied conversational agents in decreasing uncertainty and increasing perceived trust toward nonhuman agents (Bente et al., 2008; Cassel & Bickmore, 2000; de Visser et al., 2016; Gong, 2008; Jung et al., 2022; Liu 2021; Weitz et al., 2019). For example, Weitz et al. (2019) compared the effects between textual information and the same information presented by an embodied virtual agent Gloria; participants showed greater trust and were less wary of the system when it was represented by Gloria. The uncertainty reduction theory and folk theory provide explanations for such phenomena—that individuals tend to rely on easily accessible physical or visual information (Mousavi & Gigerenzer, 2014; Nowak & Rauh, 2006; Pettitt et al., 2020) and use intuitive and informal information to process interaction with technology (Jung et al., 2022). Moreover, the elaboration likelihood model suggests that when individuals are less motivated or involved in a topic (e.g., a conversation with a stranger), they tend to use the peripheral route and rely on an intuitive evaluation process. Further, initial trust formation during the early stages of a relationship requires peripheral cues as individuals have relatively low involvement and high anxiety (Yang et al., 2006).

Extant studies also suggested the significant positive effect of trust in chatbots on several interaction outcomes such as purchase intention (Yen & Chiang, 2020), attitude towards chatbots (de Cicco et al., 2020), customer retention (Mozafari et al., 2021), consumer responses (Toader et al., 2019), intention to use a recommendation chatbot (Qui & Benbasat, 2009), and health chatbot acceptability (Nadarzynski et al., 2019). Based on these findings, this study argues that human representation, a direct intuitive visual cue, increases perceived trust toward a chatbot agent, and thus increases intention to comply with chatbot-generated health recommendations.

H3 Trust mediates the effect of human representation on the intention to comply with health recommendations.

Serial mediation of psychological distance and trust

Extant studies also suggest a significant relationship between psychological distance and trust (Ayeh et al., 2013; Buchan & Croson, 2004; Cadsby et al., 2008; Goto, 1996; Lin & Xu, 2017; Nowak & Rauh, 2006; Sung et al., 2020; Wang et al., 2008; Zhang et al., 2020), which implies a serial mediation between human representation and compliance intention through psychological distance and trust towards a chatbot agent. To be more specific, studies found that close social distance, homophily perception, closeness, and in-group perception positively affect source credibility (Ayeh et al., 2013), brand credibility (Sung et al., 2020), trust towards a conversational partner (Buchan et al., 2006; Cadsby et al., 2008) and online consumer reviews (Lin & Xu, 2017) and others. Wang et al. (2008) also found similar results that homophily (i.e., close psychological distance) is positively associated with credibility judgment in the context of online health communication and message outcomes.

Based on these findings, this study further proposes the following serial mediation between human representation and compliance intention.

H4. Psychological distance and trust serially mediate the effect of human representation on the intention to comply with health recommendations.

The hypothesized research model is shown in Fig. 1.

Method

Participants

A total of 409 adults from the US voluntarily participated in the study through a crowdsourcing sourcing website, Amazon Mechanical Turk. All participants submitted signed informed consent forms. This study did not limit the participants based on their mental health status because the discussion is focused on the general public. Incomplete questionnaires (24) were excluded, resulting in 385 participants. Of these, 193 (50.1%) participants were assigned to the machine-like representation condition (robot image) and 192 (49.9%) to the human representation condition (human image). The sample consisted of 233 (60.5%) male and 152 (39.5%) female participants; 338 White (87.8%), 12 Black (3.1%), 25 Asian (6.5%), and 10 participants from other races (2.6%). The mean age was 37.5 years ($SD = 10.9$). A total of 15 had completed high school and 370 held a

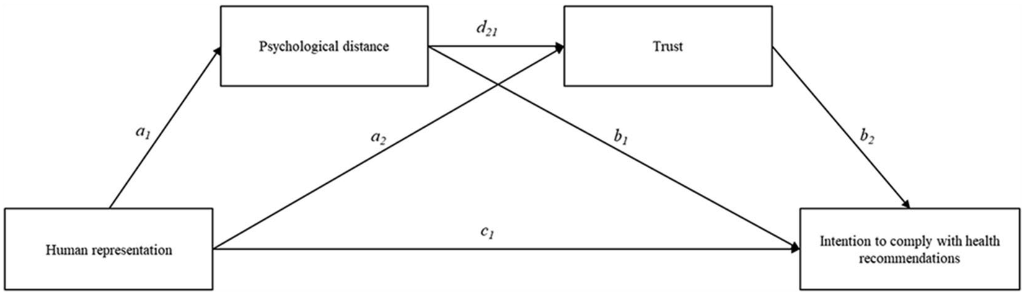

Fig. 1 Hypothesized research model. Paths a_1 and a_2 present the relationship between the predictor (Human representation) and mediators (Psychological distance and Trust). Path d_{21} indicates the relationship between the two mediators. Paths b_1 and b_2 represent the relationship between the mediators and outcome (Intention to comply with health recommendation) whilst the predictor value is controlled. Path c_1 is the total effect of the predictor on outcome both directly and indirectly through the mediators. Path c_1 is the direct effect between the predictor and the outcome excluding the mediators. The indirect effect of predictor on outcome through the mediator (Psychological distance) is a_1*b_1. The indirect effect of predictor on outcome through the mediator (Trust) is a_2*b_2. The indirect effect of predictor on outcome through the two mediators is $a_1*d_{21}*b_2$.

bachelor's degree or higher. The median annual household income was between $50,000 and $59,999.

Procedure

After participants submitted signed informed consent forms, they were presented with a link to begin a two-way conversation with a mental health AI chatbot counselor. On clicking the link, participants were directed to a new webpage and greeted by either version of the chatbot (machine-like representation vs. human representation). Each session was designed to last for about 5–10 min based on participants' level of experience. Participants interacted with the chatbot using button-type rich response options and responded to questions by clicking pre-defined button options. During the conversation, the chatbot posed general mental health-related questions, provided mental health recommendations to users (see Sect. 3.3 for details), and guided them to the questionnaire page. After the conversation, participants responded to questions about their experience with the chatbot counselor (i.e., psychological distance, trust, and intention to comply with health recommendations) and demographics. Thereafter, they were provided with a verification code as proof of completion for Amazon Mechanical Turk.

Stimuli

Chatbot agent development: To simulate an online mental health counseling conversation between a user and a chatbot agent, we developed two versions of chatbot counselors with either human representation or machine-like representation using Dialogflow, a natural language processing engine. As shown in Fig. 2, Dialogflow enables two-way conversation by matching the user expression to intent and extracts information from the intent to provide relevant feedback (Google Cloud, 2023). For example, if a user expresses "I feel depressed," Dialogflow conduct intent matching to categorize the user's intention (e.g., symptoms intent) and extract information from the expression (e.g., $feel, $depressed) (Google Cloud, 2023). The chatbots were trained to generate logical responses for users through the training, action, and parameter processes; during the training process, we input examples for each set intent so that Dialogflow can perform machine learning to expand the list and find similar expressions (Google Cloud, 2023). Then we input action definitions for each intent, and parameters allowed us to create custom entities (e.g., symptom entity: depression, anxiety, stressed) to dictate how a user expression is interpreted and responded to (Google Cloud, 2023).

Throughout the counseling session, participants were presented with either version of the facial image (human vs. machine). Moreover, based on Schrum et al.'s (2021) study

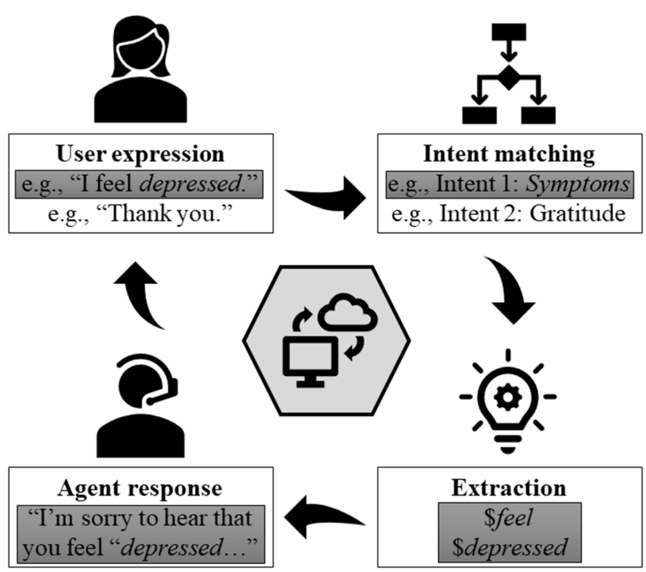

Fig. 2 Two-way user-chatbot interaction

on robot anthropomorphism, three different facial expressions were also created (i.e., smile, wink, and frown) and presented to users according to the dialog context.

Counseling content and process: In the first part of the session, the chatbot counselor greeted participants and posed general questions concerning their current mental health to simulate small talk. These questions were developed by a certified mental health counselor (e.g., "During the COVID-19 pandemic, how well could you enjoy your favorite activities?" "Have you experienced any problems during the COVID-19 pandemic?"). After the small talk interaction, the chatbot provided mental health recommendations, which were developed by a certified mental health counselor based on the CDC's (n.d.) "Taking care of your emotional health" guideline (e.g., "Taking care of your body with balanced meals, exercise, and adequate sleep," "Connecting with others in supportive conversation"). The chatbot concluded the session by thanking participants and providing a verification code as proof of completion for Amazon Mechanical Turk.

Measurement

Psychological distance

Five psychological distance items were adopted from Li and Sung's (2021) study on psychological distance in user-AI assistant interactions and modified to fit the context of the current study (e.g., "I felt close to the counselor during the conversation," "I developed a sense of closeness with the counselor," "I think the counselor can be someone I can be friends with."). Participants responded to the items on a seven-point Likert scale ranging from 1 = *strongly disagree* to 7 = *strongly agree* (M = 5.41, SD = .99, Cronbach's α = .89).

Trust

Trust was measured using five items adapted from Lee and Choi's (2017) study on user experience with chatbot agents and modified for the context of this study (e.g., "Overall, the counselor is trustworthy," "The counselor is honest," "I can trust the information provided by the counselor."). Respondents were asked to rate each item on a seven-point Likert scale ranging from 1 = *strongly disagree* to 7 = *strongly agree* (M = 5.55, SD = .78, Cronbach's α = .81).

Intention to comply with health recommendations

Intention to comply with health recommendations provided by the counselor was measured by adopting and modifying four items from Lennon et al.'s (2020) study on intent to comply with COVID-19 public health recommendations (e.g., "I am willing to follow the mental health measures that the counselor recommended," "I will comply with the recommended mental health recommendations when needed," "I am willing to follow the mental health recommendations when I experience mental problems."). Each item was rated on a seven-point Likert scale ranging from 1 = *strongly disagree* to 7 = *strongly agree* (M = 5.51, SD = .80, Cronbach's α = .80).

Statistical analysis

We used SPSS 26.0 to calculate descriptive statistics, Cronbach's α, and correlation coefficients for the study variables. Thereafter, we conducted independent samples *t*-test to examine differences in the two types of chatbots (machine-like vs. human-like) on intention to comply with health recommendations (H1). We also conducted Hayes's (2017) Process macro (Model 6) with a 95% bias correlated confidence interval (CI) based on 5,000 bootstrap samples to test the mediating effects of psychological distance and trust on the relationship between human representation and intention to comply with health recommendations (H2, H3, and H4).

Results

Preliminary analysis

Table 1 presents the descriptive statistics and zero-order correlation coefficients for all study variables. All variables were significantly and positively correlated.

Table 1 *Means, standard deviations, and correlations between study variables*

Variables	*M*	*SD*	1	2	3	4
1. HR	-	-	1.00			
2. PD	5.41	0.99	0.21**	1.00		
3. TRU	5.55	0.78	0.23**	0.72**	1.00	
4. ICHR	5.51	0.80	0.22**	0.69**	0.80**	1.00

** $p < .01$

Note. HR = Human representation, PD = Psychological distance, TRU = Trust, ICHR = Intention to comply with health recommendations.

Hypothesis testing

H1 predicted that the human representation would yield a higher intention to comply with health recommendations than the machine-like representation. The results showed that participants who communicated with the chatbot with human representation ($M = 5.69$, $SD = 0.61$) reported higher intention to comply with recommendations than those who interacted with the chatbot with machine-like representation ($M = 5.34$, $SD = 0.93$), $t(383) = 4.41$, $p < .001$. In other words, when individuals had a conversation with the chatbot with human representation, they were more compliant with the health recommendations provided. Therefore, H1 was supported.

H2 predicted that psychological distance would mediate the relationship between human representation (0 = machine-like representation, 1 = human representation) and intention to comply with health recommendations. As shown in Fig. 3; Table 2, the human representation was positively associated with psychological distance (Path a_1: $B = 0.41$, $SE = 0.10$, *95% CI* = 0.21, 0.60), which in turn was positively associated with the intention to comply with health recommendations (Path b_1: $B = 0.18$, $SE = 0.03$, *95% CI* = 0.11, 0.25), indicating that the indirect effect was significant (*indirect effect* ($a_1 * b_1$): $B = 0.07$, *Boot SE* = 0.04, *95% Boot CI* = 0.02, 0.16). Hence, the influence of human representation on intention to comply with health recommendations was mediated by psychological distance. Specifically, participants who communicated with the chatbot with human representation felt closer to it, which then led to a higher intention to comply with health recommendations. Thus, H2 was supported.

H3 predicted that trust would mediate the relationship between human representation and intention to comply with health recommendations. The result showed that human representation was positively linked to trust (Path a_2: $B = 0.13$, $SE = 0.06$, *95% CI* = 0.02, 0.24), which in turn was positively related to the intention to comply with health recommendations (Path b_2: $B = 0.66$, $SE = 0.04$, *95% CI* = 0.58, 0.75), representing that the indirect effect was significant (*indirect effect* ($a_2 * b_2$): $B = 0.09$, *Boot SE* = 0.05, *95% Boot CI* = 0.01, 0.19). Thus, the impact of human representation on intention to comply with health recommendations was mediated by trust. In other words, participants who conversed with the chatbot with human representation perceived more trust towards it, which in turn elicited their intention to comply with health recommendations. Therefore, H3 was supported.

H4 predicted that psychological distance and trust would serially mediate the relationship between human representation and intention to comply with health recommendations. The findings showed that human representation was positively associated with psychological distance (Path a_1: $B = 0.41$, $SE = 0.10$, *95% CI* = 0.21, 0.60), psychological distance was positively associated with trust (Path d_{21}: $B = 0.55$, $SE = 0.03$, *95% CI* = 0.50, 0.61), and trust was positively linked to intention to comply with health recommendations (Path b_2: $B = 0.66$, $SE = 0.04$, *95% CI* = 0.58, 0.75), sequentially, indicating that the indirect effect was significant (*indirect effect* ($a_1 * d_{21} * b_2$): $B = 0.15$, *Boot SE* = 0.04, *95% Boot CI* = 0.07, 0.24). This shows that when participants

Table 2 *Total, direct, and indirect effects of human representation on intention to comply with health recommendations*

	B	*SE*	*t*	*LLCI*	*ULCI*
Total effect of HR on ICHR	0.35	0.08	4.41	0.20	0.51
Direct effect of HR on ICHR	0.04	0.05	0.91	− 0.05	0.14
Indirect effects of HR on ICHR	*B*	*Boot SE*		*Boot LLCI*	*Boot ULCI*
Total indirect effect of HR on ICHR	0.31	0.07		0.18	0.46
Indirect effect 1: HR → PD → ICHR	0.07	0.04	-	0.02	0.16
Indirect effect 2: HR → TRU → ICHR	0.09	0.05	-	0.01	0.19
Indirect effect 3: HR → PD → TRU → ICHR	0.15	0.04	-	0.07	0.24

Note. HR = Human representation, PD = Psychological distance, TRU = Trust, ICHR = Intention to comply with health recommendations. The number of bootstrap samples for bias-corrected bootstrap confidence intervals: 5,000. The level of confidence for all confidence intervals: 95

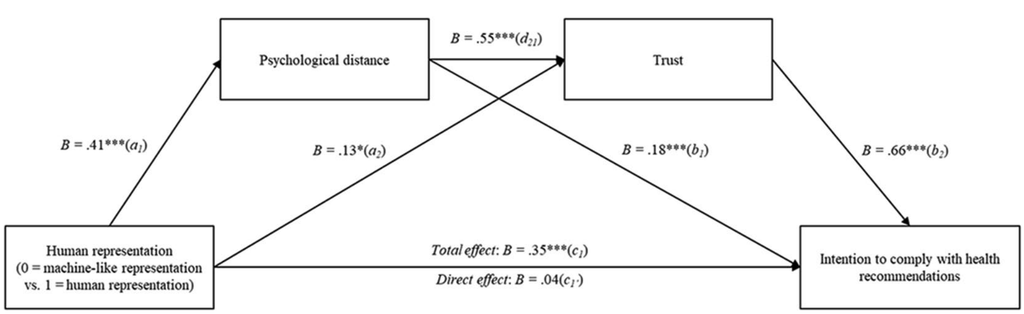

Fig. 3 Serial multiple mediation of human representation relationship to intention to comply with health recommendations, including psychological distance as the first mediator and trust as the second mediator. Values are unstandardized path coefficients.
* $p < .05$, *** $p < .001$

communicated with the chatbot counselor with human representation, compared to the machine-like representation, they felt psychologically closer to it, which in turn led them to perceive more trust towards it, and led to higher intention to comply with health recommendations. Hence, H4 was supported.

Discussion

Key findings

This study examined the effect of chatbot human representation on intention to comply with mental health recommendations and the independent and serial mediating roles of psychological distance and trust. The results confirmed the significant role of human representation in increasing compliance intention. Moreover, the results also supported the hypotheses that psychological distance and trust mediate the relationship between human representation and compliance intention, both independently and serially.

Implications

This study employed several theoretical frameworks to support the proposed relationship between the determinants of intention to comply with chatbots' health recommendations, such as the elaboration likelihood model (Petty & Cacioppo, 1984), folk theory (Jung et al., 2022), construal level theory (Trope & Liberman, 2010); theory of anthropomorphism (Epley et al., 2008), CASA paradigm (Reeves & Nass, 1996; Nass & Moon, 2000), and uncertainty reduction theory (Berger & Calabrese, 1975). This study attempted to extend the body of knowledge on human-chatbot interaction by connecting the above-mentioned interdisciplinary theories. For example, unlike the majority of human-chatbot interaction studies that highlighted the physical and technical aspects of the interaction, this study has offered an analysis of the psychological mechanism between humanlike design and intention changes by borrowing variables that are relevant in the context of mental health counseling such as psychological distance and trust based on an interdisciplinary approach. Moreover, this study adds to the extant literature, where there is a conflicting understanding of the role of humanness, by providing evidence on how humanlike visual cues function in human-chatbot interaction, reduce perceived psychological distance, and enhance trust towards a conversational partner.

Moreover, the findings of this research also provide important practical implications for chatbot developers and mental health practitioners. There has been an increased demand for mental health services during the COVID-19 pandemic causing a severe labor shortage, which was exacerbated due to the increase in the preference for non-face-to-face interactions (Miner et al., 2020). Therefore, it is critical to develop quality AI chatbot agents that are accessible around the clock. However, there is a limited understanding of the psychological mechanism behind the effect of chatbot human likeness and how chatbot's visual representation can reduce perceived psychological distance and increase trust and compliance intention, which are key factors in mental health counseling. For example, there is a mixed understanding of the definition of humanness, and some studies combine various aspects of humanness to examine its effectiveness, which is arguably part of the reason why there are conflicting results on the effect of human likeness (e.g., uncanny valley effect vs. CASA paradigm). This study provides practical suggestions to chatbot developers that employing a human representation, in particular, can increase counselees' compliance intentions.

Another key practical implication is that we provided evidence of the effect of chatbots' human representation in the context of mental healthcare counseling. To our knowledge, this is a novel approach that offers an understanding of which mental health-related variables (i.e., the psychological distance between a counselee and a counselor and perceived trust toward a counselor) connect the dots between chatbots' human representation and intention changes. The majority of health 4.0 (the technology-focused healthcare paradigm of the industry 4.0 era) studies have been conducted in the field of computing and technology science and therefore lack an understanding of psychological and social factors (Tortorella et al., 2020). This study attempted to fill the gap by employing key psychological variables and social science perspectives to examine the effect of chatbot human representation in the context of mental health counseling. Moreover, this study has attempted to improve the understanding of the chatbot-counselee relationship by employing user-centered perspectives whereas the majority of the studies are focused on chatbot developers' or service providers' perspectives. Therefore, the results of this paper are expected to provide practical insights for chatbot developers and mental healthcare practitioners on user perception, which is crucial for the successful application of chatbot counselors and their commercialization.

Limitations and future research avenues

This study has several limitations. First, it focused on a chatbot's physical representation only and did not explore other humanness cues such as conversational or identity cues, which have a significant interaction effect with physical cues (Go & Sundar, 2019). Future research is necessary to examine the interaction between conversational and visual cues of chatbots due to the increased demand for more complex social interaction with machines. People now require more than an imitation of humanness or social interaction and active implementation of real-life social interaction (Powell, 2019). We recommend that future studies should test both the independent and interaction effects among the three types of humanness cues and the hierarchical relationship between them (Nazlan et al., 2018). Moreover, based on Schrum et al.'s (2021) study, we developed different facial expressions for both versions of the chatbots (humanlike vs. machine-like: smile, wink, and frown) and presented different facial expressions to match the dialog context. However, we did not examine the independent effect of these facial expressions. Future research should test the effect of chatbot facial expressions since they can add liveliness to chatbots and increase humanness and anthropomorphism.

Another possible future research area is the influence of increased expectations caused by human-like images or identity disclosure of AI agents. Some researchers highlight that synthetic images of AI agents may increase users' expectations of the agent and their interactions with it, causing negative interaction outcomes when their expectations are not met (Gong, 2008; Go & Sundar, 2019). It is necessary for future studies to explore the roles of users' expectations, satisfaction, and disappointment toward human-chatbot interaction in the relationship between chatbot humanness and interaction outcomes such as psychological distance, attitudes, and behaviors. Moreover, some studies suggest excessive humanness can cause uncanniness and eeriness that make AI agents unpleasant and result in negative interaction outcomes (Bailey & Blackmore, 2022; Hepperle et al., 2022; Lewkowicz & Ghazanfar, 2012; Mori & MacDorman, 2012; Shin et al., 2019). Future studies should also explore the conditions where the uncanny valley effect occurs in the context of human-chatbot interaction.

Moreover, user characteristics such as involvement and self-efficacy could also be considered key variables in the model presented in this study, since they may moderate the effect of humanlike cues on outcome variables and determine the activation of the central or peripheral routes. The central route (conversation quality) is activated when individuals have high involvement and self-efficacy whereas the peripheral route is activated when they have low involvement and self-efficacy (Zhou, 2012). Social anxiety and social phobia are also important variables to investigate in future studies because they are important considerations in mental health counseling given that individuals with difficulties in human-to-human interaction tend to prefer virtual agents over humans (Kang & Gratch, 2010; Pickard et al., 2016). Future studies may also investigate the effect of demographic variables such as gender, age, and ethnicity of both a user and a chatbot agent. Studies have found that the gender of both a chatbot and a user may moderate several human-chatbot interaction outcomes (Nass et al., 1994; Nass & Moon, 2000; Zhang et al., 2020), as well as age (Vollmer et al., 2018) and culture (Buchan & Croson, 2004). Another important possible user characteristic for the proposed model would be users' mental health. This study did not include users' mental health status in the model because it focused on the general applicability of the model and the chatbot. We suggest future studies to examine the moderating and/or mediating role of users' mental health to add to the studies demonstrating chatbot counselor efficacy.

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Data Availability The data used to support the findings of this study are available from the corresponding author upon request.

Declarations

Conflict of Interest The authors declare no potential conflict of interest concerning the research, authorship, and/or publication of this article.

Ethical Approval All procedures performed in the study involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent Informed consent was obtained from all individual participants.

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