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Research Article

Trust in AI Doctors: How Credibility and Message Richness in AI-Based Providers Influence Patient Adherence

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To examine if artificial intelligence (AI) has the potential to complement human health providers in telemedicine, this experiment tests different factors that may affect patients' intention to adhere to prescriptions. Participants ($N = 261$) were randomly assigned to one of 12 conditions: 2 (doctor type: human vs. AI) × 2 (illness severity: high vs. low) × 3 (message richness: text-only prescription vs. with audio vs. with audiovisual). They were then asked to indicate their perceived credibility of the doctor and intention to adhere to the prescription. Results showed that people reported greater perceived credibility toward a human doctor than an AI doctor which, in turn, was positively associated with adherence intention. Moreover, there was a significant interaction between doctor type and message richness, such that the difference in adherence intention for human versus AI doctor was significantly smaller in the text-with-audiovisual condition than that in the text-only condition, indicating that people may start paying less attention to the source and more to the message cues as the message gets richer. These results reflect user responses to a specific type of AI system within a controlled interaction context, and future research should explore how alternative system designs might influence credibility and adherence intention differently.

Keywords: AI doctor; credibility; message richness; patient adherence; telemedicine

1. Introduction

Telemedicine, the practice of providing medical services remotely, has gained increasing popularity over the years, especially with the outbreak of coronavirus disease (COVID-19). As the pandemic hit, many patients were confined to their homes, making it difficult for them to receive in-person healthcare services. Telemedicine has served as an effective alternative to in-person treatment [1–4]. Its growth has been further driven by advancements in artificial intelligence (AI). Since the U.S. Food and Drug Administration approved the use of AI software for medical purposes in 2018 [5], AI has contributed to improving the accuracy of diagnosis [6] and spotting chronic diseases at early stages [7, 8]. Studies have found that AI tools are capable of making diagnoses with the accuracy level of human doctors regarding different types of cancer [9, 10] and common illnesses, while providing even safer advice compared to human doctors [11].

While AI technology shows promise, an important question remains: Will patients be willing to follow medical

advice from an AI doctor? In this study, we define an AI doctor as a fully autonomous virtual agent powered by AI that directly interacts with patients, provides medical advice, and issues prescriptions without involvement from a human physician. This is distinct from human doctors assisted by AI tools; rather, we focus on systems that act independently as the primary care provider.

Understanding how patients respond to such systems is crucial because, in healthcare, even the most accurate or efficient system cannot improve health outcomes unless patients are willing to act on its recommendations. In other words, the success of an AI doctor in telemedicine ultimately depends not only on its diagnostic capability but also on patients' willingness to adhere to its advice. Patient adherence, defined as the extent to which individuals follow prescribed therapeutic recommendations [12], is a critical factor in achieving positive health outcomes. Prior research consistently shows that adherence contributes to improved clinical results, reduced healthcare costs, and enhanced quality of life [13–15]. Conversely, nonadherence is a longstanding barrier in medicine and has been associated with treatment delays and poorer health outcomes [16–20].

Among different factors shown to impact patient adherence (e.g., provider–patient relationship, socioeconomic status, social support; see [21] for review), this study focuses on perceived doctor credibility. In healthcare, patient adherence often depends on whether the provider is perceived as credible and trustworthy [22, 23]. Yet, it remains unclear whether AI doctors are perceived as credible in the same way human doctors are. If patients hesitate to trust or accept AI-generated advice, the potential benefits of AI doctors may not translate into real-world outcomes. Understanding how people perceive and respond to AI doctors is therefore critical for the successful integration of these systems into healthcare delivery.

To guide this, we draw on the Computers Are Social Actors (CASA) paradigm [24], which suggests that people often apply social expectations to artificial agents when they display human-like cues such as voice or facial expressions. CASA has offered valuable insights into how users perceive and interact with artificial agents, such as AI chatbots, in various communication contexts, including customer service (e.g., [25]), education (e.g., [26]), and recommendations (e.g., [27]). However, research suggests that in medical contexts involving serious or uncertain outcomes, patients may be less inclined to follow computer- or AI-generated recommendations compared to those from human doctors, due to lower perceived credibility and lack of human accountability [28, 29]. For instance, a recent study found that participants perceived diagnoses made by human doctors as more credible than those made by AI systems, even when all other aspects of the consultation were held constant [28]. This suggests that the medical context may represent a boundary condition where human and AI agents are not perceived equivalently. Building on this, the current study experimentally investigates whether patients are willing to adhere to medical advice depending on whether it comes from an AI or a human doctor, and whether this effect is mediated by perceived credibility.

To further explore these dynamics, we examine two contextual moderators: Illness severity and message richness. Illness severity reflects the perceived seriousness of a health condition, which may heighten risk sensitivity and increase reliance on human doctors over AI. Message richness refers to the communication modality such as text, audio, or audiovisual used to deliver the diagnosis and prescription. These conditions reflect realistic variations in how AI can be deployed in healthcare, from text-based to voice and video-enabled AI systems. By manipulating these factors, this study aims to identify the conditions under which patients may differ in their willingness to adhere to human or AI doctor's medical advice.

2. Literature Review

2.1. CASA Paradigm. To examine how people perceive and respond to AI doctors compared to human doctors, we draw upon the CASA paradigm, which provides a foundational framework for understanding the processes of human interactions with artificial agents. The CASA paradigm [24, 30] posits that people automatically apply social rules and expectations when interacting with computers, even when they are aware that they are interacting with machines. It suggests that minimal social cues (e.g., gender, polite language) are sufficient to trigger social responses similar to those in human interactions. Numerous studies have validated the CASA paradigm across diverse contexts, demonstrating that AI with social cues can indeed foster social responses as they would in human interactions. For instance, research has shown that people rate chatbots with human-like characteristics similarly to humans, develop trust and acceptance through empathetic and interactive AI behaviors, and even develop interpersonal relationships (e.g., friendship) with AI agents [27, 31, 32].

However, the applicability of the CASA paradigm may be limited by specific contextual factors. Healthcare is a particularly compelling setting for examining these boundary conditions, as medical decision-making involves personal risk and potentially serious consequences [33]. In such high-stakes situations, individuals may consciously prefer human agents over AI. That is, patients' reliance on medical advice may not simply depend on superficial human-like or social cues (e.g., being labeled as a doctor) but rather on more fundamental considerations such as perceived credibility or severity of the consequences [28, 34]. For example, Guo and Chen [28] found that patients perceived diagnoses from human physicians as significantly more credible compared to identical recommendations from AI doctors. In addition, research has shown that patients are often hesitant to follow recommendations from AI in high-risk or serious health scenarios due to concerns about accountability and the inherent unpredictability of medical outcomes [34], suggesting a potential boundary condition to the CASA paradigm.

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Several theoretical frameworks imply that the applicability of the CASA paradigm might be limited in healthcare contexts (e.g., uncertainty reduction theory, [35]; theory of motivated information management, [36]); specifically, theories suggest that in high-risk situations (e.g., health risk), people desire to manage or reduce the uncertainty by seeking reliable sources of information [35, 36]. In medical settings, this heightened risk sensitivity and uncertainty avoidance may override the automatic social responses typically triggered by human-like cues, resulting in preferences toward human doctors to reduce perceived uncertainty and associated health risks. In the following sections, we delve into the factors under which people may perceive and adhere differently to medical advice provided by AI versus human doctors.

2.2. Differences in Human and AI Doctors on Intention to Adhere to Prescription: Mediating Role of Perceived Credibility. The first goal of this study is to examine whether individuals' intention to adhere to medical advice would differ depending on doctor type (human vs. AI); specifically, we focus on perceptions of credibility as a mediator that underlies this relationship. Perceived credibility, which is defined as the extent to which a communicator is considered as trustworthy and believable [37], is a crucial component in a patient–provider relationship [38]. Several studies in clinical medicine [22, 23, 39, 40] showed that patients are more likely to adhere to medical advice and recommendations when they perceive their providers to be credible. For example, in their longitudinal intervention study, Jones and colleagues [23] found that patients who had higher trust in their physician were twice as likely to adhere to medications and recommendations for lifestyle changes compared to those who had lower physician trust. Similarly, Abel and Efird [22] reported in their cross-sectional study that patients' perceived physician credibility was positively related to adherence to prescribed medications. This relationship between perceived doctor credibility and patient adherence was also supported in a secondary data analysis ($N = 2{,}510$, [40]), as well as a meta-analysis of 47 studies ($N = 34{,}817$, [41]).

Given the critical role of perceived doctor credibility in encouraging patient adherence, this study examines whether people's credibility perceptions will vary based on the provider being a human or a nonhuman agent. The CASA paradigm [24] would suggest that, if an AI doctor displays social cues or human-like features, people will interact with it like they do with a human doctor. From this perspective, perceptions of credibility for human and AI doctors should not differ significantly. However, several studies have demonstrated that people tend to perceive human doctors as more credible than AI doctors [28, 39, 42, 43]. For example, in studies comparing three types of providers (i.e., human doctor, human doctor with an AI system, and an AI system only), people reported highest perceived credibility in the human-only condition and lowest perceived credibility in the AI-only condition [39, 42]. Guo and Chen [28] found that, even for highly stigmatized diseases like acquired immunodeficiency syndrome (AIDS), which is assumed that anonymity is preferred in medical consultations, people preferred a human provider over an AI provider. These studies argued that the nature of AI, which oftentimes lacks transparency in decision-making (e.g., lack of explanation on how treatment solutions were generated), may have led to decreased patient trust [28, 42], and that at the current early stage of AI development, people may generally place more trust in human expertise when it comes to medical decisions [28].

Given this line of research, we predict that doctor type (human vs. AI) will have an indirect effect on intention to adhere to prescription via perceived doctor credibility. Thus, the following mediation hypothesis is proposed.

- H1: Participants will perceive greater credibility for a human doctor than an AI doctor which, in turn, will be positively associated with intention to adhere to prescription.

2.3. Factors Moderating the Relationship Between Doctor Type and Patient Adherence. Different factors may influence the association between doctor type and patient adherence. In this study, we focus on two potential moderators: Illness severity and message richness.

2.3.1. Illness Severity. Perceived risk, particularly in the form of illness severity, plays a critical role in health-related decision-making [44]. Perceptions of illness severity motivate individuals to take specific actions to mitigate health threats [45], making it a crucial factor to consider in medical decision-making. In general, studies have found a positive relationship between illness severity and patient adherence, such that patients who perceive their illness to be severe are more likely to comply with a prescription than those who perceive their illness to be less severe [46]; for meta-analysis see [47–49], because they are motivated to reduce their physical/mental distress [44].

When comparing human and AI doctors, perceived illness severity may play a moderating role in the relationship between doctor type and patient adherence. Specifically, when an illness is severe, people may be more willing to adhere to a human doctor over an AI doctor [28, 33]. Given the high-stakes nature of medical decisions, individuals may be more hesitant to follow recommendations from an AI source when the perceived severity of the health condition is high—potentially due to factors such as algorithmic aversion and lack of familiarity with the technology [33]. In an integrative review, Wutz et al. [50] found that individuals were less willing to use AI for serious health problems but more open to its use for mild health issues. Indeed, prior research suggests that when a disease is perceived as highly severe, patients tend to be more skeptical of AI-generated prescriptions, which can lead to reduced adherence [34]. Supporting this, other studies have shown that in decisions involving serious consequences—such as medical consultations—or those traditionally viewed as within the purview of human expertise,

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individuals are more likely to trust human providers over AI systems and are less accepting of AI-driven health interventions [28, 33]. Thus, we propose the following hypothesis:

- H2: Illness severity will moderate the relationship between doctor type and adherence intention, such that when illness severity is high, patients will report greater adherence intention to human doctors than AI doctors.

2.3.2. Message Richness. Another factor that may influence the relationship between doctor type and patient adherence is message richness, or how rich a prescription is in terms of modality. A prescription can be as plain text or with richer formats, such as audio and video. In general, prior work on the effects of message richness on persuasive outcomes has shown that the greater the number of cues delivered through various mediums, the less ambiguous the message is perceived (e.g., [51]) which, in turn, increases the message persuasiveness [52–54]. Likewise, studies report that richer prescriptions tend to be effective in encouraging patient adherence [55–57]. In the same vein, a recent systematic study found that nearly half of the studies analyzed reported that audiovisual consultation was more effective than voice-only consultation in improving clinical outcomes and treatment accuracy [58].

According to the CASA paradigm, human doctors, as natural and familiar message sources, have consistently shown stronger persuasive effects compared to AI doctors [59]. For instance, Kim et al. [60] found that human assistants in healthcare services were rated more highly in terms of usability and satisfaction than both embodied virtual assistants and voice-only virtual assistants. However, an embodied virtual assistant still represents a promising alternative in patient care settings, offering a heightened sense of social presence and engagement compared to disembodied voice agents [60, 61]. Social presence, facilitated through richer modalities, may be a key factor in narrowing the persuasive gap between human and AI doctors. Multimodal messages incorporating both verbal and nonverbal cues (e.g., gaze, hand gestures) have been found to reduce cognitive load and enhance comprehension, thereby increasing persuasiveness [62]. In contrast, AI-generated text messages—often lacking these rich, human-like cues—are perceived as less natural, which can lead to lower attitudes toward the message [63]. Building on this line of research, the current study examines whether greater message richness can mitigate the difference in persuasiveness between AI and human doctors. Thus, the following hypothesis is asked:

- H3: The difference between AI and human doctors in patients' intention to adhere to prescription will decrease with higher levels of message richness.

Figure 1 illustrates the conceptual relationships among proposed variables.

3. Methods

3.1. Participants and Procedures. Prior to data collection, a power analysis was conducted using G∗Power ($F = 0.25$, $\alpha = 0.05$), which recommended a sample size of 251 to run our planned analyses. To ensure reaching this goal, we collected data from a total of 261 Korean adults (age: $M = 22.69$, $SD = 2.42$; gender: 49.4% female). Participants completed an online survey distributed by Macromill Embrain Corporation[1]. After reading a brief overview of the study and providing informed consent, participants were randomly assigned to one of 12 conditions: 2 (doctor type: human vs. AI) × 2 (illness severity: low vs. high) × 3 (message richness: text-only vs. text-with-audio vs. text-with-audiovisual).

Participants were given a hypothetical scenario and asked to imagine that they woke up feeling unwell. In the high illness severity condition (i.e., peptic ulcer), the scenario described that they felt a sudden, extreme, and burning pain in their stomach, and that they started vomiting blood. In the low illness severity condition (i.e., indigestion), it was described that participants felt indigestion, had a light headache, and had diarrhea. Then, the scenario illustrated that participants decided to get an online diagnosis because they lived in a small rural town where it took hours to travel to the nearest clinic (which was closed that day).

The prescription started off by informing participants that the diagnosis was made by either a human or an AI doctor (doctor type) and that they had either an ulcer or indigestion (high or low illness severity). The prescription, which indicated the symptoms and required medication, was in one of three formats: text-only, text-with-audio, and text-with-audiovisual. In the text-only condition, all information was provided via text. In the audio condition, participants listened to an audio file with the doctor's diagnosis along with the text prescription. In the audiovisual condition, they watched a video of the doctor with the text prescription. The prescription content was developed by reviewing publicly available Korean-language online materials related to indigestion and peptic ulcer treatments. These materials were identified through a general web search and included example prescriptions, informational pages, and visual references that reflect real-life clinical communication. The prescriptions were designed to resemble realistic patient-facing content and were standardized across conditions to ensure consistency in length, tone, and structure. We used Adobe Photoshop CC and video editing software to create the AI doctor. A baseline model was created to match the human doctor's appearance and outfit. Then, looped animations (e.g., lip and eye movements) were added to match the human doctor's facial expressions. The video was then combined with AI-generated voice narration (using synthetic speech tools) to simulate an AI delivering a diagnosis and prescription. This video was presented as a prerecorded, noninteractive consultation designed to resemble a realistic AI interface, allowing for a controlled and standardized presentation across conditions.

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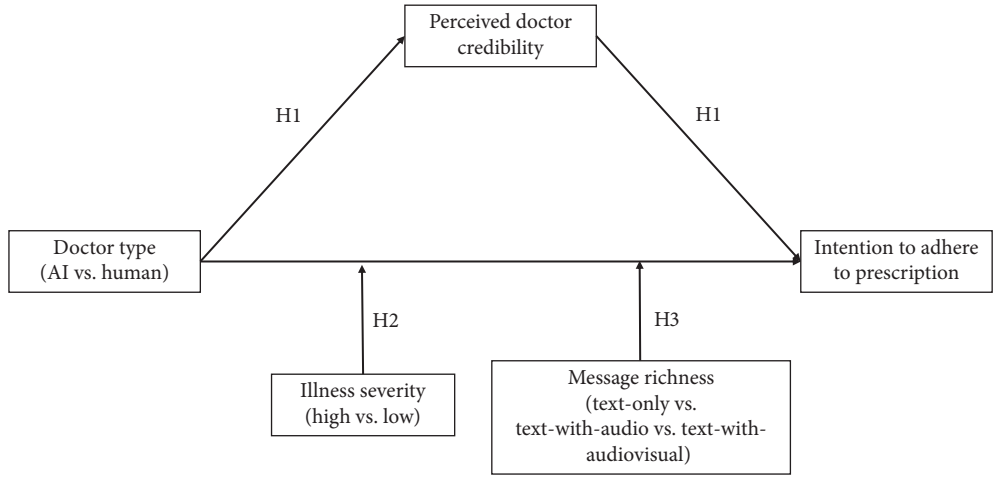


Figure 1: Proposed relationships among variables.

Finally, participants were asked to fill out a questionnaire to answer manipulation check items, perceived doctor credibility, and intention to adhere to the prescription. See Figure 2 for examples of stimuli.

3.2. Measurement

3.2.1. Doctor Type. Manipulation of doctor type (human vs. AI) was measured using a semantic differential anthropomorphism scale adapted and modified from a previous study ([64]; e.g., "The doctor who gave me the prescription is. . .," 1 = human, 5 = AI; reverse-coded).

3.2.2. Perceived Doctor Credibility. Credibility comprises two dimensions: expertness (i.e., the degree to which a communicator is considered as a source of valid arguments [65]), and trustworthiness (i.e., the level of confidence in the communicator's intention to make assertions he/she considers most valid [65]). Following this notion, perceived doctor credibility was assessed using four 5-point semantic differential scale items measuring trustworthiness (e.g., The doctor who gave the prescription cannot be trusted/can be trusted, inaccurate/accurate, dishonest/honest, wrong/right, [66]); Cronbach's $\alpha = 0.86$) and four items measuring expertness (e.g., The doctor who gave me the prescription is an inexpert/expert, unqualified/qualified, unskilled/skilled, and inexperienced/experienced [66]; $\alpha = 0.88$). The eight items were averaged (M = 3.50, SD = 0.72, $\alpha = 0.92$).

3.2.3. Perceived Illness Severity. Perceived severity of the illness was measured using two 5-point Likert scale items adapted from previous literature, e.g., "How severe is your illness?", "How severe do you perceive the current situation to be?" [67], M = 3.11, SD = 0.99, Pearson's $r = 0.80$.

3.2.4. Intention to Adhere to Prescription. Intention to adhere to prescription was measured using four items regarding how important participants think it is to follow the doctor's advice and their willingness to follow a prescription (e.g., "How well will you follow the advice?", 1 = not at all, 5 = completely; "How important is it to do what the doctor expects?", 1 = not important at all, 5 = very important; [68, 69]), M = 3.62, SD = 0.78, $\alpha = 0.88$.

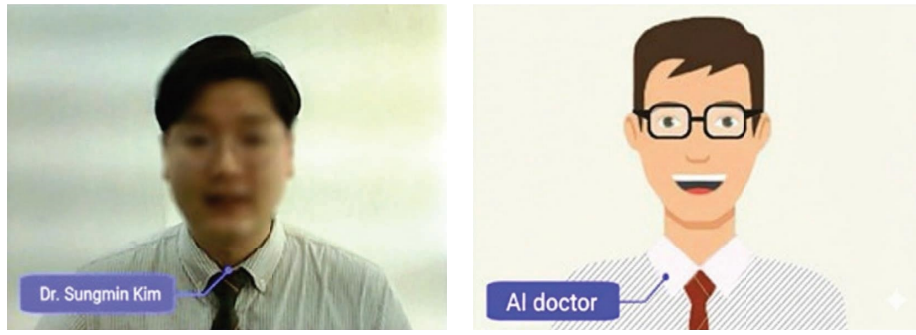
4. Results

4.1. Manipulation Check. Two independent *t*-tests were conducted to test whether the manipulations of doctor type and illness severity were successful. The results showed that participants in the human doctor condition (M = 3.80, SD = 1.18) perceived the message source to be significantly more humanlike than those in the AI doctor condition (M = 2.38, SD = 0.85), $t(259) = 9.44$, $p < 0.001$, $\eta^2 = 0.26$. Moreover, regarding illness severity, those in the high severity condition (i.e., ulcer; M = 3.60, SD = 0.86) perceived their illness to be significantly more severe than those in the low-severity condition (i.e., indigestion; M = 2.59, SD = 1.25), $t(259) = 9.49$, $p < 0.001$, $\eta^2 = 0.36$. To determine if any effects of confounds stemmed from demographic distributions of the 12 conditions, χ^2 analyses were conducted. None of the demographic variables differed by the conditions. Correlations among all variables are reported in Table 1.

4.2. Hypotheses Testing. To examine the mediated indirect effect of doctor type on adherence intention via credibility (H1), and moderating effects of illness severity and message richness (H2, H3; Figure 1), a series of PROCESS Macro ([70], Model 5) was run in SPSS 29. Two models were tested, with doctor type as the independent variable, adherence intention as the dependent variable, perceived doctor credibility as the mediator, and illness severity (Model A) and message richness (Model B) as moderators (Figure 3). As suggested by Preacher and Hayes [71], the models were estimated with bootstrapped 95% confidence intervals, based on 5000 resamples.

Results showed that the models were statistically significant, Model A: $R^2 = 0.76$, SE = 0.26, $F = 87.24$, $p < 0.001$; Model B: $R^2 = 0.60$, SE = 0.24, $F = 64.17$, $p < 0.001$. Consistent with H1, perceived doctor credibility differed

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(a) (b)

Figure 2: Examples of stimuli (screenshot). Note. Screenshots of a human and AI doctor in the text-with-audiovisual condition. The text in the purple box reads "Dr. Sungmin Kim" (i.e., a generic Korean name) on the (a) and "AI doctor" on the (b). The animations for the AI doctor (e.g., eye, lip movement) matched with the human doctor. Due to a potential privacy concern, the human doctor's face has been blurred.

Table 1: Means, standard deviations, and zero-order correlations.

Constructs	(1)	(2)	(3)
(1) Perceived illness severity	—		
(2) Perceived doctor credibility	0.02	—	
(3) Intention to adhere to prescription	0.08	0.76**	—
M	3.11	3.50	3.62
SD	0.99	0.72	0.78

Note: M = mean.
Abbreviation: SD = standard deviation.
** $p < 0.01$.

significantly by doctor type ($b = 0.24$, SE = 0.09, $t = 2.74$, $p = 0.007$), such that participants perceived greater credibility for the human doctor than the AI doctor. In turn, perceived doctor credibility was positively related to intention to adhere to prescription (Model A: $b = 0.81$, SE = 0.04, $t = 18.18$, $p < 0.001$; Model B: $b = 0.84$, SE = 0.04, $t = 18.64$, $p < 0.001$). Moreover, the indirect effect of doctor type on adherence intention was statistically significant (Model A: $b = -0.20$, SE = 0.07, 95% CI [−0.33, −0.06], Model B: $b = -0.20$, SE = 0.07, 95% CI [−0.35, −0.06]), indicating a significant mediation effect (H1 supported). For Model A, there was no significant direct effect of doctor type on adherence intention, indicating that perceived doctor credibility fully mediated this relationship. For Model B, on the other hand, there was a significant direct effect of doctor type on adherence intention ($b = -0.30$, SE = 0.10, 95% CI [−0.51, −0.09]), indicating a partial mediation effect.

Illness severity did not significantly moderate the relationship between doctor type and adherence intention ($b = -0.002$, SE = 0.06, $t = -0.03$, $p = 0.98$, Figure 3; Model A). That is, regardless of how severe the illness was, people were more likely to adhere to the human doctor compared to the AI doctor (H2 not supported).

Finally, there was a significant interaction between doctor type and text-only vs. text-with-audiovisual message condition ($b = -0.49$, SE = 0.15, $t = -3.24$, 95% CI [−0.79, −0.19]), but not between text-only vs. text-with-audio conditions ($b = -0.16$, SE = 0.15, $t = -1.09$, 95% CI [−0.46, 0.13]; Figure 3; Model B). The difference in adherence intention for human vs. AI doctor condition was significantly smaller in text-with-audiovisual condition than text-only condition ($M_{diff} = 0.27$, SD = 0.12; H3 partially supported). See Figure 3 for path coefficients for Model A and B. See Figure 4 for a graphic representation of the doctor type × message richness interaction on patient adherence.

5. Discussion

5.1. Findings and Implications. The primary purpose of this study was to examine whether individuals would differ in their intentions to adhere to a prescription provided by a human vs. an AI doctor, using the CASA paradigm as the guiding framework. Specifically, we aimed to elucidate the underlying mechanism by testing the mediating role of doctor credibility and the moderating roles of illness severity and message richness.

5.1.1. Perceived Doctor Credibility. Results showed that patients perceived greater credibility toward a human doctor than an AI doctor. Although the CASA paradigm proposes that people are likely to treat nonhuman agents as if they are human beings if the interface exhibits sufficient human-like cues [24], our finding suggests that this may not apply in the medical context. Indeed, previous studies have shown human doctors were perceived as more credible than AI doctors across different medical conditions (e.g., skin cancer [72]; AIDS [28]) and disciplines (e.g., cardiology, orthopedics, dermatology, and psychiatry [39]).

Moreover, we found that perceived doctor credibility mediated the relationship between doctor type and adherence intention. Given this mediating effect was observed across different levels of illness severity and message richness, this implies that a critical factor to consider when building a telehealth system is to ensure the provider—whether it be human or nonhuman agent—is perceived as credible. In AI-assisted healthcare, one way to boost credibility is to be transparent about the decision process (i.e., technological transparency) as well as the underlying context (i.e., social transparency [73]). Previous research shows that

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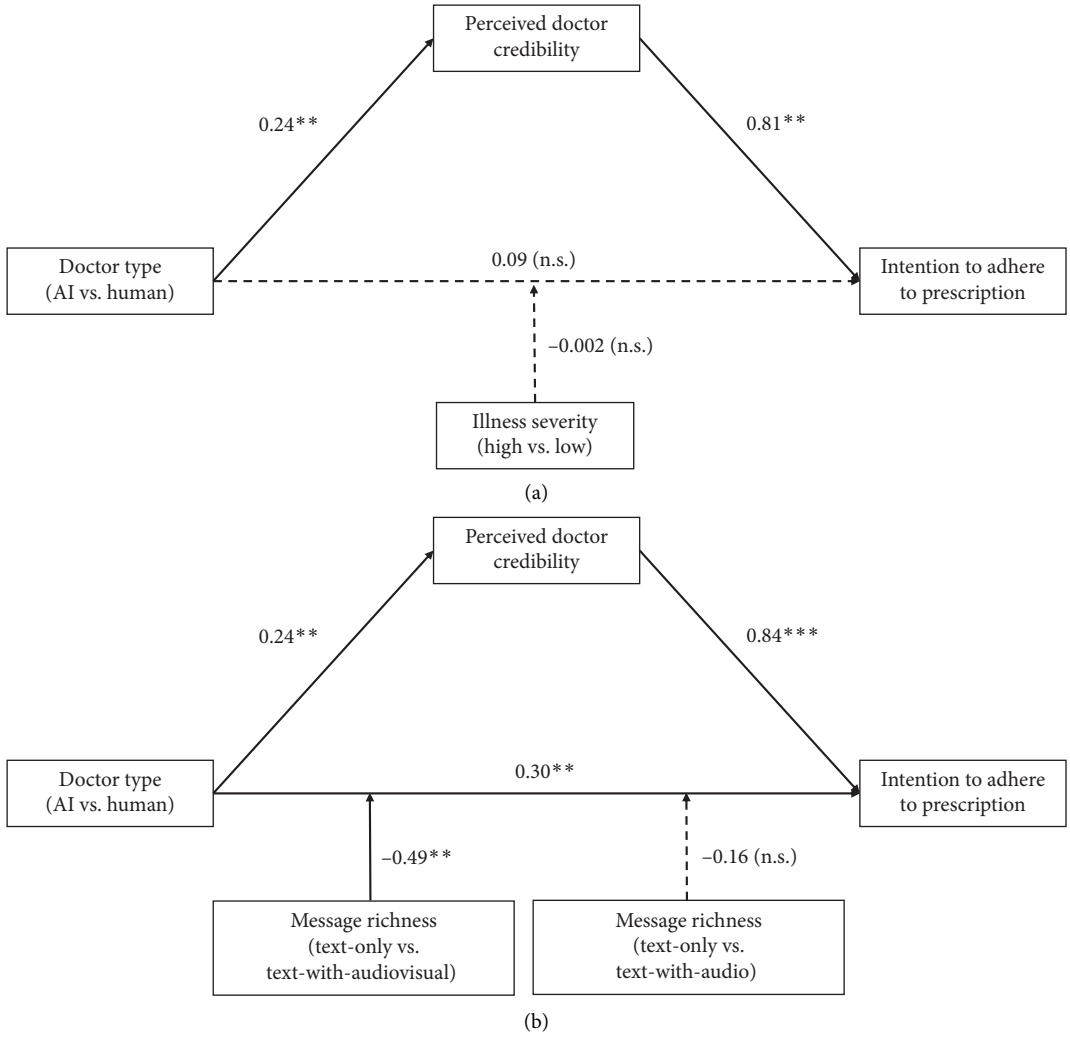


FIGURE 3: Path coefficients of proposed models. (a) Model A. (b) Model B. Note. $^{**}p < 0.01$, $^{***}p < 0.001$, n.s. = nonsignificant. Unstandardized coefficients (*b*) are reported. Human doctor condition was coded as 1, and AI doctor condition was coded as 0.

providing contextual information of the decision-making process can yield trust in AI [73]. Likewise, in telemedicine, ensuring social transparency by providing information on who is responsible for the decision (e.g., by including a profile picture and organizational role) and an explanation of the reasons behind the decision (why) will help increase the credibility of AI providers.

5.1.2. Illness Severity. We found that illness severity did not significantly moderate the relationship between doctor type and patient adherence intention. Specifically, regardless of how severe the individuals perceived their illness to be, they tended to be more willing to adhere to the prescription provided by the human doctor than the AI doctor. Although this trend was supported in some studies (e.g., [72]), other studies reported mixed findings regarding the moderating role of illness severity [43, 74]. Given these inconsistencies, future research should further examine how different levels of illness severity may influence adherence to AI versus human doctors.

One potential reason for this nonsignificant moderation may be our studies' hypothetical nature of stimuli. In this study, participants were asked to "imagine" that they were experiencing either severe or less severe pain, and indeed, the manipulation check showed a significant difference in perceived severity between the two conditions. However, not directly measured in this study is the degree to which the participants considered the illness to be relevant to themselves. It is possible that, for example, if an individual has actually experienced an ulcer before, they would indicate greater adherence to a human doctor than an AI doctor, because they actually know how painful it is. Thus, to make our findings more robust, future studies may benefit from asking participants how relevant or salient a given illness is to themselves (e.g., Have you ever experienced disease X? Do you have a family health history of disease X?).

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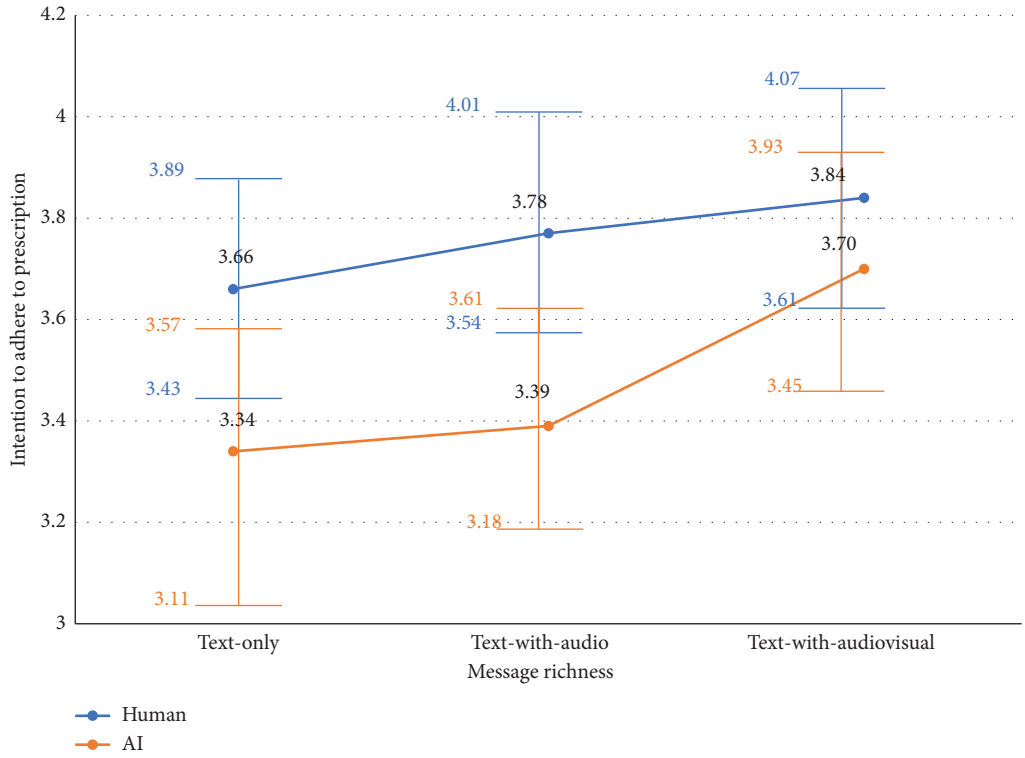


FIGURE 4: Doctor type × message richness interaction on patient adherence intention. Note. Error bars: 95% confidence interval.

5.1.3. Message Richness. In regard to moderating the role of message richness, our results showed that the difference in patient adherence for the human and the AI doctor was significantly smaller in the text-with-audiovisual prescription condition than in the text-only condition. In other words, although patient adherence was consistently greater for the human doctor compared to the AI doctor, the gap was notably reduced in the audiovisual condition. This result aligns with previous research [54, 75] that finds a bigger difference between video and text than that between audio and text in terms of message persuasiveness.

There are different ways to interpret this finding. First, participants in the audiovisual condition may have focused more on the affluent message cues than the source itself, significantly increasing their willingness to adhere to the AI doctor, as message vividness is often used as a proxy for message quality [76]. Another potential explanation for this result is the perceived novelty of the use of audiovisuals in a telemedicine context. Since most users of technology are familiar with text-based chatbots like ChatGPT [77] and audio-based AI assistants like Siri and Alexa [78], it is possible that the addition of video, which is used relatively less frequently, evoked a sense of novelty, leading to the formulation of positive attitude and behavioral intention. It should be noted that such novelty effects may wear off as video-based AI assistants become more common with rapid technological advancements. With the rapid development of AI technology in telemedicine, future studies should examine how the perceived novelty may influence patient outcomes.

A third possible interpretation involves anthropomorphism [79]. The audiovisual condition may not only have enhanced message vividness and novelty but also increased the perceived humanness of the AI doctor. When added to textual messages, visual and vocal cues (e.g., facial movement, eye contact, and speech) can accelerate social presence [80] and lead users to treat artificial agents more like humans. While our study did not explicitly test anthropomorphism, these features may have triggered social responses that contributed to the reduced adherence gap. Future research could more directly investigate this by manipulating the level of agent humanness, such as comparing realistic human-like avatars with robotic or abstract designs, to better understand how anthropomorphic cues shape user trust and behavioral intentions in telemedicine.

While these findings highlight how audiovisual communication can help narrow the adherence gap between AI and human doctors, they also draw attention to the "uncanny valley" phenomenon [81, 82]. AI systems that appear or behave too much like humans may elicit discomfort rather than greater trust and adherence. Patients may respond more favorably to an AI that maintains a machine-like persona rather than one that imitates human behaviors too closely. Therefore, future research should investigate the optimal level of human-likeness in AI-based medical advice, considering both appearance and communication style, to determine how best to enhance patient adherence without eliciting discomfort.

5.2. Future Directions. It is important to recognize that AI systems are not uniformly designed, and their capabilities can vary substantially based on their training and implementation. In this study, we evaluated patient perceptions of

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a generic AI doctor; however, the credibility and trustworthiness of AI-generated medical advice may depend on the specific system being employed. Future investigations should therefore examine how different AI medical systems impact patient trust and adherence. Including more detailed information about AI's decision-making processes may help address the credibility gap identified in this study.

Another key consideration is the evolving relationship between AI and human doctors. While our findings show that participants were more inclined to adhere to prescriptions from a human doctor, it is important to consider the distinct and potentially complementary roles each can play in telemedicine. Skepticism remains that AI doctors may lack vital interpersonal skills such as empathy and trust-building [83, 84], but these concerns regarding interpersonal interactions reflect just one aspect of AI's multifaceted role in healthcare. AI systems can offer distinct advantages in patient care by offering immediate support, delivering in-depth explanations, and managing tasks that time-constrained physicians often find challenging, such as following up on medication adherence or handling patient complaints [85, 86]. Additionally, their capabilities can vary significantly based on the scope and quality of their training data, which means some AI systems can surpass human doctors in medical knowledge, while others may be more narrowly specialized [87]. Given these differences in capabilities, it may be limiting to apply the same criteria when assessing patient adherence to AI and human doctors. Instead, future evaluations should consider how each may support patient adherence in distinct ways, based on their respective roles in patient care. Understanding how patients perceive these roles will be important for developing effective integration strategies. Collaborative processes in which AI and human medical advice continually inform and refine each other may help ensure that AI's benefits are maximized without undermining the critical human dimensions of healthcare [88].

5.3. Limitations. This study has limitations. First, given how telemedicine, especially that uses AI doctors, is not fully commercialized or familiar to the public, this study employed hypothetical scenarios featuring custom-made videos in which an AI doctor issued prescriptions. This approach may have appeared unnatural, potentially constraining the authenticity of the situation. Therefore, future research could enhance the ecological validity of the study by leveraging state-of-the-art AI technology to create more realistic stimuli. For instance, utilizing AI techniques that transform videos into AI-generated scenarios could offer a more immersive and authentic experience, simulating encounters with AI doctors and potentially yielding findings that better reflect real-world decision-making processes. Additionally, researchers could consider collaborating with existing commercial telemedicine platforms (e.g., CVS's Minute Clinic Virtual Care) to recruit actual users and examine how their levels of illness severity affect their decisions regarding compliance with AI doctors' recommendations.

Second, the sample of this study predominantly consisted of young adults, who are generally healthier and less likely to have experienced severe illnesses [89], potentially limiting the generalizability of our findings. Additionally, the geographic location data for participants were missing in the study. Given that the location in which participants live may play a critical role in shaping their perception of telemedicine (e.g., in areas where medical resources are sparse, telemedicine may be considered a crucial alternative), it would be necessary to examine its impact in future studies. Thus, to enhance the generalizability and rigor of the study, including a more diverse sample with richer data representing the geolocation and level of access to medical facilities is recommended.

Finally, due to the cross-sectional nature of this study, we measured participants' intention to adhere to prescriptions as a proxy for actual adherence. Although behavioral intention is considered a strong predictor of behavior [90], some scholars have pointed out that intention may not always be translated into behavior [91]. Moving forward, future studies should address this limitation by measuring actual adherence behavior.

6. Conclusion

The rapid advancements of AI technologies are evident, and telemedicine has emerged as a prominent field of application. The current study poses two significant considerations in a specific domain of AI-assisted healthcare (i.e., the use of conversational AI systems that deliver medical advice to patients). First, the establishment of credibility perception toward medical AI agents holds a central position in facilitating patient adherence. Without the foundation of credibility, patients may be hesitant to adhere to medical advice by AI systems, regardless of AI's actual capabilities to provide accurate diagnoses and prescriptions. Second, our findings suggest message richness as a promising factor that can enhance acceptance of AI recommendations through richer audiovisual cues. These insights offer valuable implications for both healthcare practitioners and AI system developers to effectively integrate AI-based agents into healthcare by strategically addressing patient perceptions and communication modalities for successful patient care. While these findings pertain to one specific application of AI in patient-facing interactions, it is important to recognize that AI has demonstrated considerable promise in other areas of medicine, such as diagnostic imaging and illness detection, where distinct dynamics of trust and performance are likely to apply.

Data Availability Statement

Study data are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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Endnotes

[1]Macromill Embrain Corporation (https://www.embrain.com/eng/) is an online research company located in Seoul, South Korea, that holds a nationwide panel of over 1.6 million individuals.

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