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To Be or Not to Be . . .Human? Theorizing the Role of Human-Like Competencies in Conversational Artificial Intelligence Agents

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ABSTRACT
Driven by the need to provide continuous, timely, and efficient customer service, firms are constantly experimenting with emerging technological solutions. In recent times firms have shown an increased interest in designing and implementing artificial intelligence (AI)-based interactional technologies, such as conversational AI agents and chatbots, that obviate the need for having human service agents for the provision of customer service. However, the business impact of conversational AI is contingent on customers using and adequately engaging with these tools. This engagement depends, in turn, on conversational AI's similarity, or likeness to the human beings it is intended to replace. Businesses therefore need to understand what human-like characteristics and competencies should be embedded in customer-facing conversational AI agents to facilitate smooth user interaction. This focus on "human-likeness" for facilitating user engagement in the case of conversational AI agents is in sharp contrast to most prior information systems (IS) user engagement research, which is predicated on the "instrumental value" of information technology (IT). Grounding our work in the individual human competency and media naturalness literatures, we theorize the key role of human-like interactional competencies in conversational AI agents—specifically, cognitive, relational, and emotional competencies—in facilitating user engagement. We also hypothesize the mediating role of user trust in these relationships. Following a sequential mixed methods approach, we use a quantitative two-wave, survey-based study to test our model. We then examine the results in light of findings from qualitative follow-up interviews with a sampled set of conversational AI users. Together, the results offer a nuanced understanding of desirable human-like competencies in conversational AI agents and the salient role of user trust in fostering user engagement with them. We also discuss the implications of our study for research and practice.

KEYWORDS
Artificial Intelligence; AI; chatbot; human-like competencies; human-like trust; media naturalness theory; user engagement; mixed methods; conversational agents

Introduction

Guided by the mantra that customer engagement is the key to business success, firms have been experimenting with new initiatives to better interact with customers both offline and online [144]. Whether it be sales personnel catering to the unique needs of customers offline

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or machine learning algorithms providing relevant offerings to potential customers online, the objective is to foster deeper customer engagement. Lately, conversational artificial intelligence (AI) agents such as chatbots have been recognized for their potential to offer enhanced opportunities in this area [28]. Social distancing protocols implemented during the COVID-19 pandemic have only accelerated their adoption [100, 143].

Conversational AI agents such as chatbots are typically available through messaging applications or chat windows on company websites, providing inquiry-based customer service [6]. To produce natural and intuitive interactions, such agents use natural language processing (NLP), machine learning (ML), and other AI applications to mimic human-to-human communication [112]. Big tech companies such as Google, Amazon, Facebook, and Microsoft have acknowledged the transformative potential of AI-powered conversational agents, declaring them as the next big thing [16]. Adoption rates of conversational AI tools have been projected to more than double over the next five years [26].

Despite its potential, skepticism about the business use of conversational AI remains, as do questions about its practicality and effectiveness in providing an engaging user experience [9]. Indeed, a 2019 study reported that 86% of customers prefer humans to chatbots for interactional services [46]. Moreover, despite intense industry interest in conversational AI, most firms are still running ad hoc pilot projects or are using conversational agents only for sporadic business processes [42]. The viability of customer-interfacing conversational AI as a business solution clearly depends on users' willingness to engage with it [7], which hinges on how they perceive, value, and assess their interactions with conversational AI [100]. Research that examines contextual challenges for fostering deeper user engagement with conversational AI agents will therefore be of value to both research and practice.

Prior information systems (IS) research focusing on user engagement with technology is largely premised on its "instrumental value" [29, 67]. However, conversational AI is different, providing positive and engaging interactional experiences as well as instrumental value [100]. For instance, chatbots may promote a seamless customer service experience by identifying customers' needs and transferring them to human agents when necessary. Such humanized tasks may be operated through ML algorithms simulating human intelligence [100]. Although conversational AI is based on the technology's ability to think and act like humans [15], most present-day conversational AI agents rely on narrowly defined intelligence to perform specific tasks focused on providing instrumental value. For example, Singapore Airlines' chatbot "Kris" provides simple, informative answers to basic queries but does not respond to more complex, contextual questions that may require a deeper understanding of the user's needs and even necessitate engaging in conversation [120]. We have yet to see conversational AI agents designed to deal with more intricate tasks, using humanized social skills to query, reason, plan, and solve problems [64]. The shift in the desired capabilities of humanized AI from providing purely instrumental value to being capable of human-like interaction calls for a rethinking of the mechanisms that facilitate user engagement with conversational AI agents [64].

Unlike prior technological systems, conversational AI agents need to create a natural, human-like interpersonal environment that facilitates user engagement [109]. Suitably training conversational AI algorithms with specific human-like interactional competencies may allow them to do so [37]. However, this would entail a focused understanding of the human-like competencies that must be embedded in conversational AI agents. This leads to our first research question:

Research Question 1 (RQ1): What human-like competencies in conversational AI agents will foster user engagement?

Although conversational AI is expected to foster user engagement, uncertainty related to the "black box" that hides AI inputs and operations from users may discourage it [110]. User engagement with a technology depends on users' trusting beliefs in that technology. Prior research has shown that *trust in technology* influences its use in different contexts, such as m-commerce portals, business information systems, and knowledge management systems [129, 133]. In addition, users often trust interactive technologies that possess human-like features such as voice and animation [137]. Such trust is expected to be more pronounced in the case of AI-driven customer interactions. This is because customers have the opportunity to constantly gauge the AI's value in terms of its human-like attributes; conversational AI agents that possess human-like interactional competencies are expected to make trustworthy suggestions and decisions [84, 111]. While prior studies have examined the association between AI and user trust in different contexts [48, 112, 145], researchers have yet to identify what competencies will help customers trust and engage with these specific AIs.

We propose that *user trust in conversational AI agents* is the key mechanism that mediates the relationship between human-like interactional competencies in AI and user engagement with conversational AI agents. The mediation perspective suggests that AI-driven human-like competencies will enhance the user's trust in conversational AI, encouraging user engagement. Consequently, the second research question that we examine in this study is:

Research Questions 2 (RQ2): Does users' trust in conversational AI agents mediate the relationship between human-like competencies in AI and user engagement?

Grounding our research in the individual human competency literature and media naturalness theory (MNT) [71], we first propose an initial model that associates human-like conversational AI competencies with user engagement. Next, we conceptualize the mechanisms through which user trust mediates this relationship. Our work makes several significant contributions. First, we draw on the competency literature and MNT to identify the specific human-like competencies that are relevant to the context of conversational AI agents. Our study acknowledges the calls for enriching, contextualized theory development by assimilating variables pertinent to AI-driven technologies for facilitating user engagement [58, 61]. Such a theoretical inquiry into the means and modalities of keeping users engaged in an artificially simulated environment is pertinent in the current scenario, where conversational AI-driven technologies are connecting with humans across many industries [141]. Given that prior research has primarily examined the *instrumental value* of technologies in keeping users engaged [29, 67], our work contributes to the literature by drawing on the competency literature and MNT to examine how an artificially simulated interpersonal environment influences user engagement in conversational AI. This theory-grounded examination of human-like conversational AI competencies helps deepen our understanding of the significance of MNT for keeping AI users engaged.

Second, we examine the mediating role of user trust in the relationship between human-like AI competencies and user engagement with conversational AI agents. Our work extends previous research on AI trust by identifying three desirable human-like AI competencies that serve as innate trust-building mechanisms for fostering user engagement with chatbots. Such knowledge will help us better appreciate the mechanisms through which human-like AI competencies influence user engagement in conversational AI. Our findings will therefore be useful to firms that are planning to invest in AI-based interactional solutions but are unsure about their potential impact on user engagement.

Background and Theory

User Engagement with Conversational AI

Prior IS research recognizes potential business impact of systems designed to provide their users with an engaging experience [90]. Engaging experiences enhance users' perception of a system's functionality, promoting higher levels of attention, interactivity, and control. With a view to enhancing their sales and profitability, firms are increasingly adopting new user engagement initiatives to hold their customers' attention [89]. Prior management research has shown that enhanced customer engagement not only helps retain customers [56], it also impacts firms' performance outcomes [57].

User engagement is the behavioral flow experienced by a user independent of intentional mindsets such as control, attention, curiosity, focus, and/or intrinsic interest [23]. Engagement is a positive and fulfilling state of mind characterized by energy, involvement, and efficacy, and it can be represented by the three subconstructs: *vigor, absorption*, and *dedication* [107]. In the IS context, *vigor* signifies high levels of energy and mental resilience while using a system, the willingness to expend effort on its use, and the tenacity to endure difficulties during that use. *Absorption* is a state in which the user is fully engrossed in and concentrating on the system. Finally, *dedication* refers to the enthusiasm, inspiration, pride, and challenge that the user derives from the system [107].

Given its business relevance, user engagement has been a subject of great interest for IS researchers. In the context of online customer interactions, IS researchers have emphasized the need to use rich media, such as animation and video, to promote interactivity and socialization. Research has also highlighted the need to intensify the aesthetics and sensory appeal of the technologies involved in order to offer an engaging experience to online users [90, 139]. However, the specific context of conversational AI agents such as chatbots is governed by their ability to display human-like interactional competencies [131] that ensure natural and engaged communication [31, 108]: Conversational AI's ability to understand, respond, engage, and converse with humans in a natural fashion is desirable [8]. Accordingly, we leverage MNT to examine and identify the key interactional competencies that humanized AI agents should incorporate to keep their users engaged. In the following sections, we first discuss the three "naturalness-providing mechanisms" proposed by MNT and then map these mechanisms onto the human-like AI competencies that can possibly facilitate AI-user engagement.

Media Naturalness and Human-like Conversational AI

MNT suggests that face-to-face communication is the most natural and preferred form of human communication. Because technologically mediated interactions suppress many features of their face-to-face counterparts, IS design should attempt to incorporate features that make those interactions feel natural [115]. Media naturalness is interactional media's ability to mimic real face-to-face interaction through technological features that can display facial expressions, body language, and speech, coupled with a feeling of synchronicity and colocation among interacting partners [70]. This perceived naturalness motivates users to continue using the technology for their interactions. Perceived naturalness is even more important in the context of conversational AI agents, where the technology design and organizational intent is premised on mimicking humanized interactions.

Centered around user experience, MNT identifies three mechanisms that lead to increased media naturalness: a decrease in cognitive effort, a reduction in communication ambiguities, and an increase in physiological arousal [69-71]. *Cognitive effort* is the amount of mental activity a user expends communicating with the technology [70]. *Communication ambiguities* are gaps in the information-giving stimuli that allow the user to interpret the message conveyed through the technology, and they result in misinterpretations and confusion [70]. *Physiological arousal* describes the excitement and pleasure that users derive from interacting with the technology [70]. Focusing on these three naturalness-providing mechanisms, prior research has used MNT to examine the effectiveness of virtual teamwork [31], e-learning environments [59], and online group work [105]. We posit that conversational AI competencies that stimulate the three naturalness-providing MNT mechanisms can humanize conversational AI, resulting in deeper user engagement.

Human-like Conversational AI Competencies

Building on the discussion in the previous section, the desired competencies in conversational AI should help users experience less cognitive effort, fewer communication ambiguities, and a high degree of physiological arousal. Systems imbued with such competencies would keep interactions between AI agents and their users smooth and engaging.

Prior management literature defines human *competencies* as the learned abilities to execute tasks, duties, or roles in a distinct work setting, incorporating several types of knowledge, skills, and attitudes [52]. Because conversational AI is often expected to replace human beings, it should possess the interactional competencies that are normally expected in human beings. Prior IS research has highlighted the key role of perceived *task* and *social* competencies as significant determinants of positive user outcomes in technologically mediated interactions [18, 138]. Furthermore, similar to the context of human interactions, studies have highlighted the significance of *emotions* displayed by conversational AI in encouraging effective exchanges in which the AI successfully mimics a human being [55, 80]. Guided by prior research on creating and maintaining interactions among individuals, as well as prior competency literature, we posit that the three desirable interactive competencies in conversational AI are *cognitive, relational*, and *emotional competencies*.

AI Competencies as Facilitators of Natural Human-like Interaction

In this section, we further develop the meaning of the three identified competencies (cognitive, relational, and emotional) in the context of conversational AI and use the MNT naturalness-providing mechanisms to theorize their role in facilitating user engagement with these tools.

Cognitive competency is the mental activity of processing all available information and using it in the active interpretation of events to maximize task performance [40]. In the context of conversational AI, cognitive competency would be the ability of an AI agent to consider and apply its problem-solving and decision-making skills to effectively complete assigned tasks [18]. For example, Grammarly's writing skills indicate its cognitive competency as an AI-powered interactive writing tool.

Relational competency means cooperating with others and making an effort to develop and maintain harmonious interpersonal relationships. It refers to relationship-building skills that can facilitate engaged communication with others. In the context of conversational AI, relational competency would refer to the AI agent's interpersonal skills, such as supporting, cooperating, and collaborating with its users [18, 138]. For example, an AI-powered algorithm may use interactions with users to learn about their preferences, allowing it to suggest movies (Netflix), books (Amazon), or news stories (social media).

In the present-day context, where AI is rapidly replacing human beings in customer service interactions, *cognitive* and *relational* competencies are desired capabilities in conversational AI because they can make it more effective and efficient in handling tasks. Prior research has also highlighted the need to build capabilities that will allow AI to fulfill users' needs intuitively, offering adequate and considerate responses to queries [14, 18]. For example, Lyft uses the cognitive and relational competencies of its AI-powered self-service app to minimize the effort needed for routine operations such as calling a cab, arranging a pick-up point, and directing the driver, relying on its knowledge of users' preferences for guidance.

However, cognitive and relational competencies may not be sufficient to allow conversational AI to address users' emotional needs through empathetic interactions [39]. Although cognitive and relational AI competencies can handle routine customer interactions; more may be required for those that are urgent or emotionally charged [91]. For example, customer emotions may run high when checking-in for recently canceled flights that should have taken them to a significant business meeting or an important family occasion. As another example, a customer waiting for a late food delivery may urgently need to leave the house. Such scenarios, which are high on the emotional spectrum, require a compassionate human touch, meaning emotional competency may need to be built into conversational AI. Even during routine interactions, individuals often prefer to have communication suffused with human-like warmth [140].

We posit *emotional* competency as the third important ability that conversational AI should display to keep customers engaged [44, 60]. *Emotional competency* signifies an aroused emotional state and is linked to intense feelings. It refers to an individual's ability to feel for and empathize with others while interacting with them [95]. In the context of conversational AI, emotional competency would be the ability of AI agent to self-manage and moderate its interactions with users, accounting for their moods, feelings, and reactions through appropriate expressions and behavior [39, 122]. For example, the voice-analytics software used in Cogito (a company co-founded by MIT Sloan alumni) guides call center agents to recognize customers' moods over the phone, helping human agents adjust their conversations with customers in real time.

To confirm that the three identified competencies facilitate natural communication between a conversational AI and its user, we analyzed how they might act as naturalness-providing mechanisms. Based on the details provided in cure 1, we observed that *cognitive, relational*, and *emotional* competencies in conversational AI tend to make exchanges natural by lowering cognitive effort, diminishing communication ambiguities, and enhancing physiological arousal, respectively. Because the three identified AI competencies activate the MNT naturalness-providing mechanisms, we contend that cognitive, relational, and emotional competencies constitute the desirable human-like conversational AI competencies needed to foster user engagement. In the next section, we further ground our arguments in MNT to develop our research hypotheses.

Hypothesis Development

Moving beyond the pure "instrumental use" of technology, we posit that conversational AI agents need to be imbued with the three specific competencies previously described and in Figure 1, to foster user engagement. In addition, past studies have identified the key role of the user's trust in technology for fostering user engagement [87, 133, 137]. In contrast to most prior research, which has examined *human-like interactional competencies* and *user trust in conversational AI* separately, in a piecemeal approach [18, 72, 125], we integrate the two perspectives and propose the mediating role of *user trust in AI* through which *human-like conversational AI competencies* influence *user engagement with conversational AI*. The contextualized conversational AI competency trust model (along with the control variables) is presented in Figure 2. In the following section, we develop the direct and mediation hypotheses as indicated in the research model.

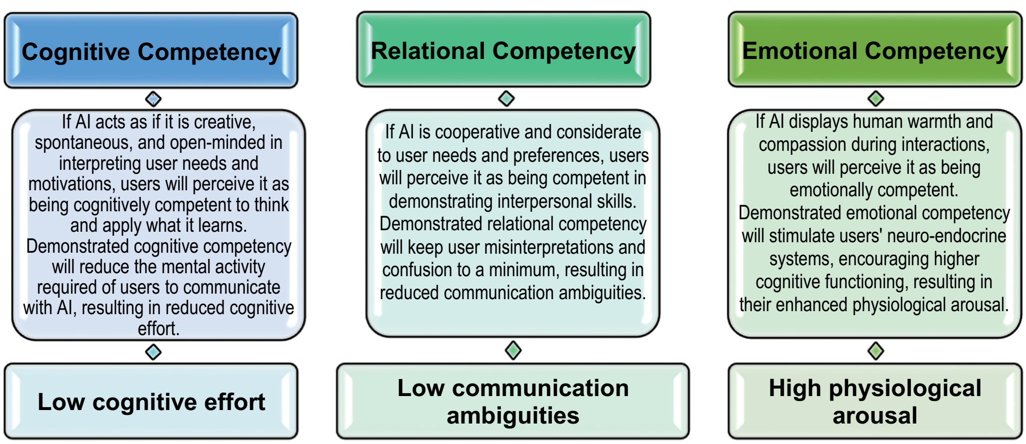

Figure 1. Human-like artificial intelligence (AI) competencies linked to MNT user perceptions.

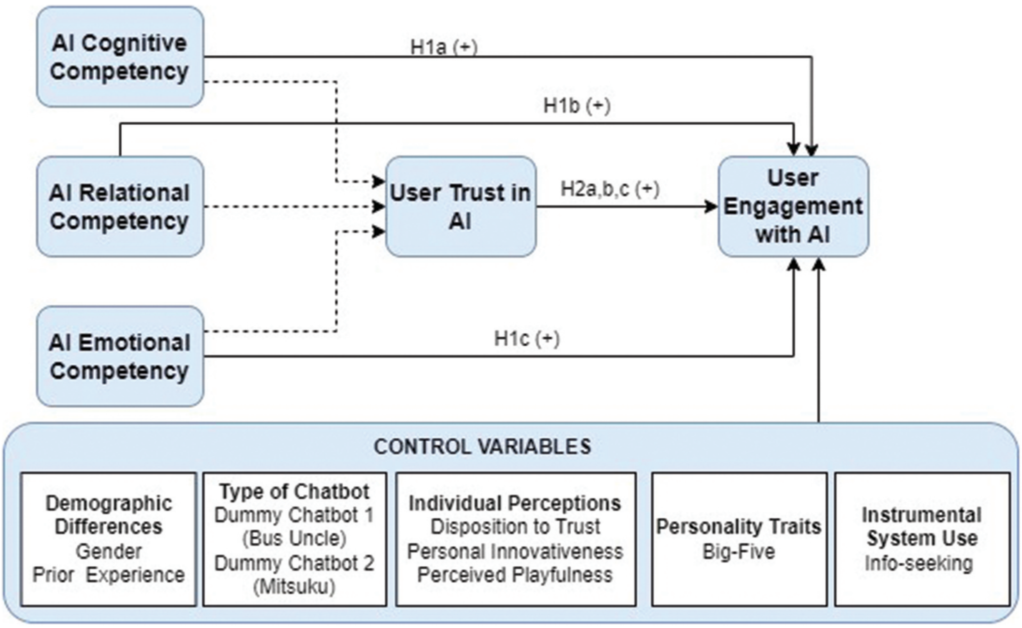

Figure 2. Human-like conversational artificial intelligence (AI) competency: Trust model for user engagement.

Human-like Conversational AI Competencies and User Engagement: The MNT Perspective

AI Cognitive Competency and User Engagement

Cognitive competency refers to the ability to effectively interpret all the available information for participating productively in the assigned tasks [40]. Such an ability enables individuals to perform appropriate actions to maximize task performance [17, 73]. For conversational AI, cognitive competency comprises the set of abilities that would enable the AI to effectively interpret the interactional information to complete a user-defined task [18, 138]. If the conversational AI acts as if it is creative, spontaneous, and open-minded in interpreting and acting on user needs and motivations, users will perceive it as being cognitively competent to interpret and perform the assigned task [48].

Displaying cognitive competency gives users the confidence to rely on the conversational AI. In such situations, users relinquish their control, ceding that task to the AI [64], thereby reducing the cognitive effort that they must expend to execute and monitor it [28, 36]. For example, Tencent's WeChat, an AI-based chatbot, is very popular in China because of its display of task proficiency by bringing services such as orders, purchases, and payments for transactions into the messenger service without the user needing to leave the WeChat app. This perceived task efficiency reduces the cognitive effort required of its users [25].

Because prior research has shown that reduced cognitive effort is linked to increased user engagement in various contexts, such as older adults interacting with technology, gamified online discussions for students, and video game engagement [34, 38, 117], we expect that the reduced effort for users brought about by cognitively competent conversational AI will positively influence user engagement. Thus, we hypothesize:

Hypothesis 1a (H1a): Cognitive competency in a conversational AI agent is positively related to user engagement.

AI Relational Competency and User Engagement

Relational competency is the ability to cooperate with others for developing and maintaining a harmonious relationship. In the context of conversational AI, relational competency can be defined as skills that enable the AI to support, cooperate, and collaborate with the user [18]. For example, a relationally competent hiring AI, through its considerate and cooperative demeanor, would develop a fair relationship with the candidate. This would help unearth the candidate's true abilities needed for job-fit assessment.

A relationally competent conversational AI is perceived to be considerate, cooperative, and fair by the user. Relational cues affirming these qualities help strengthen the AI's relationship with its interacting user [13, 125]. The immediacy and intimacy thus developed reduces communication ambiguities [13, 43]. For example, chatbots display relational competency by applying natural language processing to better understand user preferences, simulate personalized human conversations, and adjust responses based on what comes up in specific conversations [93].

Prior research has shown that reduced communication ambiguities are linked to heightened user engagement in various contexts, including organizations, crowdsourcing, and virtual interactions [30, 82, 127]. Hence, we expect that reduced communication ambiguities for users interacting with relationally competent AI will enhance the users' engagement. Thus, we hypothesize:

Hypothesis 1b (H1b): Relational competency in a conversational AI agent is positively related to user engagement.

AI Emotional Competency and User Engagement

Emotional competency is individuals' ability to effectively manage themselves and their actions by being sensitive to the feelings of their interactional partners. It is the necessary skill set for perceiving emotions—both one's own and another's—regulating those emotions, and using information about them to guide one's thinking and actions [66]. Emotional competency in conversational AI is its ability to create a spontaneous emotional connection with its users by understanding and managing their moods, feelings, and reactions [122]. A conversational AI agent is emotionally competent if it can recognize and appropriately respond to diverse human emotions such as pleasure, thrill, anger, boredom, and distress [8, 101]. For example, a chatbot should be able to sense a dissatisfied customer's anger and respond appropriately in real time.

Emotionally competent AI offers empathetic human-like warmth and compassion, thereby simulating an interpersonal environment of presence or "being there" [13, 45]. This feeling of presence affords conversational AI an impression of being natural and real, which keeps users emotionally aroused and engaged [70]. For example, the Woebot chatbot describes itself as a charming robot friend and uses AI to offer emotional support through talk therapy, as a friend would, while the Cogito chatbot uses AI to analyze people's voices on the phone and guides human customer service agents to be empathetic when it detects frustration. Another human-like emotional robot named Pepper uses AI to detect sadness, anger, or other feelings in interacting users and tempers its interactions accordingly [92].

If an AI maintains a real-time emotional connection with its users, meeting emotional sensitivity with human-like warmth and compassion, we expect that this emotional care will stimulate users' neuro-endocrine systems, encouraging higher cognitive functioning and positive emotional states and resulting in increased user engagement [102]. Thus, we hypothesize:

Hypothesis 1c (H1c): Emotional competency in a conversational AI agent is positively related to user engagement.

User Trust in Conversational AI

Notwithstanding the important role of human-like interactional competencies in offering humanized AI interactions, it is important to note that trust is the backbone of all social interactions [78, 79]. In the context of interactional technologies, user trust is defined as the user's willingness to believe in the technology [78, 128]. User trust in conversational AI is of utmost importance, as AI's decision-making processes are far too complex for users to understand, making them feel vulnerable and anxious due to a perceived loss of control. There might be situations where conversational AI agents take up serious roles, acting as medical interviewers, virtual personal assistants, or therapists for depression and anxiety, or detecting fraud and deception [109]. Unintended or intended scripting errors, lapses in data management, and misjudgments in model-training data in AI-driven systems can all lead to undesirable consequences, including security snags, models delivering biased results, and even the revelation of sensitive information hidden among anonymized data. Such unintended or intended consequences may deter users from trusting AI, preventing them from disclosing potentially sensitive information [27, 97]. For example, users may behave deceptively with an AI while answering sensitive questions in a doctor's clinic because they fear that chatbot customer service representatives may gain access to their personal information [110]. This may result in the algorithm being trained on faulty data leading to future prediction errors. Organization-level efforts are required to move from cataloging AI's risks to overcoming them by building trust, ensuring conversational AI agents' responses are tailored to the needs of specific customers [24].

Prior studies have confirmed that attributing human qualities to nonhuman technological agents builds user trust [48, 112, 145]. For example, Gong [48] emphasized how anthropomorphism in computer agents prompts more social responses from users, Zhou et al. [145] endorsed trusted AI principles for developing trustworthy AI solutions, and Seeger et al. [112] identified three groups of factors to stimulate anthropomorphism, resulting in trust and connectedness in conversational AI agents. However, the question of what desirable human-like competencies might serve as intuitive trust-building mechanisms for fostering user engagement with conversational AI agents is, as of yet, unexplored. Thus motivated, we posit that human-like competencies in conversational AI agents will enhance user trust by overcoming users' uncertainties and consequently keeping them engaged.

Prior research has used human-like trust constructs designed to assess the level of interpersonal trust in the interactional partner to measure user trust in technology [128, 133, 137]. Such an approach is well suited for technologies that possess human-like attributes such as voice and animation [138]. In our research, we adopt a similar approach because conversational AI agents and chatbots are expected to replace real human beings [72]. In the next section, we describe the mechanisms through which we expect user trust in AI to mediate the relationship between human-like conversational AI competencies and user engagement in conversational AI.

The Mediating Role of User Trust

User engagement is viewed as a desirable human response to interpersonal exchanges with conversational AI. In their interactions with AI tools such as chatbots, users assess how similar their interactions with the AI are to their prior interactions with real human beings. A sense of similarity with real human interactions will power users' trust in conversational AI, leading to an enhanced level of user engagement [72, 78, 137]. The human-like interactional competencies that we have described as cognitive, relational, and emotional are expected to foster a *naturalness* in users' interactions with AI [68, 71]. This increased naturalness reassures the user of conversational AI's validity as an interactional partner [81]. Thus, human-like interactional competencies in AI provide users with appropriate trust-building cues, alleviating their perceptions of risk and vulnerability [45, 125]. This enhanced level of trust will foster deeper user engagement with conversational AI.

Human-like conversations may encourage users to anthropomorphize AI, helping them forge effective connections with AI tools [111]. Contrarily, conversational AIs perceived to be low in human-like interactional competencies are not anthropomorphized by users, resulting in lower levels of trusting beliefs in the ability, integrity, and benevolence of the AI agent [87]. For example, a study conducted with a financial advisory chatbot known as "Robo advisor" demonstrated high levels of user trust in the recommendations provided by human-like Robo advisors. Even when knowledgeable investors were presented with objectively incorrect advice and additional warnings, they were three times more likely to accept an incorrect recommendation from the humanized Robo advisor than from a traditional, static web interface [53]. In a similar vein, customers had an increased willingness to pay for a dress shirt customized by a human-like chatbot than one created through a static e-commerce web portal [53]. It is the *naturalness* of these human–AI interactions, created by the three human-like competencies we have identified, that builds user trust in AI technologies.

According to social response theory, users tend to respond to technologies that possess human-like attributes as though they are human [45]. Hence, users personify conversational AI agents that are able to generate a high level of human-like trusting belief and respond to it in much the same way as they would respond to a human [72]. Demonstrating higher levels of human-like interactional competencies will increase user confidence and trust in such an AI, leading to higher levels of user engagement. While we suggest that the three human-like interactional competencies we identify are essential attributes of conversational AI, creating favorable user perceptions of naturalness that encourage user engagement (as proposed in H1a, b, and c), we also expect that user trust in AI is one of the salient mechanisms through which this happens. Thus, we hypothesize:

Hypothesis 2 (H2): The relationships between (a) AI cognitive competency and user engagement, (b) AI relational competency and user engagement, and (c) AI emotional competency and user engagement are mediated by user trust in a conversational AI agent.

Research Methodology

Sample and Data Collection Procedure

The use of chatbots is relatively new, and organizations are continuously exploring ways to use conversational AI to create business value. A mixed methods approach is generally recommended when examining an emerging phenomenon as it can provide a more nuanced understanding of the underlying mechanisms, enriching the theory they are used to develop [8]. Accordingly, for this research, in which we seek to conceptualize human-like interactional competencies in conversational AI agents and the mediating role of trust for user engagement, we closely followed the mixed methods research guidelines suggested by Venkatesh et al. [135]. Specifically, we adopted a sequential mixed methods approach comprising a quantitative study followed by a qualitative study.

In the quantitative study, we employed a two-wave survey method to test the theorized model with data from relatively new chatbot users. In the first wave of the quantitative study, we collected data regarding the individual characteristics of our respondents and their general perceptions about chatbots. We used this data to derive our control variables. Next, the study respondents were exposed to one of the three selected study chatbots for a fixed period of time. They were then surveyed about their interactional experience with the chatbot.

In the follow-up qualitative study, we conducted semi-structured interviews with frequent chatbot users to confirm the results from the quantitative study and, more importantly, to understand and reconcile the counterintuitive findings [125]. The aim of the follow-up qualitative study was to develop meta-inferences by integrating and synthesizing the findings from the quantitative and qualitative analyses [135, 136]. This helped us unearth boundary conditions for the results from the quantitative study, thereby offering a more holistic understanding of the phenomenon [125].

In the subsequent sections, we discuss the quantitative and qualitative research separately in terms of their design, analysis, and inferences. We then integrate our quantitative and qualitative research findings to delineate meta-inferences. The contradictions observed in the follow-up qualitative study helped us unearth the boundary conditions to the theorized model.

Quantitative Survey Method: Survey Design and Design Validity

To maintain methodological rigor in the two-wave survey, we used validated scales from the literature and adapted them to our research context to formulate questionnaires for both waves (see Online Supplemental Appendix 1). All the survey items were measured using a 7-point Likert or semantic differential scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). The adapted instruments were pilot tested with a sample of 20 graduate students. Based on their feedback, the questions were suitably modified before rolling out the final survey to the sampled respondents in two waves, separated by a period of 4 weeks.

The survey respondents were undergraduate students in a business management course at a university in Singapore. Participants were invited to the study if they had marginal or no experience with chatbots. Furthermore, we ensured that none of the invited respondents had previously used the specific messenger chatbots selected for the study, namely *Mitsuku, Bus Uncle*, and *Woebot*. Although the three chatbots have different functionalities, they all sufficiently display the three human-like competencies that are our focus here (details presented in Online Supplemental Appendix 2). The diversity of the selected chatbots and the random allocation of the chatbots to the study participants helped us alleviate the possibility of any response bias, such as the influence of demand characteristics.[1] This aspect needs special attention because the measures used in our study are self-reported [86, 103].

A total of 225 participants were invited to complete the first wave of the questionnaire. During the first phase, we collected demographic information and data about individual-level attributes. Additionally, the respondents answered a question about their "willingness to use chatbots" based on a brief explanatory note describing chatbots that was included in the introduction section of the survey form and a short general overview provided by the survey administrator.

The second wave of the survey was conducted 4 weeks after the first and included only 213 of the first-wave respondents. The remaining 12 initial respondents were dropped because of inaccurate or incomplete responses during the first wave. The second wave of data collection was conducted during an hour-long research methods class. Because some research participants had no prior experience with chatbot use, all the second-wave respondents were first introduced to the functionalities of messenger bots, following which they were randomly assigned to one of the three study chatbots for interactional experience. This introduction and allocation took about 15 minutes of the hour allocated for the study. Subsequently, the research participants were given about 30 minutes to interact with their allocated chatbot and explore its different functionalities. They were then asked to fill out a survey comprising questions designed to capture their interactional experience with their designated chatbot.

The respondents were given some flexibility in terms of time to interact with the chatbot before filling out the survey responses. However, they were aware of the constraint that the survey had to be submitted within their class time. The introduction section of the survey form clearly indicated that completing the final survey would take roughly 15 minutes. The participants were free to plan their interaction with the chatbots accordingly. Though participation in the study was voluntary, the survey respondents were apprised beforehand that bonus class participation credits would be awarded based on their participation and on the accuracy and completeness of their survey responses in both study waves. Participants were assured the collected data would remain confidential and that the results would be reported only in an aggregated form for research purposes.

Common Method Bias

The study was planned in two waves separated by a period of 4 weeks to reduce the possibility of common method bias. Nonetheless, as the data were self-reported, we performed Harman's one factor test [96] and Lindell and Whitney's [74] marker-variable method test. Our analysis (Online Supplemental Appendix 3) shows that there is no significant likelihood of common method bias.

Control Variables

Because user engagement can be influenced by factors other than those in the hypothesized model, we incorporated appropriate controls in the regression equations to better understand the variance explained by the research variables over and above that described by the control variables. Based on prior studies, we used five types of control variables in our research model: (1) *respondent characteristics to account for demographic differences*—these included the respondents' gender [3] and prior experience using chatbots [134]; (2) *the type of chatbot to rule out the instrumentality of the different chatbots used in our research*—this included the dummy variables for the three chatbots with which the respondents interacted before filling out the second wave of the survey [132]; and (3) *individual perceptual differences to control for user perceptions*—these included "disposition to trust," "personal innovativeness," and "perceived playfulness." Individual dispositions have been identified as an important determinant of perceived anthropomorphism in conversational agents [112]. Prior studies have found that individuals with a higher propensity to trust will generally be more trusting [e.g., 78, 125]. Also, "personal innovativeness" and "perceived playfulness" are necessary individual-level characteristics in the context of engaging technologies [e.g., 2, 22]; (4) *individual personality traits to control for user personality characteristics* [e.g., 33, 123]—these included the big five personality traits as human trust in intelligent agents may depend on users' personality traits [146]; and lastly (5) *instrumental use to examine factors beyond the long-established instrumental system use*—this included information-seeking motives [29].

Demographics

Online Supplemental Appendix 4 provides the demographics of the survey respondents. Among the 213 respondents, 51.6% were male and 48.4% were female. Gender was coded as a dummy variable, with females coded as 0 and males coded as 1. The average age of the respondents was 18.2, with a standard deviation of 1.2. Although 44.6% of the respondents had heard of chatbots, only 39% had prior experience using chatbots. Subsequently, following the two-stage analytical procedure [49], we first evaluated the validity and reliability of the variables and then examined the hypothesized relationships.

Validity and Reliability

Online Supplemental Appendix 5 presents means, standard deviations, and a correlation matrix for all the variables used in our study. The Cronbach alphas for all research constructs are higher than 0.7, indicating that all the constructs have adequate reliability [88]. By carefully adopting and adapting all construct items from prior validated scales, we ensured that all the research constructs fulfilled the criterion of content validity. Our factor analysis table, presented in Online Supplemental Appendix 6, shows that the factor loadings of all the items on the intended focal construct were above 0.5 and that the cross-loadings of the items on other constructs were low, supporting their convergent and discriminant validity.

As user trust and user engagement are multi-dimensional concepts comprising three dimensions each, we assigned equal weight to each of the dimensions in our aggregation procedure [22, 94]. However, to be confident of our procedures, we tested the psychometric properties for each of the dimensions of user trust and user engagement, which were found to be satisfactory.

Table 1. Results: Predicting user engagement with artificial intelligence using ordinary least squares.

	User Engagement with Chatbots			
	Control Variables Model		Direct Path Model	
	Block1		Block 2	
Control Variables	β (se)	t	β	t
Demographics				
Gender	-0.092 (0.167)	-0.554	-0.111 (0.146)	-0.760
Prior Chatbot Experience	-0.049 (0.158)	-0.314	0.023 (0.139)	0.169
Type of chatbots				
Dummy chatbot 1 (Bus Uncle)	0.263 (0.189)	1.392	0.210 (0.167)	1.255
Dummy chatbot 2 (Mitsuku)	**0.528** (0.186)**	**2.842**	**0.429* (0.165)**	**2.601**
Individual Perceptual Differences				
Disposition to Trust	**0.223** (0.067)**	**3.321**	**0.163** (0.060)**	**2.730**
Information Seeking Motive	**0.464** (0.063)**	**7.416**	**0.337** (0.057)**	**5.872**
Personal Innovativeness	0.086 (0.082)	1.046	0.027 (0.072)	0.377
Perceived Playfulness	0.015 (0.092)	0.162	-0.008 (0.080)	-0.097
Individual Personality Traits				
Extraversion	-0.051 (0.081)	-0.632	-0.068 (0.071)	-0.951
Openness	-0.053 (0.090)	-0.588	-0.051 (0.079)	-0.651
Neuroticism	0.056 (0.053)	1.061	0.031 (0.046)	0.681
Agreeableness	0.049 (0.083)	0.591	0.046 (0.073)	0.625
Conscientiousness	0.039 (0.068)	0.567	0.003 (0.060)	0.056
Independent Variables				
Cognitive Competency			**0.260** (0.057)**	**4.564**
Relational Competency			-0.027 (0.078)	-0.349
Emotional Competency			**0.243** (0.069)**	**3.527**
R^2	0.314		0.485	
ΔR^2			0.170	
ΔF	**7.021****		**21.595****	

Note: n = 213Abbreviations: se, standard error. . $^{*}p < 0.05$; $^{**}p < 0.01$.

Quantitative Study Results

The results for our stepwise hierarchical regression analyses are presented in Table 1. In step 1 of our analysis, we entered only the control variables in the regression equation (gender, type of chatbot, individual perceptual differences, and individual personality traits). In step 2, we entered the main research variables (human-like interactional competencies: cognitive, relational, and emotional) in addition to the control variables in the regression equation to examine their relationships to user engagement in AI-enabled chatbots. We also tested for multicollinearity among the independent variables by examining the variance inflation factors (VIFs), which ranged from 1.01 to 2.03. As all VIF values are less than 5 there are no significant multicollinearity problems [50, 125].

OLS Regression Model

The results in block 1 showed that among the control variables, the dummy chatbot 2 ($\beta = 0.528$, $p < 0.01$), disposition to trust ($\beta = 0.223$, $p < 0.01$), and information-seeking motive ($\beta = 0.464$, $p < 0.01$) have a significant relationship with user engagement. The variance explained by the control variables was 31.4%, which establishes the appropriateness of the choice of the control variables for this study. The results in block 2 showed that the human-like conversational AI competencies of cognitive competency ($\beta = 0.260$, $p < 0.01$) and emotional competency ($\beta = 0.243$, $p < 0.01$) were significantly related to user engagement, thereby supporting H1a and H1c. However, relational competency ($\beta = -0.027$, $p > 0.05$) did not have a significant relationship with user engagement, indicating nonsupport of H1b. The human-like conversational AI competencies together explained an additional 17% variance over the control variables in predicting user engagement. A significant F-change demonstrates that, along with the chosen controls, human-like competencies significantly improved the prediction of user engagement in our model.

Endogeneity Bias

Although our research model is theoretically grounded in MNT, we needed to be confident that the interactional competencies in AI were not endogenous predictors of user engagement. The important assumption of the ordinary least squares (OLS) regression model examining the influence of competencies on user engagement is exogeneity, which assumes that the explanatory variables (competencies) are completely uncorrelated to the error term, which may contain omitted variables. However, the empirical challenge is that human-like interactional competencies may be endogenous to the outcome variable—user engagement, resulting in endogeneity bias. Omitted variables and unobserved relationships may bias the observed association between the outcome (user engagement) and explanatory (human-like competencies) variables, making the results misleading.

We used the two-stage least squares (2SLS) regression model to mitigate the bias endogeneity introduces to the regression coefficient in OLS regression. The most important aspect of a 2SLS model is finding suitable instrument variables that are correlated with the explanatory variable but uncorrelated with the outcome variable [5]. The instrument variable will produce an unbiased coefficient estimate even if there is an omitted variable that is correlated with both the explanatory (competencies) and outcome (user engagement) variables. Instrument variables are often used to address endogeneity issues arising from omitted variables, making them a good identification strategy for our research [5]. We identified our instruments and conducted robustness tests as detailed in Online Supplemental Appendix 7.

Instrumental Variable (2SLS) Regression Model

To further confirm the influence of AI competencies on user engagement and mitigate any endogeneity bias that may be present due to unobserved relationships, we employed the 2SLS instrumental variable approach using STATA. Online Supplemental Appendix 7, Table 7c shows the total effects model directly linking human-like conversational AI competencies with user engagement using 2SLS regression. The results in Online

Supplemental Appendix 7, Table 7c using the 2SLS regression approach further validate the significant influence of cognitive and emotional competencies on user engagement that was demonstrated using OLS analysis in Table 1.

Mediating Role of User Trust

In addition to the direct association of the human-like conversational AI competencies with user engagement, we also hypothesized the mediating influence of user trust in this relationship. However, since relational competency did not have a direct relationship with user engagement, we discuss the mediation results only for cognitive and emotional competencies. We tested the mediation influence of trust using both the product of coefficients (Sobel test) and bootstrap confidence intervals (CIs; Preacher and Hayes test) [98, 99].

The Sobel test (Table 2, Upper Panel) suggests that cognitive competency ($Z = 3.59$, $p = 0.0003$) and emotional competency ($Z = 3.74$, $p = 0.0002$) have a positive influence on user engagement through user trust, thereby supporting hypotheses H2a and H2c, although H2b is not supported. However, the Sobel test assumes that the sampling distribution of the mediation effect is normal, when in fact it is often skewed and may lead to biased estimates [124]. Methodologists such as Preacher and Hayes [51, 98, 119] therefore suggest that such a test be supplemented with the bootstrapping method with bias-corrected CIs [75, 98]; bootstrapping overcomes this problem by repeatedly sampling with replacements from the dataset and estimating the mediation effect in each resampled dataset. By resampling thousands of times, the sampling distribution for indirect effects (mediation) can be approximated and used to construct CIs for the examined effects [99]. If the CIs exclude zero, the indirect effect is considered meaningful [124]. The present study achieved a 95% CI for the mediation effect across 5,000 bootstrap resamples. These results appear in the lower panel of Table 2.

The results of the mediation analyses for the relationship between cognitive competency ($\beta = 0.1052$, CI = 0.0528–0.1875) and user engagement (non-zero CI) as well as between emotional competency ($\beta = 0.1428$, CI = 0.0659–0.2282) and user engagement (non-zero CI) confirm the mediating role of user trust, supporting H2a and H2c. However, H2b is not supported because the results indicate that relational competency does not have a direct relationship with user engagement; therefore, a mediating role of user trust cannot exist.

Table 2. Mediation analysis.

Test of the Indirect Effect of Competencies on User Engagement				
	Product of Coefficients			
	Cognitive Competency		Emotional Competency	
	Z-test	Significance	Z-test	Significance
User Trust	3.5517	0.0004	3.7036	0.0002
	Bootstrap Confidence Interval			
	Cognitive Competency		Emotional Competency	
	β (se)	Bias-Corrected CI	β (se)	Bias-Corrected CI
User Trust	0.1084 (0.03)	0.0527-0.1944	0.1466 (0.04)	0.0750–0.2482

Note: Abbreviations: se, standard error; CI, confidence interval.

Robustness Tests

We conducted additional robustness tests using Smart PLS-SEM to be confident of our findings. The SEM results testing user trust as a mediating variable predicting user engagement with chatbots are presented in Online Supplemental Appendix 8. The results are essentially similar to those from the OLS, 2SLS, and mediation tests presented in Tables 1 and 2 and Online Supplemental Appendix 7, Table 7d.

Examining Business Relevance of User Engagement with Conversational AI Agent

Although not hypothesized in the current study, previous research has clearly demonstrated a theoretical linkage between the user engagement with technology and their willingness to use as well as their satisfaction with technology in several contexts such as telerehabilitation [114] and online consumer experience [83]. Research has viewed system use and engagement as the missing link for deriving business value from IT [20, 32]. Prior research has shown that to actualize benefits from customer-facing technologies, technology use by the intended users is the first step. Without adequate use and engagement with the technology, the intended benefits from the technology cannot be achieved [21, 126]. Prior research has even viewed use and engagement as the missing link for deriving business value from IT [20, 32]. This is because engaged users tend to feel the technology satisficing its utility and relevance and begin to get emotionally bonded with it. Engagement is a reflection of such positive reactions which is indicated by curiosity, focused attention, and absorption in the task [15]. Thus, engagement with technology is viewed as a cognitive and affective commitment to a dynamic relationship with the technology [41]. Prior research has emphasized the role of users' affective engagement with technology for an appreciable impact [126]. Engaging affectively with technology has influenced several business-oriented outcomes such as performance and innovativeness [65, 130]. As chatbots embed human-like competencies, the process of using chatbots becomes more and more experience-oriented. Without adequate user engagement, the other user-related benefits cannot be achieved from chatbots or any user-centric IT tool [12, 126]. Consequently, the positive reactions of using chatbots will influence their future usage behavior [21, 126]. Engaged users tend to be more active and sustained in immersing themselves in chatbot usage, thereby willingly using chatbots and feeling satisfied.

Though user engagement has been a key consideration in designing and adopting new communication technologies [19], we wanted to be confident that it is related to the bottom line—a primary concern for businesses. To confirm the business relevance of our study, we followed a two-pronged approach.

First, we conducted additional tests to show the importance of examining user engagement in enhancing chatbot use, which is necessary for making any business impact. Our data set clearly shows the influence of user engagement in increasing their willingness to use chatbots and satisfaction with chatbots. We had collected data on willingness to use chatbots during both the waves of our two-wave survey. In the first wave (at time t1), the respondents answered to the willingness to use chatbots based on a verbal and textual description of chatbots alone. In the second wave (at time t2), the respondents answered to the willingness to use chatbots after giving them time to engage with chatbots.

In order to test the significance of user engagement, we analyzed the user responses at time t2 to ascertain whether their willingness to use chatbots increased after giving them engaging experiences with chatbots. For this purpose, we compared willingness to use chatbots for the time t2 after giving users an engaging experience with chatbots (i.e., second-wave survey) with that of the pre-engagement time t1 (i.e., first wave survey). Pairwise comparison of means (paired t-test) for the user data from the two waves of the survey showed that the willingness to use chatbots significantly increased in time t2 following the engaging experiences with chatbots (at t1, mean = 4.16, std dev = 1.16) as compared to time t2 (at t2, mean = 4.73, std dev =1.48), $p < 0.001$. The t-test shows a significant difference in means of the willingness to use chatbots at the two points in time, which indicates that engaging experiences determine users' willingness to use chatbots, which is a prerequisite to derive other use-related benefits.

Second, we demonstrate that enhanced user engagement leads to an improvement in business-oriented measures such as "willingness to use" and "user satisfaction" with chatbots. Our results at time t2 demonstrate a strong positive relationship of user engagement with the willingness to use chatbots (ß = 0.846, t = 37.228, $p < 0.01$) and with overall satisfaction with chatbots (ß = 0.824, 36.020, $p < 0.01$), reaffirming the need to develop engaging user experiences with chatbot usage. The high variance (R^2) explained by user engagement further validates its importance in determining willingness to use chatbots (R^2 = 71.7%) and satisfaction with chatbots (R^2 = 68%).

Qualitative Study: Interview Design and Design Validity

As a follow-up to the two-wave survey, we conducted 10 interviews screened to represent frequent chatbot users for gathering additional qualitative information about their interactional experience. The interview questions and the interviewee profiles are presented in Online Supplemental Appendices 9 and 10, respectively. The three different types of validity relevant for qualitative study are design validity, analytical validity, and inferential validity [135].

Design validity establishes the credibility and transferability of findings by ensuring that the qualitative study has been designed and executed appropriately. The design validity of the qualitative study was ensured by maintaining rigor in selecting the interview participants [125, 135]. Unlike the survey respondents, the interviewees were carefully chosen to be frequent chatbot users. Furthermore, the interview respondents were invited to participate in the study only if they were adept at using both text- and voice-based chatbots. In addition, the interviewees came from varied professions and countries (see Online Supplemental Appendix 10). This ensured that their responses could provide a different perspective from those of the survey respondents. The diversity in perspectives from the qualitative study helped us *corroborate* and *complement* the findings from the quantitative research, thus providing completeness for our understanding of the subject [125, 136]. The interviews were conducted individually through online tools such as Zoom and Microsoft Teams. Each interview lasted for about an hour. After seeking permission from the interviewees, all interviews were recorded and transcribed for analysis.

Qualitative Study: Analytical Validity and Analysis-

Analytical validity, which ensures the credibility and trustworthiness of the data [135], was established through rigorous data collection, analysis, and reporting. After transcribing the interview responses, we analyzed the qualitative data to identify general themes. To do so we used a coding scheme based on our research questions and theoretical constructs developed by two of the study's authors, who then used a multiple classification scheme to manually code the data, classifying each response as belonging to one or more categories [11]. When the coders' assessments diverged, a consensus was reached through discussion [125]. We also identified the valence (positive or negative) for each category and noted any off-quadrant or divergent responses.

Prior to examining the hypotheses, we explored the qualitative data to understand the salience of our study. All the interview respondents echoed the importance of providing engaging user experiences through conversational AI. One interview respondent remarked:

> *I get **involved**[2] with chatbots. Our **conversations are so long**, I would try all the nodes for different questions. Even if I got the answer, I would try to ask other questions to see how it would react.* (R4)[3]

However, our data also revealed the importance of further humanizing conversational AI.

> *Based on my current experience, I feel I am talking to a search engine which is just faster. There should **be human element** in the chatbot. For example, if the chatbot pops up on the website and I don't reply to it then it should try to make the conversations more **fun and engaging** to draw my attention.* (R8)

> *I **often feel non-engaged** with the current chatbots as I must fine tune the way I asked the question. It's more of **me learning to interact** with the chatbot rather than it learning about me. If we talk to **humans**, they **understand** our problems. That is something I want to see in chatbots.* (R10)

Qualitative Inferences: Corroboration and Confirmation

In this section, we describe the bridging approach we used to strengthen the quantitative findings via the results from the qualitative study [135]. In order to develop a consensus between the quantitative and qualitative findings, we situate the findings from the qualitative study within the results obtained from the quantitative study, delineating corroborated meta-inferences. Accordingly, we first discuss the hypotheses supported by the quantitative study.

Bridging Approach for Supported Hypotheses

Consistent with our research design, we coded the data from the qualitative interviews according to the hypothesized relationships following a *hypothesis coding method* in which the most relevant and representative quotations from each category were identified for each respondent [10, 106]. This method for hypothesis testing using qualitative interview data has been used in prior studies [125]. Our analysis revealed frequent occurrences of all the supported hypothesized relationships in our data. For illustrative purposes, Online Supplemental Appendix 11 presents sample qualitative responses with initial and consensus coding by the two coders.

Based on this analysis, we found that the qualitative study generally confirmed the supported hypotheses (H1a and H1c) regarding the salient role of *cognitive* and *emotional competencies*. Regarding cognitive competency, two interview respondents remarked:

> *If the chatbot can **think better**, then the level of engagement with chatbot increases.* (R1)

To stay engaged, chatbots should be able to give ***spontaneous, creative, and unique kind of responses*** *as per what has been asked. I had travel plans to Singapore in Feb 2020 . . . . Plenty of travel cancellations were happening at that time—the* ***creativity in chatbots*** *for choosing useful words to communicate as well as* ***response time*** *to meet customer expectations became critical to keep the user* ***engaged****.* (R2)

Respondents also highlighted the significance of the chatbots' emotional competency for user engagement:

Chatbots should go beyond giving clinical rule-based responses and become ***emotionally sensitive*** *to the users when the users get* ***anxious, impatient, and overwhelmed****. The chatbots should understand the process or background for which they are being used to keep the users engaged.* (R2)

For example, if a chatbot is asking me questions and I keep closing the window, rather than just saying "Hey! How can I help you?" every time the chatbot window is opened . . . it should be ***emotionally sensitive*** *and able to say "I am sorry to bother you. I understand you are not in a good* ***mood****. But please feel free to contact me when you need". It should be able to pick up the user's* ***mood*** *and* ***respond*** *accordingly. Then I will be* ***interested*** *in using it.* (R8)

As hypothesized (H2), trust in AI emerged as one of the key concerns for using this conversational tool.

Only if the chatbot responds to my questions and fulfills my expectations, I will begin ***trusting*** *the chatbot.* (R2)

I would use the chatbot to find the cheapest airline ticket for me because I ***trust*** *that the chatbot would have compared various airline rates and given me fair information.* (R3)

These responses validate our choice of trust as a salient factor in keeping users engaged during their interactions. In addition, two respondents emphasized the mediating role of trust theorized in H2 and confirmed in the results to the quantitative study:

Humans *have the greatest characteristic of being* ***empathetic*** *and that makes us* ***trustworthy****. I want to see proactive and empathetic chatbots. Then I will have a good experience with them.* (R10)

If the chatbot is ***competent****, then it will be* ***legitimate*** *in its actions, and so I will be happy to use it. For example, when people chat with chatbot they think it is not* ***trustworthy*** *and it is just a robot to send a message, and they don't* ***feel comfortable****. But when chatbots show them that they are giving accurate information and understanding their feelings, people will feel that their* ***expectations are being met****. Then they will have* ***better experience*** *with chatbots.* (R4)

Hence, based on our analysis, the results from the qualitative study validate our choice of constructs for the quantitative study and *corroborate* its supported hypotheses and inferences [136]. In addition, the qualitative study provides a peek into the actual anecdotal mechanisms behind the supported hypotheses. However, the issue of the unsupported hypotheses for relational competency remains. We will attempt to address this issue in the next section.

Meta-Inferences: Complementarity

Prior research suggests that the mixed methods approach can not only confirm and corroborate the results obtained from the quantitative study but also unravel valuable complementary insights that might be overlooked with a single method [125, 135]. To unearth such findings, we followed the bracketing approach, which uses diverse and opposing views about the phenomenon of interest to reveal hidden information in the findings [125, 135]. We adopted this approach to examine the unsupported hypothesis related to relational competency in the quantitative study.

Bracketing Approach for Unsupported Hypothesis

Surprisingly, contrary to what we hypothesized in H1b, our quantitative results showed a non-significant relationship between *relational competency* and *user engagement*. To dig deeper into the reasons for the nonsupport of H1b, we revisited the relevant literature and examined our qualitative interview transcripts to uncover richer complementarity insights that might have been missed by applying a quantitative method alone [125, 135].

From the literature, we identified three possible reasons that could explain this non-significant relationship. First, prior research indicates that although a particular user may have had extensive previous conversations with a chatbot, the chatbot may be unaware of these previous interactions and therefore unable to refer to them to build a meaningful relationship in subsequent conversations [54]. Human–chatbot conversations are usually tentative and short, which restricts users from developing relationships with the chatbot that might lead to engaging experiences. Second, our quantitative research design required the study participants to respond to the survey questionnaire after a brief dyadic interaction with the assigned chatbot. Past research has shown that only experienced chatbot users can perceive relational qualities in a dyadic-based conversational AI [54]. Hence, it is possible that the survey respondents, who were relatively new chatbot users, were not able to experience the AI's relational competency. However, in contrast to our survey respondents, our interview participants were frequent AI chatbot users and could perhaps provide more nuanced insights due to their experience-specific differences [125]. Third, the type of chatbot usage becomes critical when determining the role of relational competency for user engagement. A recent literature review shows that less than 10% of the available bots are community bots that can enable one-to-many interactions [113]. The frequently occurring dyadic chatbots may not offer an optimal space to elicit the social characteristics explaining relational competency in chatbots [113].

Armed with these three theoretically driven plausible reasons, we analyzed the responses from a divergent set of interviewees to go deeper into the reasons for the unsupported hypothesis. Although all of the experienced interview respondents agreed on the key role of relational competency in enhancing user engagement, they were of the view that current conversational AI agents are unable to adequately express relational competency in their designs:

> *Once I log in to my banking account with my user ID and password, the bank knows my history and personal transactional details. If a chatbot provides* ***personalized help*** *and* ***reminds*** *me to make pending payments, that kind of* ***relationship*** *with the chatbot will* ***keep me engaged.*** (R1)

> *A chatbot should be able to ask a set of questions to* ***understand their customer needs*** *and solve their problems through alternative options to build a* ***strong relationship.*** (R7)

To better understand this contradiction, we delved deeper into those qualitative responses that offered complementary insights in the form of boundary conditions or limits to the quantitatively validated theoretical model [125, 135]. Our analysis revealed four critical boundary conditions on which the salience of *relational competency* is contingent for keeping users engaged.

Boundary Condition #1. Although interview respondents agreed on the critical role of relational competency in keeping users engaged, the first constraining factor is the **inability of chatbots to capture prior interactions with the same user**:

> *My interaction with a functional chatbot designed for a Dubai school has been the* ***least engaging*** *experience I have had. It was for my daughter's school admission and gave preliminary information such as contact information, name, etc. However, the bot* ***could not record my prior interactions, nor*** *was it* ***user friendly*** *in my subsequent interactions. I could not build any trust or engagement in this scenario.* (R5)

Boundary Condition #2. The second factor that restrains users from perceiving relational competency as relevant for user engagement is the **type of chatbot used**:

> *For* ***simple transactional tasks****, I don't expect to see a* ***friendly chatbot****. But if I am using a chatbot for some* ***problem-driven activity*** *such as a doctor's appointment or troubleshooting my computer, then a friendly chatbot is required to* ***listen to my needs*** *and keep me engaged.* (R3)

Boundary Condition #3. The third factor that holds users back from viewing relational competency as imperative is the **type of user and their characteristics**:

> *The* ***inexperienced user of a chatbot*** *cannot distinguish the human way of communication and the chatbot way of communication . . . . I have overseen an internal chatbot implementation within my client's company [an insurance firm]. I saw that many inexperienced employees, both* ***young and old****, were* ***reluctantly engaging*** *with the chatbots and they don't develop trust in them at all . . . .* (R4)

Boundary Condition #4. The fourth factor highlighted by the interviewees that prevents them from viewing relational competency as an essential ingredient for user engagement is users' **privacy concerns**:

> *If the chatbot tries to* ***build a relationship****, it will reach a level where it* ***should get all information*** *about me. I wonder how the chatbot knows so much about me.* (R1)

The meta-inferences in the form of the four identified boundary conditions can inform future research on the subject. The use of a mixed methods approach not only helped us confirm the results from the quantitative study but also provided additional nuanced insights into the unsupported relationship.

Discussion

Taking a holistic approach, the present study is one of the first to use MNT to theorize and test the role of human-like competencies in fostering user trust and engagement with conversational-AI agents.

Theoretical Implications

First, we propose and test an integrated model that conceptualizes the mechanisms and pathways through which human-like competencies in conversational AI agents (cognitive, relational, and emotional) can help foster user engagement. Inspired by the rationale offered by MNT, we first identify three desirable human-like competencies in conversational AI that could serve as naturalness-providing mechanisms for fostering user engagement. Next, through an appropriately designed study, we test the empirical validity of the theorized model. The proposed model lays the initial foundation for a new theory of user engagement with conversational AI agents. We emphasize building user trust and engagement in conversational AI agents through three human-like AI competencies. Although relational competency was not significantly associated with user engagement in the quantitative model, the qualitative interviews provided us with four salient boundary conditions that may influence this relationship.

Our findings from the qualitative study demonstrate the importance of not disregarding the significance of relational competency. Rather, relational competency should be viewed in light of the identified boundary conditions, which offers a rich avenue for future research. In addition, future research can move beyond our proposed competency-based theory of user engagement to identify human-like personas that can be built into conversational AI to enhance user trust and engagement for specific sets of users [62]. For example, there could be an array of personas—such as goal-directed personas, role-based personas, fictional personas, and engaging personas—which, when embedded in conversational AI, would foster deeper user engagement [104].

Second, the rapid rise of digital transformation has encouraged businesses to swiftly embrace AI agents in the absence of much theory-driven research or many use cases involving the interactional environment afforded by these technologies. Although businesses realize that conversational AI agents have not been able to deliver the expected results [77], coordinated research efforts in this direction are sparse. One of the main reasons for the high number of failures in customer-interfacing conversational AI projects is the tendency of organizations to hastily endorse "fast followers" without realizing that there are marked differences between conversational AI and other recent technological innovations [76], differences related to both usage characteristics and the characteristics of the AI technology.

In this study, focusing on the usage characteristics and building on some of the contextual idiosyncrasies of conversational AI, we leverage MNT and the trust literature to theorize the mechanisms through which human-like competencies in conversational AI relate to user engagement. Given that a conversational AI agent is notably different from traditional technologies focused on instrumental use and that several aspects of the interactional experiences of AI users are still unfolding, the theoretical framework we have presented will be helpful in triggering future research on this important subject. In addition, many of the characteristics of AI, such as the simultaneous existence of *low barriers to entry* and the *absence of a centralized core platform* [4], are markedly different from other new technologies and call for enriching, AI-specific theory-based research.

Third, we extend the current discourse on the design of conversational AI and provide initial evidence about human-like competencies that can improve user engagement—which is the first step towards making a business impact. We contribute to the competency literature by theoretically delineating three specific human-like competencies in conversational AI that can contribute to developing user trust in such technologies, which in turn will lead to enhanced user engagement. Although past research has examined some of the identified factors in different contexts [18, 80, 133], by leveraging MNT we synthesize these variables to discern how human-like competency and trust together influence user engagement with conversational AI.

The integration of trust into our theorized model is especially relevant, for three reasons: (1) The "black box" nature of emerging applications of conversational AI means that users often do not understand the underlying mechanisms through which the systems work and make user recommendations. This perceived opacity of AI may constrain users from engaging with it, and user trust may play a critical role in fostering user engagement. (2) A continuous stream of large volumes of user data is needed to train the learning-based ML that enriches users' ongoing interactional experience with conversational AI. However, sharing personal data with these systems increases the user's sense of vulnerability, which can possibly be overcome through adequate levels of user trust. (3) From a purely transactional perspective, users might expect improved interaction with AI agents as a payoff for the data shared in previous interactions. If they are to continue engaging with AI agents, users should trust in the fairness of their perceived payoffs, which can be a fertile topic for future research.

In addition, our research also alludes to the evolving role of different human-like competencies in influencing user engagement with conversational AI. Specifically, our qualitative interviews show the important role of temporality and the user experience in making relational competency a significant determinant of user engagement. Our study clarifies the need for human-like competencies in conversational AI, complementing similar studies that emphasize how adequate conversational flow and demeanor may influence the feelings of pleasantness and human-like affinity in the context of text-based AI [121]. Future studies can explore various design features through which human-like competencies can be incorporated into different AI applications to enhance perceptions of their trustworthiness. Finally, our study prods AI researchers to examine appropriate levels of user engagement with ML-based AI agents such as chatbots. This is fundamental if they are to generate copious amounts of good quality learning data for conversational AI and consequently enhance its performance. Researchers can also extend our AI competency–trust model to incorporate other variables affecting user engagement.

Practical Implications

In addition to its theoretical contributions, our research also has significant practical implications for conversational AI designers and customer service providers. Moreover, though our study is set in the context of chatbots, the findings may be relevant for other kinds of interactional AI where user engagement is extremely important for actualizing business benefits.

First, our study demonstrates the need for building conversational AI agents embedded with not only an "artificial brain" but also an "artificial heart" to maneuver both cognitive and emotional interactional processes. Organizations should plan and design their AI services with both these attributes.

Second, further elaborating on the idea of an "artificial brain," AI-based conversational agents often provide inapt responses to user requests, resulting in inconsistencies between customer expectations and system performance. Such a display of cognitive incompetence might inhibit users from freely exchanging with conversational AI agents [25]. The significant relationship between AI's cognitive competency and user engagement underscores the need to sharpen the thinking processes embedded in AI. However, a display of adequate cognitive competency by AI can also be achieved by assigning it the right tasks. Because conversational AI can learn about human behavior patterns by continually updating historical data in its learning algorithms, it may be more suitable for performing specific, well-defined tasks rather than non-specific tasks [47]. Thus, the cognitive competency of AI-driven service can be fostered by creating the appearance that the conversational AI can think.

To imitate the human thinking process, it is critical for AI developers to pause and recognize the two key thinking systems in the human brain: a fast, automated thinking system and a slow, more deliberative thinking system [63]. AI designers usually focus on the fast, automatic thinking approach and miss out on integrating the equally meaningful slow thinking approach when developing AI systems. Consequently, AI designers fail to demonstrate the key cognitive competencies in conversational AI, resulting in disappointed users who do not experience AI systems as viable automation or augmentation mechanisms. In their efforts to anthropomorphize AI, designers developing the human-like cognitive capabilities in conversational AI should pay special attention to the way human beings think [116]. Commenting on the context of cognitive competency, one of the respondents mentioned:

> *The **capability** of the chatbot to **understand the question** and **rephrase** an ill-designed question for the customer is critical to keep the **customer engaged**.* (R1)

Third, building on the idea of a much needed "artificial heart" in conversational AI, this research calls on businesses and AI designers to enable AI agents to understand the range of emotions experienced by humans and to provide personalized, emotionally sensitive experiences that impact users physiologically. For example, AI emotional competency is being used in vehicles to recognize passenger emotions such as joy and anger and use personalized content and route recommendations to adjust the in-cabin environment in accordance with their needs [1]. Chatbots should become emotionally sensitive to user needs, understanding their profiles before starting conversations with them. This will help to keep users engaged.

> *If I meet someone and then I know that this person is into dancing, then, as a human, I know how to talk to her and kickstart a conversation around dancing to keep the **person engaged**. This might be difficult for the chatbot. There might be situations where the chatbot needs to **ask the user what he likes** . . . . to keep the user engaged.* (R8)

In addition, an emotionally equipped AI chatbot should be able, based on customer responses, to sense complex emotions such as frustration and decide to forward customers to a live service agent when appropriate, such was when a customer is unusually frustrated [142]. When designing emotional competency in chatbots, designers should reassure users that their information will not be misused in any form. In addition, users' reactions to conversational AI agents that look, feel, and act almost as a human would can abruptly shift from empathy to revulsion, descending into an eerie zone known as the uncanny valley [85]. This concern was highlighted by one of the interview respondents, who commented:

> *When the chatbot* ***empathizes****, it will go to the level where it would know* ***all information*** *about me . . . . it lands in a* ***creepy*** *area and collects all the information about me to show empathy. I should get the confidence that my information will not be misused.* (R1)

Fourth, the results from our quantitative study showed a nonsignificant relationship between relational competency and user engagement. On the contrary, the findings from the qualitative interviews highlight the significant role of relational competency in fostering user engagement. The contradictory results are possibly due to the ambiguity of relational design features in current chatbots, despite their importance. Practitioners and designers should consider ways and means to increase relational competency in conversational AI agents and chatbots by introducing human attributes in artificial agents to which users can relate easily. Such attributes may enhance user perception of personalized services coupled with a perception of fairness. The prominence of relational competency in conversational AI for user engagement requires AI designers to carefully add the bias-free social connectedness in AI only after they clearly understand their users: Socialness may also be subjective [101]. AI designers therefore need to be cautious regarding such social aspects when training their conversational AI agents to evoke "humanness" without inducing the "uncanny valley effect" [8]. Highlighting this aspect, two interviewees commented:

> *Chatbots don't tend to develop relationships because chatbots interact with many customers through a* ***common page****. To increase the relationship with the chatbots, there should be a user profile for each and every customer. This would help me* ***get personalized service*** *from the chatbot.* (R2)

> *If I meet with a road accident and submit my insurance claim through a chatbot, the chatbot can develop an* ***interpersonal relationship*** *with me instantly by tracking my GPS, and once an accident is reported, it should be able to guess that I have met with an accident and pop up a message to* ***help me****.* (R1)

Fifth, the significant role of user trust as a mechanism for fostering user engagement calls for AI designers to develop trustworthy conversational AI. To develop such AI agents, designers should have a clear understanding of the human-like competencies that are desired in the specific AI [28]. For example, rule-based systems and robotic process automation are transparent in how they perform a given task, but they are incapable of learning and improving. Deep learning algorithms, in contrast, offer minimum transparency and are often viewed by users as "black boxes" because they are not able to reveal their decision-making processes. However, these technologies are capable of learning and offering customized services according to clients' needs. A black-box AI algorithm may be undesirable for certain industries, such as financial services, where users look for greater transparency in the services they receive. AI designers should therefore be mindful of the unique sets of user needs across industries as they build the necessary competencies into their conversational AI to keep their users engaged [142].

Limitations and Conclusion

The current study, contextualized to conversational AI agents, provides a theoretically grounded model delineating the salient role of human-like interactional competencies and user trust in fostering user engagement. Future research can examine whether the identified conversational AI competencies impact other system success metrics, such as system quality and continued use. This research is one of the few studies that emphasize the importance of incorporating *human naturalness* rather than pure *instrumental efficiency* into conversational AI. Using MNT, the study maps cognitive, relational, and emotional competencies to low cognitive effort, low communication ambiguities, and high physiological arousal. Future research can move beyond theoretical linkages and provide methodological links such as establishing a connection between the arousal and a pencil-and-paper assessment of the arousal.

Our findings also call on AI researchers and designers to focus on *similarity* with human beings or *naturalness* as the primary characteristic of an engaging AI. Such a view calls for deeper research into viewing AI as a partner rather than an instrumental tool for executing a specific task. Although we have identified three human-like competencies that are desirable in conversational AI, we also believe that the usage context plays a significant role in defining the desired competencies. For example, our quantitative results showed a nonsignificant role of relational competency for infrequent users, but the qualitative interviews with experienced users provided a different result. The usage context is clearly a fertile subject for future research that seeks to understand the required competencies for conversational AI.

Our research presents one possible theoretical lens for viewing user engagement with conversational AI. It would also be interesting to study the specific effects of the design motives for the AI on user engagement, using an experimental method to further tease out the exact human-like AI competencies that are pertinent to specific conversational AI agents. In addition, our study is restricted to the user level of analysis in the context of a dyadic-based conversational AI agent, but there may also be other variables at different levels of analysis in the context of community-based conversational AI agents that could influence the theorized relationships. With firms' growing interest in AI-based customer-interfacing technologies, especially in response to the COVID-19 pandemic, it is imperative to understand the modalities and mechanisms that can enhance user engagement [35]. However, it must be noted that efforts to enhance user engagement can also be used by unscrupulous agents to commit fraud and deception [109, 110]. Future research can study means and modalities for fact-checking conversational AI so that vulnerable users are able to discern fact from deception [e.g.118]. We believe that this shift towards conversational AI will continue even beyond the pandemic, and it is certainly an area of interest for both research and practice. Future studies can look at other variables of interest such as customer loyalty, repeat transactions, rapid trust at the user level of analysis, innovation culture, and leadership styles at the organizational level of analysis. Our research is one initial, modest step in this direction.

Notes

1 Demand characteristics are a type of response bias whereby respondents tend to alter their response or behavior if they figure out the study's purpose.
2 All boldfacing here and elsewhere has been done by the authors to emphasize relevant portions of the interview quotes.
3 Respondent code here and elsewhere as indicated in Online Supplemental Appendix 9.

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