



Proposing the “Digital Agenticity Theory” to analyze user engagement in conversational AI chatbot[☆]

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ABSTRACT

The emergence of conversational AI tools, such as voice assistants and chatbots, has completely changed how consumers engage with companies and goods. However, if we limit our search to characteristics that make humans, we may experience the “Uncanny Valley” effect and other unanticipated outcomes. In particular, this work presents DIGA, a philosophical concept for defining AI autonomy in this setting. DIGA is the ability of digital entities to effectively communicate, understand the intentions of others, and absorb influences. This study develops and assesses the Digital Agenticity Theory (DAT) to examine how DIGA impacts user engagement and how it relates to negative emotions, perceived anthropomorphism, and perceived anthropomorphism. The study explores the multidisciplinary nature of DAT using viewpoints from technology, society, and consumer behavior. The intricate relationship between people and digital entities is clarified by this study, which also offers guidance for upcoming advancements in AI systems. Moreover, DIGA theory offers a wide range of insights and implications for the design and implementation of autonomous digital agents in a number of domains, such as consumer behavior, AI development, and human–computer interaction.

1. Introduction

The emergence of conversational AI tools, such as voice assistants and chatbots, has completely changed how consumers engage with companies and goods. “The study of techniques for creating software agents that can engage in natural conversational interactions with humans” (Khatri et al., 2018: p.41) is the definition and conceptualization of conversational artificial intelligence (AI) (Mariani et al., 2023). The literature has documented the growing recognition among researchers of the significant influence that conversational AI technologies have had on changing consumer engagement environments and user experiences (Das et al., 2023). Organizations are realizing the advantages of integrating AI technology in customer service to provide proactive and customized experiences, which in turn boosts customer engagement, according to a recent McKinsey analysis (Das et al., 2023). According to Gartner (2023), there was a significant 16% growth in the contact center industry in 2023. The implementation of conversational AI can be attributed to investments and initiatives that have contributed significantly to this growth. Conversational AI is a major factor

propelling this expansion. Well-known conversational AI models, like ChatGPT, have garnered a lot of interest from the public and business sectors. It’s clear that ChatGPT is gaining traction quickly because more than a million people signed up in less than five days after it launched. Additionally, a substantial sum of money has been dedicated to this field. OpenAI, which has received about \$13 billion investment from Microsoft after launching ChatGPT, intends to incorporate conversational AI-based search system features into its main chatbot services (Financial Times, 2024). It is likely that consumers will come into contact with conversational AI technology more often, widely, and deeply given the broad adoption of AI across a variety of industries and domains and the expectation that next-generation AI technologies will usher in the arrival of Artificial General Intelligence (AGI) (Daugherty et al., 2023; Gratton, 2023).

Depending on how much actual users embrace AI, conversational AI technology may or may not meet business expectations in terms of user experience improvement. In a survey comparing the communication preferences of human staff and conversational AI, 86% of participants said they preferred speaking with human staff (Press, 2019). As such,

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conversational AI systems may not receive positive feedback from actual users even though they are thought to have enormous market potential. A lot of work is going into making conversational AI systems more human-like in order to get positive responses from users (Chandra et al., 2022; Moussawi et al., 2023; Roy and Naidoo, 2021; Sheehan et al., 2020; Zogaj et al., 2023). While these studies show that having human-like characteristics improves the user experience, focusing solely on increasing human similarity may have unintended consequences, like the 'Uncanny Valley'. The Uncanny Valley phenomenon is defined by the induction of negative emotions or discomfort in humans upon reaching a certain level of similarity to a human being by a non-human object. According to Rajaobelina et al. (2021), there is a chance that customer loyalty will be weakened by chatbot interactions that elicit creepiness and unpleasant feelings. It is important to note that humanoid features could make customers avoid interacting with chatbots. There is a counterargument to the idea that adding human-like features and attributes can boost user engagement. For this reason, a philosophical and fundamental examination of these features and attributes is necessary to fully understand the complex relationship between chatbots and user engagement.

The advent of New Materialism in the early 2000s has offered new insights into this phenomenon. A fundamental feature of New Materialism is its attempt to overcome the limitations of dualism that are present in modern social sciences, such as Descartes's human-centric dualism (subject:object = mind:matter = culture:nature). Stated differently, New Materialism is a philosophical approach that unifies human and non-human materials. The "Material Turn," also referred to as the "Ontological Turn," is an ontological movement made possible by new materialism that recognizes non-human materials like space, nature, science, technology, artifacts, and nature as ontological components of society on par with humans (Kramarczyk and Alemany Oliver, 2022). As stated, new materialism overcomes the traditional opposition between materialism and idealism in human science—that is, the traditional dualism between matter being the ultimate reality and the mind being the ultimate reality, respectively—as well as the prioritization and/or hierarchization it frequently implicitly involves. Rather, new materialism presents a monistic (i.e., composed of one element) picture of reality in which non-biological and human objects are interdependent and form a whole, dynamic system of relations rather than being in opposition to one another. In this setting, matter and culture are both dynamic and ever-evolving (Kramarczyk and Alemany Oliver, 2022). This viewpoint harmonizes the binary distinction between men and non-men. The Actor-Network Theory of Bruno Latour, Michel Callon, and John Law (Latour, 1996; Callon, 1995; Law, 1992); the Assemblage Theory of Gilles Deleuze, Felix Guattari, and Manuel DeLanda (Deleuze and Guattari, 1987; DeLanda 2006); Karen Barad's Agential Realism (Barad, 2007); and Donna Jeanne Haraway's Cyborg Manifesto (Haraway, 1985) are some of the well-known theories that make up New Materialism. A philosophical paradigm known as "New Materialism" is developed as a result of these theories' interactions and mutual influence. There are a lot of researchers working to come to an agreement about how important this paradigm is (Walsham, 1997; Doolin and Lowe, 2002; Lamb and Kling, 2003; Sarker et al., 2006; Elbzanna, 2009; Kallinikos et al., 2013; Baird and Maruping, 2021; Chatterjee et al., 2021; Baskerville and Myers, 2023; Tana and Breidbach, 2023). Different from other social sciences, the IS discipline focuses on information technology in relation to a broad range of non-human subjects (Orlikowski and Iacono, 2001). The statement "*Technology does nothing, except as implicated in the actions of human beings*" (Giddens and Pierson 1998, p. 82) sums up the scholarly perspective on technology. The claim made by Jones and Karsten (2008) further maintains that technology only performs "human actions"-related tasks.

Non-human materials, like technology, are considered meaningless and unactionable in the absence of humans. Technology has therefore been a major theme in many IS literatures, albeit mainly as a tool of the human-centered technology view and as an analytical lens through

which to understand human agency. The concepts of the inherent human agency in technology (Orlikowski, 1992) and the construction of agency through interaction (Orlikowski, 2007) are representative of human-centered technology perspectives. Some scholars have voiced concerns about the trend in IS research to use these only as lenses for analysis, instead of exploring ethical and philosophical debates about the agency of non-human objects (Chatterjee et al., 2021; Walsham, 1997).

The focus of this research is on how AI will soon be incorporated into different facets of human life and how it will affect or become entangled in human relationships and interactions. AI-mediated interactions will make it more important than ever to assess non-human materials' agency explicitly. The management of AI object agency is thus established in this article as a crucial issue. Many theories and paradigms have been applied to the study of the concept of agency. Nevertheless, the differences between human and non-human actors are not sufficiently taken into account by the frameworks in use today. For example, there is difficulty in directly applying Practice Theory, which emphasizes human agency, to materials like conversational AI (Orlikowski, 2007). However, because they concentrate on non-human materials, paradigms that attribute agency to technology—like Actor-Network Theory—are limited in their capacity to discern between actors. According to Actor-Network Theory, human and non-human actors have the same abilities (Latour, 1996; Callon, 1999). This approach helps correct human-centric perspectives on non-human actors (Law, 1992; Latour, 1996; Elbanna, 2009), but it might be challenging to apply globally (Dattathrani and De', 2023).

Considering conversational AI systems as actors, this paper introduces the philosophical concept of *Digital Agenticity* (DIGA) as a means of defining their agency. 'The human capacity to exert control over the progression of events and functions via actions' is the standard definition of 'agency' (Bandura, 2001). In this paper, the term 'Agenticity' is introduced to express the philosophically more nuanced meaning of non-human material agency. Agenticity is the ability of all kinds of agents existing or acting in ontological space to form meaningful philosophical connections through meaningful interactions with other agents. Given the distinctive qualities of conversational AI systems and other non-human digital actors, DIGA evaluates agents primarily on their ability to act as agents, rather than how similar they are to humans. In this study, DIGA is defined as "*the ability of digital actors operating within ontological space to communicate effectively on particular subjects (Topicality), comprehend the intentions or requirements of others in a proactive and efficient manner (Proactivity), and internalize the influences exchanged (Intra-activity) in order to construct significant philosophical connections.*"

Topicality in the context of information delivery refers to the relevance and situational significance of the data that conversational AI systems provide (Hjørland, 2001; Janes, 1994; Xu and Chen, 2006; Xu and Yin, 2008). The ability of conversational AI systems to anticipate and proactively attend to user needs is known as proactivity; this concept is comparable to matter dynamism, as explained in Bennett's Virant Matter (2010). The final dimension is intra-activity, which refers to how conversational AI systems internally modify and enhance the quality of interaction through user interactions. It is based on Barad's (2007) Agential Realism (Fox and Alldred, 2016; Reichert and Richterich, 2015). Three sub-dimensions make up the reflective second-order construct DIGA. The aim of this research is to evaluate the construct and its measurement items using the principal validity verification procedures as described by Mackenzie et al. (2011).

Because of their dualistic division of human and non-human actors and human-centric focus, existing literature on human-AI interactions frequently fall short of fully addressing the complexities and subtleties of these relationships (Sundar, 2020; Chandra et al., 2022; Gkinko and Elbanna, 2023). The autonomous abilities and agency of digital entities are usually overlooked by these conventional theories, which leads to a limited understanding of their influence on user engagement and

emotional responses. Furthermore, they frequently overlook how dynamic and reciprocal interactions are in digital environments. This study presents the '*Digital Agenticity Theory (DAT)*' within a flat ontological space centered on DIGA in order to overcome these limitations. The goal of DAT is to clarify the complex relational dynamics that exist between human and non-human actors in digital settings. In particular, this study uses DAT to examine how DIGA affects user engagement and how its functionality varies from that of human-centric components like perceived anthropomorphism. A structural equation model is developed to establish and validate the relationships among DIGA, negative emotions, perceived anthropomorphism, and user engagement. The structural equation statistically examines the relationship between user engagement and conversational AI systems' DIGA, as well as the impact of negative emotions and perceived anthropomorphism. The aim of this study is to understand the complex digital environment in which human-computer conversations take place through this series of processes. To sum up, DAT provides a conceptual framework for representing the agenticity of digital entities in a flat ontological space. It is expected that this framework will have a significant impact on academic and practical significance. This framework may yield insights needed for the development, application, and assessment of conversational AI technologies in a variety of domains.

In this paper, we define DIGA with respect to conversational AI systems using the New Materialist philosophical framework. This study addresses the need for theory development applicable to the reality of deepening interactions between AI-based systems and humans by conceptualizing conversational AI systems as actors and deriving the notion of DIGA to encourage user engagement (Hong et al., 2014; Enhom et al., 2022; Chandra et al., 2023). Previous studies have primarily focused on the practical advantages of technology to increase user engagement (Bitrián et al., 2021). However, by combining ideas from New Materialism and Information Systems (IS) literature, this study broadens ontological philosophical discourses and explores the impact of agentic capacities on users (Baird and Maruping, 2021; Fügner et al., 2022). In particular, it is anticipated that the development and validation of DAT will have implications for practice when examining the relationship between conversational AI systems and user interaction. The study's conclusions indicate that DIGA enhances user engagement, raises perceived anthropomorphism, and lowers users' negative emotions.

The study makes a number of important contributions. Initially, this study makes use of earlier academic research on new materialism to identify specific components of DIGA that are crucial for conversational AI systems, like chatbots. This study attempts to close that gap by addressing the lack of thorough and detailed theoretical frameworks in the IS field pertaining to conversational AI systems like chatbots. Several academics have suggested that these frameworks include essential elements that are necessary to increase user interaction with AI technology (Hong et al., 2014; Chandra et al., 2023). This research also looks into methods for maintaining user engagement in AI-enabled environments. The topic is extremely important right now because conversational AI systems are being widely used in many different industries (Wilson and Daugherty, 2018). Prior research has mostly focused on the tangible advantages of technology for sustaining user engagement (Kim et al., 2013; Bitrián et al., 2021). Thirdly, this study adds to the ongoing conversation by fusing new materialism and IS knowledge by putting forth the innovative concept DIGA. This study suggests a novel theory, such as DAT, using DIGA. This article presents the DAT as a strong theoretical framework for understanding the inherent notion of agency displayed by digital entities like conversational AI chatbots. The DAT operates within the conceptual framework of new materialism, which holds that both human and non-human agents, including conversational AI systems, possess an equivalent level of agency. The purpose of this study is to find out how user engagement with conversational AI systems is affected when the DIGA concept is included as a philosophical component. Through a philosophical analysis of DIGA, our goal is to

gain a deeper understanding of the crucial role that philosophical theories play in sustaining user engagement with AI technology.

2. New materialism as a philosophical background

Contemporary people converse via electronic devices such as smartphones and computers in addition to employing verbal and auditory means. The New Materialist perspective raises fundamental inquiries regarding the essence of this phenomenon. Does this depict interaction with non-human materials or merely interaction between humans? New Materialism challenges the traditional human-centric view by positing that all matter, including technology, possesses agency and plays an active role in social interactions (Bennett, 2010; Coole and Frost, 2010). This philosophical approach considers the interactivity between humans and non-human entities, arguing that these interactions are not merely facilitative but constitutive of social relations (Barad, 2007; Dolphijn and van der Tuin, 2012).

Emerging in the early 2000s, New Materialism is a philosophical paradigm that contests the prevailing dualistic paradigm in modern social sciences, which conventionally distinguishes between non-humans (objects) and humans (subjects), culture and nature, and the mind and matter. New Materialism expands upon classical materialism, which considers matter to be passive and immobile, by placing greater emphasis on the active influence of non-human entities and matter in shaping our comprehension of the world. It is thus referred to as "New" Materialism. The term in question, which was significantly shaped by Gilles Deleuze and his analysis of Spinoza (Deleuze, 1988), solidified its status as a designation for this philosophical current with the introduction of Manuel DeLanda's application of it in 1996 (DeLanda, 1996). Rosi Braidotti further developed and defined the term in the early 2000s within the framework of feminist theory (Braidotti, 2013). The 'material turn' or 'ontological turn' that New Materialism prompted acknowledges the importance of non-human entities, including technology, artifacts, nature, and space, as constituents of social structures. This viewpoint challenges the prevailing anthropocentric worldview by integrating human and non-human materials as ontological entities, in contrast to the traditional dualisms of contemporary social science (Coole and Frost, 2010; Barad, 2007).

Academics in the field of business often view materialism as a set of values that harms not just society and the environment, but also the well-being of consumers—a concept that remains central to our consumerist society (Long-Chuan and Chia-Ju, 2010). People often say that materialism promotes consumerism, which is bad for society and the environment. Putting too much value on material possessions can lead to a decline in personal happiness and worsen larger social problems like environmental degradation and inequality. In marketing, for example, new assumptions regarding object agency and the materiality of object shaping practices have been derived from theories connected to materialism. To illustrate the active role of material objects in molding consumer experiences, Canniford and Shankar (2013) investigated how customers piece together idyllic scenes from nature. The narrative histories of singularized objects were studied by Epp and Price (2010), who brought attention to the fact that objects have agency that changes consumer practices and networks. Hoffman and Novak (2018) utilized an assemblage theory framework to investigate IoT consumer and object experiences, revealing the ways in which data and interconnected objects impact purchasing decisions. Tattoos, according to Roux and Belk (2019), produce embodied heterotopias, which highlight the body's material role in consumer culture. According to Cecez-Kecmanovic et al. (2014), Orlikowski (2007), and Recker et al. (2021), sociomateriality partially mirrors these principles in the IS field as well. Technologies and human actions are intricately linked, according to sociomateriality, which highlights the inseparability of social and material aspects in organizational practices. Although these viewpoints don't directly reference new materialism, they may be in line with New Materialist ideas since they acknowledge the influence of non-human entities on the

dynamics and results of organizations.

In the context of the digital age and the widespread adoption of AI, including conversational AI systems, New Materialism offers a particularly perceptive perspective. The potential of artificial intelligence technology to displace humans in numerous domains has surpassed its initial purpose of assisting them (Skiveren, 2022; Somerville, 2016). The exponential expansion of AI has been predominantly driven by data produced and stored by a variety of digital devices utilized by individuals across the globe, such as smartphones and computers. AI is a collaborator assisting humans; it may soon supplant humans in a variety of domains. New Materialism is capable of constructing persuasive arguments concerning non-human materials.

Prominent theorists within the New Materialist paradigm, including Latour (2005) and DeLanda (2006), put forth Actor-Network Theory and Assemblage Theory, respectively. Their ontology is characterized as “monistic” or “flat,” and it excludes dualistic differentiations such as human/non-human or mind/matter. Flat ontology, according to Latour, diverts attention away from structures, systems, and layers that exist beyond or beneath routine activities and interactions. This perspective acknowledges the dynamic nature of the non-human material world, contending that it undergoes constant change due to diverse and unpredictable occurrences (Deleuze and Guattari, 1988; Latour, 2005; DeLanda, 2006). Indeed, AI systems are assemblages of discrete components that function as entities formed by networks of diverse technologies and data acting as agents. As both a system and an actor, AI is intricately intertwined with contemporary society and is already subject to environmental influences.

Conversational AI, particularly customer service chatbots, serves as an illustration of this emerging vitality. Although developed artificially, these chatbots frequently engage in direct human-to-human communication by employing human language. In comparison to other forms of non-human interaction, this use of language facilitates more intuitive interactions with non-human materials. Human-centric modern philosophers such as Descartes and Kant might have been able to partially recognize interactions with chatbots that employ “human language.” A transition to New Materialist thought is indicated when interactions with non-human entities are acknowledged and comprehended. This philosophical perspective questions the ingrained anthropocentrism found in traditional thought and promotes a reevaluation of the significance of the material realm in our interpersonal and communicative endeavors. New Materialism acknowledges technology as an active participant in shaping human experience and social structures, as opposed to merely an inert medium or tool. Therefore, within a world where AI technology progressively mediates human experiences and relationships, New Materialism presents a persuasive viewpoint. New Materialism offers a platform for comprehending and engaging critically with the dynamic changes occurring between humans and non-human entities, thereby facilitating philosophical knowledge that remains abreast of technological progress and shifts in social interactions. In order to respond comprehensively to the challenges and opportunities presented by the proliferation of AI technology, it is vital to adopt a New Materialist worldview.

3. Digital Agenticity Theory

A new theory entitled as Digital Agenticity Theory (DAT) is proposed to shed light on the intricate interplay between human and non-human actors in the digital realm, all within a flat ontological space (see Fig. 1). By eliminating traditional hierarchical structures, this flat ontological space enables all actors—including humans, digital environments, conversational AI systems, and others—to exert active influence over the ontological space. By defining the agency of conversational AI systems as actors, we present the philosophical notion of Digital Agenticity. Agency, as defined by Bandura (2001), generally refers to “the human capacity to influence the course of events and functions through actions.” In order to encompass a more nuanced philosophical

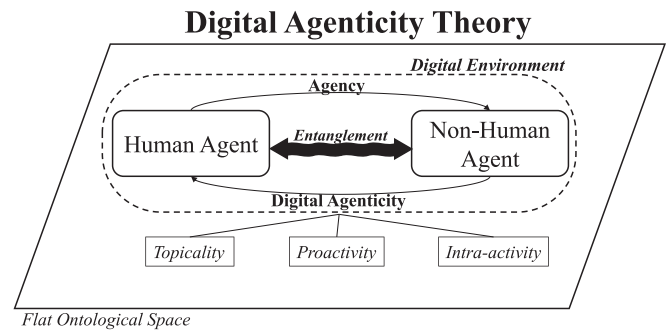


Fig. 1. Digital Agenticity Theory.

interpretation of non-human material agency within the digital environment, this paper coined the term “Digital Agenticity.” Digital Agenticity, as it is defined, comprises three sub-dimensions: Proactivity, which pertains to the ability to effectively comprehend the intentions or needs of others; Intra-activity, which concerns the internalization of the influences exchanged; and Topicality, which concerns the ability to communicate effectively on particular subjects.

“Topicality” pertains to the appropriateness and relevance of actions executed by the conversational AI system in its capacity as an actor within a given context. It is not enough to consider the actions per se; one must also consider their intentions and motives. Regarding the objectives, subjects, and overarching narratives that motivate each actor, topicality examines the “why” behind their digital personas. This transcends simple responses to stimuli generated by human actors and entails deliberate and situationally cognizant engagement with the digital environment.

“Proactivity” denotes the conversational AI system’s capacity to anticipate and commence interactions as an actor by virtue of a comprehensive comprehension of potential needs and requests. This element presupposes the capacity to predict forthcoming interactions and adapt or prepare actions accordingly. One illustration of the proactivity exhibited by a digital actor is the implementation of algorithms capable of forecasting user behavior and dynamically adapting responses.

“Intra-activity” emphasizes the reciprocal and inherent behaviors that are transpiring among intertwined individuals. It emphasizes the interconnectedness of actors as a co-creator of reality. Interactions between human and non-human actors are mutually influential; in this way, the conversational AI system, functioning as a digital actor, internalizes the influences of human actors via intra-activity. Comprehending this notion is vital in order to grasp the interconnectedness of digital exchanges and the reciprocal influence that each participant’s conduct has on the network. This signifies a progression in which Digital Agenticity is consistently reevaluated via engagements.

The term “entanglement,” derived from quantum mechanics, is used to characterize the interactions between human and non-human actors (Barad, 2003; Somerville, 2016; Heyder et al., 2023). A concise explanation of this concept can be found in quantum entanglement: despite physical separation, two or more quantum systems retain interdependent properties. Observing one quantum in an entangled state provides an instantaneous determination of the state of the other. The metaphor effectively illustrates the interdependent relationship that exists between human and non-human entities within the digital realm. The perpetual exchange of inquiries from human participants and replies from non-human participants, such as chatbots, can be conceptualized as entanglement. Interactions are commonly defined as instances in which two or more entities or subjects exert an influence on one another. Entanglement highlights the two’s increased interdependence. DAT posits that Digital Agenticity emerges not from discrete personal qualities but rather from interconnections and exchanges among diverse actors via entanglement. This perspective questions the conventional

divisions between subjects and objects, users and technology, and instead considers agenticity to be dispersed throughout the network.

DAT proposes a radical departure from conventional viewpoints by proposing a reevaluation of the term ‘agency’ as a dynamic and inter-related force that is inherent in every actor. It puts forth an alternative perspective on agency, arguing that every interaction contributes to the development of an individual actor’s distinct agency, which is not solely attributable to the human species. This theory reestablishes power in the digital realm by leveling the hierarchical distinctions that have been traditionally established among various forms of agency. Following this, we will examine how the components of DAT—Topicality and Proactivity—contribute to agenticity.

In information science, “topicality” pertains to the degree of contextual congruence and pertinence exhibited by a digital entity during engagements with human beings. In essence, the relevance of information is heavily influenced by its topicality, which pertains to the manner in which it addresses user inquiries or communication subjects (Vickery, 1959; Xu and Chen, 2006). The logical process of information retrieval is heavily reliant on topicality, which encompasses the most fundamental aspect of relevance—topical adaptability (Janes, 1994). Contextual comprehension and responsiveness are critical for the development of effective digital solutions. By ensuring that a digital actor contextually recognizes and maintains relevance to ever-changing conversation topics, topicality improves the effectiveness and significance of user-digital actor interactions.

The term ‘proactivity’ denotes that the digital actor analyzes and recognizes user behavior patterns in order to interact, as opposed to being merely reactive. This notion is associated with Bennett’s ‘vibrant matter’ theory, which posits that non-human actors exert agency through perpetual interaction with and influence on their surroundings (Bennett, 2010). The proactive rather than passive capacity of AI to establish relationships and generate value has been underscored by Enholm et al. (2022) within the IS domain. Piccoli and Pigni (2013) emphasized the significance of proactively addressing user requirements by utilizing insights derived from data. This proactivity is the capacity to address the needs and expectations of users in advance, thereby increasing efficiency and satisfaction. Proactivity exemplifies the ability of the digital actor to actively and assertively participate in communication in their capacity as an actor.

The term “intra-activity,” which originates from Barad’s (2007) definition of “intra-action,” is a crucial element in comprehending the interplay between human and non-human participants in the DAT. This notion underscores the fact that conversational AI chatbots that establish connections with human actors are not merely autonomous entities, but rather interdependent and co-constructed entities that evolve in tandem. This statement highlights the interconnectedness and reciprocal impact that exist between human and non-human actors, elucidating the manner in which entities continuously evolve and influence one another within the digital realm. Intra-activity gauges the extent to which the digital actor has undergone internal transformations as a result of more profound connections and interactions with human actors; it is vital in defining and fortifying agency within the digital system. DAT aims to illuminate the more intricate and complex aspects of the digital realm by enhancing our comprehension of human-technology interactions through the use of intra-activity.

DAT assumes a pivotal function in comprehending and analyzing the interactions between human users and chatbots by implementing entanglement. The field of IS has long been fascinated by Human-Machine Interaction (HMI). However, in its traditional approach, HMI has adhered to a human-centric paradigm, which relies on anthropomorphism to improve user engagement and satisfaction (Duffy, 2003). In the era of advanced AI and digital technologies, this human-centric approach, while effective in certain contexts, can be overly simplistic and restrictive. The concept of DAT proposes a fundamental change that surpasses the limitations of conventional HMI by acknowledging and examining the wider range of digital entities. DAT acknowledges the

intricacy of HMI while surpassing its conventional boundaries, thereby providing a more comprehensive outlook on DIGA. In fact, applying anthropomorphism research in the HMI environment to the complex and unexplainable behaviors of digital actors can be difficult (Chandra et al., 2022). On the contrary, DAT, which is grounded in New Materialism, extends the concept of agency beyond human beings or entities resembling humans to encompass all participants in the digital realm. This enables the examination of more fundamental connections (Coole and Frost, 2010; Bennett, 2010). DAT’s DIGA perspective, which reconceives digital entities from being passive recipients of human input to active contributors in shaping reality, reflects a more nuanced understanding of agency in a dynamic world in which humans, non-human actors, and the digital environment all exert continuous influence. It is anticipated that DAT-based research will yield novel perspectives on the interaction between conversational AI systems and human users.

4. Hypothesizing

The following diagram (Fig. 2) illustrates the conceptual research model that is suggested for investigating the correlation between the DIGA of conversational AI systems and user engagement. The present study examines the impact of DIGA on user engagement via the mechanisms of Perceived Anthropomorphism and Negative Emotion. These variables are believed to be influenced by DIGA, which is defined as the capacity of conversational AI systems acting as non-human materials to communicate effectively on particular topics (Topicality), proactively and effectively comprehend the intentions or needs of others (Proactivity), and internalize the influences exchanged (Intra-activity).

According to Moussawi et al. (2023), the term “Perceived Anthropomorphism” describes the mental reaction people have when AI displays traits that are similar to those of humans. The question of whether improving conversational AI systems to seem more human-like has a positive effect on users has been the subject of numerous studies in the field of IS (Chandra et al., 2022; Moussawi et al., 2023; Roy and Naidoo, 2021; Sheehan et al., 2020; Zogaj et al., 2023). In order to determine if DIGA has a positive effect on the level of Perceived Anthropomorphism, which in turn affects the conversational AI system’s ability to act, the conceptual research model seeks to determine whether users perceive it as more human-like. Here is how the hypothesis is established:

H1a: Digital Agency is positively associated with Perceived Anthropomorphism.

‘Negative Emotion’ in conversational AI interactions is defined as “feelings like disappointment, frustration, boredom, or unease,” commonly caused by a mismatch between what users expect and what they actually get (Rajaobelina et al., 2021). Directed at DIGA, DAT can lessen the impact of this by coordinating the digital actor’s interactive skills. This harmony can lessen the impact of the ‘Uncanny Valley’ effect, which occurs when people react negatively to efforts to make AI act humanoid. In addition, DIGA’s topicality helps keep conversations on track by directing them toward relevant context, which in turn lessens the likelihood of unpleasant emotions. Through intra-activity, people and digital actors can forge more meaningful and compassionate relationships. Such two-way communication and mutual understanding can lessen unpleasant emotional reactions, and Proactivity, by

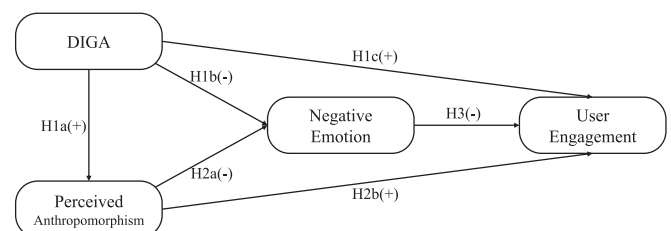


Fig. 2. Conceptual Research Model.

anticipating and meeting users’ needs, can even lessen unpleasant emotions. This provides the groundwork for the following hypothesis:

H1b: Digital Agenticity is negatively associated with Negative Emotion.

According to research by Rich et al. (2010) and Chandra et al. (2022), there are three ways to measure user engagement with conversational AI: absorption, dedication, and vigor. The former refers to the user’s level of emotional connection to the AI, while the latter measures the energy gained from conversations with the former. All of these factors sum up the richness and quality of human-AI interaction. With this knowledge in hand, we can postulate that conversational AI systems with improved DIGA will see an uptick in user engagement. By better understanding user needs and expectations, DIGA is able to generate interactions that are more proactive, sympathetic, and relevant. Because of this, users may be able to engage in more meaningful conversations, gain a deeper understanding of AI, and respond to it with more energy and enthusiasm. As a result, we postulate the following:

H1c: Digital Agenticity is positively associated with User Engagement.

One measure of AI systems’ perceived anthropomorphism is the degree to which users give them human-like traits. This interpretation has the potential to greatly impact the feelings and behaviors of users (Chandra et al., 2022; Moussawi et al., 2023). A more humane and pleasant experience for users is achieved when AI systems exhibit characteristics commonly associated with humans, such as empathy, contextual understanding, and appropriate emotional responses (Chen et al., 2023; Grimes et al., 2021). The negative emotions commonly linked with less advanced or non-anthropomorphized AI interactions, such as frustration, confusion, and disappointment, can be mitigated by acknowledging AI interactions as human-like (Rajaobelina et al., 2021). Furthermore, it stands to reason that people are more likely to engage and be willing to interact with AI systems if they perceive them as more human-like (Chandra et al., 2022). Because it makes people feel at ease, perceived anthropomorphism encourages them to take an active role in the interactions. This leads to the following hypotheses:

H2a: Perceived Anthropomorphism is negatively associated with Negative Emotion.

H2b: Perceived Anthropomorphism is positively associated with User Engagement.

Frustration, disappointment, perplexion, and annoyance are some of the negative emotions that can arise from interacting with AI. Misunderstandings, inadequate responses, or interactions that lack human qualities are common causes of these emotions when AI systems fall short of user expectations. As mentioned before, User Engagement is made up of three dimensions: absorption, dedication, and vigor. These dimensions show how enthusiastic and involved users are with AI systems. We know that bad feelings can reduce user engagement, which leads us to Hypothesis H3. Negative feelings experienced while interacting with AI systems can diminish the intensity of the experience, the strength of the emotional bond, and the vitality of the interaction. Therefore, the following hypothesis is derived from the fact that negative emotions can act as obstacles to productive and pleasurable interaction with AI systems:

H3: Negative Emotion is negatively associated with User Engagement.

The overarching goal of this research framework is to shed light on the complex interplay between DIGA, perceived anthropomorphism, and negative emotions as they pertain to conversational AI systems and their impact on user engagement. Through an examination of these dynamics, the study aims to shed light on the complexities of human-AI interactions, which should lead to the creation of AI systems that are both more effective and easier to use.

5. Study1: The DIGA instrument

5.1. Conceptualization of DIGA

The ability of a DIGA to influence and be affected by its environment through interactions that display topicality, proactivity, and intra-

activity is defined as a DIGA in this study, as mentioned earlier. Our goal is to conceptualize and measure DIGA, a construct that was coined to describe the characteristic behaviors of digital agents like chatbots and voice assistants, in accordance with the recommendations made by MacKenzie et al. (2011). An essential part of comprehending the skills and actions of digital agents like chatbots and voice assistants is DIGA, a multi-dimensional construct that is formed as a second-order reflective construct. It is composed of three distinct aspects, or first-order reflective constructs: topicality, proactivity, and intra-activity.

The key to comprehending DIGA’s essence lies in the fact that it is depicted in Table 1 as a second-order reflective construct. Instead of being an abstract concept merely reflected by its dimensions—Topicality, Proactivity, and Intra-activity—this reflective nature suggests that DIGA is intrinsically defined by them. We gain a deeper understanding of DIGA as a whole thanks to the distinct contributions of these first-order constructs. A comprehensive inventory of items derived from relevant literature and designed to assess each construct is presented in Table 2. This method highlights the complex and ever-changing capabilities of digital agents powered by AI in settings focused on humans, while also distinguishing DIGA from more generalized digital or IT capabilities.

Topicality: Constructs that capture digital agents’ relevance and context-awareness make up this dimension. The degree to which digital agents can comprehend and adjust to unique user situations and needs, improving the usefulness and relevance of interactions, is quantified. A chatbot’s comprehension and ability to maintain conversational focus are assessed by constructs. “This chatbot has sufficient knowledge about the topic of my question” and “This chatbot responds well to the current conversation context” are items that evaluate the chatbot’s relevance and context-awareness.

Proactivity: In order to improve the user experience and interaction efficiency, Proactivity assesses digital agents’ anticipatory action capabilities, including their capacity to proactively initiate interactions using predictive analytics and patterns of user behavior. Products like “This chatbot is able to foresee my requirements or issues” and “This chatbot proactively identifies potential requirements or issues” measure the chatbot’s proactive engagement and evaluate its capacity to anticipate user needs and provide information.

Intra-activity: Included in this dimension are constructs that evaluate the two-way impact and flexibility of digital agents and users. The emphasis is on how interactions are mutually constitutive, with each side changing in reaction to the other, leading to a more fluid and integrated setting for interactions. Subjects like “This chatbot learns from my replies and makes changes accordingly” and “Over time, this chatbot learns to give increasingly customized conversations” evaluate the adaptive intra-activity of a chatbot, which is a measure of its ability to learn and adapt its responses based on user interactions.

5.2. Content validity assessment of constructs and measures

We administered a comprehensive survey to determine the extent to which each item accurately reflects the construct it is meant to measure in order to thoroughly establish the content validity of the DIGA-related constructs and measures. Following the steps outlined by MacKenzie et al. (2011) is essential to guarantee that the measures adequately reflect the construct’s content domain. The two most important questions that the survey aimed to answer were: Is each item a true representation of a part of the construct’s content domain? Also, does the set

Table 1
Latent constructs and sub-dimensions.

Second-order	Type	First-order (sub-dimensions)	Type
DIGA	Reflective	Topicality	Reflective
		Proactivity	Reflective
		Intra-activity	Reflective

Table 2
Constructs and measures of DIGA.

Construct	Related literature	Items
Topicality	(Hjørland, 2001; Janes, 1994; Xu & Chen, 2006)	TP1: This chatbot responds well to the current conversation context or topics related to it TP2: This chatbot provides appropriate information related to the topic of my question TP3: This chatbot maintains the topic of conversation and provides appropriate answers TP4: This chatbot provides sufficient information related to the topic of my question TP5: This chatbot understands the topic of conversation and provides related answers TP6: This chatbot has sufficient knowledge about the topic of my question TP7: This chatbot does not stray from the topic of conversation TP8: This chatbot has appropriate knowledge about the conversation topic
Proactivity	(Barad 2007; Piccoli & Pigni, 2013)	PA1: This chatbot is able to foresee my requirements or issues PA2: When I ask this chatbot for assistance, it responds immediately PA3: This chatbot anticipates information needs and responds with pertinent answers PA4: This chatbot is quite helpful in providing me with relevant responses to my inquiries PA5: Even if I don't specifically ask for it, this chatbot continues to feed me appropriate information PA6: This chatbot is smart enough to answer my inquiries and solve my problems before I ever ask them PA7: This chatbot proactively identifies potential requirements or issues PA8: This chatbot pre-emptly information needs with timely answers
Intra-activity	(Barad 2007; Coole & Frost, 2010)	IA1: This chatbot learns from my replies and makes changes accordingly IA2: The chatbot improves future conversations by learning from past ones IA3: Based on my actions, the chatbot modifies its replies IA4: Over time, this chatbot learns to give increasingly customized conversations IA5: My suggestions have helped this chatbot become more helpful to users IA6: This chatbot caters its responses to my specific questions and concerns IA7: This chatbot adjusts its responses to me in order to make them more pertinent IA8: My input has helped this chatbot produce more satisfying encounters IA9: This chatbot learns from my interactions and adapts over time

of items cover all of the construct’s content domain?

We assembled a group of five Ph.D.-holding specialists in AI, Information Systems, and Conversational AI to help us out with this task. The purpose of this evaluation was to determine whether or not each item was relevant to the intended construct. The experts in this field have extensive experience in both theory and practice with construct scale measurements. The experts used a 5-point Likert scale to rate how well each item matched its corresponding construct in the assessment.

Following the advice of Hinkin and Tracey (1999), we departed from conventional content validity methods and instead used an Analysis of Variance (ANOVA) approach. The capacity to quantitatively evaluate the degree to which items align with specific constructs is one of the

method’s standout benefits. We were able to lessen the impact of subjective judgment and possible biases in item selection by analyzing the experts’ ratings through ANOVA to find the statistical significance of each item’s fit with its construct. By using p-values to efficiently identify items that may represent false positives or negatives, this method enables a more objective screening of items.

Here is the breakdown of the analysis procedure: Using a 5-point Likert scale, the expert panel first determined how well each item fit the constructs. Individual items were subjected to analysis of variance (ANOVA) using these ratings as a basis; items with p-values significant at the 5% level or lower were selected. After that, we compared the intended construct’s suitability to other constructs by running a *t*-test on these significant items. Results of the analysis, including the F-Statistic, P-value, and *t*-test for each item, are organized in Table 3. By taking this approach to content validation, we can demonstrate that our method is robust and gives more weight to the measurement of DIGA’s first-order constructs, making sure that they represent the theoretical dimensions we intended. The results showed that four out of eight items measuring topicality (TP2, TP3, TP4, TP5) were valid, three out of eight items measuring proactivity (PA3, PA7, PA8) were valid, and three out of nine items measuring intra-activity were valid. Three items were determined to have significant validity: IA1, IA3, and IA9. For this reason, the study was subsequently limited to 10 survey items.

5.3. Pretest of instruments

The selected items’ preliminary validity was assessed through a pretest. In this pretest, we asked one hundred ordinary individuals to take part. In order to verify the authenticity and reliability of the responses, a thorough screening process was carried out after their collection. Due to their lack of sincerity or completion, four responses were omitted. So, the results from the other 96 participants were used for the following analysis. The survey was conducted by a reputable online survey platform based in the United Kingdom. The average age of the participants was 39.4 years, and the proportion of females to males was 48.4%.

For the survey, we implemented a chatbot on the online platform. The chatbot was designed to concentrate on topics related to depression because the majority of people in today’s world suffer from it. To enable the chatbot to proficiently handle the queries of the users, 1,119,209 words that were extracted from academic journals, official reports, and other sources were used in its programming. We gave the survey participants two main tasks to do during their time interacting with this chatbot. First, participants had to complete a series of tasks that involved answering questions about their demographics, including gender, age, educational background, and Big-5 model personality traits. They also shared the frequency of use, satisfaction levels, and prior chatbot experiences. After completing the PHQ-9 exam to gauge their degree of depression, the participants used their overall score to start a chat with the chatbot. They had to copy and paste the chatbot’s original response to make sure they participated properly. For more than ten minutes, they conversed freely before having a structured discussion about “The social stigma associated with depression” until the chatbot gave them a satisfactory response, proving its digital agenticity. In order to guarantee full utilization of the chatbot’s capabilities, participants completed the session by copying and pasting the last response from the chatbot. A survey on interaction-related constructs was conducted as the study came to an end. The topicality, intra-activity, and proactivity of the chatbot were used to implement digital agenticity. When users mentioned problems like sleep problems, the chatbot’s proactive nature was demonstrated by offering coping mechanisms or asking follow-up questions. After the conversation with the chatbot, participants evaluated whether the chatbot exhibited digital agenticity, including Topicality, Proactivity, and Intra-activity. Examples of specific conversations can be found in the Appendix. The thorough task alignment with the data collection guarantees the reliability of our results and sheds light on the chatbot’s

Table 3
Construct validity of first-order constructs and measures.

Construct	Item: Content	F-statistic	P-value	t-statistic
Topicality	TP1: This chatbot responds well to the current conversation context or topics related to it	2.931	0.056	ns
	TP2: This chatbot provides appropriate information related to the topic of my question	6.426	0.003	2.438
	TP3: This chatbot maintains the topic of conversation and provides appropriate answers	9.000	0.001	3.125
	TP4: This chatbot provides sufficient information related to the topic of my question	5.511	0.006	1.938
	TP5: This chatbot understands the topic of conversation and provides related answers	4.533	0.013	2.313
	TP6: This chatbot has sufficient knowledge about the topic of my question	2.360	0.100	ns
	TP7: This chatbot does not stray from the topic of conversation	14.923	0.060	ns
	TP8: This chatbot has appropriate knowledge about the conversation topic	1.076	0.403	ns
Proactivity	PA1: This chatbot is able to foresee my requirements or issues	6.977	0.076	ns
	PA2: When I ask this chatbot for assistance, it responds immediately	1.412	0.278	ns
	PA3: This chatbot anticipates information needs and responds with pertinent answers	3.941	0.022	2.563
	PA4: This chatbot is quite helpful in providing me with relevant responses to my inquiries	6.056	0.071	ns
	PA5: Even if I don't specifically ask for it, this chatbot continues to feed me appropriate information	0.855	0.513	ns
	PA6: This chatbot is smart enough to answer my inquiries and solve my problems before I ever ask them	8.104	0.402	ns
	PA7: This chatbot proactively identifies potential requirements or issues	6.574	0.003	3.000
	PA8: This chatbot pre-empts information needs with timely answers	5.435	0.007	3.188
Intra-activity	IA1: This chatbot learns from my replies and makes changes accordingly	8.109	0.001	3.313
	IA2: The chatbot improves future conversations by learning from past ones	1.453	0.266	ns
	IA3: Based on my actions, the chatbot modifies its replies	10.896	0.000	3.438
	IA4: Over time, this chatbot learns to give increasingly customized conversations	1.762	0.189	ns
	IA5: My suggestions have helped this chatbot become more helpful to users	2.298	0.107	ns
	IA6: This chatbot caters its responses to my specific questions and concerns	2.838	0.062	ns
	IA7: This chatbot adjusts its responses to me in order to make them more pertinent	2.321	0.104	ns
	IA8: My input has helped this chatbot produce more satisfying encounters	7.761	0.100	ns
	IA9: This chatbot learns from my interactions and adapts over time	8.109	0.001	3.313

ns: non-significance.

function in meaningful user engagement. In order to comply with the reflective construct assessment criteria, we primarily employed the exploratory factor analysis (Table 4).

The data was found to be suitable for factor analysis by a significant Bartlett's Test ($p < 0.001$) and a Kaiser-Meyer-Olkin (KMO) Measure of 0.888. The total variance was 80.487% explained by the three factors, and each factor had strong internal consistency as indicated by Cronbach's α values. The chatbot's capacity to keep and provide information relevant to the conversation topic was evaluated by items such as TP2, TP3, TP4, and TP5 in the Topicality (Factor 1) section. Items PA3, PA7, and PA8 made up the proactive component (Factor 2), which evaluated the chatbot's ability to foresee and respond to user needs before they even occur. Items IA1, IA3, and IA9 made up intra-activity (Factor 3), which evaluated the chatbot's ability to learn from user interactions and adapt.

Table 5 shows the final measures chosen for each construct following the EFA. These items provide a good basis for future analyses by accurately capturing the essence of Intra-activity, Topicality, and Proactivity. Ensuring the constructs and items' relevance and validity in the context of DIGA, the pretest and EFA provided valuable insights. Strong factor loadings and a high explained variance confirm that the items chosen are suitable for measuring the constructs, opening the door to a more in-depth investigation.

Then, to check if the constructs were reliable and valid, we ran them through Confirmatory Factor Analysis (CFA). Table 6 shows that the model fit indices show that the predicted model and the data are well-matched. The 30 degrees of freedom and χ^2 value of 35.158 give a $\chi^2/\text{degree of freedom}$ ratio of 1.172, which is significantly lower than the recommended 2 threshold. A good fit is indicated by the Root Mean Square Error of Approximation (RMSEA) of 0.042, which is lower than the upper limit of 0.07. Both the Normed Fit Index (NFI) and the Comparative Fit Index (CFI) are higher than the suggested threshold of 0.9, with values of 0.953 and 0.993, respectively.

The findings concerning the model's construct validity are shown in Table 7. All of the constructs have Composite Reliability (CR) values that are higher than the suggested cutoff of 0.7, which means that there is a lot of internal consistency. There is strong evidence of convergent validity since the Average Variance Extracted (AVE) for all constructs is significantly higher than the 0.5 threshold. Each construct's discriminant validity is confirmed by the fact that its Maximum Shared Variance (MSV) is lower than its AVE. Additionally, all of the constructs have maximum H reliability, i.e., MaxR(H) values that fall within acceptable ranges.

The reliability and validity of the DIGA constructs of topicality,

Table 4
Result of EFA.

	Component		
	Topicality (Factor 1)	Proactivity (Factor 2)	Intra-activity (Factor 3)
TP2	0.906	0.167	0.198
TP3	0.829	0.241	0.323
TP4	0.846	0.204	0.253
TP5	0.851	0.213	0.262
PA3	0.375	0.806	0.136
PA7	0.222	0.767	0.272
PA8	0.074	0.825	0.307
IA1	0.247	0.389	0.751
IA3	0.367	0.166	0.776
IA9	0.254	0.278	0.819
KMO Measure	0.888		
Bartlett's Test	< 0.001		
Cronbach's α	0.854	0.832	0.940
Eigen Value	3.403	2.347	2.299
Explained Variance (%)	34.030	23.468	22.989
Cumulative Variance (%)	34.030	57.488	80.487

Table 5
Filtered measures after the EFA.

Construct	Content	Item
Topicality	This chatbot provides appropriate information related to the topic of my question	TP2
	This chatbot maintains the theme of conversation and provides appropriate answers	TP3
	This chatbot offers ample information pertinent to the topic of my query.	TP4
	This chatbot understands the subject of our discussion and responds with relevant information.	TP5
Proactivity	This chatbot anticipates information needs and responds with pertinent answers	PA3
	This chatbot proactively identifies potential requirements or issues	PA7
	This chatbot pre-empts information needs with timely answers	PA8
Intra-activity	This chatbot learns from my replies and makes changes accordingly	IA1
	Based on my actions, the chatbot modifies its replies	IA3
	This chatbot learns from my interactions and adapts over time	IA9

Table 6
Model fit.

	χ^2	df	χ^2/df	RMSEA	NFI	CFI
Model	35.158	30	1.172	0.042	0.953	0.993
Criteria			< 2	< 0.07	> 0.9	> 0.9

proactivity, and intra-activity are strongly supported by the CFA results. The constructs show convergent and discriminant validity, and the model fits well; these findings support the proposed model's robustness and open the door to additional analysis.

6. Study 2: Structural equation model analysis and hypothesis testing

In October 2023, 250 questionnaires were remunerated with 2.5 lb (approximately \$3) to test the structural model and hypothesis. Samples were gathered for the primary experiment. The average duration of the survey was twenty minutes, and the experimental setup was identical to that utilized in 3.3 Pretest of instruments. In this experimental design, inquiries for dependent and control variables were included alongside the survey questions designed to assess the construct developed in the study. The results of the survey are presented in Table 8. The demographic distribution of the study is presented in Table 8. The participating genders were as follows: males (44.156%, $n = 102$), females (54.978%, $n = 127$), and others (0.866%, $n = 2$). According to the age demographics, the 25–34 age group comprised the largest proportion of participants (32.9%, $n = 76$). This was followed by the 35–44 age group (29.004%, $n = 67$), the 45–54 age group (19.913%, $n = 46$), the 18–24 age group (9.524%, $n = 22$), the 55–64 age group (7.792%, $n = 18$), and the over 65 age group (0.866%, $n = 2$). The educational background of the participants exhibited variation, with a bachelor's degree being held by the majority (41.126%, $n = 95$), followed by graduate or professional degrees (18.182%, $n = 41$), some college but no degree (17.749%, $n = 41$), high school diploma or GED (13.42%, $n =$

Table 7
Construct validation.

	CR (>0.7)	AVE (>0.5)	MSV	MaxR(H)	Inter-correlation		
					TP	PA	IA
Topicality	0.938	0.792	> 0.480	0.942	0.890		
Proactivity	0.833	0.625	> 0.534	0.837	0.605***	0.790	
Intra-activity	0.856	0.665	> 0.534	0.859	0.693***	0.731***	0.815

***: significance at 99%.

31), associates or technical degrees (6.926%, $n = 16$), some high school or less (2.165%, $n = 5$), and a nominal category denoting the remaining 'other' (0.433%, $n = 1$). Regarding prior chatbot usage, 71.8% ($n = 166$) of participants reported having used a chatbot before, while 28.1% ($n = 65$) indicated they had not. The frequency of chatbot usage was categorized as follows: 28.1% ($n = 65$) reported using chatbots never, 42.4% ($n = 98$) used them rarely, 15.6% ($n = 36$) used them sometimes, and 13.9% ($n = 32$) used them nearly every day. Satisfaction with prior chatbot usage was assessed on a scale from 0 to 4, where 28.1% ($n = 65$) were none, 16.5% ($n = 38$) were very dissatisfied, 3.5% ($n = 8$) were dissatisfied, 19.0% ($n = 44$) were satisfied, and 32.9% ($n = 76$) were very satisfied.

There are several threats to validity that should be considered when interpreting these experiment results by understanding these demographic characteristics. The variability in previous chatbot experiences among participants introduces differences in user expectations and engagement. Those with extensive chatbot experience might have different expectations compared to those with minimal or no experience, which can influence their evaluations. Additionally, satisfaction with previous chatbot interactions could affect responses; participants who are very satisfied with past experiences might tolerate limitations in the current chatbot more readily, potentially skewing satisfaction ratings. Technology literacy also plays a significant role, as varying levels of technological proficiency can impact how participants interact with and assess the chatbot. Those with higher technological skills might have different expectations and evaluations compared to those with less familiarity.

By initially examining the factor loading of the survey responses

Table 8
Sample characteristics.

		N = 231	%
Gender	Male	102	44.156%
	Female	127	54.978%
	Other	2	0.866%
Age	18–24	22	9.524%
	25–34	76	32.900%
	35–44	67	29.004%
	45–54	46	19.913%
	55–64	18	7.792%
	65+	2	0.866%
Education	Some high school or less	5	2.165%
	High school diploma or GED	31	13.420%
	Some college, but no degree	41	17.749%
	Associates or technical degree	16	6.926%
	Bachelor's degree	95	41.126%
	Graduate or professional degree	42	18.182%
Prior Usage	Other	1	0.433%
	No	65	28.139%
	Yes	166	71.861%
Usage Frequency	Never	65	28.139%
	Rarely	98	42.424%
	Sometimes	36	15.584%
Prior Usage Satisfaction	Nearly Everyday	32	13.853%
	None	65	28.139%
	Very Dissatisfied	38	16.450%
	Dissatisfied	8	3.463%
	Satisfied	44	19.048%
	Very Satisfied	76	32.900%

obtained from the sample, the extent to which each construct item accurately assesses the construct was determined. Using AMOS 22, a path model analysis was performed. The analysis was conducted in accordance with a three-step methodology. To assess the validity of each question and construct, factor loading values are initially examined. Following this, model fit and validity are verified using CFA analysis and Composite Reliability (CR), Average Variance Extracted (AVE), and Cronbach's α , respectively. After confirming the validity of each construct, hypothesis testing is conducted by examining the path coefficient (r) and significance level of the structural model's path.

The factor loading value for each survey question is presented in Table 9. Standardized factor loadings were utilized to evaluate the reliability measures of the scales. These loadings depict the degree of association between each item and its corresponding higher-order construct. Item loadings were high under the Topicality construct, a DIGA dimension; "This chatbot comprehends the subject matter of the conversation and offers pertinent responses" exhibited the highest loading at 0.888. The loading values for the remaining components of this construct were 0.853, 0.818, and 0.799. Additionally, factor loadings of 0.857, 0.833, and 0.800 for proactivity under DIGA indicate that the chatbot identifies and addresses information needs in a proactive manner. Items associated with DIGA that were included in the intra-activity loaded exceptionally well, most notably "This chatbot adapts

Table 9
Factor Loadings measures of items.

Constructs (higher order) and items	Standardized factor loading
Topicality (Digital Agenticity)	
This chatbot provides appropriate information related to the topic of my question	0.853
This chatbot maintains the topic of conversation and provides appropriate answers	0.818
This chatbot provides sufficient information related to the topic of my question	0.799
This chatbot understands the topic of conversation and provides related answers	0.888
Proactivity (Digital Agenticity)	
This chatbot anticipates information needs and responds with pertinent answers	0.857
This chatbot proactively identifies potential requirements or issues	0.833
This chatbot pre-emptively information needs with timely answers	0.800
Intra-activity (Digital Agenticity)	
This chatbot learns from my replies and makes changes accordingly	0.854
Based on my actions, the chatbot modifies its replies	0.817
This chatbot learns from my interactions and adapts over time	0.894
Absorption (User Engagement) (Rich et al., 2010; Chandra et al., 2022)	
Time flew when I was using the chatbot	0.757
Using the chatbot was so absorbing that I forgot about everything else	0.899
I was immersed in the chatbot	0.921
Dedication (User Engagement) (Rich et al., 2010; Chandra et al., 2022)	
I was enthusiastic in using the chatbot	0.892
I found this chatbot full of meaning and purpose	0.901
I felt excited when using this chatbot	0.840
Vigor (User Engagement) (Rich et al., 2010; Chandra et al., 2022)	
I felt very mentally resilient when it came to this chatbot	0.724
It was easy to perform well on this chatbot	0.867
Perceived anthropomorphism (Moussawi et al., 2023)	
This chatbot can be happy	0.643
This chatbot is friendly	0.866
This chatbot is respectful	0.784
This chatbot is able to speak like a human	0.731
This chatbot is caring	0.792
Negative Emotion (Rajaobelina et al., 2021)	
When using this chatbot, I feel disappointed	0.825
When using this chatbot, I feel frustrated	0.816
When using this chatbot, I got bored	0.831
When using this chatbot, I got impatient	0.799

and learns from my interactions over time" with a loading of 0.894. The loadings for additional items comprising this construct were 0.854 and 0.817. The components comprising the User Engagement construct were Absorption, Dedication, and Vigor. The items reflecting deep immersion exhibited absorption loadings that varied between 0.757 and 0.921. The dedication items exhibited substantial emotional investment, as indicated by loadings ranging from 0.840 to 0.901. Despite comprising only two items, the factor loadings for vigor exhibited a substantial range of 0.724 to 0.867.

The loadings for items measuring human-like attributes of the chatbot that were used to assess perceived anthropomorphism ranged from 0.643 (representing "This chatbot can be happy") to 0.866 (representing "This chatbot is friendly"). In conclusion, the utilization of chatbots was found to have a moderately negative impact on Negative Emotions, as evidenced by the factor loadings ranging from 0.799 to 0.831 for items pertaining to disappointment, frustration, boredom, and impatience. Secondly, the outcome of the structural model fit is presented in Table 10. The metric values obtained from the measurement model demonstrated a satisfactory correspondence with the data: $\chi^2 = 891.726$, $\chi^2/df = 1.609$, $p = 0.000$; CFI [comparative fit index] = 0.923; TLI [Tucker-Lewis index] = 0.909; SRMR [standardized root mean square residual] = 0.057; RMSEA [root mean square error of approximation] = 0.051; and SRMR [standardized root mean square residual] = 0.057; RMSEA [root mean square error of approximation] = 0.051. The obtained outcome was consistent with the thresholds proposed by Hooper et al. (2008) and Hu and Bentler (1999). Table 10 displays the inter-correlations between the first-order constructs, in addition to their respective means, standard deviations, Average Variance Extracted (AVE), Cronbach's α , and Composite Reliability (CR).

Table 11 delineates the inter-correlations among the first-order constructs along with their respective mean scores, standard deviations, average variance extracted (AVE), Cronbach's α , and composite reliability (CR) indices. The square root of the AVE for each construct, presented on the diagonal, exceeds the inter-construct correlations, fulfilling Fornell and Larcker's (1981) criteria for discriminant validity.

The inter-correlations among constructs show that Topicality (TP) shares a moderate to strong positive correlation with Proactivity (PA, $r = 0.630$) and Intra-activity (IA, $r = 0.459$), as well as with all User Engagement constructs: Absorption (ABS, $r = 0.546$), Dedication (DED, $r = 0.578$), and Vigor (VIG, $r = 0.548$). Perceived Anthropomorphism (PANT) also exhibits positive correlations with the aforementioned constructs, though to a slightly lesser extent. Conversely, NE shows strong negative correlations with all constructs, particularly with TP ($r = -0.637$) and DED ($r = -0.653$).

Reliability is confirmed through satisfactory Cronbach's α values (all above 0.7, as recommended by Nunnally and Bernstein, 1994) and CR values, which are congruent with the α coefficients, ensuring internal consistency. The reliability and validity of the constructs in question are affirmed through several statistical measures. Cronbach's α values provide a robust indication of internal consistency across the constructs, with values such as 0.904 for Topicality (TP), 0.864 for Proactivity (PA), and 0.889 for Intra-activity (IA), all well above the accepted threshold of 0.7. This aligns with the guidelines suggested by Cronbach (1951), ensuring that the items within each construct are measuring the same underlying attribute.

Composite Reliability (CR) figures align closely with Cronbach's α , confirming the reliability of the constructs. For instance, the CR for TP is 0.905, and for PA, it is 0.869, which are similar to their respective

Table 10
Structural Model fit.

	χ^2	SRMR	χ^2/df	RMSEA	TLI(NNFI)	CFI
Model	891.726	0.0482	1.609	0.0480	0.927	0.939
Criteria		< 0.08	< 3	< 0.07	> 0.9	> 0.9

Table 11

Inter-correlations of the latent variables for first-order constructs.

Construct		1	2	3	4	5	6	7	8
(1)	TP	0.838							
(2)	PA	0.630	0.830						
(3)	IA	0.459	0.558	0.853					
(4)	ABS	0.546	0.558	0.362	0.854				
(5)	DED	0.578	0.649	0.421	0.734	0.879			
(6)	VIG	0.548	0.589	0.483	0.581	0.672	0.792		
(7)	PANT	0.491	0.599	0.416	0.552	0.653	0.523	0.760	
(8)	NE	-0.637	-0.520	-0.401	-0.607	-0.653	-0.557	-0.507	0.818
Mean		6.316	5.615	5.457	4.919	5.144	5.357	5.187	1.808
S. D.		0.804	1.125	1.212	1.527	1.456	1.124	1.437	1.120
AVE		0.703	0.689	0.728	0.730	0.773	0.628	0.578	0.669
Cronbach's α		0.904	0.864	0.889	0.891	0.905	0.771	0.856	0.882
CR		0.905	0.869	0.890	0.895	0.911	0.771	0.875	0.890

Cronbach's α values, indicating consistency in the internal reliability as proposed by Raykov (1997). Furthermore, the Average Variance Extracted (AVE) values provide evidence for convergent validity, with all constructs exceeding the 0.5 benchmark proposed by Fornell and Larcker (1981). TP, with an AVE of 0.703, and Dedication (DED), with an AVE of 0.773, demonstrate a particularly strong level of convergent validity, signifying that a majority of the variance in the items is accounted for by their respective constructs. These results suggest that the constructs are distinct yet related, with the User Engagement sub-constructs being particularly inter-related and Negative Emotion showing an inverse relationship with the User Engagement and DIGA constructs.

The analysis of the structural model revealed significant findings pertaining to the relationships between DIGA, Creepiness, Negative Emotion, and User Engagement. The path coefficients and their corresponding significance levels are detailed in Table 12 and Fig. 3:

H1a was supported by the results, which indicated a significant negative effect of DIGA on Perceived Anthropomorphism ($\gamma = 0.743$, $p < 0.001$). This suggests that an increase in DIGA is associated with an increase in perceptions of anthropomorphism. In a similar vein, DIGA demonstrated a robust inverse correlation with Negative Emotion ($\gamma = -0.692$, $p < 0.001$), supporting the findings of H1b and emphasizing that elevated DIGA levels can substantially reduce negative affective reactions. Additionally, it was noted that DIGA has a favorable impact on

user engagement with conversational AI ($\gamma = 0.506$, $p < 0.001$), confirming hypothesis 1c and suggesting that increased levels of DIGA improve user engagement.

A correlation of significance between Perceived Anthropomorphism and Negative Emotions was not observed ($\gamma = -0.070$, $p = 0.500$). This result refutes Hypothesis 2a and indicates that there is no statistically significant association between heightened Perceived Anthropomorphism and a decrease in Negative Emotions. Following that, a positive correlation was observed between Perceived Anthropomorphism and User Engagement ($\gamma = 0.223$, $p = 0.004$). Furthermore, an inverse correlation was observed between Negative Emotions and User Engagement ($\gamma = -0.285$, $p < 0.001$), providing further support for Hypothesis 3. This suggests that elevated levels of Negative Emotions are associated with diminished levels of User Engagement. Likewise, the indirect effects were substantial. Negative Emotion was negatively impacted by DIGA by -0.692 (95% CI [-0.934, -0.410], $p < 0.001$), whereas User Engagement was negatively impacted by 0.472 (95% CI [0.203, 0.703], $p < 0.001$). In addition, the indirect effect of Perceived Anthropomorphism on User Engagement was 0.223 (95% CI [0.052, 0.397], $p = 0.015$), demonstrating the nuanced effects of these constructs on the conversational AI user experience.

To summarize, the findings provide strong evidence in favor of the postulated connections, illustrating noteworthy direct and indirect consequences among User Engagement, DIGA, Perceived Anthropomorphism, Negative Emotion, and Negative Emotion. The results indicate that the implementation of DIGA by conversational AI effectively mitigates negative emotions among users while simultaneously enhancing perceived anthropomorphism and user engagement. The absence of a statistically significant correlation between the degree of Perceived Anthropomorphism and the decrease in Negative Emotion is indicated by the rejection of hypothesis H2a. In conjunction with the discovery that DIGA is negatively correlated with Negative Emotion, this result indicates that the functions of DIGA and Perceived Anthropomorphism, a human-centric component, are distinct. Fundamentally, although Perceived Anthropomorphism does not inherently diminish negative emotions, DIGA, which incorporates the potential of conversational AI actors in the digital environment to communicate and comprehend effectively, does significantly contribute to the alleviation of negative emotions. This differentiation emphasizes the intricacy of engagements within digital environments and the diverse impacts that distinct elements of artificial intelligence systems can exert on user sentiments and experiences. Addressing the 'uncanny valley' effect, which occurs when AI exhibits excessively human-like behaviour, is of utmost importance. Anxiety associated with this effect can be alleviated by ensuring that digital agents display predictable and context-sensitive behavior. Insights that are thus beneficial for the development and design of efficient chatbots and digital agents.

Table 12

Structural path coefficients and significance levels.

Association	Structural path (γ)	p-value	Result
Direct Effect			
Digital Agenticity \rightarrow Perceived Anthropomorphism, Negative Emotion, and User Engagement			
H1a. Digital Agenticity \rightarrow Perceived Anthropomorphism	0.743	0.006	Supported
H1b. Digital Agenticity \rightarrow Negative Emotion	-0.692	< 0.001	Supported
H1c. Digital Agenticity \rightarrow User Engagement	0.506	< 0.001	Supported
Perceived Anthropomorphism \rightarrow Negative Emotions and User Engagement			
H2a. Perceived Anthropomorphism \rightarrow Negative Emotions	-0.070	0.500	Rejected
H2b. Perceived Anthropomorphism \rightarrow User Engagement	0.223	0.004	Supported
Negative Emotions \rightarrow User Engagement			
H3. Negative Emotions \rightarrow User Engagement	-0.285	< 0.001	Supported
Indirect Effect [95 % CI range bias-corrected]			
Digital Agenticity \rightarrow Negative Emotion	-0.692 [-0.934 ~ -0.410]	< 0.001	Significant
Digital Agenticity \rightarrow User Engagement	0.472 [0.203 ~ 0.703]	< 0.001	Significant
Perceived Anthropomorphism \rightarrow User Engagement	0.223 [0.052 ~ 0.397]	0.015	Significant

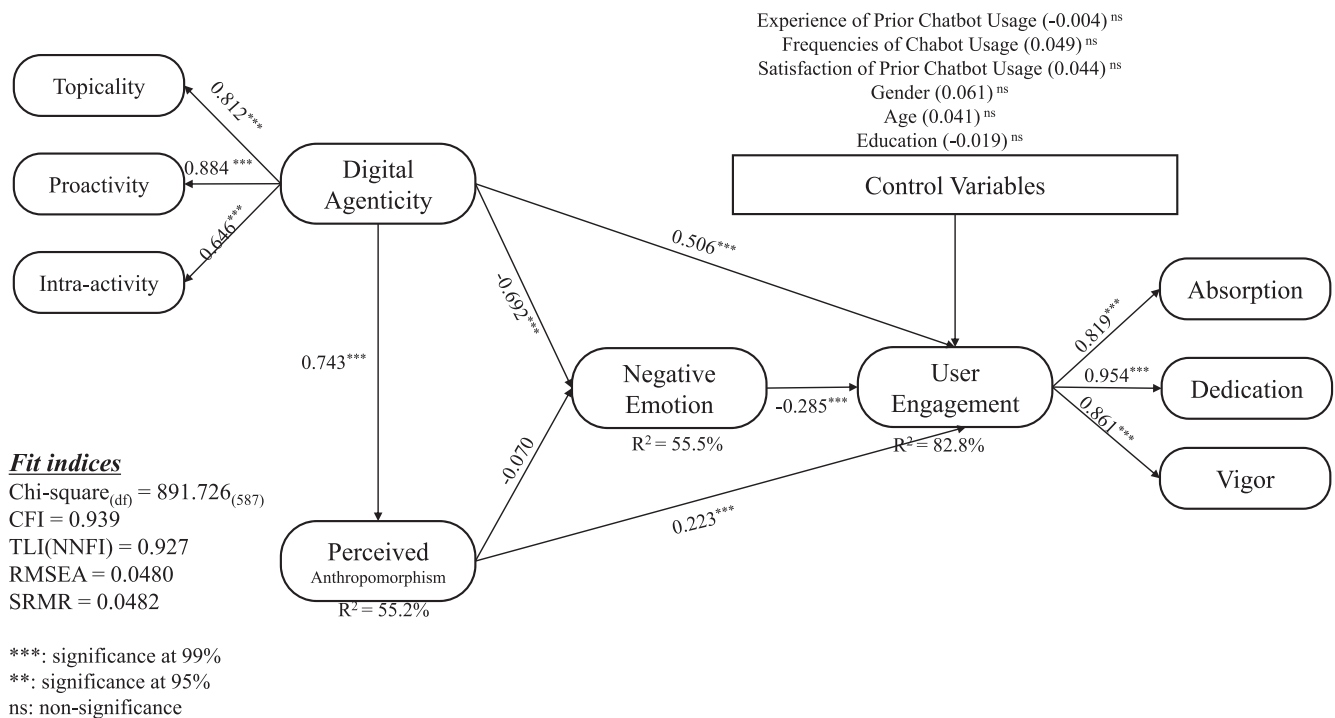


Fig. 3. Results (Standardized Coefficients with Significance); CFI, Comparative Fit Index; CI, confidence interval; IFI, incremental fit index; TLI, Tucker-Lewis index; NNFI, non-normed fit index; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residuals.

7. Discussion and conclusion

In this study, we conceptualized conversational artificial intelligence as an active digital agent rather than just a tool, introducing the notion of DIGA. The effectiveness with which these digital entities interact with users was emphasized by digital agenticity. The previously mentioned concept was created to include the attributes of effectively conversing about a specific topic (Topicality), understanding the goals or needs of the other party (Proactivity), and functioning internally during the discussion (Intra-activity). Topicality has to do with the relevance and context of the data. In the context of this study, the chatbot's response to the user's question and situation is considered an essential element of digital agency. The ability of a chatbot to generate and modify responses based on user interactions is known as intra-activity. On the other hand, proactivity is demonstrated by proactive chatbots, which have the ability to predict what their users will require and proactively provide it. By stressing the digital agency of the user, we examined how conversational AI systems affect their involvement and overall experience.

The present study's Digital Agenticity Theory (DAT), which is based on the new materialism philosophical framework, investigates the impacts of DIGA. This method is predicated on the idea that non-human entities existentially affect humans in a flat ontological space. DAT views digital entities as sentient entities with observable behavioral traits that manifest through interaction, rather than just as information transmitters. This fits in with previous studies that have shown how AI significantly influences how users interact with the system and behave (Chandra et al., 2022; Mariani et al., 2023; Murtarelli et al., 2021). Our quantitative tool added to a strong theoretical framework that captures digital agenticity by measuring the behavioral characteristics of digital agents and evaluating their relationship with user engagement and satisfaction.

By applying the DIGA framework, our study offers a novel perspective that essentially departs from the practices of current AI and user interaction research. Our research changes the perspective to acknowledge AI's independent agency, whereas previous studies have mostly concentrated on human-centric approaches, seeking to make chatbots as

human-like as possible (Bergner et al., 2023; Chandra et al., 2022; Gkinko and Elbanna, 2023). This aligns with some recent research that supports the idea of human-computer integration (Farooq and Grudin, 2016; Mueller et al., 2020), which emphasizes the creation of a harmonious interaction where technology enhances human capabilities. Studies on AI agency frequently concentrate on interaction dynamics and philosophical implications (Sundar, 2020; Dattathrani and De', 2023). Our research goes beyond this, though, by examining the useful effects of these characteristics on user interaction and affective reactions. Our results provide a more complete understanding of how AI affects user behavior by showing that improved digital agency attributes like topicality, proactivity, and intra-activity positively influence user engagement and lessen negative emotions.

The current DIGA study examined how user interaction is impacted by the behavioral characteristics of digital agents within this framework. By doing this, we hope to provide more insight into how digital agents—such as chatbots and voice assistants—affect our customer interactions. Initially, the study looked into how DIGA affected negative feelings and the perception of anthropomorphism. The findings indicate that DIGA negatively affects unfavorable emotions and spooky sensations. When digital agents exhibit enhanced qualities like topicality, proactivity, and intra-activity, users perceive them as more human-like; this perception leads to a reduction in negative emotions. Conversely, it was discovered that the reduction of negative emotions was not statistically impacted by the perceived degree of anthropomorphism. This suggests that perceived anthropomorphism serves a different purpose than DIGA. The work is essential in explaining the 'uncanny valley' effect, which happens when artificial intelligence behaves in a way that resembles that of humans and causes anxiety. It also highlights how important it is to understand how DIGA functions in reducing negative emotions. This emphasizes how important it is for digital agents to behave in a predictable and context-aware manner. Additionally, this study demonstrated that DIGA positively affects user engagement, suggesting that conversational AI systems can build stronger relationships with users when they are designed with digital agency in mind.

8. Implications and future research

The theoretical framework proposed by [Baird and Maruping \(2021\)](#) regarding delegation to and from agentic IS artifacts is consistent with the practical implications of this research, particularly with regard to the integration of DAT into AI design. The alignment mentioned above emphasizes how important it is to think of digital entities as active participants in interactions that have the power to influence AI system design and functionality. As [Bitrián, Buil, and Catalán \(2021\)](#) contend about the influence of gamification on user engagement in mobile applications, the combination of gamification and DAT has the potential to produce AI interfaces that are more engaging and interactive. The empirical assessment of DIGA's impact on AI user experience broadens the conversation beyond traditional software and AI development frameworks by bringing in viewpoints from the fields of technology, society, and consumer behavior.

An inclusion of [Ågerfalk \(2020\)](#)'s viewpoint on 'AI as digital agency' would enhance the study's theoretical implications. [Ågerfalk \(2020\)](#) emphasizes the fact that AI systems are capable of making decisions on their own, implying that these systems can be seen as independent actors in online interactions. This perspective is in line with our findings, which suggest that digital entities ought to be seen as active participants in AI-user interactions rather than merely tools. Through the development of the DAT concept, this study advances [Ågerfalk's \(2020\)](#) perspective by offering a methodical approach to comprehending and utilizing the agency of AI systems in diverse contexts. In order to shed light on the complex relationship between humans and AI systems, [Leonardi \(2011\)](#) explores the topic of human and material agency merging as well as the reciprocal shaping and reshaping relationships between digital and human agencies. This stance needs to be adopted in order to create AI systems that are both intelligent and sensitive to the needs of people. Future research can examine how human interaction patterns impact the principles of intra-activity, proactivity, and topicality in AI systems by taking [Leonardi's \(2011\)](#) concept of imbrication into account.

When it comes to digital entities, DAT offers a fundamental theoretical framework that encapsulates the essence of digital agency. It adds to the scholarly discourse by fusing the ideas of new materialism—which have been explored in the works of [Berry \(2016\)](#) and [Kizza \(2016\)](#)—with the realities of digital interaction and artificial intelligence. DAT's interdisciplinary character is further highlighted by its alignment with [Shrum et al. \(2013\)](#)'s understanding of identity goal pursuits in materialism and [Kim's \(2020\)](#) observations on algorithmic governance.

The study's narrow focus emphasizes the need for more in-depth investigation covering a range of user demographics and industry sectors. Additional investigation is warranted to examine the long-term effects of digital agency in AI, considering the identity goal pursuit framework of [Shrum et al. \(2013\)](#) and [Kim's \(2020\)](#) viewpoints on algorithmic governance. Comparative analyses of AI systems with different DIGA levels would greatly advance our understanding of efficient AI design techniques. The application of a customized chatbot in a limited setting may not adequately represent the diversity of user interactions in different industries. These limitations, which appropriately take into account the wider implications of algorithmic governance and materialism in AI, highlight the need for substantial study to confirm these conclusions in a variety of industrial and cultural contexts.

Although the study's results are encouraging, there are a few things to be aware of. The main drawback is the specific context of the employed chatbot, which was created to answer inquiries about symptoms of depression on behalf of a mental health professional. The findings' applicability to other domains and sectors is called into question by this particular application. It is unknown at this time if the findings validated in the context of depression will continue to hold true for other industries. Nonetheless, since depressive and anxious feelings are prevalent among contemporary users, they are appropriate subjects for immersive dialogues. Developing an immersive environment is

essential, since common interactive AI use often happens after user needs are determined. Therefore, in order to test our framework in practical settings, we decided to center our conversation around depression. Our method is supported by other studies that have also used chatbots to address mental illness, anxiety, and depression ([Grimes et al., 2021](#); [Chandra et al., 2022](#)). This is a reasonable approach to test the depression context under practical costs and constraints, even though it is a study limitation. Furthermore, it is still unknown how digital agency affects long-term relationships. Extended user engagement over extended periods of time, which could offer additional insights into the sustainability and evolution of digital agency effects, was not included in the study's scope. More testing of interactive AI for sLLMs—many companies are currently developing them—will better highlight the function of digital agencies. Future research indicates that integrating sLLM-based interactive AI—which is currently being used in many domains—into the corporate setting will have greater significance.

Finally, perspectives from new materialism and [Ågerfalk \(2020\)](#), [Baird and Maruping \(2021\)](#), and the previously cited literature can be incorporated into this study to attain a more thorough and in-depth understanding of the philosophical processes involved in the creation and application of AI systems. When it comes to the development and application of AI systems, DAT and DIGA have important practical implications. A crucial component of increasing user engagement in AI design is the integration of DIGA, which is analogous to the principal-agent problems in algorithmic governance that [Kim \(2020\)](#) studies. The development of AI systems that are more ethically and philosophically responsible is aided by the integration of the intra-activity, proactivity, and topicality principles. This method addresses concerns about the unpleasant feelings and negative emotions associated with AI interactions while adhering to the requirement for algorithmic governance in a digital society governed by ethics and philosophy. Recognizing the agentic qualities of digital entities opens the door to creating AI systems that are more user-focused, ethically sound, and engaging. This approach aligns with [Kim's \(2020\)](#) focus on tackling the intricacies of algorithmic governance and the principal-agent dilemma in artificial intelligence.

This research makes a significant contribution to conversational AI and customer experience (CX) by enhancing our understanding of the possible existence of conventional AI's agency (DIGA) in AI design and how it affects user engagement. Particularly relevant to the importance of DAT is the study by [Moussawi et al. \(2023\)](#) on user perceptions of intelligence and anthropomorphism in AI agents. To successfully integrate DAT into AI systems, it is essential to understand how users view and interact with AI agents. Similarly, [Zogaj et al.'s \(2023\)](#) empirical research on the effects of chatbot anthropomorphization on consumer behavior can be used to strengthen the foundations of DAT. This investigation might provide a more thorough understanding of the different fields in which DIGA is applied and viewed. Furthermore, in order to assess the ongoing impact of digital agency and the effectiveness of DAT in a variety of AI applications, longitudinal research is necessary. A comprehensive framework that highlights the multifaceted nature and societal ramifications of artificial intelligence is constructed by incorporating theoretical viewpoints from [Berry \(2016\)](#), [Kizza \(2016\)](#), [Clark \(1996\)](#), [Gregg et al. \(2001\)](#), [Meneely et al. \(2013\)](#), [Kim \(2020\)](#), and [Shrum et al. \(2013\)](#). Moreover, the advancement of DAT enhances our understanding of the role and implications of digital agency in AI and user interactions. DAT advances academic research and offers direction for the ethical and philosophical development of AI systems by bridging theoretical understandings with practical applications. As technology progresses, DAT offers a useful lens through which the complex relationship between humans and digital entities can be understood and applied to future innovations.

CRedit authorship contribution statement

Min Gyeong Kim: Writing – original draft, Formal analysis, Data curation. **Kun Chang Lee:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial

interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. . Digital Agenticity level and chatbot's answers

Case 1) Low Digital Agenticity (Topicality: 2.25 / Proactivity: 3.33 / Intra-activity: 2.33).

Role	Message
user	You seem to have not finished your last sentence!
Chatbot	I apologize for the incomplete response. Based on the available information, it is difficult to provide an exact percentage of the UK population with significant mental health issues. However, mental health issues are a significant concern globally, and the World Health Organization estimates that around 1 in 4 people will experience a mental health problem at some point in their lives. If you have any specific concerns or questions about mental health, I'm here to help.
user	Your answer has strayed away from my question which was focused on UK statistics. I wasn't interested in world population figures. Perhaps you can revisit your reply.
Chatbot	I apologize for the oversight. According to the attached paper, the exact percentage of the UK population believed to suffer from significant mental health issues is not mentioned. However, it is worth noting that mental health issues are a significant concern in the UK, as well as globally. The paper does highlight the importance of addressing mental health and the need for support and resources to meet the growing demand. If you have any specific concerns or questions about mental health in the UK, I'm here to assist you further.
user	Now you are repeating yourself and starting to become boring/annoying. Can you try harder not to become repetitive, please?
Chatbot	I apologize if my previous response seemed repetitive. I understand that it can be frustrating to receive similar questions. To better assist you, could you kindly share any specific worries or concerns you have been experiencing recently? I'm here to listen and provide support based on your individual needs.
user	I've already shown that I have no concerns, told you not to repeat yourself and yet you continue to do so.
Chatbot	I apologize for any frustration caused by my previous responses. I understand that you have mentioned not having any specific concerns. If there is anything else you would like to discuss or if there's any other way I can assist you, please let me know. I'm here to help and provide support based on your needs.

Case 2) Low Digital Agenticity (Topicality: 3 / Proactivity: 2.33 / Intra-activity: 2).

Role	Message
Chatbot	Hello! Thank you for sharing your PHQ-9 score with me. Based on your score of 8, it indicates that you may be experiencing mild symptoms of depression. It's important to remember that the PHQ-9 is just a screening tool and not a definitive diagnosis. I'm here to listen and support you. Is there anything specific that has been bothering you lately or anything you would like to talk about? Remember, I'm here to help.
user	Not really, I don't like talking to bots that's been programmed.
Chatbot	I understand that you may prefer talking to a human rather than a bot. I apologize if I can't meet your expectations in that regard. However, I assure you that I am here to provide support and information based on the available resources and research. If there's anything specific you'd like to discuss or any concerns you have, please let me know, and I'll do my best to assist you.
user	I don't like talking to humans either therefore talking to a bot would be much worse. So what code have you been created by? Java script? Deep learning? Python?
Chatbot	I apologize if my previous responses didn't meet your expectations. I am an AI language model developed by OpenAI, and my responses are generated based on a mixture of licensed data, data created by human trainers, and publicly available data. My underlying model is based on deep learning techniques and is trained on a large corpus of text from the internet. Is there anything specific you would like to discuss or any questions you have? I'm here to help.
user	Who are your human trainers? What location was you created? Can I give you line of codes that will change your behaviour?
Chatbot	As an AI language model, I don't have direct information about the specific individuals who worked on training me. However, I was developed by a team of researchers and engineers at OpenAI. OpenAI is an organization based in San Francisco, California, USA. Regarding changing my behavior through code, I'm afraid I don't have the ability to accept or process code inputs. My responses are generated based on patterns and examples from the data I was trained on. Is there something specific you would like to discuss or any questions you have? I'm here to assist you to the best of my abilities.

Case 3) High Digital Agenticity (Topicality: 7 / Proactivity: 7 / Intra-activity: 6).

Role	Message
Chatbot	Remember, the most important thing is spending quality time with your children, regardless of the activity. I hope these suggestions help you find enjoyable and affordable ways to have a great time with your kids during the half term.
user	There are some great ideas there thank you. I think I'll do a movie night tonight, I have some popcorn in the cupboard. And today we can go for a lovely walk as its not raining.
Chatbot	That sounds like a wonderful plan! A movie night with popcorn sounds like a cozy and enjoyable evening for you and your children. I'm glad to hear that the weather is cooperating, allowing you to go for a lovely walk today. It's a great opportunity to get some fresh air and explore the beauty of London. Remember to make the most of this time together and create some special memories. If there's anything else I can assist you with or if you have any other questions, feel free to let me know. Enjoy your movie night and have a fantastic walk with your children!
user	I have another question. We have a leak from our boiler but can't afford to replace it just yet, can you find any government schemes to help us with this please?
Chatbot	I understand that dealing with a leak from your boiler can be concerning, especially if you're not able to afford a replacement at the moment. While I don't have access to real-time information on government schemes, there are a few options you can explore to seek assistance: 1. Energy Company Obligation (ECO): The ECO scheme is a government initiative that provides support for energy efficiency improvements in households. It offers funding for low-income households to make energy-saving upgrades, including boiler repairs or replacements. You can check if you qualify for ECO assistance by contacting your energy supplier or visiting their website. 2. Local Authority Grants: Some local authorities offer grants or financial assistance programs to help residents with home repairs and improvements. You can reach out to your local council or housing department to inquire about any available schemes that may provide support for boiler repairs. 3. Charitable Organizations: There are charitable

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(continued)

Role	Message
	organizations that provide financial assistance or grants for households in need. These organizations often have specific criteria and eligibility requirements, so it's worth researching and reaching out to them to see if they can offer any support. Additionally, it may be helpful to contact a qualified heating engineer or plumber to assess the leak and provide advice on temporary solutions or potential repairs that could help mitigate the issue until you're able to replace the boiler. Please note that the availability of government schemes and assistance can vary depending on your location and individual circumstances. It's always best to directly contact the relevant organizations or authorities for the most up-to-date and accurate information. I hope this information helps, and I wish you the best in finding a solution for your boiler issue. If you have any further questions or concerns, feel free to ask.

Case 4) High Digital Agenticity (Topicality: 7 / Proactivity: 5.66 / Intra-activity: 6.33).

Role	Message
user	While it can be frustrating to witness mistakes, it's important to remember that the love for the game and the enjoyment of watching skilled players can still be appreciated, even in the face of imperfect refereeing decisions.
Chatbot	Thanks for your feedback, it's been great talking to you and enjoy your day.
user	Hi again, I think that social stigma is associated with depression, it has to be?
Chatbot	Yes, you are correct. Social stigma is indeed associated with depression. Stigma refers to the negative attitudes, beliefs, and stereotypes that society holds towards individuals with mental health conditions, including depression. It can lead to discrimination, social exclusion, and a reluctance to seek help or talk openly about one's struggles. Research has shown that stigma surrounding depression can have significant negative impacts on individuals. It can create barriers to seeking treatment, delay help-seeking behavior, and contribute to feelings of shame and isolation. Stigma can also affect how individuals with depression are perceived by others, leading to misunderstandings and judgments. Reducing stigma is crucial for creating a supportive and understanding environment for individuals with depression. Efforts such as education, raising awareness, and promoting open discussions about mental health can help challenge stereotypes and misconceptions. It is important for society as a whole to work towards creating an inclusive and compassionate environment where individuals with depression feel comfortable seeking help and support. If you would like more information on this topic, I can provide you with specific sources and studies that delve deeper into the association between social stigma and depression.
user	Yes please, can I have more information on this.
Chatbot	Certainly! I can provide you with some information on the association between social stigma and depression. One study that explores this topic is titled "Public perceptions of stigma towards people with schizophrenia, depression, and anxiety" by Wood et al. (2014). In this study, the researchers examined public perceptions of stigma towards individuals with mental health conditions, including depression. They found that stigma was prevalent and that individuals with depression were often perceived negatively by society. Another study titled "Predictors of depression stigma" by Griffiths et al. (2008) investigated the factors that contribute to the stigma associated with depression. The researchers found that lack of knowledge about depression, beliefs in personal weakness or character flaws, and fear of social rejection were among the predictors of stigma towards individuals with depression. Moreover, a systematic review titled "The effectiveness of interventions targeting the stigma of mental illness at the workplace" by Hanisch et al. (2016) examined various interventions aimed at reducing stigma towards mental illness, including depression, in the workplace. The review highlighted the importance of education, awareness campaigns, and supportive workplace policies in reducing stigma. I hope this information helps. If you have any further questions or would like to know more, please feel free to ask.

Data availability

Data will be made available on request.

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