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Great Chain of Agents: The Role of Metaphorical Representation of Agents in Conversational Crowdsourcing

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ABSTRACT

Conversational agents are being widely adopted across several domains to serve a variety of purposes ranging from providing intelligent assistance to companionship. Recent literature has shown that users develop intuitive folk theories and a metaphorical understanding of conversational agents (CAs) due to the lack of a mental model of the agents. However, investigation of metaphorical agent representation in the HCI community has mainly focused on the human level, despite non-human metaphors for agents being prevalent in the real world. We adopted Lakoff and Turner's 'Great Chain of Being' framework to systematically investigate the impact of using non-human metaphors to represent conversational agents on worker engagement in crowdsourcing marketplaces. We designed a text-based conversational agent that assists crowd workers in task execution. Through a between-subjects experimental study ($N = 341$), we explored how different human and non-human metaphors affect worker engagement, the perceived cognitive load of workers, intrinsic motivation, and their trust in the agents. Our findings bridge the gap of how users experience CAs with non-human metaphors in the context of conversational crowdsourcing.

KEYWORDS

Conceptual metaphors; Conversational agent; Crowdsourcing; Engagement; Trust; Great chain of being; Human-agent interaction; Human-AI interaction

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1 INTRODUCTION

Conversational interfaces have been argued to have advantages over conventional GUIs due to facilitating a more human-like interaction [74]. The rise in popularity of conversational AI agents has enabled humans to interact with machines more naturally [39]. In addition, people have a growing familiarity with conversational interactions mediated by technology due to the widespread use of mobile devices and messaging services. This has contributed to a steep rise in the use of conversational agents across several domains [41, 46, 51, 101]. Recent work has also shown that crowd workers in microtask marketplaces can complete various human intelligence tasks (HITS) using conversational interfaces, resulting in a similar output quality compared to traditional Web interfaces while exhibiting more engagement and satisfaction [69, 85, 86, 88].

Research in the HCI community has paid attention to the metaphorical representation of artificial intelligence (AI) agents to improve human-agent interaction and inform future design choices. For instance, Khadpe *et al.* revealed that metaphors with different degrees of perceived warmth and competency shape pre-use user expectation towards the agent, which leads to disparate effects on intention to adopt, desire to co-operate, and intention to try out a system [56]. Most prior works have only investigated agent metaphors at a human level. However, non-human representation of conversational agents is widespread in the real world, often in the form of a robot (e.g., Woebot¹) or a bird (e.g., on Duolingo² or Stanford's QuizBot³). Social simulation games, such as Animal Crossing⁴ and its vast commercial success, show that conversation with animal-looking agents who "act like a human" can be as engaging as interacting with agents resembling humans. This can be explained on the grounds that such agents representing animals still encompass dimensions that evoke anthropomorphic perceptions, such as facial expression, body language, or use of human language followed by verbal social cues (joking, response time, body gestures, etc.).

Although conversation, in general, is a highly human trait, metaphorical understanding is often conducted semantically and

¹<https://woebothealth.com/>

²<https://www.duolingo.com/log-in>

³<https://hci.stanford.edu/research/smartprimer/projects/quizbot.html>

⁴<https://www.nintendo.com/games/detail/animal-crossing-new-horizons-switch/>

is often used with non-human attributes. For example, metaphors like ‘*The man is a wolf*’ or ‘*Achilles is a lion*’ have a <A is a B> format. Here A is explained with certain instinctive traits of a B. Likewise, people might have different perceptions of Animal Crossing non-player characters (NPC), between an NPC represented as an eagle or a lion and an NPC represented as a raccoon or a monkey. However, there is a limited understanding of how non-human metaphorical representations of conversational agents shape user engagement, perceived cognitive load, intrinsic motivation, and trust in the agent.

To address the knowledge gap, in this paper, we adopted the ‘*Great Chain of Being* (GCoB)’ framework by Lakoff and Turner [52, 64] (Figure 2 (b)). By doing so, we introduce a new lens to frame and design non-human agent metaphors. This can help agent designers base their design choices in a conceptually more structured way that extends the current understanding of agent metaphors.

GCoB metaphor is composed of hierarchical scales of god, human, animal, plant, and inorganic object. According to Lakoff and Turner, the GCoB metaphor is one of the unconscious cognitive models that we as humans use to understand and categorize the world around us [64]. GCoB’s hierarchical and vertical scale suggests that entities in any level have all the properties that any lower levels possess, in addition to their distinctive property that a lower level does not have. Therefore, it is helpful to understand the complex faculties of human beings in terms of the lower-level property. Furthermore, based on the previous findings from Khapede *et al.* that metaphors with higher perceived competence resulted in lower intention to adopt a given system [56], hypothesizing that such a vertical scale also links to the level of competence and warmth, it is interesting to see if agents designed with metaphors from the higher level have a different impact on users.

In addition, humans subconsciously maintain separate schemas that characterize our knowledge about people from schemas of the physical world (p.162, [64]). The GCoB metaphor allows us to link such disparate schemas. For example, if someone were to be called a rock, most people would interpret the person as strong, persistent, or stubborn. Such inferences can be drawn from people’s understanding of the characteristics of a rock, for example, that rock is usually firm, and if a rock is large, the rock is likely heavy and hard to move around. Such examples can also be found in the famous ‘*Computer is a Desktop*’ metaphor (Figure 2 (a)), where it helped people comprehend the unfamiliar concept (Computer) as attributes of the well-understood concepts (desktop). This GCoB framework was developed to extend Lakoff’s well-known work on the Conceptual Metaphor theory [63]. Conceptual metaphor theory treats metaphors as conceptual rather than purely linguistic entities, which involves a systemic projection between two mental representations (conceptual domains).

Research on embodied conversational agents (ECAs) has explored the effect of anthropomorphism on users. ECAs have been proposed to handle multimodal input and output, the production and interpretation of gestures and emotions, and the development of avatars and talking heads [73]. This can be shown by commercial software such as Apple’s Memoji, where people can create personalized “animoji (animated emoji)” that has a shape of a dog, monkey, bear, and so on. Such software is developed in order to support expressive digital communication. Drawing inspiration, one can

design conversational agents and utilize non-human metaphors to explain the agent and adjust users’ expectations towards the agent.

We adopted the lens of conversational microtask crowdsourcing in this work, where improving worker satisfaction remains a challenge [57]. With a growing demand around human input due to the rapid advancement of automation, robotics, and AI, designing human intelligence tasks (HITs) that are engaging is a crucial research topic. However, HITs on microtasking platforms can be painfully monotonous, leading to high drop-out, rejection, and task abandonment rates [25, 44, 45, 72]. In order to improve this, recent literature suggested using a conversational interface to conduct HITs of different types (e.g., image transcription, information finding, sentiment analysis, image classification) in microtasking platforms. Results showed that a conversational interface improved perceived worker engagement and significantly high worker retention while maintaining output quality compared to conventional web task execution interfaces [86, 87].

Furthermore, in a domain where users (i.e., crowd workers) are primarily motivated by monetary rewards, recent work has shown the potential of using worker avatars to improve worker engagement and experience [84]. In this context of conversational crowdsourcing, it is exciting to study and better understand the role and potential of metaphorical representations of a conversational agent. Thus, we investigate the following research question:

RQ: How do different metaphorical representations of a conversational agent impact worker engagement, perceived cognitive load, intrinsic motivation, and trust in conversational microtask crowdsourcing?

To address the research question, we developed a text-based conversational interface using TickTalkTurk [88]. We carried out a between-subjects study spanning 12 experimental conditions (6 metaphors \times 2 task types), and recruited 341 workers from Prolific⁵ – a crowdsourcing marketplace. We present empirical findings of different agent metaphors derived from five hierarchical categories based on the Great Chain of Being, and their impact on worker engagement, perceived cognitive task load, intrinsic motivation, and trust. We found that metaphorical representations derived from the Great Chain of Being’s hierarchical categories can affect worker engagement, intrinsic motivation, and cognitive task load. We show that there is a trade-off in terms of using different metaphors. For instance, using an inorganic object metaphor (book) can significantly reduce the cognitive workload but negatively affect intrinsic motivation. Our study highlights the importance of choosing an appropriate metaphor to represent a conversational agent when designing crowdsourcing tasks.

Original Contributions. This paper makes the following contributions:

- We find evidence for the trade-offs between using different representations from the Great Chain of Being’s levels, and provide design implications for conversational crowdsourcing and conversational agents.

⁵<https://www.prolific.co>

- We propose a method to systematically analyze non-human metaphorical representations in a conceptually structured framework that can be used by agent designers and by researchers studying human-agent interaction.
- We enrich the current discourse on users' metaphorical understanding of conversational agents and address the knowledge gap on metaphorical agent representations.

2 BACKGROUND AND RELATED WORK

2.1 Conversational Agents Explained with Conceptual Metaphors

Over the last few years, conversational agents (CA) have been increasingly studied in the HCI community due to the human-like interaction that they facilitate, touted as “the next natural form of HCI” [67]. In the wake of such CAs, conversational user interfaces are being widely embedded across several domains in personal technologies and devices.

The term conversational agent has various connotations ranging from voice interfaces, virtual companions, virtual agents, autonomous agents, embodied conversational agents (ECAs), to chatbots. In this research, we focus on chatbots [39, 104]. Chatbots have been shown to predict users' attitudes by checking how users greet bots [65], enhance the collaborative experience of users [6], train non-expert users for skill acquisition [4], or improve patient engagement for health literacy [9].

Despite the promising possibilities of CAs in improving user experiences [74], people still lack mental models of such agents and fail to bridge the gap between user expectations and agent operation [67], which also can be explained by Norman's ‘*gulf of execution*’ [77]. Gulf of execution refers to a gap between what a user intends to do and what the system requires the users to do. Norman argues that the gulf of execution should be as small as possible to achieve higher usability. In an attempt to understand user behavior towards AI systems and CAs, recent literature has argued that people develop *folk theories* [36, 82] to reason about cyber-social systems [24, 28, 96]. The folk theory argues that users form an intuitive and informal understanding of the system, for example, how a *helicopter*, *gravity*, or *artificial intelligence* works, to explain their outcomes and consequences. Therefore, users' understanding is often imprecise. Their mental representation of technology is an implicit collection of beliefs rather than a blueprint of inputs and outputs [28]. In a similar vein, the conceptual metaphor theory provides a framework that can potentially reveal how users interact with CAs.

Metaphor has been one of the central themes of the design research discipline [10]. Previous studies have suggested metaphors can not only be a tool for designers to help users understand the system better (e.g., ‘*Computer is a Desktop*’) [68, 92], but also help designers to frame the problem using the Generative Metaphor framework [91]. Lakoff and Johnson [63] argue in their work “*Metaphors We Live By* [63]” that our conceptual system is fundamentally metaphoric. It is essentially human to understand and explain the world, concept, or ideas by “cross-domain mapping” the target to the source (Figure 2 (a)). Adopting this Conceptual Metaphor framework, a recent study by Khadpe *et al.* investigated how different human metaphors, based on their perceived warmth and

competence, influence their expectations, intention to adopt an AI system, and desire to co-operate with the system [56]. Similar to Khadpe *et al.*'s findings, although not in the context of metaphorical representation but also using perceived warmth and competence, Gilad *et al.* identified a primacy for warmth over competence when interacting with AI systems [37]. Our work complements these findings and introduces a new lens to investigate the metaphorical understanding of users via a cross-domain mapping on different hierarchical metaphors in the context of conversational microtask crowdsourcing.

2.2 Non-human Metaphors and Conversational Agents

To simulate human-human dialogue, prior works related to embodied conversational agents (ECAs) have explored the degree of anthropomorphism and its effect on user trust [17, 20, 102], user satisfaction [55, 83], sympathetic social behavior [34, 99], telepresence [79], and user interaction [14]. A recent study by Kuzminykh *et al.* demonstrated that users consistently perceive such agents based on the agent's anthropomorphized behavioral and visual perceptions [62]. As such, the works mentioned here and most recent research efforts in the HCI community have primarily focused on human representations. However, people's metaphorical understanding of an agent is not solely manifested in a human form [37, 42, 64]. Real-world use cases provide an abundance of clear examples of how users can metaphorically understand an agent when the agent is in non-human form (Figure 1). These examples “provide a provocative contrast with the feminine yet disembodied virtual assistants of today” (e.g., Amazon's Alexa, Apple's Siri) [7].

Lakoff and Turner (2009) adopted the *Great Chain of Being* metaphor and argued that “when the hierarchy of the basic Great Chain is combined [...] we get a more elaborated, hierarchical folk theory of forms of being and how they behave” (p.171 [64]). The authors discussed how the Great Chain of Being metaphor is “a tool of great power and scope” (p.172 [64]) because it explains a tendency of people to comprehend complex concepts, subjects, or objects such as general human traits in terms of well-understood non-human attributes, and vice versa. The extended version of the framework [61] can be represented as illustrated in Figure 2 (b).

GCoB's hierarchical structure implies that entities corresponding to a higher level of the GCoB have all the qualities that the lower levels possess, in addition to their distinct qualities. For example, in the “*A man is a wolf*” metaphor, a human (man) is associated with possessing an animal-like aggressiveness. The GCoB metaphor allows us to project characteristics of well-known or understood from one category onto another. For example, humans can call a glass of red wine “suggestive” or “romantic,” exploiting a higher-order feature to explain its taste or surrounding context. On the other hand, the metaphor “*A lie has no legs*” projects an abstract concept onto a physical trait, implying that a lie has nothing to support it or ‘no legs’ to stand on.

If an entity corresponds to a higher level of the GCoB metaphor, it is unclear whether one would attribute a higher competence to the entity. This is a difficult question to answer since an entity's competence will differ based on the entity's task. For example, a

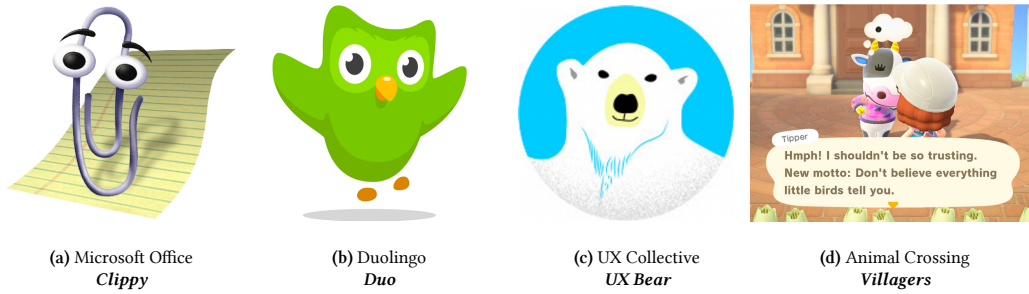


Figure 1: Popular examples of non-human agents employed in different contexts. (a) Clippy used in Microsoft’s Office 97 until Office 2017, (b) Duo, pedagogical agent from Duolingo, (c) UX bear, a chatbot from the UX collective, (d) A Villager in Nintendo’s social simulation game Animal Crossing.

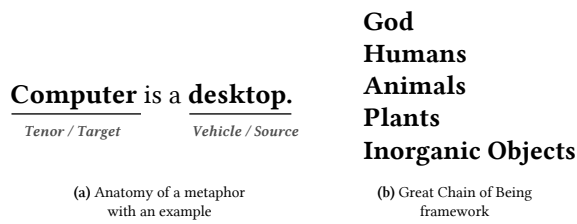


Figure 2: (a) Anatomy of a metaphor with the ‘computer is a desktop’ metaphor, and (b) the Great Chain of Being represented schematically.

wolf will perform better in the task of hunting than an inexperienced graduate student, but the graduate student will be better at writing an academic paper. However, when non-human metaphors are used in a conversational user interface, they speak fluent human language, which anthropomorphizes the non-human agent. Therefore, we can hypothesize that the perceived competency of an agent might correspond to the hierarchy of the GCoB. To this end, the GCoB metaphor can be used as a framework to analyze anthropomorphized conversational agents for their warmth and competence.

Nowak and Biocca reported that when a virtual agent’s image was more unusual and iconic (less anthropomorphic), people got more immersed in the virtual environment and found less anthropomorphic images to be more credible and likable than the more anthropomorphic images [78, 79]. This result poses a question around whether non-human representations of agents –by virtue of being more “iconic”– can immerse users in interacting with them to a greater extent when compared to agents emulating the human form. If so, this can potentially mean that users can feel more engaged while interacting with agents depicted in non-human metaphors or exhibit a higher retention rate due to a greater degree of immersion in their work environment. This, however, remains to be explored, and we empirically address these questions in our work.

Although little research has investigated non-human representations in the context of conversational agents, Nowak and Rauh investigated how people perceive avatars with human, animal, and object forms in terms of their attractiveness and credibility. The

study has shown that more anthropomorphic avatars were perceived as more attractive and credible [80]. In addition, several works in games research and electronic commerce have shown that agent avatars with realistic human-like appearances, but with animal features are perceived as being less attractive [31, 76, 90]. This result is either explained by the “uncanny valley effect” [75] or by the mental schema theory as human-like animals elicit categorization tension, which reflects in lower attractiveness or negative attitude towards the avatar [31]. However, other work has shown that older adults have low telepresence in anthropomorphic avatars in human form while they showed higher attractiveness toward animal avatars [18]. This contrasts the argument that iconic images might induce a stronger sense of immersion. Based on these results, one can argue that anthropomorphized non-human avatars might not fit into the human conceptual understanding, resulting in lower user satisfaction. However, discussion over non-human metaphors in existing literature has not been systematically grounded, and the corresponding exploration has been inconsistent.

Some studies in HCI explored techno-spirituality in the form of design fiction, which also can be called transcendent experiences (TXs). For example, Blythe and Buie presented a few imaginary design fictions as a critical design to the research community to explore possible user reactions to techno-spirituality [11]. Buie further made a game prototype to facilitate the techno-spiritual design that attempts to connect user experience and spiritual experience [15]. Dove and Fayard explored utilizing the ‘*technology as monster*’ metaphor in an early-stage generative design workshop for designers to probe and frame machine learning technology [23]. These studies are relevant to the highest category of ‘*God*’ in the Great Chain of Being that we leverage in this paper.

In summary, we currently lack a clear understanding of how different levels of non-human metaphors can affect user interaction with conversational agents and the potential consequences of using non-human metaphors on user engagement and trust in the agents.

2.3 Conversational Crowdsourcing

Conversational agents have been extensively applied in microtask crowdsourcing. Researchers have used crowdsourcing to aid conversational agents in answering questions [49, 50]. Others have proposed the use of conversational agents to train non-expert crowd workers on picking up domain-specific skills [4]. Crowd-powered

conversational systems have also been proposed to overcome challenges that go beyond existing AI technologies [2, 3]. More recently, conversational agents have been introduced in crowdsourcing marketplaces as an interface to interact with crowd workers [69].

Crowdsourcing work often requires workers to conduct manual human intelligence tasks (HITs), often deployed with similar tasks in large batches [5, 22]. Such repetitive and monotonous tasks risk reducing well-being, creating lower-quality output, and decreasing worker retention [60]. In order to improve worker retention and work quality, Dai *et al.* investigated using “micro-diversions,” a small amount of entertainment in between tasks [19].

In addition, prior work used conversational agents to acquire knowledge from crowd work to construct a knowledge base [13]. Recent studies have also developed a conversational interface to support microtask execution in crowdsourcing marketplaces [69], where workers were redirected to Telegram and completed the microtasks with an agent. Consequently, Qiu *et al.* investigated the effect of conversational interface on worker engagement based on different conversational styles and moods. The study showed that conversational interface improved the perceived worker engagement and significantly higher worker retention [86, 87]. Further investigating worker engagement, authors adopted findings from the games research domain and implemented worker avatars to promote self-identification and enhance intrinsic motivation [84]. Results showed that using worker avatars effectively reduced cognitive workload and increased worker retention.

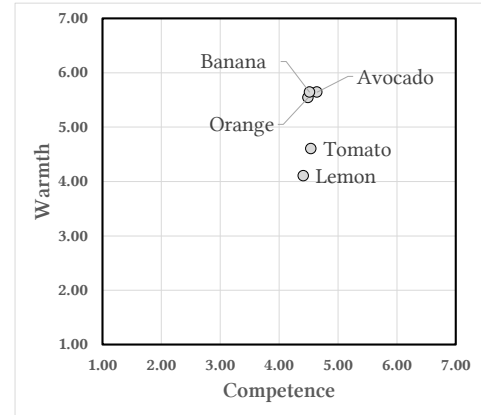
Although prior work has explored avatar customization in crowdsourcing, there is a lack of investigation into how different agent metaphors’ visual representations (agent avatars) impact worker engagement, perceived cognitive workload, and trust. In this work, we design a between-subjects study to comprehensively understand the effects of using different metaphor representations on conversational crowdsourcing.

3 STUDY DESIGN

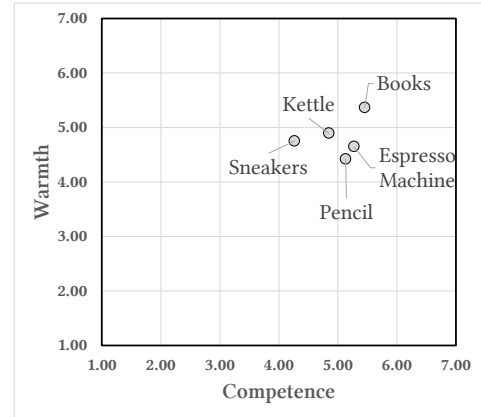
This study aims is to understand how different metaphorical representations could affect workers’ subjective perceptions. Therefore, we conducted a 6×2 between-subject experiment to investigate the effect of metaphorical representation of conversational agents on worker engagement, perceived cognitive load, enjoyment, and trust based on the crowdsourcing platform Prolific. Workers were asked to converse with a chatbot with one of six agent representations consisting of five metaphors derived from the Great Chain of Being — God, Human, Animal, Plant, Inorganic Object, and a Control condition with no representation (cf. Figure 4). Workers were also randomly assigned to one of two distinct tasks — image classification tasks and information finding tasks (cf. Figure 5), resulting in 12 experimental conditions [30].

3.1 Preliminary Study: Metaphor Sampling and Selection

Previous studies that investigated the impact of users’ perception on AI systems reported a clear difference in how users react to the system based on perceived warmth and competency of the system [37, 56]. Therefore, instead of using random metaphors, we chose metaphors that manifest similar degrees of warmth and



(a) Plant metaphors



(b) Object metaphors

Figure 3: Scatter plots showing the average warmth and competence for the measured metaphors for Inorganic Object and Plant.

competency. High warmth and high competency were reported to ensure a positive attitude toward the system [37, 56]. Therefore, being aware of the trade-off that high-competency might elicit lower intention to adapt to the system [35, 37, 56], we decided to unify the warmth and competency metaphors across conditions.

Therefore in this study, we used five different metaphors for each variable from the five levels of the Great Chain of Being apart from the Control condition. As a previous study from Khadpe *et al.* [56] drew upon, the Stereotype Content Model (SCM) [27] was used to sample metaphors coherently. In addition, we decided to use results from previous literature on human and animal metaphors that were reported to correspond to high-warmth and high-competence. As a result, we chose “dog” as a metaphor to represent an Animal agent [93] and “trained professional” as a metaphor to represent a Human agent [56]. We decided not to sample a specific metaphor for God but to represent it plainly as “God” since different representations of God can have socio-cultural and religious connotations that might inadvertently affect participants’ perception and behavior [105].

To decide the Plant and Inorganic Object metaphor with high-warmth and high-competence, we conducted two pre-tests on Plant and Inorganic Object on Prolific.⁶ We recruited workers with an approval rate of over 90% and who speak English as their native language to ensure quality results. Based on prior literature on human perception of warmth and competence [8], the authors of this paper (who were the experts in the related field) selected a sample of 5 candidate metaphors for each category (Plant and Inorganic Objects) that were deemed to exhibit high warmth and high competence. We chose avocado, banana, lemon, tomato, and orange for the Plant metaphor. Moreover, we chose book, espresso machine, kettle, pencil, and sneakers for the Object metaphor.

Next, we deployed a study on a crowdsourcing platform in which we asked crowd workers to rate the perceived warmth and competence of 5 candidate metaphors for each category (Plant and Inorganic Objects, respectively) using 7-point Likert scales. Workers were asked to respond to 22 questions (10 questions for each category and 2 attention check questions to ensure reliability). All items (including the attention check questions) were randomized in the questionnaire. We paid workers on average an hourly wage of GBP £12.19. Finally, we collected 100 responses for both categories (Plant and Inorganic Object) and filtered out responses from workers who failed to pass at least one of the two attention check questions. This left us with 97 valid responses corresponding to the Inorganic Object category and 98 valid responses for the Plant category.

As shown in Figure 3, our results demonstrate that the chosen metaphors were in the high-warmth and high-competence categories on average. Based on these findings, we chose Avocado to represent the Plant metaphor (cf. Table 1) and Book to represent the Inorganic Object metaphor (cf. Table 2). These were reported to exhibit the highest perceived warmth and perceived competence among the subjects considered in the preliminary study. Table 3 shows our final selection of metaphors to represent each Great Chain of Being category.

Table 1: Warmth and competence values (average \pm standard deviation) corresponding to Plants in the preliminary study.

	Avocado	Tomato	Banana	Orange	Lemon
Competence	4.64 \pm 1.63	4.54 \pm 1.60	4.52 \pm 1.67	4.49 \pm 1.58	4.41 \pm 1.61
Warmth	5.64 \pm 1.44	4.60 \pm 1.72	5.64 \pm 1.34	5.54 \pm 1.58	4.10 \pm 1.90

Table 2: Warmth and competence values (average \pm standard deviation) corresponding to Inorganic Objects in the preliminary study.

	Books	Sneakers	Kettle	Espresso machine	Pencil
Competence	5.45 \pm 1.58	4.26 \pm 1.80	4.85 \pm 1.62	5.27 \pm 1.56	5.13 \pm 1.55
Warmth	5.36 \pm 1.41	4.75 \pm 1.66	4.90 \pm 1.64	4.65 \pm 1.68	4.42 \pm 1.70

Although the SCM framework has been highly influential and has been repeatedly adopted in previous literature, it has received

⁶<https://www.prolific.com>

Table 3: Six experimental conditions to represent different metaphors based on the Great Chain of Being (informed by the preliminary study), including a Control condition to help analyse the impact of these metaphorical representations of the agent.

#	Category	Selected Metaphor
1	God	God
2	Human	Trained Professional
3	Animal	Dog
4	Plant	Avocado
5	Inorganic object	Book
6	Control	No representation

criticism for inconsistent operationalization of both SCM dimensions: two factors of warmth and competence [12, 43]. To reduce such concern, we used the recent study conducted by Halkias and Diamantopoulos that suggested a more accurate and consistent operationalization of measuring warmth and competence [43]. In addition, one might be concerned about using the SCM on subjects like plants or animals. Nevertheless, previous studies, notably from the consumer psychology domain, have demonstrated that the perceived warmth and competence of non-human entities can be reliably measured using a Likert scale [1, 38].

3.2 Microtask Design

We chose the two task types of Information Finding and Image Classification, covering two data types (text and images). These task types are prevalent in microtask crowdsourcing marketplaces [22, 30] and have been the subject of recent research. Participants were assigned to a single experimental condition on one of these task types, with one of the six different agent metaphors. Therefore, our study resulted in 12 experimental conditions (2 task types \times 6 agent metaphors). Previous studies in conversational microtask crowdsourcing employed agents and designed conversations that had no direct relation to the task at hand (e.g., Information Finding task of finding restaurants, and Image Classification task with classifying animal species) [86]. In this work, however, we argue that a metaphorical understanding can be further acquired by demonstrating the characteristics and traits of the metaphor through explicit conversation and not only limiting this to a visual representation through an agent avatar, for example, by explicitly conveying that avocado is nutritious, and that a book relates to knowledge through a well-defined narrative. This design choice ensures that users conversing with the conversational agent can fully experience the metaphor of the agent. Therefore, we used the same topic, a task related to a bird, in both task conditions to unify the narrative between each agent and the task that users are asked to execute. Workers from both task conditions, either Image Classification or Information Finding tasks, are required to look and think about birds and listen to the same narrative from a metaphor agent that they are talking to (e.g., “*God created different shapes of bird, and the God is asking you to either find information about birds or classify images about birds.*”).

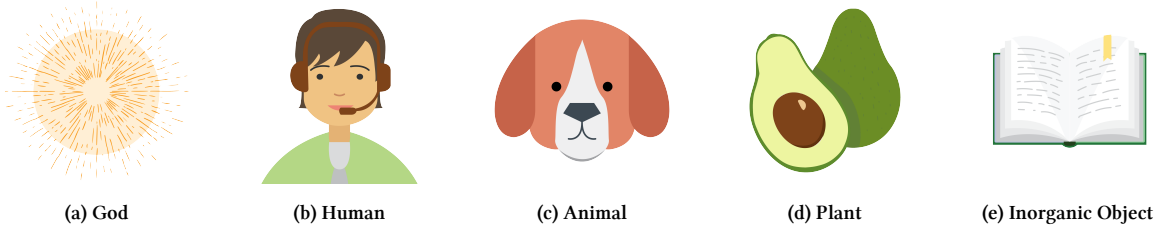


Figure 4: Conversational agent avatars to visually represent the five different metaphors.

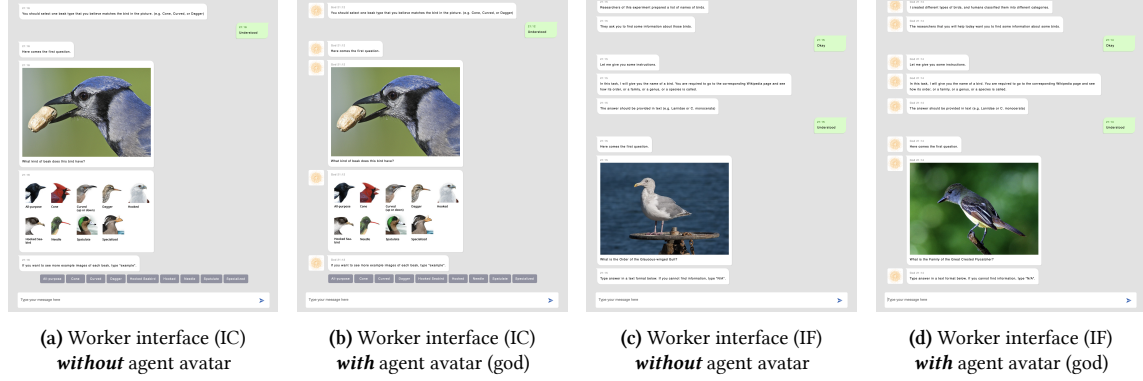


Figure 5: The comparison of conversational interfaces with and without agent avatar, and between two microtask types.

We decided to use Caltech-UCSD Birds 200 Dataset [100], an image dataset comprising 200 bird species with annotations. Each task comprised a total of 36 questions about 36 different birds. Participants could answer as many questions as they wished to, and they were free to leave whenever they wanted to, after completing of 10 mandatory tasks.

(1) *Information Finding (IF) Task*. Workers were asked to find either an Order, a Family, a Genus, or a Species of a given bird on Wikipedia (cf. Figure 5 (c),(d)). These information finding tasks are based on the taxonomic classification system of birds. The Class is divided into Orders; the Orders are composed of Families; the Families are divided into Genera, and the Genera are composed of distinct Species.

(2) *Image Classification (IC) Task*. Workers were asked to analyze images of birds and to classify the shape of their beak, also called ‘a bill’ (cf. Figure 5 (a) and (b)). This task was adapted from a previous study by Wah C. *et al.* [100]. We added images of 10 birds that were not included in the Caltech-UCSD Birds 200 dataset for this task to balance the number of birds across nine distinct categories of beaks sampled for the set of 36 tasks, a criterion that was difficult to fulfill with the existing dataset. The IC task was chosen to ensure that different data types were tested in the study — text for IF tasks and images for IC tasks — because previous studies revealed different UES-SF results between image-based tasks and text-based tasks [86]. In addition, IC tasks are one of the most common task types prevalent on crowdsourcing platforms. Since conversational interfaces that are HTML-based (e.g., TickTalkTurk [88]) can be

easily ported from traditional web interfaces, it will be interesting to see the impact of the IC tasks presented in a conversational style.

3.3 Agent Avatar Design

As shown in Table 3, we selected six metaphors to represent the conversational agent. We decided not to visualize the Control condition to avoid any visual bias that might affect the participant’s impression of the agent. In addition, previous research conducted within conversational crowdsourcing has tested interfaces without agent metaphors, and their result can serve as a baseline to interpret our treatment conditions [84, 86]. Next, we designed five avatars to represent the different metaphors (Figure 4). The Naturalism-stylization framework is one that designers can decide on in the virtual agent visualization [40, 42]. We used stylized visuals for our agent because they have been reported to affect users’ interactions positively. Stylized pedagogical agents are more likely to be chosen by female students [42]. Also, stylized e-commerce agents are reported to produce a higher social perception of an agent, perceived website social presence, and perceived website social support compared to an agent with naturalistic visualization [97].

3.4 Worker Interface

The conversational interface was built using TickTalkTurk [88], a Web-based application that is created with HTML, CSS, and Javascript. For Control conditions, no avatars were displayed to prevent bias from participants (Figure 5 (a) and (c)). The interface

Table 4: Conversation template for the metaphor conditions, with excerpts demonstrating variations in narratives across the conditions. The complete conversational template is available at our companion web page: <https://sites.google.com/view/agent-metaphors>.

	Opening greetings	Agent Narrative
God	Greetings, I am the lord thy god. You shall help researchers at a university by participating in this research. So I ask you, does this sound good to you?	I created different types of birds, and they all have different shapes of beaks.
Human	Hello, pleasure to meet you! I'm a trained professional who will guide you here. Researchers in a university asked me to facilitate this research. Does this sound good to you?	They (researchers) asked me to help you because I am trained for helping people like you!
Animal	Woof woof, nice to meet you! I'm a dog that will help you conduct this research (...)	They asked me to help you because I am super good at finding stuff!
Plant	Hello, nice to meet you! I'm an avocado that will help you conduct this research (...)	They asked me to help you because I'm full of healthy nutrition and I can nourish you throughout this task.
Inorganic Object	Hello, nice to meet you! I'm a book that will help you conduct this research (...)	They asked me to help you because I'm full of information and knowledge.
Control	Hello! Can you help researchers in a university by conducting this research?	N/A

displayed the agent avatar next to the text bubble of the agent's dialogue with five other metaphors.

Workers could answer microtask questions in two different input types: free text and multiple-choice. Free text input required workers to answer questions by typing and sending them to the conversational agent as a chat interface message. Multiple choice input allows workers to choose one answer using customized radio buttons. We employed multiple choice options for IC tasks and free text for IF tasks. After the microtasks, workers were asked to move to a Google Forms page to complete post-task surveys.

3.5 Conversation Design

All the metaphor conditions shared the same structure and order in dialogues. However, different words and vocabularies are used to enhance the experience of workers interacting with the metaphor. Table 4 highlights dialogue excerpts that showcase the variation in conversation templates between the metaphors. The complete conversation template can be found on our companion web page.⁷

While designing the conversation, we ensured that the agent acted as a "moderator" of the task to make the narrative consistent across all metaphors. Therefore the agent asked workers if they would like to help the researchers rather than the agents themselves. If agents were not a moderator and intended to ask specific tasks to a worker (e.g., that a dog wants to hunt or that a book is missing information), it might affect participants' perception of the task and bias their responses.

However, we still had to embody an experiential aspect of a specific metaphor. Therefore, we explained why the agent became a moderator by raising their characteristics and attributes. After

they received the task instructions, this narrative was presented to workers (Table 4).

3.6 Measures

The dependent variables of our experiment are worker engagement, task load, enjoyment, and trust.

Worker Engagement is measured using a short form of the User Engagement Scale (UES-SF) [81], which is a scale that measures self-reported user engagement.

Enjoyment is measured using the Intrinsic Motivation Inventory (IMI) [71], an instrument that measures participants' subjective experience on the target activity. IMI has been widely adopted in research and has been validated in different contexts [66, 70]. We adopted a relevant subset of the IMI to reduce the number of post-task questions that we asked workers to respond to. We covered two dimensions of the IMI, spanning 10 questions that were most relevant to our research: Interest-Enjoyment (INT-ENJ) and Perceived Competence.

Cognitive Task Load is measured with the NASA-TLX questionnaire [47, 48]. Through this measure, we investigate any significant difference in perceived cognitive load between agent metaphors.

Trust is measured through the Trust in Automation (TiA) questionnaire [54, 59]. As we did with the IMI questionnaire, we used a relevant subset of TiA to limit the post-task questions that workers were asked to complete. We selected *Propensity to Trust* and the *Trust in Automation* dimensions, which spanned 5 questions in total. TiA is a validated questionnaire [59] that has been widely used to measure trust in human-AI interaction [98, 102].

Moreover, other measures such as task execution time and output accuracy are also recorded for evaluating worker performance and behavior.

⁷<https://sites.google.com/view/agent-metaphors>

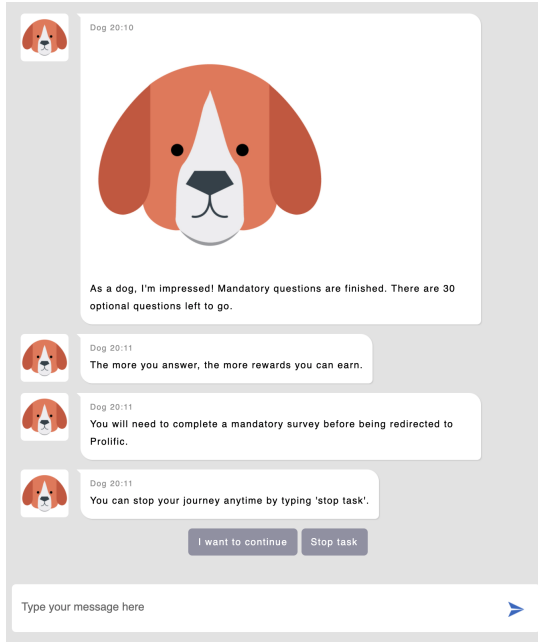


Figure 6: The conversational agent (Animal metaphor) reminding workers that they can stop after 10 mandatory tasks. This message was shown either every 10 tasks (IC) or 5 tasks (IF) based on a priori estimated task completion time for each task type.

3.7 Participants

We recruited workers from the Prolific crowdsourcing platform. To avoid potential biases, workers who participated in the preliminary study were not allowed to partake in this main study. We recruited workers who speak English as their first language and whose approval rates were greater than 93%. Workers were not allowed to accept and execute the task multiple times and were randomly assigned to one of twelve conditions (6 agent representations \times 2 task types). We compensated workers GBP £1.13 (USD \$1.6) and GBP £1.88 (USD \$2.6) for Image Classification and Information Finding tasks, respectively. Furthermore, we rewarded workers 4 pennies for answering each optional question. As a result, workers received an hourly wage of £6.5 on average (USD \$9.0 / hour).

A power analysis using G*Power [26] indicated that a minimum sample size of 27 participants for each group is needed. Therefore, we recruited 360 unique workers to account for potential participant exclusion in our analysis. We excluded 19 workers who failed to correctly answer one or more of the four attention check questions. Therefore, we only consider responses from 341 workers for further analysis.

3.8 Experimental Setup and Procedure

First, workers were redirected to the conversational interface we designed. Here, workers were asked to complete 10 mandatory microtasks. After workers completed the mandatory tasks, the conversational agent notified them that the mandatory session was finished and that they could continue with optional questions. At

this stage, a bigger size image file of the agent avatar was displayed on the screen to reinforce the agent metaphor that they were interacting with (Figure 6). This break message is induced after 10 consecutive questions in the Image Classification task and 5 in the Information Finding task. The different interval between task types was based on a task completion time we measured a priori to the experiment. We decided to design this micro-diversion to prevent fatigue and boredom of workers based on prior work [19, 89], inform workers on the number of optional questions left, and remind them that they could stop anytime they wished.

After workers finished completing tasks, they were redirected to the survey page based on Google Form.⁸ They were asked to answer the 5-point Likert scale of the User Engagement Scale Short Form (UES-SF), the NASA Task Load Index form (NASA-TLX), a subscale of Intrinsic Motivation Inventory (IMI) form, and a subscale of Trust in Automation form (TiA). Lastly, workers answered one demographic question about educational background. The ethics committee of our institute has approved this study.

4 RESULTS

4.1 Worker Demographics

Among 341 unique workers, 61.5% were female, and 38.5% were male. 62.9% of workers were under 29 years old, 38.2% between 30 and 49, and 4.1% over 50. In addition, 64.5% of the workers reported that they received higher than Bachelor's degree in educational level.

4.2 Worker Engagement

According to the normality test (Shapiro-Wilk tests, $\alpha = 0.05$), UES-SF scores did not come from a normal distribution. Therefore we conducted the Kruskal-Wallis test to check statistical differences across different conditions. The distributions of UES-SF scores are shown in Figure 7 using boxplots, while the mean values and standard deviations in all the dimensions are reported in Table 5. The detailed statistical report can be found in Appendix A.

A Kruskal-Wallis test revealed that different metaphorical representations significantly affect the overall UES-SF score, the Perceived Usability, and Aesthetic Appeal subscales. We thereby conducted a post-hoc analysis using Mann-Whitney U tests using a Bonferroni-adjusted alpha level of .008 (0.05/6) to compare all pairs of metaphors. For the overall UES-SF score, the Object metaphor (Book) received a significantly lower score than the Animal metaphor (Dog). Moreover, the Aesthetic Appeal of the Book metaphor was significantly lower than the Dog metaphor.

Afterward, each metaphor was compared with the Control condition. As post-hoc Kruskal Wallis tests with Bonferroni corrected alpha values revealed that the Perceived Usability of the Control condition was significantly higher than the God metaphor. In addition, we found that the Perceived Usability of the Control condition without any agent metaphors was significantly higher than the agents with metaphorical representations.

We exploratively looked at the difference in UES-SF score between two task types. Mann-Whitney test revealed a significant

⁸<https://www.google.com/forms/about/>

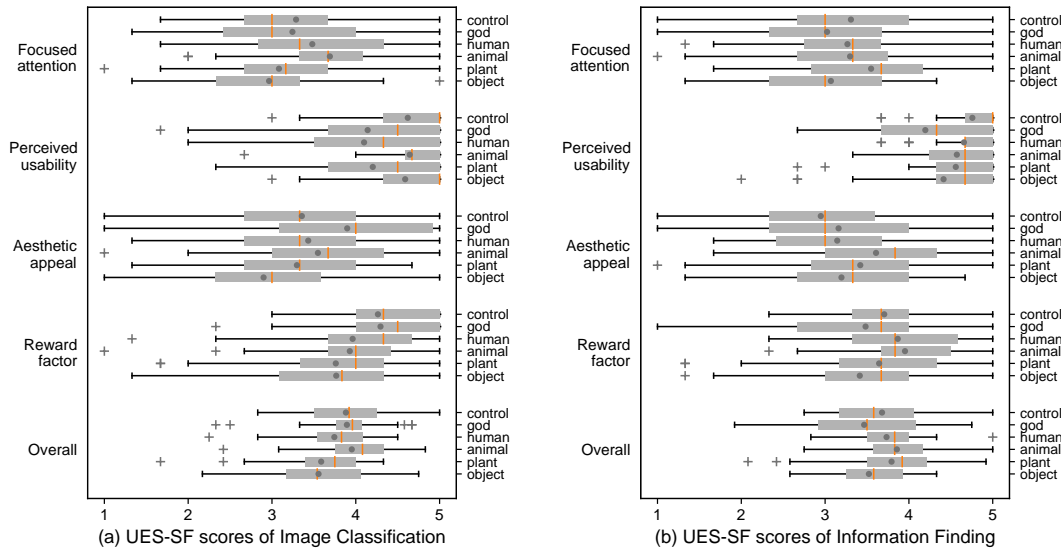


Figure 7: Boxplots showing worker engagement measured by UES-SF, where red lines represent medians and black points represent mean values.

Table 5: The UES-SF score ($\mu \pm \sigma$: mean and standard deviation) of all task types with six metaphor conditions.

	Control	God	Human	Animal	Plant	Object	Overall
Image Classification							
Focused Attention	3.29 \pm 0.86	3.24 \pm 1.15	3.48 \pm 1.01	3.69 \pm 0.75	3.08 \pm 0.85	2.97 \pm 0.90	3.29 \pm 0.94
Perceived Usability	4.62 \pm 0.59	4.14 \pm 1.03	4.10 \pm 1.02	4.64 \pm 0.50	4.20 \pm 0.89	4.59 \pm 0.58	4.39 \pm 0.81
Aesthetic Appeal	3.36 \pm 1.09	3.90 \pm 1.12	3.43 \pm 0.87	3.55 \pm 0.90	3.30 \pm 0.94	2.90 \pm 1.03	3.39 \pm 1.03
Reward Factor	4.26 \pm 0.67	4.29 \pm 0.73	3.96 \pm 0.88	3.93 \pm 0.87	3.76 \pm 0.93	3.77 \pm 0.88	3.99 \pm 0.85
Overall	3.88 \pm 0.54	3.89 \pm 0.56	3.74 \pm 0.52	3.95 \pm 0.54	3.59 \pm 0.60	3.56 \pm 0.63	3.77 \pm 0.58
Information Finding							
Focused Attention	3.31 \pm 1.02	3.02 \pm 0.98	3.27 \pm 0.89	3.30 \pm 1.08	3.55 \pm 0.94	3.07 \pm 0.84	3.25 \pm 0.96
Perceived Usability	4.76 \pm 0.42	4.20 \pm 0.80	4.66 \pm 0.42	4.57 \pm 0.49	4.56 \pm 0.59	4.41 \pm 0.82	4.52 \pm 0.63
Aesthetic Appeal	2.95 \pm 1.14	3.16 \pm 1.15	3.14 \pm 0.88	3.61 \pm 1.02	3.42 \pm 1.00	3.20 \pm 0.82	3.25 \pm 1.01
Reward Factor	3.71 \pm 0.74	3.48 \pm 1.15	3.87 \pm 0.78	3.95 \pm 0.75	3.65 \pm 1.04	3.41 \pm 0.90	3.68 \pm 0.92
Overall	3.68 \pm 0.60	3.47 \pm 0.73	3.73 \pm 0.49	3.86 \pm 0.53	3.79 \pm 0.71	3.52 \pm 0.53	3.68 \pm 0.61

difference in the Reward Factor dimension. Reward Factor in Image Classification task ($Md = 4.00$, $n = 168$) was significantly higher than the Information Finding task ($Md = 3.67$, $n = 173$), $U = 11336.00$, $z = -3.543$, $p < .001$, with small effect size $r = .19$.

Summary: Animal (Dog) received a significantly higher overall UES-SF and Aesthetic Appeal subscale score than the Object (Book), while no significant difference was found in the Perceived Usability subscale. Perceived Usability for God was significantly lower than the Control condition.

4.3 Intrinsic Motivation

According to the normality test (Shapiro-Wilk tests, $\alpha = 0.05$), IMI scores did not come from a normal distribution. We, therefore, conducted the Kruskal-Wallis test to find statistical differences across different conditions. Worker IMI scores are shown in Figure 8 with boxplots, and the mean values and the standard deviation are reported in Table 6. The detailed statistical report can be found in Appendix B.

After conducting a Kruskal-Wallis test, we found a statistically significant difference in the Interest-Enjoyment dimension between at least two metaphor groups. Therefore, the Man-Whitney tests with a Bonferroni-adjusted alpha level of .008 (0.05/6) were conducted between different conditions. We consistently found that

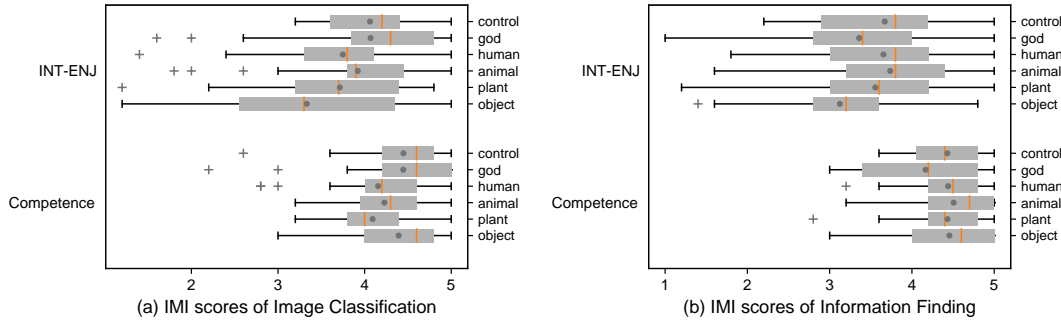


Figure 8: Boxplots showing worker intrinsic motivation measured by IMI, where red lines represent medians and black points represent mean values.

Table 6: The IMI score ($\mu \pm \sigma$: mean and standard deviation, unit: the number of optional question answered) of all task types with six metaphor conditions.

	Control	God	Human	Animal	Plant	Object	Overall
Image Classification							
Interest-Enjoyment	4.06 ± 0.55	4.07 ± 0.97	3.75 ± 0.79	3.92 ± 0.83	3.71 ± 0.81	3.33 ± 1.16	3.80 ± 0.90
Competence	4.45 ± 0.56	4.45 ± 0.66	4.16 ± 0.62	4.23 ± 0.50	4.09 ± 0.51	4.39 ± 0.55	4.30 ± 0.58
Information Finding							
Interest-Enjoyment	3.67 ± 0.90	3.36 ± 1.02	3.65 ± 0.82	3.74 ± 0.87	3.55 ± 0.97	3.12 ± 0.77	3.51 ± 0.91
Competence	4.43 ± 0.45	4.17 ± 0.67	4.44 ± 0.50	4.51 ± 0.56	4.43 ± 0.50	4.46 ± 0.59	4.40 ± 0.55

the Object (Book) metaphor received a lower Interest-Enjoyment score than any other metaphor. Especially, Interest-Enjoyment for the Object (Book) was significantly lower than the Human (Trained Professional), Animal (Dog), and the Control condition. Although not statistically significant, Object (Book) still received a notably lower score than the God and the Plant (Avocado) metaphors after the Bonferroni correction.

According to the Mann-Whitney test, there was a significant difference in Interest-Enjoyment dimension between two different task types. Image Classification ($Md = 4.00$, $n = 168$) scored higher than the Information Finding ($Md = 3.60$, $n = 174$), $U = 11508.00$, $z = -3.331$, $p = .001$, with a small effect size $r = .18$.

Summary: Overall, the Inorganic Object metaphor (Book) relates to lower interest-enjoyment than other conditions. In addition, the Image Classification task received a higher interest-enjoyment score than the Information Finding task.

4.4 Perceived Cognitive Task Load

According to the normality test (Shapiro-Wilk tests, $\alpha = 0.05$), TLX scores did not come from a normal distribution. We, therefore, conducted the Kruskal-Wallis test to find statistical differences across different conditions. The distributions of overall TLX scores are shown in Figure 9. The mean values and standard deviations of TLX scores in each dimension are reported in Table 7. The detailed statistical report can be found in Appendix C.

A Kruskal-Wallis test revealed a statistically significant difference between at least two metaphor groups concerning the overall TLX score. Therefore, we conducted post-hoc Mann-Whitney tests using Bonferroni-adjusted alpha level of .008 (0.05/6). Consistent with the IMI result, the Object (Book) metaphor resulted in a lower perceived task load in comparison to the God, Human (Trained Professional), and Plant (Avocado) metaphors with a statistically significant difference. The cognitive load for the Control condition was significantly lower than the God metaphor.

According to the Mann-Whitney test, image classification task received a significantly higher score than the information finding task in overall TLX score, IC: $Md = 25.00$, $n = 168$ | IF: $Md = 16.67$, $n = 173$ | $U = 11462.50$, $z = -3.384$, $p = .001$, small effect $r = .18$.

Summary: Results show that the Inorganic Object metaphor (Book) corresponds to a lower cognitive load. The perceived cognitive load corresponding to the God metaphor was significantly higher than the Control condition.

4.5 Trust

Trust score was not normally distributed (Shapiro-Wilk tests, $\alpha = 0.05$). Therefore we conducted the Kruskal-Wallis test and found no significant difference in dimensions of Trust in Automation (TiA) scales across different metaphor conditions and between task types (Table 18). Also, no difference was found between Control conditions and conditions with metaphor representation. Table 8 shows the unweighted TiA score of the two dimensions we used,

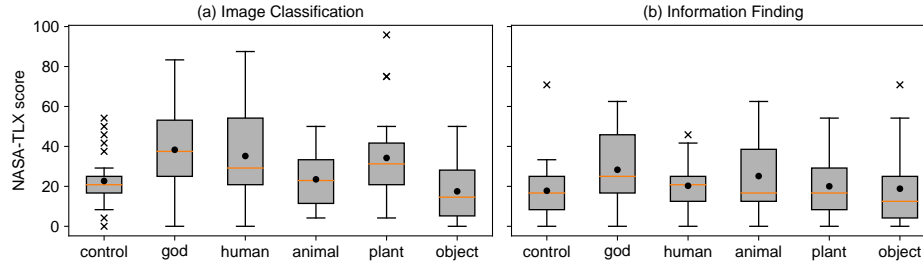


Figure 9: Boxplots showing perceived cognitive task load measured by NASA-TLX, where red lines represent medians and black points represent mean values.

Table 7: The NASA-TLX score ($\mu \pm \sigma$: mean and standard deviation, unit: the number of optional question answered) of all task types with six metaphor conditions.

	Control	God	Human	Animal	Plant	Object	Overall
Image Classification	22.70 \pm 12.82	38.30 \pm 20.45	35.19 \pm 23.35	23.51 \pm 13.28	34.23 \pm 20.71	17.50 \pm 14.70	28.25 \pm 19.23
Information Finding	17.79 \pm 14.79	28.30 \pm 20.15	20.28 \pm 11.77	25.15 \pm 17.77	20.03 \pm 14.65	18.82 \pm 17.35	21.75 \pm 16.46

and Figure 10 shows the TiA score across six metaphor conditions in two task types. The detailed statistical report can be found in Appendix D.

Summary: We found no significant differences in trust across the different metaphorical representations and task types.

4.6 Output Accuracy and Task Execution Time

In this study, we also measured output accuracy and active task execution time to understand worker performance. According to the normality test (Shapiro-Wilk tests, $\alpha = 0.05$), results of worker performance did not come from normal distributions. The distributions of worker performance measures are shown in Figure 11. We found no significant result in output accuracy and task execution time between different metaphors. The detailed statistical report can be found in Appendix E.

Summary: We found no statistically significant difference in output accuracy and task execution time across different metaphorical representations, control conditions, and task types.

5 DISCUSSION

Metaphorical understanding of agents has been identified as a potential explanation for how users expect a system to behave and how users react to the system [56]. While discussion within the HCI community has primarily focused on human and anthropomorphic representations, agents with non-human representation are abundantly used in the real world despite a lack of complete understanding of their effects. Although such a tendency to apply non-human metaphors to agents can be explained by the desire to create a particular impression of the system, few works have

explored the impact of non-human metaphor agents. This lack of attention is partly due to anthropomorphism shown to affect and enhance user interest, engagement, and credibility towards the agent [58, 80, 102, 103]. However, some studies have shown that anthropomorphic images are perceived as less credible and likable [78]. Moreover, when the degree of anthropomorphism in an image inversely matched the system’s ability, people’s perception of the system deteriorated [35].

Although few studies investigated the impact of a virtual agent with animal and inorganic representations [18, 31, 76, 80], they have not been grounded in the Conceptual Metaphor theory but rather within the context of manipulating the degree of anthropomorphism. Therefore, a more systematic approach is needed to understand the non-human agent representation based on the Conceptual Metaphor theory. Hence, we borrowed the Great Chain of Being framework to understand the effect of a range of hierarchical cross-species metaphors. In this paper, we carried out an experimental study to understand the impact of different agent metaphors based on the Great Chain of Being framework in the context of conversational crowdsourcing.

Our findings suggest the absence of a consistent trend across different agent metaphors regarding their impact on the considered dependent variables and the task types. Nonetheless, the Object (Book) metaphor generated the most significant difference with other conditions. For example, the Animal (Dog) metaphor resulted in a higher worker engagement and a higher cognitive task load than the Object metaphor. In contrast, the Inorganic Object (Book) metaphor, which is the lowest level in the hierarchical Great Chain of Being framework, stood out in its effect on lowering the perceived cognitive load of the workers, yet impairing workers’ interest and enjoyment while conducting the tasks. Similarly, the Image Classification task resulted in a higher Reward Factor (UES) and Interest-Enjoyment scale (IMI) than the Information Finding task, but cost more cognitive task load. This contrasts previous findings that when workers are more engaged with work, they

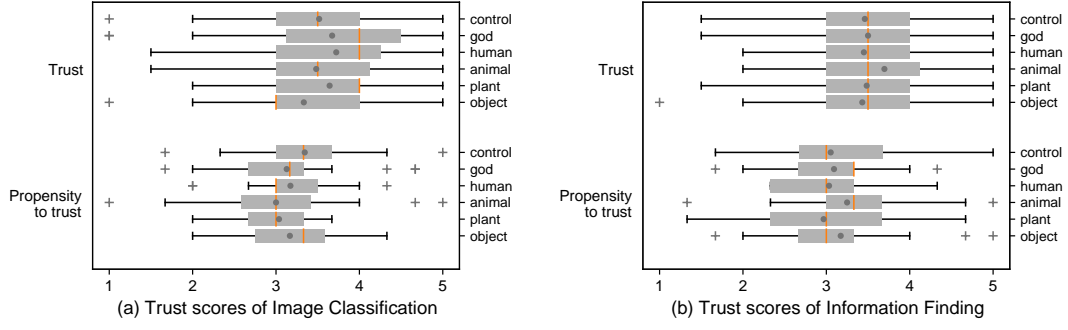


Figure 10: Boxplots showing worker trust measured by Trust in Automation, where red lines represent medians and black points represent mean values.

Table 8: The TiA dimension score ($\mu \pm \sigma$: mean and standard deviation, unit: the number of optional question answered) of all task types with six metaphor conditions.

Metaphors	Control	God	Human	Animal	Plant	Object	Overall
Image Classification							
Trust	3.52 ± 1.02	3.67 ± 1.16	3.72 ± 0.92	3.48 ± 1.00	3.64 ± 0.78	3.33 ± 0.93	3.56 ± 0.97
Propensity to Trust	3.34 ± 0.69	3.13 ± 0.74	3.17 ± 0.55	3.00 ± 0.90	3.04 ± 0.45	3.17 ± 0.55	3.14 ± 0.66
Information Finding							
Trust	3.46 ± 0.85	3.50 ± 0.93	3.45 ± 0.75	3.70 ± 0.82	3.48 ± 0.83	3.43 ± 0.90	3.50 ± 0.84
Propensity to Trust	3.05 ± 0.79	3.09 ± 0.62	3.03 ± 0.59	3.25 ± 0.76	2.97 ± 0.84	3.17 ± 0.74	3.09 ± 0.72

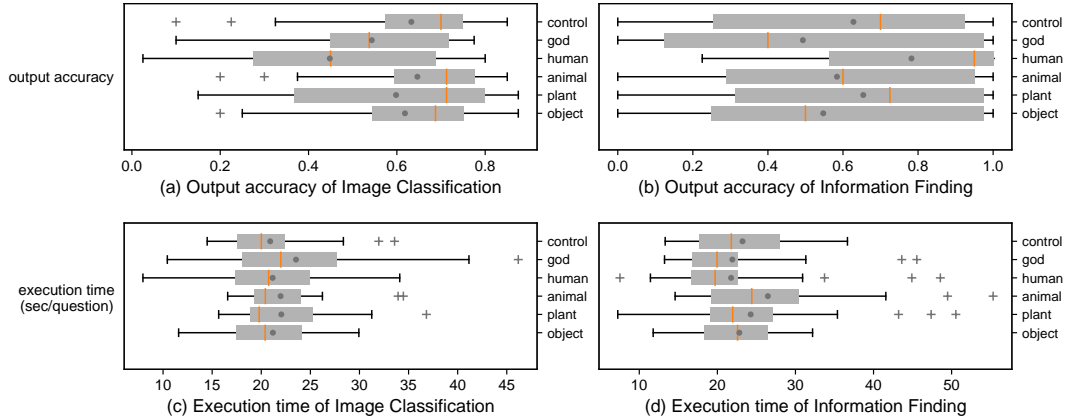


Figure 11: Boxplots showing workers' output accuracy and active task execution time, where red lines represent medians and black points represent mean values.

perceive less cognitive load [84, 106]. We could potentially explain this variance that the Animal (Dog) metaphor dragged workers' attention more towards the agent than the task at hand, and cost workers' working memory. Exploring the exact mechanism behind it is a promising research opportunity.

Contrary to our understanding informed by previous work [58, 80, 102, 103] that the Human (Trained Professional) metaphor will enhance engagement, intrinsic motivation, and trust in the context of crowd work, our result shows that the Human metaphor had

no significant difference over non-human metaphors. The Human metaphor showed significantly higher Interest-Enjoyment than the Object metaphor, but its effect was smaller than the Animal and Control condition. In addition, it resulted in a higher cognitive load than the Object metaphor with a statistically significant difference. This result can be potentially explained by the findings of Garau *et al.*, where authors showed that when agent representation does not meet users' expectations of a system, this hampers user perception

Table 9: A table with a summarized view of significant results. Results that are considered more positive are colored in light blue, while negative results are colored in light red. Trust and Accuracy measurements were omitted since they did not vary significantly across the experimental conditions.

	User Engagement Scale	Perceived Usability (UES)	Aesthetic Appeal (UES)	Interest-Enjoyment (IMI)	Cognitive Load
God	-	↓ than Control	-	-	↑ than Object, Control
Human	-	-	-	↑ than Object	↑ than Object
Animal	↑ than Object	-	↑ than Object	↑ than Object	-
Plant	-	-	-	-	↑ than Object
Object	↓ than Animal	-	↓ than Animal	↓ than Human, Animal, Control	↓ than God, Human, Plant
Control	-	↑ than God	-	↑ than Object	↓ than God

of the system. Since our task design used a relatively simple conversational agent with limited ability, this may have caused workers to be disappointed with the system’s actual ability [35].

The God metaphor, the highest level in the hierarchical Great Chain of Being framework, consistently resulted in a higher cognitive task load than the Control condition and the lowest level in the framework — Inorganic Object (book). Also, the God metaphor resulted in a lower Perceived Usability than the Control condition without an agent metaphor. This can be related to the previous finding that supports contrast theory [95]; users’ higher expectations of the system capability can lead to disappointment when said expectations are not met, leading to lower satisfaction [67]. Users are less forgiving of lower performance and more willing to adapt to the system when interacting with metaphors of a higher competence [56]. Moreover, workers’ lower engagement and higher cognitive task load observed in the condition with the God metaphor can also be explained via the lens of worker autonomy. Previous studies argued that the autonomous nature of crowd work is a prime motivator for crowd workers [16, 53]. Therefore, the God metaphor instructing workers to do tasks may have appeared to violate their agency, which could have lowered their engagement and thereby increased the perceived cognitive load. In addition, the God metaphor impairing worker experience can also be explained that the God may exhibit high competency but arguably conveys low warmth in our experiment setting.

In this study, we found no significant difference in trust across the different metaphorical representations of the conversational agent. This contrasts a previous study conducted in the domain of explainable artificial intelligence (XAI) within the speech recognition context, where an embodied agent (in human form) that was used to explain system behavior resulted in a higher user trust in the system [102]. However, this could be possibly explained by the fact that the study mentioned above was conducted with a multi-modal human agent in a face-to-face interaction context, while our study only represented the agent in a graphical avatar with textual interaction.

We found that some of our experimental conditions with different metaphorical agent representations showed no significant improvement in interest and enjoyment, trust, and cognitive load compared to the Control condition. This contrasts with a previous finding from conversational crowdsourcing research that allowing workers to customize their avatars while conversing with a Human agent led to a higher worker engagement and lower cognitive load [84]. Our result shows that worker engagement is only improved when workers deploy self-identified avatars in crowdsourcing, while the

agent they interact with does not affect. We wonder if this result was due to the lack of autonomy that workers could manifest as the mentioned work allowed workers to customize their avatars. Future work can explore the potential of facilitating the customization of agent metaphors or aligning agent metaphors according to worker preferences.

5.1 Design Implications for HCI

Using an agent metaphor that locates higher than Human in the Great Chain of Being framework may disappoint workers in the system’s ability due to high expectations, leading to a lower engagement and a higher perceived cognitive task load. We found that the Human metaphor in the crowdsourcing context did not show overpowering benefits compared to the Animal (Dog) metaphor or a Control condition without any representation in enhancing engagement and intrinsic motivation, and Inorganic Object (Book) metaphor in lowering the cognitive load. We found clear evidence suggesting that the God metaphor should be avoided in conversational crowdsourcing agent design. The conversational agent represented using the God metaphor was perceived to have significantly lower usability than the Control condition while corresponding to a higher cognitive load than the Control condition and the Object (Book) metaphor. Task designers should be mindful of these trade-offs while making design choices about agent representation in conversational crowdsourcing.

The Inorganic Object (Book) metaphor was found to reduce the cognitive load while decreasing the interest and enjoyment of the context. Therefore, in tasks with higher complexity [107], task requesters or designers can consider using an Inorganic Object metaphor to represent the conversational agent. On the contrary, when the task is relatively easy but requires more interest due to its less challenging work, one may consider using the Animal metaphor to increase the interest and enjoyment during task completion.

Lastly, in a conversational crowdsourcing context, an agent without any metaphorical representation can be a safe choice to ensure higher perceived usability than the God metaphor and a higher interest-enjoyment than the Object metaphor, while not costing a significant difference in cognitive task load than other agents with GCoB metaphors.

5.2 Caveats, Limitations and Future Work

One of the goals of this research was to improve worker engagement. Since it is well-understood that a primary motivation for

workers is typically to maximize their monetary rewards in crowdsourcing marketplaces, it is not easy to distill the effect of different metaphorical representations on worker engagement. However, our design choices and controlled experiment allow us to draw meaningful conclusions. Pay per unit time was identical across all the conditions and the task types.

Our experimental design considered an Image Classification task to measure the impact of different representations of CAs across two different data types (text and image). Prior work has discussed how different types of tasks could be adapted to the conversational crowdsourcing setting [69] to improve worker engagement. This entails a trade-off between the effort required for task adaptation with potential gains through improved worker engagement. However, we acknowledge that the Image Classification task may not be intuitively conversational. Future work can use tasks that are inherently more flexible from the design standpoint and arguably benefit more from a conversational interface (for example, image annotation tasks).

Metaphors can be interpreted, comprehended, and received differently by workers based on their cultural background (e.g., In the U.S., modern business is understood metaphorically through American football, and in Japan, their national value is understood through the Japanese garden [32, 33]). Although we controlled the demographic pool of participants in our study and restricted participation to those workers who could speak English as a native language (e.g., US, Canada, UK), it is possible that workers interpreted metaphorical representations differently (i.e., we can expect there to be individual differences among workers on their perception of agent metaphors).

In addition, the only agent that was not gender-neutral corresponded to the Human metaphor (Figure 4 (b)) agent avatar. This design choice was based on a previous study with an agent embodying female face enhanced participants' rapport, perceived human-likeness, and trustworthiness towards the agent [94]. However, certain genders might affect a user's perception and reaction to the agent. We aim to address this limitation in our imminent future work. One way to address this could be by adopting human metaphor agents from different genders to see if there is any difference in worker engagement based on the agent's gender.

We intentionally chose the general metaphor 'God' rather than representing a specific God to avoid implying any social or religious connotation. By making this design choice, we did not explicitly control for this particular agent metaphor's perceived competence and warmth. As Gilad *et al.* have shown, warmth perception of an AI system can overpower the perceived competence of the system [37]. Future work can explore how different metaphors at the level of 'God,' which are perceived to have high competence and high warmth, would affect work dynamics in conversational crowdsourcing.

Furthermore, we acknowledge the overhead of designing and adapting metaphorical representations of agents in the crowdsourcing context. However, the HCI community can build adaptable toolkits for agent representations to better understand how metaphorical representations of agents can influence work in conversational crowdsourcing. From a requesters' standpoint, in the absence of such solutions, one can argue that such overhead can be seen as a reasonable trade-off since an appropriate metaphor design for

conversational agents could benefit large batches of crowdsourcing microtasks. After all, prior works that have explored mechanisms to improve worker engagement in crowdsourcing have argued that meaningful benefits can be reaped through said mechanisms by retaining workers in large batches of tasks [21, 29, 84].

Finally, it can be argued that the hierarchical categories within the Great Chain of Being are not mutually exclusive and, in some cases, rather complementary. An example can be a metaphor of a humanoid, a human-like robot, which also is one of the most common representations of commercial chatbots. A humanoid has a special place in the Great Chain of Being, as it is a combination of a general human constitution with inorganic objects. As the humanoid metaphor case shows, when non-human agents are used, they are in between the lines of great chains of being as a conversation is a highly human trait. Our study deliberately avoided anthropomorphism to investigate strict mapping on the Great Chain of Being, although complemented by the fact that they spoke the human language, a necessary pre-requisite. Along this vein, this paper has investigated the performance of the metaphorical agent within the Great Chain of Being framework to gain insights into the conceptual structure. However, how the result of this study compares with "traditional" avatars (e.g., anthropomorphized or a humanoid metaphor) is still to be investigated. Exploring this difference might help explain the results shown in this study.

6 CONCLUSION

We investigated the Great Chain of Being metaphor as a tool to traverse an agent metaphor space that extends beyond the human metaphor, which the HCI community has widely studied. Results from our study suggest that it is possible to understand non-human metaphors in a conceptually structured fashion. By being aware of the anatomy of metaphorical agent representation, designers and researchers studying human-agent interaction can more deliberately apply metaphors to an agent. To the best of our knowledge, this is the first study presenting evidence that worker engagement, intrinsic motivation, cognitive task load, and worker trust can be affected when conversational agents embody metaphors from different Great Chain of Being hierarchical categories. Our findings suggest that there is a potential trade-off in using metaphors from each level of being, e.g., some improve worker engagement while others decrease the cognitive task load. Specifically, using the lowest chain of being (an inorganic object metaphor — book) may significantly reduce the perceived workload of workers but may reduce intrinsic interest and enjoyment of the workers. In contrast to what existing HCI studies suggest, the human metaphor did not enhance user engagement or user trust towards the agent within the conversational crowdsourcing context. We therefore argue that the choice of the category from the Great Chain of Being with which to represent a given conversational agent, should be a deliberate design choice for crowdsourcing task designers.

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A WORKER ENGAGEMENT: RESULTS

Table 10: The Kruskal-Wallis test result across overall UES-SF score and subscales of UES-SF. Significant results are marked in italic bold. ($\alpha = 0.05$, $N=341$)

	Overall UES	Focused Attention	Perceived Usability	Aesthetic Appeal	Reward Factor
Kruskal-Wallis H	11.20	10.05	13.57	12.12	7.94
df	5	5	5	5	5
sig	.048	.074	.019	.033	.159

Table 11: Overall UES-SF score Mann-Whitney post-hoc results between conditions. Significant results are marked in italic bold (Bonferroni-corrected alpha level 0.008). We calculated the effect size only when the statistical difference was significant. (* = all five metaphors)

Measure	Metaphor	Compared metaphor group	<i>U</i>	<i>z</i>	<i>p</i>	effect size
Overall UES-SF score	God (<i>Md</i> = 3.83, <i>n</i> = 55)	Human (<i>Md</i> = 3.83, <i>n</i> = 57)	1535.00	-.190	.850	-
		Animal (<i>Md</i> = 3.83, <i>n</i> = 56)	1277.00	-1.553	.120	-
		Plant (<i>Md</i> = 3.83, <i>n</i> = 59)	1584.00	-.219	.827	-
		Object (<i>Md</i> = 3.58, <i>n</i> = 57)	1374.00	-1.411	.158	-
		Control (<i>Md</i> = 3.83, <i>n</i> = 55)	1418.00	-.566	.572	-
	Human	Animal	1315.00	-1.617	.106	-
		Plant	1681.00	-.003	.998	-
		Object	1347.00	-1.851	.064	-
		Control	1504.50	-.367	.713	-
	Animal	Plant	1386.00	-1.491	.136	-
		Object	1046.00	-3.396	.001	moderate (<i>r</i> = .32)
		Control	1339.50	-1.185	.236	-
	Plant	Object	1425.50	-1.698	0.90	-
		Control	1566.50	-.318	.751	-
	Object	Control	1264.50	-2.033	0.42	-
	Control	Agent Avatar* (<i>Md</i> = 3.75, <i>n</i> = 286)	7494.00	-.555	.579	-

B INTRINSIC MOTIVATION: INTEREST-ENJOYMENT RESULTS

C COGNITIVE TASK LOAD: RESULTS

D TRUST: RESULTS

E OUTPUT ACCURACY AND TASK EXECUTION TIME: RESULTS

Table 12: Perceived Usability Mann-Whitney post-hoc results between conditions. Significant results are marked in italic bold (Bonferroni-corrected alpha level 0.008). We calculated the effect size only when the statistical difference was significant. (* = all five metaphors)

Measure	Metaphor	Compared metaphor group	<i>U</i>	<i>z</i>	<i>p</i>	effect size	
Perceived Usability subscale	God (<i>Md</i> = 4.33, <i>n</i> = 55)	Human (<i>Md</i> = 4.67, <i>n</i> = 57)	1362.00	-1.241	.215	-	
		Animal (<i>Md</i> = 4.67, <i>n</i> = 56)	1172.00	-2.258	.024	-	
		Plant (<i>Md</i> = 4.67, <i>n</i> = 59)	1430.00	-1.127	.260	-	
		Object (<i>Md</i> = 5.00, <i>n</i> = 59)	1282.00	-2.029	.043	-	
		Control (<i>Md</i> = 5.00, <i>n</i> = 55)	1014.00	-3.193	.001	moderate (<i>r</i> = .30)	
		Human	Animal	1457.00	-.838	.402	-
			Plant	1630.00	-.296	.768	-
	Object		1544.00	-.804	.422	-	
	Control		1224.00	-2.162	.031	-	
	Animal	Plant	1447.00	-1.197	.231	-	
		Object	1651.50	-.003	.998	-	
		Control	1300.00	-1.538	.124	-	
	Plant	Object	1546.50	-1.098	.272	-	
		Control	1201.50	-2.556	.011	-	
	Object	Control	1401.00	-1.389	.165	-	
	Control	Agent Avatar* (<i>Md</i> = 4.66, <i>n</i> = 286)	6140.50	-2.717	.007	lower than small (<i>r</i> = .06)	

Table 13: Aesthetic Appeal Mann-Whitney post-hoc results between conditions. Significant results are marked in italic bold (Bonferroni-corrected alpha level 0.008). We calculated the effect size only when the statistical difference was significant. (* = all five metaphors)

Measure	Metaphor	Compared metaphor group	<i>U</i>	<i>z</i>	<i>p</i>	effect size
Aesthetic Appeal subscale	God (<i>Md</i> = 3.67, <i>n</i> = 55)	Human (<i>Md</i> = 3.33, <i>n</i> = 57)	1323.50	-1.429	.153	-
		Animal (<i>Md</i> = 3.67, <i>n</i> = 56)	1526.50	-0.80	.936	-
		Plant (<i>Md</i> = 3.33, <i>n</i> = 59)	1455.00	-.955	.340	-
		Object (<i>Md</i> = 3.33, <i>n</i> = 59)	1215.00	-2.324	0.20	-
		Control (<i>Md</i> = 3.33, <i>n</i> = 55)	1242.00	-1.626	.104	-
	Human	Animal	1252.50	-1.985	0.47	-
		Plant	1556.50	-.695	.487	-
		Object	1483.50	-1.101	.271	-
		Control	1484.50	-.486	.627	-
	Animal	Plant	1426.50	-1.269	.204	-
		Object	1115.00	-3.023	.003	small (<i>r</i> = .28)
		Control	1189.50	-2.078	0.38	-
	Plant	Object	1411.00	-1.784	.074	-
		Control	1383.00	-1.372	.170	-
	Object	Control	1526.00	-.550	.582	-
	Control	Agent Avatar* (<i>Md</i> = 3.33, <i>n</i> = 286)	7086.00	-1.170	.242	-

Table 14: The Kruskal-Wallis test result across overall IMI score and subscales of IMI. Significant results are marked in italic bold. ($\alpha = 0.05$, $N=341$)

	Overall IMI	Interest-Enjoyment	Competence
Kruskal-Wallis H	9.64	17.46	4.52
df	5	5	5
sig	0.86	.004	.478

Table 15: The post-hoc Mann-Whitney test of Interest-Enjoyment subscale from the IMI score. Significant results are marked in italic bold (Bonferroni-corrected alpha level 0.008). We calculated the effect size only when the statistical difference was significant. (*=all five metaphors together)

Measure	Metaphor	Compared metaphor group	U	z	p	effect size
Interest-Enjoyment	God (Md = 3.80, n = 55)	Human (Md = 3.80, n = 57)	1490.50	-.449	.653	-
		Animal (Md = 3.80, n = 56)	1472.00	-.403	.687	-
		Plant (Md = 3.60, n = 59)	1516.00	-.606	.545	-
		Object (Md = 3.20, n = 59)	1178.50	-2.524	.012	-
		Control (Md = 4.00, n = 55)	1428.50	-.504	.614	-
	Human	Animal	1415.00	-1.045	.296	
		Plant	1642.50	-.216	.829	-
		Object	1206.00	-2.634	.008	small (r = .24)
		Control	1353.00	-1.253	.210	-
	Animal	Plant	1416.00	-1.325	.185	-
		Object	1034.00	-3.470	.001	moderate (r = .32)
		Control	1516.00	-.142	.887	-
	Plant	Object	1308.50	-2.332	.020	-
		Control	1376.00	-1.403	.161	-
	Object	Control	974.00	-3.690	.000	moderate (r = .35)
	Control	Agent Avatar* (Md =, n = 286)	6647.50	-1.823	.068	-

Table 16: Kruskal-Wallis test result for the NASA-TLX. Significant results are marked in italic bold. ($\alpha = 0.05$, $N=341$)

	TLX
Kruskal-Wallis H	23.74
df	5
sig	.000

Table 17: The post-hoc Mann-Whitney test of NASA-TLX. Significant results are marked in *italic bold* (Bonferroni-corrected alpha level 0.008). (*=all five metaphors together). We calculated the effect size only when the statistical difference was significant.

Measure	Metaphor	Compared metaphor group	<i>U</i>	<i>z</i>	<i>p</i>	effect size
NASA-TLX	God (<i>Md</i> = 29.17, <i>n</i> = 55)	Human (<i>Md</i> = 20.83, <i>n</i> = 57)	1271.00	-1.732	.083	-
		Animal (<i>Md</i> = 20.83, <i>n</i> = 56)	1157.50	-2.263	.024	-
		Plant (<i>Md</i> = 25.00, <i>n</i> = 59)	1310.00	-1.777	.076	-
		Object (<i>Md</i> = 12.50, <i>n</i> = 59)	925.00	-3.967	.000	moderate (<i>r</i> = .37)
		Control (<i>Md</i> = 16.67, <i>n</i> = 55)	937.00	-3.455	.001	moderate (<i>r</i> = .33)
		Human				
		Animal	1485.50	-.638	.524	-
	Human	Plant	1668.00	-.075	.940	-
		Object	1160.00	-2.893	.004	small (<i>r</i> = .27)
		Control	1241.50	-1.909	.056	-
	Animal	Plant	1576.00	-.427	.669	-
		Object	1231.00	-2.365	.018	-
		Control	1326.00	-1.269	.204	-
	Plant	Object	1230.50	-2.755	.006	small (<i>r</i> = .25)
		Control	1307.00	-1.789	.072	-
	Object	Control	1393.50	-1.306	.192	-
	Control	Agent Avatar* (<i>Md</i> = 20.83, <i>n</i> = 286)	6663.00	-1.801	.072	-

Table 18: Kruskal-Wallis test result for the TiA. There was no significant difference between different metaphors ($\alpha = 0.05$, *N*=341).

	Trust	Propensity to Trust
Kruskal-Wallis H	2.482	3.013
df	5	5
sig	.779	.698

Table 19: Kruskal-Wallis test for the output accuracy and task execution time. There was no significant difference in output accuracy and task execution time between different metaphors.

	Accuracy	Execution time
Kruskal-Wallis H	6.386	8.299
df	5	5
sig	.270	.141