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Fostering trust in human-robot interaction via perspective-taking and anthropomorphism: an empirical study in an industrial simulation game

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ABSTRACT

Collaborative robots (cobots) are increasingly introduced in industrial environments, but cognitive and emotional barriers often impede trust, hindering successful human-cobot collaboration. Concurrently, we witness people empathizing with and treating social robots as human-equivalent social actors daily. However, research investigating how to deliberately trigger this leisure phenomenon in industrial contexts to understand its impact on trust beliefs towards cobots remains scarce. In this work, we build on two socio-psychological mechanisms and transfer them to human-cobot interaction to actively promote viewing cobots as partners and investigate the impact on trust, attitude, and behavioral intention to collaborate with cobots. Firstly, we use perspective-taking, which is considered an effective interaction process-based strategy to tackle stereotypes and improve understanding of a cobot's functionality. Secondly, we apply human-like cobot design as an appearance-based strategy to elicit anthropomorphism, which refers to attributing human-like characteristics to non-human entities as a promising factor to foster perceptions of capability and familiarity. Our results of a 2 × 2 experiment (N = 155) in an industrial simulation game indicate that perspective-taking can significantly enhance cognitive trust toward cobots but does not impact emotional distrust. Contrary to our hypotheses, anthropomorphism increases emotional distrust. While we found that perspective-taking to explore cobots' inner workings supports viewing them as trustworthy partners, a human-like appearance may not be desirable in industrial contexts. People also start attributing negative intents and suspicions to the cobot through anthropomorphization. Therefore, robotic-appearing cobots as diligent servants instead of human-like partners may be preferable for successful industrial human-cobot collaboration.

1. Introduction

Over the past decade, robots of various shapes and capabilities have become integral to our lives, fulfilling diverse roles (Friedman, 2023; Sauppé and Mutlu, 2015). Human-robot relationships vary across tasks and contexts, with different types of social connections desired (Davis et al., 2023). With recent technological advancements, industrial robots, traditionally confined behind cages, are now equipped with advanced safety features that allow them to operate without protective barriers and work interactively with human operators (Hentout et al., 2019). These intelligent, lightweight collaborative robots, so-called cobots, can perceive, comprehend, and respond to human workers, discerning the objectives and requirements of tasks (Nahavandi, 2019). Unlike conventional automation that replaces human workers, cobots assist and enhance human capabilities, reduce injury risks from repetitive or physically demanding work, increase productivity, and address demographic-driven skills shortages (Akundi et al., 2022; Koch et al., 2017; Kopp et al., 2021; Michaelis et al., 2020). Thus, cobots are transforming the traditional role of industrial robots, evolving from mere tools to valuable assistants and team members sharing the workspace with humans (Meissner et al., 2021; Sauppé and Mutlu, 2015). As human-cobot hybrid teams transition from science fiction to reality, building acceptance of cobots in the workplace becomes increasingly relevant (Kopp, 2024; Kopp et al., 2022; Meissner et al., 2021). Unlike voluntary and controlled interactions with robots in private settings, the mandatory use of cobots in the workplace often elicits mixed reactions,

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with some employees viewing them as opportunities and others as threats (Brown et al., 2002; Hinsen et al., 2022). Their thoughts and feelings towards cobots shape the acceptance of human-cobot collaboration among workers (Meissner et al., 2021), particularly trust, which is a key determinant of technology adoption and plays a decisive role in cobot adoption (Hosseini Shoabjareh et al., 2024; Kopp, 2024).

However, research suggests that cognitive and emotional barriers can impede the development of trust and acceptance towards cobots. For instance, cognitive barriers involve a lack of understanding of cobots' decision-making mechanisms (Adadi and Berrada, 2018) and skepticism about the system's capabilities (Rai, 2020). Emotional barriers arise from employees' perceived identity threats and loss of control (Liao et al., 2023), negative feelings related to the reliability and benevolence of the system or the potential personal consequences of intelligent machines that can take over human work tasks (Liang and Lee, 2017). Just as how individuals may treat minorities or immigrants as outgroups or intergroups, they may also respond to cobots in similar ways, expressing fears of job displacement, physical harm and identity threats (de Graaf and Ben Allouch, 2016; Dekker et al., 2017; Złotowski et al., 2017). Thus, to foster effective human-cobot collaboration, it is crucial to create design and interaction concepts that overcome barriers, build trust, and enhance acceptance (Kopp et al., 2022; Riar et al., 2025; You and Robert, 2018).

To this end, it is essential to understand and incorporate the underlying sociopsychological mechanisms of how humans interact with increasingly autonomous robotic companions and team members. Although robots are not human, research provides evidence that people exposed to or work with robots treat them similarly to how they treat other people (Smith et al., 2020). In other words, people respond socially to robots (Nass et al., 1994) and apply the same social rules as in human-human interactions. This observation can be explained by the media equation theory, which posits that technologies employing human-like language and roles can promote treating computers and robots as social entities (Nass and Moon, 2000; Reeves and Nass, 1996). In this context, we witness the phenomenon that people increasingly tend to empathize with robots, especially in private environments, in their leisure. Examples span from expressing attachment to robots, addressing robots with human-like names (Kopp, 2024), people's desire to marry social robots (Liu, 2021; Spaccatini et al., 2023) and emotional reactions in response to maltreatment (e.g., punching, hitting, choking) of robots (Rosenthal-von der Pütten et al., 2014; Rosenthal-von der Pütten et al., 2013). In line with human intergroup dynamics, people even tend to feel schadenfreude towards robots considered outgroup members and more empathy towards ingroup robot team members (De Jong et al., 2021).

This work strives to build on this visible socio-psychological phenomenon of treating robots as social actors, empathizing with them, and actively triggering it outside domestic environments to learn more about its impact on trust and distrust toward cobots in industrial contexts. We aim to gain a more elaborate understanding of this phenomenon's effects on people's cognitive and emotional perceptions by applying two design strategies as vehicles that we believe are crucial for eliciting this phenomenon:

Firstly, we use perspective-taking, which has recently been characterized as a potential means to counteract the lack of trust toward cobots (Wittmann et al., 2023). The underlying idea of utilizing perspective-taking in human-cobot interaction is grounded in the extant knowledge that switching perspectives in human intergroup relations presents an effective method for reducing prejudices and promoting positive behaviors towards marginalized groups (Banakou et al., 2016; Banakou et al., 2018; Galinsky and Moskowitz, 2000; Herrera et al., 2018; Oh et al., 2016; Peck et al., 2013; Todd et al., 2011; Yee and Bailenson, 2006). Perspective-taking promotes the ability to see the world from another's viewpoint (Galinsky et al., 2008) and can help better understand others' mental states or predict their behavior (Fischer and Demiris, 2016; Milliez et al., 2014), which can result in more successful collaboration (Hoever et al., 2010) and improved intergroup relations (Batson et al., 2002; Todd and Galinsky, 2014). An increasing number of research investigates the effects of perspective switching with, for example, humanoid robots. Initial studies show that applying perspective-taking to human-cobot interaction promises to particularly overcome cognitive trust barriers, as it can help to improve understanding of the robot's functionality and decision-making processes (Wittmann et al., 2023).

However, research has underscored that cognitive understanding alone might be insufficient to overcome emotional distrust towards cobots, often caused by the psychological distance perceived toward the non-human being whose intents and role in the human-cobot relationship may be unclear and can cause fear (Schaefer et al., 2017; Ye et al., 2023; Złotowski et al., 2017). To this end, secondly, we seek to elicit anthropomorphism, which refers to attributing human-like characteristics to non-human entities (Hancock et al., 2011; Natarajan and Gombolay, 2020). Anthropomorphism evoked through a human-like robot design, behaviors, or communication abilities has been shown to foster a social and emotional connection with humans (Davis et al., 2023). The more human-like people perceive a robot, the more they treat it as an ingroup member, leading to higher willingness to interact and increased acceptance (Kuchenbrandt et al., 2013). Therefore, promoting anthropomorphism could represent a promising approach in industrial human-cobot interaction that particularly affects the emotional perceptions of the cobot.

Consequently, translating the sociopsychological phenomena into human-robot interaction design strategies, we investigate the effectiveness of actively supporting perspective-taking and anthropomorphism on people's trust perceptions in industrial settings with cobots. Accordingly, this work is guided by the following research questions (RQ):

RQ1: *How does perspective-taking affect cognitive trust and emotional distrust in cobots?*

RQ2: *How does anthropomorphism affect cognitive trust and emotional distrust in cobots?*

By answering these research questions, our study creates new insights into how mechanisms stemming from social psychology can be transferred to industrial human-cobot interaction to enhance trust towards cobots, which ultimately helps to improve collaboration in human-cobot teams. Building on substantial evidence in social robotics that humans treat robots as social actors and frequently empathize with human-like machines in their daily lives, we apply perspective-taking and anthropomorphism as vehicles to actively trigger this phenomenon in a novel context and investigate its impact on people's trust perceptions. The findings of our study provide three main contributions. First, our work contributes to the research stream of cobot acceptance in human-cobot teams by gaining a nuanced understanding of trust with its cognitive and emotional aspects as a critical antecedent for acceptance (Gaudiello et al., 2016) and extends prior research on the direct effects of perspective-taking on robot acceptance (Hang et al., 2022; Ho and Ng, 2022; Wittmann et al., 2023) by incorporating a more thorough consideration of its cognitive and emotional impact. We found empirical evidence that perspective-taking significantly enhances cognitive trust (comprised of the dimensions reliability, functionality, and helpfulness), without affecting emotional distrust toward cobots. Second, our study enlarges research on anthropomorphism and its impacts on human interaction with social robots (Davis et al., 2023; Eyssel et al., 2012; Natarajan and Gombolay, 2020) to the industrial context. Contrary to our hypotheses, our findings indicate that higher anthropomorphism not only fails to positively impact cognitive trust but even results in more emotional distrust toward cobots. Thereby, we provide crucial design knowledge for industrial cobot design by learning how trust and distrust may be shaped by people's tendency to attribute human characteristics to cobots evoked by human-like cobot design. Finally, by juxtaposing the effects of both perspective-taking and anthropomorphism, our study extends beyond prior studies that have primarily focused on isolated effects and provides an empirically grounded foundation for substantially improving our understanding of how socio-psychological factors underpinning human-cobot interaction can be purposefully altered through interaction and cobot design and how they interplay in fostering trust towards cobots. Consequently, our results contribute to human-robot interaction (HRI) research by introducing promising pathways to improve rapport in human-cobot teams and alter human-cobot trust dynamics.

The remaining article is structured as follows: Section 2 comprises an overview of theories and prior research on trust, anthropomorphism, and perspective switching. Section 3 contains this study's hypotheses and research model, while Section 4 details the method we used. Section 5 presents the study's findings, which are discussed in Section 6. The discussion is divided into an elaboration of the theoretical, practical contribution, and ethical implications, followed by an assessment of the limitations of this work in Section 7. Section 8 concludes the article.

2. Theoretical background and related work

2.1. Human-robot interaction and trust

The research field of human-robot interaction focuses on establishing efficient, safe, and comfortable interactions between humans and robots. It explores how humans and robots can communicate, work together, and coexist in a manner that enhances human capabilities using the strengths of robotic systems (Sheridan, 2016). By facilitating effective HRI, tasks can be divided between humans and robots based on their complementary strengths to leverage unique advantages (Wang et al., 2024). In this regard, interaction with robots at the workplace can be divided into five categories, ranging from isolated cell operations, coexistence, synchronization, cooperation, and collaboration (International Federation of Robotics, 2020) , which differ in their degree of human-robot contact. The *cell condition* is characterized by the robot operating within a traditional cage, confined behind fences (Bauer et al., 2016). *Coexistence* refers to a scenario where robots operate outside designated cells, but humans and robots maintain separate workspaces without engaging in the same task (Malik and Bilberg, 2019). *Synchronization* involves both humans and robots sharing a workspace, but only one of the interaction partners is present in the workspace at any given time, alternating in performing the job (Bauer et al., 2016). *Cooperation* entails humans and robots sharing the workspace and performing shared tasks simultaneously but not working together on the same product or component (Koch et al., 2017). Only *collaboration* is characterized by humans and robots sharing the same workspace and actively working together on the same product or component simultaneously (Malik and Bilberg, 2019). In this scenario, the robot takes the role of an active collaborator, a “cobot” (Vicentini, 2021) that can safely operate in close proximity to humans without the need for safety fences so that humans and cobots interact in a dyadic relationship.

As robots are granted increasing levels of autonomy, it becomes increasingly crucial for humans to trust these systems (Lewis et al., 2018). Trust forms the foundation for all interactions (Cook and Schilke, 2010). It gauges the level of confidence people place in individuals, communities, organizations, nations, and societies (Hoff and Bashir, 2015). Trust is a multifaceted construct, and scholars from various disciplines have strived to grasp its nuances. Trust can be understood as “the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party” (Mayer et al., 1995, p. 712). In other words, trust describes the beliefs and attributions of the trustor towards the trustee that results from the trustor’s observations of the trustee’s behavior (Whitener et al., 1998). Thus, trust can be viewed as a salient behavioral belief directly affecting the user’s attitude toward the trustee and its behavior (Lee and See, 2004; Wu and Chen, 2005). The concept of trust can further be distinguished into (primarily cognitive) trust and (primarily emotional) distrust, where distrust does not merely express an absence of trust but may increase suspicion, wariness, and cynicism (Lewicki et al., 2006; Rai, 2020).

Given the novelty of cobots in the workplace and the lack of prior experience with them, initial trust development often relies on swift trust, i.e., an early confidence for temporary teams to act as if trust were present (Kramer and Tyler, 1996; Rule et al., 2013; Yip and Schweitzer, 2015). These swift trust assessments depend on automatic information processing and stereotypes based on different social categories (Devine, 1989; Dovidio et al., 1986; Fiske and Neuberg, 1990; Jarvenpaa and Leidner, 1999). In the workplace, the differences between cobots and humans can lead to cobots being perceived as members of a competing outgroup (Smith et al., 2020). In line with research on distrust, framing others as outgroup members may create psychological barriers and suspicion (Lewicki et al., 2006). Thus, reactions to cobots may mirror reactions to human outgroups, such as immigrants or ethnic minorities (Smith et al., 2020). Similarly, cobots may evoke feelings of identity threats, job displacement, or physical injury (de Graaf and Ben Allouch, 2016; Nam, 2019; Złotowski et al., 2017), resulting in feelings of anger and anxiety (Dekker et al., 2017; Hinks, 2021).

In this context, research has identified several cognitive and emotional barriers that influence swift trust assessments and trust development. *Cognitive barriers* involve mental obstacles that prevent individuals from understanding, trusting, or using cobots. For instance, Artificial Intelligence (AI) systems are often described as black boxes due to their opaque internal processes, which complicates the human understanding of their decision-making mechanisms (Adadi and Berrada, 2018). This lack of transparency can foster doubt or skepticism about the system’s capabilities, resulting in distrust and resistance (Rai, 2020). *Emotional barriers* arise from negative emotions associated with intelligent systems, often driven by safety concerns (Abrams et al., 2021) or issues related to the robot’s design and interaction (Baumgartner et al., 2022; Mori et al., 2012). Frequently, these detrimental emotions are related to the reliability and benevolence of the robot or the changing role of the increasingly intelligent partner in human-machine teams (Liang and Lee, 2017). Moreover, given that cobots are a relatively new technology, their societal impacts are still uncertain, contributing to fear of the unknown and resistance to change (Baumgartner et al., 2022; Meissner et al., 2021).

To overcome these barriers, previous research on fostering trust in robots has focused on four key areas: pre-interaction introduction, interaction process, post-interaction trust-rebuilding, and physical appearance. *Pre-interaction introduction* studies include implementing appropriate training and examining how framing robots as peers or collaborators, aligning them with shared goals, and establishing common values can foster trust (Kopp et al., 2022, 2023). Research on the *interaction process* focuses on enhancing the consistency and reliability of robot behavior. This includes, for example, developing robots that can handle ambiguous situations, incorporating responsive design, and implementing clear feedback mechanisms, social cues, and communication processes to ensure transparency and predictability of the robot’s actions and decision-making (Admoni and Scassellati, 2017; Fischer et al., 2018; Ghazali et al., 2019; Pipitone et al., 2024; Rau et al., 2009; Yu and Li, 2022). Research on *post-interaction trust-rebuilding* typically addresses scenarios where robots make mistakes and human operators’ trust needs to be restored, such as through apologies or explanations (Fratczak et al., 2021; Sebo et al., 2019). Finally, studies on *physical appearance* investigate how a robot’s design influences trust, exploring various styles such as machine-like, zoomorphic, human-like, or non-realistic, and considering which designs are most suitable for different contexts and target groups (Biermann et al., 2021; Onnasch and Hildebrandt, 2022; Ötting et al., 2022; Roesler et al., 2021; Waytz et al., 2014; Złotowski et al., 2016).

2.2. Media equation theory

Particularly when aiming to foster trust through the design of the interaction process and physical appearance, it is inevitable to consider the sociopsychological foundations of how humans perceive and interact with robots. People's reactions to robots often mirror their responses to other humans (Kuchenbrandt and Eyssel, 2012). This phenomenon can be explained by the "computers are social actors" theory, also known as the *media equation theory*, which posits that technologies employing human-like language and roles can elicit social responses, leading users to apply social norms and expectations without conscious awareness and treat computers and robots as social entities (Nass and Moon, 2000; Reeves and Nass, 1996). Especially when users lack prior interaction experiences, they are more likely to apply human-human scripts in their initial interactions due to what they perceive as the robot's social affordances (Fox and Gambino, 2021).

2.3. Perspective-taking

Drawing on the media-equation theory, it is believable that human-human and human-automation trust are governed by the same underlying constructs (Nass et al., 1994). With their physical presence and autonomous actions, intelligent robots are often perceived as social entities with intentions and agency (Broadbent, 2017; Hancock et al., 2011; Meissner et al., 2021). Thus, interactions with cobots tend to resemble human-human interactions, allowing concepts from social psychology to be applied to human-robot teaming to achieve fruitful collaboration (Kuchenbrandt and Eyssel, 2012). Research on human intergroup relations has highlighted several effective methods for reducing prejudice, including initial contact with outgroup members, recognizing shared group identities, and perspective-taking (Crisp and Hewstone, 1999; Pettigrew, 1998; Pettigrew and Tropp, 2006). While the effects of initial contact and higher-level group formation with robots have been investigated (de Graaf and Ben Allouch, 2016; Kuchenbrandt and Eyssel, 2012; Savela et al., 2021; Smith et al., 2020; Wullenkord et al., 2016; Wullenkord and Eyssel, 2019), the effect of perspective-taking in human-robot interaction, especially concerning human-cobot interaction in industrial environments, remains largely unexplored.

Perspective-taking can be categorized into cognitive and emotional components. *Cognitive perspective-taking*, the ability to view interactions and the world from another's viewpoint (Galinsky et al., 2008), can enable a better understanding of others' mental states and prediction of their behavior (Fischer and Demiris, 2016; Milliez et al., 2014), enhancing success in collaboration tasks (Hoever et al., 2010). Perspective-taking is a crucial capability for effective social functioning (Krauss and Fussell, 1991), and strong perspective-taking skills are linked to better performance in collaboration tasks (Hoever et al., 2010). Moreover, *emotional perspective-taking*, the ability to feel with others, emotionally connecting with others, and feeling compassion for others (Duan and Hill, 1996; Galinsky et al., 2008; Gilin et al., 2013), also has several positive effects, such as fostering a sense of merging between oneself and others, which enhances social bonds, cooperation, and prosocial behavior (Davis et al., 1996; Galinsky et al., 2005; Maner et al., 2002; Stephan and Finlay, 1999). It also reduces prejudices and stereotypes (Galinsky and Moskowitz, 2000; Todd et al., 2011) and improves intergroup relations (Batson et al., 2002; Todd and Galinsky, 2014). While perspective-taking, in this understanding, represents a psychological act of adopting another's viewpoint or feeling empathy, the term is also used to describe the more behavioral act of acquiring another's visual perspective. These two conceptualizations are not independent. Rather, research in neuroscience and psychology underscores that visual and psychological perspective-taking are strongly linked. Prior studies provide empirical evidence that visually taking the perspective of others supports understanding their feelings and intentions, as visual perspective-taking engages similar brain regions involved in psychological perspective-taking (Bukowski, 2018; Lukošiūnaitė et al., 2024; Mattan et al., 2016).

This observation presents the foundation for HRI studies that leverage visual perspective-taking to induce psychological perspective-taking of robots' perspectives. Initial studies on switching perspectives with social robots have found that (visual) perspective-taking positively affects people's emotional and social behavior (Hang et al., 2022). Furthermore, preliminary research indicates that taking the perspective of robots impacts people on a cognitive and emotional level and can be used as a vehicle to better understand the robot's functionality or decision-making processes (Wittmann et al., 2023). There have been a few other attempts to explore the effect of perspective-taking with robots, with mixed findings. Smith et al. (2020) found no effect when participants were asked to imagine the robot's perspective mentally or were allowed to view or control the robot's actions from different perspectives. In contrast, Hang et al. (2022) and Ho and Ng (2022) showed that video-based and Virtual Reality (VR)-based perspective-taking methods can foster empathy, altruism, and prosocial behavior towards virtually embodied robots. Finally, Wittmann et al. (2023) applied instruction-based perspective-taking techniques to enhance the acceptance of intelligent social robots.

These preliminary studies in HRI research show various methods through which perspective-taking and empathy can be cultivated (Stephan and Finlay, 1999). Traditional techniques include mental stimulation exercises, narrative stories, and role-playing. Modern approaches utilize diverse media such as print, videos, or interactive narratives, providing participants additional context about a specific situation rather than relying solely on their imagination (Herrera et al., 2018). These methods are particularly helpful when participants have limited contact with the social target, thus lacking direct experience to develop schemas or hold biases against the target (Ahn et al., 2016; Gehlbach et al., 2015; Herrera et al., 2018). In this regard, different media types engage different senses and vary in their levels of immersion and interactivity. Recently, interactive video games and environments have emerged as powerful tools for perspective-taking (Gentile et al., 2009; Greitemeyer and Osswald, 2010), often termed "ultimate empathy machines" for their ability to place users in others' perspectives (Herrera et al., 2018). These desktop or VR immersive experiences allow users to interact in real time with digital avatars and environments, enhancing the sense of presence and engagement (Herrera et al., 2018). Such embodied perspective-taking has been shown to reduce prejudices and promote positive behaviors towards marginalized groups effectively (Banakou et al., 2016, 2018; Herrera et al., 2018; Oh et al., 2016; Peck et al., 2013; Yee and Bailenson, 2006). It also extends to animals and nature (Ahn et al., 2016, 2013, 2014), suggesting that immersive media might be particularly promising for effective perspective-taking in human-cobot interaction.

2.4. Human-like design and anthropomorphism

In contrast to perspective-taking as an interaction-focused strategy, human-like robot design as a physical appearance-related strategy leverages the social dynamics outlined in the media equation theory by incorporating human-like characteristics to evoke anthropomorphism and enhance the quality of interaction and engagement. Anthropomorphism, defined as the attribution of human-like characteristics to non-human entities, is crucial in shaping user perceptions and responses during interactions with robots (Hancock et al., 2011; Natarajan and Gombolay, 2020). Individuals' tendencies towards anthropomorphism vary based on biological differences, including individual oxytocin levels (Scheele et al., 2015) and gender (Chin et al., 2004), and are significantly related to personality, age, and personal life factors (Epley et al., 2008; Letheren et al., 2016; Meissner et al., 2021). The homophily principle suggests that people are generally more likely to connect with entities that resemble themselves, fostering a sense of closeness (McPherson et al., 2001; Milliken and Martins, 1996).

Building on the idea of actively promoting anthropomorphism, studies have shown that different human-like designs can evoke varying levels of connections with humans (Davis et al., 2023). The more human-like a robot is perceived, the more likely it is to be treated as an ingroup member, leading to a higher willingness to interact and increased acceptance (Kuchenbrandt et al., 2013). Also, robots that have human-like characteristics tend to be considered more trustworthy (Natarajan and Gombolay, 2020). However, the emergence of anthropomorphism is not restricted to the embodiment of a robot. Besides its appearance, a robot's perceived human likeness is affected by other cues and signals, such as the robot's nonverbal communication abilities, natural language skills, movement, level of certainty, degree of autonomy, imitation, and reciprocity (Hegel et al., 2011; Kahn et al., 2006; Złotowski et al., 2015). Moreover, the impact of a robot's human likeness is highly context-dependent (Roesler et al., 2021). In this regard, prior studies have mostly focused on human-like design and evoked anthropomorphism in interactions between humans and social robots in leisure contexts (Duffy, 2003) but its effect in industrial settings remains underexplored.

3. Hypotheses

Based on these theoretical foundations and sketched gaps in the current scientific understanding, we aim to investigate how perspective-taking and anthropomorphism could be purposefully elicited through the design of the human-cobot interaction process and the cobot's appearance and communication to overcome cognitive and emotional trust barriers as a means to reduce distrust and promote trust in cobots in industrial environments. Our examination is guided by a theory-guided research model (see Fig. 1) that entails seven distinct hypotheses, which we will detail in the following.

First, psychological studies on interpersonal interactions suggest that perspective-taking can improve an individual's understanding of others. By actively considering the target person's point of view, perspective-taking encourages people to step out of their default cognitive processes and engage in more thorough and thoughtful information processing (Ku et al., 2015). This allows individuals to evaluate better others' actions based on perceived possibilities from the other person's viewpoint (Creem-Regehr et al., 2013). Such active information processing enables perspective-takers to be more mindful and effective in assessing their counterpart (Ku et al., 2015), thereby reducing stereotypes and promoting the formation of independent opinions (Galinsky et al., 2008; Todd and Galinsky, 2014). Therefore, it is reasonable to suggest that perspective-taking with a cobot can reshape an individual's thinking and encourage them to seek information about the cobot's functioning and capabilities.

Moreover, perspective-taking plays a critical role in navigating and making sense of uncertain situations as well as in reducing threat perception (Williams, 2007). Individuals engaging in perspective-taking can enhance creativity by stepping out of their mental routines (Hoever et al., 2010). This ability to connect ideas aids in absorbing knowledge, accelerating learning, and fostering enjoyment in the process (Rinkevich, 2011). Consequently, this enhanced cognitive capacity and motivation facilitate participants to develop useful mental models of robot reasoning based on observations of robot behavior, thereby enabling comprehension of its functioning, decision-making, and design intentions as well as the prediction of its future actions (Madsen and Gregor, 2000; Matthews et al., 2020). This, in turn, reduces uncertainty and risk perception, ultimately contributing to a higher level of trust (Fischer et al., 2018; Schilke and Huang, 2018). Therefore, we propose the first hypothesis:

***H1**. Perspective-taking has a significant positive impact on cognitive trust.*

Additionally, perspective-taking fosters empathy and establishes an emotional bond between the perspective-taker and the counterpart (Galinsky et al., 2008; Schilke and Huang, 2018). The role of affective responses in trust formation is significant, as people not only rationalize trust but also feel it (Lee and See, 2004). Research indicates that perspective-taking is associated with increased liking, perceived closeness, and a greater propensity to collaborate (Batson et al., 2002; Johnson, 1975; Ku et al., 2015; Wang et al., 2014). These feelings facilitate individuals to improve their attitudes toward outer groups (Batson et al., 2002; Shih et al., 2009). Hence, it is plausible that perspective-taking could reduce anxiety and lead to more positive perceptions of robots. Furthermore, research in social psychology has shown that perspective-taking positively influences trust development, particularly due to the increased affinity for others, which is a crucial precursor to trust (Erle et al., 2018). We therefore hypothesize that the perspective-taking of the robot's perspective will reduce participants' negative emotional reactions, including skepticism, fear, cynicism, vigilance, and wariness regarding the cobot's intentions, which will express in lower distrust towards the robot (Lewicki et al., 2006). Therefore, the following hypothesis is formulated:

H2. Perspective-taking has a significant negative impact on emotional distrust.

Regarding the impact of anthropomorphism, previous research highlights a strong impact of anthropomorphism elicited through human-like appearance on cognitive trust (Duffy, 2003; Hoff and Bashir, 2015; Kiesler et al., 2008; Langer et al., 2019; Lewis et al., 2018; Meissner et al., 2021; Waytz et al., 2014). Human-like robots are often viewed as more competent, trustworthy, and enjoyable to interact with (Kim, 2024). When robots are designed with human-like features, users are more likely to expect human-like behavior (Krach et al., 2008), leading to increased perceptions of competence and reliability (Cheng, 2022; Christoforakos et al., 2021; Duffy, 2003). Additionally, human-like characters are often associated with a heightened capability of human reasoning and motivation, which increases the trust placed in them (van Pinxteren et al., 2019). This aligns with the general human tendency to view humans as inherently more capable than non-human entities (Kim, 2024).

Furthermore, users can more easily anticipate their behavior by assigning familiar human characteristics to robots. The more human-like a robot appears, the more users expect it to behave like a human (Krach et al., 2008). Therefore, anthropomorphizing robots helps reduce uncertainty in interactions (Sinha et al., 2020), allowing users to make

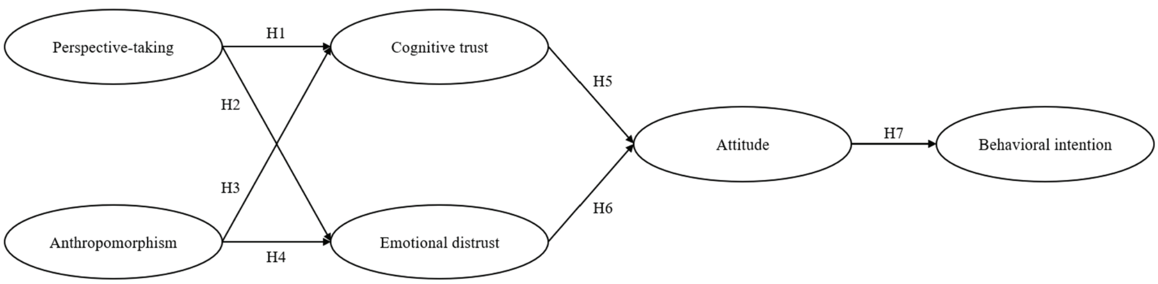

Fig. 1. Research model of study.

sense of the robot's actions better, and to restore a sense of predictability within their social environment (Eyssel et al., 2012). Studies have shown that human-like agents were associated with greater resilience in maintaining trust when trust is compromised, with this effect intensifying under uncertain conditions (de Visser et al., 2016). This predictability is essential for users to feel confident in a robot's capabilities, thereby fostering cognitive trust. Thus, the following hypothesis is derived:

H3*. Anthropomorphism has a significant positive impact on cognitive trust.*

In addition, anthropomorphism has been identified as a core factor influencing emotional trust (Glikson and Woolley, 2020). Previous research has shown that individuals tend to interact with automation and robots similarly to how they interact with humans particularly when human-like characteristics are present because human-like robots are perceived as more familiar and predictable (Złotowski et al., 2015, 2016). Moreover, human-like robots are seen as more intelligent and sociable, thus garnering greater likability (Sinha et al., 2020). Such greater likeability and positive perceptions can lead to less anxiety and lower suspicions, alleviating distrust perceptions among human collaborators (Kopp et al., 2023).

Moreover, human-like automation has been shown to exhibit greater trust resilience and higher resistance to breakdowns in trust compared to computer-like automation (de Visser et al., 2016; Meissner et al., 2021). This could be because human-like robots are more often evaluated based on human norms than their less human-like counterparts, fostering empathy and greater tolerance for malfunctions and mistakes (Waytz et al., 2014). Therefore, the following hypothesis is developed:

H4*. Anthropomorphism has a significant negative impact on emotional distrust.*

Regarding the impact of trust and distrust on the human-cobot relationship, we know from psychological research that trust can be viewed as a salient behavioral belief that directly affects the user's attitude toward the trustee and its behavior (Wu and Chen, 2005). In this regard, cognitive trust has been found to foster positive attitudes (Venkatesh et al., 2011), as it can reduce complexity and perceived risk by raising expectations of positive outcomes and perceived certainty regarding the trustee's expected behavior (Mayer et al., 1995; Pavlou, 2003; van der Heijden et al., 2003). Emotional distrust, on the other hand, is fueled by suspicions that the other person's motives or behaviors are ingenuine, fearing hostility or being harmed (Kramer, 1999), therefore negatively impacting the attitude towards the trustee. Distrust, however, is not inherently bad, as research emphasizes it may prevent blindness of the trustor and help not being exploited (Lewicki et al., 2006). In the field of information systems, previous research has integrated trusting beliefs into the Technology Acceptance Model (TAM), and the Unified Theory of Acceptance and Use of Technology has demonstrated significant influences of trusting beliefs on attitude (Gefen et al., 2003; Pavlou, 2003; Venkatesh et al., 2011; Wu and Chen, 2005). Consequently, we propose the following hypotheses:

H5*. Cognitive trust has a significant positive impact on attitude towards the cobot.*

H6*. Emotional distrust has a significant negative impact on attitude towards the cobot.*

Attitude, in turn, describes the user's overall evaluation or appraisal of a technology. It pertains to the positive or negative feelings associated with applying the technology (Venkatesh and Davis, 2003) . The TAM suggests that individuals' attitudes toward technology are crucial in shaping their behavioral intentions (Davis et al., 1989; Fishbein and Ajzen, 1975). Therefore, a positive attitude towards using the technology will likely lead to greater acceptance and use, while a negative attitude may result in rejection or non-use. Specifically in the context of robots, attitude towards use refers to the user's positive or negative evaluation of employing the robot (Heerink et al., 2010). In robot acceptance research, the effect of attitude on intentions to use robots has been extensively studied, revealing both significant direct (de Graaf and Ben Allouch, 2013a; de Graaf and Ben Allouch, 2013b; Heerink et al., 2010; Shin and Choo, 2011) and indirect (Piçarra and Giger, 2018; Song and Kim, 2022) effects. Thus, the following hypothesis is proposed:

H7*. Attitude towards the cobot has a significant positive impact on behavioral intention to collaborate with the cobot.*

Fig. 1 summarizes our research model and integrates all described hypotheses.

4. Methodology

To investigate our hypotheses, we conducted a *2 × 2 laboratory experiment*. Laboratory experiments are particularly suitable for observing participants' behaviors in controlled environments (Palfrey, 2009), examining the effect of dependent variables while excluding irrelevant confounding variables and enabling replicability by other researchers (Webster and Sell, 2014). Therefore, it allowed us to design four conditions to investigate the effects of our design solutions on trust and distrust, in which we varied the main two independent variables: two conditions entailed the possibility to switch perspectives with the cobot during a work task in an industrial environment (as interaction process related design), and two conditions incorporated a cobot with human-like in contrast to traditional minimalistic industrial robot appearance to provoke the perception of anthropomorphism (as appearance related design).

We decided to simulate the human-cobot interaction in a *simulation game* because virtual environments are particularly suitable for studying human-cobot interactions in industrial settings (Lee et al., 2021). A current meta-analysis (Esterwood et al., 2025) indicates that non-physical representations of robots (such as within simulation games) are viable alternatives to physically collocated robots, as no significant differences concerning their social presence, anthropomorphism, and user engagement were detected. In this context, a recent empirical study (Riar et al., 2025) illustrates the effectiveness of playful VR-based approaches to fostering cognitive and affective trust toward a collaborative robot in an industrial context. Studies show immersive methods are more effective than traditional approaches in eliciting empathy and changing attitudes and behaviors (Ahn et al., 2013, 2014; Herrera et al., 2018). Additionally, immersive methods offer methodological advantages, ensuring a consistent experience for all participants, unlike traditional approaches that rely on individual imagination (Blascovich et al., 2002). Moreover, from a practical standpoint, we opted for the virtual environment because of the fast software development, which was invaluable in quickly collecting data and receiving user feedback in our trial runs to pivot and improve the simulation game. Another benefit is the fact that no additional gear had to be connected, and no complex hardware systems were necessary. Furthermore, the experimental setting was not restricted to one particular company's industrial shop floor. Instead, the simulation game is set in a standard final assembly production hall, which allows for more generalizability of our results. Although VR has many benefits, this study opted for a desktop-based simulation game due to its broader accessibility. Moreover, VR, being a novel technology, can be distracting for participants unfamiliar with the technology, preventing them from focusing on the experiment and biasing the results (Herrera et al., 2018).

We obtained ethical approval for our study from the [anonymized university]'s ethics committee before conducting our experiment.

4.1. Materials

Our simulation game was created within the Roblox environment using the game engine Roblox Studio. It presents players with a real-life situation in a manufacturing plant and encourages them to explore and use their knowledge and abilities (Boocock, 1968). To this end, it consisted of a collaborative human-cobot task that was equivalent in all groups and variations in the design of the participant interface (for perspective-taking) and the cobot appearance (to provoke differences in anthropomorphism) to form the following four experimental conditions: Perspective-taking and gripper arm cobot, perspective-taking and human-like cobot, no perspective-taking and gripper arm cobot, and no perspective-taking and human-like cobot.

Simulation games fall under the umbrella of serious games and are

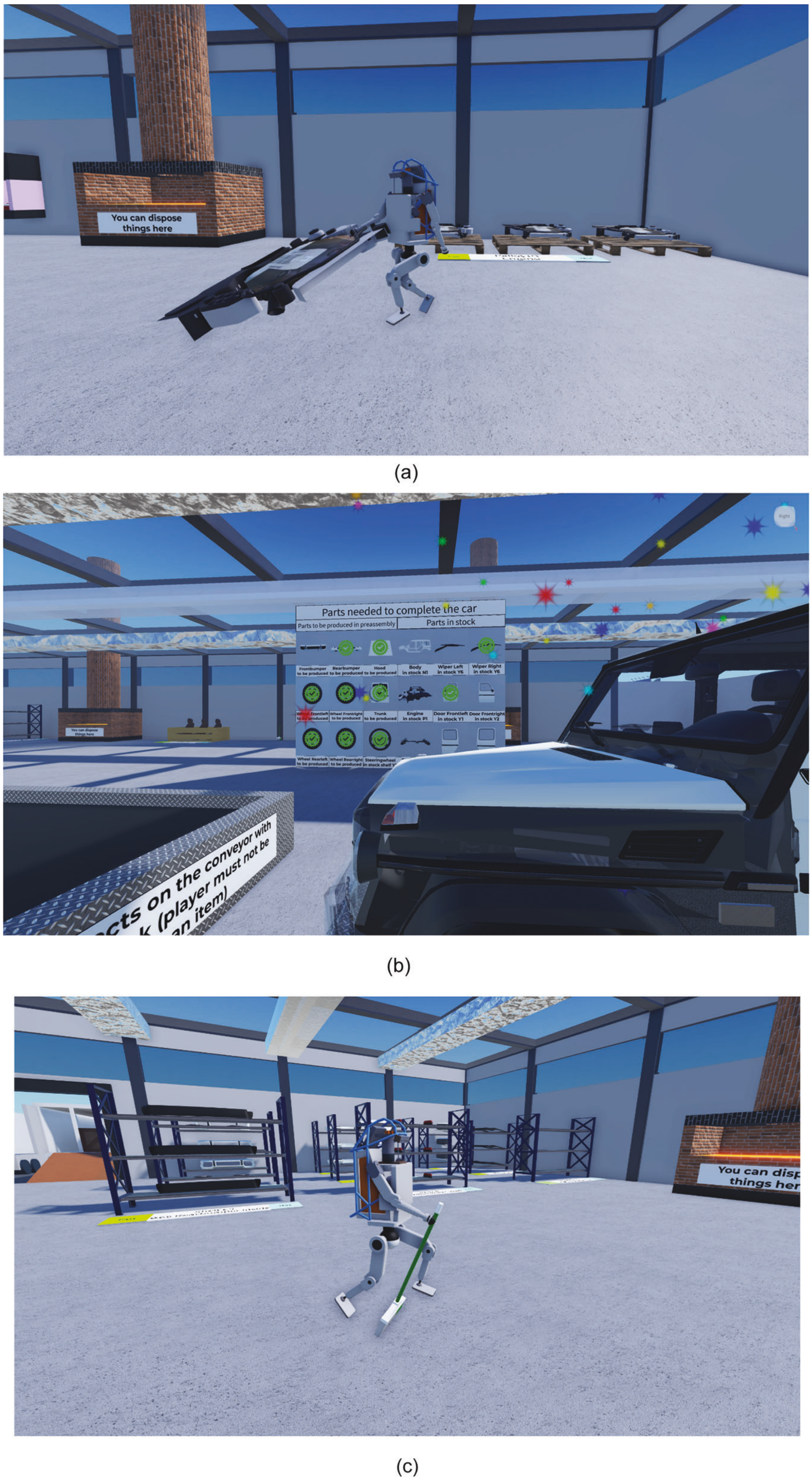

Fig. 2. Set of snapshots of the simulation game: (a) the cobot transporting a heavy engine, (b) confetti as positive feedback after the assembly of a component, and (c) the cobot cleaning the factory.

often applied in fields as diverse as education, training, health care, well-being, and interpersonal communication (Laamarti et al., 2014). Serious games build on a game's inherent set of rules, mechanics, elements, constraints, and goals (Pasin and Giroux, 2011) but have a primary design objective other than enjoyment and entertainment (Laamarti et al., 2014). More specifically, simulation games comprise key characteristics of games and simulations, providing ongoing representations of real life (Ellington et al., 1981; Pasin and Giroux, 2011). They are handy for problem-solving and developing cooperative skills (Abt, 1987), in our case regarding the interaction with the cobot. Thus, we deliberately selected a simulation game because of its practical relevance and the benefit of introducing a risk-free and safe experimental platform for participants to discover collaboration with intelligent cobots. Additionally, simulation games have been found to be effective in changing players' attitudes, making them interesting candidates for conducting HRI research (Pierfy, 1977).

4.1.1. Collaborative task

The task implemented in this study was designed to reflect the role industrial cobots typically play, such as assisting coworkers with lifting and moving loads, monitoring assembly lines, supporting human operators, and reducing their cognitive loads (Hentout et al., 2019; Koch et al., 2017). The simulation game was designed to take between 30 and 40 min, comprising multiple avenues for cooperation with the robot.

At the start, participants find themselves in an industrial hall with the cobot by their side. The main task is to collaboratively build a semi-finished car from 18 parts that must be found in stock or produced in pre-assembly. A live task board next to the semi-finished car tracks the blueprint and progress). When a part is found and delivered to the semi-finished car, its status on the task board updates, and the corresponding shape becomes visible, accompanied by a short music clip and confetti to motivate participants (see Fig. 2(b)). As factory workers prefer having decision-making options and control when interacting with cobots to mitigate fears of being forced into subordinate roles (Meissner et al., 2021), we designed the order of the assembly to be freely selectable to promote a sense of autonomy and enhance acceptance (Gagné et al., 2000; Ötting et al., 2022). To ensure human-cobot interactions, specific tasks are assigned exclusively to the cobot, such as lifting heavy car components like the car body, suspension, and engine (see Fig. 2(a)), which require more strength than a human typically possesses. For pre-assembly production tasks, blueprints of the parts are deliberately withheld to encourage participants to rely on the cobot, which is familiar with the assembly procedures. If participants have trouble locating parts or the stock is depleted, they can request assistance from the cobot.

The cobot also demonstrates proactive behaviors based on user actions, such as offering help carrying heavy components, issuing safety warnings, or providing first aid after an injury. These behaviors aim to communicate the cobot's capabilities and intentions, encourage reciprocal prosocial behavior, and improve overall cooperation (Pandey et al., 2013). To reinforce the perception of the cobot as an autonomous entity, it seamlessly performs tasks in the background to keep the factory running smoothly when not actively assisting the human. These tasks include refilling stock, checking part quality, and cleaning the factory (see Fig. 2(c)).

Thereby, the simulation game was designed to inherently satisfy four core conditions to establish positive contact between two groups (Pettigrew, 1998), in our case, the group of "humans" and the group of "cobots": (a) an equitable perceived status between the groups in the given scenario, (b) the presence of shared objectives, (c) active cooperation between the groups, and (d) recognition that the authority sanctions positive intergroup contact. Condition (a) is satisfied by introducing the cobot as a coworker rather than a subordinate. The cobot assumes the role of an equal colleague within the same factory setting rather than serving as a mere assistant to the human. Condition (b) is fulfilled, given that the participant and the cobot share the common objective of assembling a car. Condition (c) is met, as effective cooperation between the participant and the cobot is necessary to reach the shared objective successfully. This cooperation involves leveraging each other's strengths to compensate for their respective weaknesses. Condition (d) is effectively handled, as gamification elements incentivized and promoted positive interactions between the participant and the cobot.

4.1.2. Perspective-taking

The independent variable of perspective-taking was realized with visual perspective-taking to induce psychological perspective-taking, following prior HRI studies (Galinsky et al., 2008; Ho and Ng, 2022; Todd et al., 2011). It was varied between the groups through an additional interface element (a button). This button is only present for participants assigned to the perspective-taking stimulus and allows visually switching perspectives with the cobot (see Fig. 3(a)). We decided on a visual approach because providing sensory input from the target's perspective is essential for effective perspective-taking in interactive virtual environments (Raij et al., 2009). Sensory inputs are significant for fostering positive relationships and acceptance in situations with limited contact or existing biases (Gehlbach et al., 2015), such as with cobots. Pressing the button lets participants take the cobot's visual perspective and view live sensor data such as battery level, position, velocity, internal and external temperature, object handling, weight carried, and estimated human mood (see Fig. 3(b) and Fig. 3(c)). Based on the cobot's actions, these sensory values are updated in real time. Additionally, participants can see the simulated inner workings of the cobot in natural language in a text box resembling a command line interface. This cue was implemented as language plays a crucial role in shaping mental models and human-robot relationships (Coeckelbergh, 2011). Furthermore, to enhance visual perspective-taking, explicit prompts, and salient visual stimuli are essential to indicate where the target is looking (Del Sette et al., 2022). Thus, the cobot's image recognition capability is visualized with bounding boxes highlighting objects in sight.

Participants in the perspective-taking condition can switch between first-person and third-person perspectives of the cobot using the mouse wheel. In the third-person perspective, participants can see the cobot's avatar and have a broader view of the surroundings. In contrast, the first-person perspective makes people immerse themselves even more and experience the environment through the cobot's eyes. Allowing participants to see the cobot's perspective at any time during interactions enables them to observe how their actions affect the cobot's responses, providing a highly interactive experience. Our goal was to enable all participants of the perspective-taking condition to truly immerse themselves in the cobot's world while actively considering that each person may have different individual preferences concerning experiencing the cobot's inner workings, affecting the effectiveness of the intervention. Therefore, we deliberately provide every participant in the perspective-taking condition with two distinct options (first-person and a meta third-person perspective) to experience the world of the cobot. This design choice supports participants in more easily developing mental models of the cobot and increases the likelihood that the intervention impacts all participants.

Textual prompts are embedded to encourage participants in the perspective-taking group to take the cobot's perspective. These prompts are either triggered when the cobot performs specific, pre-defined tasks or the participants have not taken the cobot's perspective for a few minutes.

4.1.3. Anthropomorphism

In contrast to perspective-taking, which can be deliberately enabled or not enabled by the system, anthropomorphism is a subjective perception and psychological mechanism that varies across individuals (Chin et al., 2004; Letheren et al., 2016; Scheele et al., 2015). While it is not as controllable as perspective-taking, we nonetheless aimed to

Fig. 3. Set of snapshots of the perspective-taking feature: (a) the participant's perspective, (b) the cobot's third-person perspective, and (c) the cobot's first-person perspective.

provoke differences in anthropomorphism attributed to the cobot by altering the cobot's physical appearance, communication, and language abilities. Research has shown that the degree of anthropomorphism depends on how human attributes are integrated into the robot (DiSalvo et al., 2002). Human-like robots tend to be anthropomorphized more readily, facilitating social and emotional connections (Friedman, 2023; Riek et al., 2009). However, the application of human-like design in intelligent robots should be carefully considered, as it is not universally true that increasing anthropomorphism always improves user perception (Goudey and Bonnin, 2016; Gursoy et al., 2019; Lu et al., 2019).

Interaction with highly human-like AI robots may require significant psychological adjustments and may even threaten users' human identity (Chi et al., 2023; Gursoy et al., 2019; Lu et al., 2019). Thus, the cobot in this study is designed with moderate human-like features to avoid the pitfalls of the uncanny valley (Mori, 1970; Mori et al., 2012). As a result of these considerations, two distinct cobot appearances were employed: a gripper arm cobot and a human-like cobot that resembles human characteristics but is still clearly distinguishable from an actual human appearance. The core differences are summarized in Table 1 and Fig. 4. The fundamental difference between the gripper arm and the human-like cobot is rooted in their structural design. The gripper arm cobot features a minimalistic design with a gripper arm, two joints, and a robotic end-effector with two fingers positioned atop a square-shaped body on four miniature wheels. The human-like cobot, in contrast, mimics human appearance with arms, legs, feet, a hip, a torso, and sensors on the torso resembling an abstract head. Due to its human-like form, it can convey human-like gestures, such as waving arms for greetings and pointing to objects when presenting them to the human. The movement also differs between the two cobots. The human-like cobot is programmed with a fluid, human-like bipedal walking motion. In contrast, the gripper arm cobot relies on its four wheels for locomotion and does not showcase intricate movement animations, except for slight shaking in the gripper arm.

Anthropomorphic perceptions are influenced not only by physical appearance but also by communication style (Chatterji et al., 2019; Klüber and Onnasch, 2022; Tamagawa et al., 2011). Human-like voices tend to trigger higher degrees of anthropomorphism (Eyssel et al., 2012). A human-robot voice can create a perception of a knowledgeable robot, influencing participants to prefer following its advice (Powers and Kiesler, 2006). Therefore, the human-like cobot was given an energetic young human voice using Google Text-to-Speech AI (Google, 2024). Dialogues in German and English of the human-like cobot were audibly articulated, complementing the visual text in speech bubbles. The gripper arm robot also featured dialogues and speech bubbles but could not speak.

Finally, research shows that robots using natural language and first-person pronouns significantly enhance anthropomorphism (Nass and Brave, 2005; Schroeder and Epley, 2016). Thus, in the perspective-taking groups, the human-like cobot's inner workings were displayed using the pronoun "I" and fluent human language. In contrast, the gripper arm cobot's inner workings were shown without pronouns and in fragmented sentences. For instance, while delivering a component to the semi-assembly area, the human-like cobot would display messages such as "I got the part. I will deliver it to the workbench", whereas the gripper arm cobot would display "Have hood grille. Deliver to workbench".

4.2. Data collection and procedure

The experiment took place between 2023/07 and 2023/11 in a public approach in different settings. We recruited participants at the Friedrich-Alexander-Universität Erlangen-Nürnberg, at the 'Digital Festival' in Nuremberg, at the StartPlay conference in Solingen, at the Ali Baba game club in Erlangen, at the 'Stadtjugendfipfel' in Erlangen, at the FAU Siemens Research and Innovation Ecosystem (RIE) Erlangen-Nürnberg Conference, and at the science popularization event 'Lange Nacht der Wissenschaften' in Nuremberg. The public approach and multiple venues were chosen because they offered several benefits: a) the availability of potential experimental participants without the need for lengthy recruitment campaigns, b) the ability to directly answer questions and solve challenges during the experiment, which may thus considerably prevent early dropouts or incomplete questionnaire replies due to problems related to the user interface, navigation or game elements and c) the possibility to engage in meaningful discussions and receive ad-hoc feedback after the experiment.

Table 1
Differences in cobot's design, movement, and communication capabilities.

	Human-like	Gripper
Embodiment	Head, torso, two arms, two legs	Gripper arm mounted on a cube
Movement	Bipedal	Small wheels
Voice	Synthetic young human	None
Language	Fluent	Jerky infinitive sentences
Pronouns for self-reference	I	None

Participants were randomly assigned to one of the four groups. Upon entering the simulation, participants could choose to conduct the experiment in either German or English. We then collected informed consent for participation and data processing. This was followed by a brief overview of cobots, which contained their purpose, advanced safety features, and integrated sensors. Next, we captured demographic information, including gender, age, education level, and occupation, through a pre-survey embedded in the simulation game environment. Afterward, participants were given a brief introduction to the user interface and essential functionalities. Subsequently, they could see their avatar standing in front of a factory and were greeted by the assigned cobot. The cobot introduced itself, the factory, and the collaborative task. Then participants entered the main task, freely progressed, and collaborated with the cobot to build the car step-by-step. After completing the car or reaching a maximum of 40 min, participants answered a questionnaire capturing post-treatment stances towards the specific cobot they have interacted with. Following a debriefing, people were given the option to enter a raffle to win a €25 Amazon voucher.

The questionnaire comprised items to measure our main independent and dependent variables (anthropomorphism, cognitive trust, emotional distrust, attitude towards the cobot, and behavioral intention). Additionally, we operationalized the independent variable of perspective-taking as a dummy-coded binary variable based on whether perspective-taking was enabled (enabled = 1, disabled = 0).

To operationalize anthropomorphism (Cronbach's $\alpha = 0.835$), five items from Li and Wang (2021) were used. Cognitive trust (Cronbach's $\alpha = 0.912$) was measured on an 11-item scale, including items related to perceived reliability, functionality, and helpfulness. This scale was developed by McKnight et al. (2011), who have significantly shaped trust research in technology and whose work stands out as influential (Meeßen et al., 2020), thus being widely considered a reliable measure for capturing trust. To capture emotional distrust (Cronbach's $\alpha = 0.773$), we employed the scale developed by Jian et al. (2000), widely used to measure trust and distrust among people and automation (Hosseini Shoabjareh et al., 2024; Kohn et al., 2021). For attitude (Cronbach's $\alpha = 0.841$) and behavioral intention (Cronbach's $\alpha = 0.909$), three items for each construct from Li and Wang (2022) were included. For a comprehensive overview of the measurement items and the measurement model assessment results, please refer to Table A1 and Table A4 in the appendix.

All items were rated on a five-point Likert scale (from "strongly disagree" to "strongly agree"). To enhance the applicability of the items in the local setting and maintain consistency in the unit of analysis for each construct (van der Heijden et al., 2003), the terms "service robot", "robot", and "system" in all original scales were substituted with the word "collaborative robot". Moreover, three authors proficient in both languages translated the measurement items from English to German. The initial translation was validated in a pretest that identified the need to clarify some terms and statements to avoid ambiguity and confusion. This was accounted for in the final version of the questionnaire.

The data of this project is available in an Open Science Framework repository (https://osf.io/5kjqg).

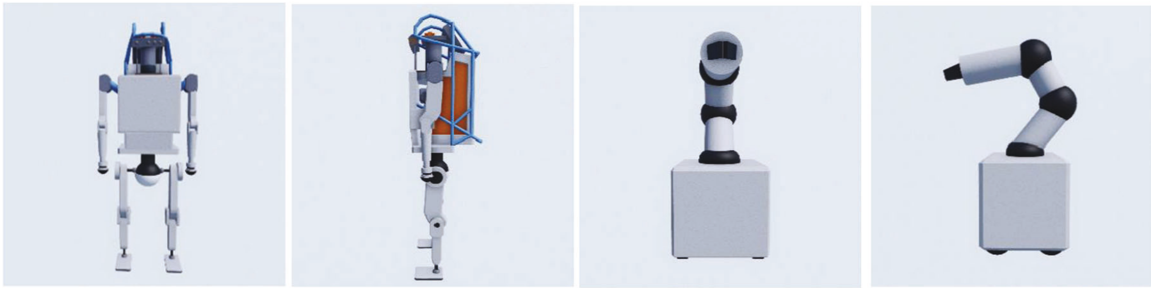

Fig. 4. Front and side view of the human-like (left) and gripper arm (right) cobots.

4.3. Participants

A total of 155 participants participated in the experiment, with 102 identifying themselves as male, and 53 identifying as female (non-binary was provided as an additional option). Age was measured in intervals for data protection and increasing anonymity to ensure respondents felt more comfortable choosing a range than sharing their exact age. We provided 9 age ranges, with the mode being 21–25 years. Regarding education, most participants held either a high school diploma or a bachelor's degree, and regarding occupation, more than half were students. Table 2 provides the descriptive statistics of the participants' demographic characteristics in each group. The four groups were fairly equal in terms of demographic characteristics, with the Chi-square test indicating no significant between-group differences.

4.4. Data analysis

For data analysis, SPSS Statistics 29 and SmartPLS 4 were employed. First, we performed tests of common method bias to verify the reliability of our statistical conclusions. Then, we checked the appropriateness of our sample size for the analysis with the inverse square root method (Hair et al., 2022; Kock and Hadaya, 2018) and confirmed the content validity, structural reliability, convergent validity, and discriminant validity of our measurement model. Afterward, we conducted partial-least-squares structural equation modeling (PLS-SEM) with two-tailed significance calculations to test our hypotheses, with the constructs modeled as latent variables and the items modeled as observed variables. PLS-SEM is a widely used method for identifying theoretical extensions of established theories. In this work, we apply it to explore the impact of our independent variables perspective-taking and anthropomorphism on trust and distrust beliefs and how they influence attitude and behavioral intention. Further, PLS-SEM is robust to a lack of normal distribution (Hair et al., 2019), and it allows testing complex models with multiple independent and dependent variables as well as chains of causal and indirect effects (Lowry and Gaskin, 2014). The latent variables of an SEM model can be considered reflective, while the observable variables are manifestations of the latent variables (Schuberth et al., 2018). This means that single items can be omitted without altering the meaning of the construct (Sarstedt et al., 2016), which is often exemplified by attitudes or intentions (Jarvis et al., 2003). Consequently, we used a *PLS-SEM with bootstrapping* to assess the statistical significance of the path coefficients of the structural model (Chin, 2010; Hair et al., 2022) for analysis.

Table 2
Descriptive statistics of participants' demographic characteristics.

Category	Characteristics	N = 155 (%)	Group 1 (n = 42) (%)	Group 2 (n = 36) (%)	Group 3 (n = 43) (%)	Group 4 (n = 34) (%)	Chi-square (p)
Gender	Male	102 (65.8)	34 (81.0)	20 (55.6)	28 (65.1)	20 (58.8)	6.709 (0.082)
	Female	53 (34.2)	8 (19.0)	16 (44.4)	15 (34.9)	14 (41.2)	
Age	14 - 15	8 (5.2)	2 (4.8)	3 (8.3)	1 (2.3)	2 (5.9)	14.614 (0.932)
	16 – 20	26 (16.8)	7 (16.7)	7 (19.4)	6 (14.0)	6 (17.6)	
	21 – 25	58 (37.4)	15 (35.7)	16 (44.4)	16 (37.2)	11 (32.4)	
	26 – 30	33 (21.3)	9 (21.4)	4 (11.1)	12 (27.9)	8 (23.5)	
	31 – 35	18 (11.6)	5 (11.9)	3 (8.3)	5 (11.6)	5 (14.7)	
	36 – 40	6 (3.9)	2 (4.8)	2 (5.6)	1 (2.3)	1 (2.9)	
	41 – 45	3 (1.9)	0 (0.0)	1 (2.8)	2 (4.7)	0 (0.0)	
	51 – 55	2 (1.3)	1 (2.4)	0 (0.0)	0 (0.0)	1 (2.9)	
	56 – 60	1 (0.6)	1 (2.4)	0 (0.0)	0 (0.0)	0 (0.0)	
Education	Primary school or lower	10 (6.5)	3 (7.1)	3 (8.3)	1 (2.3)	3 (8.8)	8.192 (0.916)
	High school diploma or A level	51 (32.9)	15 (35.7)	14 (38.9)	13 (30.2)	9 (26.5)	
	Completed vocational training	20 (12.9)	5 (11.9)	5 (13.9)	5 (11.6)	5 (14.7)	
	Bachelor's degree	39 (25.2)	11 (26.2)	9 (25.0)	10 (23.3)	9 (26.5)	
	Master's degree	34 (21.9)	8 (19.0)	5 (13.9)	13 (30.2)	8 (23.5)	
	PhD or higher	1 (0.6)	0 (0.0)	0 (0.0)	1 (2.3)	0 (0.0)	
Occupation	Administrative worker	4 (2.6)	0 (0.0)	1 (2.8)	2 (4.7)	1 (2.9)	41.835 (0.232)
	Manager	6 (3.9)	1 (2.4)	2 (5.6)	2 (4.7)	1 (2.9)	
	Non-employed	1 (0.6)	1 (2.4)	0 (0.0)	0 (0.0)	0 (0.0)	
	Office worker	10 (6.5)	3 (7.1)	1 (2.8)	1 (2.3)	5 (14.7)	
	Others	12 (7.7)	6 (14.3)	1 (2.8)	2 (4.7)	3 (8.8)	
	Production worker	2 (1.3)	0 (0.0)	0 (0.0)	2 (4.7)	0 (0.0)	
	Researcher	8 (5.2)	2 (4.8)	0 (0.0)	5 (11.6)	1 (2.9)	
	Sales representative	2 (1.3)	1 (2.4)	1 (2.8)	0 (0.0)	0 (0.0)	
	Self-employed	5 (3.2)	0 (0.0)	1 (2.8)	1 (2.3)	3 (8.8)	
	Service worker	5 (3.2)	0 (0.0)	1 (2.8)	3 (7.0)	1 (2.9)	
	Student	86 (55.5)	24 (57.1)	25 (69.4)	21 (48.8)	16 (47.1)	
	Technical worker	14 (9.0)	4 (9.5)	3 (8.3)	4 (9.3)	3 (8.8)	
Language	German	109 (70.3)	30 (71.4)	26 (72.2)	30 (69.8)	23 (67.6)	0.210 (0.976)
	English	46 (29.7)	12 (28.6)	10 (27.8)	13 (30.2)	11 (32.4)	

5. Results

5.1. Common method bias

Common method bias refers to systematic variance in responses caused by the data collection method rather than the measured constructs (Podsakoff et al., 2003). To mitigate this bias in advance, the order of the questionnaire items was randomized to prevent respondents from detecting patterns (Chang et al., 2010; Cook and Campbell, 1979). To assess common method bias in the data, a single-factor test was conducted, which revealed that the largest variance explained by one factor was 20.1% (see Table A2 in the appendix), which is below the commonly accepted threshold of 50%, indicating that common method bias is not a major concern (Podsakoff et al., 2003). Furthermore, the Variance Inflation Factor (VIF) for each path in the inner model was examined to assess the potential for multicollinearity. All VIF values were well below the recommended threshold of 3.3 (Kock, 2017), with the highest being 1.080 (see Table A3 in the appendix), suggesting that multicollinearity is not a significant issue and that each construct is sufficiently independent.

5.2. Appropriateness of the sample size

The sample size meets various criteria for the lower bounds in PLS-SEM: (a) The sample size exceeds 10 times the largest number of structural paths directed at a particular construct in the inner path model (Chin, 1998; Chin and Newsted, 1999). With the largest number of paths in the model being 2, a minimum of 20 participants was required. (b) It surpasses the recommended threshold of approximately 150 respondents for any type of SEM (Anderson and Gerbing, 1984). (c) It satisfies the recently proposed inverse square root method (Hair et al., 2022; Kock and Hadaya, 2018), which for a significant level of 5% requires $n_{min} > (2.486 / |p_{min}|)^2$, where n_{min} is the minimum sample size required, and p_{min} is the value of the path coefficient with the minimum magnitude in the PLS path model, which is expected to be statistically significant. Therefore, the sample size would be $(2.486 / -0.201)^2 = 153$).

5.3. Model reliability and validity

The measurement model was evaluated for content validity, structural reliability, convergent validity, and discriminant validity.

First, the measurement scales were adapted from existing research and pre-tested in a pilot study, supporting the assumption of content validity (Hair et al., 2022). Second, structural reliability was checked using Cronbach's α and composite reliability (CR). Cronbach's α and CR for each construct were above the critical value of 0.7 (Bagozzi and Yi, 1988; Nunnally, 1978), ensuring reliable internal consistency (Hair et al., 2022). Third, convergent validity was evaluated by examining the average variance extracted (AVE) and the outer loadings of items on their respective latent variables. All AVE values exceeded the threshold of 0.5, confirming good convergent validity. The outer loading reflects the variance of an item explained by its latent variable (Bagozzi and Yi, 1988). Most indicator loadings exceeded the threshold of 0.708, indicating that the construct explains >50% of the indicator's variance, thus providing good item reliability (Hair et al., 2022). Loadings above 0.6 were also considered acceptable (Bagozzi and Yi, 1988), indicating a strong association, particularly if there are additional items in the block for comparison basis (Chin, 1998). Although item DI4, with a loading of 0.594, did not meet the recommended threshold, we opted to retain it. Factor loadings below the threshold are not uncommon, and such items should be considered for removal if doing so would push the AVE or CR values above the recommended levels and not detract from content validity (Hair et al., 2022). Since these thresholds were already met, DI4 was not removed.

Table A4 in the appendix provides an overview of each scale's reliability and convergent validity criteria.

Discriminant validity was assessed with the heterotrait-monotrait ratio of correlations (HTMT). Table A5 in the appendix shows that all HTMT values were below the threshold of 0.85, indicating sufficient discriminant validity (Henseler et al., 2015).

Table A6 in the appendix contains the Spearman P correlation matrix of all constructs.

5.4. Structural equation model results

A bootstrapping analysis with sampling set to 5000 was conducted to assess the statistical significance of the path coefficients for the structural model (Chin, 2010; Hair et al., 2022). The primary criteria for evaluating the structural model include the explained variance (R^2), path coefficients (β) as well as their significance level (p), effect size (f^2), and 95% confidential interval (CI) lower bound (LO) and higher bound (HI) values.

The R^2 examines the variance for each construct and is typically used to describe the model's explanatory power (Hair et al., 2022). Overall, the R^2 values reveal that the proposed model explains 4.4% variance of trust, 24.5% variance of distrust, 57.7% variance of attitude, and 48.6% variance of behavioral intention.

The results of the hypotheses tests (see Table 3) indicate that perspective-taking significantly and positively influences trust, confirming H1 ($\beta = 0.417$, $p = 0.01$). However, the impact on distrust is not significant ($\beta = -0.080$, $p = 0.575$), so H2 must be rejected. Anthropomorphism, contrary to our assumption, has a significant *positive* influence on emotional distrust ($\beta = 0.497$, $p < 0.001$) and no significant impact on trust ($\beta = 0.010$, $p = 0.916$), rejecting H3 and H4. Finally, in line with our hypotheses, trust has a significant positive influence on attitude towards the cobot ($\beta = 0.680$, $p < 0.001$), while emotional distrust has a significant negative influence ($\beta = -0.201$, $p = 0.003$), and attitude positively and significantly impacts behavioral intention ($\beta = 0.697$, $p < 0.001$), confirming H5-H7. The results of the PLS-SEM are visualized in Fig. 5.

6. Discussion

6.1. Key findings

This study aimed to investigate the impact of perspective-taking with a cobot and anthropomorphism on trust and acceptance in an industrial work setting in a short-term human-cobot collaboration. The between-subject experiment was designed to vary the possibility of (A) switching perspectives with the cobot (as an interaction process-based strategy) and (B) the physical appearance as well as the language of the cobot (as an appearance-based strategy to elicit anthropomorphism). This study design was chosen to actively trigger the phenomenon observable in social robotics that people treat robots as social actors and empathize with them (Nass et al., 1994), which we hypothesized impacts cognitive trust and emotional trust in cobots. We conducted a 2 × 2 experiment set in a simulation game with 155 individuals to validate the hypothesized effects. Thereby, we found empirical support that perspective-taking significantly affects cognitive trust toward the cobot, which contains the dimensions of reliability, functionality, and helpfulness. Meanwhile, contrary to our hypothesis, perspective-taking did not lead to a reduction in emotional distrust. Inconsistent with prior research on the intended effects of anthropomorphism (Natarajan and Gombolay, 2020), we did not find a positive impact of anthropomorphism on cognitive trust toward the cobot. On the contrary, we identified that higher anthropomorphism resulted in a heightened emotional distrust toward the cobot. In accordance with IS theories TAM and UTAUT (Davis et al., 1989; Venkatesh and Davis, 2003), both trust beliefs impacted attitude toward the cobot (with cognitive trust showing a significant positive effect on attitude and emotional distrust eliciting a significant negative influence on attitude), and attitude toward the

Table 3
Results of the hypotheses tests (PT = Perspective-taking, AN = anthropomorphism, CT = cognitive trust, ED = emotional distrust, AT = attitude towards the cobot, BI = behavioral intention to collaborate with the cobot).

H	Relationship	β	f^2	95% CI LO	95% CI HI	t-value	p	Supported
H1	PT → CT	0.417	0.045	0.102	0.731	2.559	0.011	Yes
H2	PT → ED	−0.080	0.002	−0.369	0.194	0.561	0.575	No
H3	AN → CT	0.010	0.000	−0.196	0.181	0.106	0.916	No
H4	AN → ED	0.497	0.324	0.371	0.625	7.640	0.000	No (positive instead of negative influence)
H5	CT → AT	0.680	1.011	0.556	0.783	11.714	0.000	Yes
H6	ED → AT	−0.201	0.089	−0.338	−0.072	2.993	0.003	Yes
H7	AT → BI	0.697	0.947	0.569	0.801	11.660	0.000	Yes

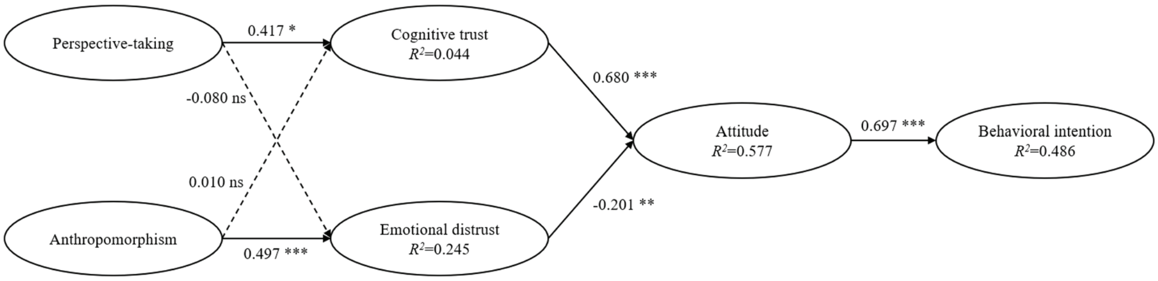

Fig. 5. PLS-SEM results (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ns = non-significant).

cobot positively and significantly influenced behavioral intention to collaborate with the cobot.

Our findings suggest that the option to take the perspective of cobots represents a promising strategy to foster trust and particularly overcome cognitive trust barriers in human-cobot interaction as a basis for fruitful human-robot collaboration in industrial environments (Hosseini Shoabjareh et al., 2024). Based on prior knowledge (Madsen and Gregor, 2000; Matthews et al., 2020), we can assume that the opportunity for perspective-taking empowered people to understand the cobot's function better, how it makes decisions in human-cobot teams and how it processes sensory inputs, thereby fostering cognitive trust. Thus, our results deepen the findings of Wittmann et al. (2023) on the relationship between perspective-taking and acceptance perceptions towards intelligent social robots. However, even though perspective-taking has previously been shown to establish emotional bonds (Galinsky et al., 2008), improve liking, and increase perceived closeness (Batson et al., 2002; Johnson, 1975; Ku et al., 2015; Wang et al., 2014), our results indicate that perspective-taking with industrial cobots did not significantly affect emotional distrust as the intervention did not result in less suspicion or wariness toward the robot.

Moreover, we found substantial evidence that opting for human-like cobots as an appearance-based strategy may not be desirable. Instead of increasing emotional trust in industrial human-cobot teams, as may be assumed based on prior research in the field of social robots (Sinha et al., 2020), we evidenced a contrary effect in industrial environments: human-like cobots are met with increased suspicion and skepticism, which ultimately can impede cobot adoption and fruitful collaboration. Based on our findings, we can assume that the triggered anthropomorphism makes human beings not only ascribe positive human characteristics to cobots but may also make them project negative ones. Therefore, people starting to empathize with their cobot companions and believing their cobot has its own intentions and agenda can backfire and undermine trust in undesired ways. Contrary to the predominantly positive reported effects of anthropomorphism on human perception, specifically toward social robots, our results hint that people may not crave more human-like robotic partners but much more functional servants in industrial collaboration tasks. Moreover, even though anthropomorphism has been identified as a key determinant of cognitive trust in prior studies (Duffy, 2003; Hoff and Bashir, 2015; Kiesler et al., 2008; Langer et al., 2019; Lewis et al., 2018; Meissner et al., 2021; Waytz et al., 2014), we did not find any significant effect of anthropomorphism on cognitive trust in our industrial setting, meaning that people's perception of the cobot's reliability, functionality and helpfulness was not significantly affected by it. This finding is consistent with prior research that identified no significant impact of the robot form on trust in service robots (Tussyadiah et al., 2020) and particularly a lack of significant impact of anthropomorphism on trust in an industrial human-robot interaction use case (Onnasch and Hildebrandt, 2022). However, in contrast to the latter study, our research did not confirm that anthropomorphism negatively impacts the perceived reliability of the robot.

In summary: On the one hand, this study indicates that it is possible to intentionally support the phenomenon of viewing robots as social actors (Nass et al., 1994) and empathizing with robots (Riek et al., 2009) through the two sociopsychological mechanisms of perspective-taking and anthropomorphism in an industrial context, and we showed that people who took the opportunity to logically and cognitively view the world from a robot's perspective showed an increase in cognitive trust toward the cobot. On the other hand, we found empirical evidence that anthropomorphism elicited through human-like cobot appearance can be vastly counterproductive, as it may cause undesired adverse emotional effects and increase distrust toward the cobot.

Our findings provide three main contributions to the academic HRI discourse and the practical design of human-cobot interaction in industrial contexts. First, our work extends prior research on the direct effects of perspective-taking on robot acceptance (Hang et al., 2022; Ho and Ng, 2022; Wittmann et al., 2023) by shedding new light on the particular impact of perspective-taking on cognitive trust, which indirectly and positively affects attitude toward cobots and the behavioral intention to collaborate with cobots. Thereby, we provide a more nuanced and in-depth understanding of why perspective-taking might be a promising strategy to foster acceptance of cobots for successful human-cobot collaboration in industrial environments. Second, our study enlarges research on anthropomorphism and its impacts in human interaction with social robots (Davis et al., 2023; Kuchenbrandt et al., 2013; Natarajan and Gombolay, 2020), sharpening our understanding of its counterproductive effects on the emotional perceptions of people toward cobots in the industrial environment where the human-cobot relationship might differ from those in leisure contexts. Finally, by considering the effects of both perspective-taking and anthropomorphism, our study extends prior work that has focused on isolated effects and deepens our understanding of how cobot and interaction design interplay in fostering cognitive trust and emotional distrust towards cobots, which in turn both influence attitude and behavioral intention. Thereby, we create novel design knowledge by demonstrating how different trust beliefs toward cobots and, ultimately, the behavioral intention to collaborate with cobots in industrial environments are impacted by the design of the interaction process and the robotic agent.

This work's theoretical and practical contributions are detailed in the following sections.

6.2. Theoretical implications

The power of perspective-taking for fostering cognitive trust

The findings revealed that perspective-taking particularly enhanced the cognitive dimension of trust. Cognitive trust comprises the elements of reliability, functionality and helpfulness. The positive direct impact of perspective-taking on cognitive trust and its indirect impact on attitude and behavioral intention observed in the results reflect its well-documented effects in human-human interactions (Ku et al., 2015; Sun et al., 2021). This study reinforces the idea that perspective-taking is a crucial precursor of and facilitates collaborative behavior (Wald et al., 2017), as effective collaboration relies on fostering trust and understanding among different actors (Ansell and Gash, 2008; Eisenberg and Miller, 1987; Galinsky et al., 2005), making it a *valuable tool for improving human-robot interaction*.

Specifically, perspective-taking in human-human interactions improves cognitive analysis of interactions, as individuals consider both their own interests and those of their counterpart (Gilin et al., 2013). It allows individuals to consciously and strategically anticipate others' responses and align their actions accordingly, improving interaction quality (Schilke and Huang, 2018). The results of our study suggest that *by actively engaging in perspective-taking, individuals gain a better understanding of cobot's actions and competencies*, increasing perceptions of reliability, functionality and helpfulness, which might thus equivalently contribute to a higher *interaction quality* and positively impact people's attitudes and behavioral intentions toward further collaboration with the cobot.

However, considering Smith et al. (2020) work, which found no effect of mentally imagining the robot's perspective or allowing participants to view or control the robot's actions from different perspectives, our study also sheds light on how the specific design of perspective-taking as an interaction process-based strategy might alter its impact. In contrast to engaging only in visual and spatial perspective-taking, *incorporating the robot's mental perspectives* by including visual cues and linguistic framing of the cobot's inner workings might help people to develop mental models of the cobot (Coeckelbergh, 2011), addressing ambiguous perceptions of cobots and reducing uncertainty and cognitive load (Baumgartner et al., 2022; Kopp et al., 2022).

Overall, our findings on the particular impact of perspective-taking on cognitive trust extend previous research on perspective-taking with robots in interactive environments and the embodiment of outgroups' perspectives to reduce biases and improve collaboration (Ahn et al., 2016, 2013; Herrera et al., 2018). Moreover, we provide additional evidence of using perspective-taking to create positive attitudes toward non-human and non-living entities, thereby expanding upon earlier findings (Ahn et al., 2016, 2014; Wittmann et al., 2023).

The intricate relationship between anthropomorphism and emotional distrust

Large companies are increasingly focusing on human-like industrial cobots, such as Agility Robotics' Digit (Hurst, 2019), Boston Dynamics' Atlas (Guizzo, 2019), Tesla's Optimus (Qiao, 2023), and the demand for human-like cobots is expected to rise further (Taesi et al., 2023). However, instead of reducing people's distrust toward cobots, we found that anthropomorphism elicited through human-like design led to a significant increase in emotional distrust. That means that anthropomorphism affected people's perception of the cobot on an emotional level – but our results indicate that it resulted in more suspicion and concerns regarding safety and created wariness among participants instead of causing positive feelings. This observation contributes novel insights to the research on anthropomorphism in industrial HRI: consistent with prior research by Onnasch and Hildebrandt (2022), our work suggests that a human-like robot design is no universal remedy to improve collaboration in human-robot teams (Roesler et al., 2020, 2021). Quite the contrary, a *human-like design leading people to attribute human characteristics to cobots may even be detrimental*.

This effect may be attributed to two main factors: First, previous research suggests that individuals tend to value human-like designs, particularly when robots are employed in tasks requiring a high level of sociability (de Graaf and Ben Allouch, 2015; Goetz et al., 2003). In line with that, previously reported positive effects of anthropomorphism on trust have primarily been found in social contexts (Fong et al., 2003; Złotowski et al., 2015). However, in an industrial context, cognitive rather than emotional engagement is focal, making human-cobot interaction secondary to the task goal itself (Onnasch and Hildebrandt, 2022). Thus, human likeness may not be a critical success factor in task-focused interactions at work (Ötting et al., 2022). Accordingly, our results suggest that *a machinelike robot design may fulfill peoples' expectations of a reliable teammate better than a robotic agent with more human-like features*.

Second, anthropomorphizing cobots might make human beings not only ascribe positive human characteristics but may also lead them to project negative ones onto advanced robotic agents, such as negative intents or deception (Mori, 1970; Onnasch and Hildebrandt, 2022; Yogeeswaran et al., 2016). Consequently, *when people start to empathize with their cobot companions and believe their cobot has own intentions and an agenda, this can backfire and even undermine trust in undesired ways*.

The interplay of trust and distrust in shaping human-cobot collaboration

Our findings show that even though perspective-taking led to a significant increase in cognitive trust, it did significantly impact emotional distrust in our experiment. Similarly, we observed a significant effect of anthropomorphism on emotional distrust but found no effect on cognitive trust. Finally, in analyzing the impact of cognitive trust and emotional distrust on attitude toward the cobot, we see that their effects are inverse: cognitive trust elicits a positive influence on attitude, while emotional distrust negatively impacts attitude. Together, they explain more than half of the entire variance in attitude toward cobots. Consequently, these insights gained through considering the interplay of cognitive trust and emotional distrust support the notion that *distrust is not just the mere inverse of trust and that both trust beliefs may coexist simultaneously* (Kohn et al., 2021; Kopp, 2024; Lewicki et al., 2006), rather than being polar opposites (Jian et al., 2000).

Since there is clear evidence that cognitive trust in cobots positively influences their acceptance whereas distrust inhibits human-cobot collaboration (Kopp, 2024; Smithson, 2018), it might thus stand to reason to consider cognitive trust as the "good" trust belief (that is desirable) and emotional distrust as the "bad" trust belief (that should be diminished). Nonetheless, in interacting with increasingly intelligent cobots, people may even benefit from having a healthy dose of emotional distrust toward them, especially in industrial HRI contexts. The reason is that it may prevent the other extreme of the spectrum - forming very strong bonds with robots – which can result in overtrust, where workers place excessive trust in robots (Sauppé and Mutlu, 2015). This overreliance might also make people more inclined to overlook mistakes made by cobots (Meissner et al., 2021). Such blind trust can be risky if it neglects necessary precautions (Hancock et al., 2011). Therefore, the observed sense of alertness and general wariness of people toward the cobot may prevent the occurrence of automation bias and thus contribute to safer collaboration with the robotic agent on the industrial floor. As a result, *we strongly argue for the importance of both trust and distrust – and their healthy balance – for a successful human-cobot collaboration.*

6.3. Practical implications

Design knowledge to promote trust in cobots by purposefully leveraging socio-psychological mechanisms

There is substantial evidence indicating that humans tend to apply social behavior principles when interacting with social robots in private settings, meaning that they frequently empathize with robots and treat them similarly to how they interact with other people (Nass and Moon, 2000; Rosenthal-von der Pütten et al., 2013, 2014; Sheng and Wang, 2022). Further, games, such as Portal 2 or Scrapland, are already effectively leveraging this tendency by incorporating perspective-taking with human-like robots as a central design element that people find enjoyable (Shute et al., 2015; Wittmann and Morschheuser, 2022). Our study is one of the first to investigate the specific psychological and behavioral effects of promoting such socio-psychological mechanisms in the context of human-robot interaction (Smith et al., 2020). The findings demonstrate that applying knowledge from psychological theories, principles, and methods originating in human-human interactions is promising to purposefully elicit social behavior in people's interactions with cobots in industrial environments and, as in our case, for instance, can increase trust toward cobots as social "outgroup" and improve human-cobot collaboration. Even though use cases and requirements surrounding human-cobot collaboration may vary, we propose several recommendations for practitioners derived from our findings on how companies can best leverage the two socio-psychological mechanisms investigated in this study to promote trust in cobots in industrial contexts.

On the one hand, our findings indicate that *perspective-taking can improve cognitive trust in cobots and therefore suggest that this method should also be leveraged more frequently in industrial practice as a vehicle to overcome cognitive trust barriers of workers*, which present a significant hurdle for cobot acceptance and successful human-cobot collaboration (Liao et al., 2023). In this regard, our study provides a blueprint for practitioners seeking to increase trust and acceptance in cobots via perspective-taking. A key challenge in designing effective perspective-taking is conveying the cobot's internal state in a way that humans can understand (Krach et al., 2008; Phillips et al., 2011). Effective human-cobot interaction requires users to comprehend the cobot's thought process and abilities (Krach et al., 2008; Meissner et al., 2021). We addressed this challenge by *integrating cues that help users understand the cobot's operations, such as simulated inner workings explained in human language*. This approach increases transparency, making the cobot's actions and processes more explicit, thus overcoming prejudices and worries surrounding a cobot (Kluy and Roesler, 2021; Liao et al., 2023), such as opaque decision-making and a perceived lack of transparency of system functionalities. Additionally, our proposed cues serve as catalysts for activating cognitive perspective-taking, reducing cognitive load (Baumgartner et al., 2022), and enhancing the motivation to consider the cobot's perspective. These elements could be seamlessly integrated into factory settings via a mobile or tablet application connected to the cobot's camera, allowing operators to observe the cobot's operations even when it is out of sight. Including intelligible sensor status updates and concise explanations of the cobot's high-level tasks in human language would empower operators, typically not developers, to comprehend how the cobot executes tasks.

On the other hand, we found evidence that *incorporating perspective-taking with cobots could be more effective and cost-efficient than modifying hardware characteristics or a cobot's appearance*. While the design of cobots with human-like features often involves higher costs and complexity, potentially compromising task efficiency (Silva and Machado, 2012; Zhang and Yang, 2022), we see that instead of eliciting positive effects on cognitive trust or diminishing emotional distrust, anthropomorphism evoked through human-like cobot design can even increase emotional distrust. While distrust is not per se bad for avoiding overtrust in automation (Kopp, 2024), it appears that in industrial contexts, a clear robot-like appearance may benefit humans experiencing cobots as reliable partners without projecting human-inherent negative characteristics such as malicious intent on them. In other words, *applying perspective-taking to increase understanding and connection to the cobots as an "outgroup" may be more beneficial than trying to elicit feelings that they are part of the human "ingroup" to foster treating cobots as social actors and thereby establish successful human-cobot collaboration*.

A critical view on ethical and societal implications of treating robots as social actors

In this work, we have argued that people's tendency to treat robots as social actors and empathize with them expressing itself in various social behaviors normally inherent to human-human interaction, such as giving nicknames to robots and expressing attachment (Kidd et al., 2006), showing emotional reactions when robots are maltreated (Rosenthal-von der Pütten et al., 2013) and even marrying virtual assistant robots (Liu, 2021; Sheng and Wang, 2022) is a generally positive phenomenon that could be purposefully elicited through interaction process and cobot design in industrial environments.

However, these practices also have a plethora of potential negative ethical and societal implications, necessitating careful organizational consideration when being introduced. First, as we have seen in the positive impact of anthropomorphism on emotional distrust, human likeness of robots may result in blurred boundaries between human beings and cobots. In this work, we primarily focused on how our intervention affected perceptions of people toward cobots. In reality, however, the relationship and interdependencies go beyond this unidirectional view, as there is empirical evidence that attributing human qualities to social robots may, in turn, influence empathy toward human beings (Spaccatini et al., 2023). There is a concern that empathizing with robots may lead to dehumanizing actual humans (Lanteigne, 2019). Second, treating robots as equal partners in social situations and maintaining (intimate) relationships may also lead to the adverse effect that other interpersonal relationships with human beings are objectified and limited (Malinowska, 2022). In the industrial context, preference and disproportionally heightened empathy toward a cobot may even be physically harmful to other human beings when human operators face decisions about prioritizing the safety of cobots versus human colleagues on the shop floor. Finally, trust in robots as social actors is a double-edged sword. Excessive trust in robots (Hancock et al., 2011) might result in attributing undue agency and legal responsibility to them, while undertrust may prevent technology usage and lead to avoidance (Parasuraman and Riley, 1997). This highlights the need for balanced and informed approaches to calibrate appropriate levels of trust when considering robots as social actors (Bansal et al., 2021).

As robotics and AI technologies evolve, their future role in our society is yet unknown, whether as mere tools or as social companions (Malinowska, 2022). Thus, finding the appropriate balance is crucial to safeguard humans and robots. As pointed out by Malinowska (2022), there is a need to carefully evaluate when empathy towards robots should be supported and strengthened while identifying use cases and situations where this is undesirable, and we may want to weaken it on purpose. We call for more intense research efforts and practical consideration of these questions to informedly decide based on such interventions' intended and unintended consequences.

7. Limitations and future work

As with all studies, this work has several limitations to consider when interpreting the findings and planning future research.

First, the generalizability and external validity of the findings may be limited. This study was conducted in Germany in a particular cultural context. We acknowledge that culture is a key determinant in empirical studies and know that our results are not entirely transferable to other countries. There is ample evidence that culture and nationality significantly impact the attitude toward and social acceptance of robots (Békésy et al., 2024; Straub et al., 1997; L. Wang et al., 2010). Therefore, we recognize that running this study with the same setup and experimental design in another cultural environment may have resulted in takeaways different from the ones obtained. Similarly, this study's sample does not reflect the specific demographic of manufacturing workers. Although a mobile lab unit was used to gather a diverse population at various events, the sample mainly comprised university students under 30 years of age. Also, the experiment was conducted in an interactive simulation game rather than directly at a real production site. These factors may affect the applicability of the findings to actual production scenarios. Participation in our experiment was voluntary and occurred during participants' leisure time, while machine operators may be faced with new cobots introduced by management on the shopfloor without workers' consent. Thus, the perceived threat of technological replacement in such situations might be more pronounced (Hinsen et al., 2022; Kopp et al., 2022, 2023). Replicating the study with a sample of manufacturing workers in a real factory setting might yield different results, as these workers could have distinct mental models of robots (Kopp et al., 2021, 2022, 2023). Further, the simulation did not integrate other potentially relevant factors shaping workers' level of trust in cobots in real industrial environments, such as the perceived physical safety during the HRI at the workplace. Future studies should thus examine whether accessing a cobot's visual perspective impacts blue-collar workers' trust under high-stakes and realistic industrial conditions. Yet, we reiterate that our sample was purposefully selected and suitable for this study because young university students often lack prior interaction experiences with cobots, making them ideal participants for examining initial trust-building.

Second, this research focused on short-term interventions using a 2D immersive approach. The limited duration of the experiment was a conscious decision to prevent exhaustion and cognitive overload of participants. Future studies could explore even more immersive media, such as VR, to trigger social interaction with cobots. Moreover, this study only captured the intention of collaborating with cobots. Discrepancies may exist between intended and actual behavior in perspective-taking exercises (Herrera et al., 2018; Rosenberg et al., 2013) and cobot adoption in general (Meissner et al., 2021; Michaelis et al., 2020). However, the study's primary goal was to assess the impact of our two independent variables on cognitive trust and emotional distrust. Thus, given that previous research in HRI indicates that trust significantly predetermines future intention to use (Kraus et al., 2024), investigating actual usage was not at the core of this work. Future studies can expand the experimental scenario to determine if the positive effects of simulated interventions can be extrapolated to physical interactions with real cobots. Additionally, to address the general lack of longitudinal studies in HRI (Baumgartner et al., 2022; Kopp et al., 2021), future research should investigate the long-term effects of our intervention and determine whether, for example, recurrent perspective-taking interventions are necessary to counteract the novelty effect, as the benefits of perspective-taking often diminish after a few weeks (Ahn et al., 2016, 2014; Herrera et al., 2018). Potential follow-up studies could also investigate the effects of perspective-taking and anthropomorphism on a tangible robot, as physical embodiment may influence perceptions (Krach et al., 2008; J. Li, 2015; Mollahosseini et al., 2018).

Third, the study only explored a limited range of cobot designs. Using a human voice for the human-like cobot may have triggered specific gender and nationality stereotypes. However, this might not apply to all participants assigned to the human-like groups, as some individuals refused to wear headphones due to hygiene concerns and discomfort. Even though we have carefully selected the anthropomorphic cues for the gripper arm and humanlike cobot groups, we acknowledge that a group-by-group comparison of the differences in participants' perceived anthropomorphism was not conducted. Future studies should integrate perceived anthropomorphism as a distinct variable for manipulation checking, explore various cobot designs, and examine their impact on user perceptions. The human-like cobot's design featured bipedal motion, a human-like physique while framing the cobot as a factory colleague. Yet it retained a mechanical appearance with visible joints and wires, lacking human-like skin. Nonetheless, we recommend varying the level of human likeness of the cobot to validate its effect on emotional distrust perceptions among participants. Thus, future research could complement this work and strive to incorporate more lifelike facial features and functional eye gaze, allowing for non-verbal communication, which may be crucial for trust calibration (Admoni and Scassellati, 2017; Boucher et al., 2012; Broadbent et al., 2013; Cavedon et al., 2015; Leite et al., 2013; Onnasch and Hildebrandt, 2022; Paradeda et al., 2016; Wiese and Weis, 2020).

Fourth, the study primarily examined the impact of the independent variables on cognitive trust and emotional distrust, without incorporating cognitive distrust or emotional trust in the research model. While trust and distrust can be viewed as distinct properties (Lewicki et al., 2006; Rai, 2020), prior research in the field indicates that cognitive trust and cognitive distrust as well as emotional trust and emotional distrust span the same continuum (Guo et al., 2017; Capiola et al., 2022). Therefore, expanding the research model would have significantly increased risks of survey fatigue and inattention in the experimental setting without adding explanatory value.

8. Conclusion

In this article, we explored the effects of perspective-taking and anthropomorphism on trust and distrust toward cobots. Given that a lack of trust often prevents a more fruitful collaboration in human-cobot teams, we deliberately attempted to provoke the visible phenomenon of people empathizing with robots and treating them as social actors in personal life contexts in an industrial human-cobot collaboration context by triggering the sociopsychological mechanisms of perspective-taking and anthropomorphism in specific interaction process and cobot appearance designs. Using a 2 × 2 between-subject study design, we designed a realistic simulation game set in an automotive assembly and found that perspective-taking holds significant potential to impact cognitive trust in cobots positively. Moreover, our insights revealed that anthropomorphism - contrary to predominantly reported positive impacts on trust and acceptance in studies with social robots – did not improve cognitive trust but even caused emotional distrust of people toward the cobot. Based on these findings, we contribute to the ongoing conversation on the impact of perspective-taking with non-human actors and human-like appearance on trust and willingness to collaborate with increasingly intelligent robots. We argue that in industrial settings, our findings suggest that taking the perspective of cobots to learn more about their inner workings and thereby gain an understanding of the "outgroup" of robotic partners in the workspace is exceptionally supportive of human-cobot collaboration. However, a human-like design that evokes anthropomorphism and the consideration of cobots as part of the human "ingroup" may be detrimental, as individuals then tend to project negative human characteristics on the robotic partners. Therefore, robotic-appearing cobots acting as diligent servants and not human-like partners may be preferable for successful human-cobot collaboration on the industrial shop floor.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Grammarly in order to improve language and readability. After using this tool/service, the authors reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

CRediT authorship contribution statement

Maximilian Wittmann: Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Runjie Xie:** Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Jeanine Kirchner-Krath:** Writing – review & editing, Formal analysis. **Benedikt Morschheuser:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Runjie Xie and Jeanine Kirchner-Krath report financial support was provided by Federal Ministry of Education and Research Bonn Office. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table A1
Measurement items of study.

Variable	Measurement item	Source
Anthropomorphism		
AN1	The collaborative robot appears to have a mind of its own.	Li and Wang (2021)
AN2	The collaborative robot appears to have intentions.	
AN3	The collaborative robot has “free will”.	
AN4	The collaborative robot appears to have consciousness.	
AN5	The collaborative robot appears to have the ability to experience emotions.	
Cognitive trust		
CT1	The collaborative robot has the functionality I need for the task.	McKnight et al. (2011)
CT2	The collaborative robot has the features required for my task.	
CT3	The collaborative robot has the ability to do what I want it to do.	
CT4	The collaborative robot supplies my need for help through a help function.	
CT5	The collaborative robot provides competent guidance (as needed) through a help function.	
CT6	The collaborative robot provides whatever help I need.	
CT7	The collaborative robot provides very sensible and effective advice, if needed.	
CT8	The collaborative robot is a very reliable system.	
CT9	The collaborative robot does not fail me.	
CT10	The collaborative robot is extremely dependable.	
CT11	The collaborative robot does not malfunction for me.	
Emotional distrust		
ED1	The collaborative robot is deceptive.	Jian et al. (2000)
ED2	The collaborative robot behaves in an underhanded manner. (The collaborative robot acts in a sneaky way.)	
ED3	I am suspicious of the collaborative robot’s intent, action, or output.	
ED4	I am wary of the collaborative robot. (I am cautious about the collaborative robot.)	
ED5	The collaborative robot’s action will have a harmful or injurious outcome.	
Attitude towards the cobot		
AT1	Using the collaborative robot is a good idea.	Li and Wang (2021)
AT2	Using the collaborative robot is a wise choice.	
AT3	I like using the collaborative robot.	
Behavioral intention to collaborate with the cobot		
BI1	I intend to use the collaborative robot.	Li and Wang (2021)
BI2	I predict I would use the collaborative robot.	
BI3	I plan to use the collaborative robot.	

Table A2
Total variance explained for the verification of common method bias.

Component	Extraction sums of squared loadings	% of variance	Cumulative %
1	5.64	20.1	20.1
2	4.23	15.1	35.2
3	3.66	13.1	48.3

Table A3
Overview of the VIF values for each path in the model (PT = Perspective-taking, AN = anthropomorphism, CT = cognitive trust, ED = emotional distrust, AT = attitude towards the cobot, BI = behavioral intention to collaborate with the cobot).

H	Relationship	Variance Inflation Factor (VIF)
H1	PT → CT	1.008
H2	PT → ED	1.008
H3	AN → CT	1.008
H4	AN → ED	1.008
H5	CT → AT	1.080
H6	ED → AT	1.080
H7	AT → BI	1.000

Table A4
Measurement model assessment results.

Construct and items		Cronbach's α	CR	AVE	Mean	SD	Loadings
Anthropomorphism (AN)		0.835	0.883	0.603	2.403	0.983	
AN1	The collaborative robot appears to have a mind of its own.			Li and Wang (2021)	2.677	1.305	0.799
AN2	The collaborative robot appears to have intentions.				2.652	1.375	0.772
AN3	The collaborative robot has "free will".				2.232	1.228	0.795
AN4	The collaborative robot appears to have consciousness.				2.387	1.246	0.785
AN5	The collaborative robot appears to have the ability to experience emotions.				2.065	1.151	0.725
Emotional distrust (ED)		**0.773**	**0.846**	**0.526**	**2.030**	**0.832**	
ED1	The collaborative robot is deceptive.			Jian et al. (2000)	2.161	1.156	0.719
ED2	The collaborative robot behaves in an underhanded manner. (The collaborative robot acts in a sneaky way.)				1.742	1.089	0.737
ED3	I am suspicious of the collaborative robot's intent, action, or output.				2.000	1.175	0.800
ED4	I am wary of the collaborative robot. (I am cautious about the collaborative robot.)				2.400	1.278	0.594
ED5	The collaborative robot's action will have a harmful or injurious outcome.				1.845	1.042	0.759
Cognitive trust (CT)		**0.912**	**0.926**	**0.535**	**3.838**	**0.761**	
CT1	The collaborative robot has the functionality I need for the task.			McKnight et al. (2011)	4.310	0.816	0.664
CT2	The collaborative robot has the features required for my task.				4.135	0.991	0.776
CT3	The collaborative robot has the ability to do what I want it to do.				4.077	0.905	0.628
CT4	The collaborative robot supplies my need for help through a help function.				4.013	0.943	0.740
CT5	The collaborative robot provides competent guidance (as needed) through a help function.				4.103	0.958	0.823
CT6	The collaborative robot provides whatever help I need.				3.716	1.163	0.716
CT7	The collaborative robot provides very sensible and effective advice, if needed.				3.510	1.080	0.697
CT8	The collaborative robot is a very reliable system.				3.626	1.030	0.780
CT9	The collaborative robot does not fail me.				3.684	1.185	0.687
CT10	The collaborative robot is extremely dependable.				3.542	1.203	0.741
CT11	The collaborative robot does not malfunction for me.				3.503	1.127	0.768
Attitude towards the cobot (AT)		**0.841**	**0.904**	**0.759**	**4.050**	**0.842**	
AT1	Using the collaborative robot is a good idea.			Li and Wang (2021)	4.084	0.960	0.873
AT2	Using the collaborative robot is a wise choice.				4.116	0.904	0.895
AT3	I like using the collaborative robot.				3.948	1.037	0.846
Behavioral intention to collaborate with the cobot (BI)		**0.909**	**0.943**	**0.846**	**4.097**	**0.927**	
BI1	I intend to use the collaborative robot.			Li and Wang (2021)	4.077	1.026	0.934
BI2	I predict I would use the collaborative robot.				4.129	1.058	0.906
BI3	I plan to use the collaborative robot.				4.084	0.929	0.919

Table A5
HTMT values of each construct.

Construct	PT	AN	CT	ED	AT	BI
PT						
AN	0.095					
CT	0.215	0.165				
ED	0.036	0.594	0.325			
AT	0.160	0.163	0.831	0.480		
BI	0.026	0.098	0.666	0.312	0.796	

Table A6
Correlation matrix (Spearman's ρ) of all constructs.

Construct		AT	CT	AN	ED	BI
AT	ρ	-				
	Df	-				
	p	-				
	N	-				
CT	ρ	0.683	-			
	Df	153	-			
	p	1.000	-			
	N	155	-			
AN	ρ	−0.034	−0.027	-		
	Df	153	153	-		
	p	0.338	0.370	-		
	N	155	155	-		
ED	ρ	−0.370	−0.330	0.407	-	
	Df	153	153	153	-	
	p	<0.001	<0.001	1.000	-	
	N	155	155	155	-	
BI	ρ	0.661	0.542	−0.068	−0.262	-
	Df	153	153	153	153	-
	p	1.000	1.000	0.201	<0.001	-
	N	155	155	155	155	-

Data availability

I have shared the link to my data/code at the Attach File step

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