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RESEARCH ARTICLE

TRUSTING AND WORKING WITH ROBOTS: A RELATIONAL DEMOGRAPHY THEORY OF PREFERENCE FOR ROBOTIC OVER HUMAN CO-WORKERS[1]

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Organizations are facing the new challenge of integrating humans and robots into one cohesive workforce. Relational demography theory (RDT) explains the impact of dissimilarities on when and why humans trust and prefer to work with others. This paper proposes RDT as a useful lens to help organizations understand how to integrate humans and robots into a cohesive workforce. We offer a research model based on RDT and examine dissimilarities in gender and co-worker type (human vs. robot) along with dissimilarities in work style and personality. To empirically examine the research model, we conducted two experiments with 347 and 422 warehouse workers, respectively. The results suggest that the negative impacts of gender, work style, and personality dissimilarities on swift trust depend on the co-worker type. In our experiments, gender dissimilarity had a stronger negative impact on swift trust in a robot co-worker, while work style and personality had a weaker negative impact on swift trust in a robot co-worker. Also, swift trust in a robot co-worker increased the preference for a robot co-worker over a human co-worker, while swift trust in a human co-worker decreased such preferences. Overall, this research contributes to our current understanding of human-robot collaboration by identifying the importance of dissimilarity from the perspective of RDT.

Keywords: Relational demography theory, swift trust, human-robot interaction, robot, ascribed dissimilarity, achieved dissimilarity, mind attribution, and preference for robotic co-worker

Introduction

Organizations are increasingly relying on human-robot collaboration to accomplish work and now face the challenge of integrating humans and robots into one cohesive workforce. For instance, White Castle, a fast-food restaurant franchise, adopted robots to make french fries along with humans as a result of the labor shortage during the coronavirus 2019 (COVID-19) pandemic (Mims, 2021). Robots are expected to replace as much as half the workforce in the next 10-20 years, creating growth in industrial robots from $16 billion to $37 billion over the next 10 years (Repko, 2021). The challenge of integrating humans and robots into one cohesive workforce is made harder, in part, by the fear of job loss (Takayama et al., 2008). There is a growing concern that robots are taking jobs from humans (Graetz & Michaels, 2018; Liang et al., 2021). This fear has engendered negative attitudes toward robots (Elprama et al., 2017).

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Relational demography theory (RDT) has been used to explain why humans choose to work together as a cohesive, integrated workforce by examining their dyadic dissimilarities (Tsui et al., 1989). Dissimilarity among co-workers is a significant predictor of whether co-workers will effectively collaborate (Ertug et al., 2022; Robert et al., 2018; Schaubroeck & Lam, 2002). Although the importance of dissimilarities in human relationships has been demonstrated, we know very little with regard to its impacts on human-robot relationships. Nonetheless, dissimilarities could prove to be more crucial to understanding relationships between humans and robots (Esterwood et al., 2021) because, in the absence of any interventions, employees are more likely to view their robot co-workers as being dissimilar rather than similar (Bernier & Scassellati, 2010). Therefore, it is essential to understand whether such dissimilarities pose a challenge—and, if so, how big—for human-robot collaborations.

To address these issues, we focused on two types of dissimilarities: ascribed and achieved dissimilarity. Ascribed dissimilarity refers to the differences based on nominal characteristics acquired at birth, such as gender or race, or those acquired involuntarily later in life, (Ertug et al., 2022; Gramzow et al., 2001; Taylor & Jaggi, 1974). Achieved dissimilarity is based on characteristics that are malleable and influenced by one's behaviors, values, experiences, and personalities (Ertug et al., 2022). We propose an RDT-based research model, which theorizes the impacts of ascribed dissimilarities, such as gender and co-worker type (human vs. robot) differences, as well as achieved dissimilarities, such as work style and personality differences. Specifically, the research model proposes that the impact of dissimilarities such as gender, work style, and personality on a co-worker's swift trust depends on the co-worker type (human vs. robot). The research model also theorizes that as swift trust in a human co-worker decreases, preferences for a robot co-worker increase.

We empirically examined the research model using two experiments. Studies 1 and 2 involved 347 and 422 warehouse workers, respectively. Results indicated that ascribed dissimilarities in gender had a stronger negative impact on swift trust in robot co-workers (i.e., dissimilar co-worker type) than on human co-workers (i.e., similar co-worker type). On the contrary, achieved dissimilarities had a weaker negative impact on swift trust in robot co-workers compared to human co-workers. The latter effect is due to a lack of *mind attribution*, which is the degree to which individuals attribute mental states—such as intentions or beliefs—to nonhuman agents, including robots (Quesque & Rossetti, 2020). We found that individuals attribute a higher degree of mental state to human co-workers compared to robotic co-workers. We also found that swift trust in a robot co-worker increased the preference for working with a robot over a human, whereas swift trust in a human co-worker actually decreased such preferences.

This study contributes to the literature in three ways. First, by adopting RDT, this paper responds to the call for next-generation theorizing for collaborations involving AI-enabled technologies (Burton-Jones et al., 2021; Rai et al., 2019). In this study, RDT was theoretically extended and empirically shown to explain the impacts of dissimilarity on swift trust in robot co-workers compared to human co-workers. Second, this study identifies co-worker type dissimilarity and its critical role in determining how the impacts of other dissimilarities differ between robotic and human co-workers. In doing so, this study shows how the type of co-worker (i.e., robot vs. human) can alter the manifestation of RDT in surprising and unexpected ways. To this end, the paper explores the consequences of human interactions with emerging technologies and how theorizing is likely to be impacted (Baird & Maruping, 2021; Fügener et al., 2021; Kane et al., 2021; Schuetz & Venkatesh, 2020; Seeber et al., 2020). Finally, this paper contributes to the understanding of when humans would prefer to work with robotic co-workers by identifying and demonstrating that people's trust in human co-workers can undermine their preference for robotic co-workers.

Background

AI-Enabled Work in the IS Literature

AI-enabled technologies (AI-ET) are increasingly being adopted by organizations to work with humans as co-workers rather than strictly as tools (Fügener et al., 2021; Graetz & Michaels, 2018; Rai et al., 2019). This has driven IS scholars to expand their view of human-technology interaction to include intelligent assistants, algorithms, and robots (Berente et al., 2021; Vreede & Briggs, 2019). Recent calls for research acknowledge the need to view AI-ET differently from traditional technologies (Baird & Maruping, 2021; Seeber et al., 2020; Zhang et al., 2021). For instance, You and Robert (2018a) proposed that the impacts of physical robots are distinct from traditional technologies such as decision support systems because of their embodied physical action (EPA). Thus, IS scholars are beginning to propose new theories incorporating AI-ET (Berente et al., 2021; Burton-Jones et al., 2021).

Collaboration between humans and AI-ET and the questions derived from those collaborations are at the heart of recent calls for research (Baird & Maruping, 2021; Seeber et al., 2020; You & Robert, 2023; Zhang et al., 2021). Questions arise because AI-ET has the potential to traverse the line between being viewed simply as tools (i.e., inanimate objects) to being viewed as teammates (i.e., social actors) with real or perceived agency. For example, Seeber et al.

(2020) invoked the idea of AI-ETs becoming teammates that can engage in complex problem-solving, but it is largely unknown when such collaborations can lead to positive or negative consequences. Baird and Maruping (2021) proposed that humans and AI-ET are both social agents that delegate responsibilities and exercise autonomy over each other without presumed human primacy, and research is beginning to theorize and discover how humans perceive AI-ET with regard to its relative characteristics and consequences (Baird & Maruping, 2021).

Mind attribution is likely to be both theoretically and empirically important to illuminate the implications associated with human and AI-ET collaborations. Mind attribution is the act of attributing emotions, intentions, or beliefs—to nonhuman agents, including robots (Morewedge et al., 2007). Mind attribution is a "pre-attributional process, identifying the kinds of causes that might explain or predict another's behavior" (Epley & Waytz, 2010, p. 499). Attributing a mind to an agent assumes that the agent has the capacity not only to feel but also to remember past experiences (Shank et al., 2021). Not attributing a mind to an AI-ET assumes that the emotions, intentions, or beliefs displayed by the AI-ET belong not to the agent but to those who created it. When this occurs, humans are less likely to react to an AI-ET collaborator in the same way as they do to a human collaborator.

While the need for and the lack of theories on human trust in AI-ET, which underlie questions of relative characteristics and collaboration, have drawn particular attention, fundamental questions still remain. Berente et al. (2021) identified the challenges associated with overcoming trust issues to promote effective human collaboration with AI-ET. Baird and Maruping (2021) acknowledged the importance of trust in understanding when humans choose to work with AI-ET as peers rather than subordinates. Based on this brief review, it is apparent that IS research is only beginning to explore the impacts of human collaboration in AI-ET (Berente et al., 2021; Zhang et al., 2021). What is clear is that there is a lack of both theorizing and the empirical verification of evidence needed to help guide future research (Burton-Jones et al., 2021).

Relational Demography Theory (RDT) and Swift Trust

Relational demography theory (RDT), proposed by Tsui and O'Reilly (1989), is used to understand how comparative dissimilarity impacts work collaborations (King et al., 2017; Riordan & Shore, 1997). RDT relies on social categorization, or the tendency of individuals to place themselves and others into in- and out-groups according to their respective similar and dissimilar characteristics (Chatman & Spataro, 2005; Tsui et al., 1989; Turner et al., 1987). Individuals placed in an in-group are perceived to be similar, while those placed in an out-group are perceived to be dissimilar (Tsui et al., 1989; Turner et al., 1987). Dissimilar others are often evaluated less positively than those perceived to be similar (Riordan & Shore, 1997; Robert et al., 2018).

The RDT literature has employed various types of dissimilarities, but most fall into one of two types: ascribed and achieved dissimilarity (Ertug et al., 2022). Ascribed dissimilarities are attributed to individuals based purely on their affiliation (Lazarsfeld & Merton, 1954). Ascribed dissimilarities include demographic characteristics, such as gender and race, that are relatively easy to observe (Ertug et al., 2022). Achieved dissimilarities are attributed to individuals based on their internal attitudes, beliefs, and values. Achieved dissimilarities are viewed as malleable because, in contrast to ascribed dissimilarities, individuals can change them (Ertug et al., 2022). However, achieved dissimilarities are more subtle and require more information to recognize (Ertug et al., 2022; Liao et al., 2008). Whereas ascribed dissimilarity is based on *who someone is*, achieved dissimilarity is based on *what someone believes, feels, or intends to do.* Therefore, achieved dissimilarities require a level of agency in that individuals are assumed to have their own values, attitudes, and preferences, but the same is not necessarily true for ascribed dissimilarities. Research on social cognition suggests that people are less likely to attribute complex emotions, experiences, and social agency to people who are perceived to be different from them (Kteily et al., 2016; Li et al., 2014).

Trust is often used to understand how dissimilarities among co-workers influence their willingness to work together. Trust is defined as one's willingness to be vulnerable to the actions of another, and effective work collaborations require such vulnerability (Mayer et al., 1995). Research on trust in co-workers has demonstrated its positive impact on work collaboration, justifying its use in examining the impacts of dissimilarities (De Jong et al., 2016). It is widely accepted that trust is essential to enhancing work collaboration across various settings (Langfred, 2007; Paul & McDaniel Jr., 2004). For instance, trust is known to increase the cooperative behaviors of co-workers in face-to-face and virtual work environments (Dennis et al., 2012; Langfred, 2007; Paul & McDaniel Jr., 2004; Sarker et al., 2011).

RDT explains why dissimilarity can decrease swift trust, which is a type of depersonalized trust. Swift trust is driven by social categorization formed a priori before the trustor has interacted with the trustee (Meyerson et al., 1996; Robert et al., 2009). Swift trust is distinguished from knowledge-based trust, which is formed after the trustor has interacted with the trustee (Robert et al., 2009; van der Werff & Buckley, 2017). Unlike knowledge-based trust, swift trust does not require direct interactions between trusting parties (Schilke & Huang, 2018). According to swift trust theories, self-categorization contributes to the formation of trust (Crisp & Jarvenpaa, 2013; Kramer, 1991; Zakaria & Mohd Yusof, 2020). Specifically, Robert et al. (2009) reported that in-group favoritism based on self-categorization increases the formation of swift trust. Swift trust is particularly important because it has been shown to have downstream consequences for collaboration (Lount & Pettit, 2012; Robert et al., 2009). Taken together, co-worker dissimilarity can decrease swift trust, a precursor to work-related collaborations.

Trust in Human-Robot Interaction

Although not focused on the impact of dissimilarities, trust is essential to human-robot collaborations. Effective human-robot collaborations occur when humans are willing to be vulnerable to the actions of their robot collaborator. Trust in a robot is associated with higher levels of engagement and a stronger relationship with the robot (Gaudiello et al., 2016). Trust in a robot increases the perception of safety and subsequent willingness to work with the robot on a construction task (You et al., 2018). It has been shown that trust is crucial to success in exercise tasks involving a robot. Fasola and Mataric (2013) found that trust in a robot enhanced individuals' motivation to perform exercise tasks and their overall engagement in tasks involving robot-guided rehabilitation. This explains why trust in robots is generally expected to enhance performance on human-robot team tasks (Lewis et al., 2018; You & Robert, 2019).

Prior literature on promoting trust in robots has examined both the ascribed and achieved characteristics of humans and robots. Research on ascribed characteristics, such as gender, has shown that women trust robots more than men (Kuchenbrandt et al., 2012). Other research has found that gender similarity between humans and robots can promote trust in robots (Robert et al., 2020) and that matching gender to existing stereotypes can promote trust (Tay et al., 2014). Humans' achieved characteristics like personality traits such as extraversion and confidence have been shown to be positively related to trust in robots (Hancock et al., 2011; Haring et al., 2013; Robert et al., 2020). Robot's achieved characteristics, such as ability or capabilities, have also been found to promote trust. In particular, robots' technical and functional capabilities are essential to promoting trust; these include their movements, social interactions, and demonstration of ability (Gaudiello et al., 2016; Hancock et al., 2011; Robert et al., 2020; Salem et al., 2015).

Summary of Relevant Literature

Based on the literature reviewed in this paper and the recent calls for additional studies, it is apparent that research is only beginning to explore collaboration with AI-ET (Berente et al., 2021; Zhang et al., 2021). Although prior literature provides ample evidence for ways to promote trust in human-robot collaboration, it tells us little about the impacts of dissimilarity on trust in robots or whether or how trust formed toward robots might have distinct impacts on attitudes toward working with humans. Despite the potential for RDT to advance the literature, we lack both a theoretical understanding and an empirical examination of RDT in the context of robot co-workers. This is important because enhancing swift trust through RDT might play an essential role in overcoming workers' initial negative attitudes toward robots and promoting their acceptance of robots as co-workers.

Theoretical Development and Hypotheses

To examine the impacts of dissimilarity, we propose an RDT-based research model. This model is predicated on RDT's central argument that how individuals respond to another's dissimilarity is influenced by their own characteristics relative to that other (Chattopadhyay et al., 2016). Building on this tenet, we propose that co-worker type represents a form of ascribed dissimilarity represented in the HRI literature by the low degree of anthropomorphism associated with robots relative to humans (Eyssel et al., 2012; Heo & Kim, 2013). This paper asserts that co-worker-type dissimilarity sets the backdrop for how other dissimilarities, both ascribed and achieved, are interpreted relative to the individual. Although gender and co-worker type are both ascribed characteristics, being of nominal status, they should be understood differently when theorizing their impacts. While gender, as a much older ascription, has an established understanding regarding how it can determine the impacts of RDT, co-worker type is a relatively new ascription. Thus, we propose that it serves as a better lens for understanding how humans interpret and react to other's dissimilarities. The hypotheses presented in Figure 1 are derived from two overarching theoretically driven assertions: (1) Dissimilarity increases the cognitive load needed to assess a co-worker, which can have negative implications. (2) Dissimilarity in co-worker type, through a lack of mind attribution, can reduce this cognitive load and its corresponding negative effects for a robotic co-worker. A detailed explanation of each assertion is presented below.

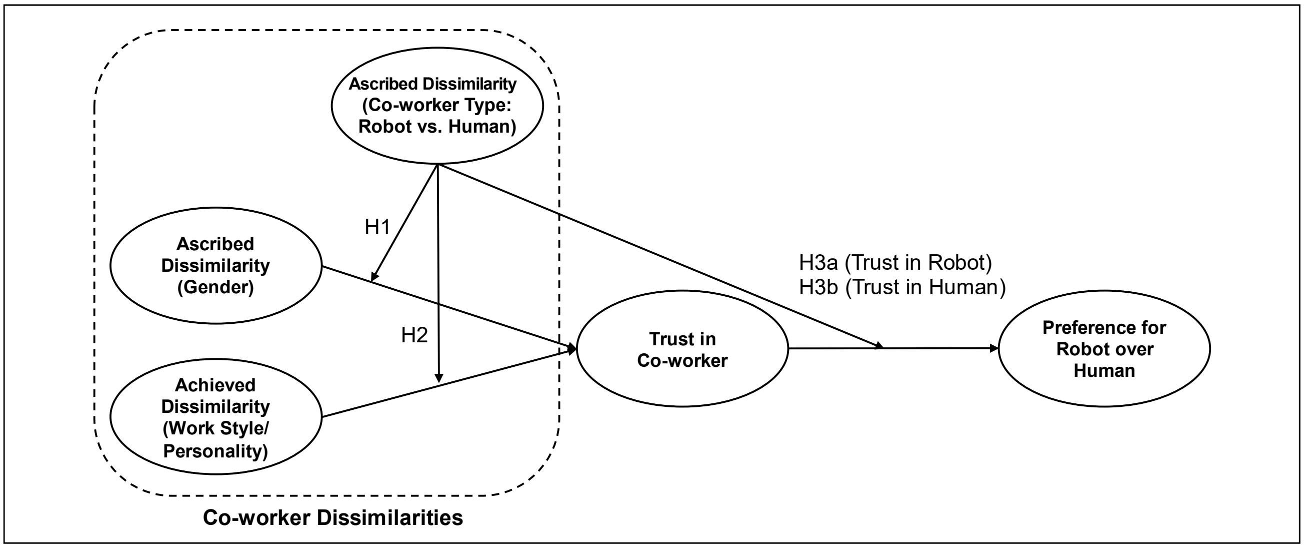


Figure 1. Proposed Research Model

Ascribed Dissimilarity and Swift Trust in a Co-Worker

Generally, ascribed dissimilarity influences the positive or negative assessment of others by increasing the cognitive load needed to assess them. According to the seminal research by Taylor and Jaggi (1974), individuals find it relatively easy to form positive expectations about those who are similar to them because individuals are motivated to maintain their own positive self-esteem (Guillaume et al., 2014; Tajfel & Turner, 2004). According to Taylor and Jaggi (1974), individuals also find it easy to import existing positive expectations of themselves to evaluate similar others. This decreases the cognitive resources needed for assessment and promotes swift trust in similar others while reinforcing their own positive self-esteem (Robert et al., 2009; Singh & Simons, 2010; Taylor & Jaggi, 1974).

In contrast, individuals often find it much more difficult to form positive expectations about dissimilar others. Unlike for similar others, where the self operates as a basis for expectations, no such cues are available to evaluate dissimilar others (Gramzow et al., 2001). Because of this lack of guidance, more cognitive resources are needed to evaluate dissimilar others with regard to assessments of swift trust. According to Peeters and Czapinski (1990), dissimilar attributions that trigger the need for more cognitive resources are thus often viewed more negatively. This phenomenon is often referred to as the similarity-dissimilarity asymmetry, where dissimilar attributes are viewed more negatively and are often weighted more heavily in decision-making (Peeters & Czapinski, 1990). This difficulty increases the cognitive resources needed for assessment, leading to a more negative assessment of dissimilar others (Singh & Simons, 2010).

In this paper, we propose that gender dissimilarity should have a more negative impact on a robotic co-worker than a human co-worker. Co-worker type and gender dissimilarity each represent a form of ascribed dissimilarity. Although co-worker type as a form of ascribed dissimilarity is relatively new, gender has long been one of the most salient cues of ascribed dissimilarity (Robert et al., 2018; Sacco et al., 2003). Gender has often been used to represent ascribed dissimilarity because it is a relatively stable characteristic and plays a crucial role in accounting for an individual's identity (Hogg & Terry, 2000; Robert et al., 2018). Therefore, it is not surprising that gender dissimilarities have, at times, been associated with decreases in swift trust (Meyerson et al., 1996; Robert et al., 2009).

Nonhuman agents, including robots, can also have gender (Karniol et al., 2000; Nowak & Rauh, 2008; van den Hende & Mugge, 2014). For example, humans tend to assign gender to animals and inanimate objects (e.g., rifles, wallets, and mobile phones) (Karniol et al., 2000; Meagher, 2017). This explains why gender is widely used to investigate feelings and attitudes toward robots (Eyssel & Hegel, 2012; Nomura, 2017; Tay et al., 2014). For example, humans paired with same-gender robots were found to be more inclined to accept those robots than humans paired with opposite-gender robots (Eyssel et al., 2012). Likewise, gender dissimilarities between humans and robots can decrease psychological closeness (Eyssel & Kuchenbrandt, 2012).

The negative effects of gender dissimilarity on a co-worker's swift trust should be stronger for a robot co-worker because of the increase in cognitive load needed to assess a co-worker who is dissimilar in terms of both gender and co-worker type. Theory and research suggest that increases in dissimilarity attributed to another are likely to be viewed more negatively (Chattopadhyay et al., 2016). In essence, a compounded negative effect is likely when gender dissimilarity is coupled with co-worker-type dissimilarity, leading gender dissimilarity to have a stronger negative impact on a robotic co-worker when compared to a human co-worker.

H1: *Ascribed dissimilarity as co-worker type moderates the negative effect of ascribed dissimilarity as gender on swift trust in a co-worker such that the negative effect of a gender dissimilarity on swift trust in a co-worker is stronger for a robot co-worker than for a human co-worker.*

Achieved Dissimilarity, Ascribed Dissimilarity, and Swift Trust in a Co-Worker

According to RDT, ascribed dissimilarities should also moderate the impact of achieved dissimilarities on trust in a co-worker. However, in contrast to the potential impacts regarding human-human relationships, in human-robot relationships a lack of mind attribution would be expected to weaken rather than strengthen the negative impact of achieved dissimilarity on swift trust in a dissimilar co-worker. In this case, the negative impacts of achieved dissimilarity would likely be undermined by the dissimilar characteristics of a robot due to the lack of mind attribution.

This paper proposes that co-workers' work styles and personalities represent achieved dissimilarity. Work styles and personalities are among the most relevant individual characteristics in work relationships in both general and human-robot interactions (Esterwood et al., 2021; Zellmer-Bruhn et al., 2008). Prior literature has shown that, to some extent, individuals can perceive robots as having work-related preferences and personalities, such as extraversion (Robert, 2018; Tapus & Matarić, 2008).

Achieved dissimilarities would be expected to decrease swift trust in a co-worker. Research on RDT has shown that achieved dissimilarities are vital to understanding collaboration in work settings (Liao et al., 2008; Zellmer-Bruhn et al., 2008). Achieved dissimilarities are known to be a signal for social categorization, such that similarities or differences in values, including work styles, personality, and attitudes, between co-workers, can engender negative or more negative perceptions of co-workers (Montoya et al., 2008; Zellmer-Bruhn et al., 2008). In particular, achieved dissimilarities can decrease swift trust in a collaborator (Phillips et al., 2006).

Research on human-robot interaction also provides evidence that swift trust in a robot can be impacted by achieved dissimilarities (Tapus & Matarić, 2008). Andrist et al. (2015) reported that a mismatch between a user's and a robot's personality can lead to a decrease in positive evaluations of the robot. Other research has shown that achieved dissimilarities between humans and robots are associated with negative outcomes like a decreased willingness to cooperate (Hancock et al., 2011; Nikolaidis & Shah, 2013). This is particularly true in contexts involving job-related orientation (Hancock et al., 2011). These findings suggest that achieved dissimilarities can negatively affect the evaluation of a robot and, ultimately, swift trust in the robot. Like the findings related to ascribed dissimilarities, studies on achieved dissimilarities are based on human-to-human interactions, suggesting that achieved dissimilarities can deteriorate trust.

A lack of mind attribution toward robots may explain the weakened impacts of achieved dissimilarities on robot co-workers. While humans are less likely to attribute achieved dissimilarities to robots, the opposite is true for human co-workers. Generally, humans attribute more mind or thought processes to other humans (Li et al., 2014; Morewedge et al., 2007) than to robots. For instance, Gray et al. (2007) found that social robots are perceived to be incapable of having experiences, which form the basis of achieved characteristics like work styles and personality, explaining why humans are less likely to attribute achieved dissimilarities, such as preferences, personalities, and attitudes, to robots (Gray & Wegner, 2012). Instead, individuals attribute the achieved dissimilarities of the robot co-worker to the people who designed and programmed the robot. Specifically, even when a robot demonstrates a work style or personality, individuals will likely believe that those properties were programmed into the robot by the human developer rather than being essential to the robot itself.

Individuals are likely to allocate fewer cognitive resources to assess a robotic co-worker's achieved dissimilarities when they attribute those dissimilarities to the robot's designers and programmers. This reduction in cognitive resources needed to process achieved dissimilarities would thus be expected to reduce the negative assessment of a robotic co-worker (Peeters & Czapinski, 1990; Singh & Simons, 2010; Taylor & Jaggi, 1974). The reduced cognitive load may lead individuals to believe that work styles and personalities are less relevant to their robotic co-workers than their human counterparts, weakening their effects. As a result, a lack of mind attribution to the robot should weaken the negative impact of achieved dissimilarities on swift trust in a robotic co-worker. Since humans tend to fully attribute achieved dissimilarities to their human co-workers, dissimilarities in work-related values are likely to have a weaker negative effect on swift trust in robotic co-workers compared to human co-workers.

H2: *Ascribed dissimilarity as co-worker type moderates the negative effect of achieved dissimilarities as either work style or personality on swift trust in a co-worker, such that the negative effect of either work style or personality on swift trust in a co-worker is weaker for a robot co-worker than for a human co-worker.*

Swift Trust, Ascribed Dissimilarity, and Preference for a Robot Co-Worker over a Human Co-Worker

Ascribed dissimilarity as co-worker type would be expected to moderate the impact of co-worker swift trust on an individual's preference to work with a robot over a human co-worker. More specifically, the more swift trust someone has in a human co-worker, the less likely they are to prefer to work with a robot over a human. Likewise, the more swift trust someone has toward a robot co-worker, the more likely they are to prefer to work with a robot over a human. We provide detailed arguments in the following paragraphs. We start by explaining why we chose to study the preference to work with a robot versus a human. Then, we provide the theoretical arguments that outline the causal linkage between a co-worker's swift trust and the preference to work with a robot co-worker versus a human co-worker.

Despite rich evidence on the positive impacts of swift trust on team outcomes and human-robot collaboration, there is little evidence on the comparative effects of swift trust in different types of co-workers or the attitudes toward them. To investigate this relationship, we examined the preference to work with a robot over a human. The construct goes beyond the *acceptance* of a robot co-worker itself, which has been employed to measure an individual's behavioral intention to adopt a technology or not (Beaudry & Pinsonneault, 2010; Maruping et al., 2017). There are two advantages of examining this construct. First, it is timely, considering the current practice of human-robot collaboration, where robots are increasingly replacing human workers on work teams (Ackerman, 2014). Given that working with robots instead of humans is a choice made by management rather than workers, it is essential to examine whether workers will willingly work with robots as co-workers rather than humans without experiencing resentment. The second reason is empirical. The unified measurement of the construct allowed us to test the differential effects of trust that can be moderated by co-worker types (i.e., robot vs. human).

Swift trust in a robot co-worker would be expected to increase one's preference to work with a robot versus a human. Research on ascribed dissimilarity clearly highlights the challenges it presents to developing trust (Chattopadhyay & George, 2001). However, once trust is developed in a dissimilar other, that trust has the same positive impacts (Lount & Pettit, 2012). In human-robot relationships, this is explained by the fact that humans who have formed swift trust toward a robot co-worker are likely to have a strong positive attitude toward that robot (Gaudiello et al., 2016; Tay et al., 2014). Positive attitudes toward the robot are associated with decreases in fear, worry, and concern about working with a robot (de Visser & Parasuraman, 2011; Nomura et al., 2007). These individuals are also likely to have either developed a bond with the robot co-worker or seen the potential to develop such a bond and are likely to believe that they can get many of the same social benefits from their robot co-worker that they expect from human co-workers (Groom & Nass, 2007; Oistad et al., 2016). For example, research has shown that trust in a robotic exercise coach is essential to promoting motivation to perform rehabilitation tasks (Fasola & Mataric, 2013). Motivating a trainee is one of the desired impacts of human trainers.

Swift trust in a human co-worker would be expected to decrease one's preference to work with a robot versus a human. Research has shown that ascribed dissimilarities provide the context that alters one's trust in another (Li et al., 2016; Lount & Pettit, 2012). In the case of a human-robot relationship, individuals who develop a bond with a human co-worker might not see any potential for developing a similar bond with a robot co-worker. Swift trust among human co-workers is a kind of social capital that can provide both work-related and non-work-related benefits like social support (Costa et al., 2009; Robert et al., 2008). Individuals who have formed swift trust with a human co-worker may have difficulty conceiving how such a relationship could be equally beneficial with a robot co-worker (Takayama et al., 2008). Such individuals may find it difficult to believe they could enjoy the same social benefits with a robot co-worker (Takayama et al., 2008). Therefore, when faced with a choice between a human or robot co-worker, these individuals would be unlikely to prefer working with a robot versus a human.

H3: *Ascribed dissimilarity as co-worker type moderates the relationship between swift trust and preference for a robot over a human co-worker, such that* ***(a)*** *swift trust in a robot co-worker increases the preference for working with a robot, while* ***(b)*** *swift trust in a human co-worker decreases it.*

Study Overview

Next, we present the two experimental studies we used to examine the research model (see Figure 1). Studies 1 and 2 both used gender as a type of ascribed dissimilarity. While Study 1 used work style, Study 2 used personality to operationalize achieved dissimilarity. In both studies, co-worker type was represented via ascribed dissimilarity. RDT research has demonstrated that dissimilarity can be examined through demographic and value attributes commonly found in work relationships (Fisher et al., 2012; Liao et al., 2008; Tsui et al., 1995). Study 2 was designed to complement, validate, and extend the findings from Study 1 by employing different experimental design choices, measurements, and another sample. For instance, Study 2 used co-worker personality to manipulate achieved dissimilarity instead of work style, which was used in Study 1. Also, while Study 1 measured swift trust using a measure adapted from the HRI research (Jian et al., 2000), Study 2 captured swift trust based on situational normality adapted from IS research to better capture swift trust in work contexts (Mcknight et al., 2011).[2]

Study 1

Study 1 Design

We conducted an experimental 2 (ascribed dissimilarity: robot vs. human) × 2 (ascribed dissimilarity: same vs. different gender) × 2 (achieved dissimilarity: same vs. different work style) × 2 (risk of physical danger: high vs. low) between-subjects design with 347 experienced warehouse workers. The study also included the risk of physical danger as a control variable for two reasons. First, research suggests that trust can be contingent upon the level of risk (Das & Teng, 2001). Second, robots are often used to engaging in work that is too dangerous or risky for humans (Atkinson & Clark, 2014; Groom & Nass, 2007).

Participants

We used Qualtrics, which manages targeted samples based on individuals' employment status, job title, and industry, to recruit participants in November and December 2018. We worked with Qualtrics to ensure the sample quality by selecting only warehouse workers. The final sample consisted of 347 warehouse workers across various industries living in the United States (see Appendix A for details). Based on a power analysis conducted using G*Power software, our target sample size was 207 individuals, for a medium effect size of 0.25 (alpha = 0.05; power = 0.8) (Faul et al., 2009). The final sample of 347 exceeded the needed sample size.

Task and Robots

This study employed a hypothetical scenario consisting of two parts. First, participants read a vignette informing them that they would be working with a co-worker in a warehouse. Second, participants were presented with either a human co-worker or a robot co-worker via an online video. Video manipulation is widely employed in HRI research and is considered effective in immersing participants in the experimental context (Woods et al., 2006). Videos provide rich and multimodal information about the experimental situation, especially when the task involves a physical task (Atkinson & Clark, 2014). Our video manipulations involved descriptions of participants' potential co-workers completing a warehouse task. The video illustrated physical activities generally performed in warehouses, including loading and unloading, moving, handing over cargo objects to another person, and avoiding obstacles. The task described in the video was intended to provide the general sense of working at a warehouse and purposefully did not provide types of work in detail for two reasons. First, our sample comprised experienced warehouse workers who were aware of the work. Second, participants might have had different experiences working with robots during their careers. Thus, fine-grained descriptions might have prevented the experimental scenario from being relatable to participants, which would have reduced the ecological validity (Aguinis & Bradley, 2014).

A PR2 robot was used for the videos (see Appendix B) to represent the robot co-worker. The robot was chosen based on two criteria. First, the robot was gender-neutral in its appearance (Phillips et al., 2018). This allowed us to manipulate the robot's gender strictly through its voice and name, ruling out any confounding visual cues. Second, the robot's form implied some degree of self-navigation motor ability along with the ability to move objects. The hypothetical task involved moving physical objects in the warehouse. Thus, it was essential to use a robot that could complete such tasks while working with the participant.

Independent Variables

Co-Worker Type (Ascribed Dissimilarity)

Co-worker types were manipulated through the vignette that described the work context and the video of the co-worker (i.e., robot or human; Appendix B). In the robot video, the robot introduced itself by stating its model number, name, and functional capabilities. In the human video, similar content was presented, but sentences about the robot's technical functions were replaced with a description of the human's capabilities.

[2] The transparency material can be found at https://osf.io/6qgfp (OSF Registry) and https://osf.io/pgnq5 (the associated OSF project). The transparency material includes more information about the method, including elaborated study design and measurement items, data dictionaries, and explanations of the analytic method used in this article.

Gender (Ascribed Dissimilarity)

Robot gender was manipulated using voice and name. Specifically, the female robot had a female voice and the model name "RX-01 Jessica," whereas the male robot had a male voice with the model name "RX-01 David." Gender dissimilarity in the human condition was dubbed with professional human male and female voices. The videos did not show any depiction of human faces and skin colors in order to rule out potentially confounding effects of similarity other than gender.

Work Style (Achieved Dissimilarity)

Participants were given a series of five questions regarding different work styles based on Zellmer-Bruhn et al. (2008). The questions were intended to elicit participants' work preferences (see Appendix C). In the similar work style condition, a robot chose the same answer as the participant each time after the participant made a choice and showed the sentence: "I also chose the same statement. Your answer was [the participant's choice]. My answer was [the participant's choice]." In the different condition, a robot chose the other answer and stated: "I chose the different statement. Your answer was [the participant's choice]. My answer was [the opposite choice of the participant's choice]." For a manipulation check, we measured perceived dissimilarity related to the work styles. An index of six items was adapted from Zellmer-Bruhn et al. (2008) based on a 5-point scale (1 = *strongly disagree* to 5 = *strongly agree*).

Risk of Physical Danger

Participants in the high-risk condition read a scenario in which they had to collaborate with the robot to load highly toxic and hazardous containers. In the low-risk condition, participants helped load wooden boxes. We measured perceived risk to capture an individual's risk assessment. The scale was an index of six items from Kim and McGill (2011) and Jermier, Gaines, and McIntosh (1989) based on a 5-point scale (Appendix D).

Dependent Variables

There were two dependent variables: trust in the co-worker and preference for working with a robot over a human co-worker. We captured trust in the robot co-worker using a six-item measure on a 5-point Likert scale (Jian et al., 2000). For the scales in human conditions, we adapted each item to the condition by replacing the word "robots" and the robot names with human names. Also, based on a three-item scale using a 5-point Likert scale, participants were asked the indicate their preference for working with the co-worker. Preference for a human co-worker over a robot was reversed to obtain preference for a robot (Appendix D).

Control Variables

Control variables included the perceived level of knowledge of technologies relevant to robots and the Negative Attitudes toward Robots Scale (NARS) (Nomura et al., 2006; You & Robert, 2018a). In addition, control variables that were relevant to the warehouse workers were also included: job tenure, warehouse industry experience, job competency, and experience working with a robot. Finally, the study included perceived risk as a control variable (Appendix D).

Procedure

Participants logged on to a website and were randomly assigned to one of the 16 online conditions, which were followed by measurements of the dependent variables and demographic information. Figure 2 displays the overall experimental procedure for Study 1.

Upon entering the experimental session, participants were greeted and asked to fill out a consent form. Participants were given brief instructions about the experimental procedure. In the instructions, participants were asked to read a scenario about collaboration with the robot and view accompanying illustrative images. On all the stimuli pages in the experiment, participants were unable to proceed until the "next" button appeared after the manipulations were completed. This was to ensure that participants paid attention to the stimuli.

For gender similarity, the robot's and participant's gender were matched based on the participant's self-reported gender. For gender dissimilarity, participants were presented with a video of a robot that had a dissimilar gender. For the work style dissimilarity, participants were asked to choose responses to five questions about work styles. Immediately after the participant's response to each of the questions, the robot's choice was shown as either agreeing or disagreeing with the participant, according to the assigned condition. After all the questions were shown, a summary table that compared the robot's and the participant's answers was displayed. Then, participants were exposed to the risk manipulation through images and a written description.

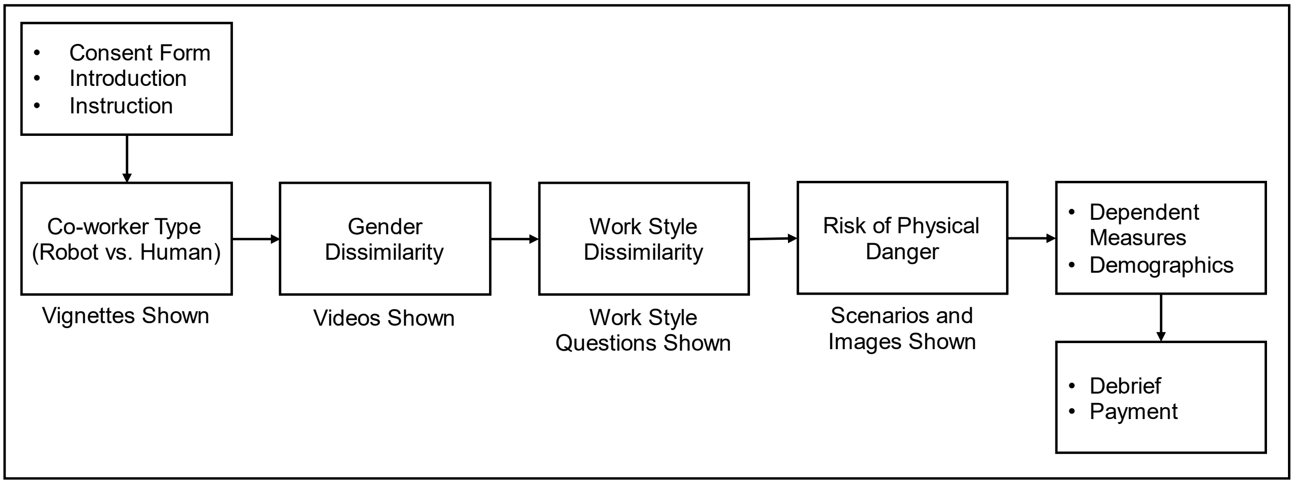


Figure 2. Experiment Procedure of Study 1 Experiment

Participants were asked to respond to manipulation-check items along with attention-check items to ensure that they were paying attention to the experiment. Sessions were terminated for those who failed to pass the attention-check items. Finally, participants were asked to fill out a post-task questionnaire, which included dependent measures. Upon completion of the experiment, participants were debriefed, paid 30 USD, and dismissed.

Data Analysis and Results

Construct Reliability and Validity

All constructs were found to be reliable and valid. Perceived work style dissimilarity ($\alpha = 0.98$) and perceived risk were also reliable ($\alpha = 0.91$). Knowledge of technology relevant to robots ($\alpha = 0.91$) and NARS ($\alpha = 0.87$) were also reliable. Both dependent variables were reliable: co-worker trust ($\alpha = 0.93$) and preference for a robot over a human co-worker ($\alpha = 0.76$).

We assessed convergent and discriminant validity in multiple ways. First, exploratory factor analysis demonstrated discriminant and convergent validity (Fornell & Larcker, 1981). We also tested correlations among the constructs to ensure discriminant and convergent validity (see Appendix E). Correlations among the variables were below the square root of the average variance extracted (AVEs), demonstrating discriminant validity. Second, all constructs' AVEs in our model were well above 0.50, further demonstrating convergent validity (see Appendix E) (Fornell & Larcker, 1981).

Manipulation Checks

To check the manipulation of gender dissimilarity, we asked participants to identify the gender of their co-workers. All participants correctly identified the gender of the co-worker. The work style manipulation was also successful, such that the perceived similarity was lower in the dissimilar work style condition ($M = 1.98$, $SD = 0.99$) than in the similar work style condition ($M = 4.33$, $SD = 0.70$, $t(345) = 25.58$, $p < 0.001$). Risk manipulation was successful; perceived risk was higher in the high-risk condition ($M = 4.34$, $SD = 0.56$) than in the low-risk condition ($M = 3.19$, $SD = 0.73$, t(345) = 16. 45, $p < 0.001$).

Results

Based on Levene's test for the homogeneity of variance, co-worker trust across conditions did not have homogeneous variance ($F(1, 345) = 7.08$, $p < 0.01$). This violated one of the assumptions underlying the use of ordinary least squares (OLS). To address this issue, we employed generalized least squares (GLS) using SPSS 26. GLS is used in situations when the OLS estimator is not BLUE (best linear unbiased estimator) (Hansen, 2007).

H1 posited that the negative effect of gender dissimilarity on trust would be stronger with a robot co-worker. The moderation effect was significant for gender dissimilarity (B = -0.39, $p < 0.05$; Table 1). Figure 3a depicts the moderation effect supporting an increased negative effect of gender dissimilarity on trust. Therefore, H1 was supported.

Table 1. Results of GLS for Trust in a Co-Worker

IV	*Dependent variable: Trust in a co-worker*											
	Model 1				**Model 2**				**Model 3**			
	B	***SE***	**LLCI**	**ULCI**	***B***	***SE***	**LLCI**	**ULCI**	***B***	***SE***	**LLCI**	**ULCI**
Constant	3.63***	0.05	3.53	3.73	3.9***	0.12	3.68	4.17	3.96***	0.14	3.67	4.24
Control variables												
Age	-0.05	0.06	-0.17	0.08	-0.06	0.06	-0.18	0.06	-0.07	0.06	-0.18	0.05
Education	-0.06	0.05	-0.17	0.04	-0.04	0.05	-0.14	0.06	-0.04	0.05	-0.14	0.06
KnowTech	0.15*	0.06	0.03	0.27	0.14*	0.06	0.3	0.25	0.15**	0.06	0.03	0.26
PercRisk	0.06	0.05	-0.04	0.17	0.08	0.07	-0.06	0.22	0.10	0.07	-0.04	0.23
NARS	-0.11†	0.05	-0.21	0.00	0.07	0.05	-0.17	0.03	-0.07	0.05	-0.17	0.03
RobotExp	0.13*	0.06	0.01	0.26	0.11†	0.06	-0.01	0.23	0.11*	0.06	-0.01	0.23
IndusExp	-0.29	0.08	-0.18	0.12	-0.03	0.07	-0.17	0.11	-0.04	0.07	-0.18	0.10
CurJobTen	0.11	0.07	-0.04	0.25	0.08	0.07	-0.06	0.22	0.09	0.07	-0.06	0.22
JobComp	0.08	0.05	-0.02	0.18	0.10*	0.05	0.01	0.19	0.10*	0.05	0.01	0.19
Main effects												
Co-worker type					0.17†	0.10	-0.03	0.36	0.12	0.18	-0.23	0.47
Gender dissimilarity					0.03	0.10	-0.16	0.22	0.21	0.13	-0.05	0.47
Work style dissimilarity					-0.58***	0.10	-0.78	-0.39	-0.77***	0.14	-1.04	-0.50
Risk of physical danger					-0.19	0.14	-0.46	0.08	-0.22	0.14	-0.48	0.05
Interaction												
Co-worker type x Gender dissimilarity									-0.39*	0.19	-0.76	-0.01
Co-worker type x Work style dissimilarity									0.40*	0.19	0.02	0.78
Goodness of fit												
AIC	949.35				921.69				917.41			
Df	9				13				15			
χ^2	33.77				69.47				77.74			

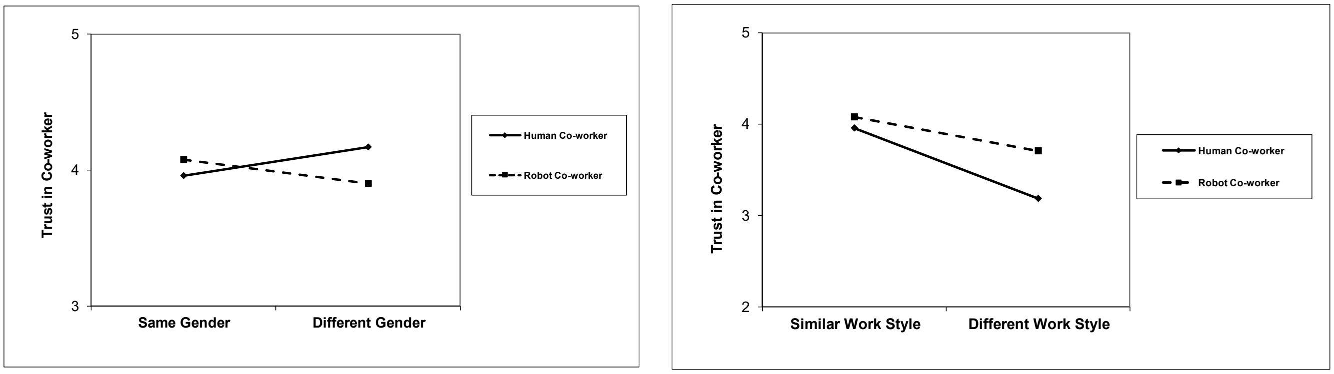
Note: N = 347, † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. KnowTech: Knowledge of relevant technology, PercRisk: perceived risk, NARS: Negative Attitudes toward Robots Scale, RobotExp: experience of working with robots, IndusExp: industry experience, CurJobTen: current job tenure, JobComp: job competency. Co-worker type, gender dissimilarity, work style dissimilarity, and risk of physical danger were coded as binary (0 = human/low, 1 = robot/high). Control variables were standardized.

H2 posited a weaker effect of work style dissimilarity on trust in a robot co-worker. The moderation effect was significant for work style dissimilarity (B = -0.39, $p < 0.05$). As seen in Figure 3b, work style dissimilarity demonstrated a stronger impact on trust in a human co-worker, whereas its effect was weaker in a robot co-worker. These results suggest that co-worker type moderates work style dissimilarity on trust in a co-worker, supporting H2.

H3 posited that co-worker type would moderate the relationship between trust in a co-worker and preference for a robot over a human co-worker (Table 2). Specifically, we hypothesized that individuals would prefer a robot co-worker as trust in the robot increased, whereas their preference for a robot co-worker would be reduced as trust in a human co-worker increased. Results confirmed that there was an interaction effect between co-worker type and trust in the co-worker (B = 1.19, $p < 0.001$). As seen in Figure 4, when the co-worker was a robot, trust positively predicted the preference for working with a robot (H3a). In contrast, the increases in trust in a human co-worker decreased the preference for a robot over a human co-worker (H3b). Therefore, H3 was supported.

Study 2

Although Study 1 provided support for the research model, it had five limitations that Study 2 was designed to address. First, Study 1 did not include a measure of ascribed dissimilarity in co-worker type to determine whether participants viewed the robot co-worker as more or less human than the human co-worker. Study 2 addressed this by examining perceptions of anthropomorphism as a manipulation check to determine whether participants actually distinguished robots from human co-workers. Second, gender dissimilarity was always shown before work style dissimilarity in Study 1, introducing potential ordering effects. In Study 2, gender and work style dissimilarity manipulations were shown to participants in random order. Third, work style dissimilarity was manipulated by asking all the work style questions in the same order and showing the comparison between the participant's choice and the co-worker's choice after each response. This repeated response might have overly influenced participants. Thus, in Study 2, participants saw a comparison table of the responses only once after finishing all eight questions.



(a) (b)

Figure 3. Interaction Effect: (a) Co-worker Type and Gender Dissimilarity on Swift Trust and (b) Co-worker Type and Work Style Dissimilarity on Swift Trust

Table 2. Results of GLS for Preference for Robot

IV	*Dependent variable: Preference for robot over human*											
	Model 1				**Model 2**				**Model 3**			
	B	***SE***	**LLCI**	**ULCI**	***B***	***SE***	**LLCI**	**ULCI**	***B***	***SE***	**LLCI**	**ULCI**
Constant	2.82***	0.06	2.71	2.94	2.20***	0.12	1.97	2.43	2.30***	0.10	2.10	2.49
Age	-0.02	0.07	-0.16	0.13	-0.08	0.06	-0.20	0.04	-0.04	0.05	-0.14	0.06
Education	0.07	0.06	-0.05	0.20	0.05	0.05	-0.05	0.16	0.00	0.04	-0.08	0.08
KnowTech	0.11	0.07	-0.03	0.25	0.10†	0.06	-0.02	0.22	0.07	0.05	-0.02	0.17
PercRisk	0.10	0.06	-0.01	0.22	0.06	0.07	-0.07	0.19	0.03	0.05	-0.07	0.14
NARS	-0.14*	0.06	-0.26	-0.03	-0.15***	0.05	-0.25	-0.04	-0.08	0.04	-0.16	0.00
RobotExp	-0.08	0.07	-0.21	0.06	-0.02	0.06	-0.14	0.10	0.01	0.05	-0.08	0.11
IndusExp	0.01	0.09	-0.18	0.19	0.08	0.08	-0.07	0.24	0.06	0.06	-0.06	0.18
CurJobTen	0.03	0.10	-0.16	0.23	-0.02	0.08	-0.19	0.15	-0.03	0.06	-0.15	0.09
JobComp	-0.08	0.06	-0.21	0.05	-0.04	0.05	-0.14	0.07	-0.06	0.04	-0.14	0.02
Main effects												
Co-worker type					1.07***	0.11	0.85	1.29	0.92***	0.08	0.76	1.08
Gender dissimilarity					0.01	0.10	-0.19	0.21	0.03	0.08	-0.13	0.19
Work style dissimilarity					0.17	0.11	-0.04	0.38	0.16	0.09	-0.01	0.32
Risk of physical danger					0.01	0.14	-0.26	0.28	0.08	0.11	-0.13	0.30
Trust in a co-worker					-0.29***	0.06	-0.40	-0.18	-0.56***	0.05	-0.66	-0.45
Interaction												
Trust in a co-worker x Co-worker type									1.19***	0.08	1.03	1.36
Goodness of fit												
AIC	1042.23				961.81				799.12			
Df	9				14				15			
χ^2	15.97				107.05				261.57			

Note: N = 347, * p < 0.05, ** p < 0.01, *** p < 0.001. KnowTech: Knowledge of relevant technology, PercRisk: perceived risk, NARS: Negative Attitudes toward Robots Scale, RobotExp: experience of working with robots, IndusExp: industry experience, CurJobTen: current job tenure, JobComp: job competency. Co-worker type, gender dissimilarity, work style dissimilarity, and risk of physical danger were coded as binary (0 = human/low, 1 = robot/high). Control variables were standardized.

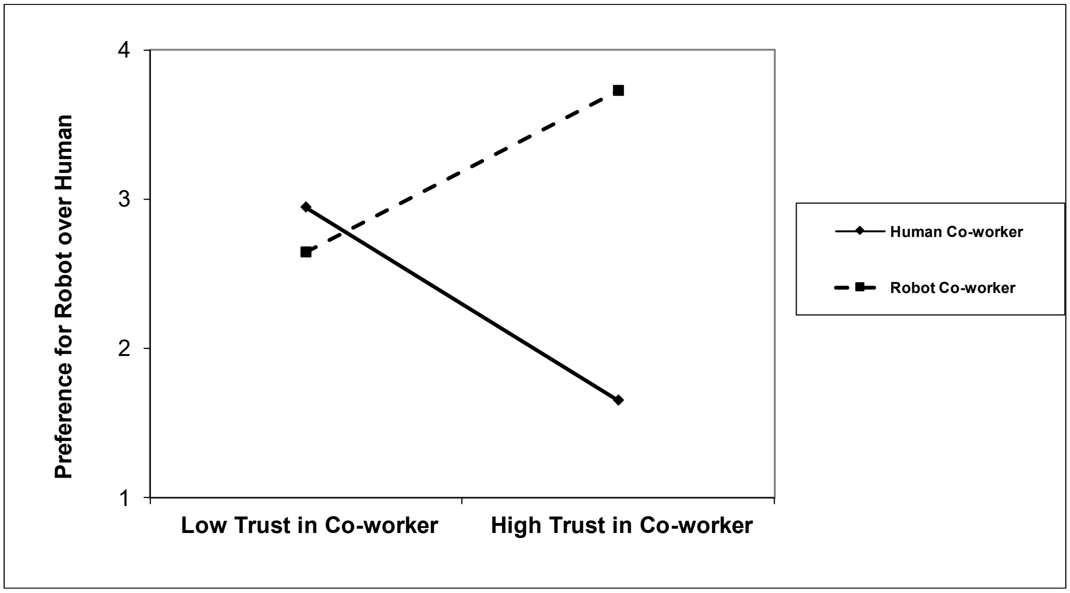


Figure 4. Interaction Effect: Co-worker Type and Trust on Preference for Robot

Fourth, in Study 1, participants were completely similar or completely dissimilar with regard to the work style manipulation. This might be unrealistic and might not have made sense to participants that their co-workers would totally agree or disagree with them on all the work style questions. In Study 2, the co-worker's responses were programmed to be the same as or different from the participant's in seven questions, while one question was always programmed to be the opposite, ensuring that there was never any total agreement or disagreement. Finally, Study 1 used binary measures of gender and work style dissimilarities; however, perceptions of dissimilarities may vary along a continuum. Study 2 instead used continuum measures of perceived dissimilarity.

In addition, to address the shortcomings of Study 1, Study 2 had two other changes to extend the findings of Study 1. First, to extend the generalizability of the results, Study 2 used personality as the achieved dissimilarity manipulation. Personality is one of the most salient and stable demographic factors in work relationships (Liao et al., 2008). Moreover, research on robot personality suggests that extraversion/introversion is one of the most believable, salient, and immediate personality traits that can be captured in human-robot interactions (Robert et al., 2020). Second, Study 1's swift trust measurement was adapted from the HRI literature and may not have captured swift trust relevant to work relationships specifically. In Study 2, we measured swift trust using situational normality, which refers to the perception that the other is trustworthy and dependable and that one is comfortable with the other's roles in a particular setting (McKnight et al., 1998; Mcknight et al., 2011). Situational normality in IS research has been measured in swift trust by capturing the feeling of comfort while working or interacting with a teammate in a particular setting (Robert et al., 2009) or as initial trusting beliefs regarding comfort with and confidence in teammates in a specific setting (Crisp & Jarvenpaa, 2013). Our measurement of swift trust in Study 2 is consistent with these approaches.

Design and Participants

As a result, Study 2 employed a 2 (ascribed dissimilarity: robot vs. human) × 2 (ascribed dissimilarity: same vs. different gender) × 2 (achieved dissimilarity: same vs. different personality) design. We recruited 422 U.S. participants who had worked in a warehouse from CloudResearch, another market panel company. We recruited the sample via a different company to ensure the generalizability of our findings. Participants were asked to verify their work experience by providing the name and location of the warehouse. The sample size was beyond our 126 target for a medium effect size of 0.25 based on a G*Power (alpha = 0.05; power = 0.8) (Faul et al., 2009). See Appendix A for more details.

Independent Variables

Similar to Study 1, there were three independent variables in Study 2: co-worker type (ascribed) dissimilarity, gender (ascribed) dissimilarity, and personality (achieved) dissimilarity. The manipulations of co-worker type and gender dissimilarity were identical to those in Study 2. The risk manipulation was not included in Study 2 because of its nonsignificance in Study 1.

In Study 2, we used the statements regarding extraversion adapted from the Big Five Inventory for the personality manipulation (McCrae & John, 1992). Participants were given a series of eight statements representing an extroverted personality (see Appendix C for the statements). In the similar personality condition, the robot chose the same answer as the participant each time. After the participant made their choice, the following sentence was displayed: "I also chose the same statement. Your answer was [the participant's choice]. My answer was [the participant's choice]." In the different personality condition, the robot chose the other answer and stated: "I chose the different statement. Your answer was [the participant's choice]. My answer was [the opposite choice of the participant's choice]." The extraversion statements were shown in random order. For a manipulation check, we measured perceived dissimilarity related to extroversion. An index of five items was used based on a 5-point scale (1 = *strongly disagree* to 5 = *strongly agree*) (see Appendix D for measurement items).

Dependent and Control Variables

Swift trust in a co-worker was measured using an index of four items on a 5-point Likert scale (Mcknight et al., 2011). Similar to Study 1, we adapted each item to the condition by using the word "robot" for the robot co-worker condition and "human" for the human co-worker condition. Also, preference for working with the co-worker was captured in the same way as in Study 1. We added the degree of warehouse working experience and the Individual Differences Measure of Anthropomorphism (IDAQ) (Waytz et al., 2010) as control variables. The IDAQ captures the possibility of stable individual differences in perceiving humanlike qualities of nonhuman objects and has been widely used to rule out the effects of individual dispositions regarding anthropomorphism (Waytz et al., 2010) (see Appendix D for measurement items).

Task and Procedure

Study 2 employed the same task and robots used in Study 1. As in Study 1, participants were asked to immerse themselves in the hypothetical scenario. As stated above, in Study 2, the manipulations of gender and personality dissimilarities were shown in random order. About half of the participants in Study 2 were exposed to gender dissimilarity manipulations first and then personality dissimilarity, while others were exposed to them in reverse order (Figure 5).

Data Analysis and Results

Construct Reliability and Validity

We used the same approaches as in Study 1 to assess reliability and validity. All latent variables demonstrated good reliability, Cronbach's α measurements were all greater than 0.70. The factor loadings demonstrated discriminant and convergent validity (Fornell & Larcker, 1981). All measured variables in the model showed AVEs that were well above the threshold of 0.50 and loadings without cross-loading values that were greater than 0.40. Study 2's measurement model is found in Appendix E.

Manipulation Checks

Gender manipulation was performed by asking participants to indicate the degree to which the co-worker's gender was similar to or dissimilar from theirs (1 = *very similar to me*, 5 = *very different from me*). The gender dissimilarity manipulation was successful. Perceived gender dissimilarity was lower in the similar gender condition (M = 1.84, SD = 1.26) than in the dissimilar gender condition (M = 4.64, SD = 0.88, $t(420)$ = 26.32, $p < 0.001$). Personality dissimilarity manipulation was also successful. Participants in the similar personality condition had lower perceived dissimilarity (M = 2.28, SD = 0.95) than participants in the dissimilar personality condition (M = 4.56, SD = 0.64, $t(420)$ = 28.97, $p < 0.001$). Finally, we measured perceived anthropomorphism to ensure the manipulation of the robot and the human co-worker using an index of six items adapted from Waytz et al. (2010). Results showed lower degrees of anthropomorphism in the robot co-worker (M = 2.15, SD = 0.86) than in the human co-worker condition (M = 4.37, SD = 0.69, $t(420)$ = 28.89, $p < 0.001$).

Results

Co-worker trust variance was not homogeneous across the conditions based on Levene's test ($F(1, 420) = 15.60$, $p < 0.01$). As such, we employed GLS, as in Study 1, for Study 2. The moderation effect of co-worker type was significant for gender dissimilarity (B = -0.20, $p < 0.05$) but not for personality dissimilarity (B = -0.09, p = 0.34; Table 3). The moderation effect is illustrated in Figure 6a, demonstrating a stronger negative effect of perceived gender dissimilarity on robot co-worker trust than on human co-worker trust. The preference for a robot over a human co-worker was similar to findings in Study 1 (Table 4 and Figure 6b). Hypothesis testing results from Studies 1 and 2 are summarized in Table 5.

Table 3. Results of GLS for H1 and H2 in Study 2

IV	***Dependent variable: Swift trust in a co-worker***											
	Model 1				**Model 2**				**Model 3**			
	B	***SE***	**LLCI**	**ULCI**	***B***	***SE***	**LLCI**	**ULCI**	***B***	***SE***	**LLCI**	**ULCI**
Constant	3.90***	0.05	3.81	4.00	4.01***	0.15	3.72	4.31	4.06***	0.15	3.76	4.36
Control Variables												
Age	-0.07	0.06	-0.18	0.05	-0.08	0.06	-0.19	0.03	-0.08	0.06	-0.19	0.03
Education	0.09†	0.05	-0.01	0.19	0.10*	0.05	0.01	0.19	0.11*	0.05	0.01	0.20
Gender	-0.05	0.05	-0.15	0.05	-0.07	0.05	-0.16	0.02	-0.07	0.05	-0.17	0.02
KnowTech	-0.02	0.05	-0.13	0.09	-0.08	0.05	-0.19	0.02	-0.09	0.05	-0.19	0.02
IndusExp	0.12†	0.07	-0.02	0.26	0.13†	0.07	0.00	0.27	0.14*	0.07	0.01	0.27
CurJobTen	-0.11†	0.06	-0.23	0.00	-0.11†	0.06	-0.22	0.01	-0.12*	0.06	-0.24	-0.01
WHExp	-0.01	0.05	-0.11	0.09	-0.02	0.05	-0.11	0.08	-0.01	0.05	-0.11	0.09
IDAQ	0.02	0.05	-0.08	0.11	0.00	0.05	-0.09	0.09	0.00	0.05	-0.09	0.09
NARS	-0.30**	0.05	-0.40	-0.21	-0.36**	0.05	-0.46	-0.26	-0.36**	0.05	-0.46	-0.27
RobotExp	0.04	0.06	-0.07	0.15	0.06	0.05	-0.05	0.16	0.06	0.05	-0.04	0.17
Main effects												
Co-worker Type					-0.09	0.17	-0.42	0.25	-0.11	0.17	-0.44	0.23
Perceived Anthropomorphism					0.22**	0.08	0.06	0.38	0.20*	0.08	0.04	0.37
Gender Dissimilarity					0.29†	0.15	-0.01	0.59	0.27†	0.15	-0.03	0.57
Personality Dissimilarity					-0.40*	0.17	-0.73	-0.08	-0.42*	0.17	-0.75	-0.09
Perceived Gender Dissimilarity					-0.13†	0.08	-0.28	0.03	-0.01	0.10	-0.20	0.17
Perceived Personality Dissimilarity					0.04	0.09	-0.13	0.21	0.09	0.10	-0.10	0.29
Interaction												
Co-worker Type x Perceived Gender Dissimilarity									-0.20*	0.10	-0.39	-0.01
Co-worker Type x Perceived Personality Dissimilarity									-0.09	0.10	-0.28	0.10
Goodness of fit												
AIC	1207.32				1175.52				1173.80			
Df	10				16				18			
χ^2	47.14				90.95				96.67			

Note: *N* = 422, † *p* < 0.10, * *p* < 0.05, ** *p* < 0.01, *** *p* < 0.001. KnowTech: Knowledge of relevant technology, IndusExp: industry experience, CurJobTen: current job tenure, WHExp: warehouse experience, IDAQ: individual differences measure of anthropomorphism, NARS: Negative Attitudes toward Robots Scale, RobotExp: experience of working with robots. Co-worker type, gender dissimilarity, and personality dissimilarity are coded binary (0 = human/same, 1 = robot/different). All measured variables are standardized.

Table 4. Results of GLS for H3 in Study 2

IV	**Dependent variable: Preference for robot over human**											
	Model 1				**Model 2**				**Model 3**			
	B	***SE***	**LLCI**	**ULCI**	***B***	***SE***	**LLCI**	**ULCI**	***B***	***SE***	**LLCI**	**ULCI**
Constant	2.44	0.05	2.34	2.54	2.04	0.13	1.78	2.30	1.93	0.11	1.71	2.15
Control variables												
Age	-0.10†	0.06	-0.21	0.01	-0.07	0.05	-0.18	0.04	-0.07	0.05	-0.17	0.02
Education	-0.01	0.05	-0.10	0.08	0.00	0.04	-0.09	0.08	-0.01	0.04	-0.09	0.07
Gender	-0.15*	0.05	-0.25	-0.06	-0.11*	0.05	-0.20	-0.02	-0.07†	0.04	-0.15	0.01
KnowTech	-0.03	0.05	-0.13	0.08	-0.01	0.05	-0.11	0.09	0.03	0.04	-0.05	0.11
IndusExp	0.16*	0.07	0.03	0.29	0.10†	0.06	-0.01	0.22	0.16**	0.05	0.06	0.27
CurJobTen	-0.02	0.05	-0.12	0.08	0.00	0.04	-0.09	0.08	-0.07	0.04	-0.16	0.02
WHExp	0.09†	0.05	-0.01	0.18	0.06	0.04	-0.02	0.15	0.07†	0.04	0.00	0.15
IDAQ	0.07	0.05	-0.03	0.16	0.08†	0.04	-0.01	0.16	0.08†	0.04	0.00	0.16
NARS	-0.51**	0.05	-0.60	-0.41	-0.40**	0.05	-0.49	-0.31	-0.29**	0.04	-0.37	-0.21
RobotExp	0.09†	0.05	-0.01	0.19	0.05	0.05	-0.04	0.15	0.03	0.04	-0.06	0.11
Main effects												
Co-worker type					0.72**	0.15	0.42	1.02	0.90**	0.14	0.62	1.18
Perceived anthropomorphism					0.02	0.08	-0.14	0.18	0.03	0.07	-0.11	0.18
Gender dissimilarity					0.01	0.15	-0.28	0.29	0.11	0.13	-0.14	0.36
Personality dissimilarity					-0.01	0.16	-0.32	0.30	0.01	0.12	-0.23	0.26
Perceived gender dissimilarity					-0.03	0.07	-0.18	0.12	-0.04	0.07	-0.17	0.09
Perceived personality dissimilarity					0.00	0.08	-0.15	0.16	0.01	0.06	-0.11	0.13
Trust in a co-worker					0.04	0.05	-0.06	0.14	-0.33**	0.07	-0.46	-0.20

Interaction						
Co-worker type x Trust in a co-worker			0.73**	0.08	0.57	0.89
Goodness of fit						
AIC	1172.90	1134.04	1063.90			
Df	10	17	18			
χ^2	110.28	163.145	235.28			

Note: *N* = 422, † *p* < 0.10, * *p* < 0.05, ** *p* < 0.01, *** *p* < 0.001. KnowTech: Knowledge of relevant technology, IndusExp: industry experience, CurJobTen: current job tenure, WHExp: warehouse experience, IDAQ: individual differences measure of anthropomorphism, NARS: Negative Attitudes toward Robots Scale, RobotExp: experience of working with robots. Co-worker type, gender dissimilarity, and personality dissimilarity are coded binary (0 = human/same, 1 = robot/different). All measured variables are standardized.

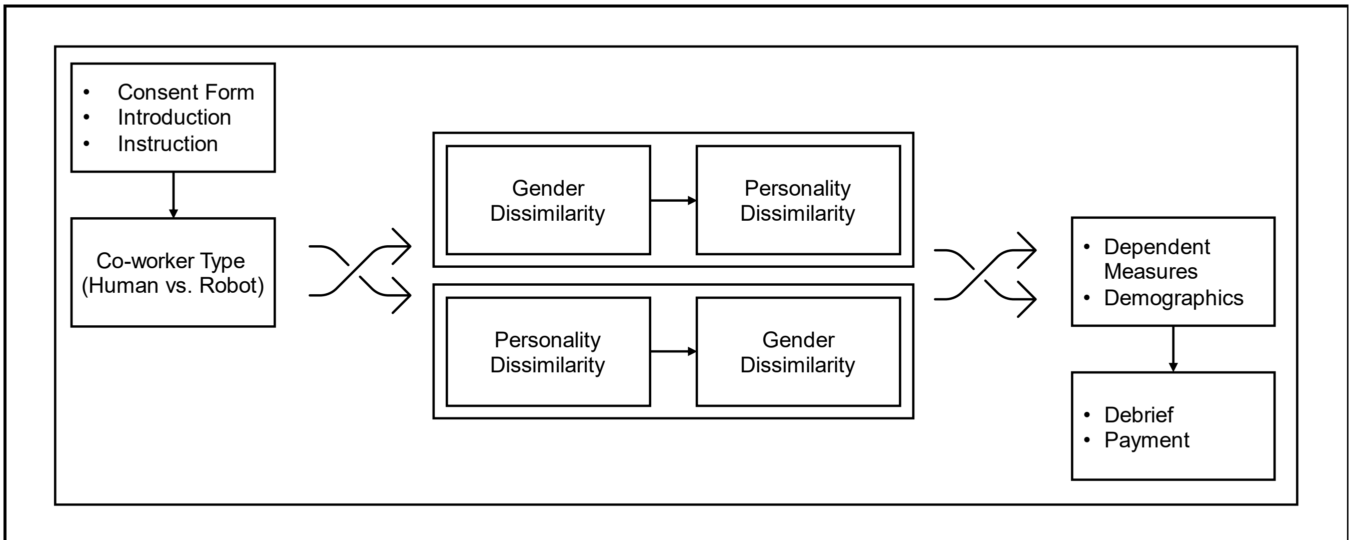
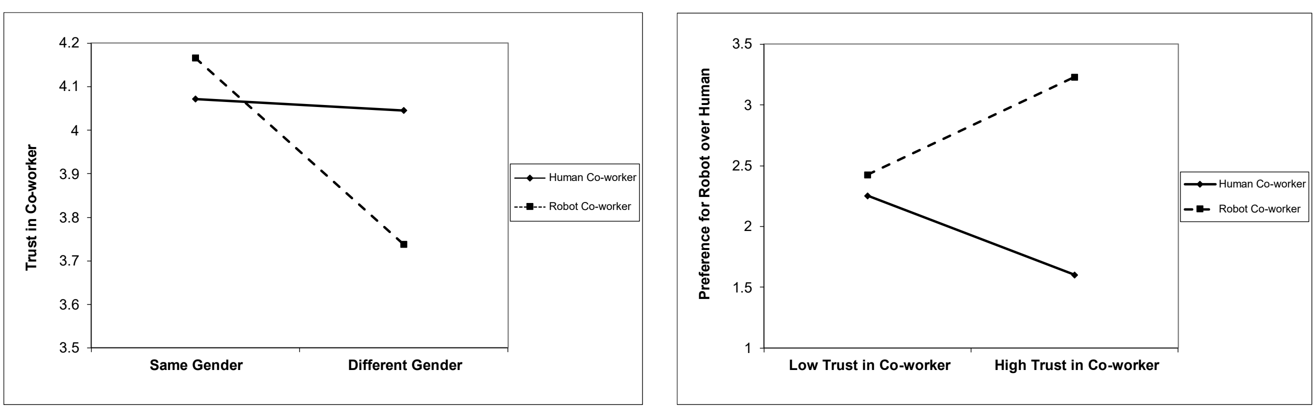


Figure 5. Experiment Procedure of Study 2



(a) **(b)**

Figure 6. Interaction Effect: (a) Perceived Gender Difference and Co-worker Type on Swift Trust and (b) Trust in a Co-worker and Co-worker Type on Preference for Robot over Human in Study 2

Table 5. Summary of Hypotheses Testing

Hypothesis		Study 1	Study 2
H1	The negative effect of ascribed dissimilarities in gender on swift trust in a co-worker is stronger for a robot co-worker than for a human co-worker.	Supported	Supported
H2	The negative effect of achieved dissimilarities on swift trust in a co-worker is weaker for a robot co-worker than for a human co-worker.	Supported	Not Supported
H3	(a) Swift trust in a robot co-worker increases the preference for working with a robot, (b) while swift trust in a human co-worker decreases it.	Supported	Supported

Discussion

This study has three overarching findings based on types of co-worker dissimilarities from the perspective of RDT. First, impacts regarding RDT with a robot co-worker appear to unfold differently with a human co-worker. Second, the type of dissimilarity matters. For a robot co-worker, the negative impacts of ascribed dissimilarity become stronger, while the negative impacts of achieved dissimilarity become weaker. Finally, swift trust in a robot co-worker leads to a preference for working with a robot co-worker over a human. In contrast, swift trust in a human co-worker reduces the preference for working with a robot co-worker.

Although results from both experiments are generally similar, we should note that H2 had mixed results across the two studies. In Study 1, H2 was supported in that achieved dissimilarity had weaker effects on trust in a robot than on trust in a human co-worker. However, the moderation effect was not found in Study 2. One possible explanation for the insignificant results is that personality dissimilarity as achieved dissimilarity is less relevant to the context of warehouse work when compared to the work style used in Study 1. Based on these findings, we cautiously conclude that the effects of achieved dissimilarity and co-worker type might be contingent upon the kind of achieved dissimilarity (i.e., the relevance to the work context).

Implications for Theory and Research

This paper has three research implications. First, this paper answers recent calls for more theorizing on AI-ET by examining collaborations with a robot co-worker based on RDT. The widespread introduction of technology with the potential for social agency (i.e., robots) requires new theorizing in areas, such as the changing role of both humans and AI-ET in work contexts and how we should leverage the new relationships for better outcomes (Baird & Maruping, 2021; Seeber et al., 2020). Our contribution to theorizing on AI-ET comes from examining different types of dissimilarity based on RDT, such as co-worker type (i.e., robot vs. human), gender, work style, and personality. In particular, we examined the impacts of dissimilarities not only between human co-workers but also between a human and a robot co-worker, allowing for an examination of how RDT unfolds in human and AI-ET relationships. By doing so, this study goes beyond the existing literature on the impacts of dissimilarity between human co-workers *through* technology (Liao et al., 2008; Robert et al., 2018; Van der Vegt & Van de Vliert, 2005) and provides an initial understanding of how dissimilarity impacts collaborations *with* technology as a social agent. Therefore, our findings contribute to the next-generation theorizing on collaborations involving AI-ET and the future of work as the recent calls for more attention on this direction in IS research (Berente et al., 2021; Burton-Jones et al., 2021; Fügener et al., 2021).

In this sense, this paper demonstrates the potential for further exploration of the impacts of ascribed dissimilarity between humans and AI-ET. Past research on traditional technologies has tended to view humans as users and technologies as tools, presuming that humans possess primacy based on their control and supervision over technologies (Schuetz & Venkatesh, 2020). On the other hand, recent research has proposed that humans lose their supremacy over technology by delegating work and reducing human intervention (Baird & Maruping, 2021; Rai et al., 2019). Despite the recent acknowledgment of the importance of relative characteristics between humans and AI-ET, more theorizing is needed to explore this area fully. Thus, future research could explore the impact of RDT on trust in AI co-workers when AI-ET elicits the perception of similar agency based on advanced machine agency as part of a human-AI hybrid system (Fügener et al., 2021; Rai et al., 2019). For instance, increases in machine agency can lead to increases in mind attribution (Banks, 2020). However, increases in machine agency can also impact other less explored areas (e.g., emotional attachment) that also need to be examined.

Second, this study has implications for collaboration research on dissimilarity. Achieved dissimilarity has long been acknowledged by collaboration scholars as a double-edged sword (Williams, 2001). On the one hand, providing unique and valuable information promotes group performance. On the other hand, it decreases trust in collaborators and hinders the ultimate use of unique information. However, we reported that the negative effect of achieved dissimilarity was weaker when channeled through a robot co-worker than with a human co-worker. This implies that the effects of achieved dissimilarity may be harnessed and leveraged when introduced through AI-ET rather than a human collaborator. For instance, injecting achieved dissimilarity into AI-ET co-workers could increase the chance that the human collaborator uses this information. To this end, leveraging achieved dissimilarity and taking advantage of it should be interesting for the next-generation theorizing uniquely in the human-AI hybrid systems (Rai et al., 2019). Future research is needed to explore this area further.

Furthermore, this paper questions the advantages of promoting the perception of machine agency. Most research on human interactions with AI-ET suggests that there are psychological and work-related outcomes that benefit from humans viewing technology as human-like (i.e., anthropomorphizing) (Natarajan & Gombolay, 2020; Waytz et al., 2010). This often requires efforts to make AI-ET humanlike, essentially obscuring the dissimilarities between machines and humans at work. However, our findings imply that there may be an unseen benefit to viewing AI-ET as less than humans and more machines keeping the AI-ET dissimilar from humans, such as the weakened negative effects of ascribed dissimilarity. We believe that future research is needed that both acknowledges and seeks to explore further this duality of promoting machine agency when examining human and AI-ET interactions. For example, research may seek to identify when the benefits associated with viewing AI-ET as an equal outweigh the costs.

Finally, our study goes beyond the previous literature while complementing and extending it by demonstrating a comparative benefit of considering two types of trust in determining one's preference for a robot over a human co-worker. Specifically, we demonstrated that preference for a robot over a human co-worker could be altered not only by trust in a robot co-worker but also by trust in a human co-worker. It would appear that promoting trust in a human co-worker is likely to be associated with a decrease in the preference for a robot over a human co-worker. In other words, trust in a human co-worker can hamper one's preference for a robot co-worker. The results of this study also imply that humans working with a human co-worker whom they perceive to be different from them might be more open to working with a robot co-worker, especially if they perceive that robot co-worker to be similar to them. Likewise, humans working with a human co-worker whom they perceive to be similar to them might be less open to working with a robot co-worker, especially if they perceive that robot co-worker to be different from them.

Previous findings on trust in robots only examined trust in a robot to predict intentions of future interaction (Gaudiello et al., 2016; Hancock et al., 2011; Natarajan & Gombolay, 2020). Such trends were found in the IS literature, where trust in technology provided insights into promoting the adoption of a particular technology by an individual or an organization (Komiak & Benbasat, 2006). However, unlike previous technology adoption studies, robot co-workers are likely to be used in place of existing human co-workers and regarded as an alternative. Individuals will encounter situations where they have to choose between a human co-worker and a robotic alternative and, conversely, compete to be chosen over a robot by their human co-workers (Fraune et al., 2019; Kshirsagar et al., 2019). In this case, preference for a robot over a human co-worker can better be explained by considering trust in a human co-worker as well as trust in a robot. Therefore, our findings suggest that intentions to work with AI-ET should be understood by considering the comparative preferences between a robot and a human co-worker.

Implications for Practice

First, managers can promote the acceptance of robots in the workplace by leveraging similarities between humans and robots. Given that it is increasingly inevitable for organizations to include robots in their workforce, social dynamics and psychology between humans and robots will be equally crucial to those among human workers (Vreede & Briggs, 2019; You & Robert, 2023). The results of this study indicate that robots should be designed to minimize the adverse impacts of dissimilarity and ensure higher levels of trust. For instance, a workplace where most employees are women might choose to adopt a robot displaying female characteristics to promote ad hoc membership and trust in the robot. Likewise, different genders and work styles between an individual and a robot co-worker were found to be less effective in eliciting swift trust in the robot co-worker. Hence, managers and organizations might benefit from embedding employee-specific characteristics into robotic co-workers.

Second, our results suggest that organizations planning to adopt robots alongside their human workers must secure high levels of worker trust in robot co-workers. However, given that trust in human co-workers decreases preference for working with a robot co-worker, organizations should be cautious about deploying robots to worksites where human workers have already established highly trusting relationships. It is possible that, because of the high levels of trust in existing human co-workers, workers might be repulsed by the robots that would replace their existing human co-workers.

Disrupting trusted relationships among workers might cause adverse effects on various aspects of workers' minds and behaviors, such as psychological well-being, task performance, and even employee turnover (Costa et al., 2009; De Jong et al., 2016; Spector & Jones, 2004). On the other hand, organizations might benefit from the trust established between a human and a robot co-worker when trust among human workers is not high. The deployment of robots might be particularly effective and smooth in organizations that have employees with short job tenure. We recommend that organizations assess their workers' trust levels to create a cohesive workforce that includes both robots and humans.

Third, managers will face trade-offs between the potential and problems associated with the use of relational demography as a design intervention with robotic co-workers. On the one hand, designing robotic co-workers to be similar to their human co-workers can enhance trust and, ultimately, their acceptance (You & Robert, 2018b). On the other hand, problems can arise when humans build emotional bonds with their robots. Past research has shown that humans are less willing to put robots in harm's way, even when the robot's purpose is to be employed in a dangerous situation to prevent human harm (Carpenter, 2016). There is also evidence that humans can develop strong bonds with robots, which can create subgroups in human-robot teams (You & Robert, 2023). Managers should be aware of potential privacy and security issues related to the use of relational demography. Humans are more likely to let their guard down and disclose private and sensitive information with robotic co-workers. Robots can easily be used to collect information from human co-workers without their knowledge or personal consent. For example, OpenAI's ChatGPT and Google's Bard have benefited from data based on countless human interactions. Yet it is not clear whether those involved were aware of or gave consent to use their data. Managers must acknowledge the potential ethical issues associated with promoting the bond between their employees and robots.

Finally, our results broadly speak to the recent AI Bill of Rights released by the U.S. White House. The document proposes a framework for developing and deploying automated systems, including AI-ET and robots, for the public (The White House, 2022). In particular, according to the principle of safe and effective AI systems, humans' safety and well-being must be the priority in employing AI-ET in various contexts. Trust in robotic co-workers forms the basis of physical and psychological safety in robot-enabled workplaces (Maurtua et al., 2017). In this sense, according to the bill, our results regarding the importance of harnessing trust in robotic co-workers and AI-ET may provide actionable guidelines for organizations to achieve safe and effective use of AI-ET at work.

Limitations

This study is not without limitations. First, it was conducted using two online experiments to examine interactions with robots based on pre-recorded videos. Although online experiments using videos are widely used and validated in studies of interaction with robots, the results might be different in situations where individuals interact with real robots. To this end, a field study that involves interviews and observations of workers could address such shortcomings of experimental studies (Beane & Orlikowski, 2015). For instance, perceptions of dissimilarities could be captured in more nuanced ways that go beyond individuals' self-reports, potentially avoiding response biases from controlled experimental manipulations.

Second, we used warehouses as the experimental context because of the rapid adoption of robots in such work contexts (Shead, 2017). It is possible that task types and characteristics, such as physical and knowledge-based factors, play a role in predicting the inherent preference for a particular type of co-worker and robot. For instance, given the physical nature of warehouse tasks, individuals might prefer co-workers who are physically more capable to ensure better work efficiency. Future research could explore whether task types and characteristics alter the findings on RDT with co-workers.

Third, the participants were paid different amounts of compensation in two experiments because the market survey companies used for the studies had different selection criteria and pricing for their panels. However, our results from Study 1 and Study 2 were generally consistent, indicating that it is unlikely that this issue presents a major concern. We also screened unqualified participants and removed incomplete observations from our final datasets. Nevertheless, our results might not be entirely free from potential biases from different compensation amounts, and we recommend caution in future studies (Beckford & Broome, 2007).

Finally, this study examined only one aspect of each dissimilarity. Perceptions of dissimilarity can be elicited by many factors other than the ones used in this paper, such as place of origin, ad hoc membership, abilities, and knowledge (Robert, 2013; Van der Vegt & Van de Vliert, 2005). Also, the salience of dissimilarity might not be uniform but differ by type and presentation, meaning, for instance, that achieved dissimilarity could be more or less salient than ascribed dissimilarity. Thus, we call for more research investigating the impacts of RDT in various aspects to further enhance our understanding of teamwork with robots.

Conclusion

Based on RDT, this study examined the impacts of ascribed and achieved dissimilarities between an individual and a robot co-worker on trust in the robot and preference for working with a robot co-worker over a human co-worker. Results from two controlled experiments showed moderation effects of ascribed dissimilarity in co-worker type, such that ascribed dissimilarity in gender and achieved dissimilarity in work style and personality between individuals and their co-workers yielded adverse effects on trust in a robot co-worker and a human co-worker. The adverse effects of achieved dissimilarity were observed with weaker intensity in the participants' relationships with robot co-workers vs. with human co-workers. We further found that trust in a robot co-worker positively predicted a preference for working with a robot co-worker over a human counterpart. Overall, this research contributes to theory and practice regarding the development of a cohesive workforce involving both humans and robots.

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References

Ackerman, E. (2014). *U.S. Army considers replacing thousands of soldiers with robots*. IEEE Spectrum: Technology, Engineering, and Science News. https://spectrum.ieee.org/automaton/robotics/military-robots/army-considers-replacing-thousands-of-soldiers-with-robots

Aguinis, H., & Bradley, K. J. (2014). Best practice recommendations for designing and implementing experimental vignette methodology studies. *Organizational Research Methods*, *17*(4), 351-371.

Andrist, S., Mutlu, B., & Tapus, A. (2015). Look like me: Matching robot personality via gaze to increase motivation. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (pp. 3603-3612). http://dl.acm.org/citation.cfm?id=2702592

Atkinson, D. J., & Clark, M. H. (2014). Methodology for study of human-robot social interaction in dangerous situations. In *Proceedings of the Second International Conference on Human-Agent Interaction* (pp. 371-376). http://dl.acm.org/citation.cfm?id=2658871

Baird, A., & Maruping, L. (2021). The next generation of research on IS Use: A theoretical framework of delegation to and from agentic IS artifacts. *Management Information Systems Quarterly*, *45*(1), 315-341.

Banks, J. (2020). Theory of mind in social robots: Replication of five established human tests. *International Journal of Social Robotics*, *12*(2), 403-414. https://doi.org/10.1007/s12369-019-00588-x

Beane, M., & Orlikowski, W. J. (2015). What Difference does a robot make? The material enactment of distributed coordination. *Organization Science*, *26*(6), 1553-1573. https://doi.org/10.1287/orsc.2015.1004

Beaudry, A., & Pinsonneault, A. (2010). The other side of acceptance: Studying the direct and indirect effects of emotions on information technology use. *MIS Quarterly*, *34*(4), 689-710.

Beckford, L., & Broome, M. R. (2007). Ethics and the payment of research subjects. *Psychiatry*, *6*(2), 83-85. https://doi.org/10.1016/j.mppsy.2006.11.001

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Special issue editor's comments: Managing artificial intelligence. *Management Information Systems Quarterly*, *45*(3), 1433-1450.

Bernier, E. P., & Scassellati, B. (2010). The similarity-attraction effect in human-robot interaction. In *Proceedings of the 2010 IEEE 9th International Conference on Development and Learning*, (pp. 286-290). http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=5578828

Burton-Jones, A., Butler, B., Scott, S., & Xu, S. X. (2021). Next-generation information systems theorizing: A call to action. *Management Information Systems Quarterly*, *45*(1), 301-314.

Carpenter, J. (2016). *Culture and human-robot interaction in militarized spaces: A war story*. Routledge.

Chatman, J. A., & Spataro, S. E. (2005). Using self-categorization theory to understand relational demography-based variations in people's responsiveness to organizational culture. *Academy of Management Journal*, *48*(2), 321-331. https://doi.org/10.5465/amj.2005.16928415

Chattopadhyay, P., & George, E. (2001). Examining the effects of work externalization through the lens of social identity theory. *Journal of Applied Psychology*, *86*(4), 781-788. https://doi.org/10.1037/0021-9010.86.4.781

Chattopadhyay, P., George, E., & Ng, C. K. (2016). Hearts and minds: Integrating regulatory focus and relational demography to explain responses to dissimilarity. *Organizational Psychology Review*, *6*(2), 119-144. https://doi.org/10.1177/2041386615574540

Costa, A. C., Bijlsma-Frankema, K., & de Jong, B. (2009). The role of social capital on trust development and dynamics: Implications for cooperation, monitoring and team performance. *Social Science Information*, *48*(2), 199-228.

Crisp, C. B., & Jarvenpaa, S. L. (2013). Swift trust in global virtual teams: Trusting beliefs and normative actions. *Journal of Personnel Psychology*, *12*(1), 45-56. https://doi.org/10.1027/1866-5888/a000075

Das, T. K., & Teng, B.-S. (2001). Trust, control, and risk in strategic alliances: An integrated framework. *Organization Studies*, *22*(2), 251-283.

De Jong, B. A., Dirks, K. T., & Gillespie, N. (2016). Trust and team performance: A meta-analysis of main effects, moderators, and covariates. *Journal of Applied Psychology*, *101*(8), 1134-1150. https://doi.org/10.1037/apl0000110

de Visser, E., & Parasuraman, R. (2011). Adaptive aiding of human-robot teaming effects of imperfect automation on performance, trust, and workload. *Journal of Cognitive Engineering and Decision Making*, *5*(2), 209-231.

Dennis, A. R., Robert, L. P., Curtis, A. M., Kowalczyk, S. T., & Hasty, B. K. (2012). Research note—Trust is in the eye of the beholder: A vignette study of postevent behavioral controls' effects on individual trust in virtual teams. *Information Systems Research*, *23*(2), 546-558.

Elprama, S. A., Jewell, C. I., Jacobs, A., El Makrini, I., & Vanderborght, B. (2017). Attitudes of factory workers towards industrial and collaborative robots. In *Proceedings of the Companion of the 2017 ACM/IEEE International Conference on Human-Robot Interaction* (pp. 113-114).

Epley, N., & Waytz, A. (2010). Mind perception. In *Handbook of social psychology* (Vol. 1, 5th ed., pp. 498-541). John Wiley & Sons, Inc. https://doi.org/10.1002/9780470561119.socpsy001014

Ertug, G., Brennecke, J., Kovács, B., & Zou, T. (2022). What does homophily do? A review of the consequences of homophily. *Academy of Management Annals*, *16*(1), 38-69. https://doi.org/10.5465/annals.2020.0230

Esterwood, C., Essenmacher, K., Yang, H., Zeng, F., & Robert, L. P. (2021). Birds of a feather flock together: But do humans and robots? a meta-analysis of human and robot personality matching. In *Proceedings of the 30th IEEE International Conference on Robot Human Interactive Communication* (pp. 343-348). https://doi.org/10.1109/RO-MAN50785.2021.9515394

Eyssel, F., & Hegel, F. (2012). (S)he's got the look: Gender stereotyping of robots. *Journal of Applied Social Psychology*, *42*(9), 2213-2230. https://doi.org/10.1111/j.1559-1816.2012.00937.x

Eyssel, F., & Kuchenbrandt, D. (2012). Social categorization of social robots: Anthropomorphism as a function of robot group membership. *British Journal of Social Psychology*, *51*(4), 724-731. https://doi.org/10.1111/j.2044-8309.2011.02082.x

Eyssel, F., Kuchenbrandt, D., Bobinger, S., de Ruiter, L., & Hegel, F. (2012). "If you sound like me, you must be more human": On the interplay of robot and user features on human-robot acceptance and anthropomorphism. In *Proceedings of the Seventh Annual ACM/IEEE International Conference on Human-Robot Interaction* (pp. 125-126). https://doi.org/10.1145/2157689.2157717

Fasola, J., & Mataric, M. (2013). A socially assistive robot exercise coach for the elderly. *Journal of Human-Robot Interaction*, *2*(2), 3-32.

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*(4), 1149-1160. https://doi.org/10.3758/BRM.41.4.1149

Fisher, D. M., Bell, S. T., Dierdorff, E. C., & Belohlav, J. A. (2012). Facet personality and surface-level diversity as team mental model antecedents: Implications for implicit coordination. *Journal of Applied Psychology*, *97*(4), 825-841. https://doi.org/10.1037/a0027851

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50.

Fraune, M. R., Sherrin, S., Šabanović, S., & Smith, E. R. (2019). Is human-robot interaction more competitive between groups than between individuals? In *Proceedings of the 14th ACM/IEEE International Conference on Human-Robot Interaction* (pp. 104-113). https://doi.org/10.1109/HRI.2019.8673241

Fügener, A., Grahl, J., Gupta, A., Ketter, W. (2021). Will humans-in-the-loop become borgs? Merits and pitfalls of working with AI. *MIS Quarterly*, *45*(3), 1527-1556. https://doi.org/10.25300/MISQ/2021/16553

Gaudiello, I., Zibetti, E., Lefort, S., Chetouani, M., & Ivaldi, S. (2016). Trust as indicator of robot functional and social acceptance. An experimental study on user conformation to iCub answers. *Computers in Human Behavior*, *61*, 633-655. https://doi.org/10.1016/j.chb.2016.03.057

Graetz, G., & Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, *100*(5), 753-768.

Gramzow, R. H., Gaertner, L., & Sedikides, C. (2001). Memory for in-group and out-group information in a minimal group context: The self as an informational base. *Journal of Personality and Social Psychology*, *80*, 188-205. https://doi.org/10.1037/0022-3514.80.2.188

Gray, H. M., Gray, K., & Wegner, D. M. (2007). Dimensions of mind perception. *Science*, *315*(5812), 619-619. https://doi.org/10.1126/science.1134475

Gray, K., & Wegner, D. M. (2012). Feeling robots and human zombies: Mind perception and the uncanny valley. *Cognition*, *125*(1), 125-130.

Groom, V., & Nass, C. (2007). Can robots be teammates? Benchmarks in human-robot teams. *Interaction Studies*, *8*(3), 483-500.

Guillaume, Y. R. F., van Knippenberg, D., & Brodbeck, F. C. (2014). Nothing succeeds like moderation: A social self-regulation perspective on cultural dissimilarity and performance. *Academy of Management Journal*, *57*(5), 1284-1308. https://doi.org/10.5465/amj.2013.0046

Hancock, P. A., Billings, D. R., Schaefer, K. E., Chen, J. Y., De Visser, E. J., & Parasuraman, R. (2011). A meta-analysis of factors affecting trust in human-robot interaction. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *53*(5), 517-527.

Hansen, C. B. (2007). Generalized least squares inference in panel and multilevel models with serial correlation and fixed effects. *Journal of Econometrics*, *140*(2), 670-694. https://doi.org/10.1016/j.jeconom.2006.07.011

Haring, K. S., Matsumoto, Y., & Watanabe, K. (2013). How do people perceive and trust a lifelike robot. In *Proceedings of the World Congress on Engineering and Computer Science*.

Heo, H.-H., & Kim, M.-S. (2013). The effects of multiculturalism and mechanistic disdain for robots in human-to-robot communication scenarios. *Interaction Studies*, *14*(1), 81-106. https://doi.org/10.1075/is.14.1.06heo

Hogg, M. A., & Terry, D. I. (2000). Social identity and self-categorization processes in organizational contexts. *Academy of Management Review*, *25*(1), 121-140.

Jermier, J. M., Gaines, J., & McIntosh, N. J. (1989). Reactions to physically dangerous work: A conceptual and empirical analysis. *Journal of Organizational Behavior*, *10*(1), 15-33.

Jian, J.-Y., Bisantz, A. M., & Drury, C. G. (2000). Foundations for an empirically determined scale of trust in automated systems. *International Journal of Cognitive Ergonomics*, *4*(1), 53-71.

Kane, G. C., Young, A. G., Majchrzak, A., & Ransbotham, S. (2021). Avoiding an oppressive future of machine learning: A design theory for emancipatory assistants. *MIS Quarterly*, *45*(1), 371-396. https://doi.org/10.25300/MISQ/2021/1578

Karniol, R., Reichman, S., & Fund, L. (2000). Children's gender orientation and perceptions of female, male, and gender-ambiguous animal characters. *Sex Roles*, *43*, 377-393.

Kim, S., & McGill, A. L. (2011). Gaming with Mr. Slot or gaming the slot machine? Power, anthropomorphism, and risk perception. *Journal of Consumer Research*, *38*(1), 94-107. https://doi.org/10.1086/658148

King, E., Dawson, J., Jensen, J., & Jones, K. (2017). A socioecological approach to relational demography: How relative representation and respectful coworkers affect job attitudes. *Journal of Business and Psychology*, *32*(1), 1-19. https://doi.org/10.1007/s10869-016-9439-8

Komiak, S. Y., & Benbasat, I. (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS Quarterly*, *30*(4), 941-960.

Kramer, R. M. (1991). Intergroup relations and organizational dilemmas: The role of categorization processes. *Research in Organizational Behavior*, *13*, 191-228.

Kshirsagar, A., Dreyfuss, B., Ishai, G., Heffetz, O., & Hoffman, G. (2019). *Monetary-incentive competition between humans and robots: Experimental results*. SSRN. https://papers.ssrn.com/abstract=3323698

Kteily, N., Hodson, G., & Bruneau, E. (2016). They see us as less than human: Metadehumanization predicts intergroup conflict via reciprocal dehumanization. *Journal of Personality and Social Psychology*, *110*(3), 343-370. https://doi.org/10.1037/pspa0000044

Kuchenbrandt, D., Häring, M., Eichberg, J., & Eyssel, F. (2012). Keep an eye on the task! How gender typicality of tasks influence human-robot interactions. In *Social Robotics* (pp. 448-457). Springer. http://link.springer.com/chapter/10.1007/978-3-642-34103-8_45

Langfred, C. W. (2007). The downside of self-management: A longitudinal study of the effects of conflict on trust, autonomy, and task interdependence in self-managing teams. *Academy of Management Journal*, *50*(4), 885-900.

Lazarsfeld, P. F., & Merton, R. K. (1954). Friendship as a social process: A substantive and methodological analysis. *Freedom and Control in Modern Society*, *18*(1), 18-66.

Lewis, M., Sycara, K., & Walker, P. (2018). The role of trust in human-robot interaction. In H. Abbass, J. Scholz, J., & D. Reid (Eds.), *Foundations of trusted autonomy* (pp. 135-159). Springer. https://doi.org/10.1007/978-3-319-64816-3_8

Li, H., Chen, Y.-R., & Blader, S. L. (2016). Where is context? Advancing status research with a contextual value perspective. *Research in Organizational Behavior*, *36*, 185-198. https://doi.org/10.1016/j.riob.2016.10.003

Li, M., Leidner, B., & Castano, E. (2014). Toward a comprehensive taxonomy of dehumanization:Integrating two senses of humaness, mind perception theory, and stereotype content model. *Testing, Psychometrics, Methodology in Applied Psychology*, *3*, 285-300. https://doi.org/10.4473/TPM21.3.4

Liang, T.-P., Robert, L. P., Sarker, S., Cheung, C. M. K., Matt, C., Trenz, M., & Turel, O. (2021). Artificial intelligence and robots in individuals' lives: How to align technological possibilities and ethical issues. *Internet Research*, *31*(1), 1-10. https://doi.org/10.1108/INTR-11-2020-0668

Liao, H., Chuang, A., & Joshi, A. (2008). Perceived deep-level dissimilarity: Personality antecedents and impact on overall job attitude, helping, work withdrawal, and turnover. *Organizational Behavior and Human Decision Processes*, *106*(2), 106-124. https://doi.org/10.1016/j.obhdp.2008.01.002

Lount, R. B., & Pettit, N. C. (2012). The social context of trust: The role of status. *Organizational Behavior and Human Decision Processes*, *117*(1), 15-23. https://doi.org/10.1016/j.obhdp.2011.07.005

Maruping, L. M., Bala, H., Venkatesh, V., & Brown, S. A. (2017). Going beyond intention: Integrating behavioral expectation into the unified theory of acceptance and use of technology. *Journal of the Association for Information Science and Technology*, *68*(3), 623-637. https://doi.org/10.1002/asi.23699

Maurtua, I., Ibarguren, A., Kildal, J., Susperregi, L., & Sierra, B. (2017). Human-robot collaboration in industrial applications: Safety, interaction and trust. *International Journal of Advanced Robotic Systems*, *14*(4), 1-10. https://doi.org/10.1177/1729881417716010

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, *20*(3), 709-734.

McCrae, R. R., & John, O. P. (1992). An introduction to the five-factor model and its applications. *Journal of Personality*, *60*(2), 175-215. https://doi.org/10.1111/j.1467-6494.1992.tb00970.x

Mcknight, D. H., Carter, M., Thatcher, J. B., & Clay, P. F. (2011). Trust in a specific technology: An investigation of its components and measures. *ACM Transactions on Management Information Systems*, *2*(2), Articl 12.

McKnight, D. H., Cummings, L. L., & Chervany, N. L. (1998). Initial trust formation in new organizational relationships. *The Academy of Management Review*, *23*(3), 473-490. https://doi.org/10.2307/259290

Meagher, B. R. (2017). Judging the gender of the inanimate: Benevolent sexism and gender stereotypes guide impressions of physical objects. *British Journal of Social Psychology*, *56*(3), 537-560. https://doi.org/10.1111/bjso.12198

Meyerson, D., Weick, K. E., & Kramer, R. M. (1996). Swift trust and temporary groups. In R. M. Kramer & T. R. Tyler (Eds.), *Trust in organizations: Frontiers of theory and research* (pp. 166-195). SAGE.

Mims, C. (2021). Amid the labor shortage, robots step in to make the french fries. *The Wall Street Journal*. https://www.wsj.com/articles/restaurant-robots-kitchen-labor-shortage-11628290623

Montoya, R. M., Horton, R. S., & Kirchner, J. (2008). Is actual similarity necessary for attraction? A meta-analysis of actual and perceived similarity. *Journal of Social and Personal Relationships*, *25*(6), 889-922.

Morewedge, C. K., Preston, J., & Wegner, D. M. (2007). Timescale bias in the attribution of mind. *Journal of Personality and Social Psychology*, *93*(1), 1-11. https://doi.org/10.1037/0022-3514.93.1.1

Natarajan, M., & Gombolay, M. (2020). Effects of anthropomorphism and accountability on trust in human robot interaction. In *Proceedings of the 2020 ACM/IEEE International Conference on Human-Robot Interaction* (pp. 33-42). https://doi.org/10.1145/3319502.3374839

Nikolaidis, S., & Shah, J. (2013). Human-robot Cross-training: Computational formulation, modeling and evaluation of a human team training strategy. In *Proceedings of the 8th ACM/IEEE International Conference on Human-Robot Interaction* (pp. 33-40). http://dl.acm.org/citation.cfm?id=2447556.2447563

Nomura, T. (2017). Robots and gender. *Gender and the Genome*, *1*(1), 18-26. https://doi.org/10.1089/gg.2016.29002.nom

Nomura, T., Shintani, T., Fujii, K., & Hokabe, K. (2007). Experimental investigation of relationships between anxiety, negative attitudes, and allowable distance of robots. In *Proceedings of the 2nd IASTED International Conference on Human Computer Interaction* (pp. 13-18).

Nomura, T., Suzuki, T., Kanda, T., & Kato, K. (2006). Measurement of negative attitudes toward robots. *Interaction Studies*, *7*(3), 437-454.

Nowak, K. L., & Rauh, C. (2008). Choose your "buddy icon" carefully: The influence of avatar androgyny, anthropomorphism and credibility in online interactions. *Computers in Human Behavior*, *24*(4), 1473-1493. https://doi.org/10.1016/j.chb.2007.05.005

Oistad, B. C., Sembroski, C. E., Gates, K. A., Krupp, M. M., Fraune, M. R., & Šabanović, S. (2016). Colleague or tool? Interactivity increases positive perceptions of and willingness to interact with a robotic co-worker. In *Proceedings of the International Conference on Social Robotics* (pp. 774-785). https://doi.org/10.1007/978-3-319-47437-3_76

Paul, D. L., & McDaniel Jr., R. R. (2004). A field study of the effect of interpersonal trust on virtual collaborative relationship performance. *MIS Quarterly*, *28*(2), 183-227.

Peeters, G., & Czapinski, J. (1990). Positive-negative asymmetry in evaluations: The distinction between affective and informational negativity effects. *European Review of Social Psychology*, *1*(1), 33-60. https://doi.org/10.1080/14792779108401856

Phillips, E., Zhao, X., Ullman, D., & Malle, B. F. (2018). What is human-like? Decomposing robots' human-like appearance using the anthropomorphic roBOT (ABOT) database. In *Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction* (pp. 105-113). https://doi.org/10.1145/3171221.3171268

Phillips, K. W., Northcraft, G. B., & Neale, M. A. (2006). Surface-level diversity and decision-making in groups: When does deep-level similarity help? *Group Processes & Intergroup Relations*, *9*(4), 467-482. https://doi.org/10.1177/1368430206067557

Quesque, F., & Rossetti, Y. (2020). What do theory-of-mind tasks actually measure? Theory and practice. *Perspectives on Psychological Science*, *15*(2), 384-396. https://doi.org/10.1177/1745691619896607

Rai, A., Constantinides, P., & Sarker, S. (2019). Editor's comments—Next-generation digital platforms: Toward human-AI hybrids. *MIS Quarterly*, *43*(1), iii-ix.

Repko, M. (2021, December 27). *The robot work force isn't coming. It's already here*. CNBC. https://www.cnbc.com/2021/12/27/the-robot-work-force-isnt-coming-its-already-here-.html

Riordan, C. M., & Shore, L. M. (1997). Demographic diversity and employee attitudes: An empirical examination of relational demography within work units. *Journal of Applied Psychology*, *82*(3), 342-358.

Robert, L. P. (2013). A multi-level analysis of the impact of shared leadership in diverse virtual teams. In *Proceedings of the 2013 Conference on Computer Supported Cooperative Work* (pp. 363-374). http://dl.acm.org/citation.cfm?id=2441818

Robert, L. P. (2018). Personality in the human robot interaction literature: A review and brief critique. In *Proceedings of the Americas Conference on Information Systems*.

Robert, L. P., Alahmad, R., Esterwood, C., Kim, S., You, S., & Zhang, Q. (2020). A review of personality in human-robot interactions. *Foundations and Trends® in Information Systems*, *4*(2), 107-212. https://doi.org/10.1561/2900000018

Robert, L. P., Dennis, A., & Hung, Y.-T. (2009). Individual swift trust and knowledge-based trust in face-to-face and virtual team members. *Journal of Management Information Systems*, *26*, 241-279. https://doi.org/10.2753/MIS0742-1222260210

Robert, L. P., Dennis, A. R., & Ahuja, M. K. (2008). Social capital and knowledge integration in digitally enabled teams. *Information Systems Research*, *19*(3), 314-334. https://doi.org/10.1287/isre.1080.0177

Robert, L. P., Dennis, A. R., & Ahuja, M. K. (2018). Differences are different: Examining the effects of communication media on the impacts of racial and gender diversity in decision-making teams. *Information Systems Research*, *29*(3), 525-545. https://doi.org/10.1287/isre.2018.0773

Sacco, J. M., Scheu, C. R., Ryan, A. M., & Schmitt, N. (2003). An investigation of race and sex similarity effects in interviews: A multilevel approach to relational demography. *Journal of Applied Psychology*, *88*(5), 852-865. https://doi.org/10.1037/0021-9010.88.5.852

Salem, M., Lakatos, G., Amirabdollahian, F., & Dautenhahn, K. (2015). *Would you trust a (faulty) robot?: Effects of error, task type and personality on human-robot cooperation and trust*. 141-148. http://dl.acm.org/citation.cfm?id=2696497

Sarker, S., Ahuja, M., Sarker, S., & Kirkeby, S. (2011). The role of communication and trust in global virtual teams: A social network perspective. *Journal of Management Information Systems*, *28*(1), 273-310.

Schaubroeck, J., & Lam, S. S. K. (2002). How similarity to peers and supervisor influences organizational advancement in different cultures. *Academy of Management Journal*, *45*(6), 1120-1136. https://doi.org/10.5465/3069428

Schilke, O., & Huang, L. (2018). Worthy of swift trust? How brief interpersonal contact affects trust accuracy. *Journal of Applied Psychology*, *103*(11), 1181-1197. https://doi.org/10.1037/apl0000321

Schuetz, S., & Venkatesh, V. (2020). Research perspectives: The rise of human machines: How cognitive computing systems challenge assumptions of user-system interaction. *Journal of the Association for Information Systems*, *21*(2). https://doi.org/10.17705/1jais.00608

Seeber, I., Bittner, E., Briggs, R. O., de Vreede, T., de Vreede, G.-J., Elkins, A., Maier, R., Merz, A. B., Oeste-Reiß, S., Randrup, N., Schwabe, G., & Söllner, M. (2020). Machines as teammates: A research agenda on AI in team collaboration. *Information & Management*, *57*(2), Article 103174. https://doi.org/10.1016/j.im.2019.103174

Shank, D. B., North, M., Arnold, C., & Gamez, P. (2021). Can mind perception explain virtuous character judgments of artificial

intelligence? *Technology, Mind, and Behavior*, *2*(2). https://doi.org/10.1037/tmb0000047
Shead, S. (2017). *Amazon now has 45,000 robots in its warehouses.* Business Insider. http://www.businessinsider.com/amazons-robot-army-has-grown-by-50-2017-1
Singh, R., & Simons, J. J. P. (2010). Attitudes and attraction: Optimism and weight as explanations for the similarity-dissimilarity asymmetry. *Social and Personality Psychology Compass*, *4*(12), 1206-1219. https://doi.org/10.1111/j.1751-9004.2010.00328.x
Spector, M. D., & Jones, G. E. (2004). Trust in the workplace: Factors affecting trust formation between team members. *The Journal of Social Psychology*, *144*(3), 311-321.
Tajfel, H., & Turner, J. C. (2004). *The social identity theory of intergroup behavior.* In J. T. Jost & J. Sidanius (Eds.), *Political psychology: Key readings* (pp. 276–293). Psychology Press. http://psycnet.apa.org/psycinfo/2004-13697-016
Takayama, L., Ju, W., & Nass, C. (2008). Beyond dirty, dangerous and dull: What everyday people think robots should do. In *Proceedings of the 3rd ACM/IEEE International Conference on Human Robot Interaction* (pp. 25-32). http://dl.acm.org/citation.cfm?id=1349827
Tapus, A., & Matarić, M. J. (2008). User personality matching with a hands-off robot for post-stroke rehabilitation therapy. In O. Khatib, V. Kumar, & D. Rus (Eds.), *Experimental robotics.* (pp. 165-175). Springer. https://doi.org/10.1007/978-3-540-77457-0_16
Tay, B., Jung, Y., & Park, T. (2014). When stereotypes meet robots: The double-edge sword of robot gender and personality in human-robot interaction. *Computers in Human Behavior*, *38*, 75-84.
Taylor, D. M., & Jaggi, V. (1974). Ethnocentrism and causal attribution in a South Indian Context. *Journal of Cross-Cultural Psychology*, *5*(2), 162-171. https://doi.org/10.1177/002202217400500202
Tsui, A. S., O'Reilly, C. A., & others. (1989). Beyond simple demographic effects: The importance of relational demography in superior-subordinate dyads. *Academy of Management Journal*, *32*(2), 402-423.
Tsui, A. S., Xin, K. R., & Egan, T. D. (1995). *Relational demography: The missing link in vertical dyad linkage.* In S. E. Jackson & M. N. Ruderman (Eds.), *Diversity in work teams: Research paradigms for a changing workplace* (pp. 97–129). American Psychological Association. http://psycnet.apa.org/psycinfo/1996-97206-004
Turner, J. C., Hogg, M. A., Oakes, P. J., Reicher, S. D., & Wetherell, M. S. (1987). *Rediscovering the social group: A self-categorization theory.* Basil Blackwell. http://psycnet.apa.org/psycinfo/1987-98657-000
van den Hende, E. A., & Mugge, R. (2014). Investigating gender-schema congruity effects on consumers' evaluation of anthropomorphized products: Gender-schema congruity and anthropomorphism. *Psychology & Marketing*, *31*(4), 264-277. https://doi.org/10.1002/mar.20693
Van der Vegt, G. S., & Van de Vliert, E. (2005). Effects of perceived skill dissimilarity and task interdependence on helping in work teams. *Journal of Management*, *31*(1), 73-89.
van der Werff, L., & Buckley, F. (2017). Getting to know you: A longitudinal examination of trust cues and trust development during socialization. *Journal of Management*, *43*(3), 742-770. https://doi.org/10.1177/0149206314543475
Vreede, G.-J. de, & Briggs, R. O. (2019). A program of collaboration engineering research and practice: Contributions, insights, and future directions. *Journal of Management Information Systems*, *36*(1), 74-119. https://doi.org/10.1080/07421222.2018.1550552
Waytz, A., Cacioppo, J., & Epley, N. (2010). Who sees human? The stability and importance of individual differences in anthropomorphism. *Perspectives on Psychological Science*, *5*(3), 219-232.
The White House (2022). *Blueprint for an AI Bill of Rights*. https://www.whitehouse.gov/ostp/ai-bill-of-rights/
Williams, M. (2001). In whom we trust: Group membership as an affective context for trust development. *Academy of Management Review*, *26*(3), 377-396.
Woods, S., Walters, M., Kheng Lee Koay, & Dautenhahn, K. (2006). Comparing human robot interaction scenarios using live and video based methods: Towards a novel methodological approach. In *Proceedings of the 9th IEEE International Workshop on Advanced Motion Control* (pp. 750-755). https://doi.org/10.1109/AMC.2006.1631754
You, S., Kim, J.-H., Lee, S., Kamat, V., & Robert, L. P. (2018). Enhancing perceived safety in human-robot collaborative construction using immersive virtual environments. *Automation in Construction*, *96*, 161-170. https://doi.org/10.1016/j.autcon.2018.09.008
You, S., & Robert, L. P. (2018a). Emotional attachment, performance, and viability in teams collaborating with embodied physical action (EPA) robots. *Journal of the Association for Information Systems*, *19*(5), 377-407.
You, S., & Robert, L. P. (2018b). Human-robot similarity and willingness to work with a robotic co-worker. In *Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction* (pp. 251-260).
You, S., & Robert, L. P. (2019, January 8). Trusting robots in teams: Examining the impacts of trusting robots on team performance and satisfaction. In *Proceedings of the 52nd Hawaii International Conference on System Sciences*. https://doi.org/10.24251/HICSS.2019.031
You, S., & Robert, L. P. (2023). Subgroup formation in human-robot teams: A multi-study mixed-method approach with implications for theory and practice. *Journal of the Association for Information Science and Technology*, *74*(3), 323-338. https://doi.org/10.1002/asi.24626
Zakaria, N., & Mohd Yusof, S. A. (2020). Crossing cultural boundaries using the internet: Toward building a model of swift trust formation in global virtual teams. *Journal of International Management*, *26*(1), Article 100654. https://doi.org/10.1016/j.intman.2018.10.004
Zellmer-Bruhn, M. E., Maloney, M. M., Bhappu, A. D., & Salvador, R. (Bombie). (2008). When and how do differences matter? An exploration of perceived similarity in teams. *Organizational Behavior and Human Decision Processes*, *107*(1), 41-59. https://doi.org/10.1016/j.obhdp.2008.01.004
Zhang, Z., Yoo, Y., Lyytinen, K., & Lindberg, A. (2021). The unknowability of autonomous tools and the liminal experience of their use. *Information Systems Research*, *32*(4), 1192-1213. https://doi.org/10.1287/isre.2021.1022

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Appendix A

Demographic Information for Studies 1 and 2

Table A1. Demographic Information for Studies 1 and 2

Variable	Study 1	Study 2
Gender		
Male	172 (49.6)	190 (45.0)
Female	175 (50.4)	232 (55.0)
Age		
18-29	81 (23.4)	84 (19.9)
30-39	109 (31.5)	156 (36.9)
40-49	76 (22.0)	77 (18.2)
50-59	59 (16.9)	59 (14.0)
60-69	22 (6.5)	46 (10.7)
Ethnicity		
White	231 (66.6)	317 (75.1)
Black	57 (16.4)	46 (10.9)
Asian	13 (3.7)	7 (1.7)
American Indian or Alaska Native	3 (0.9)	33 (7.8)
Native Hawaiian or other Pacific Islander	-	2 (0.5)
Hispanic or Latino	43 (12.4)	17 (4.0)
Education		
No college	76 (22.2)	51 (12.0)
Attended college but did not finish	86 (24.8)	87 (20.6)
College graduate	150 (43.3)	215 (51.0)
Graduate degree	34 (9.8)	7 (1.7)
Industry		
Manufacturing	158 (45.5)	47 (11.1)
Automotive	23 (6.6)	8 (1.9)
Consumer goods and packaging	22 (6.3)	24 (5.7)
Shipping, distribution, and logistics	133 (38.3)	96 (22.7)
Sales of goods	-	46 (10.9)
Technology	-	95 (22.5)
Service	-	38 (9.0)
Student	-	50 (11.8)
Other	11 (3.2)	18 (4.2)

Appendix B

Links to Videos Used in Studies 1 and 2

1. Robot male: https://www.youtube.com/watch?v=R5bkZm6TFC4
2. Robot female: https://www.youtube.com/watch?v=wWNfwgRf0Wk
3. Human male: https://www.youtube.com/watch?v=7daINZfvV9Q
4. Human female: https://www.youtube.com/watch?v=EUypzOywRdo

Appendix C

Vignettes, images, and Dissimilarity Manipulations

Study 1: You are an employee of "OKDepot Co. Ltd.," a facility management company. Your job is to keep track of the inventory and ship and rearrange materials at a repository. Your company purchased a robot [person] to work with human workers like you at your repository. You will be introduced to the robot [person] that your company wants you to work with.

Study 2: You are an employee of "OKDepot Co. Ltd.," a facility management company. Your job is to keep track of the inventory and perform maintenance of the warehouse. Your company purchased a robot to work with human workers like you at your warehouse. You will be introduced to the robot that your company wants you to work with as a co-worker.

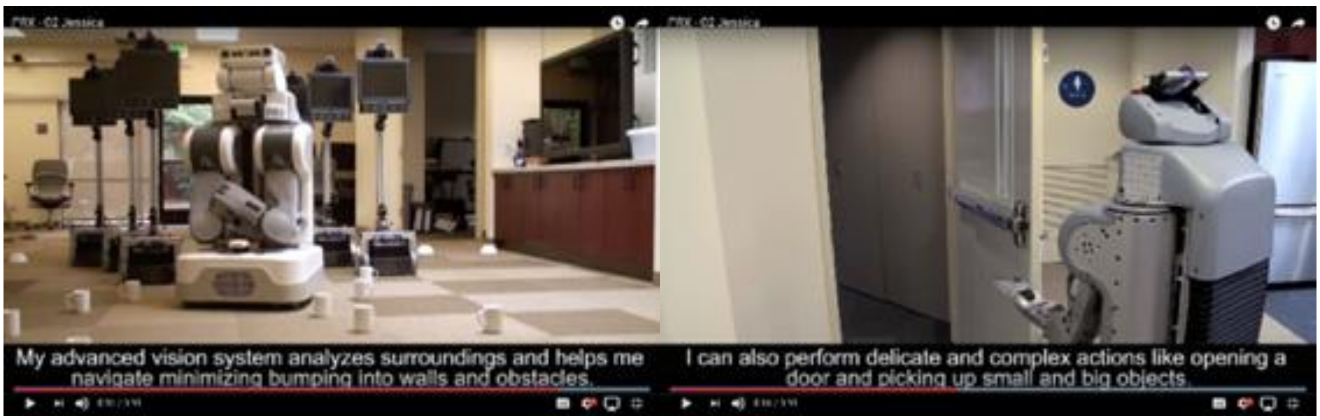

Figure C1. Example Images of Robots Taken from Videos (Studies 1 and 2)

Robot co-worker

Human co-worker

Figure C2. Manipulations of Co-Worker Type (Studies 1 and 2)

Table C1. Questions for Manipulation of Work Style Dissimilarity (Study 1)

Dimension	Choice 1	Choice 2
Work Ethic	It is okay to be 20 minutes late for a meeting because sometimes we cannot control unexpected events— traffic jams, medical conditions, etc.	It is NOT okay to be 20 minutes late for a meeting because other team members' time will be wasted due to the delay.
	In order to maintain a good team, performance is the most important thing.	In order to maintain a good team, the relationship between team members is the most important thing.
	Efficiency is more important than effectiveness.	Effectiveness is more important than efficiency.
Work Habits	I prefer to work in the morning and perform better during the day. I get the most work done in the morning.	I prefer to work at night and perform better at night. I get the most work done in the evening.
Communication Style	Face-to-face communication is better and easier than mediated communication like telephone or Skype because it allows people to see one another's face and read richer social cues.	Mediated communication like telephone or Skype is better and easier because technologies allow people to communicate from a distance and in different time zones.

Table C2. Questions for Manipulation of Personality Dissimilarity (Study 2)

Personality dimension	Personality statements
Extraversion	I see myself as a person who is talkative.
	I see myself as a person who is rarely reserved.
	I see myself as a person who is full of energy.
	I see myself as a person who generates a lot of enthusiasm.
	I see myself as a person who tends to be loud.
	I see myself as a person who has an assertive personality.
	I see myself as a person who is rarely shy, inhibited.
	I see myself as a person who is outgoing, sociable.

Note: Participants indicated their extraversion by expressing agreement with each of the statements. The statements were shown in random order.

Appendix D

Measurement Items for Studies 1 and 2

Table D1. Measurement Items for Studies 1 and 2

Study	Construct	Items
2	Perceived anthropomorphism (Waytz et al., 2010)	The robot [person] appears to have a mind of their own.
		The robot [person] appears to have intentions.
		The robot [person] appears to have free will.
		The robot [person] appears to have consciousness.
		The robot [person] appears to have beliefs and desires.
		The robot [person] appears to have the ability to experience emotions.
2	Perceived gender dissimilarity	To what degree is the gender of the robot [person] similar or different from you? (Very similar to me to Very different from me)
1	Perceived work style dissimilarity	[The name of the human co-worker or the robot in the video] shares a similar work ethic with me.
		[The name of the human co-worker or the robot in the video] has similar work habits with me.
		[The name of the human co-worker or the robot in the video] has similar communication styles with me.
		[The name of the human co-worker or the robot in the video] has similar interaction styles with me.
		[The name of the human co-worker or the robot in the video] has a similar work style with me.
		[The name of the human co-worker or the robot in the video] and I have similar opinions regarding work.
2	Perceived personality dissimilarity	The robot [person] has a different personality than me.
		The robot [person] has different ways of thinking than me.
		The robot [person] seems to be an entity who has a different personality than I do.
		The robot [person] may behave in different ways than me.
		The robot [person] and I seem to have more differences in personality than similarities.
1	Perceived risk	This is potentially a hazardous task.
		This task potentially involves physical danger.
		This task seems to be risky.
		There is a chance that something could go wrong and someone could be harmed.
		It is difficult to complete this task safely.
		I will be exposed to physical harm when carrying out this task.
1	Swift trust in co-worker (Jian et al. 2000)	I am trustful of [the name of the human co-worker or the robot in the video].
		[The name of the human co-worker or the robot in the video]'s actions would not have a harmful or injurious outcome.
		I am confident in [the name of the human co-worker or the robot in the video].
		[The name of the human co-worker or the robot in the video] provides security.
		[The name of the human co-worker or the robot in the video] is dependable.
		[The name of the human co-worker or the robot in the video] is reliable.

2	Swift trust in co-worker (McKnight et al., 2011)	I would be totally comfortable working with this robot [person].
		I would feel very good about how things go when I work with this robot [person].
		I would feel confident that the right things will happen when I work with this robot [person].
		It appears that things will be fine when I work with this robot [person].
1,2	Preference for robot over human	For this job, I would prefer to work with [the name of the human co-worker or the robot in the video] instead of a human [robot].
		For this job, I would rather replace a human [robot] with [the name of the human co-worker or the robot in the video].
		For this job, I would rather team up with [the name of the human co-worker or the robot in the video] than a human [robot].
		For this job, I would choose the [The co-worker's name] instead of a human [robot]. (Study 2)
1,2	Knowledge of relevant technology	How would you describe your knowledge of computer programming?
		How would you describe your knowledge of robotics?
		How would you describe your knowledge of artificial intelligence?
1,2	Negative attitudes toward robots	I would hate the idea that robots or artificial intelligence were making judgments about things.
		I would feel very nervous just standing in front of a robot.
		I would feel paranoid talking with a robot.
		I would feel uneasy if robots really had emotions.
		I am concerned that a robot would be a bad influence on children.
		I feel that in the future, society will be dominated by robots.
		I would not feel relaxed talking with robots.
		If robots had emotions, I would not be able to make friends with them.
		I do not feel comfortable being with robots that have emotions.
1,2	Experience working with robots	How would you describe your experience of working with robots and automated machines at workplaces? (1 for never and 5 for always)
1,2	Industry tenure	How long have you worked in your industry? (In the number of months)
1,2	Current job tenure	How long have you worked at your current workplace? (In the number of months)
1	Job competency	How competent do you think you are at your workplace? (1 for extremely incompetent and 5 for extremely competent)
2	Warehouse experience	To what degree are you familiar with working in logistics, warehouses, distribution centers, or fulfillment centers (including your past and current experiences)? (1 for extremely familiar and 5 for not familiar at all)
2	Individual differences measure of anthropomorphism (IDAQ from Waytz et al., 2010)	Technologies and machines (e.g., computers, cars, television sets) have intentions.
		A mountain has free will.
		A television set experiences emotions. A robot has consciousness.
		A car has free will.
		The ocean has consciousness.
		A computer has a mind of its own.
		A tree has a mind of its own.
		The wind has intentions.

Appendix E

Correlations and Factor Loadings in Studies 1 and 2

Correlation Matrix and AVEs in Study 1

Table E1. Correlation Matrix and AVEs in Study 1

Construct	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Co-worker type	0.51	0.50	-														
2. Gender dissimilarity	0.49	0.50	-0.01	-													
3. Work style dissimilarity	0.50	0.50	0.00	-0.01	-												
4. Risk of physical danger	0.50	0.50	0.03	0.05	-0.04	-											
5. Perceived risk	3.77	0.87	-0.01	0.07	-0.03	0.66**	**0.81**										
6. Age	39.46	12.24	0.18**	-0.09	0.02	-0.11*	-0.04	-									
7. Education	3.79	1.36	0.05	0.00	0.06	0.08	0.11*	-0.01	-								
8. Knowledge on technology	2.79	1.04	-0.09	0.08	-0.06	0.01	0.09	-0.21**	0.24**	**0.86**							
9. Negative attitude toward robots	2.85	0.90	-0.12*	-0.02	0.07	-0.01	0.09	-0.09	-0.10	-0.08	**0.78**						
10. Current job tenure	83.31	83.23	0.12*	-0.07	-0.06	-0.09	-0.04	0.52**	0.06	-0.04	-0.14*	-					
11. Industry experience	114.27	105.97	0.08	-0.08	-0.05	-0.08	-0.03	0.58**	0.02	-0.05	-0.12*	0.75**	-				
12. Job competency	4.20	1.31	-0.05	0.01	0.04	0.05	0.09	-0.04	0.13*	0.10	-0.01	0.01	0.02	-			
13. Experience of working with robots	2.17	1.20	-0.14*	0.08	-0.10	0.04	0.10	-0.24**	0.16**	0.53**	-0.04	-0.20**	-0.14**	0.05	-		
14. Trust in co-worker	3.64	0.88	0.04	0.03	-0.36**	0.01	0.09	-0.08	0.02	0.27**	-0.13*	0.04	-0.01	0.12*	0.24**	**0.86**	
15. Preference for robot over human	2.83	1.07	0.43**	-0.03	0.09	0.10	0.12*	0.03	0.09	0.09	-0.15**	0.06	0.04	-0.04	0.00	-0.06	**0.81**

Note: *N* = 347, M = mean, *SD* = Standard Deviation, *: *p* < 0.05, **: *p* < 0.01. Values on the diagonals represent the square root of the AVE for each factor. "Co-worker type," "gender dissimilarity," "work style dissimilarity," and "risk of physical danger" were coded binary (0 = human/low, 1 = robot/high). Current job tenure and industry experience were measured in the number of months.

Correlation Matrix and AVEs in Study 2

Table E2. Correlation Matrix and AVEs in Study 2

Construct	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Co-worker type	0.54	0.5	-																	
2. Gender dissimilarity	0.5	0.5	0.11*	-																
3. Personality dissimilarity	0.5	0.5	-0.09	0.02	-															
4. Perceived gender dissimilarity	3.2	1.77	0.17**	0.79**	0.08	-														
5. Perceived personality dissimilarity	3.42	1.4	-0.04	-0.02	0.82**	0.07	**0.91**													
6. Perceived anthropomorphism	3.18	1.36	-0.82**	-0.05	0.04	-0.16**	-0.01	**0.90**												

7. Age	40.8	13.17	0.05	0.08	0.07	0.04	0.03	-0.03	-										
8. Education	4.3	1.32	0	0.02	-0.06	0.01	-0.07	-0.02	0.10*	-									
9. Gender	0.5	0.5	-0.01	-0.01	-0.06	0.02	-0.05	-0.03	-0.06	-0.05	-								
10. Knowledge on technology	2.62	0.89	-0.01	-0.05	-0.11*	-0.08	-0.07	0.05	-0.12*	0.10*	0.19**	**0.87**							
11. Industry experience	101.64	105.03	0.06	-0.04	0.06	-0.05	0.04	-0.04	0.57**	0.10*	0.08	0.03	-						
12. Current job experience	61.63	69.33	0.04	0.00	0.06	-0.03	0.01	-0.03	0.40**	0.09	0.02	-0.03	0.46**	-					
13. Warehouse experience	2.8	1.03	0	0.05	0.04	0.01	0.02	0.03	0.09	0.05	-0.13*	-0.23**	0.05	0.11*	-				
14. IDAQ	1.72	0.74	-0.09	-0.10*	0.00	-0.08	0.03	0.06	-0.08	-0.08	-0.13**	0.03	-0.01	-0.05	-0.06	**0.72**			
15. NARS	2.82	0.86	-0.13**	-0.04	0.09	0.01	0.10*	0.11*	-0.07	-0.14**	-0.05	-0.12*	-0.09	-0.08	-0.08	0.09	**0.69**		
16. Experience of working with robots	1.8	0.88	0.04	-0.09	-0.04	-0.06	-0.04	-0.05	-0.15**	0.00	0.10*	0.30**	-0.11*	-0.09	-0.32**	0.12*	-0.03	-	
17. Trust in Co-worker (situational normality)	3.9	0.9	-0.12*	0.03	-0.19**	-0.06	-0.19**	0.18**	0.00	0.14**	-0.04	0.04	0.06	-0.03	0.00	-0.02	-0.35**	0.06	**0.88**	
18. Preference for robot over human	2.43	1.14	0.40**	0.06	-0.07	0.03	-0.05	-0.29**	0.02	0.08	-0.07	0.06	0.08	0.03	0.11*	0.03	-0.42**	0.06	0.19**	**0.90**

Note: N = 422, M = mean, SD = standard deviation, *: $p < 0.05$, **: $p < 0.01$. Values on the diagonals represent the square root of the AVE for each factor. IDAQ = Individual Differences Measure of Anthropomorphism Questionnaire. NARS = Negative Attitudes toward Robots Scale "Co-workertype", "gender dissimilarity", and "personality dissimilarity" were coded binary (0 = human/similar, 1 = robot/different). Current job tenure and industry experience were measured in the number of months.

Factor Loadings in Study 1

Table A3. Factor Loadings in Study 1

Item	1	2	3	4	5
Knowledge on Technology 01	**0.80**	0.00	-0.06	0.22	0.03
Knowledge on Technology 02	**0.90**	0.06	0.00	0.11	0.01
Knowledge on Technology 03	**0.89**	0.07	-0.05	0.13	0.03
Perceived Risk 01	-0.03	**0.88**	0.00	0.06	-0.10
Perceived Risk 02	-0.08	**0.86**	-0.05	0.14	-0.06
Perceived Risk 03	0.00	**0.87**	0.06	0.05	0.07
Perceived Risk 04	-0.05	**0.88**	-0.07	0.08	-0.04
Perceived Risk 05	0.21	**0.60**	0.16	-0.07	0.23
Perceived Risk 06	0.16	**0.71**	0.16	-0.03	0.20
Negative Attitudes Toward Robots 01	-0.06	0.05	**0.78**	-0.04	-0.14
Negative Attitudes Toward Robots 02	0.08	0.05	**0.75**	-0.02	0.03
Negative Attitudes Toward Robots 03	-0.12	0.04	**0.77**	-0.11	-0.11
Negative Attitudes Toward Robots 04	0.15	-0.07	**0.79**	0.00	-0.02
Negative Attitudes Toward Robots 05	-0.17	0.05	**0.74**	-0.06	-0.08
Negative Attitudes Toward Robots 06	0.19	0.02	**0.78**	-0.05	0.04
Negative Attitudes Toward Robots 07	0.13	-0.04	**0.82**	-0.05	0.02
Negative Attitudes Toward Robots 08	-0.16	0.10	**0.84**	-0.05	-0.07
Negative Attitudes Toward Robots 09	-0.29	0.06	**0.72**	-0.04	-0.07
Trust in Co-worker 01	0.13	0.02	-0.10	**0.86**	-0.04
Trust in Co-worker 02	-0.02	0.04	-0.01	**0.83**	0.01
Trust in Co-worker 03	0.12	-0.03	-0.04	**0.90**	-0.01
Trust in Co-worker 04	0.17	0.04	-0.06	**0.82**	0.07
Trust in Co-worker 05	0.06	0.11	-0.07	**0.86**	-0.08
Trust in Co-worker 06	0.08	0.06	-0.07	**0.88**	-0.03
Preference for Robot over Human 01	0.06	0.07	-0.12	-0.12	**0.90**
Preference for Robot over Human 02	-0.05	0.02	-0.05	0.12	**0.60**
Preference for Robot over Human 03	0.08	0.07	-0.11	-0.13	**0.89**

Note: Principal component analysis with Varimax as rotation method

Factor Loadings in Study 2

Table E4. Factor Loadings in Study 2

Item	1	2	3	4	5	6	7
Knowledge on Technology 1	**0.82**	-0.01	-0.04	0.04	-0.03	-0.02	0.01
Knowledge on Technology 2	**0.90**	0.06	-0.06	0.00	-0.02	0.02	0.01
Knowledge on Technology 3	**0.89**	0.02	-0.11	0.04	-0.04	0.03	0.04
IDAQ 1	0.05	**0.61**	0.04	0.08	-0.03	0.05	0.06
IDAQ 2	0.01	**0.73**	-0.01	-0.03	0.12	0.03	-0.02
IDAQ 3	0.09	**0.76**	0.02	0.08	-0.07	-0.04	0.06
IDAQ 4	0.07	**0.72**	0.00	0.07	-0.04	-0.14	0.06
IDAQ 5	-0.02	**0.75**	0.02	-0.08	0.05	0.03	-0.05
IDAQ 6	-0.01	**0.67**	0.09	0.13	-0.11	-0.03	0.11
IDAQ 7	-0.09	**0.69**	-0.01	-0.08	0.08	0.05	-0.09
IDAQ 8	-0.03	**0.80**	0.07	0.01	0.06	0.00	-0.03
NARS 1	0.10	0.07	**0.61**	-0.02	-0.02	-0.14	-0.26
NARS 2	0.06	0.04	**0.69**	0.01	0.03	-0.16	-0.25
NARS 3	0.06	-0.09	**0.67**	0.05	0.08	-0.06	-0.05
NARS 4	-0.08	-0.06	**0.77**	-0.02	0.08	0.04	-0.11
NARS 5	0.03	0.14	**0.66**	0.09	0.02	-0.34	-0.19
NARS 6	-0.04	0.21	**0.62**	0.09	0.04	-0.12	-0.02
NARS 7	-0.10	-0.01	**0.73**	0.07	0.00	-0.15	-0.13
NARS 8	-0.03	0.20	**0.70**	0.13	-0.08	-0.21	-0.01
NARS 9	-0.03	0.18	**0.73**	0.10	-0.04	-0.17	-0.04
NARS 10	-0.15	-0.11	**0.78**	-0.06	0.06	0.03	-0.07
NARS 11	-0.10	-0.11	**0.66**	-0.04	0.10	0.09	-0.09
Perceived Anthropomorphism 1	-0.02	-0.04	0.04	**0.89**	0.00	0.04	-0.03
Perceived Anthropomorphism 2	0.01	0.05	0.03	**0.84**	0.07	0.08	-0.03
Perceived Anthropomorphism 3	0.02	0.04	0.06	**0.93**	0.01	0.09	-0.11
Perceived Anthropomorphism 4	0.05	0.05	0.06	**0.93**	0.00	0.10	-0.14
Perceived Anthropomorphism 5	0.04	0.04	0.05	**0.92**	-0.04	0.09	-0.16
Perceived Anthropomorphism 6	0.01	0.06	0.06	**0.91**	-0.04	0.08	-0.19
Perceived Personality Dissimilarity 1	-0.03	0.00	0.04	-0.01	**0.94**	-0.10	-0.02
Perceived Personality Dissimilarity 2	-0.04	0.01	0.05	-0.06	**0.91**	-0.06	-0.02
Perceived Personality Dissimilarity 3	-0.02	0.02	0.04	0.06	**0.94**	-0.05	0.01
Perceived Personality Dissimilarity 4	0.00	0.00	0.05	0.00	**0.86**	-0.03	-0.03
Perceived Personality Dissimilarity 5	-0.03	0.03	0.04	0.02	**0.91**	-0.13	0.00
Trust in Co-worker (Situational Normality) 1	0.00	0.00	-0.21	0.10	-0.10	**0.87**	0.11
Trust in Co-worker (Situational Normality) 2	0.02	0.03	-0.19	0.15	-0.11	**0.86**	0.09
Trust in Co-worker (Situational Normality) 3	0.04	0.01	-0.20	0.15	-0.11	**0.88**	0.05
Trust in Co-worker (Situational Normality) 4	-0.02	-0.02	-0.17	0.10	-0.08	**0.90**	0.06
Preference for Robot over Human 1	0.03	0.02	-0.29	-0.22	-0.01	0.08	**0.88**
Preference for Robot over Human 2	0.01	0.04	-0.24	-0.16	-0.04	0.08	**0.90**
Preference for Robot over Human 3	0.03	0.05	-0.25	-0.17	-0.01	0.09	**0.91**
Preference for Robot over Human 4	0.02	0.04	-0.22	-0.15	0.00	0.09	**0.90**

Note: Principal component analysis with Varimax as rotation method