Technology with Embodied Physical Actions: Understanding Interactions and Effectiveness Gains in Teams Working with Robots

by

Sangseok You

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Information)
in the University of Michigan
2017

Doctoral Committee:

Associate Professor Lionel P. Robert Jr., Chair
Professor Thomas Finholt
Professor Vineet Kamat
Associate Professor Soo Young Rieh

Sangseok You

sangyou@umich.edu

orcid.org/0000-0003-0101-8408

DEDICATION

To my parents, Okeun You and Jin Young Doo.

ACKNOWLEDGEMENTS

Working toward a PhD degree was a long but fulfilling journey. I am indebted to numerous people who provided me consistent support, inspiration, and solidarity. Without help from all of the people I met during my studies, it would not have been possible for me to reach the end of this degree program and complete this dissertation research. I feel honored and grateful to know all of these people and to be able to share memories of persistence and joy with them.

To begin with, I would like to thank Lionel Robert, my advisor and the chair of my dissertation committee, for an enormous amount of intellectual and emotional support throughout the duration of my study. I still remember the day we first met, when I walked into his office and ranted about half-baked research ideas about teams and robots. From that very moment, he has been intellectually challenging, inspiring, and guiding me to become a scholar who thinks critically, writes rigorously, and considers the broader impact of my research. Thank you tremendously for pushing me to pursue the idea of teams working with robots and for supporting me to overcome obstacles until I made it this far.

I owe a great deal to my committee members – Drs. Thomas Finholt, Soo Young Rieh, and Vineet Kamat. In particular, Tom provided me with profound and constructive feedback on my research. He has also shown tremendous support during my job search. I would like to offer special thanks to Soo for being a true mentor for my research, academic life, and job search. Her door was always open to me whenever I sought sympathy, advice, and encouragement. I am grateful to have had Vineet Kamat as a cognate member. Since we met during the MCubed interdisciplinary research project, he has offered valuable insights and expertise for my research.

My luck doesn't end with the excellent faculty members from whom I received an enormous amount of support. I have been truly blessed to have the most supportive PhD cohort peers ever during my study. Among all of them, I particularly thank people with whom I shared the most joyful memories and agonies: Daphne Chang, Sam Carton, Andrea Barbarin, Jasmine Jones, Padma Chirumamilla, Pei-Yao Hung, and Rebecca Frank. You guys have been my closest friends and listeners throughout my years in Ann Arbor. The encouragement and empathy all of you offered me have been the source of my persistence and energy during this long pursuit.

I spent an uncountable number of hours in my office and have never been lonely because of my office mates. Teng Ye and Rasha Alahmad, thank you very much for listening to my research ideas, asking critical questions, and attending all of my practice talks. I am looking forward to working with you in the future once we all become doctors. Zhe Zhao and his two cats should be thanked for giving me so many happy memories. I thank Cindy Lin and Jean Hardy for being jolly colleagues who made me laugh and for providing different perspectives on my research approach.

I owe an additional debt of gratitude to my dear friends at the School of Information. To name a few, I would like to thank the members of QualGroup, which was a perfect place to try out my initial research ideas and receive constructive feedback. My gratitude is owed to Rayoung Yang, Tao Dong, Xuan Zhao, Stanley Chang, and Karina Kervin. Friends from DoIIIt Makers, include Gaurav Paruthi, Jeff Chuan-Che Huang, Hariharan Subramonyam, Lucia He, Joey Hsiao, and Allan Martell. I would also like thank Priyank Chandra. Every bit of conversation with him has given me an intellectual spark along with brilliant wit. Thank you, as well, to Dr. Casey Pierce. I appreciate your advice regarding my academic career. I also deeply thank Allison Sweet and Kelly Iott for all of their administrative support.

My life outside the PhD program was full of unforgettable moments of joy thanks to dear Korean friends. I profoundly thank Rayoung Yang, Souneil Park, Hankyong Yun, Mun-seon Kim, Jamin Koo, Manchul Han, Sungjin Nam, Jungwon Yang, Sangjung Han, Jay Jeong, Nuri Bae, Jiyeon Yang, Grace Jeon, and Jihye Song, for their emotional support and friendship.

Lastly and the most importantly, I thank infinitely the people whom I love the most. Kyoo Hye Lim, the love of my life: Thank you for believing in me, encouraging me, reading drafts, and critiquing my practice presentations. Your unwavering love has been the greatest power that sustains and pushes me forward. To my beloved family – my parents and my sister: Thank you for supporting me throughout my studies. I am eternally grateful to you for believing in me and for listening to my ups and downs all the time, even from the other side of the globe. To my dearest friend Jaejin Lee: Thank you for the encouragement.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

ABSTRACT

Teams in different areas are increasingly adopting robots to perform various mission operations. The inclusion of robots in teams has drawn consistent attention from scholars in relevant fields such as human-computer interaction (HCI) and human-robot interaction (HRI). Yet, the current literature has not fully addressed issues regarding teamwork by mainly focusing on the collaboration between a single robot and an individual. The limited scope of human-robot collaboration in the existing research hinders uncovering the mechanism of performance gains in teams that involve multiple robots and people.

This dissertation research is an effort to address the issue by achieving two goals. First, this dissertation examines the impacts of interaction between human teammates alone and interaction between humans and robots on outcomes in teams working with robots. Second, I provide insight into the development of teams working with robots by examining ways to promote a team member's intention to work with robots.

In this dissertation, I conducted three studies in an endeavor to accomplish the aforementioned goals. The first study, in Chapter 2, turns to theory trust in teams to explain outcome gains in teams working with robots. This study reports result from a lab experiment, in which two people fulfilled a collaborative task using two robots. The results show that trust in robots and trust in teammates can be enhanced by a robot-building activity and team identification, respectively. The enhanced trust revealed unique impacts on different team outcomes: trust in robots increased only team performance while trust in

teammates increased only satisfaction. Theoretical and practical contributions of the findings are discussed in the chapter.

The second study, in Chapter 3, uncovers how team member's efficacy beliefs interplay with team diversity to promote performance in teams working with robots. Results from a lab experiment reveal that individual operator's performance is enhanced by team potency perception only when the team is ethnically diverse. This study contributes to theory by identifying team diversity as a limiting condition of performance gains for robot operators in teams.

The third study, in Chapter 4, focuses on factors leading to the development of teams working with robots. I conducted an online experiment to examine how surface-level and deep-level similarity contribute to trust in a robotic partner and the impact of the trust on a team member's intention to work with the robot in varying degrees of danger. This study generally shows that the possibility of danger regulates not only the positive link between the surface-level similarity and trust in robot and but also the link between intention to work with the robot and intention to replace a human teammate with the robot.

Chapter 5, as a concluding chapter of this dissertation, discusses the theoretical and practical implications drawn from the three studies.

CHAPTER 1
INTRODUCTION OF DISSERTATION

1.1 MOTIVATION

A wide range of technologies have enabled teams in many areas of work to accomplish their goals, facilitate collaborations and interactions among team members, and improve collaborative experiences (Robert, Dennis, & Ahuja, 2008; Sidorova, Evangelopoulos, Valacich, & Ramakrishnan, 2008). These technologies have evolved from electronic brainstorming (EBS), group decision support systems (GDSS) and video conferencing systems to avatars and crowdsourcing knowledge management tools (Y. Lee, Kozar, & Larsen, 2003; Tannenbaum, Mathieu, Salas, & Cohen, 2012). Scholars in the fields of information systems (IS) and human-computer interaction (HCI) have long investigated how these technologies influence teamwork, how teams adopt and implement these technologies, and how interaction among team members is reshaped by these technologies (Sidorova et al., 2008).

Robots are becoming commonplace, not only in our everyday lives but also in collaboration in many areas of work. First-responder teams send remote-control robots and unmanned vehicles into dangerous areas to assess situations, save human lives and remove threats (Dole, Sirkin, Currano, Murphy, & Nass, 2013). Some construction sites use robots for tasks including wall-building and excavation (Feng, Dong, Lundeen, Xiao, & Kamat, 2015; Feng, Xiao, Willette, McGee, & Kamat, 2015; J. Kim, You, Lee, Kamat, & Robert, 2015). Moreover, the recent development of robots with artificial intelligence is expected to be incorporated into human teams; scholars have envisioned that working with robots will become more commonplace with artificial intelligence embedded into the physical bodies of these robots (Krämer, Eimler, von der Pütten, & Payr, 2011). Defense Advanced Research Projects Agency (DARPA) Robotics Challenge is an excellent example of the future of such teamwork, in which humans work with intelligent robots to achieve various team objectives that are physically and cognitively challenging (Yanco et al., 2015).

Despite the increasing incorporation of robots into many teams, research has not paid much attention to how robots can reshape teamwork and its potential outcomes. In fact, the field of human–robot interaction (HRI) has studied interaction and collaboration between people and robots extensively (Bauer, Wollherr, & Buss, 2008; Thrun, 2004). However, most of these studies only focus on the collaboration between individuals and robots (Robert & You, 2014, 2015) rather than on team interactions. This leaves many questions unanswered, including how a robot can facilitate or hinder interaction among teammates and thus, influence team outcomes, as well as how team members interact with such robot. These questions can only be answered through investigations of teamwork that incorporate robots by acknowledging both the uniqueness of robots from other technologies and the characteristics of teamwork as they differ from one-on-one interactions (Robert & You, 2014).

1.2 WHAT IS ROBOT

We need to discuss what makes robots unique from other technologies in order to set the boundary of this dissertation research. This is an important issue in studies that involve human interactions with robots. The term ‘robot’ has been used for almost 100 years since the term was first introduced to describe a humanoid machine in a play, R.U.R. written by a Czech writer, Karel Čapek, in 1920. Robots are defined in general as a machine that is programmable and has the capability of performing a complex action automatically (Wikipedia, 2017). However, not all robots in our lives are programmable, capable of a complex action, or able to behave autonomously.

Since the word ‘robot’ was coined by the Czech writer, the meaning of the word ‘robot’ has been expanded to refer to many different types of technology in research. For instance, machines used in manufacturing plants have been called robots (Garg & Kamat, 2013; J. D. Lee & See, 2004). These machines often carry out heavy duty and repetitive tasks based on a pre-programmed course of action (Trzcielinski & Karwowski, 2012). Drones and unmanned aerial vehicles (UAV) are also regarded as types of robotic technology. They can be operated by human pilots remotely or an automated aviation program for fulfilling various missions (de Visser & Parasuraman, 2011). In addition, construction sites are increasingly employing robotic machines for different types of tasks such as masonry and excavation (Kamat & Martinez, 2005; J. Kim et al., 2015). As such, despite the increasing volume of literature on robots, the definition of the robot is not converging to one that is commonly agreed by scholars across different fields of study (Dautenhahn et al., 2005; Thrun, 2004).

The diverging definition of the robot leads to the importance of conceptualizing the robot per study. Rather than try to propose a widely accepted definition of robot across the fields, I believe that it is more important to conceptually distinguish robots from other types of technology. By doing so, this dissertation research can be based on a narrow but solid conceptual foundation of the robot and provide clear implications to theorizing interactions regarding the characteristics of robots in teams. This can be done through identifying a characteristic that is not present in traditional technologies but commonly present in the type of technologies referred to as robots. For instance, the physical embodiment is one distinctive characteristic of robots. Most aforementioned technologies that are regarded as a robot have a physical body or casing and exist only as a physical object regardless of the degree to which they are programmable, capable of complex actions, and able to behave cautiously.

In this dissertation, I view the physical embodiment as the crucial characteristic that defines robots uniquely from other technologies (Groom, Nass, et al., 2009). The embodiment is understood to mean having a visible or tangible form of idea or quality (Dourish, 2001; Ziemke, 2003). The embodiment of technology can either be in the physical or virtual form: robots are physically embodied and allow physical interactions, while avatars rendered in graphical representations are examples of the virtual embodiment. The physical embodiment is a manner in which a robot manifests its form and physical actions, as opposed to representing its existence and interactions only through on-screen interfaces and verbal communications (K. M. Lee, Jung, Kim, & Kim, 2006;

Longo, Schüür, Kammers, Tsakiris, & Haggard, 2008). The physical embodiment can invoke strong socio-emotional responses that lead individuals to project identities and personalities onto robots and treat them as something more than mere technological pieces of apparatus (Groom & Nass, 2007; Wainer, Feil-Seifer, Shell, & Mataric, 2007). Thus, human interaction with robots in teamwork is qualitatively different from their interaction with other technologies in teamwork and engenders socio-emotional phenomena within teams that work with robots.

1.3 WHY STUDY TEAMS WORKING WITH ROBOTS?

A team amounts to more than just a sum of individuals (Kozlowski & Klein, 2000). Thus, interactions among multiple entities often demonstrate more complexity and dynamism and as such these interactions comprise of a unique entity in research (Sarker & Valacich, 2010). This is because teams consist of people with different backgrounds, personalities, knowledge, skills, and attitudes, all of which are combined to produce an emergent process that can be exclusively present in a particular team (Kozlowski & Klein, 2000; Robert, 2013). Therefore, the addition of one more individual to a dyad of two individuals does not result in easily predictable outcomes based on our knowledge of interaction between a single robot and a single individual. This is why teams working with robots in different circumstances should be viewed differently from those using 1:1 human–robot collaboration (Robert & You, 2014). Owing to the fact that research has accumulated knowledge on how teams work using different technologies, taking a team perspective from the literature can benefit our understanding of how teams working with robots utilize robots in order to improve overall team effectiveness.

1.4 RESEARCH QUESTIONS

Despite the HRI research highlighting the uniqueness of robots based on the physical embodiment and the well-grounded research on teamwork with technology, little research has been done to understand teamwork with robots by encompassing these two areas of research. Such research should be aligned with other efforts to expand the current theory of teamwork and technology use by embracing new technologies, like robots, which are becoming integral parts of more teams (Suh, Kim, & Suh, 2011; Tannenbaum et al., 2012). Therefore, for this dissertation, I conducted a series of studies to answer the overarching research questions below about the robot's influence on team outcomes, drawing from both the human–robot interaction and the information systems research.

> *RQ1) What are the impacts of interaction between human teammates and interaction between humans and robots on outcomes in teams working with robots?*

> *RQ2) How can we facilitate the development of teams working with robots? Can we promote an individual team member's intention to work with robots?*

1.5 A THEORETICAL FRAMEWORK[1]

This dissertation begins to answer the research questions above by proposing a theoretical framework for research on teams working with robots. The research framework integrates

---

[1] An earlier version of this section (You and Robert, 2017) appeared as a position paper at Robots in Groups workshop at CSCW 2017. The development of the framework was principally conducted by me, but with a considerable amount of feedback and intellectual contributions from Lionel P. Robert.

the literature on teamwork and human–robot interaction (Figure 1). This framework attempts to capture the dynamic, adaptive, and developmental nature of teams working with robots. In doing so, this framework incorporates the inputs, mediators, and outputs of human–robot teams with an iterative process of feedback loops.

The framework is based on previous frameworks of teamwork, where inputs, mediators, and outputs are identified as key elements in the team's life cycle (see Mathieu, Maynard, Rapp, & Gilson, 2008 for a review). Constructs in the inputs influence emergent states of teamwork with robots (i.e. mediators), eventually producing outputs. The model is based on IMOI (inputs-mediators-outputs-inputs) framework by (Ilgen, Hollenbeck, Johnson, & Jundt, 2005) to represent the cyclic nature of human–robot teams with feedback loops from outputs to subsequent inputs and mediators during the teams' lifecycle.

I believe that this framework is an initial step toward motivating the theoretical development of the subject. This framework also provides a theoretical guide for scholars to examine a variety of phenomena in teamwork with robots. Hence, this dissertation is the platform for the empirical validation of the framework by examining constructs and their relationships during the lifecycle of teams working with robots in the subsequent chapters 2, 3, and 4.

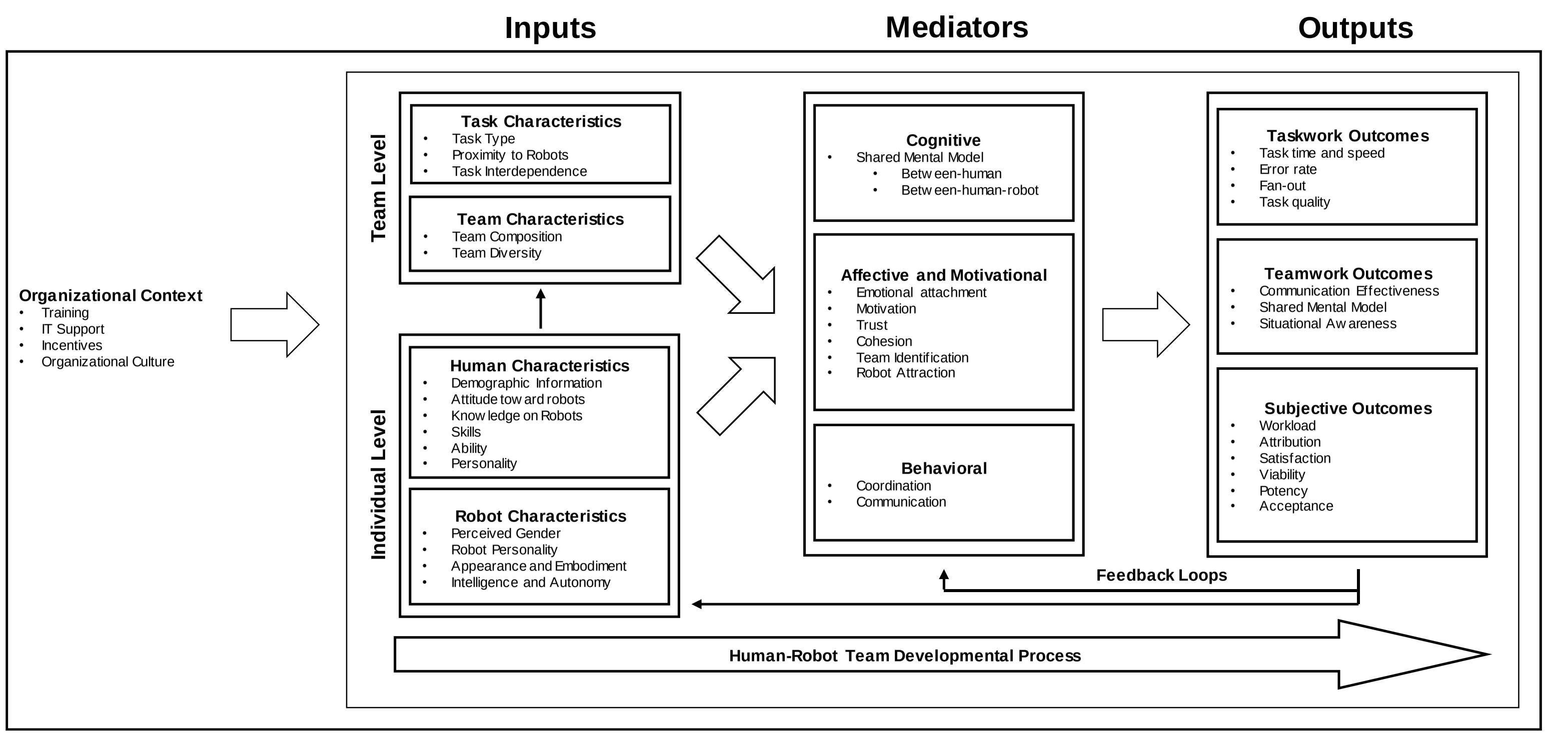


Figure 1 Theoretical framework of human-robot teamwork

1.5.1 Inputs

The inputs represent resources and properties available to teams (Kozlowski & Bell, 2003). This includes multiple levels from the individual level, including characteristics of individual team members and robots, and the team level, including team composition and job characteristics. The team-level inputs are influenced by the individual-level inputs and are shown by the solid line from the individual level to the team level on the left side of Figure 1.

The framework includes the combination of both robot and human characteristics that can manifest unique team compositions and structures in human–robot teamwork. Robots in teams can be perceived to possess humanlike attributes such as gender, ethnicity, knowledge, ability, and personality (Bernier & Scassellati, 2010; D. Li, Rau, & Li, 2010). This is because people often ascribe agency to robots and treat them as social entities (Groom & Nass, 2007). For instance, a human–robot team can be considered homogeneous when a robot is perceived to have the same ethnic attributes as other team members (Makatchev et al., 2013). Therefore, this framework puts the same emphasis on robot characteristics as it does on human characteristics when it comes to the makeup of team-level characteristics.

> *Proposition 1: Individual-level characteristics of robots and humans can influence team-level characteristics of human–robot teams.*

This framework depicts inputs influencing subsequent mediators and eventually outputs. This relationship can occur at both the team and the individual levels. For example, at the team level, task interdependence is critical to communication and coordination between humans and robots during teamwork (H. Jones & Hinds, 2002). Task interdependence between humans and robots is proved to help achieve better mental models on task and team performance (Nikolaidis & Shah, 2013). Also, at the individual level, research suggests that individuals positively evaluate robots that are perceived to have similar personality and social identities such as ethnicity (Bernier & Scassellati, 2010; F. A. Eyssel & Loughnan, 2013).

Inputs at the team level can influence mediators and outcomes at the individual level. For instance, the composition of a human–robot team may determine the level of individual motivation and satisfaction of its team members. In teams that involve multiple human team members, individual effectiveness may be a function of both team-level inputs and individual-level inputs (Ilgen et al., 2005; You & Robert, 2016).

> *Proposition 2: Inputs influence mediators and subsequent outputs in human–robot teams.*

> *Proposition 3: The influence of team-level inputs can occur at the individual and team levels.*

1.5.2 Mediators

Mediators are emergent processes or states through which the effects of inputs are manifested. For individuals, mediators are often attitudes and beliefs. For teams and groups, they are typically processes that result from the interactions necessary for combining different inputs (McGrath, 1984). Mediators can also be viewed as an output of the team's input.

Mediators of human–robot teams can be present between humans alone, and between humans and robots. For example, shared mental models are important cognitive mediators. Accurate mental models usually promote team performance and reduce cognitive load (Robert et al., 2008). Shared mental models can exist between humans and robots (Nikolaidis & Shah, 2013), as well as between humans alone (Robert et al., 2008). In first-responder teams, team members are often scattered across locations (Burke, Murphy, Coovert, & Riddle, 2004; H. Jones & Hinds, 2002). Communication among humans and robots is required to maintain accurate shared mental models of the situation at hand (Burke et al., 2004).

Emotional attachment is a mediator, defined as an affective reaction toward robots or other humans (Carpenter, 2014). When team members are emotionally attached to their robots, they are likely to be more motivated to perform tasks with the robots and often perceive the work with the robots to be more rewarding (Carpenter, 2014; Robert & You, 2015). However, emotional attachment can also deter teams from deploying robots in risky situations (Carpenter, 2014). As behavioral mediators, it is shown that effective communication and coordination are important to improve team outcomes with (Breazeal, Hoffman, & Lockerd, 2004) and without robots (Kozlowski & Bell, 2003).

Proposition 4: Cognitive, affective, and behavioral mediators influence outputs.

Team-level mediators can also influence individual-level outputs. Team trust can influence the relationship between individual trust and individual performance (Jarvenpaa et al., 2004). It is also possible that mediators such as team cohesion and communication can influence team members’ decision on whether or not to remain on the team.

Proposition 5: The influence of team-level mediators can occur at the individual and team levels.

1.5.3 Outputs

Outputs have three categories: taskwork, teamwork, and perceptual outcomes. In human–robot teams, taskwork can include the task time, solution quality, and error rate, while teamwork can include communication efficiency and effectiveness, awareness, and coordination. Perceptual outcomes are the attitudinal and emotional reactions, such as satisfaction.

The framework attempts to capture the role of time. The original IPO (input-process-output) model has been criticized for focusing only on a linear path, from inputs through outcomes. However, most teams undergo developmental processes and feedback loops as they mature (Mathieu et al., 2008). This means that mediators and outputs can influence subsequent inputs and mediators through feedback loops (shown by solid lines on the right side of Figure 1). In other words, time matters, and we should expect past interactions to play a key role in the future interactions of human–robot teams.

As an example, time matters in the role of task knowledge and skill. For instance, a human–robot team could have little task knowledge (inputs), which could influence its shared mental models (mediators) and ultimately its initial performance (outputs). When a human–robot team repeats the task, the team becomes better, which influences mediators and the outputs of future tasks. However, the influence of previous outputs can be more influential than the feedback from previous mediators. Mediators are often subject to change based on a team's previous performances and experiences. Inputs, including specifications of robots and individual traits, tend to be static and less dynamic.

> *Proposition 6: There are feedback loops, in which mediators and outputs influence subsequent mediators and inputs in a cyclic manner.*

Last, the organizational context influences inputs, mediators, and outputs associated with human–robot teams. Teams are often embedded in a larger organizational context. Organizations help determine both the operation and management of human–robot teams. Organizations provide the resources to facilitate teamwork. For instance, organizations can provide training and support to human–robot teams (Kozlowski & Bell, 2003). Consistent training and support from the organization can be critical, particularly for human–robot teams (You & Robert, 2016). Team members are likely to build strong social relationships with their robots through prolonged interactions throughout the team's life cycle.

> *Proposition 7: Organizational contexts of human–robot teams can influence their inputs, mediators, and outputs by providing positive conditions.*

1.5.4 Discussion for the Framework

There are three advantages of this framework. First, it acknowledges different compositions of human–robot teams beyond one robot and one human. Given that many human–robot teams consist of multiple robots and their operators, both human–human and human–robot collaboration should be examined to better understand how these teams achieve their goals in synergistic ways. The framework not only incorporates the different individual and robot characteristics but also various compositions among the characteristics of robots and humans. This includes *collaboration*, as a joint action between and among humans and robots, to jointly accomplish a shared goal (Breazeal et al., 2004).

Second, the framework suggests individual, team-level, and multilevel relationships. Most research focuses on the individual level — often ignoring the team context. This framework describes how team characteristics influence individual mediators and outputs. A multilevel approach is essential to investigate impacts of the team level on the individual level (Robert & You, 2013; Srinivasan, Maruping, & Robert, 2012).

Third, this framework considers the role of time by including feedback loops. It is possible to investigate how different team compositions convert to outputs through mediators. Many researchers have treated variables such as attraction and attachment toward a robot as an end-point of human–robot interaction, mainly for predicting individual adoption of social robots. However, human–robot teams often repeat similar tasks and interact with robots assigned to them during the team's life cycle. In this case, previous performance can alter a team's perception toward its robots and the ways mediators influence interactions.

Lastly, I believe this framework will be a starting point towards building a theory of teamwork with robots. The framework enumerates potential theoretical links that deserve empirical validation. Some of the links have been examined through three studies conducted for this dissertation, but more research should be directed to test other phenomena in the framework specifically in team contexts where multiple robots and people are involved. Therefore, the framework should be updated by empirical evidence, and this process should incorporate iterative and collaborative effort with other scholars in the research community in the relevant fields.

1.6 OVERVIEW OF CHAPTERS

This dissertation includes three separate studies, all of which address how robots can alter interactions among team members and result in various outcomes in the teams working with robots. Based on the theoretical framework introduced in the section above, the three studies are designed to identify key elements of processes in teams working with robots and ways to promote the effectiveness of such teams. Specifically, I designed the three studies to address affective, motivational, and cognitive aspects of teams working in collaboration with technologies. These three team dimensions — affective, motivational, and cognitive — have been integral to explaining social behaviors and attitudes (Cannon-Bowers & Bowers, 2011; Forgas, Scholar, Baumeister, & Tice, 2011; Kozlowski & Bell, 2003).

In addition, the three studies fall into two phases of teamwork — team functioning and team development (Cannon-Bowers & Bowers, 2011). Team functioning is a process that individual team members undergo to accomplish team objectives by utilizing available resources and implementing technologies (Cannon-Bowers & Bowers, 2011; Kozlowski & Bell, 2003). This stage involves team processes, in which perceptions of other team members and individuals' motivations to perform team tasks are enacted in a given circumstance. Therefore, studies in this phase are expected to tap into socio-emotional relationships between robots and team members, as well as among team members themselves. The trust study in Chapter 2, which examines trust in teams working with robots, and the team potency study in Chapter 3, which examines effects of self-efficacy in diverse teams on performance of individual team members, can be included in the team functioning phase.

Team development is related to processes that take place prior to team functioning and include a team's compositional characteristics and formation of initial attitudes toward team members and technologies (Cannon-Bowers & Bowers, 2011). In this teamwork phase, variables regarding team composition, such as individual attributes, are examined to predict better teamwork and outcomes. The third study falls into the team development phase of teams working with robots, and thus this study serves to identify what motivates individuals to have the willingness to work with a robot in teams. The mapping of the three studies is illustrated in Table 1.

Chapter	**Chapter 2**	**Chapter 3**	**Chapter 4**
Phase	**Team Functioning**		**Team Development**
Dimension	**Affective**	**Motivational**	**Cognitive**
Key Construct	Trust	Potency	Similarity
Research Question	Will team members trust robots? What are the effects of trust in enhancing team outcomes?	What promotes performance of individual robot operators in teams working with robots?	What leads to teamwork with robots? Will similarity help people to work with robots?
Outcome Variables	Team performance and viability	Individual robot operator performance	Trust in a robot, intention to work with robot, intention to replace a human with a robot

Table 1 Research Framework for Teamwork with Robots

The first study is described in Chapter 2. The first study (the trust study, hereafter) examines the effects of trust as an affective process of teams working with robots. The type of trust examined in this study is affective-based trust. Affective trust is based on the emotional bonds between individuals and leads people to make emotional investments and exert more care and motivation in relationships (McAllister, 1995). This is in contrast to cognitive trust, which is established through cognitive reasoning based on good evidence and knowledge to make a trust decision (McAllister, 1995). Affective trust can be important to predicting the initial performance of teams working with robots. The first study is designed to investigate the effects of robot-building and team identification on promoting affective trust and its subsequent influence on team performance. In this study, teams consisting of two individuals and two robots perform a collaborative task of moving objects from one place to another. The study is designed to uncover ways to promote a team member's trust in another team member and in a partnering robot. The study also examined what role the different trusting relationships play in enhancing team performance.

The second study is described in Chapter 3. The second study (the team potency study, hereafter) explores a motivational process by which outcomes of individual robot operators can be explained through their efficacy beliefs. Efficacy beliefs are associated with one's motivation to perform well based on confidence in a given task (Gist & Mitchell, 1992; Marks, Mathieu, & Zaccaro, 2001). Among the efficacy beliefs, team potency, which is defined as a team belief of ability in general, is the main interest of the second study (Gully, Incalcaterra, Joshi, & Beaubien, 2002). The second study addresses aspects of confidence and motivation in diverse teams working with robots. This study design posits an interplay among team potency, individuals' self-efficacy of using robots, and the team's demographic composition (e.g., ethnicity, gender, and nationality) in predicting individual performance and perception of team viability. Similar to the first study, teams consisting of two individuals and two robots perform a collaborative task of moving objects. The study is designed with a multi-level approach to capturing performance and viability perceptions of individual robot operators nested in teams of two people and two robots.

Chapter 4 describes the third study. The final study (the similarity study, hereafter) taps into the development of teams working with robots. The goal is to understand what motivates individuals to be willing to work with robots as a team and to choose to work with a robot instead of a human teammate. The final study seeks to understand the cognitive link between similarities with a robot and trust in the robot and its subsequent impacts on intention to work with the robot. This study proposes risk of danger as a trigger of a deliberate cognitive assessment of trustworthiness of a robot in the cognitive mechanism. I believe that understanding the cognitive mechanism regarding development of teams working with robots is important and timely. Robots are being placed in teams as a result of managerial and strategic decisions by leadership. However, individual workers' willingness to work with robots is not always guaranteed and such willingness cannot be assumed, while it is critical to team functioning. Thus, the third study investigates how and why individuals decide to work with robots. The study is grounded in theories of similarity and trust in teams, which explains how similarity helps the formation of trust in a robot and attitudes toward working with the robotic teammate (Bernier & Scassellati, 2010).

Conclusively, Chapter 5 revisits the research questions proposed in this section by highlighting key findings from each of the three studies. Findings from the three studies are discussed based on the theoretical framework in Chapter 1. This chapter also discusses the limitations and practical implications of this dissertation research.

CHAPTER 2
AFFECTIVE PROCESS: TRUST[2]

2.1 INTRODUCTION

Many teams are transformed to human–robot teams when robots are incorporated in their work. Human–robot teams can be characterized as the inclusion of both humans and robots in teamwork and collaboration with the robots to accomplish team goals (Groom & Nass, 2007). Robots in such teams often enable and aid teams in fulfilling various tasks that are dangerous and arduous for humans. For instance, success of missions and safety of individuals in bomb disposal teams rely on remote-control robots deployed to dangerous areas as proxies for humans (Carpenter, 2013). Some medical teams employ robots to perform microscopic and fine surgical operations that were not possible before the advent

[2] The work presented in this chapter was mainly conducted by me, but significantly benefited from Lionel P. Robert's contributions. An earlier version of this chapter appeared at the SIGCORE workshop at ICIS 2016. This work has not been published at a peer-reviewed outlet yet.

of these robots (Randell et al., 2014). Given that robots are often employed in high-stakes situations such as military and medical tasks, controlling and interacting with robots are critical for human–robot teams to achieve team goals successfully and secure human safety at the same time. However, despite the widespread use of robots in teams, we do not know much about how individuals in human–robot teams interact with their robots and in what circumstances these teams perform better.

Researchers have examined ways to improve quality of interaction between an individual and a robot; however, this research does not inform how to improve overall team effectiveness in teams working with robots. This is in part because there is a gap between the two bodies of literature that are independently relevant to teamwork in human–robot teams: human–robot interaction (HRI), and teamwork. In the first, research on human–robot interaction, scholars are mainly interested in interactions between a single individual and a single robot. This research has failed to examine human–robot teams that involve more than one individual and robot. The second body of research, on teamwork, focuses on teams consisting of only humans. This research could provide rich insights to better understand various types of teams, but it has not examined teams working with robots. Therefore, in order to better understand teamwork in human–robot teams, it is essential to approach human–robot teamwork by taking perspectives from both human–robot interaction research and traditional research on teamwork.

This leads to several interesting questions regarding the relationships between human and their robots. For example, is the relationship between humans and their robots just as important to team outcomes like performance and satisfaction as the relationship between human teammates? If so, what approaches can be used to promote better relationships between humans and their robots? Should we also be concerned with promoting better relationships between humans on these teams? For example, maybe the relationship between human teammates is unimportant and only the relationship with their robot matters. We can also envision a scenario where the opposite might be true. Maybe the relationship between humans and robots is relatively unimportant to team performance and only the relationship between humans is important.

To answer these questions, I turn to theories of trust. Trust is one construct that has consistently shown to be relevant across many settings involving both human-to-human relationships and human-to-technology relationships (Groom & Nass, 2007; Robert, Denis, & Hung, 2009). Trust -- the belief that another will follow through on your behalf – is an important construct in both the literature on teamwork and technology use (Mayer, Davis, & Schoorman, 1995; Mcknight, Carter, Thatcher, & Clay, 2011). In teams, trust among teammates often predicts various team outcomes, including team performance and job satisfaction (De Jong & Elfring, 2010; Morris, Marshall, & Rainer Jr, 2002; Robert & You, 2013). Trust toward a technology has also shown to be an important predictor of use with that technology (Lankton, McKnight, & Thatcher, 2014; Wu, Zhao, Zhu, Tan, & Zheng, 2011). In particular, McKnight et al. (2011) found that one's trusting beliefs in a specific technology led to a greater intention to explore and use more features of the technology. Trust has also been found to be an important element in human–robot teams. The importance of trust is emphasized particularly in teams using robots in high-risk situations

(Groom & Nass, 2007; J. D. Lee & See, 2004). This is because trust toward robots is required for individuals to follow suggestions and accept information from robots when fulfilling missions using the robots (Freedy, DeVisser, Weltman, & Coeyman, 2007).

However, there is still much to learn about antecedents and consequences of trust on outcomes of teamwork between humans and robots (Groom & Nass, 2007; Shah, Wiken, Williams, & Breazeal, 2011). Current research on trust in human–robot teams is limited to teamwork between one individual and one robot. Research still lacks evidence of the effects of trust in human–robot teams because researchers have not examined trust both between individuals and robots and between teammates at the same time. This gap in our current understanding of trust in human–robot teams leaves many questions unanswered. For example, is trust between humans and robots just as important to performance of human–robot teams as it is between people in human-only teams? If so, what approaches can be used to promote trust in human–robot teams? Human–robot teams are often composed of multiple individuals and multiple robots beyond a dyadic pair of one human and one robot (Desai et al., 2012; Hancock et al., 2011). Therefore, there is a need to understand outcomes in these teams, and this necessitates an examination of the relationships between humans and their robots as well as among human teammates. It is impossible to understand human–robot teams without examining both types of relationships. Therefore, this study has two goals:

> *1) To examine the impact of team trust in robots and team trust in humans on team performance and satisfaction in teams working with robots*

2) To examine ways to promote team trust in robots and team trust in humans in teams working with robots.

To accomplish this, I conducted an experiment examining 55 teams working with robots. The teams consisted of two humans and two robots performing a time task in an experimental laboratory setting. This study employed two manipulations to promote team trust in both robots and humans: robot-building and team identification. The robot-building was done by having team members assemble their robots before performing the team's task. For team identification, team members and their robots were given identical t-shirts and a team name to promote the perception of team identity. This study also examined whether team trust in robots and team trust in humans facilitated better team performance and higher satisfaction. In doing so, this study goes beyond prior research by not only examining these two distinct trusting relationships but also by linking them to important team outcomes such as team performance and satisfaction. Results offer new insights into teamwork with robots.

2.2 THEORETICAL BACKGROUND

In this section, I review several bodies of literature that both inform and motivate our research. First, I provide a brief introduction of the trust literature in teamwork. I particularly highlight the benefits of trust in humans for teamwork. Then, *I* discuss and present a review of the current IS literature on trust in technology. This includes a discussion of the importance of trust in the technology acceptance literature. Finally, *I* highlight the research on trust in robots. To accomplish this, *I* draw from the literature on human-robot interaction.

2.2.1 Trust in Teamwork

Trust is widely defined as the willingness to be vulnerable to another's actions (Costa, 2003; Mayer et al., 1995; Zaheer, McEvily, & Perrone, 1998). Mayer et al. (1995) further conceptualized trust as "an expectation that the other will perform a particular action important to oneself, irrespective of the ability to monitor or control that party" (p. 712). Therefore, trust has been viewed as a property of interpersonal relationships emerging across wide range of settings of collaboration between individuals, between teams, and even between organizations (Zaheer et al., 1998).

Trust is one of the most crucial predictors of success in teams (Costa, 2003; Zaheer et al., 1998).Research shows evidence that trust is positively associated with individual and team performance in many settings (Korsgaard, Schweiger, & Sapienza, 1995; Wieselquist, Rusbult, Foster, & Agnew, 1999). For instance, collocated work teams are reported to benefit from trusting relationships among employees to increase performance and satisfaction (Costa, Bijlsma-Frankema, & de Jong, 2009; De Jong & Elfring, 2010; Dirks, 1999). For example, De Jong and Elfring (2010) found that inter-team trust among employees in a multinational consultancy firm increased team performance. The positive effects of trust have also been found in virtual teams (Altschuller & Benbunan-Fich, 2010). For instance, telemedicine operational teams were reported to perform better when individuals in the teams perceived higher levels of interpersonal trust (Paul & McDaniel

Jr., 2004). Moreover, Robert (2016) found that trust in virtual teams increased team performance; this positive relationship was reduced, however, monitoring of individual behaviors.

Researchers argue that there are benefits of trust in teams because trust promotes collaboration through increased cooperation among individuals (G. R. Jones & George, 1998). Trust is often understood to help individuals deal with the complexity and uncertainty associated with collaborative work (J. D. Lee & See, 2004; Zaheer et al., 1998). In particular, trusting relationships require less effort to coordinate workload and ensure that others are complying with expectations (De Jong & Elfring, 2010). As the effort needed to coordinate decreases, team members become more willing to engage in cooperative behaviors altogether (Teasley, Covi, Krishnan, & Olson, 2000). Trust among team members leads them to put aside personal interests and focus instead on team goals (Y.-T. Hung, Dennis, & Robert, 2004; Wieselquist et al., 1999). For example, trust has been a strong contributor to team cohesion (Jarvenpaa, Shaw, & Staples, 2004; Powell, Piccoli, & Ives, 2004). Individuals in cohesive teams tend to put more effort to achieve team objectives together, which results in better team performance and satisfaction(Beal, Cohen, Burke, & McLendon, 2003; Powell et al., 2004).The fact that trust promotes collaboration in part explains why trust is linked to positive team outcomes.

2.2.2 Trust in Technology

The concept of trust has been examined for understanding relationships and interactions with various information technology (IT) artifacts (Hoffman et al., 2009; X. Li, Hess, &

Valacich, 2008). In this research, trust in technology was conceptually distinguished from the conventional notion of trust in prior studies, which mostly focus on interpersonal trust-capturing relationships between people and organizations (Vance, Elie-Dit-Cosaque, & Straub, 2008). For instance, McKnight, Carter, Thatcher, and Clay (2011) conceptualized trust in a specific technology as one's belief of functionality, helpfulness, and reliability in the specific technology. Their conceptualization of trust in a specific technology was adapted from aspects of interpersonal trust in teams and organizations, including competence, benevolence, and integrity, derived from the literature of interpersonal trust such as Mayer et al. (1995) and McKnight, Cummings, and Chervany (1998). Furthermore, they reported that trust in a specific technology positively predicted an individual's intention to explore and engage in deep-structure use of the technology (Mcknight et al., 2011).

Indeed, many scholars have looked at the role of trust in technology in predicting adoption of particular information systems and their use (Wu et al., 2011). This was mostly to extend the technology acceptance model (TAM) and to better explain how individuals intend to use a particular technology, by incorporating trust in technology as an important predictor of constructs in the model (Wu et al., 2011). For example, Wu et al. (2011) in a meta-analysis of 136 TAM studies showed that trust in using different technologies such as e-commerce and Internet banking systems positively influenced all constructs in TAM, including perceived usefulness, perceived ease of use, general attitude toward the technology, and behavioral intention to use the technology. Additionally, Lankton, McKnight, and Thatcher (2014) demonstrated that trust in a database system was positively associated with satisfaction with the system and intention to use it. X. Li et al. (2008) examined antecedents of initial trust in new technology. They reported that one's initial trust in an information system was influenced by reputation, cost/benefit calculation, and situational normality of the system and influenced their intention to trust the system in the future. These studies provide empirical evidence that trust in technology should be differentiated from interpersonal trust between people in order to better understand their technology use (Hoffman, Johnson, Bradshaw, & Underbrink, 2013).

However, despite the empirical evidence of trust in technology as a distinctive concept for understanding technology use, there seems to be a gap in the current literature of trust in technology. First, researchers have not examined trust in emerging information systems like robots. Most studies examining trust in technology were conducted in contexts of traditional information systems including spreadsheet applications (Mcknight et al., 2011), e-commerce sites (Wu et al., 2011), and database systems (Lankton et al., 2014). It was Lankton et al. (2014) who compared human-like trust in technology (i.e. integrity) and system-like trust in technology (i.e. reliability). To my best knowledge, no study describes trust in robotic systems by employing the concept of trust in technology derived from interpersonal trust (Lankton et al., 2014; Mcknight et al., 2011). Therefore, investigating trusting beliefs in robotic systems will contribute to the current literature of trust in technology.

In addition, research is mostly limited to examining trust in technology by individuals and predicting their intentions to use. Thus, the current literature cannot provide evidence of roles of trust in technology at the team-level and its consequences for team outcomes. This is a significant gap in our understanding of teamwork using technologies and trust because interpersonal trust is generally known to increase various team outcomes such as performance (Altschuller & Benbunan-Fich, 2010; Robert, 2016).Just like interpersonal trust in teams, it is likely that trust in technology would facilitate interactions and relationships with the technology and thus improve team performance. If this is true, this study has the potential to provide empirical evidence by showing positive effects of trust in robots on outcomes in teams working with robots.

2.2.3 Trust in Human–Robot Interaction

The concept of trust has been adapted to robotic systems (Hoff & Bashir, 2013; J. D. Lee & See, 2004). Many HRI scholars have argued that because individuals often project human-like traits onto robots, trust in robots should be viewed as a type of interpersonal trust (Bruemmer et al., 2004; Groom & Nass, 2007). Recent research has confirmed that the social interactions between humans and robots can lead many humans to develop interpersonal trust in robots in much the same they do with other humans (Hancock et al., 2011; Krämer, von der Pütten, & Eimler, 2012). The evidence of interpersonal trust in robots have been observed in interactions with various types of robots in varying degrees of its characteristics, such as intelligence and autonomy (Kruijff, 2013) and appearance (Hancock et al., 2011; Schaefer, Sanders, Yordon, Billings, & Hancock, 2012). Interpersonal trust is the expectation that someone will act in your best interest (Robert et al., 2009). This is somewhat different from trust based on reliability and functional dependability, which is often used to represent trust between humans and technology (Desai et al., 2012; Yagoda & Gillan, 2012).

The literature on trust in robots has several relatively unexplored areas. One, the literature has focused on the role of trust in facilitating interaction with social robots by promoting engagement and enjoyable interactions between an individual and their robot. From this literature, it is clear that humans are much more engaged with and build a stronger relationship with their robot when they trust their robot (Gaudiello, Zibetti, Lefort, Chetouani, & Ivaldi, 2016; Graaf, 2015; Kidd, 2003). Scholars investigating the social robots have ignored the potential impacts of trust on the performance of teams working with robots. Yet, in many cases teams working with robots are assembled to accomplish tasks as effectively and as efficiently as possible (Carpenter, 2013; H. Jones & Hinds, 2002). Therefore, understanding the impact on trust on team performance has the potential to contribute to our understanding of teamwork with robots.

Two, these studies have only examined the impact on trust between one human and one robot. This is problematic in at least two ways. First, teams working with robots can be composed of multiple humans and robots (Groom & Nass, 2007; Yanco & Drury, 2004). This means that the trust between multiple humans and multiple robots should be considered to better understand teamwork in teams working with robots. Second, in the context of teamwork with robots, trust between humans should also be examined alongside human’s trust in robots. Investigating the impact of only trust in robots or trust in humans at best presents an incomplete view and at worst presents an inaccurate view on potential impacts of trust in teams working with robots in predicting team outcomes. Therefore, by examining both the impact of trust in humans and the impact of trust in robots on performance and satisfaction, this study can provide new insights to the literature of teams working with robots.

Taken together, two trends emerge throughout the literature on trust between humans and robots. One, this research has focused on developing trust between an individual and a robot (Hancock et al., 2011). Yet, no researchers appear to have examined whether trust is actually important to the performance of human–robot teams. Two, these studies have not included the impact of both trust between humans and robots, and trust between humans. However, human–robot teams can be composed of multiple humans and robots (Groom & Nass, 2007; Hancock et al., 2011). Therefore, by examining trust between humans in human–robot teams, this study can provide new insights.

2.3 THEORY AND HYPOTHESIS DEVELOPMENT

I propose two ways to increase trust perception toward robots: robot-building and team identification. These ways are analogous to strategies to promote interpersonal trust in all-human teams. This section elaborates on how these mechanisms would work for human–robot teams.

In the research model for this paper, I posit that robot-building and team identification will increase interpersonal trust toward robots and toward human teammates. I also propose in this model that the interpersonal trust will result in increases in team performance and satisfaction with teamwork. The following section elaborates on these arguments, which are summarized in Figure 2.

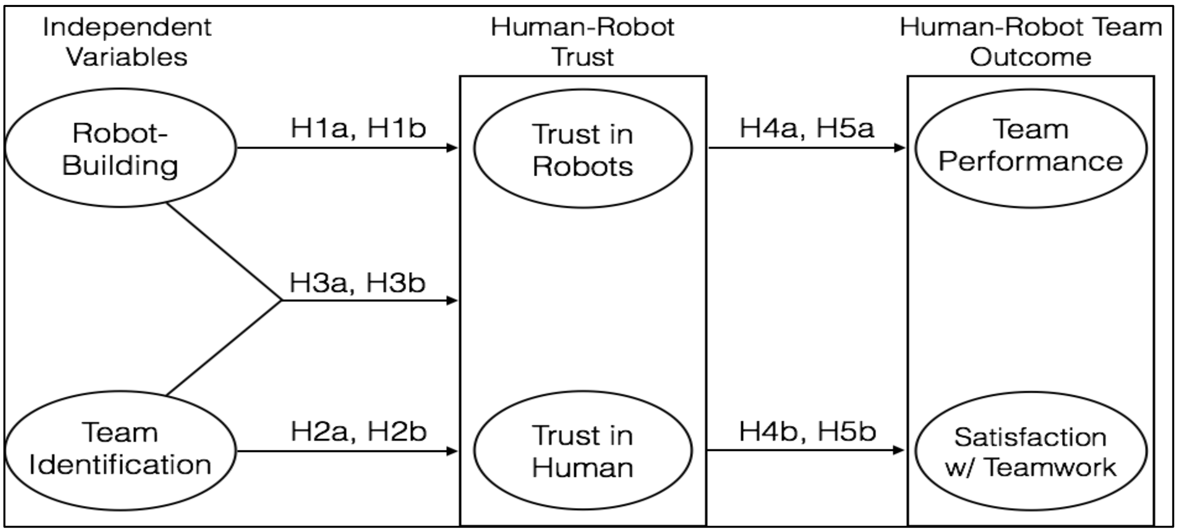


Figure 2 Proposed research model

I posit that robot-building will increase trust between humans and robots. This works in three ways: 1) by aiding in understanding of how robots work, 2) by altering attitudes toward the robots, and 3) by establishing trust between human builders. First, building robots can lead to better mental models about how they work (Nikolaidis & Shah, 2013; E. Phillips, Ososky, Grove, & Jentsch, 2011). Mental models are generally defined as structures of knowledge in one's environment and its components (Wilson & Rutherford, 1989). These knowledge structures help individuals to have a better understanding of interactions with the world around them by enabling them to describe, explain, and predict events (Rouse & Morris, 1986). Specifically, mental models have been reported to be critical to understanding and using technological systems (e.g., Krauskopf, Zahn, Hesse, & Pea, 2014; Merrill, 2000). Individuals with a clear mental model can understand the current state of their system and make predictions of its future behaviors. This ability to make predictions is associated with the important property of trust. In the theoretical background section of this chapter, trust was conceptualized as one's confidence that another will behave as expected. Similarly, a mental model helps individuals to make plausible predictions about their robots and expect the robots to work as they predicted(E. Phillips et al., 2011). By building robots by themselves, people can have a better understanding of how the robot works and what it is capable of. This knowledge results in higher trust toward robots because individuals can make more accurate predictions and base their expectations on their robot's current state (Powers & Kiesler, 2006). This might be why the STEM (Science, Technology, Engineering, and Mathematics) education programs use robot-building activities to teach students how robots work (Klassner & Anderson, 2003) — people are more inclined to trust a robot once they understand how it works (S. Kiesler & Goetz, 2002).

Second, robot-building will increase trust between humans and robots because building robots can positively alter attitudes and behaviors toward the robots when people see themselves through the robots they build (Groom, Takayama, Ochi, & Nass, 2009; T. Kiesler & Kiesler, 2004; Mugge, Schoormans, & Schifferstein, 2009). Building creates a personal bond and a sense of ownership between builders and their artifacts (Groom, Takayama, et al., 2009; T. Kiesler & Kiesler, 2004). Such personal bonds and ownership have been known to facilitate trust (Hogg, 2007; Zhang & Huxham, 2009). Additionally, the building activity itself increases interaction with robots compared to using robots that are already built and assigned. Trust is typically associated with the amount of interaction (Hancock et al., 2011; Wieselquist et al., 1999). For example, researchers have found that people who interact more with their robot through cross-training tasks trust the robot more than people who interact with their robots without cross-training (Nikolaidis & Shah, 2013).

Finally, I suggest that robot-building can increase trust between humans. The robot-building exercise represents a collaborative and shared experience between team members. Research on teams has demonstrated that such activities are often used as the basis for trust in teams (Jarvenpaa, Knoll, & Leidner, 1998; Meyerson, Weick, & Kramer, 1996). In addition, the robot-building exercise can induce a perception of shared investment in the team (Korsgaard et al., 1995). The fact that both team members are contributing to the team by building robots can promote a perception that both members are committed to the team and its success (Mayer et al., 1995). The belief that one's teammate is committed to the team is positively associated with trust in teams (Jarvenpaa et al., 2004; Wieselquist et al., 1999).Therefore, I hypothesize that:

> *Chapter 2-H1) Human–robot teams in the robot-building treatment condition have higher interpersonal trust toward their a) robots and b) human teammate than teams not in the robot-building condition.*

Team identification should increase trust in human–robot teams. Team identification is defined as the degree to which team members are psychologically identified with their team (Scott, 1997). Research on human teams generally confirms the positive effects of team identification on team inter-relationships and performance (Abrams & Hogg, 1990; Hinds & Mortensen, 2005). Team members are more likely to behave in ways to promote the team's interest rather than their own when individuals identify with the team (Robert, 2013).

Team identification increases trust by minimizing the perceived differences between teammates and maximizing the perceptions of similarities between them (Abrams & Hogg, 1990; Hogg, 2007). The similarities become the basis for a shared social identity between teammates (Hogg, 2007; Ljungblad, Kotrbova, Jacobsson, Cramer, & Niechwiadowicz, 2012; Rae, Takayama, & Mutlu, 2012). Social categorization and attraction theories tell us that people tend to trust others who are perceived to be similar to them (Hogg & Turner, 1985; Jarvenpaa et al., 2004). This explains the strong positive relationship between team identification and team trust in all-human teams (Han & Harms, 2010). Given that humans tend to project personality and social characteristics onto non-human objects like robots, it is likely that they would trust robots more if they believe they share the same social identity (Ljungblad et al., 2012; Rae et al., 2012; Reeves & Nass, 1996). Indirect evidence of this type of team attachment between humans and robots has been found in humans participating in RoboCup Soccer. Therefore, I hypothesized the positive impact of team identification on trust toward both robots and humans on a team:

Chapter 2-H2) Human–robot teams in the team identification treatment condition will have higher interpersonal trust toward their a) robots and b) human teammates than teams not in the team identification treatment condition.

Additionally, I propose that the combination of robot-building and team identification should lead to higher levels of trust in human–robot teams. When human–robot teams are exposed to both robot-building and team identification, they should have significantly higher levels of trust toward both robots and their human teammates than when exposed to either treatment alone. Robot-building and team identification serve for increasing trust in separate ways. Robot-building is a behavior that helps individuals have better mental models and establish stronger bonds, and it provides individuals opportunities to make meaningful commitment to their team. On the other hand, team identification enhances the sense of team membership, which operates at the perceptual level. Therefore, the combination of these two ways can result in a kind of double-dose impact in terms of facilitating overall trust within human–robot teams. This is because both are likely to reinforce and add to the effects of the other. This should lead to an additive interaction effect. Therefore, I hypothesize that:

Chapter 2-H3) There is an additive interaction effect between robot-building and team identification, such that trust toward a) robots and b) human teammates is highest in teams exposed to both treatment conditions.

In addition, trust toward robots and human teammates should increase team performance. The positive impact of trust on performance has been found in all-human teams (Jarvenpaa et al., 2004; McAllister, 1995). The positive relationship between trust and team performance is often explained by the heightened engagement and motivation associated with increases in confidence along with the reduction of worry, concern, and monitoring associated with low-trust collaboration (De Jong & Elfring, 2010; Jarvenpaa et al., 2004).

Countless studies have linked trust toward one's teammates to better team performance (Avolio, Jung, Murry, & Sivasbramaniam, 1996; De Jong & Elfring, 2010; Zaheer et al., 1998). However, I could only find indirect support linking trust toward a robot to individual performance. Researchers have demonstrated that trust toward a robot is positively associated with motivation to use and interact with a robot (Schaefer et al., 2012; Shah et al., 2011). Although Shah et al. (2011) suggested that human–robot performance could be improved by reducing the effort to monitor one's robot, this relationship has not been empirically verified. Taken together, prior research seems to suggest:

> *Chapter 2-H4) Trust toward a) robots and b) human teammates increases performance of human–robot teams.*

Furthermore, team satisfaction can be seen as a measure of team members' positive feelings about their team experience (Briggs, de Vreede, & Reinig, 2003). Team trust in all human teams is positively related to satisfaction (Jarvenpaa et al., 2004). Similarly, individuals in human–robot teams are likely to feel higher satisfaction with their team as their level of trust increases in either robots or their teammates. Therefore, I hypothesize that:

> *Chapter 2-H5) Trust toward a) robots and b) human teammates increases satisfaction inhuman–robot teams.*

2.4 METHOD

To investigate the effects of robot-building and team identification on trust and team effectiveness, I conducted a 2 (robot-building: building vs. no-building) × 2 (team identification: team identification vs. no team identification) between-subjects experiment in a controlled lab environment. Participants were invited to a lab to perform a collaborative task with two robots and another participant. The goal of the collaborative task was to deliver five small water bottles from one point to another point as quickly as possible using remote-control robots.

2.4.1 Participants

There were 110 participants in 55 teams working with robots recruited from a large online subject pool at a mid-western university in the United States. The mean age was 24 and 54 were males. Each team working with robots consisted of 2 humans who operated 2 robots. Individuals were randomly assigned to a team and each team was randomly assigned to one of four treatments: robot-building only, team identification only, robot-building × team identification, or the control group. There were 13 teams in the robot-building only treatment, 15 teams in the team identification only treatment, 14 teams in the robot-building and team identification treatment, and 13 teams in the control group.

2.4.2 Robots

I used robots made of Lego® Mindstorms® EV3 (see Figure 3). The robots were designed to be able to grab small objects. Infrared remote controllers were used to control the robots. The robots spoke (e.g., “Okay”) when loading and unloading the water bottles. The robot indicated directions of movement on its display located on its back. Both robots used for the experiment were identical in forms and technological specifications.

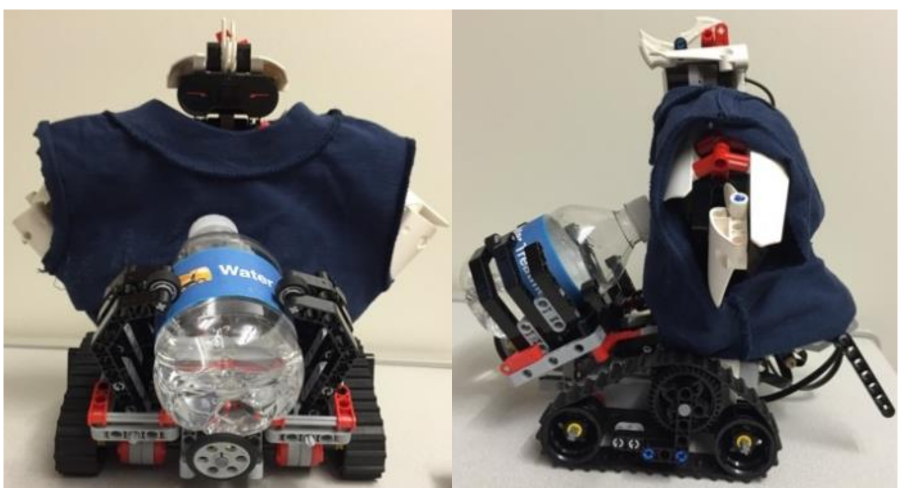


Figure 3 The robot with a water bottle and a uniform

2.4.3 Manipulations of Independent Variables

2.4.3.1 Robot-building

The independent variable robot-building had two levels: robot-building and no robot-building. Manipulation of robot-building was to elicit the perception of self-extension by assembling their own robot. In the robot-building condition, participants were asked to assemble their robot. Each participant assembled their own robot, but did so in the same room. The identical bricks and instructions were given to both participants in the team. The instructions included images of each assembling process along with texts. Participants were told that the assembling portion of the study was not a test. They were allowed to take as long as they wanted to complete the assembly task. All participants completed the assembly process.

2.4.3.2 Team Identification

The manipulation of team identification was done with uniforms and team names. Basketball jerseys with the university's name printed on the front were worn by human teammates, whereas six-month infant clothes which also had the university's name printed on the front were used as uniforms for the robots. Participants wore the uniforms while performing the experimental task and put the uniforms on their robots themselves. Along with the uniforms, participants were asked to come up with a unique team name for the team.

2.4.4 Experimental task

The objective of the task was to deliver five plastic water bottles (236 ml) from point A to point C. I created the task area with cardboards (0.44 meters × 2.91 meters) (see Figure 4).

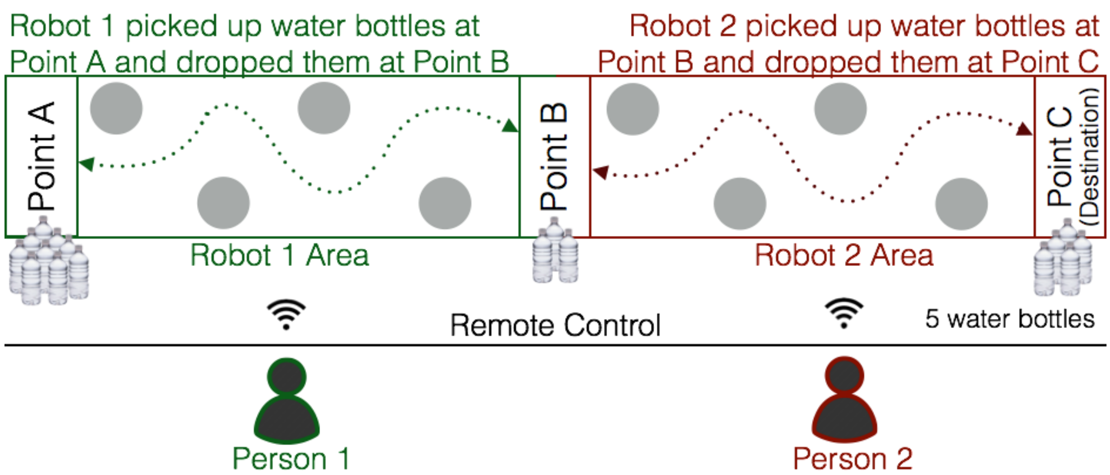


Figure 4 Experimental Task Setting

The first team member used their robot to deliver water bottles from Point A to Point B. The second team member used their robot to deliver the water bottles from Point B to Point C (Final Destination). The task was designed to be interdependent. The first team member was not allowed to deliver water bottles beyond Point B. The second team member could not use their robots to pick up any bottles than were not already at point B. This ensured that one team member could not complete the task without the help and cooperation of the other team member. The task was completed once five water bottles had been delivered from point A to point C. Four cones taped to the cardboard area were used as obstacles.

Each team was informed that they were competing with all the other teams for the best time. They were also informed that there would be an additional monetary award for the three best-performing teams in the entire study. The team with the fastest time would receive $100 and the second and third place teams would receive an additional $40 and $20, respectively. This was in addition to the $20 participation fee given to all participants.

The participants were also informed of the 3 rules of the completion. One, only robots were allowed to touch and move water bottles. Human participants were required to stay outside the work area when operating the remote-controlled robots. Two, robots had to stay inside their designated work area. For example, the first robot was only allowed to move between points A and point B, while the second robot was only allowed to move between point B and C. Three, participants could not swap out robots.

2.4.4 Procedure

The experiment took place in two separate rooms: a treatment room and a task room. The treatment room was used for greeting, briefing, answering questionnaires, and experimental manipulations. The task room was only used for the experimental task.

The experimental procedure began by welcoming participants and providing them with a brief introduction of the study. Participants were then given consent forms. If they consented, they were asked to fill out a short pre-questionnaire on their demographic information. Participants were then provided with both instructions on the experimental task along with instructions about how to operate the remote-controlled robot. Next, a video was shown which went over the same instructions but also provided visual images of the instructions.

After the video, participants who were assigned to the robot-building condition were given the building instructions and asked to build their robot. Participants who were assigned to team identification treatment were asked to select a uniform and team name. In the robot-building and team identification treatment, participants went through the building activity first and then the team identification treatment. In the control group, team members went directly to the next step below.

The experimenter guided participants to the task room. Participants were asked to turn the robots on. Next, participants engaged in two different types of training. First, they were allowed to operate their robots freely for 2 to 3 minutes outside of the work area. Second, they practiced moving 5 water bottles as a team from point A to point C. They were allowed 2 complete trial runs to simulate the actual timed task. Afterward, the timed task was conducted. A stopwatch was used to record the time it took participants to deliver the fifth water bottle to Point C. Once the time tasked was completed, participants were given their time. Typically, the entire task from initial training to the timed run took between 25 and 30 minutes.

When participants were finished with the task, they were guided to the treatment room to complete a post-questionnaire. The experimenter then debriefed, thanked, paid, and dismissed the participants.

2.4.5 Measures

2.4.5.1 Self-extension

The manipulation check for the independent variable robot-building will be done by testing the participants' level of self-extension. Self-extension measures the degree to which participants believe the robot is an extension of themselves (Schifferstein & Zwartkruis-Pelgrim, 2008). Self-extension was measured with 7 items using 5-point Likert scale ('1' strongly disagree to '5' strongly agree) adopted from (Schifferstein & Zwartkruis-Pelgrim, 2008). One example item is "If I never worked with this robot, I would feel like I had lost a little bit of myself". The scale reliability was 0.86.

2.4.5.2 Perceived team identification

The manipulation check for team identification was done by testing the extent to which participants identify themselves with their team. The scale consisted of 6 items including "I had a sense of belonging toward the team" adapted from (Brown, Condor, Mathews, Wade, & Williams, 1986). The scale was measured using a 5-point Likert scale. The scale reliability was 0.94.

2.3.5.3 Interpersonal trust toward robots and human teammates

Interpersonal trust was measured as a network construct. Both team members rated their level of trust in both robots and their human teammate. The items they used to rate their teammate and the two robots were taken from (Jarvenpaa et al., 2004; Mayer et al., 1995). An example item was "I really wish I had a good way to oversee the work of this team member on the task". The scale was measured using a 5-point Likert and was reliable, 0.87.

To calculate the team trust in robots, each team member's rating of both robots were averaged. Next, both team members' scores were averaged together to create a team level measure of trust in robots. The procedure to calculate the measure of team trust in human teammates was similar. The two individual ratings toward each other were averaged to create the team trust in human teammates. In order to aggregate the individual measurement to the team level, I calculated intra-class correlation coefficient (ICC(1)). According to Bliese (2000), values greater than 0.1 justifies aggregation. ICC(1) for trust in robots were 0.26 and 0.29 for trust in teammate, both of which justifies aggregation to the team level.

2.4.5.4 Team performance

Task duration measured in seconds was used as team performance. The task was completed once the fifth water bottle was delivered to Point C.

2.3.5.5 Satisfaction with teamwork

Team satisfaction was measured using 3 items adapted from (Briggs et al., 2003) based on 5-point Likert scale. Items included "Looking back I was pleased with how we complete the team task". The scale reliability was 0.93. ICC(1) for satisfaction with teamwork was 0.8.

2.4.5.6 Disposition to trust

Disposition to trust was included as a control variable. Prior studies have found that individuals different significantly when it comes to their propensity to trust (Robert et al., 2009; Sanders, Oleson, Billings, Chen, & Hancock, 2011). Disposition to trust was measured with 6 items that measured an individual's general predisposition to trust (Mayer et al., 1995; Robert et al., 2009). The items were adopted from (Schoorman, Mayer, & Davis, 1996) and measured using a 5-point Likert scale. Items included "Many people are honest in describing their experience and abilities". The scale reliability was 0.74. ICC(1) for disposition to trust was 0.25.

2.5 RESULTS

All analyses in the following section included disposition to trust as a control variable. In addition, I also tested Negative Attitudes Toward Robots (NARS) scale (Nomura, Kanda, & Suzuki, 2006), participants' gender, age, and previous knowledge on computer, robotics, and Mindstorms as covariates in the analysis based on prior studies (Takayama, Groom, & Nass, 2009). None of these variables had significant effects on the results, and were excluded in the results.

2.5.1 Manipulation Checks

There were two manipulation checks. Self-extension was used as the manipulation check for robot-building. Self-extension was higher in teams that built robots, $M = 3.08$, $SD = 0.52$, than teams that did not, $M = 2.76$, $SD = 0.62$, $t(53) = 2.08$, $p < 0.05$. Perceived team identification was used as the manipulation check for the team identification treatment. Teams exposed to the team identification treatment had significantly higher levels of perceived team identification, $M = 4.28$, $SD = 0.49$, than teams who did not, $M = 3.98$, $SD = 0.51$, $t(53) = 2.26$, $p < 0.05$.

2.5.2 Trust in Robots and Human Teammate

H1, posited the main effects of robot-building on trust, was tested by using ANCOVA. The result showed that trust in robot was significantly higher in teams that built their robots, $M = 2.76$, $SE = 0.13$, than teams who did not, $M = 2.42$, $SE = 0.13$, $F(1, 51) = 4.07$, $p < 0.05$, $\eta p^2 = 0.07$. There was no main effect of disposition to trust, $F(1, 51) = 0.91$, $p = 0.34$, $\eta p^2 = 0.02$. Therefore, H1a was supported.

However, trust in humans was not significantly different between the teams in the robot-building condition, $M = 3.81$, $SE = 0.11$, and those that were not, $M = 3.79$, $SE = 0.11$, $F(1, 51) = 0.13$, $p = 0.72$, $\eta p^2 = 0.002$. Disposition to trust, $F(1, 51) = 1.5$, $p = 0.23$, $\eta p^2 = 0.03$, was not statistically significant. H1b was not supported (see Figure 5).

H2 proposed the main effects of team identification on trust. H2a posited that team identification will increase team trust in robots. The results of ANCOVA revealed that there was no significant difference in team trust in robots between teams in the team identification treatment, $M = 2.68$, $SE = 0.12$, and those that were not, $M = 2.49$, $SE = 0.13$, $F(1,51) = 1.12$, $p = 0.29$. No main effect of disposition to trust was found, $F(1, 51) = 0.91$, p = 0.34, $\eta p^2 = 0.02$. H2a was not supported.

H2b posited that team identification will increase trust in humans. Teams in the team identification treatment had a significantly higher level of trust in humans, *M* = 3.98, *SE* = 0.11, than those teams that were not, *M* = 3.61, *SE* = 0.11, $F(1, 51) = 5.64$, $p < 0.05$, ηp^2 = 0.10. There was no main effect of disposition to trust, $F(1, 51) = 1.5$, $p = 0.23$, $\eta p^2 = 0.03$. H2b was supported (see Figure 6).

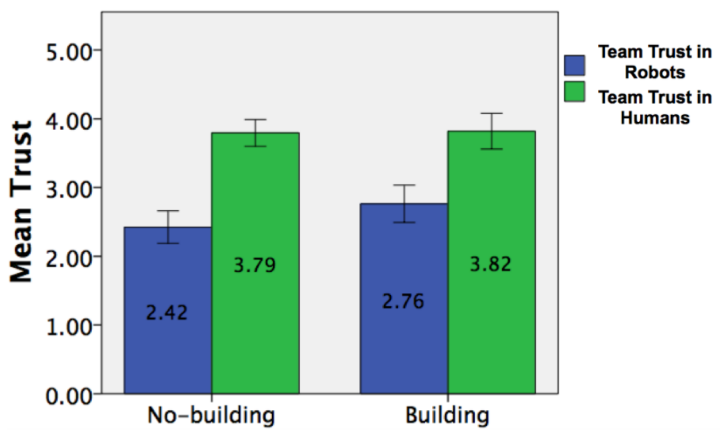


Figure 5 Main effects of robot-building on trust in robots and human teammate (H1a & H1b)

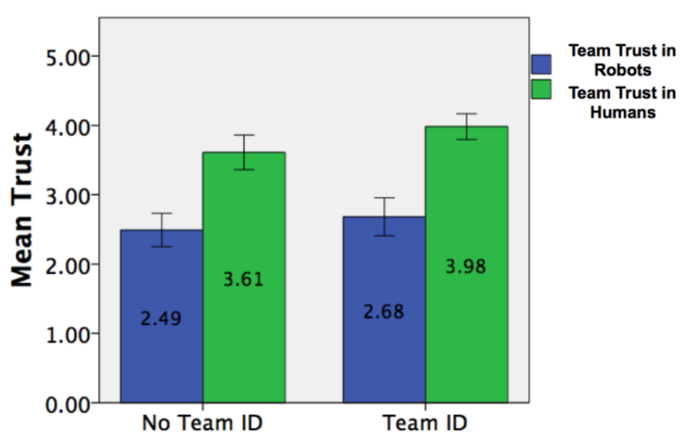


Figure 6 Main effects of team identification on trust in robots and human teammate (H2a & H2b)

H3 proposed that there will be an interaction effect between robot-building and team identification on trust in robots and in humans. More specifically, H3a, that there would be an interaction effect on team trust in robots, was supported. An ANCOVA revealed that a statistically significant interaction effect between robot-building and team identification, $F(1, 50) = 5.06$, $p < 0.05$, $\eta p^2 = 0.09$, on team trust in robots. No main effect of disposition to trust as a covariate was found, $F(1, 50) = 0.24$, $p = 0.63$, $\eta p^2 = 0.01$. A post-hoc analysis using Student's t showed that trust in robots were highest in teams, $p < 0.05$, with both robot-building and team identification. All other comparisons were not significant (see Figure 7).

H3b, the interaction effect on team trust in humans, was also tested. The interaction between robot-building and team identification was not statistically significant, $F(1, 50) = 0.54$, $p = 0.47$, $\eta p^2 = 0.01$. No main effect of disposition to trust was found, $F(1, 50) = 1.82$, $p = 0.18$, $\eta p^2 = 0.03$. Therefore, H3b was not supported.

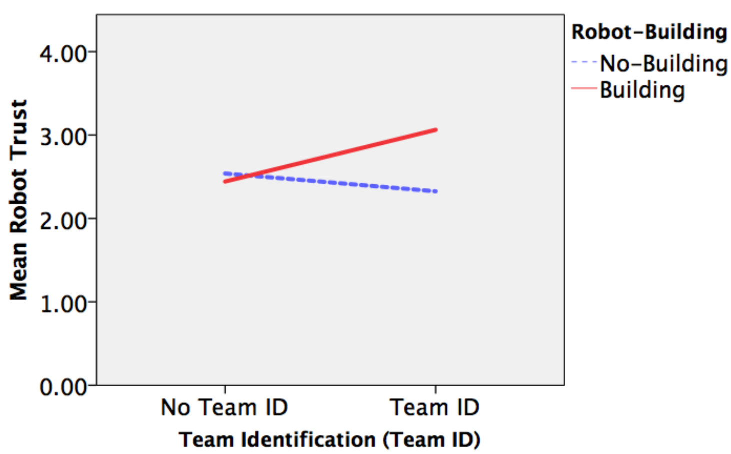


Figure 7 Interaction between robot-building and team identification on trust in robots (H3a)

2.5.3 Trust on Performance and Satisfaction

H4 and H5 were tested using regression controlling for disposition to trust. More specifically, H4a, which stated that team trust in robots would increase performance, was supported. Team trust in robots was a significant predictor of performance, $\beta = -0.27$, $p < 0.05$. Disposition to trust was not a significant predictor, $\beta = -0.039$, $p = 0.78$. However, H4b, which stated that team trust in humans would increase performance, was not supported, $\beta = -0.23$, $p > 0.11$. Disposition to trust, $\beta = -0.02$, $p = 0.90$, had no effect. Therefore, H4b was not supported.

H5 generally proposed that team trust in robots and in humans would increase satisfaction. H5a, which posited that team trust in robots would be significantly related to satisfaction, $\beta = 0.20$, $p = 0.15$, was not supported. There was no effect of disposition to trust, $\beta = 0.211$, $p = 0.12$. H5b, which stated that team trust in humans would increase satisfaction, $\beta = 0.34$, $p < 0.05$, was supported. Disposition to trust had no effect on satisfaction, $\beta = 0.173$, $p = 0.18$. The model fit was $r^2 = 0.16$. The summary of the results of the hypotheses is listed above (see Table 2).

Hypothesis		**Result**
H1a	Robot-building → Team Trust in Robots	Yes
H1b	Robot-building → Team Trust in humans	No
H2a	Team Identification → Team Trust in Robots	No
H2b	Team Identification → Team Trust in humans	Yes

H3a	Interaction effect → Team Trust in Robots	Yes
H3b	Interaction effect → Team Trust in humans	No
H4a	Team Trust in Robots → Performance	Yes
H4b	Team Trust in humans → Performance	No
H5a	Team Trust in Robots → Satisfaction	No
H5b	Team Trust in humans → Satisfaction	Yes

Table 2 Summary of hypothesis testing

2.6 DISCUSSION

The objective of this study was to better understand how to promote team trust in robots and in humans as well as to examine their implications team performance and satisfaction. Results indicated that team trust in robots was important for better team performance while team trust in humans was not. Team trust in human teammates was important for team satisfaction while team trust in robots was not. Taken together, this study suggests that to better understand teams working with robots, one should consider both the relationships between humans and the relationship between humans and their robots.

2.6.1 Implications for Research

First, this study is one of the first to examine effects of trust in both human–human relationship and human–robot relationship at the same time. Research of trust in human–robot teams is heavily focused on trust between a single individual and a single robot (Groom & Nass, 2007; Schaefer et al., 2012). By examining trust toward a team member as well as toward a robot in a human–robot team, this study can enhance our understanding of the influence of trust on human–robot team outcomes by distinguishing different effects of trust between team members and between individuals and their robots.

Second, this study extends ways to foster trust toward robots and team members in human–robot teams. Researchers have identified various antecedents of trust toward robots but have failed to incorporate ways to improve trust toward teammates in human–robot teams with multiple individuals (Groom, Takayama, et al., 2009; Oleson, Billings, Kocsis, Chen, & Hancock, 2011). By examining the influence of robot-building and team identification, this study shed light on ways to facilitate trust in human–robot relationship as well as human–human relationship within a team. Taken together, this study confirms that trust is important to the success of human–robot teams and that understanding of trust in human–robot teams should be approached in a new way by differentiating trust between human team members and robots.

2.6.2 Implications for Theory

This study has several theoretical implications. First, results indicated that team trust in robots increased performance but not team trust in humans. There are several ways to interpret this finding. One way is to conclude that team trust in robots is more important to team performance than team trust in humans. However, I caution against over-generalizing from one study. Another way to view the results is that trust in robots maybe at least as important as trust in teammates to explaining team performance. This implies that trust in robots is an essential element to facilitating performance in teams working with robots (de

Visser & Parasuraman, 2011). However, the impact of trust in robots and human teammates may vary by the context and task (Hancock et al., 2011; J. D. Lee & See, 2004). For example, in high-risk work environments like military and rescue operations, trust between teammates may be more important to the performance of teams working with robots (Groom & Nass, 2007). Future studies should be conducted to identify potential moderators of the relationship between trust in robots, trust in teammates, and team performance.

It should also be noted that I examined a specific type of trust: interpersonal trust between humans and robots. I found meaningful impacts of interpersonal trust in robots on performance of teams working with robots. In doing so, this study supports Groom and Nass (2007), who proposed that humans can view robots more like teammates rather than automated systems and that this relationship can be leveraged to improve teamwork. However, it should be noted that trust in robots defined as reliability and functional dependability may not have the same effect on team performance. Future studies should examine and compare different dimensions of interpersonal trust in robots as well as technology-specific trust dimensions to understand which type of trust better predicts team outcomes.

Second, results of this study show that only trust in one’s teammate increased satisfaction with the team. Trust in robots did not lead to a more a satisfying team experience. This seems to imply that participants could clearly differentiate between the two trusting relationships. One leads to the better performance and the other leads to the better team experience. This could be explained by the fact that unlike robots, their human teammates could reciprocate feelings of trust back when fulfilling team task involving robots. This reciprocation may explain why trust in humans can increase satisfaction while trust in robots did not. If so, it would be important to conduct future studies with robots that had the ability to at least simulate reciprocal feelings of trust back to their operators.

Lastly, this study discovered that different mechanisms may be needed to facilitate team trust in humans and trust between humans and their robots. For example, in this study, robot-building increased trust in robots but not trust between teammates. Team identification alone increased trust between teammates but not toward robots. Team identification only increased trust in robots only when combined with robot-building. When you consider the potential time and cost associated with employing multiple mechanisms to promote each one separately, identifying strong mechanisms that promote both is likely to save money and time. Although I found some overlap between the factors that facilitate trust in robots and trust in teammates, more research is needed to fully identify factors that can achieve both. Taken together, this study asserts that trust is important to the success of teams working with robots and that promoting trust in such teams should be approached by distinguishing when trying to promote team trust in robots versus team trust in humans.

2.6.3 Practical Contributions

In terms of potential implications for design, the findings in this study suggest that team members should be more involved in developing and manufacturing their robots. The greater involvement can lead to higher levels of trust toward their robots and ultimately better performance. The potential is growing for people to become more involved in the design and assembly of robots. New ways of manufacturing are emerging —including rapid prototyping and the use of 3-D printing — that provide more opportunities for team members to be involved. Furthermore, the literature on maker cultures and practice offers rich insights into the benefits of democratizing design and manufacturing processes (Tanenbaum, Williams, Desjardins, & Tanenbaum, 2013).

In addition, the results from this study indicate that designers should consider designing robots that can visually fit in with the entire team to facilitate team identification among their operators. Visual aspects of robots such as exterior casing and logos have the potential to promote trust along with satisfaction in the humans who use those robots. As a result, robot designers might have to work closely with designers of human uniforms, which are often tied to safety requirements. For instance, safety uniforms of humans can be designed by incorporating logos and color schemes of robot design.

2.6.4 Limitations

The present study has several limitations. First, I examined only one type of robot. These robots were not autonomous but instead controlled by their human operators. However, there are robots in varying degrees of autonomy and intelligence, which have been used in teams in different areas. As such, more research is needed to understand if the results can be generalized to other types of robots. Second, I examined one particular type of task. There are many other types of task more or less interdependent and more or less complex than others. Both the level of task interdependency and complexity could have important implications for the results of this study. Finally, like all experimental studies this study was conducted in a controlled laboratory setting and lasted for an hour. The results of this study could be complemented with additional field studies that are normally conducted over a longer period.

2.7 CONCLUSION OF CHAPTER 2

Results of the study in this chapter suggest that team trust in robots and team trust in humans were promoted by different antecedents and had impacts on different outcomes. Robot-building enhanced team trust in robots and but not team trust in humans. Team identification led to more team trust in humans but not team trust in robots. Team trust in robots increased team performance, while team trust in humans increased satisfaction. Results of the study in this chapter demonstrate that we can enhance team performance in teams working with robots by promoting team trust in robots and enhance satisfaction by promoting team trust in humans.

CHAPTER 3
MOTIVATIONAL PROCESS: TEAM POTENCY[3]

3.1 INTRODUCTION

Teamwork with technology has become more prevalent throughout society. Technology-supported teams — teams that rely primarily on technology to perform their work — have now become the norm in many organizations (Robert, 2013). In fact, it is often difficult to imagine teamwork without the use of any type of technology. In many cases, such work requires individuals within teams to employ a technology to accomplish their work on behalf of the team (Fuller, Hardin, & Davison, 2006). The success of these teams is often predicated on the performance of their team members (Alnuaimi, Robert, & Maruping, 2010). Examining the factors that promote individual performance in these teams is critical

[3] The work presented in this chapter was mainly conducted by me, but benefited from significant contributions from Lionel P. Robert and Teng Ye. This work has not been published at a peer-reviewed outlet yet.

to comprehending the factors that facilitate team performance (Robert, 2013). Therefore, in this paper, I focus on individual rather than team performance.

Team potency has long been recognized as a critical facilitator of the performance of technology-supported teams (Fuller et al., 2006), yet many questions regarding its impact remain unresolved. Guzzo, Yost, Campbell, and Shea (1993) were among the first authors to coin the term “team potency.” Team potency is the belief that individuals have in their team’s ability to generally be successful (Guzzo et al., 1993). Despite the importance of team potency, much remains to be learned about the nature and impact it has on the conditions under which it might be beneficial or problematic (Monteiro & Vieira, 2016). The literature on team diversity suggests that the degree of diversity within the team might be one such condition to examine. Team diversity — the differences among team members on a particular attribute — is often vital to understanding the performance of individuals within teams (Van Dick, Van Knippenberg, Hägele, Guillaume, & Brodbeck, 2008). Nevertheless, I found no studies examining the potential moderating role of team diversity on the impact of team potency on team members’ individual performance.

Our lack of knowledge on this topic is problematic for several reasons. First, theoretically it is not altogether clear whether team potency always enhances performance in teams. For example, research on social loafing has shown that individuals tend to put forth less effort when they believe their team as a whole can still perform well in spite of their effort reduction (Alnuaimi et al., 2010). Second, team diversity can also decrease individual performance within technology-supported teams by undermining the effort individuals put forth on behalf of their team (Giambatista & Bhappu, 2010; Hütter & Diehl, 2011). Given this, the importance of team potency on individual performance likely depends on team diversity. Therefore, I argue that team diversity has the potential to be an important moderator of the impact of team potency on individual performance in teams.

To determine whether team diversity influences the impact of team potency, in this study, I examine teams employing robots. Robots are fast becoming a widely used technology within teams (Robert & You, 2014). In most cases, robots are not fully autonomous but are instead operated by humans (Shah et al., 2011; Zawieska & Duffy, 2014). In these teams, each individual participant uses a remote-control robot to perform individual team tasks. From a practical standpoint, robot operators offer a distinct context to examine the relationship between team potency and team diversity. A plethora of research has looked at the link between individual factors and the performance of robot operators (Robert & You, 2014). Yet, the role of team factors like team potency and team diversity remain largely ignored. From an academic standpoint, the study of individuals employing technology within teams is a major inquiry for both information science and information systems scholars. Yet, the study of robots and the individuals who employ them remains relatively unexamined in both research communities. This is disappointing because not only are robots expected to be involved in 30–45% of all work in the United States by 2025 (Sirkin, Zinser, & Rose, 2015), scholars in both areas have the potential to provide theoretical insights on the topic.

Given these gaps in the literature and the importance of team potency, I seek to understand whether team ethnic diversity moderates the impact of team potency on the individual performance and perceptions of viability. Viability is defined as an individual’s willingness to remain a member of the team and is an important predictor of future performance (Bell & Marentette, 2011). To empirically test this research model, I conducted an experimental study with 60 individuals in 30 teams using robots, each team consisting of two robots and two humans. Individual robot operators performed a task by using their remote-control robot. To manipulate team potency, I gave 15 teams and 30 robot operators team training while giving the others only individual training. In this study, I found that team ethnic diversity moderated the impact of team potency on robot operator performance. Team potency increased the individual performance of robot operators in ethnically diverse teams but had no effect on their performance in ethnically homogeneous teams. Team potency was associated with increases in viability in ethnically homogeneous teams but was actually associated with decreases in viability in ethnically diverse teams.

This study contributes to theory in several ways. One, I extend the current thinking on the impacts of team potency on the performance of individuals working in technology-supported teams. I accomplish this by identifying and examining an important contingency variable: team diversity. I provide new insights into when team potency is likely to facilitate or not facilitate the performance of individuals working in technology-supported teams. In doing so, I complement the current research on team potency in technology-supported teams — research that has paid little or no attention to the link between team potency and the performance of team members in technology-supported teams (Fuller et al., 2006; Hardin, Fuller, & Davison, 2007; Lira, Ripoll, Peiró, & González, 2007; Lira, Ripoll, Peiró, & Zornoza, 2013). Yet, understanding individual members' performance often leads to new insights regarding team performance (Alnuaimi et al., 2010; Hütter & Diehl, 2011).

Two, this study demonstrates the potential negative effects of team potency on the viability of ethnically diverse technology-supported teams. Over the years, scholars have amassed an impressive body of research documenting the positive effects of team potency across many different teams and tasks (Fuller et al., 2006; Hardin et al., 2007; Lira et al., 2013). Much less attention has been paid to understanding when these benefits are not likely to materialize, or when they are likely to have negative outcomes (Monteiro & Vieira, 2016). One exception, Lira et al. (2013), found that team potency had a stronger relationship with satisfaction and team identification in teams that relied on communication technology than in face-to-face teams. This study goes further by showing when team potency can actually harm teams. Third, this study extends the literature on team potency in technology-supported teams to include the use of robots. Whereas prior studies on team potency in technology-supported teams have focused exclusively on communication technologies (Fuller et al., 2006; Hardin et al., 2007; Lira et al., 2007, 2013), the current research complements those studies by extending this research to robots.

3.2 BACKGROUND AND RESEARCH MODEL

3.2.1 Team Potency

Team potency refers to team member's collective belief about their team's general capability (Guzzo et al., 1993). The concept of team potency extends from Bandura's self-efficacy concept (Bandura, 1986), which refers to one's belief of their capability to perform well in a particular task. Team potency and team efficacy, as a collective belief of efficacy of one's team, had been used interchangeably (Jung & Sosik, 2003). However, team potency is theoretically different from team efficacy, in that team potency refers to team's capability in general no matter the task, while team efficacy and self-efficacy are task- and domain-specific (Collins & Parker, 2010). Since team potency is a confidence regardless of a particular task, the concept is viewed as a prospective evaluation of team capability in the future, rather than a retrospective based on the previous experience (Akgün, Keskin, Byrne, & Imamoglu, 2007).

The shared belief includes confidence that the team will successfully accomplish team goals and motivation to perform well in tasks (Pearce, Gallagher, & Ensley, 2002). Team potency, as the shared belief of capabilities of their members, is a basis of better teamwork among team members such as trust and communication (Howell & Shea, 2006; Schaubroeck, Lam, & Peng, 2011). Team potency, thus, often relates to better effectiveness in teams (Gully et al., 2002; Hu & Liden, 2011). Research in general shows that team potency is a predictor of productivity and satisfaction of team members in various settings (Campion, Papper, & Medsker, 1996; Gully et al., 2002). Team potency of software development teams was reported to increase the success of their product and shorten the duration of the development (Akgün et al., 2007). In addition, team potency has been found to increase the performance of virtual teams (Hardin, Fuller, & Valacich, 2006).

3.2.2 Team Ethnic Diversity

Team ethnic diversity can be defined as the extent to which team members vary in their ethnic background. Ethnic diversity in teams can both increase and decrease team performance (Robert, 2013; Windeler, Maruping, Robert, & Riemenschneider, 2015). Ethnic diversity provides teams with unique information that facilitates more creative solutions and leads to better decisions (Giambatista & Bhappu, 2010; Shin, Kim, Lee, & Bian, 2012). However, ethnically diverse teams often have weaker social–emotional bonds (Newell, Maruping, Riemenschneider, & Robert, 2008; Robert, 2013), have more conflicts(Jehn & Bezrukova, 2010; C. Lee & Farh, 2004), and are less motivated to work together (Gully et al., 2002), all of which explain why ethnic diversity can sometimes lead to lower performance and lower satisfaction (Harrison, Price, Gavin, & Florey, 2002; Robert, 2013).

This study looked at ethnic diversity for several reasons. First, ethnic diversity has been identified as an important predictor of performance in many types of teams across many settings (Jackson & Joshi, 2011 for review). Second, ethnic diversity has been used to explain performance in teams enabled by technology (Giambatista & Bhappu, 2010; Robert, 2013). Third, ethnic diversity is one of the most common types of diversity across many societies (Ely, Padavic, & Thomas, 2012). Finally, it is becoming more common for teams using robots to be ethnically diverse (Makatchev, Simmons, Sakr, & Ziadee, 2013; Robert & You, 2014).

In this study, I propose a research model, in which team ethnic diversity should moderate the impact of team potency on individual robot-operator performance (Figure 8). Ethnically diverse teams often have weaker social–emotional bonds (Newell et al., 2008; Robert, 2013) and are less motivated to work together (Gully et al., 2002), all of which explains why ethnic diversity can sometimes lead to lower performance and lower satisfaction (Harrison et al., 2002; Robert, 2013). However, homogeneous teams can develop unwarranted high levels of team confidence and believe that they are far more capable of accomplishing objectives than they really are (Kellett, Humphrey, & Sleeth, 2000). Individuals tend to project positive attributes like competency onto others like them because it reinforces the positive perceptions they have about themselves (Whyte, 1998).

On the other hand, team potency is likely to lead to better performance in ethnically diverse teams. Members of diverse teams often believe their teammates are not as capable as themselves because they are different. This often results in team members believing their team is not capable. This in turn leads these team members to put forth less effort in their team activities (Choi & Kim, 1999). Consequently, performance in diverse teams falls short because of a lack of confidence (Ely et al., 2012). However, if diverse teams can find a way to overcome such issues, they should perform as well as or better than more homogeneous teams (Harrison et al., 2002). As such, it is very likely that when confidence is instilled in individuals in ethnically diverse teams they should be willing to exert more rather than less effort to accomplish their team objectives. Effort is a strong predictor of individual performance in teams (De Jong & Elfring, 2010; Fuller et al., 2006). Therefore, team potency should be associated with an increase in performance among individuals in ethnically diverse teams. Thus, I hypothesized that:

> *Chapter 3-H1) When ethnic diversity is high, team potency increases individual performance; however, when ethnic diversity is low, team potency decreases individual performance.*

Team viability is both an important and relevant concept in understanding teamwork (Balkundi & Harrison, 2006). Team viability represents an individual's general intention to either remain a member of the team or consider re-joining the team in the future (Bell & Marentette, 2011). Team viability is often associated with an individual's intention to continue to perform well on behalf of the team (Balkundi, Barsness, & Michael, 2009). Therefore, team viability can be viewed as both an indication of team members' assessment of their past experience with their team and their potential performance with the team in the future.

Team potency has been associated with increases in a team's socio-emotional outcomes like cohesiveness and with decreases in anxiety and stress (Gil, Rico, Alcover & Barrasa, 2005). This is because when members are more confident in their team's ability to succeed they often have a more positive experience with their team members (Gibson & Earley, 2007). Positive team experiences should increase the likelihood that individuals want to remain a member of the team. Therefore, team potency should be positively related to team viability.

The impact of team potency on team viability should be stronger because ethnically diverse teams have more challenges to overcome. In general, demographic diversity among team members has been shown to decrease socio-emotional outcomes like team viability (Webber & Donahue, 2001). This is often explained by the difficulty team members in diverse teams have bonding with their teammates (Newell et al., 2008; Robert, 2013). Individuals tend to have a much more positive attitude toward teammates who are similar rather than dissimilar to them (Van Dick et al., 2008). This positive attitude can lead to team members enjoying their interactions more with others who are like them (Harrison et al., 2002). Team potency should be needed more in diverse teams to help individuals in these teams overcome their challenge. Therefore, team potency should be more important to helping diverse teams overcome these negative effects. When this occurs, the impact of team potency on team viability should be stronger. Therefore, I hypothesized that:

Chapter 3-H2) When ethnic diversity is high, team potency has a stronger impact on viability than when ethnic diversity is low.

Taken together, it is likely that ethnic diversity plays a moderating role in technology-supported teams by altering the impact of team potency on the performance of team members and viability. A theoretical research model illustrates the cross-level moderation effects of team ethnic diversity on outcomes of teams (Figure 8).

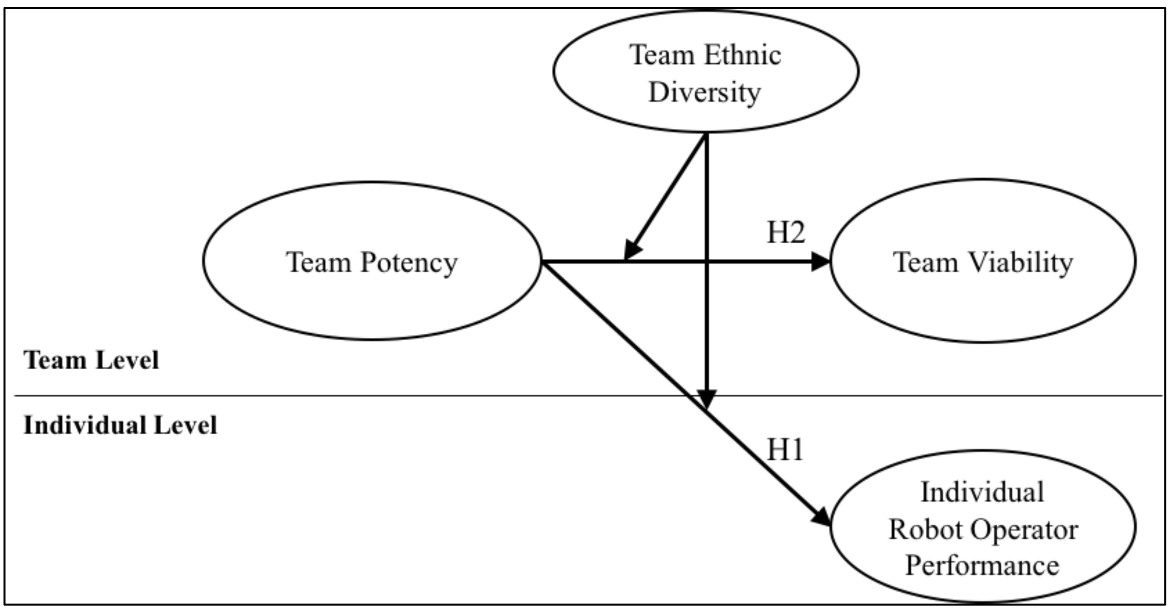


Figure 8 Research Model

3.3 METHOD

3.3.1 Participants and teams

I recruited 60 participants from a Midwestern university in the United States. A team consisted of two participants, each employing their own robot to accomplish a team task.

Participants were randomly assigned to a team to avoid creating teams with members who knew each other prior to the experiment. Nonetheless, to ensure this, I asked participants after the study whether they knew their assigned teammate. One team among the 30 teams indicated that teammates had known each other before the experimental session. I excluded this team in the analysis, which resulted in 58 individuals in 29 teams.

The mean age was 23 years (standard deviation [*SD*] = 4.33 years) and 22 were male (37.9%). The sample consisted of 35 Asian (60.3%), 17 White (29.3%), five Black or African American (8.6%), and one American Indian/Alaska Native (1.7%). Among the 29 teams in total, seventeen teams (58.6%) were ethnically diverse.

3.3.2 Robots

Each team member employed a LEGO Mindstorms EV3 to accomplish their part in the team task. These robots were modified (See Figure 9) and programmed to grasp small objects and were controlled with an infrared remote controller. The robots were capable of moving forward, backward, and side-to-side. The robots said “okay” when grasping and releasing objects. The robots were identical.

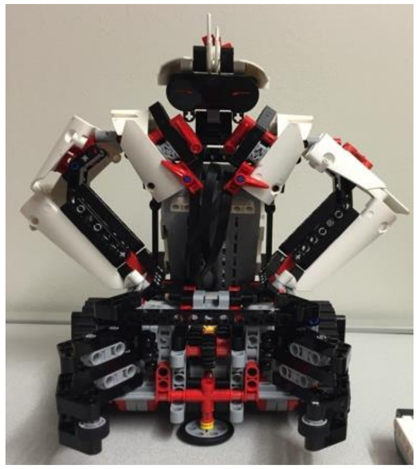


Figure 9 A Robot Used in the Experiment

3.3.3. Experimental Manipulation

Team training was employed as a method of manipulating team potency into two levels: high team potency condition and low team potency condition. Several studies have found that team training fosters team potency (Gibson, 2001; Gully et al., 2002). Training together promotes team potency by instilling a sense of confidence as a team improves (Wolf, Way, & Stewart, 2010). To manipulate team potency, teams in the high-team-potency condition had team training in which both individuals practiced how to control their robot together in the same room. In this condition, two participants went through a two-minute free training for controlling the robots and two practice runs of the experimental task without recording their performance in the same room. By doing so, team members were able to see how others were performing in the practice runs and have a better sense of how well their teammate would perform in the main task. However, for teams in the low-team-potency condition, two individuals in a team were sent to two separate rooms to practice how to control their robot separately, without seeing the other's performance. The two team members went through the practice runs without recording performance separately in the separate rooms. The separation prevented them from seeing each other's performance during the practice, so that they did not have the visibility and knowledge team member's ability in the main task.

3.3.4 Experimental Task

The experimental task required team members to employ their robots to move five small water bottles from point A to point C as quickly as possible (see Figure 10 for the task course layout). The team task consisted of two parts that were sequentially connected. Part one required the first robot operator to move his or her water bottle from point A to point B. Part two required the second robot operator to move the water bottle at point B to point C. Both operators sequentially collaborated with each other to move five water bottles from point A to point C, through point B.

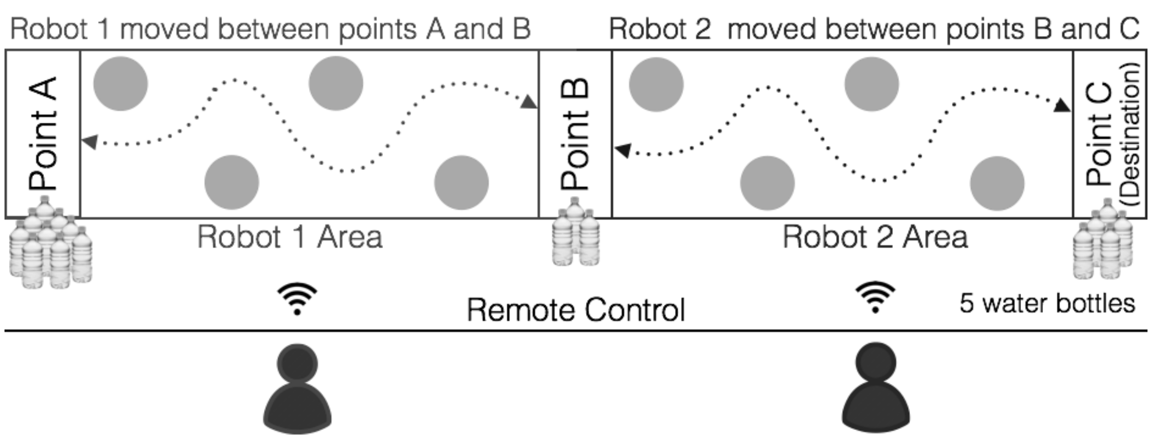


Figure 10 Experimental Setting

The task was taken from prior literature (Robert Jr & You, 2015; You & Robert Jr, 2016) and allowed us to achieve several objectives. First, I designed the task to represent the typical use of robots in the context of teamwork. In many cases, operators employ robots to move physical objects from one point to another. Construction teams employ remote-control robots to take down and put up structures. Second, the task was designed to be a collaborative, interdependent team task. Individual operators were only allowed to move water bottles using their robot and were not allowed to touch or move water bottles themselves. Therefore, one team member could not complete the task alone.

Teams were informed that the task was a team-based competition and that team performance would be determined by the time it took to move all five water bottles from point A to point C. They were also informed that the three best-performing teams would receive prize money: $100 for the team with the fastest delivery time, $40 for the second-place team, and $20 for the third-place team. Regardless of performance, all operators received $20 for participation.

3.3.5 Experimental Procedure

Participants signed up for a session using an online anonymous sign-up sheet. Participants did not know their teammate in advance of coming to the behavioral laboratory. Participants were randomly assigned to a team, and teams were randomly assigned to one of two conditions: individual training or team training. Participants were also unaware of which treatment condition they were assigned.

Upon arrival, participants were greeted and asked to fill out a consent form. Next, they took a pre-questionnaire using a laptop. The pre-questionnaire included questions regarding their gender, nationality, and ethnicity. Then, participants were provided with written instructions about the experimental procedure and task. After reading the task instructions, the participants watched a 3-minute video that provided a step-by-step visual tutorial on the experimental task. Then, they were provided with instructions on how to employ their robot using their remote control. After reading the instructions, they watched a 2-minute video tutorial on how to use the remote control.

Next, participants were guided to another room to practice the experimental task. Participants assigned to the low team potency condition trained alone in separate rooms and were allowed to freely play with their robot individually for two minutes. Individuals assigned to the high team potency condition were allowed to have the two-minute training and practice together in the same room. Once participants finished their training based on their treatment condition, they were guided to another room, where they filled out the second questionnaire, which included questions on team potency.

After participants finished the second questionnaire, they were guided to another room to perform the task. I used stopwatches to measure the performance of each individual robot operator. Team member 1's performance was determined by averaging the time it took to move each water bottle from point A to point B. Similarly, the performance of team member 2 was determined by averaging the time it took to move each water bottle from point B to point C. the "Individual performance" portion of the "Measures" section provides additional details regarding the measurement of individual performance. After the team completed the task, participants were guided to another room to fill out the final questionnaire, which included questions related to team viability. After participants completed the final questionnaire, they were debriefed, paid, and dismissed.

3.3.6 Measures

3.3.6.1 Control Variables

3.3.6.1.1 Demographic Diversity

I measured gender and nationality of individual operators along with their age. This was done because ethnic diversity is the construct of interest in this study and it was necessary to control for impacts of other diversity dimensions. Team gender diversity and team national diversity were calculated with Blau's heterogeneity index (Blau, 1977). Blau's H index has been used in research of teamwork to capture heterogeneity of teams in different dimensions including ethnicity (Robert, 2013).

Blau's index H is described as:

$$H = 1 - \sum p_i^2$$

where p_i is the proportion of group members in each of the I categories. Based on the index, the values for diversity were either "0" when two team members were in the same category or "0.5" when they were in different categories.

3.3.6.1.2 Individual Robot-specific Self-efficacy

I included additional control variables. First, I measured individual-level robot self-efficacy to capture the degree to which individual participants believed in their ability to complete the task using the robot. Individual self-efficacy contributes to one's motivation and performance and often influences individual performance in teamwork (Monteiro & Vieira, 2016). Research also shows that individual's ability and the belief in the ability are associated with individual and team performance (Gully et al., 2002). Therefore, it is important to control for the impacts of individual team members' belief in their specific ability of using robots on their performance. The scale of individual robot self-efficacy consisted of seven items adapted from Compeau, Higgins, and Huff (1999) that were measured using a 5-point Likert scale (1 = *strongly disagree* to 5 = *strongly agree*). One example of the items was "I can complete this task using this robot even if I have never used a robot like this before." Another example in the index was "I can complete this task using this robot even if there was no one around to tell me what to do as I go." The reliability of the scale (Cronbach's α) was 0.88.

3.3.6.1.3 Knowledge on Relevant Technologies

In addition, I measured each participant's general knowledge of technology to rule out alternative explanations of individual skills and experience of relevant technologies and LEGO products. This construct was captured by summing up three self-report questions about relevant technology fields to robots — computer programming, robotics, and artificial intelligence, all measured based on a 5-point Likert scale (1 = *none* to 5 = *professional*). Finally, I measured each participant's experience with LEGO products. This construct was measured by the sum of two items — LEGO products in general and Mindstorms — based on a 5-point Likert scale (1 = *never* to 5 = *all of the time*).

3.3.6.2 Team Ethnic Diversity

In this experiment, I defined ethnicity as the racial category participants self-reported. Team ethnic diversity was calculated using Blau's heterogeneity index (Blau, 1977). This is consistent with the literature on work groups in which ethnicity was used to represent physical differences (Giambatista & Bhappu, 2010; Harrison et al., 2002).

3.3.6.3 Team Potency

I measured team potency to capture the degree to which participants believed in the team's general ability to perform well. The scale of general team potency consisted of seven items that were derived from Guzzo et al. (1993). They were measured using a 5-point Likert scale (1 = *strongly disagree* to 5 = *strongly agree*). The example items included "We believe we can succeed at most any endeavor to which we set our mind", "Even when things are tough, we will perform quite well", and "We are confident that we can perform effectively on many different tasks." The reliability of the scale (Cronbach's α) was 0.85. Team potency was a team-level construct obtained through individual participants by averaging scores of the two participants on each team. The intra-class coefficient (ICC) score was used to justify this aggregation. Typically scores over 0.1 provide justification for aggregation (Bliese, 2000). The ICC score for team potency in this study was 0.49, justifying the aggregation.

3.3.6.4 Individual Performance

I measured performance of individual operators separately by calculating the average time per trip for an individual robot operator to finish delivering all five of his or her water bottles. The performance of robot operator 1 was the average duration of his or her five round trips of grabbing a water bottle at point A, dropping it at point B, and returning to point A. Similarly, the performance of robot operator 2 was the time it took to travel the path B-C-B.

I took several additional measures to avoid spillover effects between robot operators. Spillover effects are the additional wait time that the second robot operator incurs from waiting on the first robot operator to deliver a water bottle to point B. In order to remove this idle time from robot operator 2's performance, I used separate stopwatches for each operator. The stopwatch for the second robot operator was stopped when the robot returned to point B and restarted when another bottle arrived to be moved to point C.

3.3.6.5 Viability

Viability captures individuals' belief in the degree to which they are willing to remain and to continue to perform on the team (Bell & Marentette, 2011). The scale consisted of three items adapted from Balkundi and Harrison (Balkundi & Harrison, 2006) and measured using a 6-point Likert scale (1 = *strongly disagree* to 6 = *strongly agree*). The items included, for example, "This team including the robots would perform well together in the future" and "If we were assigned to another project, I am confident that this team including the robots would work well together." The reliability of the scale (Cronbach's α) was 0.95. The ICC score for team viability in this study was 0.43, justifying the aggregation.

3.4 RESULTS

3.4.1 Manipulation Check

Results of a *t*-test showed that team potency was higher in the teams that underwent team training (i.e. high team potency condition, $M = 4.01$, $SD = 0.35$) than the teams that did not (i.e. low team potency condition of individual training, $M = 3.69$, $SD = 0.36$). The manipulation of team potency was successful in terms of making a significant difference in the perception of team potency between the conditions ($t(27) = 2.41$, $p < 0.05$).

3.4.2 Measurement Validity

Convergent and discriminant validity of constructs included in the research model were evaluated by a factor analysis. There were no cross-loadings above 0.4 between two constructs (Table 3). Most items loaded at the level of 0.7 or above on their construct; the fifth item of individual robot self-efficacy did not. This item loaded at .68 and was included because of the face validity of the construct. In addition, I examined correlations among model constructs (Table 4). All constructs' average variance extracted (AVE) were above 0.50, which demonstrates convergent validity of constructs (Fornell & Larcker, 1981). The correlations among constructs were smaller than the square root of the AVEs of each construct (Table 4), demonstrating discriminant validity.

Because the model consisted of team-level and individual-level constructs, I performed a multilevel analysis. This multilevel analysis was conducted using the SPSS 22 mixed model. Model 1 is the main effect model of team potency and team ethnic diversity. Model 2 indicates the moderation between team potency and team ethnic diversity on the performance of robot operators (Table 5) and viability (Table 6).

	Team Potency (TP)	Individual Robot-specific Self-efficacy (IRSE)	General Knowledge of Technology (GKT)	Previous LEGO Experience (PLE)	Viability (VI)
TP 1	0.77	0.10	0.15	0.02	0.01
TP 2	0.80	0.02	0.08	0.02	0.03
TP 3	0.81	0.01	0.11	0.27	0.07
TP 4	0.86	0.00	0.04	0.01	0.07
TP 5	0.90	0.03	0.03	0.06	0.21
TP 6	0.79	0.10	0.11	0.07	0.16

TP 7	0.86	0.06	0.01	0.03	0.32
IRSE 1	0.05	0.87	0.22	0.01	0.05
IRSE 2	0.01	0.78	0.13	0.12	0.06
IRSE 3	0.04	0.84	0.20	0.05	0.01
IRSE 4	0.00	0.75	0.02	0.27	0.11
IRSE 5	0.09	0.68	0.40	0.04	0.23
IRSE 6	0.04	0.81	0.05	0.14	0.00
IRSE 7	0.15	0.77	0.04	0.08	0.15
GKT 1	0.00	0.12	0.88	0.11	0.01
GKT 1	0.14	0.23	0.90	0.11	0.00
GKT 1	0.16	0.18	0.88	0.04	0.00
PLE 1	0.05	0.17	0.16	0.76	0.14
PLE 2	0.03	0.01	0.17	0.84	0.21
VI 1	0.13	0.03	0.04	0.10	0.89
VI 2	0.12	0.04	0.00	0.13	0.92
VI 3	0.14	0.06	0.05	0.17	0.86

Note: Values in bold indicate items loading at the 0.7 or above on each of their constructs.
Extraction method was Principal Component Analysis using Varimax with Kaiser Normalization as a rotation method.

Table 3 Factor Loadings

	Mean	SD	TP	IRSE	GKT	PLE	VI	IP
Team Potency (TP)	3.86	0.38	0.83					
Individual Robot-specific Self-efficacy (IRSE)	3.96	0.70	-0.09	0.79				
General Knowledge of Technology (GKT)	7.14	2.94	-0.23	0.35**	0.89			
Previous LEGO Experience (PLE)	3.67	1.10	0.02	-0.13	0.03	0.80		
Team Viability (VI)	4.66	0.81	0.06	0.02	-0.01	-0.07	0.89	
Individual Performance (IP)	50.19	12.11	-0.04	-0.06	-0.12	-0.25	0.18	NA

**p < 0.01; N = 59; Values on the diagonals represent the square root of the AVE for each factor.

Table 4 Descriptive Statistics and Correlations among Constructs

3.4.3 Test of Hypotheses

Hypothesis 1, which posited that team ethnic diversity moderates the impact of team potency on the performance of individual robot operators, was supported ($\beta = -5.84$, $p < 0.05$). Results of Model 2 in Table 5 explained 76.42% of the individual performance of robot operators. As seen in Figure 11, team potency increases individual performance of robot operators when teams are ethnically diverse but makes no difference in individual performance when teams are ethnically homogeneous. The performance in this study was measured by recording time to complete the task; shorter time indicates better performance.

Independent Variable	Individual Robot Operator Performance		
	Model 1	Model 2	Model 3
Control Variables			
Age	-0.05	-0.04	0.00
Team Gender Diversity	-1.36	-2.26	-2.10
Team Nationality Diversity	1.23	1.41	3.32
Individual Robot-specific Self-efficacy	-1.26	-1.15	-0.83
General Knowledge of Technology	-0.46	-0.50	-0.60
Previous LEGO Experience	-1.36	-1.31	-1.45
Main Effects			
Team Potency		-2.11	-6.64*
Team Ethnic Diversity		-0.39	-0.07
Interaction Effect			
Team Potency × Team Ethnic Diversity			-5.84*
-2 Restricted Log Likelihood	411.97	404.11	396.74
df Change	6	2	1

R_1^2	11.11	11.56	76.42
Change in R_1^2		0.45	64.86
*: $p < 0.05$; Team Gender Diversity, Team National Diversity, Team Potency, and Team Ethnic Diversity are standardized.			

Table 5 Results of Multilevel Analysis for Performance of Individual Robot Operators

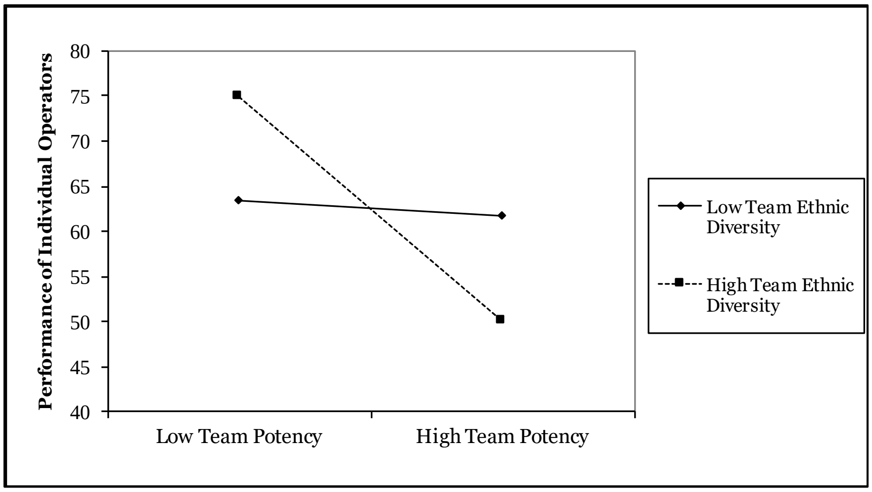


Figure 11 The Moderation Effect Between Team Potency and Ethnic Diversity on Performance of Individual Robot Operators

Hypothesis 2 posited that team ethnic diversity moderates the impact of team potency on viability. Team viability was measured at the team level, which required the use of ordinary least squares regression analysis at the team level, including control variables based on the model. The results provided evidence of a moderation effect (β = -0.29, p = 0.05) but in the opposite direction of the hypothesis (Table 6). That is, team potency decreased rather than increased viability in ethnically diverse teams.

Independent Variable	Viability		
	Model 1	Model 2	Model 3
Control Variables			
Team Age	0.00	0.00	0.02
Team Gender Diversity	-0.03	-0.01	-0.02
Team Nationality Diversity	-0.18	-0.17	-0.15
Team Robot-specific Self-efficacy	0.10	0.09	0.06
Team Knowledge of Technology	-0.05	-0.05	-0.10
Team Previous LEGO Experience	-0.11	-0.13	-0.12
Main Effects			
Team Potency		0.04	-0.20
Team Ethnic Diversity		-0.04	-0.06
Interaction Effect			
Team Potency × Team Ethnic Diversity			-0.29
R^2	0.14	0.14	0.30
Change in R^2		0.01	0.12
F	0.57	0.67	4.35
*: $p < 0.05$; Team Gender Diversity, Team National Diversity, Team Potency, and Team Ethnic Diversity are standardized.			

Table 6 Results for Viability

3.5 DISCUSSION

In this research, I sought to understand whether team ethnic diversity can moderate the impact of team potency on the performance and perceptions of viability team members. Results from the laboratory experiment provide two overarching findings. One, team potency increased individual performance in ethnically diverse teams but had no effect on the performance of individuals in ethnically homogeneous teams. Team potency decreased robot operators' perceptions of viability in ethnically diverse teams but increased it in ethnically homogeneous teams. Below, I discuss the implications of these findings.

3.5.1 Implications for Research

This study has several implications for research. First, this study contributes to theory on team potency by specifically identifying and examining team diversity as an important contingency variable. Incorporating team diversity in the nomological network of team potency is an important contribution because, as the results show, the effect of team potency on individual performance varies greatly by the level of team diversity. Team potency facilitated the performance of individuals in ethnically diverse teams but had little impact on the performance of individuals in homogeneous teams. This may imply that the effects of team potency on individual performance are directly tied to the diversity of the team.

I should also note that I did not find that team potency led to negative effects in ethnically homogeneous teams. One explanation is that homogeneous teams did not need to believe in their team to perform well. Their performance may have been driven by the need to maintain a distinctive team identity with their similar teammate. The need to maintain a distinctive team identity can be a source of motivation itself that encourages individuals to put forth greater effort on behalf of their team (Robert, 2013). As such, team potency would have little effect on performance in these teams. Future research is needed to further explore the potential relationship between factors like distinctive team identity and team potency.

Two, contrary to the exceptions team potency was associated with decreases in the perceptions of viability and not increases. Individuals in ethnically diverse teams were less likely to want to remain a member of their team when team potency was high. This finding is contrary to what I expected and much of the prior literature. Several studies have found that team potency was positively related to satisfaction a similar outcome (Lester, Meglino, & Korsgaard, 2002; Lira et al., 2007).

From a theoretical perspective, the very same contingency variable — team diversity — that enhances individual performance also seems responsible for creating the conditions that lead to the negative effects of team potency on viability. From a practical perspective, there may be tradeoffs between facilitating more viability versus promoting performance. Team potency may come at a cost to the relationships between diverse others. This becomes apparent when individuals in ethnically diverse teams with low team potency had the highest level of viability (see Figure 12). These represent the individuals in the ethnically diverse teams who did not have the training. Apparently, the interaction needed to promote team potency during team training may have led to decreases in viability.

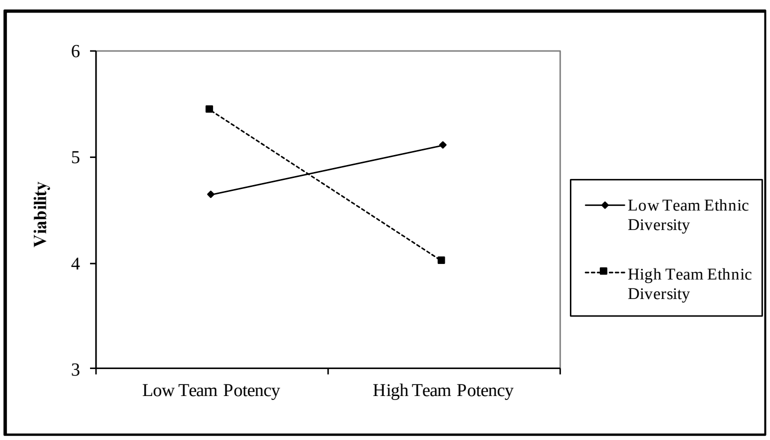


Figure 12 The moderation effect between team potency and ethnic diversity on viability

Finally, this study contributes to the literature on technology-supported teams by examining the employment of robots. Unlike previous studies that focus on communication technology, I focused instead on the use of robots because there are many situations where robot operators work in team settings (H. Jones & Hinds, 2002; Yanco & Drury, 2004). Therefore, it is vital for researchers to consider the use of robots as a new team technology when identifying new theoretical mechanisms that explain the performance of technology support teams. To that end, I believe information science and information systems scholars can contribute to this pursuit. I hope this study can help both sets of scholars to begin to engage in this endeavor.

3.5.2 Implications for Practice

This study has implications for practice. Teams and their managers should understand that promoting team potency does not always lead to better performance. The results show that although team potency increased individual performance in ethnically diverse teams, it had no positive effects on performance in ethnically homogeneous teams. This informs managers of teams using robots to be aware of any hubris or overconfidence, especially when operators are from different backgrounds. In such cases, teams using robots in dangerous situations with high stakes might be wary of heightening team potency (Groom & Nass, 2007). For instance, many teams using robots are using robots in extreme situations, such as special weapons and tactics (SWAT) teams and explosive ordnance disposal (EOD) teams (Carpenter, 2013; Dole et al., 2013; H. Jones & Hinds, 2002). Because individual performance can be directly related to human life and safety, overconfidence through heightened team potency should be avoided to maintain high performance of individual operators.

3.5.3 Limitations and Future Research

This study has several limitations. First, I employed an experimental study in a controlled environment. Although the goal was to increase the internal validity of the study, I acknowledge the limitations with external validity. Future research can be conducted in a field environment to complement the research. Second, teams in this study consisted of two people and two robots. Teams using robots in reality vary in size. Future research should examine the relationship between team potency and performance of operators in teams of different sizes. Third, this study looked at one type of diversity — ethnicity. However, there are different types of diversity such as gender, age, and education level. The moderating impacts of diversity may differ by the type of diversity. Future research can be conducted to examine this issue by varying the type of team diversity.

3.6 CONCLUSION OF CHAPTER 3

Although team potency has been shown to be a strong predictor of teamwork, we know very little about the contingency variables that influence its impact. This chapter reports that team diversity is such a variable. The study in this chapter was conducted with individuals working with robots. Given the growing number of teams using robots, results of this study are important for both research and practice.

CHAPTER 4
COGNITIVE PROCESS: SIMILARITY[4]

4.1 INTRODUCTION

Robots are increasingly deployed in workplaces where they are used to collaborate with humans in many areas. NASA has developed a humanoid robot that is capable of fulfilling space missions autonomously in collaboration with human astronauts (Nichols, 2016). Logistics and manufacturing fields have pioneered ways to employ intelligent robots in their assembly lines, fulfillment of logistics, and product inspections (Knight, 2015). These robots are designed to perform mundane tasks involved in human jobs and are often treated as colleagues working in proximity with human workers. Despite the rapid increase in the

[4] The work presented in this chapter was mainly conducted by me, but significantly benefited from Lionel P. Robert's contributions. This work has not been published at a peer-reviewed outlet yet.

numbers of robots working with humans, little is known about what contributes to the development of human-robot teams and what leads people to work with robots willingly.

Understanding what leads teams to work with robots is important, but not simple. On the one hand, as robots are being deployed to many areas to work with humans, people have begun to welcome robots into their workplace and to take advantage of robotic teammates (Dautenhahn et al., 2005). This is because robots are often more efficient and capable of enduring more physically demanding and repetitive tasks than humans. On the other hand, there is also a growing concern that robots are taking jobs away from people (Takayama, Ju, & Nass, 2008). This concern has already started to prevail among blue collar workers whose jobs involve physical labor (Miller, 2016). The fear of robots as job-killers may engender negative attitudes toward robots, which worsen the interaction and performance of teams working with robots (Nomura et al., 2006).

To understand attitudes toward robots, I turn to the similarity between an individual and a robot. The degree of similarity has been a significant predictor of quality and outcomes in interpersonal relationships (Byrne, 1961; Singh et al., 2015). The similarity between individuals and their team members often determines how people perceive others, and thus has been a good predictor of work outcomes in dyads and other teams (Goldberg, 2005; Harrison & Klein, 2007). Based on self-categorization theory, individuals tend to feel more attracted to and have more positive attitudes toward people whom they perceive to be similar to themselves (Haslam, Powell, & Turner, 2000; Van Dick et al., 2008). In addition, research on teamwork and diversity has found that similarity among individuals can result in positive collaboration outcomes and attitudes toward one another (Ely et al., 2012). For instance, similarity has been known to predict individuals' trusting intentions and trusting behaviors not only toward other team members but also toward technologies, including e-commerce websites (Gefen, 2000; Luhmann, 2000; McKnight, Choudhury, & Kacmar, 2002; Singh et al., 2015).

The effects of similarity have also been used to explain individuals' interaction with robots (Andrist, Mutlu, & Tapus, 2015). Research shows that individuals report higher levels of liking and emotional attachment toward service robots and domestic robotic pets that manifest a similar personality to theirs (K. M. Lee, Peng, Jin, & Yan, 2006; Woods et al., 2007). However, these findings cannot inform teams that use and work with robots for collaboration. Specifically, there is a lack of evidence regarding what dimensions of similarity might be at play, as well as their subsequent effects on team outcomes in collaboration between a robot and an individual. Moreover, examining one dimension of similarity, such as robots' personality, can hardly inform how similarity influences teamwork with robots when there are variations in more than one characteristic (Tsui, Egan, & O'Reilly III, 1992). Therefore, more attention should be paid to how various dimensions of similarity are associated with an individual's perception of a robot and attitude toward working with the robot.

In this study, I investigate two dimensions of similarity between a robot and an individual: surface-level similarity and deep-level similarity. Surface-level similarity refers to characteristics that are explicitly noticeable and visibly identifiable, such as gender, age, and ethnicity (Fisher, Bell, Dierdorff, & Belohlav, 2012). Most robots deployed in our everyday lives are physically embodied and thus manifest some human attributes (K. M. Lee, Jung, et al., 2006). The physical embodiment of the robot leads people to perceive similarity in terms of several attributes (Rae, Takayama, & Mutlu, 2013). For instance, gender, as one aspect at the surface level, is one of the most salient and robust characteristics that yield a perception of similarity (Tay, Jung, & Park, 2014; Van Knippenberg, De Dreu, & Homan, 2004).

On the other hand, deep-level similarity is related to similarity characteristics that are not often visible and take time and interaction to notice, such as personality, value, knowledge, and attitudes (Harrison et al., 2002). Research shows that people can perceive personality and attitudes in robots based even on simple conversational cues and behaviors (K. M. Lee, Peng, et al., 2006; Woods et al., 2007). Because robots are becoming more intelligent and more capable of communicating with people in natural ways, it will become commonplace for people to tend to believe that robots can manifest values, opinions, and personality traits (Takayama et al., 2008). This warrants an investigation of the impacts of deep-level similarity as well as surface-level similarity. Specifically, this study employs a situation where a robot has the same or a different opinion as a person in a collaborative context, a type of deep-level similarity.

However, the effects of similarity do not always result in expected outcomes, and rather vary by circumstance and characteristics of tasks (Van Knippenberg et al., 2004). Research has shown that the effects of similarity are moderated by task characteristics such as team process and interdependence among team members (Mohammed & Angell, 2004; Schippers, Den Hartog, Koopman, & Wienk, 2003). Task characteristics also moderate whether individual attributes such as gender influence attitudes toward robots (Mutlu, Osman, Forlizzi, Hodgins, & Kiesler, 2006). These findings suggest that although similarity is assumed to yield positive perceptions of robots, the effects may be altered based on circumstances where teamwork with a robot takes place. Because robots are deployed to work with humans on many different types of tasks, it is becoming more important to identify boundary conditions that influence the impacts of similarity with robots on attitudinal and behavioral outcomes toward robots. Therefore, the goal of this study is to examine a moderator of the relationship between similarity and the relationship with a robot in the context of working with that robot.

One potential moderator is a risk of danger. Tasks where robots are deployed to work with humans often involve physical labor and danger (De Santis, Siciliano, De Luca, & Bicchi, 2008; J. Kim et al., 2015). Perceptions of risk alter cognitive processes and perceptions of people and technology (Colquitt, Scott, & LePine, 2007; Gefen, 2000). Specifically, it is possible that favorable perceptions of a robot based on similarity are linked to attitudes toward that robot only in low-stakes situations. Given that robots are adopted in a wide range of teamwork, from service to life-saving missions, it is important to understand when teams can benefit from similarity to improve teamwork.

As a result, I seek to understand how surface-level similarity and deep-level similarity influence individuals' perceptions of a robot and subsequent attitudes toward working with that robot. I also investigate how the impacts of surface-level and deep-level similarity are altered by a situational moderator: risk of danger in a human-robot collaborative task.

To accomplish this, I conducted an online experiment using Amazon Mechanical Turk. The experiment was a 2 (surface-level similarity: same gender vs. different gender) x 2 (deep-level similarity: same work style vs. different work style) x 2 (risk of danger: high vs. low) between-subjects design. In this experiment, individual participants were randomly assigned to one of eight conditions and presented with a scenario in which they were asked to imagine performing a collaborative task with an intelligent robot. This study contributes to the literature by showing that impacts of different dimensions of similarity on trust in and acceptance of robots can be contingent upon the risk of danger in human-robot collaboration. Results provide theoretical and practical implications for interaction and formation of human-robot teams.

4.2 THEORETICAL BACKGROUND

4.2.1 Similarity and Diversity in Work Teams

Teams consist of people from different backgrounds and characteristics. Similarity with others is one of the robust social cues that help shape attraction and attitudes toward other team members and spark motivation to engage in teamwork (Montoya, Horton, & Kirchner, 2008). Thus, whether team members are similar to one another often determines the quality of their interaction and thus the outcomes of teamwork (Harrison, Price, & Bell, 1998; Van Knippenberg et al., 2004). Therefore, similarity (and diversity) among team members has been viewed as an important construct in explaining how teams work (Tsui & O'Reilly, 1989; Van der Vegt & Van de Vliert, 2005).

Individuals in teams make judgments regarding the degree to which they are different from or similar to other team members. Diversity in teams thus refers to differences among individuals on any attributes including age, gender, ethnicity, educational background, and knowledge (Dahlin, Weingart, & Hinds, 2005; Van Knippenberg et al., 2004). In this sense, diversity can be conceptualized as the distribution of similarity or difference among team members regarding team members' attributes (Harrison & Klein, 2007; Kearney, Gebert, & Voelpel, 2009).

Among the almost infinite number of diversity dimensions, scholars have focused on the most visible and observable attributes, including age, gender, and ethnicity. These dimensions constitute surface-level diversity (Harrison et al., 2002). Characteristics of surface-level diversity are typically associated with physical appearance, biologically immutable, and immediately observable and measurable, so that they serve as the most salient dimensions and are agreed upon across team members (Harrison et al., 1998). These dimensions are also referred to as social category dimensions (Van Knippenberg et al., 2004).

Social categorization theory accounts for the general positive links between similarity in surface-level dimensions and attitudes and perceptions of others (Chatman & Spataro, 2005). Specifically, individuals assume that the referent other would have similar beliefs and characteristics based on observable attributes, and thus expect smoother and more comfortable interactions with similar others than with others who do not share the same attributes (Hogg & Terry, 2000; Turner, Hogg, Oakes, Reicher, & Wetherell, 1987). For instance, age difference is negatively related to mutual liking between superiors and subordinates (Tsui & O'Reilly, 1989). Timmerman (2000) showed that both age and racial diversity were negatively associated with team performance.

Similarity in demographic characteristics leads to better liking (Goldberg, 2005), greater trust (Jarvenpaa et al., 2004; Spector & Jones, 2004; Williams, 2001), stronger group cohesion (C. Lee & Farh, 2004; Webber & Donahue, 2001), and fewer conflicts (Jehn, Northcraft, & Neale, 1999; J. Li & Hambrick, 2005; Pelled, Eisenhardt, & Xin, 1999). In addition to its effects on perceptions of other team members, demographic similarity has been found to increase the frequency of communication and contact among team members

(Tsui & O'Reilly, 1989). Research also demonstrates powerful effects of similarity on team performance (Horwitz & Horwitz, 2007; Horwitz, 2005; Pelled et al., 1999).

On the other hand, diversity can appear in invisible or less observable attributes. As opposed to surface-level diversity, deep-level diversity dimensions include differences among individual team members' attitudes, beliefs, and values (Harrison et al., 1998). Some scholars add skills, organizational commitment, opinions, and knowledge (Jackson & Joshi, 2011). The deep-level diversity dimensions are distinct from the surface-level dimensions because they are "subject to construal and more mutable" (Jackson, May, & Whitney, 1995, p. 217) and thus often require time and interaction to detect (Bell, 2007).

Deep-level similarity is found to be positive in interpersonal relationships. For instance, in superior-subordinate relationships, research consistently shows that attitudinal and value similarity predict higher ratings of subordinate performance (Harrison et al., 1998; Tepper, Moss, & Duffy, 2011). Also, attitudinal similarity predicts attraction and friendship (McGrath, 1984). In general, deep-level similarity demonstrates similar benefits to surface-level similarity on communication frequency and reduction of conflict (Harrison et al., 1998, 2002).

Research has also shown that teams can benefit from deep-level diversity rather than similarity. For instance, De Dreu and West (2001) found that diverse teams can make better decisions and innovate despite encountering a few conflicts in the process. In addition, Shin et al. (2012) reported that deep-level diversity increases individual team members' creativity when their creative self-efficacy is high. Further, van Knippenberg and colleagues (2004) argue that teams with diverse attitudes and skills can be exposed to diverging and innovative perspectives, which can lead to creative and novel solutions.

Despite the positive effects of similarity in teams, research has demonstrated that the implications of diversity are not always uniform; rather they are conflicting — mere difference or similarity per se does not explain benefits or harms to team functioning (Wegge, Roth, Neubach, Schmidt, & Kanfer, 2008). This is because individual perceptions of similarity or difference to the referent other are based on different dimensions of similarity in different circumstances (Harrison et al., 1998).

Acknowledging the complex contingency of diversity in teams, scholars have emphasized the importance of moderating variables in examining the effects of surface- and deep-level diversity on team outcomes (Kearney et al., 2009; Van Dick et al., 2008). For instance, time can reduce the significance of effects of surface-level diversity and increase the importance of deep-level diversity for team cohesion (Harrison et al., 1998) and performance (Harrison et al., 2002). Mohammed and Angell (2004) reported a moderation effect of team orientation, such that the negative link between surface-level diversity and conflict was reduced with high levels of team orientation in teams. Also, Kearney et al. (2009) found that high levels of a team need for cognition provided a circumstance in which both surface- and deep-level diversity increased team identification and performance.

4.2.2 Similarity in Technologies and Robots

The implications of similarity have been examined in interactions with technologies. Specifically, studies in this stream demonstrate that principles regarding similarity, such as similarity leading to attraction, can hold true in interactions between technologies and humans (Reeves & Nass, 1996). For example, matching personality with a computer-synthesized voice increased attraction toward the computer and social presence (K. M. Lee & Nass, 2003; Nass & Lee, 2001). Also, introverted individuals performed better and completed a task faster when using computer software that conveyed an introvert personality (Richter & Salvendy, 1995).

Scholars who focused on avatars have demonstrated the effects of surface-level similarity. For instance, van der Land, Schouten, Feldberg, Huysman, and van den Hooff (2015) recently showed that similarity between team members and their avatars increased team performance of virtual teams that used avatars as a communication medium. This finding is consistent with previous studies on avatar-user similarity, which demonstrated that similar-looking avatars promote more positive virtual experiences (You & Sundar, 2013), higher levels of engagement and task involvement (Van der Land, Schouten, van den Hooff, & Feldberg, 2011), more confidence (Bailenson, Blascovich, & Guadagno, 2008), and greater emotional attachment and intention to use them (Suh et al., 2011).

Although studies on avatar-user similarity have found positive effects in teams using avatars, the implications cannot be applied to teams using different technologies such as robots. Most of these studies viewed an avatar as a user’s vicarious representation for communicating with other team members (You & Sundar, 2013). This suggests that findings from these studies do not necessarily hold true in teams working with robots, which often manifest physical actions and agency without representing their user’s identity.

Similarity has also been central to understanding interaction with robots (F. Eyssel & Kuchenbrandt, 2011, 2012). Several studies have shown evidence of group membership in relationships between an individual and a robot based on similarity with robots (Kuchenbrandt, Eyssel, Bobinger, & Neufeld, 2013). For instance, Eyssel and Kuchenbrandt (2012) found that people rated robots manufactured in their home country more positively and as more humanlike. Another study by Eyssel and Loughnan (2013) showed that in-group bias could be strengthened by similarity with a robot's projected gender and ethnicity.

Scholars in human-robot interaction have also emphasized deep-level similarity (Nakajima et al., 2003). For instance, Bernier and Scassellati (2010) demonstrated that robots that express the same preference as their operators are rated as friendlier. Personality is another construct that has received attention from scholars. For instance, Woods, Dautenhahn, Kaouri, Boekhorst, and Koay (2005) showed that individuals tended to perceive more similarity in personality on the extroversion-introversion dimension compared to other dimensions such as neuroticism and agreeableness. Also, Andrist et al. (2015) found that users whose assistive robots had personalities matched to theirs reported a higher level of motivation to perform a repetitive task. Tapus, Ţăpuş, and Matarić (2008) also found that user-robot personality match led users to spend more time and engage longer with the robot. However, Lee et al. (2006) reported complementary effects between the user and robot personality, with introvert users preferring extrovert robots to introvert robots.

Through the literature review, I identified several trends. First, no study has examined both the surface- and the deep-level similarity dimensions. Robots have bodies and manifest different attributes at the same time. The physical embodiment of robots manifests more than physical and visible humanlike attributes; for example, the appearance and voice of a robot elicit gender perceptions (Wainer et al., 2007). Robots' behaviors and intelligence are also known to lead people to perceive personality and values in the robot (Tapus, Ţăpuş, & Matarić, 2008). Thus, examining only one aspect of similarity can limit our understanding of how similarity influences perceptions of robots. It is important to investigate both surface- and deep-level similarity at the same time.

The second trend is that research has rarely focused on situations where humans and robots collaborate with each other as a team. Most studies view similarity with robots as a facilitator of interaction with a service robot or a domestic robotic pet (F. Eyssel, Kuchenbrandt, Hegel, & De Ruiter, 2012; K. M. Lee, Peng, et al., 2006; Woods et al., 2005). The ultimate goals of these studies were to establish stronger emotional relationships and to prolong the use of robots (Koay, Syrdal, Walters, & Dautenhahn, 2007), rather than to improve work processes and to lead to the development of teamwork with robots. Therefore, it is necessary to examine the effects of similarity with robots in a team context where humans work with robots.

Finally, moderators are hardly identified. Previous research on similarity in teams suggests that moderators are essential to understanding the effects of similarity by addressing different team contingencies (Kearney et al., 2009; Mohammed & Angell, 2004). However, almost no study has examined how similarity effects can be altered by the specific circumstances of teams working with robots. Because robots are being deployed to different team tasks and environments, examination of the interplay among multiple similarity dimensions with the presence of a moderator is needed to form better relationships with robots in teams.

4.3 RESEARCH MODEL AND HYPOTHESES

Based on the literature review, I propose a research model in which the surface-level and deep-level similarity between a robot and an individual increase trust in the robot, intention to work with the robot, and intention to replace a human teammate with the robot. The research model also illustrates that the links among trust, work intention, and replacement intention are moderated by the risk of danger in the collaborative task (Figure 13). The research model is designed to enhance our understanding of the effects of similarity as a leading factor in promoting individuals' willingness to work with robots in a team.

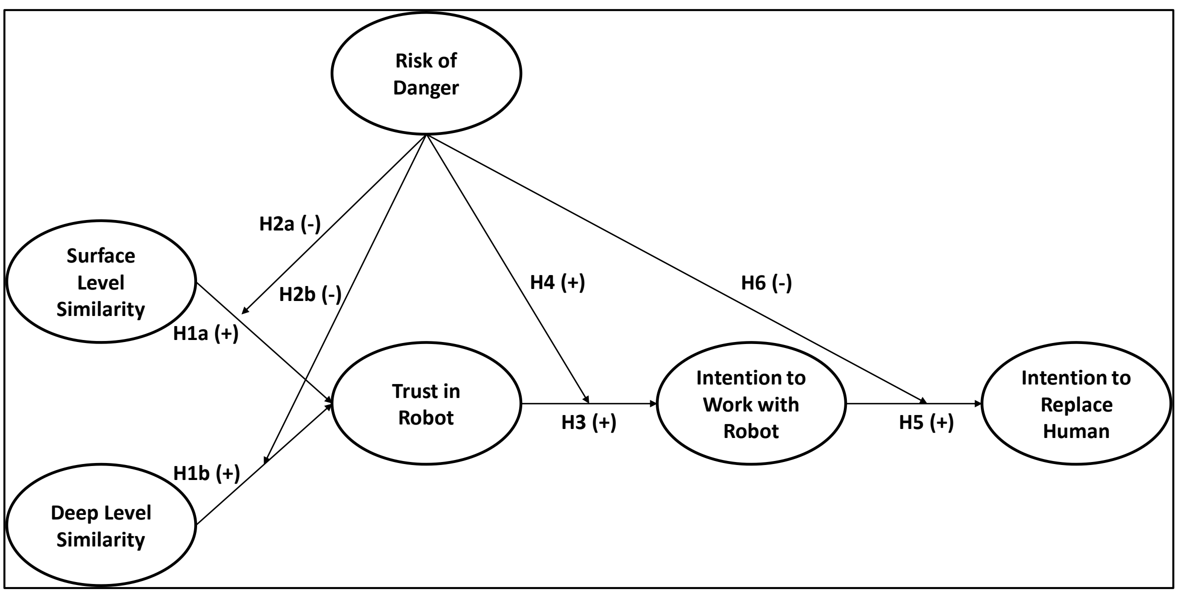


Figure 13 Proposed research model

The first hypothesis proposes that higher levels of similarity between an individual and a robot will foster trust in the robot. Trust is defined as one's volitional intention to be vulnerable to others' behaviors (Mayer et al., 1995). Trust has been considered essential to understanding interpersonal relationships and interaction with technologies (Benbasat &

Wang, 2005; Lankton et al., 2014; Robert et al., 2009) because trust provides assurance of good qualities in interaction between a person and a technology. For instance, trust in a person is a composite of beliefs regarding the benevolence, ability, and integrity of the person (Mayer et al., 1995), while trust in technology is understood as a composite of utility, functionality, and reliability (Mcknight et al., 2011). Trust in robots has been viewed to include both interpersonal and technological trust due to robots' physical embodiment, which often manifests human attributes (Groom & Nass, 2007; Hancock et al., 2011). Indeed, Gaudiello and colleagues (2016) recently found in an experiment with a social humanoid robot that individuals considered both the functional and the social aspects of the robot when determining whether to trust and accept it. In light of this, this study employs a conceptualization of trust in a robot that involves both interpersonal and technological aspects of trust: an individual's willingness to be vulnerable to and dependent on a robot's behavior.

The idea that similarity can increase trust in a robot is based on the cognitive process of developing trust. Trust is essentially an outcome of cognitive judgment in which an individual rationally believes that another person possesses a quality to be relied on (Robert et al., 2009; Webber, 2008). Information such as gender, personality, other's endorsement, and prior experience can provide a basis for that judgment (Mayer et al., 1995; Schoorman, Mayer, & Davis, 2007).

Self-categorization theory can offer an explanation for how information about shared characteristics leads to higher levels of trust (Chatman & Spataro, 2005). According to this theory, individuals determine their social identity by categorizing themselves and identifying similarities and dissimilarities with others based on social cues (Tajfel &

Turner, 2004). Individuals tend to ascribe positive qualities to others who belong to the same group (Hogg & Terry, 2000). This means that when there are similar characteristics in both the truster and the trusted, the truster can perceive less uncertainty and risk and higher levels of familiarity with the trusted (Scissors, Gill, Geraghty, & Gergle, 2009). Therefore, similarity can result in the formation of trust.

Categorizations can be made according to both surface-level and deep-level cues. Gender is one of the most salient surface-level cues for categorization (Sacco, Scheu, Ryan, & Schmitt, 2003). Surface-level similarity based on visible cues triggers a quick judgment of trustworthiness by assigning positive aspects to others of the same gender (Meyerson et al., 1996). Research shows that similarity in surface-level cues such as gender and ethnicity contributes to the development of trust in the initial stage of interaction between team members (McKnight et al., 1998; Robert et al., 2009).

Deep-level similarity also positively influences trust development (K. W. Phillips, Northcraft, & Neale, 2006). Many invisible characteristics, including personality, culture, and attitudes, elicit a sense of belonging (Aquino, Townsend, & Scott, 2001; van Emmerik & Brenninkmeijer, 2009). For instance, work style is known to promote perceptions of similarity among team members (Montoya et al., 2008; Zellmer-Bruhn, Maloney, Bhappu, & Salvador, 2008). Deep-level similarity serves as a basis for cognitive judgments about trustworthiness.

The positive effects of surface-level and deep-level similarity manifest in much the same way in teams working with robots. Research shows evidence of the positive impacts of similarity. For instance, Eyssel et al. (2012) reported that gender matching between a robot and an individual resulted in more positive feelings and psychological closeness. Similar results were reported by Andrist et al. (2015), who found that matching a user's and a robot's personality led to more positive evaluation of the robot. Also, Tapus and colleagues (2008) found that in rehabilitation therapy introvert users preferred robots that provided nurturing praise rather than challenging the user, while extrovert users preferred robots that challenged them. Although these findings do not directly address the issue of increasing trust in a robot, they suggest that similarity between an individual and a robot can promote the perception of various positive attributes in the robot. Trust in the robot can result from positive perceptions based on similarity at both the surface and the deep level. As such, I hypothesize that:

Chapter 4-H1a) Surface-level similarity with a robot will increase trust in the robot.

Chapter 4-H1b) Deep-level similarity with a robot will increase trust in the robot.

I posit that risk of danger is conducive to moderating the positive effects of similarity on trust in the robot. The risk of danger is a situational moderator, which is related to the nature of the tasks that a human and a robot work together to complete (J. Kim et al., 2015; Takayama et al., 2008). The argument is that different levels of risk in a task can prompt different cognitive processes, through which similarity between an individual and a robot influence trust in the robot.

The phenomenon can be explained by dual-process theory (Evans, 2008; Kahneman, 2011). The main account of the theory is that an individual's cognitive process can occur through two different paths: System 1 (or the peripheral route) and System 2 (or the central route) (Petty & Cacioppo, 1986; Stanovich & West, 2000). System 1 refers to a ‘fast’ cognitive process that is unconscious, implicit, and automatic, and requires low effort, whereas system 2 is a ‘slow’ cognitive process that is conscious, explicit, and deliberate, and is governed by greater cognitive effort (Chaiken & Trope, 1999; Kahneman, 2011). The dual-process theory has been useful in accounting for phenomena in social psychology and behavioral economics such as activation of stereotypical perception, formation of interpersonal trust, choice under risky situations (Duckitt, 2001; C. Hung, Dennis, & Robert, 2012; Y.-T. Hung et al., 2004; Robert et al., 2009; Yaari, 1987). Research demonstrates that situational risk is a trigger that leads an individual to engage in the more deliberate and conscious cognitive process of decision-making (i.e., system 2) (Mukherjee, 2010).

When the risk of danger is low, similarity demonstrates a stronger impact on trust in the robot. In low-risk situations, individuals will engage in the automatic cognitive process, through which available similarity cues take bigger roles in producing trust in the robot. When there is low risk, individuals are more vulnerable to the similarity that they share with the robot and do not deliberately assess other qualifiers of trust. This is in part the reason why social robots used in low-risk situations, such as robotic pets and rehabilitation robots, are preferred when they demonstrate similarities in appearance and personality with their users rather than sophisticated technical features and computational power (Friedman, Kahn Jr, & Hagman, 2003; K. M. Lee, Peng, et al., 2006; Woods et al., 2007).

On the other hand, when perceived risk is high, the positive link between similarity and trust in the robot will be weakened. Based on the dual-process theory, the automatic cognitive process of trust judgment can be inhibited when people perceive a higher risk of danger. Individuals will engage in the more thorough cognitive process of assessing the quality of the robot and will be more analytical and slower in determining whether the robot's similarity qualifies it to be trusted. For instance, aspects other than similarities, such as the robot's technical specifications and intelligence, will also come into play in determining trust in the robot. In this respect, Groom and Nass (2007) argued that trust in a robotic teammate should not simply be a function of liking of the robot and that various factors should be considered to ensure safety and trust in high-stakes situations like space missions and military operations. As such, I hypothesize that:

> *Chapter 4-H2) The risk of danger will moderate the effects of (a) surface-level similarity and (b) deep-level similarity on trust in a robot, such that the positive effects of (a) surface-level similarity and (b) deep-level similarity will be stronger when the risk is low and will be weaker or absent when the risk is high.*

The research model also proposes that heightened trust in the robot leads to greater intention to work with the robot as a team. This is in part because trust in the robot creates positive attitudes toward the robot. Positive attitudes toward the robot include, for example, reduced fear of failure of the robot's functionality and reduced concern that working with the robot will require consistent effortful monitoring. According to the theory of reasoned action (TRA) and the theory of planned behavior (TPB), one's intention to perform a behavior is susceptive to positive attitudes and experiences associated with the target (Ajzen, 1991; Fishbein, 1979; Montano & Kasprzyk, 2015). This principle has been applied to predicting intention to use technology according to trust of the target technology (Gefen, Karahanna, & Straub, 2003; Wu et al., 2011). Likewise, in teams working with robots, trust in the robot constitutes a meaningful and salient behavioral basis that results in greater intention to work with the robot. Moreover, trust in the robot reduces uncertainty about the robot's behavior and helps enhance a feeling of control over interactions with the robot. The sense of control is also an element of positive attitudes that result in greater behavioral intention (Das & Teng, 1998; Robert & Sykes, 2017). In sum, trust in a robot promotes positive attitudes and a sense of control by reducing uncertainty and generating expectations of positive experiences, which result in intention to work with the robot.

> *Chapter 4-H3) Trust in the robot will increase intention to work with the robot as a team.*

However, the positive link between trust in a robot and intention to work with the robot may not be uniform in all circumstances. I believe that the risk of danger regulates the impact of trust in the robot on intention to work with the robot. Specifically, when the risk of danger is present, trust in a robot will demonstrate a stronger impact on intention to work with the robot. As stated above, the risk of danger alters an individual's cognitive process and dictates what cognitive resources influence intention to work with a robot (Groom & Nass, 2007; Mukherjee, 2010). When there is a higher risk of danger, individuals will perceive greater uncertainty in the task and seek ways to regain the perception of control. In this case, the role of trust in a robot becomes more salient as a cognitive basis for reducing uncertainty and maintaining control. Therefore, the effect of trust in a robot on intention to work with the robot is stronger in high-risk situations.

Chapter 4-*H5) The risk of danger will moderate the relationship between trust in a robot and intention to work with the robot, such that the effect is stronger when the risk is high than when the risk is low*.

Finally, the research model examines whether the intention to work with the robot will promote an intention to replace a human teammate with that robot. According to the theory of reasoned action, it seems natural to speculate that the greater the intention to work with the robot is, the more likely it is that an individual will reveal a stronger preference for robots. A strong preference for robots is an indicator that an individual may choose a robot over a human teammate. This leads to the hypothesis below:

Chapter 4-H6) Greater intention to work with a robot will increase intention to replace a human teammate with the robot.

The last hypothesis is regarding the moderating effect of the risk of danger on the positive association between intention to work with a robot and intention to replace a human teammate with the robot. The risk of danger can provide a context where an individual judges the potential benefit of working with the robot to be greater than the benefit of working with a human teammate.

I believe that the positive association between the two intentions will exist only when the risk is high. The risk of danger triggers the deliberate and conscious cognitive process when judging whether to work with a robot or with a human teammate. In this case, individuals may conclude that it is better to deploy robots to a risky and dangerous situation than to risk precious human lives. Based on this judgment, individuals will perceive that working with the robot is more beneficial than risking human safety. On the other hand, when the risk is low, the positive impact of intention to work with the robot on the intention to replace a human teammate may be weaker, or not present. Low-risk situations will not make individuals engage in careful reasoning (i.e., system 2) when choosing between working with a human and working with a robot. When the risk is low, there may be no potential benefit to working with a robot because no teammates have to risk their lives. As such, I hypothesize that:

> *Chapter 4-H6) The risk of danger will moderate the relationship between intention to work with a robot and intention to replace a human teammate with the robot, such that the relationship is stronger when the risk is high than when the risk is low.*

4.4 METHOD

To investigate the effects of similarity between an individual and a robot on willingness to work with the robot, I conducted a 2 (surface-level similarity: the same gender vs. different gender) x 2 (deep-level similarity: human–robot agreement vs. disagreement) x 2 (risk of danger: high vs. low) between-subjects online experiment. In the online experiment, participants were randomly assigned to one of the eight conditions and viewed a video about a hypothetical scenario in which collaboration between a human and a robot would be essential.

4.4.1 Participants

A total of 200 participants were recruited using Amazon Mechanical Turk (MTurk), a crowdsourcing platform allowing workers to earn a small amount of money for engaging in a brief online task. Individual participants completed a short self-report questionnaire individually and were paid at the completion of an experimental session. The sample consisted of people of diverse education levels, ages, genders, and ethnicities. The sample included MTurk workers in the United States with good performance histories (having 95% or more of their previous online tasks marked as high quality by requesters). This was to ensure the quality of the online survey by minimizing missing data and invalid data with arbitrary numbers.

I strategically chose MTurk for several reasons. First, although workers in MTurk are younger and lower-income than average Internet users, samples from MTurk are more demographically representative and culturally diverse compared to common samples drawn from college students (Downs, Holbrook, Sheng, & Cranor, 2010; Paolacci, Chandler, & Ipeirotis, 2010). Second, studies conducted on MTurk produce good-quality data and minimize experimental biases (Paolacci & Chandler, 2014). This is because in MTurk duplicated responses from the same person are not possible, and uncontrolled exposure to stimuli is ruled out. Moreover, data from MTurk have been found to successfully replicate results from traditional behavioral studies in real settings (Casler, Bickel, & Hackett, 2013).

In the sample, there were 77 male participants and 123 female participants. The age of participants ranged from 18 to 68 years old (M = 36.5 and SD = 10.77). The sample turns out to have been ethnically diverse: 64% white, 10% Asian, 8% Black and African American, 6% Hispanic and Latino, with the rest including Native American or Alaskan Native and Native Hawaiian.

4.4.2 The Robot

A PR2 robot developed by Willow Garage was used for the videos (Figure 14). The robot was chosen based on several criteria. First, the robot was gender-neutral in its appearance. This is because the robot's gender was going to be manipulated only through its voice and name, ruling out any visual aspects of robots that might influence individuals' gender perception. The images of robots for the pilot study were adopted from previous research on robot appearance, such as studies by Mathur and Reichling (2016) and Kuchenbrandt et al. (2013). Second, the form of the robot should imply some degree of motor abilities such as navigating and moving objects from one place to another location. The hypothetical scenario in the online experiment involved physical tasks, so it was important to use robots that could complete such tasks to provide believable portrayals of a robot and an individual working together. The identical robot was used for all participants across the different experimental conditions.

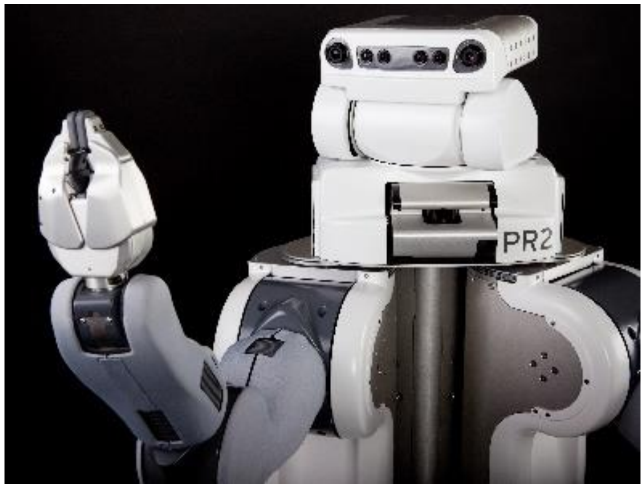


Figure 14 PR2 robot used in the experiment

4.4.3 Experimental Manipulations

Surface- and deep-level similarity were manipulated using videos that contained information about basic descriptions and technical specifications of the robot. In the video, the robot introduced itself by stating its model number and a name, and explained its functional capabilities while performing tasks. The length of the video, 38 seconds, and the content were identical regardless of the similarity manipulations throughout the sample in the experiment.

Surface-level similarity had two conditions: same gender vs. different gender between an individual and the robot. Robot gender was manipulated using a synthesized computer voice and a name suggesting a typical gender attribution. Specifically, the female robot had a female voice produced by the Mac OS X speech interface and had the model name “RX-01 Jessica,” whereas the male robot had a male voice produced by the same system and was named “RX-01 David.” Throughout the study, the robot’s model name was shown along with the image of the robot. The online questionnaire was programmed to randomly assign participants to either the same or the different gender condition. All videos had subtitles. Below, a few screenshots from the videos are shown (Figure 5).

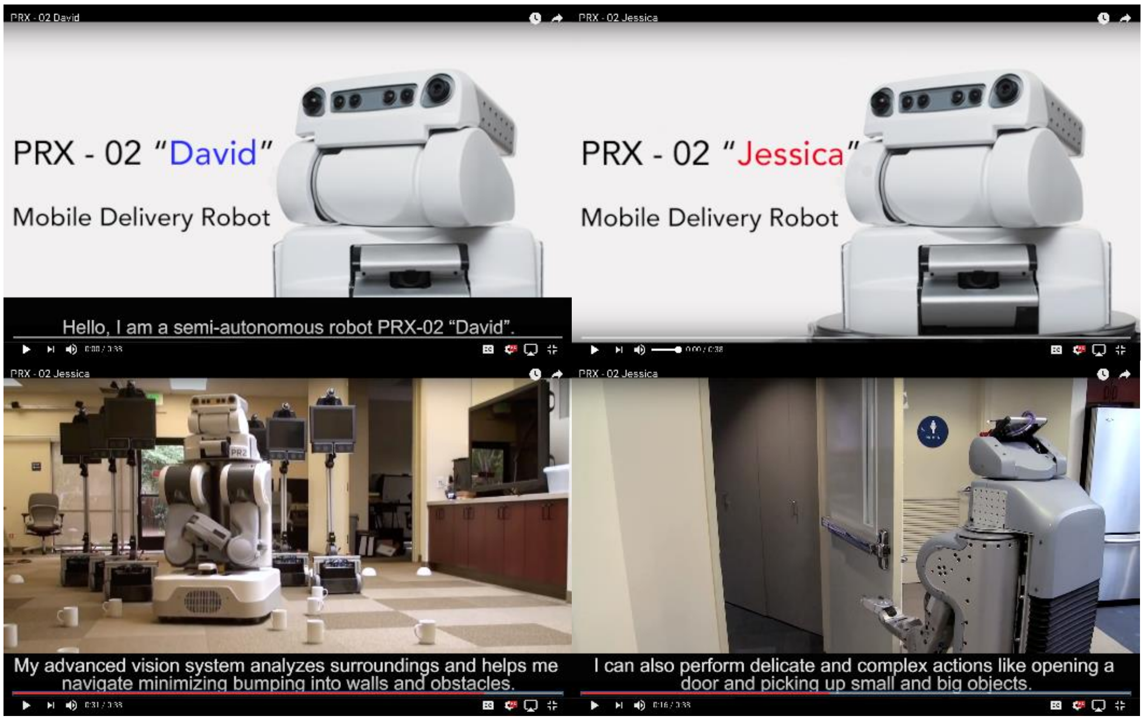


Figure 15 Screenshots from videos for the surface-level similarity manipulation

Deep-level similarity also had two levels: the same work style vs. a different work style. Individual participants were given a series of questions regarding different work styles generated for this study based on work style dimensions identified in Zellmer-Bruhn et al. (2008). The questions had no one correct answer and were intended to make participants choose a stance or opinion on matters regarding beliefs about and habits of work. The questions and dimensions are listed in Table 7.

Work Style Dimension	Items (Participants will be asked to choose only one of these two options)	
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 among team members is the most important thing.
	The ends justify the means.	How we do things is more important than how well we do them.
	Efficiency is more important than effectiveness.	Effectiveness is more important than efficiency.
Work Habits	I am a morning person and perform better during the day. I get the most work done in the morning.	I am a night owl and perform better at night. I get most the 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.
Interaction Style	I prefer a top-down process, in which I only solve problems that are given to me.	I prefer a bottom-up process, in which I find my own problems and solve them.
	A good leader can make a team succeed.	Leadership should be shared evenly among team members.
Personality	I like math and physics more than history and literature.	I like history and literature more than math and physics.

Table 7 Questions for manipulation of the deep-level similarity

In the same work style condition, a robot chose the same answer as the participant after the participant made his or her choice, and showed the sentence, "I also chose the same statement. Your answer was [It is not okay to be 20 minutes late for a meeting because others team members' time will be wasted due to the delay]. My answer was [It is not okay to be 20 minutes late for a meeting because others team members' time will be wasted due to the delay]."

On the other hand, in the different work style condition, a robot chose the other answer and stated, “I chose the different statement. Your answer was [It is okay to be 20 minutes late for a meeting because sometimes we cannot control unexpected events — traffic jams, medical conditions, etc.]. My answer was [It is NOT okay to be 20 minutes late for a meeting because other team members’ time will be wasted due to the delay].”

All participants were asked to choose an answer for each of the nine questions, rather than one question among those. This was because participants may not all have similarly strong opinions, and they may value each of the questions differently. That is, there may be a case when a participant is asked to choose an answer, and if the participant does not think the question is important or that it matters, then answer similarity between the robot and the individual may not successfully reflect deep-level similarity. Therefore, to maximize the salience of the deep-level similarity, participants were asked to answer all nine questions and interact with a robot that consistently exhibited the same answers or the opposite answers based on the assigned condition. As a result, participants who were assigned to the similar work style condition were exposed to nine answers from the robot that were the same as their own, whereas those who were assigned to the different work style condition were exposed to the nine answers from the robot that were the opposite.

The risk of danger in the task was manipulated to have two levels: high risk and low risk. Participants were given a scenario that depicted the process involved in a logistics task in robot-enabled warehouses. In the high-risk condition, participants read a scenario in which they had to collaborate with the robot to clear an area by loading highly toxic and hazardous containers onto a truck for disposal. In the low-risk condition, participants were given a similar scenario, but with ordinary wooden boxes to load onto the truck for home delivery. Both scenarios highlighted that participants should rely on the robot when coordinating paths and designating specific points where the containers should be unloaded. Written scenarios were given along with images of the robot and the containers (Figure 16).

Figure 16 Images for the containers with high risk (left) and low risk (right)

4.4.4 Procedure

All experimental procedures took place online. Participants were greeted and asked to fill out a consent form. Participants then were given brief instructions about the experimental process and task. Next, they completed a pre-task questionnaire. The pre-task questionnaire included questions regarding demographic information including gender, age, and ethnicity. The questionnaire also included items to measure their individual characteristics and control variables such as their general attitude toward robots and the need for cognition.

Then, participants were randomly assigned to either the same-gender condition or different-gender condition. In the same-gender condition, the gender of a robot and a participant were matched (i.e., the video of the male robot for male participants and the video of the female robot for female participants) based on the gender information indicated in the pre-task questionnaire. On the other hand, in the different-gender condition, participants were given the video of the robot that had a different gender from theirs. Once participants finished watching the video of the robot based on their assigned condition, a manipulation check question was given to participants to determine their perception of the robot's gender.

Next, they were asked to choose responses to the nine questions about work styles. Immediately after the participant chose a response to a question, the robot's choice was shown on the following screen next to the participant's choice, according to the condition they were assigned. In the same work style condition, the choice of the participant and the robot were the same, while they were different in the different work style condition.

Participants were asked to enter their choice and the robot's choice. This was to ensure that participants did not rush through the procedure and that the similarity or dissimilarity of each choice was well recognized. Therefore, in the similarity condition, the participant's and the robot's answers were the same, while they were different in the different condition. The total of nine questions on work style were shown individually in the same order to all participants across all conditions. Once all the questions were shown, a summary table that compared the robot's and the participant's answers to all questions was given to the participants. This summary table was followed by a set of questions to capture perceived risk.

Participants were asked to read a scenario about collaboration with the robot and view accompanying illustrative images. Participants who were randomly assigned to the high-risk condition were given a scenario about moving dangerous and hazardous objects in a nuclear waste disposal facility, whereas participants in the low-risk condition were given a scenario about moving wooden boxes in a cargo facility. It was expected to take 5–10 minutes for participants to read the scenarios, but they were allowed to take as long as they wanted before proceeding to the next page of the online survey.

Finally, participants were asked to fill out a post-task questionnaire, which included dependent measures such as trust in the robot, intention to work with the robot as a team, and intention to replace human teammates with the robot. After participants had completed the final questionnaire, they were debriefed and dismissed. Payment was completed through the Amazon MTurk process when they verified that they had completed the online experiment by entering a randomly generated code on the Amazon MTurk website.

4.4.5 Measures

4.4.5.1 Manipulation checks

To ensure that the experimental manipulations were effective, the experiment included manipulation check questions in the online survey. Surface-level similarity was manipulated by showing a video with gender-inducing names and voices. A single question was asked to capture which gender participants thought the robot was after the video was shown. The question was “What do you think the gender of the robot was?”

Manipulation for deep-level similarity was checked by a series of questions regarding perceived similarity in work style. Perceived work style similarity was an index of five items measured based on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The items were adopted from Zellmer-Bruhn et al. (2008). Example items include "The robot has similar work habits with me," and "The robot has similar interaction styles with me." The scale was reliable (Cronbach's α = 0.98).

As a manipulation check for risk of danger, perceived risk of danger was measured to capture the degree to which an individual assessed potential risk and danger in the experimental task scenario. The scale was an index of four items adapted from Kim and McGill (2011) and Jermier, Gaines, and McIntosh (1989) based on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). Examples include "I will encounter personally hazardous situations during the task when I work with the robot" and "The task seems to be risky." The scale was reliable (Cronbach's α = 0.91).

4.4.5.2 Control variables

Age, gender, and ethnicity of participants were collected. Also, need for cognition was measured as a control variable. Need for cognition is a personality trait defined as a tendency to engage in and enjoy cognitive processes (Cacioppo & Petty, 1982). Research shows that an individual's need for cognition determines the cognitive process and influences the relationships between diversity among team members and perception of team membership and the team (Kearney et al., 2009). As such findings suggest, an individual's need for cognition may influence the cognitive process that demonstrates the link between similarity and attitudes toward robots.

Participants' dispositional need for cognition consisted of an index of 14 items adopted from Cacioppo et al. (1996). The scale captures the degree to which an individual participant is likely to engage in cognitive processes in general. The scale was measured based on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). Sample items include "I really enjoy a task that involves coming up with new solutions to problem," and "The notion of thinking abstractly is appealing to me." The scale was reliable (Cronbach's $\alpha = 0.96$).

4.4.5.3 Dependent measures

Trust in the robot was measured to capture the degree to which an individual believed the robot was dependable and trustworthy. The scale consisted of eight items adapted from Jian et al. (2000) and was measured using a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The questions included items such as "I am able to trust the robot," and "The robot is reliable." The scale was reliable (Cronbach's $\alpha = 0.92$).

Intention to work with the robot was measured to capture an individual's willingness to admit the robot as a team member and work together as a team. An index of five items was adapted from Venkatesh and Davis (2000). The scale was measured based on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The questions included "Assuming I had another project similar to this one and access to this robot, I am willing to work with this robot as team," and "This robot and I will likely make a good team." The scale was reliable (Cronbach's $\alpha = 0.95$).

Finally, intention to replace human teammates with the robot was measured to capture the degree to which an individual wanted to work with the robot instead of a human teammate.

An index of three items was developed and measured based on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The three items included "For this job, I would prefer to work with the robot instead of a human," "For this job, I would rather replace a human with the robot," and "For this job, I would rather team up with the robot than a human." The scale was reliable (Cronbach's $\alpha = 0.83$).

4.5 RESULTS

4.5.1 Manipulation Checks

Manipulation checks of the independent variables were done using the measurement items described in the method section. For surface-level similarity, all participants answered the robot's gender correctly according to the gender in the video, which indicates that the manipulation of robot gender was successful. For deep-level similarity, a t-test was conducted to compare means between the two conditions. Results showed that perceived similarity in work style was significantly higher in the same work style condition (M = 4.29, SD = 0.83) than in the different work style condition (M = 1.69, SD = 0.77) ($t(198) = 22.99$, $p < 0.001$). The manipulation check for risk of danger was also done through a t-test. Results showed that perceived risk of danger was significantly higher in the high-risk condition (M = 4.58, SD = 0.50) than in the low-risk condition (M = 3.42, SD = 0.76) ($t(198) = 12.71$, $p < 0.001$). Thus, manipulations for all the independent variables were successful.

4.5.2 Analysis

All analyses in the following section were conducted by following the partial least squares (PLS) approach using SmartPLS 3.2. There were two reasons why the partial least squares structural equation modeling (SEM) technique was used for this study. First, compared to traditional analytical approaches, including the analysis of variance (ANOVA), PLS-SEM provides an integrative estimation of the relationships among variables by allowing a nomological network of variables (Streukens, Wetzels, Daryanto, & De Ruyter, 2010). Second, unlike the covariance-based structural equation modeling (CBSEM) technique, PLS-SEM requires no normality assumptions in the data and allows smaller sample sizes (Marcoulides & Saunders, 2006). In addition, PLS-SEM allows for testing of experimental data with a complex design, such as in the current study, which employs a $2 \times 2 \times 2$ factorial design (Gupta, 2014). The report of the results of the analysis in this dissertation follows guidelines provided by Gefen, Straub, and Rigdon (2011).

4.5.3 Measurement Validity

PLS-SEM provides both a measurement model and a structural model as an outcome of the analysis. All latent variables, including trust in the robot, intention to work with the robot, intention to replace a human teammate with the robot, and the need for cognition, were modeled as reflective constructs.

Discriminant validity of the measures was assessed based on a factor analysis. As Table 8 shows, all items loaded at 0.70 or above on each of their constructs and indicated no cross-loadings above 0.4. The results of the factor analysis indicate discriminant and convergent validity of the measurable latent variables in the model (Fornell & Larcker, 1981).

The discriminant and convergent validity of the variables in the model were assessed by testing correlations among them (Table 9). Average Variance Extracted (AVE) provides evidence for the convergent validity of a construct when the value is greater than 0.50 (Fornell & Larcker, 1981). In this case, the variance explained by the construct is larger than the variance explained by measurement error. The AVE values of all latent variables in the model were above 0.50 (0.64 for the need for cognition, 0.63 for trust in the robot, 0.85 for intention to work with the robot, and 0.75 for intention to replace a human teammate with the robot).

Furthermore, the square roots of AVE values of the variables were compared with the correlations of all variables to assess discriminant validity. The correlation matrix, shown in Table 9, indicates that correlations among all constructs were well below the square roots of the AVEs. Finally, the internal consistency of the variables was assessed by calculating internal composite reliability (ICR). All variables indicated values well above 0.70, which is evidence of internal consistency.

Items	Component			
	NCOG	**TR**	**IWR**	**IRHR**
Need for Cognition 1	**0.83**			
Need for Cognition 2	**0.88**			
Need for Cognition 3	**0.86**			
Need for Cognition 4	**0.85**			
Need for Cognition 5	**0.71**			
Need for Cognition 6	**0.85**			
Need for Cognition 7	**0.80**			
Need for Cognition 8	**0.77**			
Need for Cognition 9	**0.82**			
Need for Cognition 10	**0.76**			
Need for Cognition 11	**0.73**			
Need for Cognition 12	**0.73**			
Need for Cognition 13	**0.73**			
Need for Cognition 14	**0.87**			
Trust in Robot 1		**0.77**		
Trust in Robot 2		**0.79**		
Trust in Robot 3		**0.84**		
Trust in Robot 4		**0.78**		
Trust in Robot 5		**0.73**		
Trust in Robot 6		**0.72**		
Trust in Robot 7		**0.74**		
Trust in Robot 8		**0.81**		
Intention to Work with the Robot (IWR) 1			**0.85**	
Intention to Work with the Robot (IWR) 2			**0.72**	
Intention to Work with the Robot (IWR) 3			**0.88**	
Intention to Work with the Robot (IWR) 4			**0.89**	
Intention to Work with the Robot (IWR) 5			**0.87**	
Intention to Replace a Human with the Robot (IRHR) 1				**0.76**
Intention to Replace a Human with the Robot (IRHR) 2				**0.81**
Intention to Replace a Human with the Robot (IRHR) 3				**0.77**
Note: Values in bold indicate items loading at the 0.7 or above on each of their constructs. Factor loadings smaller than 0.40 were excluded for better readability. Extraction method was Principal Component Analysis using Varimax with Kaiser Normalization as a rotation method.				

Table 8 Factor loadings of measurement items in the PLS model

Variable	Mean	SD	1	2	3	4	5	6	7	8
1. Gender	0.39	0.49	**NA**							
2. Need for Cognition (NCOG)	3.50	0.91	-0.21**	**0.80 (0.96)**						
3. Surface-level Similarity (SLS)	0.45	0.50	-0.26	0.06	**NA**					
4. Deep-level Similarity (DLS)	0.51	0.50	0.23	0.04	-0.4	**NA**				
5. Risk of Physical Danger (RPD)	0.49	0.50	0.67	0.05	0.03	0.07	**NA**			
6. Trust in Robot (TR)	3.71	0.76	0.11	0.12	-0.03	0.38**	-0.15*	**0.79 (0.94)**		
7. Intention to Work with the Robot (IWR)	4.23	0.80	0.11	0.16*	-0.01	0.24**	-0.03	0.56**	**0.92 (0.96)**	
8. Intention to Replace a Human with the Robot (IRHR)	3.50	1.00	0.14*	0.06	0.05	0.19**	0.14*	0.33**	0.52**	**0.86 (0.90)**

Note: *N* = 200; SD = standard deviation. Values on the diagonals represent the square root of the AVE for each factor. ICR is indicated in parantheses on the diagonals. * p < .05, ** p < .01. "Gender" was coded binary (0 = male, 1 = female). Experimental conditions, "Surface-level Similarity" and "Deep-level similarity" were coded using 0 and 1 (0 = different and 1 = same between a robot and a participant).

Table 9 Descriptive statistics, correlations among constructs, internal composite reliability (ICR), and average variance extracted (AVE)

4.5.4 Hypothesis Testing

The hypotheses were tested by assessing the significance of the paths in the structural model. In this study, the model was analyzed with the standard bootstrapping procedure by resampling 1,000 subsamples using SmartPLS 3.2. The analysis produced variance inflation factors (VIF), which indicate the likelihood of multicollinearity influencing results of the model testing. The highest VIF value in the model was 1.10, which was well below the commonly recommended threshold of 10. Therefore, there is less likelihood of multicollinearity in the model. The model included the need for cognition and participants' gender as control variables. Other control variables mentioned above in the measurement section, such as age and ethnicity, were not included in the model because of insignificance.

H1 posited that a) surface-level and b) deep-level similarity would increase trust in the robot, respectively. Results of the model testing showed that surface-level similarity did not increase trust in the robot ($ß = -0.01$, $p = 0.87$). Thus, H1a was not supported. However, there was a significant positive impact of deep-level similarity on trust in the robot ($ß = 0.39$, $p < 0.001$), which indicates that H1b was supported.

H2a and H2b posited moderation effects of the risk of danger for the relationships between surface-level and deep-level similarity and trust in robots, respectively. Results of the model testing showed that there was a significant interaction effect between surface-level similarity and the risk of danger in predicting trust in the robot ($ß = -0.17$, $p < 0.01$). In addition to assessing the path coefficients, a test of H2a and H2b involved plotting the relationships. As hypothesized in H2a, the risk of danger moderated the impact of surface-level similarity on trust in the robot, such that the positive impact of surface-level similarity was found only in the low-risk condition (Figure 17). However, an interaction effect was not found between deep-level similarity and trust in the robot ($ß = 0.05$, $p = 0.48$). Thus, only H2a was supported.

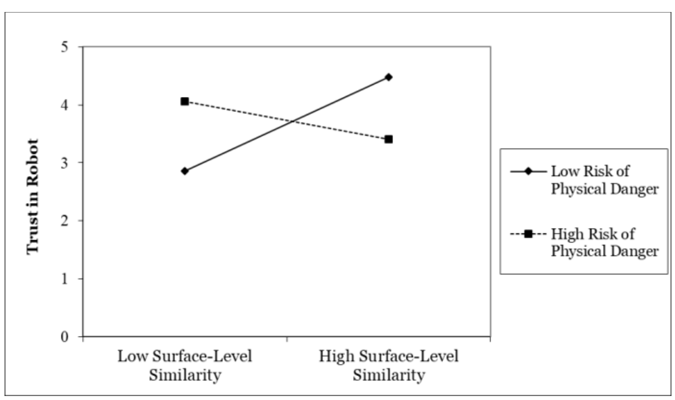


Figure 17 Moderation effect of risk of danger for the relationship between the surface-level similarity and trust in robot

H3 hypothesized that trust in the robot would increase an individual's intention to work with the robot as a team. H3 was fully supported based on the significant path coefficient ($ß = 0.58$, $p < 0.001$). H4 posited a moderation effect of risk of danger for the relationship between trust in the robot and intention to work with the robot, such that the positive impact of trust in the robot will be stronger in the high-risk condition. H4 was not supported ($ß = -0.08$, $p = 0.22$).

H5 posited the positive impact of intention to work with the robot on the individual's intention to replace a human teammate with the robot. H5 was fully supported ($ß = 0.55$, $p < 0.001$). Finally, H6 posited a moderation effect of risk of danger for the relationship between the intention to work with the robot and the intention to replace a human teammate. Specifically, I speculated that the positive impact of an intention to work with the robot would be strengthened in the high-risk condition, whereas the impact would not be present or would be weakened in the low-risk condition. The model demonstrated a marginally significant interaction effect ($ß = 0.09$, $p < 0.1$). As an additional analysis, the interaction effect was tested by a separate analysis employing a linear regression. A plot based on the results of the regression analysis showed that intention to work with the robot increased intention to replace a human teammate only in the high-risk condition ($ß = 0.32$, $p < 0.05$) (Figure 18). Thus, H6 was partially supported.

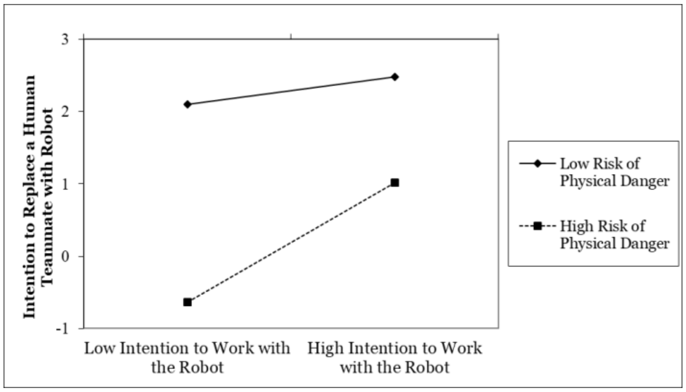


Figure 18 Moderation effect of risk of danger for the relationship between intention to work with the robot and intention to replace a human teammate

Based on the hypothesis testing, the final model was derived from the research model (Figure 19). The model illustrates the results of the model testing, where R^2 indicates the variance explained and ß indicates the standardized path coefficients of each path in the structural model. R^2 indicates that trust in the robot was explained by 26%. Intention to work with the robot and intention to replace a human teammate with the robot were explained by 37% and 36%, respectively.

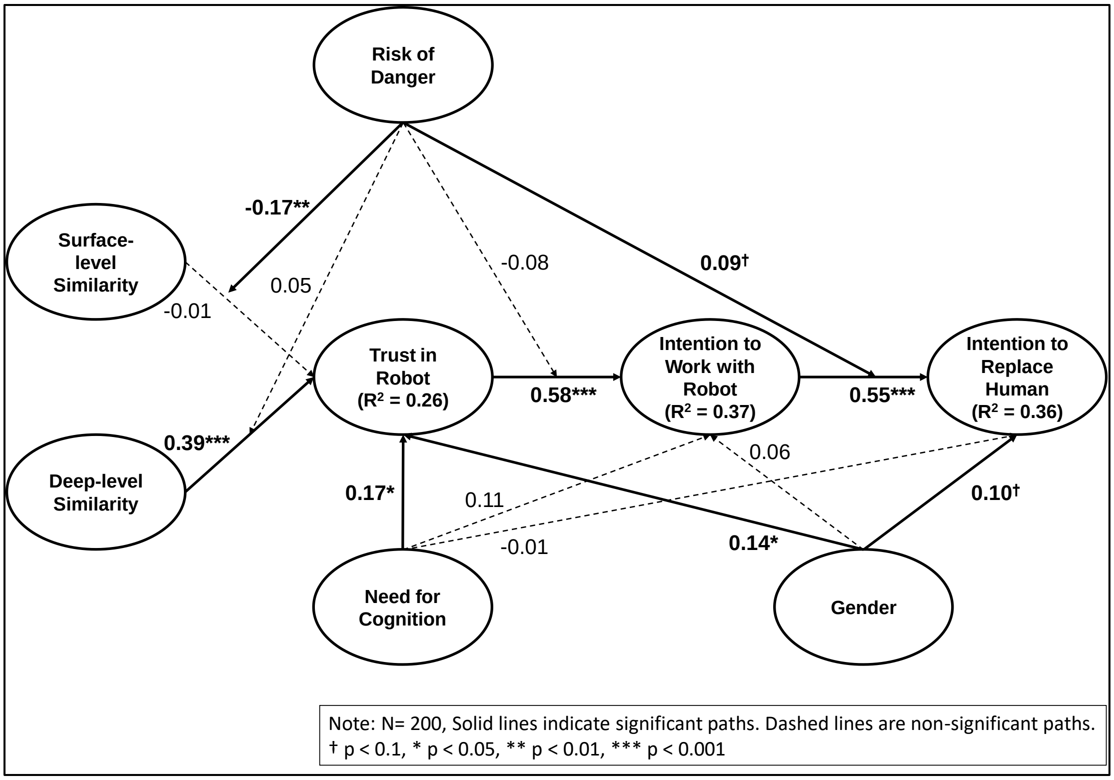


Figure 19 Results of PLS analysis

Hypotheses		Results
H1a	The surface-level similarity increases trust in the robot.	Not Supported
H1b	The deep-level similarity increases trust in the robot.	Supported
H2a	The risk of danger moderates the impact of the surface-level similarity on trust in the robot.	Supported
H2b	The risk of danger moderates the impact of the deep-level similarity on trust in the robot.	Not Supported
H3	Trust in robot increases intention to work with the robot.	Supported
H4	The risk of danger moderates the impact of trust in the robot on intention to work with the robot.	Not Supported
H5	Intention to work with the robot increases intention to replace a human teammate with the robot.	Supported

H6	The risk of danger moderates the impact of intention to work with the robot on intention to replace a human teammate with the robot.	Marginally Supported

Table 10 Summary of hypothesis testing

4.6 DISCUSSION

The objective of this study was to examine the impacts of similarity between an individual and a robot on the development of teams working with robots. In doing so, this study examined how the risk of danger in a task moderates the impacts of similarity on trust in a robot and attitudes toward the robot. Results from an online experiment showed that surface-level similarity increased trust in a robot only when the risk was low, while deep-level similarity increased trust in the robot regardless of the risk. Trust in the robot was found to increase intention to work with the robot and subsequently intention to replace a human teammate with the robot. The risk of danger also marginally moderated the relationship between intention to work with the robot and intention to replace a human with the robot. Taken together, these findings highlight the importance of considering both surface-level and deep-level similarity for creating greater trust and better attitudes toward a robot in conjunction with the risk of danger.

4.6.1 Contributions

This study contributes to research on the development of teams working with robots and prediction of workers' willingness to work with robots as a team. The first contribution to the research is that this study looked at both surface-level and deep-level similarity to predict positive perceptions toward a robot in one study. Although previous research generally showed positive impacts of similarity with a robot on forming positive perceptions of robots, the findings were limited due to examining only one aspect of similarity at a time (Bernier & Scassellati, 2010). It is important to examine both surface-level and deep-level similarity at the same time. The physical embodiment of robots inherently elicits the perception of similarity, not only in its appearance (e.g., gender and ethnicity), but also in its behaviors and intelligence (e.g., personality, ability, skills, and preferences) (Rae et al., 2013; Robert & You, 2014). As robots are becoming more humanlike in different aspects, workers' perceptions of and intentions toward robots should be examined by considering both levels of similarity.

Second, this study unpacks the cognitive path by which similarity with a robot leads to higher levels of trust and intention to work with it by identifying a boundary condition for the relationship between two constructs. Specifically, this study showed that risk of danger regulates the cognitive paths from surface-level and deep-level similarity to trust in a robot. Research has shown that the perception of similarity is automatic and universally found in using different technologies that manifest some humanlike attributes (Nass & Lee, 2001; Reeves & Nass, 1996). Similarity effects have been applied to robots to enhance positive perceptions of social robots (Bernier & Scassellati, 2010). Despite previous endeavors to examine the impacts of similarity in interacting with robots, it is largely unknown how and when similarity becomes effective in promoting positive perceptions of robots.

Identifying the boundary condition for the relationship between similarity and perceptions of robots, such as trust, is especially vital for teams working with robots. Unlike social robots, which are mostly deployed to safe environments like homes, robots used in teamwork may be required to fulfill dangerous tasks with a higher risk of physical danger. It is not guaranteed that the previous findings of similarity effects in social robot contexts can be applied to teams working with robots. The risk of danger may be one of the most common situational moderators in the context of teamwork with robots. Future research should identify other factors that alter the impacts of similarity, such as task interdependence, task duration, and competitive structure of the task. For instance, do similarity effects on trust in a robot change over time after a few initial interactions with the robot? Research shows that category-based trust is formed swiftly, but team members engage with a deeper cognitive assessment of trust after a few interactions (Meyerson et al., 1996; Robert et al., 2009). Also, similarity with a robot may yield a negative perception of the robot when someone is competing with the robot rather than cooperating (Mutlu et al., 2006).

Lastly, this study examined intention to replace a human teammate with a robot. Although there have been several studies of adoption and intention to use a robot in different contexts (Barbash, Friedman, Glied, & Steiner, 2014; Heerink, Ben, Evers, & Wielinga, 2008; Sung, Grinter, Christensen, & Guo, 2008), the research still lacks evidence about what leads people to prefer robots over human teammates. This study showed that the intention to replace a human teammate is a function of intention to work with the robot, but this relationship is also dependent upon the risk of danger. This study opens a new area of research, in which scholars should investigate in what circumstance and why an individual chooses to work with a robot, and what the psychological and performance consequences of the choice may be in teams working with robots. For instance, will people still choose to work with a robot when their existing human teammates are replaced? Will subgroups be formed between team members who are more willing to work with robots and those who do not welcome robots on the same team? As there are many unanswered questions in this area, understanding what leads to a preference for robots over humans will be vital to promoting teamwork between humans and robots.

4.6.2 Implications for Theory

This study has several implications for theory. First, the results of this study highlight that the impacts of similarity are not always present and that they are dependent upon the type of similarity and the presence of a risk of danger. Results from the experiment demonstrated that deep-level similarity increased trust in a robot, whereas the impacts of surface-level similarity were present only when the risk is low. These findings imply several theoretical issues. One, the automatic and swift cognitive processing (i.e., system 1) of surface-level similarity is susceptive to the risk of danger in the collaborative task. Surface-level similarity can be immediate and more salient despite sensitivity to a situational factor. Second, deep-level similarity predicting trust in a robot is not influenced by the risk of danger. One possible explanation is that processing deep-level similarity may have already involved a deliberate cognitive process (i.e., system 2), so risk does not add any layer of cognitive judgment of the trustworthiness of a robot. This suggests that deep-level similarity may be a stronger factor in enhancing trust in a robot regardless of a situational risk. Given the different mechanisms of surface-level and deep-level similarity in predicting trust in a robot, examining both levels of similarity is vital to enhancing our theory of similarity and diversity in teams working with robots.

In this study, dual-process theory was a useful theoretical lens to explain the moderation effects of the risk of danger. According to the results, the risk of danger turns out to trigger the more thoughtful and deliberate cognitive process, in which automatic judgment about surface-level similarity was inhibited. I believe that the dual-process approach can provide an explanation of other phenomena in teams working with robots.

Second, trust in a robot was found to be a strong predictor of intention to work with the robot and subsequent intention to replace a human teammate with the robot. These findings confirm those of previous studies that examined impacts of trust on acceptance of social robots (Heerink, Kröse, Evers, & Wielinga, 2006). However, the findings of this study imply that trust in a robot increases the intention to adopt a robot for use in a collaborative context. This is aligned with previous findings in teamwork research, in which interpersonal trust is a major factor in developing better teamwork (Costa, 2003; Robert et al., 2009).

Third, this study calls for more theorizing on intention to work with a robot in teams. Most research on robot adoption has employed existing technology adoption models, such as the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT) (Davis, 1986; Heerink et al., 2006; Venkatesh, Morris, Davis, & Davis, 2003). These studies have provided insights into adoption intention by individual users of social robots (Broadbent, Stafford, & MacDonald, 2009; Gaudiello et al., 2016; Graaf, 2015). However, the existing literature's views on adoption of robots seem unidimensional and only address the issue of whether or not an individual is willing to interact with the robot (Heerink et al., 2008). This is in part because these studies did not recognize the pervasive fear that robots will replace human labor and that a team member may be in the situation of having to choose between a robot and a human as a teammate.

This study went beyond the simplistic view of intention to work with a robot and examined intention to replace a human teammate with a robot. Results showed that the more an individual is willing to cooperate with a robot, the more likely it is that the individual will choose a robot over a human teammate to perform a collaborative task. Moreover, the results demonstrated that this phenomenon could be regulated by the risk of danger involved in a task. The phenomenon is governed by a thoughtful cognitive process triggered by risk. These results suggest that intention to replace a human teammate with a robot should conceptually be distinguished from intention to adopt a robot. Unlike an intention to work with a robot that is determined solely by a robot's characteristics, intention to replace a human teammate with a robot may address the comparative benefit of working with a robot. This may include the social desirability of choosing a robot over a person, the risk of harming another person by choosing to work with him or her, and the expectation of competitively better motor skills in a robot. In this study, the intention to replace was predicted by intention to work with the robot only when risk was high. This finding can be interpreted as indicating that people may consider the possibility that a human teammate could be in a dangerous situation, which results in preferring to risk a non-human teammate. This phenomenon opens a new area of theoretical investigation to delve into, identifying other factors influencing the choice of robotic teammates over humans.

4.6.3 Implications for Practice

Several implications for practice can be derived from the findings of this study. First, robots deployed to work with humans should be designed to display similarity with the humans to ensure higher levels of trust and intention to work with the robots. The similarity can be either at the surface level or at the deep level, or both. Similar gender and work styles were found to be effective in eliciting the perception of similarity and promoting trust in a robot. In addition to these two aspects, designers of robots can employ other aspects as long as they induce a feeling of similarity. For instance, highlighting an ad-hoc membership through wearing the same uniform can be effective. Similar voice tones and speech styles can also be useful ways to elicit the perception of similarity at the deep level.

Second, managers and leaders of teams working with robots should be wary of the level of risk in a workplace where a robot and an individual collaborate with each other. In many cases, decisions about adopting a robot in a work environment are made at an executive level and may not reflect individual workers' intention to work with them. Because usually robots are given to rather than selected by workers, managers should devise ways to minimize workers' negative opinions and foster positive attitudes toward working with the robots. According to the results of this study, they should be knowledgeable about the level of risk in the task where a robot will be deployed. Particularly when robots replace human laborers and become part of human-robot teams, managers of such teams should be aware that merely highlighting some similarity with their employee will not necessarily result in greater intention to choose to work with a robot instead of a human teammate.

4.6.4 Limitations

There are several limitations in this study. First, this study was conducted through an online experiment that involved interacting with a robot by watching a pre-recorded video. The findings in this study may appear in different directions or magnitude if an individual interacts with a robot and performs a collaborative task instead of viewing a scenario. Second, the context of this study involved only one robot and one person per team. Teams working with robots are becoming bigger and more diverse, and the relationships between robots and individuals are more dynamic in such cases (Yanco & Drury, 2004). Third, this study examined only one aspect of surface-level and deep-level diversity, respectively. Perceptions of similarity can be elicited by many different factors other than gender and work style, such as place of origin, ad-hoc membership, abilities, and knowledge (Robert, 2013; Van der Vegt & Van de Vliert, 2005). Lastly, this study employed risk of danger in a human-robot collaborative task to regulate the impacts of similarity. However, research shows that the impacts of similarity can be regulated by other factors, such as task interdependence and mode of communication via telecommunication systems (Scissors et al., 2009; Zellmer-Bruhn et al., 2008). Future research should identify other moderators to determine the boundary conditions for the impacts of similarity in teams working with robots.

4.7 CONCLUSION OF CHAPTER 4

Although adoption of robots into teams that fulfill different tasks is increasing swiftly, workers' willingness to work with a robot as a team is not always guaranteed. This is in part because robots are often regarded as job-killers for people. This means that it is vital for teams working with robots to attain positive attitudes regarding the robots and working with them in order to succeed. In light of this, this study examined the impacts of similarity between an individual and a robot on fostering trust in the robot and intention to work with the robot on tasks of different levels of risk of danger. Results showed that the positive impacts of similarity are contingent upon the degree of risk of danger in a task. Results also demonstrated that trust in a robot positively predicts subsequent intention to work with the robot and intention to replace a human teammate with the robot. Overall, this study contributes to research and practice regarding the development of teams working with robots.

CHAPTER 5
CONCLUSION OF DISSERTATION

5.1 REVISITATION

Robots are increasingly being adopted into many teams. The increasing adoption of robots has led to more challenges but also brought opportunities for teams to improve interaction among team members and produce better outcomes. As teams continue to incorporate robots, these teams' success will depend on how they leverage the benefits of having robots, from team development stages to functioning stages. This concluding chapter revisits the research questions and the theoretical framework in Chapter 1 to gain an overarching insight from the three empirical studies.

5.1.1 Research Questions

Acknowledging the importance of teamwork involving robots, this dissertation research attempts to answer research questions regarding how to improve teamwork with robots in functioning and development stages. I recall each of the research questions and answer below with a summary of the studies conducted for this dissertation.

RQ1) What are the impacts of interaction between human teammates and interaction between humans and robots on outcomes in teams working with robots?

The trust study and the team potency study can both provide answers to this research question. These two studies were designed to investigate how interactions within teams working with robots affect various outcomes of the teams, such as performance, satisfaction, and viability. The trust study examined affective trust in robots and in teammates and its performance benefits. Robot-building by team members and strong team identification increased trust in robots and trust in team members, respectively. Moreover, trust in robots increased team performance, whereas trust in teammates increased satisfaction with the teamwork. These findings provide evidence that interactions with robots and teammates yield unique effects on different team outcomes and thus warrant a unique approach to promoting trust in robots and team members separately.

The team potency study also enhances our understanding on the impacts of interaction within teams working with robots on the performance of individual members of the team. The results showed that team potency improved task performance of individual team members only when the team is ethnically diverse. These findings suggest that the mechanism of performance enhancement should be considered with team diversity. This study answers the research question above by highlighting that interaction among team members who are from different backgrounds result in a more positive impact of team potency on their performance.

Overall, the first research question is answered by conducting the first two studies. I believe these studies can tackle the team phenomena in the research question by involving teams that consist of two robots and two people. Based on the nature of the studies that involve two people in the teams, the studies employed the team-level and the multi-level approach to designing the interventions in the experiments, collecting data, and analyzing the results. The execution of these studies also emphasizes the importance of research methods beyond the individual-level interactions and require unique strategies such as the team-level and the multi-level approaches.

> *RQ2) How can we facilitate the development of teams working with robots? Can we promote an individual team member's intention to work with robots?*

The second research question is answered based on the results of the similarity study. To address issues in the team development stage, the similarity study turns to theories of similarity and trust between an individual and a robot by examining the moderation effects of a situational factor that influences an individual's cognitive process of judging attitudes toward robots. In Chapter 4, I reported results from an online experiment, which demonstrated that similarity between an individual and a robot promoted trust in a robot and intention to work with the robot as well as intention to replace a human teammate with the robot. Risk of danger is found to moderate the impacts of surface-level similarity on trust in a robot and the impacts of the work intention on the replace intention. Specifically, risk of danger activates a thoughtful cognitive process to assess trustworthiness and potential cost and benefit of working with a robot instead of a human teammate, which reduces the strength of the link between similarity and trust in the robot and intention to replace a human for the robot. As such, the similarity study illustrates the cognitive mechanism of the link between similarity and trust, which is regulated by risk of danger.

The three studies in this dissertation have great potential to make significant contributions to research on teams working with robots. First, the findings from the three studies provide evidence for the importance of a unique approach to research on teams working with robots. The literature of human-robot teamwork has mainly focused on collaboration between a single robot and an individual and still lacks empirical evidence for teamwork that involves multiple robots and people at the same time (Robert & You, 2014). Also, the existing literature of technology-supported teamwork has not been addressing issues related to robots (Tannenbaum et al., 2012; You & Robert Jr, 2016). It is generally assumed that our prior knowledge on interaction with robots and technology in the existing literature can be transferred to the context of interaction among multiple robots and people. However, the results from studies in this dissertation show that research on teamwork involving robots requires unique approaches to examining constructs and resources specifically applicable to team contexts. As such, research on teams working with robots has been in need of empirical studies that tackle interactions and mechanisms for the performance gains in teams involving multiple robots and people. My dissertation is one of the first studies that address this issue by conducting three empirical studies in the context of teams working with robots.

Second, another intellectual merit of this dissertation is that the three studies can be the first steps towards building a theory of teamwork with robots. Although scholars have attempted to tackle many team phenomena in using and collaborating with robots, a theoretical framework that incorporates different aspects of teamwork has been lacking in the available literature. The absence of a theoretical framework limits our understanding of teams working with robots by hindering the formation of a nomological network on this subject. The importance of this topic suggests the need to develop a theoretical framework directed at better understanding of teamwork with robots. A theoretical framework can help identify factors that enable or hinder the effectiveness of teams working with robots. The identification of such factors is crucial for two reasons: (1) to achieve theoretical progress in the field of teamwork with robots and (2) to gain a practical understanding of promoting outcomes in such teams. Therefore, I propose a research framework in a hope that this will guide future research. The framework will be discussed in detail in the following section of this chapter.

5.1.2 The Framework

The three studies also provide an empirical validation for the theoretical framework that was introduced in Chapter 1. As such, this section discusses theoretical contributions of the empirical studies to the proposed framework. The framework contains various constructs and resources regarding collaboration involving robots and seeks to delineate diverse phenomena in teams working with robots. The hope is that the framework and findings from the three empirical studies will interest more scholars and help advance the theory of human-robot teamwork.

The model depicts that the life cycle of teams working with robots can begin from inputs and continue to enact different properties and interactions among humans and robots (i.e., mediators) to produce a team outcome (i.e., outputs). In the framework, I view that the inputs incorporate both the individual level, such as characteristics of individual team members and robots, and the team level, which include the composition of characteristics of humans and robots in the team. When an individual and a robot are similar on the surface-level and/or the deep-level attributes, the human-robot team is homogeneous at the team-level.

The framework asserts that the inputs, mediators, and outputs influence subsequent stages of the team's life cycle and engender different teamwork phenomena and outcomes. For instance, the combination of different properties of humans and robots influence interactions among them and determines attitudinal and behavioral outcomes in the team. In this light, the similarity study in Chapter 4 showcases the impacts of composition of characteristics of a human and a robot in teamwork. Specifically, the similarity shows that homogeneity between an individual and a robot can predict trust in the robot and the individual's attitudes towards the robot – intentions to work with the robot and to replace a human teammate with the robot.

As illustrated in the theoretical framework, the mediators manifest team phenomena in three dimensions: cognitive, affective and motivational, and behavioral. Each of the three studies in this dissertation addresses team phenomena regarding the cognitive, affective, and motivational processes of teamwork with robots. For instance, the trust study in Chapter 2 examines affective trust in teams working with robots, while the team potency study in Chapter 3 explains the motivational mechanism where team potency as a motivational force can lead to better performance by behavioral enactments such as better cooperation and more effort in teamwork. The similarity study in Chapter 4 unpacks how trust in a robot as a cognitive mediator influences individuals' intention to work with the robot.

The studies conducted for this dissertation provide evidence for the assertion on the link among inputs, mediators, and outputs. The team potency study in Chapter 3, for example, shows that ethnic composition of individual robot operators (i.e., inputs) influences their performance (i.e., outputs). Further support can also be found in the similarity study in Chapter 4, where homogeneity between an individual and a robot (i.e., inputs) predicted trust in the robot (i.e., mediators) and intention to work with the robot (i.e., outputs).

This dissertation is only the beginning of the effort in providing an empirical evidence to the theoretical framework and enhancing our knowledge on how teams working with robots operate. I believe the theoretical framework bears many opportunities for scholars to pursue future research.

One area that needs attention is the impacts of different compositions of teams working with robots. I examined teams with two humans and two robots, but there can be many different compositions possible. It is worth investigating, the impacts of the imbalanced number between humans and robots on interactions and outcomes. When team members share a robot for a collaborative task, varying degrees of perceptions, such as trust and emotional attachment toward the robot, may influence team outcomes.

Another area for future research can be the examination of the organizational-level influence on the teamwork with robots. This dissertation research examined mostly, the interactions within a team, but leaves the organizational level phenomena for future research. Technical support from the organization can lead to more positive perceptions toward robots and working with them and better outcomes. Incentive structures of working with robots in a team may be influential on employees' intention to work with robots and thus, is worth examining from a managerial perspective.

Lastly, future research should investigate the iterative process of teams working with robots. The framework asserts that various team outcomes in the outputs can feed back to the subsequent inputs and mediators. The framework views that teams working with robots are dynamic and learn over time. Longitudinal studies can better describe the process of teams working with robots in more than one life cycle, which was beyond the scope of the current dissertation.

5.2 LIMITATIONS

There are limitations in the studies conducted for this dissertation. First, all the studies were conducted through an experiment in a controlled environment. The trust and team potency studies from Chapter 2 and 3, respectively, were done in a lab with college students as participants. The similarity study, in Chapter 4, was done through a pre-programmed online experiment using Amazon Mechanical Turk. There are, in fact, some advantages of using the controlled experiment. Causality can be claimed based on the experimental design. I was also able to utilize the buildable feature of Lego robots for the robot-building manipulation. The online experiment did not involve any actual risk in interaction with the robot. Despite these advantages, interactions in a controlled environment can be qualitatively different from what happens in reality. In teams, in reality, interactions among team members and robots are often not structured, but more dynamic and unpredictable. It is also possible that the results of the similarity study can manifest in different magnitudes when the individuals are faced with real risk and have their lives at stake.

Second, this dissertation did not capture the qualitative aspects of the phenomena in teams working with robots. The experiments in this dissertation employ quantitative measurements and involve interactions based on a protocol that was designed beforehand. The quantitative method used in this dissertation allows for measuring perceptions and attitudes as well as for building a nomological network based on statistical analysis. However, interactions may also be measured from qualitative methods, such as interpreting conversations among team members and directly observing their behaviors. Qualitative methods, including observation and interview, can be exploratory and thus, useful for uncovering new phenomena and understanding team members' underlying motivations and opinions in depth. Future research can benefit from the qualitative methods for discovering and examining various phenomena in teams that work with robots.

5.3 GUIDE FOR PRACTICE

Besides the theoretical merit of this dissertation research, findings across the three studies are potentially poised to provide insights for the design of robots in teams working with robots and management of such teams. First, one immediate implication for robot designers is that functionality and technical capability of robots may not be the most important requirement for robots in teams. Technical advancement is, of course, essential to developing a robot for teams that perform various types of missions. However, technical specification of the robots used in this dissertation was constant across various conditions in the experiments. On the other hand, the constructs associated with the team made a difference in the interaction among team members and possible outcomes. For instance, the team potency study showcased that performance of individual robot operators can be harnessed by the team's ethnic composition. The similarity study asserts that sharing similar quality can alter a team member's attitude toward the robot more positively.

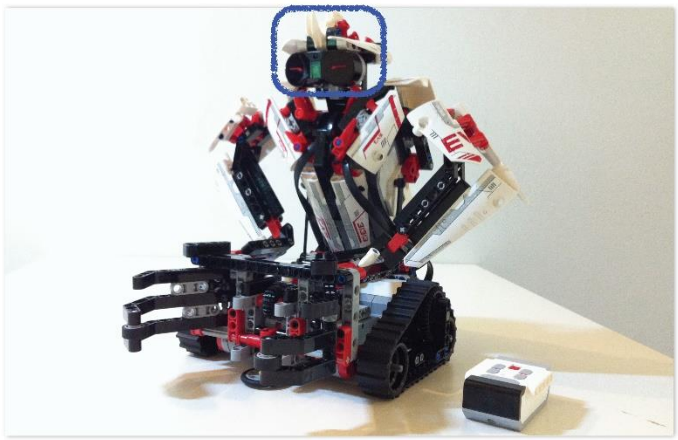
Second, designers of the robot should acknowledge that robots used in teams should be designed particularly for that team. In other words, robots used in teams are designed to facilitate the team interaction and support team functioning. The results from the trust study demonstrate that team identification and the collective robot-building activity promoted trust in the robots and teammates. This finding suggests that robots for teams should be equipped with customizability and visual indication to reinforce team membership. The similarity study also provides more evidence for the assertion by emphasizing the congruence between an individual and a robot result in more positive perception toward the robot. These benefits cannot be obtained when teams simply adopt a robot that is designed for individual interactions. In this sense, I believe this dissertation as a whole provides a valuable insight for designers of robots for teams.

Third, team leaders and managers should keep in mind that adoption of robots may engender new team phenomena and they should be prepared for potential alteration in interaction within the team. My dissertation research is an effort to weave knowledge from a few different bodies of literature: the traditional teamwork research, the human-robot interaction, and the information systems. By incorporating insights from these individual bodies of research, I can prove that teams working with robots require a new approach to understanding how such teams work in order to improve outcomes. The team potency study implies that teams working with robots can benefit from a managerial intervention to make the team more diverse. The similarity study provides a lesson for organizations that are considering adopting a robotic partner for their employees: robots will be welcomed to replace a human teammate only when there is a high risk of danger in the collaborative task.

APPENDICES

APPENDIX A: ROBOT-BUILDING INSTRUCTION FOR THE TRUST STUDY

How to Build Your Robot



1. The Robot

This is the robot that you will complete by building parts. The robot consists of three major parts: body with the head, two arms, and base. The body has a processor and a head as IR receiver. The base has wheels and the Gripper hand. Finally, the two arms are linking the body with the base and sustaining the body that is heavy.

2. About the Building

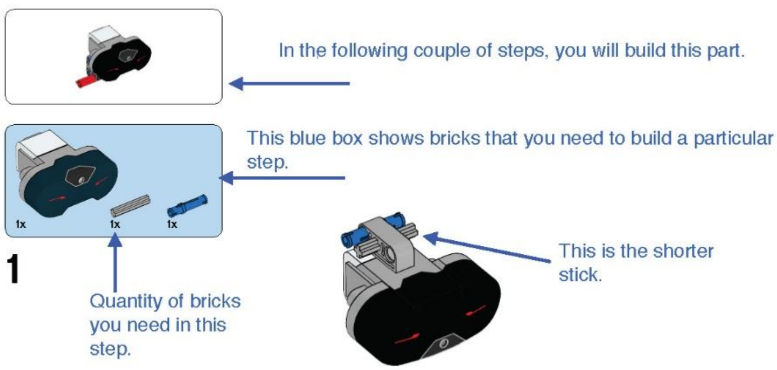
You will assemble the robot head (IR receiver) and integrate the head and two arms onto the robot body. The head is the critical compartment. The head receives IR commands from you and transmits the signal to the computer (body). If the head is not assembled properly, the robot will not function correctly.

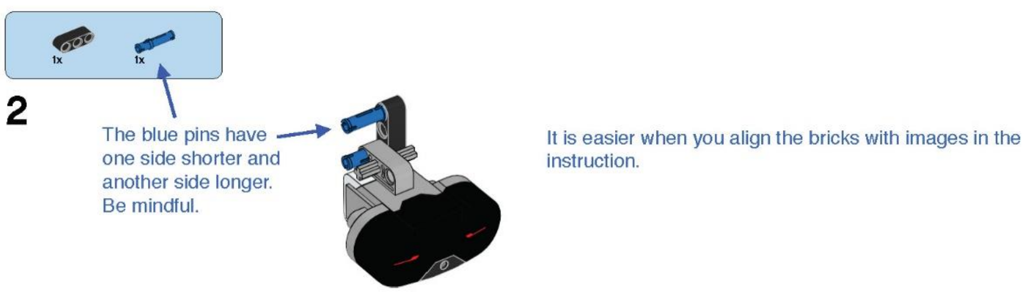
3. Instructions

Building instructions will follow from the next page. You will be given the exact number and type of pieces that are needed to complete the part. If you still have some pieces left unused on your table, it is likely that your robot is not built correctly. There is no time limit. If you have any question while building, please find the experimenter outside the room. The robot building activity is **not a test**, but to help you understand how the robots work. So you can ask questions to the experimenter whenever you need.

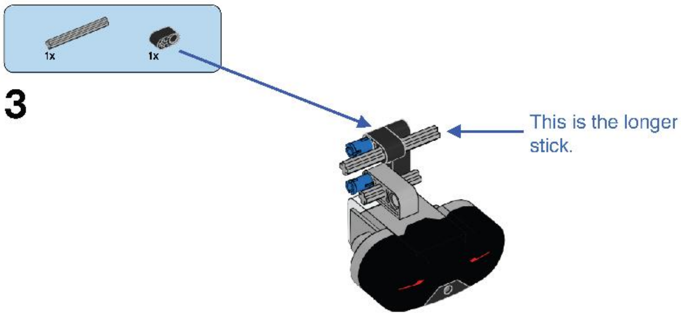
1) Assemble the head
2) Integrate the head with the head cover
3) Integrate the head assembly to the robot and complete the robot.

Let’s begin building!

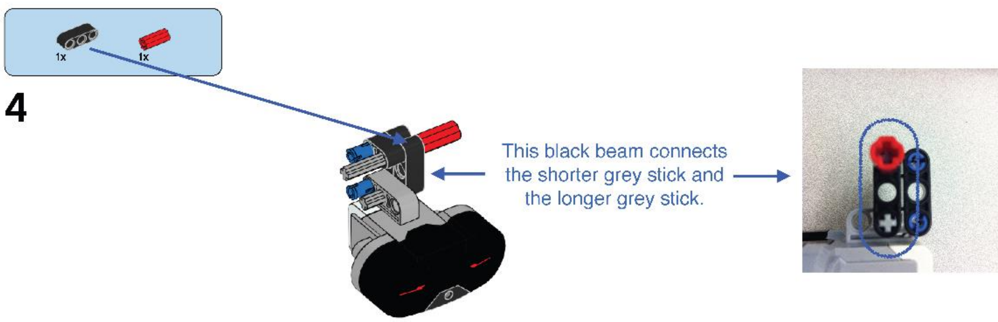

In the following couple of steps, you will build this part.
This blue box shows bricks that you need to build a particular step.
1x
1x
1x
1
Quantity of bricks you need in this step.
This is the shorter stick.

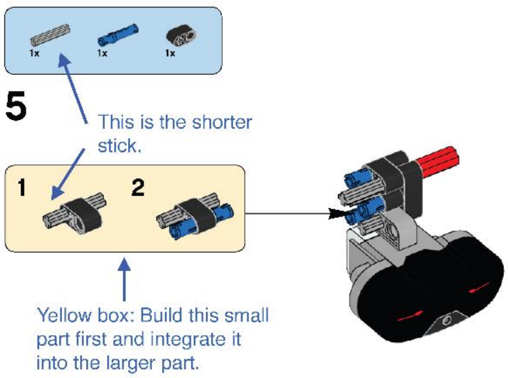

1x
1x
2
The blue pins have one side shorter and another side longer. Be mindful.
It is easier when you align the bricks with images in the instruction.

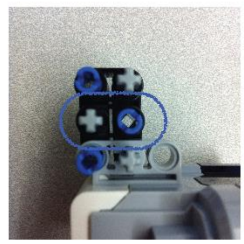
3

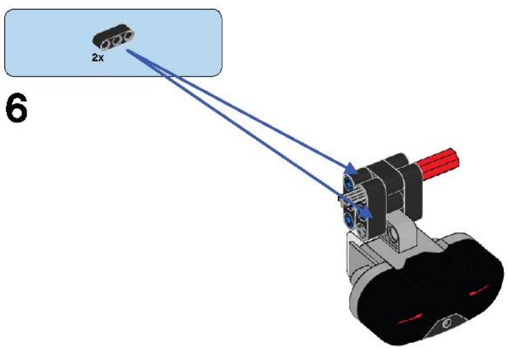

1x
1x
This is the longer stick.

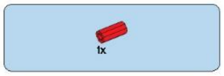
4


1x
1x
This black beam connects the shorter grey stick and the longer grey stick.

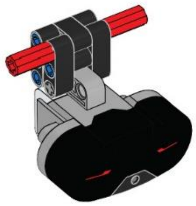

1x
1x
1x
5
This is the shorter stick.
1
2
Yellow box: Build this small part first and integrate it into the larger part.




2x
6

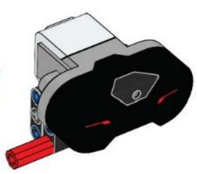


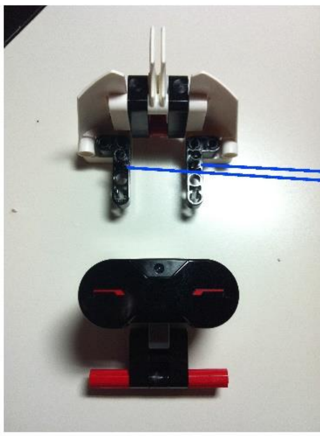
7

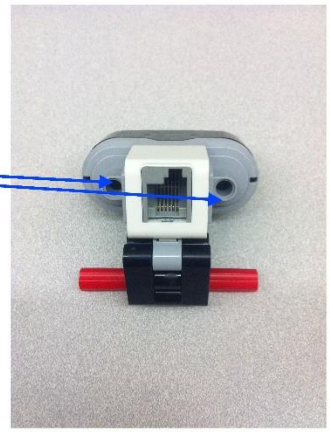


8

Rotate the brick and align with the image. If what you build looks like this image, you are done.







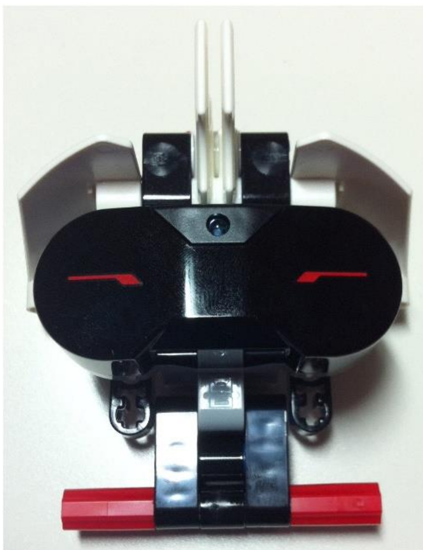
Put the black pins in the two holes in the back of the head.

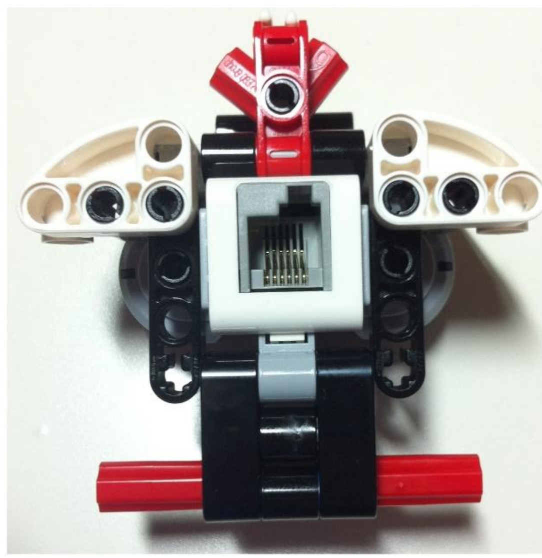
Now the head and its cover assembly are complete.

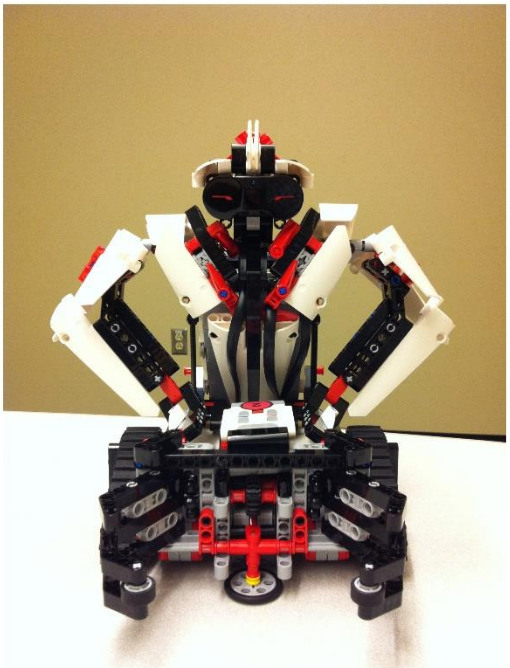
Building Instruction

This is what the robot should look like.

1) Head and its cover (front and back)







Ask the experimenter about integrating the head into the body.

This is the complete robot with the head assembly.

WHEN YOU ARE DONE BUILDING,
PLEASE LET THE EXPERIMENTER KNOW.

APPENDIX B: TEAM IDENTIFICATION INSTRUCTION FOR THE TRUST STUDY

Choose a Team Name and Uniform

1) Team Name: Please choose a team name and color between Maize and Blue. Your teammates will be you, your robot, another human, and the person's robot. Please discuss with others and choose one name.
2) Uniform: All teammates including robots will be wearing jerseys as uniform. The color of the jerseys will be matched with your team name. Jerseys are one-size and unisex. You will put the uniform on the robots.
3) Please note that the uniform is just for your preference. It is not about competition between yellow teams and blue teams.
4) Indicate your team name and uniform color below and turn in to the experimenter.

Team Color and Jersey		
Mark ONE		
Team Name		

**WHEN YOU ARE DONE,
PLEASE FIND THE EXPERIMENTER AND LET HIM KNOW ABOUT
YOUR CHOICE OF UNIFORM AND TEAM NAME.**

APPENDIX C: TASK INSTRUCTION FOR THE TRUST STUDY AND THE TEAM POTENCY STUDY

Delivering Water Tanks to A Water Treatment Facility

1. Mission

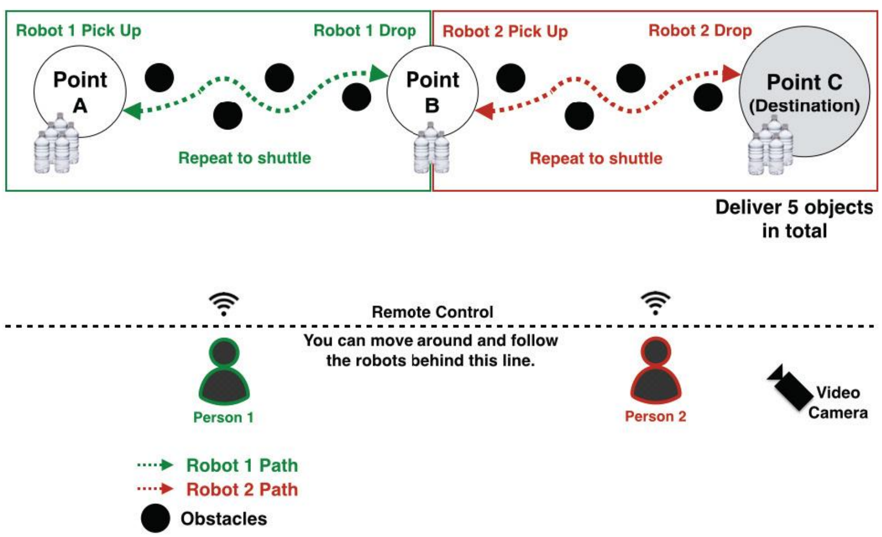
The objective of this task is to deliver water tanks from Point A to Point C via Point B as quickly as possible. Each time you will have to control the robots to deliver the water tanks avoiding obstacles. Performance will be measured by the time it takes to deliver FIVE water tanks. The team which completes the task the most quickly in the entire experiment will receive additional $100 besides the $20 show-up fee. Teams that complete the task second and third most quickly in the entire experiment will receive an additional $40 and $20 respectively.

- ✦ Task: Move the water tanks to Destination as quickly as possible
- ✦ Robot 1: Pick up water tanks at Point A, drop them at Point B, and return to Point A. Repeat this.
- ✦ Robot 2: Pick up the water tanks in Point B, drop them in Point C (Destination), and return to Point B. Repeat this.
- ✦ Rules
  - Only water tanks completely in the area of Point C will count.
  - Time will be measured until the last of five water tanks arrives at Point C.
  - Two robots work simultaneously.
  - Move only within the designated work area (Robot 1: Green, Robot 2: Red).
  - Avoid obstacles that are fixed on the floor.
  - Robots can't pick up water bottles that fell over.
  - But, fallen water bottles still count as delivered at Point C (Destination).

- Robots can drop and leave a water tank in the middle of routes, and try another water tank.
- Only robots can deliver, not humans. Humans can't touch the bottles.
- Humans cannot go beyond the white line.
- Do not swap the robots between humans.
- Performance will be recorded using a video camera.

2. Setting and Delivery Routes

These are the delivery routes. Please stay within the colored lines. A video of an example task will be shown for your understanding.



3. Procedure

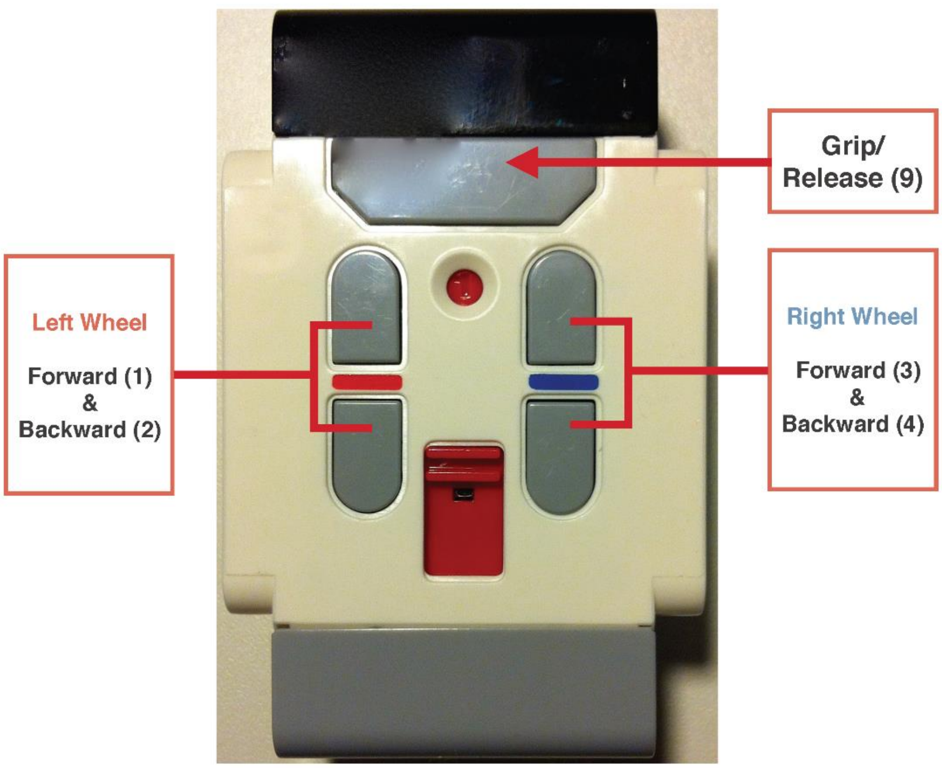
1) Free training to control the robot for two minutes
2) One practice task of delivering all two water tanks without timing
3) The main task for time

IF YOU HAVE ANY QUESTION ABOUT THE TASK AND RULES, FEEL FREE TO ASK THE EXPERIMENTER.

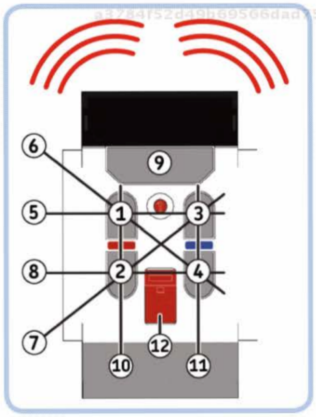
APPENDIX D: ROBOT CONTROL INSTRUCTION FOR THE TRUST STUDY AND THE TEAM POTENCY STUDY

How to Control the Robots Using IR Remote

Please read this instruction on how to control the robots. You will watch a video instruction and have a couple of practice runs on controlling the robots after reading this written instruction.



1. Steering



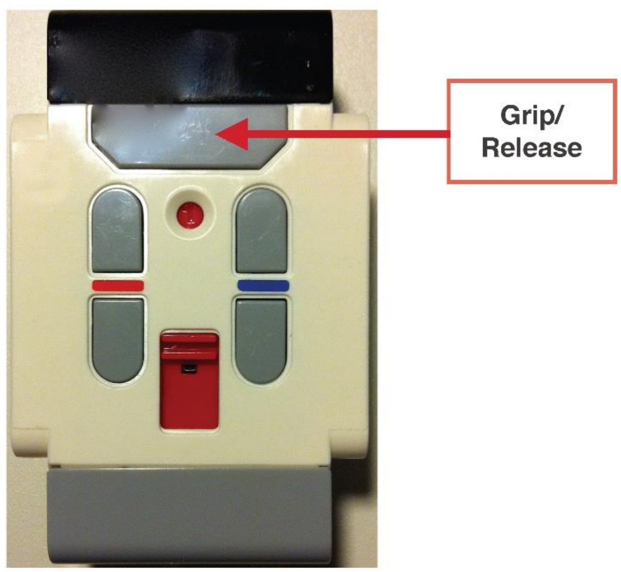
You will control the robot with a small IR remote. Please carefully read below because it is different from how you drive ordinary R/C cars. Buttons on the lefthand side control the left wheel and buttons on the right hand side control the right wheel. For example, if you press button 1, only the left wheel rotates forward. This means that if you press only button 1 to rotate the LEFT WHEEL, the robot makes a RIGHT TURN, not a left turn. It is the same mechanism for the right wheel. Therefore, if you want to go STRAIGHT, you need to press BOTH button 1 and 3. Moving backward is by the same mechanism. A table below lists the button presses for all directions.

Button Pressed	Motion (Channel 1 or 2)
1 & 3	Move forward.
2 & 4	Move backward.
1 & 4	Spin right.
2 & 3	Spin left.
1	Turn right by pivoting on the right wheel.
2	Turn left by going backward and pivoting on the right wheel.
3	Turn left by pivoting on the left wheel.
4	Turn right by going backward and pivoting on the left wheel.

2. Controlling the Gripper hand

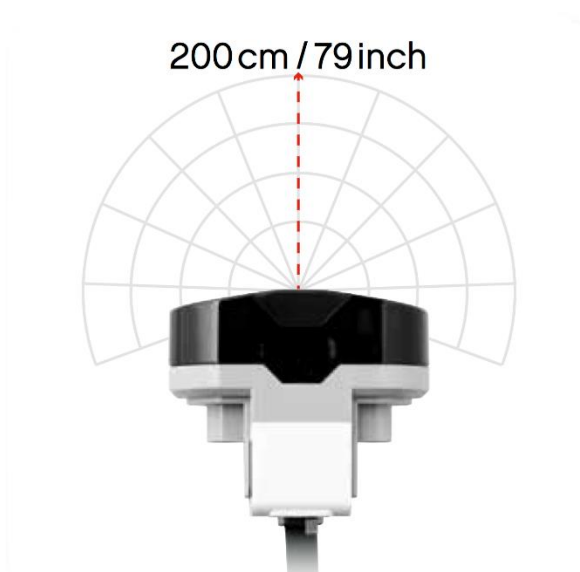
The Gripper hand will be controlled with only one button—button 9. When the hand is open, press button 9 to grip and lift objects. Move around using the steering buttons while gripping the object. When the hand is closed, press button 9 again to release.

Button Pressed	Motion (Channel 2 or 4)
9	Grip and Lift
9 (toggle)	Lower and Release



3. IR Remote Receiver

The robot's head is an IR signal receiver. This will receive commands from you based on buttons pressed in the IR remote. Please note that you may have to face the IR remote toward the head. For example, if you press buttons directly behind the robot, it may not move. When the robot is not moving according to your commands, please move closer or in front of the robot.



BIBLIOGRAPHY

Abrams, D., & Hogg, M. A. (1990). Social identification, self-categorization and social influence. *European Review of Social Psychology*, *1*(1), 195–228.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211.

Akgün, A. E., Keskin, H., Byrne, J., & Imamoglu, S. Z. (2007). Antecedents and consequences of team potency in software development projects. *Information & Management*, *44*(7), 646–656.

Alnuaimi, O. A., Robert, L. P., & Maruping, L. M. (2010). Team size, dispersion, and social loafing in technology-supported teams: A perspective on the theory of moral disengagement. *Journal of Management Information Systems*, *27*(1), 203–230.

Altschuller, S., & Benbunan-Fich, R. (2010). Trust, Performance, and the Communication Process in Ad Hoc Decision-Making Virtual Teams. *Journal of Computer-Mediated Communication*, *16*(1), 27–47.

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). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=2702592

Aquino, K., Townsend, A. M., & Scott, K. D. (2001). The Effects of Surface- and Deep-Level Dissimilarity on Individual Work Attitudes and Cogntions in Self-Directed Work Teams. In *Academy of Management Proceedings* (Vol. 2001, pp. A1–A6). https://doi.org/10.5465/APBPP.2001.6133613

Avolio, B. J., Jung, D. I., Murry, W., & Sivasbramaniam, N. (1996). Building highly developed teams: Focusing on shared leadership process, efficacy, trust, and performance. Retrieved from http://psycnet.apa.org/psycinfo/2000-07271-007

Bailenson, J. N., Blascovich, J., & Guadagno, R. E. (2008). Self-Representations in Immersive Virtual Environments1. *Journal of Applied Social Psychology*, *38*(11), 2673–2690.

Balkundi, P., Barsness, Z., & Michael, J. H. (2009). Unlocking the influence of leadership network structures on team conflict and viability. *Small Group Research*, *40*(3), 301–322.

Balkundi, P., & Harrison, D. A. (2006). Ties, leaders, and time in teams: Strong inference about network structure's effects on team viability and performance. *Academy of Management Journal*, *49*(1), 49–68.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall, Inc. Retrieved from http://psycnet.apa.org/psycinfo/1985-98423-000/

Barbash, G. I., Friedman, B., Glied, S. A., & Steiner, C. A. (2014). Factors associated with adoption of robotic surgical technology in US hospitals and relationship to radical prostatectomy procedure volume. *Annals of Surgery*, *259*(1), 1–6.

Bauer, A., Wollherr, D., & Buss, M. (2008). Human–robot collaboration: a survey. *International Journal of Humanoid Robotics*, *5*(01), 47–66.

Beal, D. J., Cohen, R. R., Burke, M. J., & McLendon, C. L. (2003). Cohesion and performance in groups: a meta-analytic clarification of construct relations. *Journal of Applied Psychology*, *88*(6), 989.

Bell, S. T. (2007). Deep-level composition variables as predictors of team performance: a meta-analysis. *Journal of Applied Psychology*, *92*(3), 595.

Bell, S. T., & Marentette, B. J. (2011). Team viability for long-term and ongoing organizational teams. *Organizational Psychology Review*, 2041386611405876.

Benbasat, I., & Wang, W. (2005). Trust in and adoption of online recommendation agents. *Journal of the Association for Information Systems*, *6*(3), 4.

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

Blau, P. M. (1977). *Inequality and heterogeneity: A primitive theory of social structure* (Vol. 7). Free Press New York. Retrieved from https://www.ncjrs.gov/App/Publications/abstract.aspx?ID=47085

Bliese, P. D. (2000). Within-group agreement, non-independence, and reliability: Implications for data aggregation and analysis. Retrieved from http://psycnet.apa.org/psycinfo/2000-16936-008

Breazeal, C., Hoffman, G., & Lockerd, A. (2004). Teaching and working with robots as a collaboration. In *Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagent Systems-Volume 3* (pp. 1030–1037). IEEE Computer Society. Retrieved from http://dl.acm.org/citation.cfm?id=1018871

Briggs, R. O., de Vreede, G., & Reinig, B. A. (2003). A theory and measurement of meeting satisfaction. In *System Sciences, 2003. Proceedings of the 36th Annual Hawaii International Conference on* (p. 8–pp). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1173677

Broadbent, E., Stafford, R., & MacDonald, B. (2009). Acceptance of healthcare robots for the older population: review and future directions. *International Journal of Social Robotics*, *1*(4), 319–330.

Brown, R., Condor, S., Mathews, A., Wade, G., & Williams, J. (1986). Explaining intergroup differentiation in an industrial organization. *Journal of Occupational Psychology*, *59*(4), 273–286. https://doi.org/10.1111/j.2044-8325.1986.tb00230.x

Bruemmer, D., Few, D., Goodrich, M., Norman, D., Sarkar, N., Scholtz, J., … Yanco, H. (2004). How to trust robots further than we can throw them. In *CHI'04 Extended Abstracts on Human Factors in Computing Systems* (pp. 1576–1577). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=986152

Burke, J. L., Murphy, R. R., Coovert, M. D., & Riddle, D. L. (2004). Moonlight in miami: Field study of human-robot interaction in the context of an urban search and rescue disaster response training exercise. *Human–Computer Interaction, 19*(1–2), 85–116.

Byrne, D. (1961). Interpersonal attraction and attitude similarity. *The Journal of Abnormal and Social Psychology*, *62*(3), 713.

Cacioppo, J. T., & Petty, R. E. (1982). The need for cognition. *Journal of Personality and Social Psychology*, *42*(1), 116.

Cacioppo, J. T., Petty, R. E., Feinstein, J. A., & Jarvis, W. B. G. (1996). Dispositional differences in cognitive motivation: The life and times of individuals varying in need for cognition. *Psychological Bulletin*, *119*(2), 197.

Campion, M. A., Papper, E. M., & Medsker, G. J. (1996). Relations between work team characteristics and effectiveness: A replication and extension. *Personnel Psychology*, *49*(2), 429–452.

Cannon-Bowers, J. A., & Bowers, C. (2011). Team development and functioning. In *APA handbook of industrial and organizational psychology, Vol 1: Building and developing the organization* (pp. 597–650). Washington, DC, US: American Psychological Association.

Carpenter, J. (2013). *The Quiet Professional: An investigation of US military Explosive Ordnance Disposal personnel interactions with everyday field robots*. Retrieved from https://digital.lib.washington.edu/researchworks/handle/1773/24197

Carpenter, J. (2014). Just Doesn't Look Right: Exploring the Impact of Humanoid Robot Integration into Explosive Ordnance Disposal Teams. Retrieved from http://www.igi-global.com/chapter/just-doesnt-look-right/84954

Casler, K., Bickel, L., & Hackett, E. (2013). Separate but equal? A comparison of participants and data gathered via Amazon's MTurk, social media, and face-to-face behavioral testing. *Computers in Human Behavior*, *29*(6), 2156–2160.

Chaiken, S., & Trope, Y. (1999). *Dual-process theories in social psychology*. Guilford Press. Retrieved from https://books.google.com/books?hl=en&lr=&id=5X_auIBx99EC&oi=fnd&pg=PA3&dq=dual+process+social+psychology&ots=OIVT7V8cqj&sig=uex0x5qlgw86m2Ah8DuwyRPH_TU

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.

Choi, J. N., & Kim, M. U. (1999). The organizational application of groupthink and its limitations in organizations. *Journal of Applied Psychology*, *84*(2), 297.

Collins, C. G., & Parker, S. K. (2010). Team capability beliefs over time: Distinguishing between team potency, team outcome efficacy, and team process efficacy. *Journal of Occupational and Organizational Psychology*, *83*(4), 1003–1023.

Colquitt, J. A., Scott, B. A., & LePine, J. A. (2007). Trust, trustworthiness, and trust propensity: a meta-analytic test of their unique relationships with risk taking and job performance. *Journal of Applied Psychology*, *92*(4), 909.

Compeau, D., Higgins, C. A., & Huff, S. (1999). Social cognitive theory and individual reactions to computing technology: A longitudinal study. *MIS Quarterly*, 145–158.

Costa, A. C. (2003). Work team trust and effectiveness. *Personnel Review*, *32*(5), 605–622.

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.

Dahlin, K. B., Weingart, L. R., & Hinds, P. J. (2005). Team diversity and information use. *Academy of Management Journal*, *48*(6), 1107–1123.

Das, T. K., & Teng, B.-S. (1998). Between trust and control: Developing confidence in partner cooperation in alliances. *Academy of Management Review*, *23*(3), 491–512.

Dautenhahn, K., Woods, S., Kaouri, C., Walters, M. L., Koay, K. L., & Werry, I. (2005). What is a robot companion-friend, assistant or butler? In *Intelligent Robots and Systems, 2005.(IROS 2005). 2005 IEEE/RSJ International Conference on* (pp. 1192–1197). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1545189

Davis, F. D. (1986). *A technology acceptance model for empirically testing new end-user information systems: Theory and results*. Massachusetts Institute of Technology. Retrieved from https://www.researchgate.net/profile/Fred_Davis2/publication/35465050_A_technology_acceptance_model_for_empirically_testing_new_enduser_information_systems__theory_and_results_/links/0c960519fbaddf3ba7000000.pdf

De Dreu, C. K., & West, M. A. (2001). Minority dissent and team innovation: the importance of participation in decision making. *Journal of Applied Psychology*, *86*(6), 1191.

De Jong, B. A., & Elfring, T. (2010). How does trust affect the performance of ongoing teams? The mediating role of reflexivity, monitoring, and effort. *Academy of Management Journal*, *53*(3), 535–549.

De Santis, A., Siciliano, B., De Luca, A., & Bicchi, A. (2008). An atlas of physical human–robot interaction. *Mechanism and Machine Theory*, *43*(3), 253–270.

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.

Desai, M., Medvedev, M., Vázquez, M., McSheehy, S., Gadea-Omelchenko, S., Bruggeman, C., … Yanco, H. (2012). Effects of Changing Reliability on Trust of Robot Systems. In *Proceedings of the Seventh Annual ACM/IEEE International Conference on Human-Robot Interaction* (pp. 73–80). New York, NY, USA: ACM. https://doi.org/10.1145/2157689.2157702

Dirks, K. T. (1999). The effects of interpersonal trust on work group performance. *Journal of Applied Psychology*, *84*(3), 445.

Dole, L. D., Sirkin, D. M., Currano, R. M., Murphy, R. R., & Nass, C. I. (2013). Where to look and who to be: Designing attention and identity for search-and-rescue robots. In *Proceedings of the 8th ACM/IEEE international conference on Human-robot interaction* (pp. 119–120). IEEE Press. Retrieved from http://dl.acm.org/citation.cfm?id=2447596

Dourish, P. (2001). Seeking a foundation for context-aware computing. *Human–Computer Interaction*, *16*(2–4), 229–241.

Downs, J. S., Holbrook, M. B., Sheng, S., & Cranor, L. F. (2010). Are your participants gaming the system?: screening mechanical turk workers. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 2399–2402). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=1753688

Duckitt, J. (2001). A dual-process cognitive-motivational theory of ideology and prejudice. *Advances in Experimental Social Psychology*, *33*, 41–113.

Ely, R. J., Padavic, I., & Thomas, D. A. (2012). Racial diversity, racial asymmetries, and team learning environment: Effects on performance. *Organization Studies*, *33*(3), 341–362.

Evans, J. S. B. T. (2008). Dual-Processing Accounts of Reasoning, Judgment, and Social Cognition. *Annual Review of Psychology*, *59*(1), 255–278. https://doi.org/10.1146/annurev.psych.59.103006.093629

Eyssel, F. A., & Loughnan, S. (2013). “It don”t matter if you’re Black or White’? Effects of robot appearance and user prejudice on evaluations of a newly developed robot companion. *Social Robotics*. Retrieved from https://pub.uni-bielefeld.de/publication/2633784

Eyssel, F., & Kuchenbrandt, D. (2011). Manipulating anthropomorphic inferences about NAO: The role of situational and dispositional aspects of effectance motivation. In *RO-MAN, 2011 IEEE* (pp. 467–472). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6005233

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.

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). New York, NY, USA: ACM. https://doi.org/10.1145/2157689.2157717

Eyssel, F., Kuchenbrandt, D., Hegel, F., & De Ruiter, L. (2012). Activating elicited agent knowledge: How robot and user features shape the perception of social robots. In *RO-MAN, 2012 IEEE* (pp. 851–857). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6343858

Eyssel, F., & Loughnan, S. (2013). “It Don’t Matter If You’re Black or White”? In *Social Robotics* (pp. 422–431). Springer. Retrieved from http://link.springer.com/10.1007/978-3-319-02675-6_42

Feng, C., Dong, S., Lundeen, K. M., Xiao, Y., & Kamat, V. R. (2015). Vision-Based Articulated Machine Pose Estimation for Excavation Monitoring and Guidance. In *Proc. International Symposium on Automation and Robotics in Construction (ISARC), ISARC*. Retrieved from http://search.proquest.com/openview/793a722cac3419239d66cb59e13e36e2/1.pdf?pq-origsite=gscholar&cbl=1646340

Feng, C., Xiao, Y., Willette, A., McGee, W., & Kamat, V. R. (2015). Vision guided autonomous robotic assembly and as-built scanning on unstructured construction sites. *Automation in Construction*, *59*, 128–138.

Fishbein, M. (1979). A theory of reasoned action: some applications and implications. Retrieved from http://psycnet.apa.org/psycinfo/1982-21121-001

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

Forgas, J. P., Scholar, F. E. E. S. and P. of P. R. F. B., Baumeister, R. F., & Tice, D. M. (2011). *Psychology of Self-Regulation: Cognitive, Affective, and Motivational Processes*. Taylor & Francis.

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research*, 382–388.

Freedy, E., DeVisser, E., Weltman, G., & Coeyman, N. (2007). Measurement of trust in human-robot collaboration. In *Collaborative Technologies and Systems, 2007. CTS 2007. International Symposium on* (pp. 106–114). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=4621745

Friedman, B., Kahn Jr, P. H., & Hagman, J. (2003). Hardware companions?: What online AIBO discussion forums reveal about the human-robotic relationship. In *Proceedings of the SIGCHI conference on Human factors in computing systems* (pp. 273–280). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=642660

Fuller, M. A., Hardin, A. M., & Davison, R. M. (2006). Efficacy in technology-mediated distributed teams. *Journal of Management Information Systems*, *23*(3), 209–235.

Garg, A., & Kamat, V. R. (2013). Virtual Prototyping for Robotic Fabrication of Rebar Cages in Manufactured Concrete Construction. *Journal of Architectural Engineering*, *20*(1), 06013002.

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

Gefen, D. (2000). E-commerce: the role of familiarity and trust. *Omega*, *28*(6), 725–737.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: an integrated model. *MIS Quarterly*, *27*(1), 51–90.

Gefen, D., Straub, D. W., & Rigdon, E. E. (2011). An update and extension to SEM guidelines for admnistrative and social science research. *Management Information Systems Quarterly*, *35*(2), iii–xiv.

Giambatista, R. C., & Bhappu, A. D. (2010). Diversity's harvest: Interactions of diversity sources and communication technology on creative group performance. *Organizational Behavior and Human Decision Processes*, *111*(2), 116–126.

Gibson, C. B. (2001). Me and us: Differential relationships among goal-setting training, efficacy and effectiveness at the individual and team level. *Journal of Organizational Behavior*, *22*(7), 789–808.

Gibson, C. B., & Earley, P. C. (2007). Collective Cognition in Action: Accumulation, Interaction, Examination, and Accommodation in the Development and Operation of Group Efficacy Beliefs in the Workplace. *The Academy of Management Review*, *32*(2), 438–458. https://doi.org/10.2307/20159310

Gist, M. E., & Mitchell, T. R. (1992). Self-efficacy: A theoretical analysis of its determinants and malleability. *Academy of Management Review*, *17*(2), 183–211.

Goldberg, C. B. (2005). Relational Demography and Similarity-Attraction in Interview Assessments and Subsequent Offer Decisions: ARE WE MISSING SOMETHING? *Group & Organization Management*, *30*(6), 597–624.

Graaf, M. M. A. (2015). *Living with robots: investigating the user acceptance of social robots in domestic environments* (Vol. 15). Universiteit Twente. Retrieved from http://doc.utwente.nl/96186/

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

Groom, V., Nass, C., Chen, T., Nielsen, A., Scarborough, J. K., & Robles, E. (2009). Evaluating the effects of behavioral realism in embodied agents. *International Journal of Human-Computer Studies*, *67*(10), 842–849. https://doi.org/10.1016/j.ijhcs.2009.07.001

Groom, V., Takayama, L., Ochi, P., & Nass, C. (2009). I am my robot: the impact of robot-building and robot form on operators. In *Human-Robot Interaction (HRI), 2009 4th ACM/IEEE International Conference on* (pp. 31–36). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6256084

Gully, S. M., Incalcaterra, K. A., Joshi, A., & Beaubien, J. M. (2002). A meta-analysis of team-efficacy, potency, and performance: interdependence and level of analysis as moderators of observed relationships. *Journal of Applied Psychology*, *87*(5), 819.

Gupta, S. (2014). SEM for Experimental Designs: An Information Systems Example. *Electronic Journal of Business Research Methods*, *12*(1), 27.

Guzzo, R. A., Yost, P. R., Campbell, R. J., & Shea, G. P. (1993). Potency in groups: Articulating a construct. *British Journal of Social Psychology*, *32*(1), 87–106.

Han, G., & Harms, P. D. (2010). Team identification, trust and conflict: a mediation model. *International Journal of Conflict Management*, *21*(1), 20–43.

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.

Hardin, A. M., Fuller, M. A., & Davison, R. M. (2007). I know I can, but can we? Culture and efficacy beliefs in global virtual teams. *Small Group Research*, *38*(1), 130–155.

Hardin, A. M., Fuller, M. A., & Valacich, J. S. (2006). Measuring group efficacy in virtual teams: New questions in an old debate. *Small Group Research*, *37*(1), 65–85.

Harrison, D. A., & Klein, K. J. (2007). What's the difference? Diversity constructs as separation, variety, or disparity in organizations. *Academy of Management Review*, *32*(4), 1199–1228.

Harrison, D. A., Price, K. H., & Bell, M. P. (1998). Beyond relational demography: Time and the effects of surface-and deep-level diversity on work group cohesion. *Academy of Management Journal*, *41*(1), 96–107.

Harrison, D. A., Price, K. H., Gavin, J. H., & Florey, A. T. (2002). Time, teams, and task performance: Changing effects of surface-and deep-level diversity on group functioning. *Academy of Management Journal*, *45*(5), 1029–1045.

Haslam, S. A., Powell, C., & Turner, J. (2000). Social Identity, Self-categorization, and Work Motivation: Rethinking the Contribution of the Group to Positive and Sustainable Organisational Outcomes. *Applied Psychology*, *49*(3), 319–339.

Heerink, M., Ben, K., Evers, V., & Wielinga, B. (2008). The influence of social presence on acceptance of a companion robot by older people. *Journal of Physical Agents*, *2*(2), 33–40.

Heerink, M., Kröse, B., Evers, V., & Wielinga, B. (2006). The influence of a robot's social abilities on acceptance by elderly users. In *Robot and Human Interactive Communication, 2006. ROMAN 2006. The 15th IEEE International Symposium on* (pp. 521–526). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=4107860

Hinds, P. J., & Mortensen, M. (2005). Understanding conflict in geographically distributed teams: The moderating effects of shared identity, shared context, and spontaneous communication. *Organization Science*, *16*(3), 290–307.

Hoff, K., & Bashir, M. (2013). A Theoretical Model for Trust in Automated Systems. In *CHI '13 Extended Abstracts on Human Factors in Computing Systems* (pp. 115–120). New York, NY, USA: ACM. https://doi.org/10.1145/2468356.2468378

Hoffman, R. R., Johnson, M., Bradshaw, J. M., & Underbrink, A. (2013). Trust in automation. *Intelligent Systems, IEEE*, *28*(1), 84–88.

Hoffman, R. R., Lee, J. D., Woods, D. D., Shadbolt, N., Miller, J., & Bradshaw, J. M. (2009). The dynamics of trust in cyberdomains. *IEEE Intelligent Systems*, (6), 5–11.

Hogg, M. A. (2007). Social identity and the group context of trust: Managing risk and building trust through belonging. *Trust in Cooperative Risk Management: Uncertainty and Scepticism in the Public Mind*, 51–72.

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

Hogg, M. A., & Turner, J. C. (1985). Interpersonal attraction, social identification and psychological group formation. *European Journal of Social Psychology*, *15*(1), 51–66.

Horwitz, S. K., & Horwitz, I. B. (2007). The Effects of Team Diversity on Team Outcomes: A Meta-Analytic Review of Team Demography. *Journal of Management*, *33*(6), 987–1015. https://doi.org/10.1177/0149206307308587

Horwitz, Sujin K. (2005). The compositional impact of team diversity on performance: Theoretical considerations. *Human Resource Development Review*, *4*(2), 219–245.

Howell, J. M., & Shea, C. M. (2006). Effects of champion behavior, team potency, and external communication activities on predicting team performance. *Group & Organization Management*, *31*(2), 180–211.

Hu, J., & Liden, R. C. (2011). Antecedents of team potency and team effectiveness: an examination of goal and process clarity and servant leadership. *Journal of Applied Psychology*, *96*(4), 851.

Hung, C., Dennis, A., & Robert, L. (2012). Trust Happens: A Multi-Route Model of Trust Formation in Virtual Teams. Retrieved from https://deepblue.lib.umich.edu/handle/2027.42/111878

Hung, Y.-T., Dennis, A. R., & Robert, L. (2004). Trust in virtual teams: Towards an integrative model of trust formation. In *System Sciences, 2004. Proceedings of the 37th Annual Hawaii International Conference on* (p. 11–pp). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1265156

Hütter, M., & Diehl, M. (2011). Motivation losses in teamwork: The effects of team diversity and equity sensitivity on reactions to free-riding. *Group Processes & Intergroup Relations*, *14*(6), 845–856.

Ilgen, D. R., Hollenbeck, J. R., Johnson, M., & Jundt, D. (2005). Teams in organizations: From input-process-output models to IMOI models. *Annu. Rev. Psychol.*, *56*, 517–543.

Jackson, S. E., & Joshi, A. (2011). Work team diversity. Retrieved from http://psycnet.apa.org/books/12169/020

Jackson, S. E., May, K. E., Whitney, K., & others. (1995). Understanding the dynamics of diversity in decision-making teams. *Team Effectiveness and Decision Making in Organizations*, *204*, 261.

Jarvenpaa, S. L., Knoll, K., & Leidner, D. E. (1998). Is Anybody Out There? Antecedents of Trust in Global. *Journal 0/Management Information Systems/Spring I998*, *4*(4), 29–64.

Jarvenpaa, S. L., Shaw, T. R., & Staples, D. S. (2004). Toward contextualized theories of trust: The role of trust in global virtual teams. *Information Systems Research*, *15*(3), 250–267.

Jehn, K. A., & Bezrukova, K. (2010). The faultline activation process and the effects of activated faultlines on coalition formation, conflict, and group outcomes. *Organizational Behavior and Human Decision Processes*, *112*(1), 24–42.

Jehn, K. A., Northcraft, G. B., & Neale, M. A. (1999). Why differences make a difference: A field study of diversity, conflict and performance in workgroups. *Administrative Science Quarterly*, *44*(4), 741–763.

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.

Jones, G. R., & George, J. M. (1998). The experience and evolution of trust: Implications for cooperation and teamwork. *Academy of Management Review*, *23*(3), 531–546.

Jones, H., & Hinds, P. (2002). Extreme work teams: using swat teams as a model for coordinating distributed robots. In *Proceedings of the 2002 ACM conference on Computer supported cooperative work* (pp. 372–381). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=587130

Jung, D. I., & Sosik, J. J. (2003). Group potency and collective efficacy examining their predictive validity, level of analysis, and effects of performance feedback on future group performance. *Group & Organization Management*, *28*(3), 366–391.

Kahneman, D. (2011). *Thinking, fast and slow*. Macmillan. Retrieved from https://books.google.com/books?hl=en&lr=&id=SHvzzuCnuv8C&oi=fnd&pg=PP2&dq=thinking+fast+and+slow&ots=NRxhUJ3iBF&sig=VlFNX9jX_N-C0mrlJr3AYMY0Doo

Kamat, V. R., & Martinez, J. C. (2005). Dynamic 3D visualization of articulated construction equipment. *Journal of Computing in Civil Engineering*, *19*(4), 356–368.

Kearney, E., Gebert, D., & Voelpel, S. C. (2009). When and How Diversity Benefits Teams: The Importance of Team Members' Need for Cognition. *The Academy of Management Journal*, *52*(3), 581–598.

Kellett, J. B., Humphrey, R. H., & Sleeth, R. G. (2000). We're great" vs."you're lazy": How goal difficulty influences social loafing, collective efficacy and perceived team ability. In *annual meeting of the Southern Management Association, Orlando, FL*. Retrieved from http://www.people.vcu.edu/~rsleeth/Papers/efficacySMA2000.htm

Kidd, C. D. (2003). *Sociable robots: The role of presence and task in human-robot interaction*. Massachusetts Institute of Technology. Retrieved from http://web.media.mit.edu/~coryk/papers/Kidd_MS_thesis.pdf

Kiesler, S., & Goetz, J. (2002). Mental Models of Robotic Assistants. In *CHI '02 Extended Abstracts on Human Factors in Computing Systems* (pp. 576–577). New York, NY, USA: ACM. https://doi.org/10.1145/506443.506491

Kiesler, T., & Kiesler, S. (2004). My pet rock and me: An experimental exploration of the self extension concept. *Human-Computer Interaction Institute*, 85.

Kim, J., You, S., Lee, S., Kamat, V., & Robert, L. (2015). Evaluation of Human Robot Collaboration in Masonry Work Using Immersive Virtual Environments. Retrieved from http://deepblue.lib.umich.edu/handle/2027.42/116277

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.

Klassner, F., & Anderson, S. D. (2003). Lego MindStorms: Not just for K-12 anymore. *IEEE Robotics & Automation Magazine*, *10*(2), 12–18.

Knight, W. (2015). Are You Ready for a Robot Colleague? Retrieved May 18, 2016, from https://www.technologyreview.com/s/541676/are-you-ready-for-a-robot-colleague/

Koay, K. L., Syrdal, D. S., Walters, M. L., & Dautenhahn, K. (2007). Living with robots: Investigating the habituation effect in participants' preferences during a longitudinal human-robot interaction study. In *Robot and Human interactive Communication, 2007. RO-MAN 2007. The 16th IEEE International Symposium on* (pp. 564–569). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=4415149

Korsgaard, M. A., Schweiger, D. M., & Sapienza, H. J. (1995). Building commitment, attachment, and trust in strategic decision-making teams: The role of procedural justice. *Academy of Management Journal*, *38*(1), 60–84.

Kozlowski, S. W., & Bell, B. S. (2003). Work groups and teams in organizations. *Handbook of Psychology*. Retrieved from http://onlinelibrary.wiley.com/doi/10.1002/0471264385.wei1214/full

Kozlowski, S. W., & Klein, K. J. (2000). A multilevel approach to theory and research in organizations: Contextual, temporal, and emergent processes. Retrieved from http://psycnet.apa.org/psycinfo/2000-16936-001

Krämer, N. C., Eimler, S., von der Pütten, A., & Payr, S. (2011). Theory of companions: what can theoretical models contribute to applications and understanding of human-robot interaction? *Applied Artificial Intelligence*, *25*(6), 474–502.

Krämer, N. C., von der Pütten, A., & Eimler, S. (2012). Human-Agent and Human-Robot Interaction Theory: Similarities to and Differences from Human-Human Interaction. In *Human-Computer Interaction: The Agency Perspective* (pp. 215–240). Springer. Retrieved from http://link.springer.com/chapter/10.1007/978-3-642-25691-2_9

Krauskopf, K., Zahn, C., Hesse, F. W., & Pea, R. D. (2014). Understanding video tools for teaching: mental models of technology affordances as inhibitors and facilitators of lesson planning in history and language arts. *Studies in Educational Evaluation*, *43*, 230–243.

Kruijff, G.-J. M. (2013). Trusting in Human-Robot Teams Given Asymmetric Agency and Social Sentience. In *AAAI Spring Symposium: Trust and Autonomous Systems*. Retrieved from http://www.aaai.org/ocs/index.php/SSS/SSS13/paper/download/5737/6003

Kuchenbrandt, D., Eyssel, F., Bobinger, S., & Neufeld, M. (2013). When a robot's group membership matters. *International Journal of Social Robotics*, *5*(3), 409–417.

Lankton, N., McKnight, D. H., & Thatcher, J. B. (2014). Incorporating trust-in-technology into Expectation Disconfirmation Theory. *The Journal of Strategic Information Systems*, *23*(2), 128–145.

Lee, C., & Farh, J.-L. (2004). Joint effects of group efficacy and gender diversity on group cohesion and performance. *Applied Psychology*, *53*(1), 136–154.

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *46*(1), 50–80.

Lee, K. M., Jung, Y., Kim, J., & Kim, S. R. (2006). Are physically embodied social agents better than disembodied social agents?: The effects of physical embodiment, tactile interaction, and people's loneliness in human–robot interaction. *International Journal of Human-Computer Studies*, *64*(10), 962–973.

Lee, K. M., & Nass, C. (2003). Designing social presence of social actors in human computer interaction. In *Proceedings of the SIGCHI conference on Human factors in computing systems* (pp. 289–296). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=642662

Lee, K. M., Peng, W., Jin, S.-A., & Yan, C. (2006). Can robots manifest personality?: An empirical test of personality recognition, social responses, and social presence in human–robot interaction. *Journal of Communication*, *56*(4), 754–772.

Lee, Y., Kozar, K. A., & Larsen, K. R. (2003). The technology acceptance model: Past, present, and future. *Communications of the Association for Information Systems*, *12*(1), 50.

Lester, S. W., Meglino, B. M., & Korsgaard, M. A. (2002). The antecedents and consequences of group potency: A longitudinal investigation of newly formed work groups. *Academy of Management Journal*, *45*(2), 352–368.

Li, D., Rau, P. P., & Li, Y. (2010). A cross-cultural study: effect of robot appearance and task. *International Journal of Social Robotics*, *2*(2), 175–186.

Li, J., & Hambrick, D. C. (2005). Factional groups: A new vantage on demographic faultlines, conflict, and disintegration in work teams. *Academy of Management Journal*, *48*(5), 794–813.

Li, X., Hess, T. J., & Valacich, J. S. (2008). Why do we trust new technology? A study of initial trust formation with organizational information systems. *The Journal of Strategic Information Systems*, *17*(1), 39–71.

Lira, E. M., Ripoll, P., Peiró, J. M., & González, P. (2007). The roles of group potency and information and communication technologies in the relationship between task conflict and team effectiveness: A longitudinal study. *Computers in Human Behavior*, *23*(6), 2888–2903.

Lira, E. M., Ripoll, P., Peiró, J. M., & Zornoza, A. M. (2013). The role of information and communication technologies in the relationship between group potency and group maintenance outcomes: a longitudinal study. *Behaviour & Information Technology*, *32*(2), 147–155.

Ljungblad, S., Kotrbova, J., Jacobsson, M., Cramer, H., & Niechwiadowicz, K. (2012). Hospital robot at work: something alien or an intelligent colleague? In *Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work* (pp. 177–186). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=2145233

Longo, M. R., Schüür, F., Kammers, M. P., Tsakiris, M., & Haggard, P. (2008). What is embodiment? A psychometric approach. *Cognition*, *107*(3), 978–998.

Luhmann, N. (2000). Familiarity, confidence, trust: Problems and alternatives. *Trust: Making and Breaking Cooperative Relations*, *6*, 94–107.

Makatchev, M., Simmons, R., Sakr, M., & Ziadee, M. (2013). Expressing ethnicity through behaviors of a robot character. In *Proceedings of the 8th ACM/IEEE international conference on Human-robot interaction* (pp. 357–364). IEEE Press. Retrieved from http://dl.acm.org/citation.cfm?id=2447681

Marcoulides, G. A., & Saunders, C. (2006). Editor's comments: PLS: a silver bullet? *MIS Quarterly*, iii–ix.

Marks, M. A., Mathieu, J. E., & Zaccaro, S. J. (2001). A temporally based framework and taxonomy of team processes. *Academy of Management Review*, *26*(3), 356–376.

Mathieu, J., Maynard, M. T., Rapp, T., & Gilson, L. (2008). Team Effectiveness 1997-2007: A Review of Recent Advancements and a Glimpse Into the Future. *Journal of Management*, *34*(3), 410–476. https://doi.org/10.1177/0149206308316061

Mathur, M. B., & Reichling, D. B. (2016). Navigating a social world with robot partners: A quantitative cartography of the Uncanny Valley. *Cognition*, *146*, 22–32.

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

McAllister, D. J. (1995). Affect-and cognition-based trust as foundations for interpersonal cooperation in organizations. *Academy of Management Journal*, *38*(1), 24–59.

McGrath, J. E. (1984). *Groups: Interaction and performance* (Vol. 14). Prentice-Hall Englewood Cliffs, NJ. Retrieved from https://www.uni-muenster.de/imperia/md/content/psyifp/aeechterhoff/wintersemester2011-12/vorlesungkommperskonflikt/mcgrath_groupinteractperfom_1984.pdf

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 (TMIS)*, *2*(2), 12.

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). The impact of initial consumer trust on intentions to transact with a web site: a trust building model. *The Journal of Strategic Information Systems*, *11*(3), 297–323.

McKnight, D. H., Cummings, L. L., & Chervany, N. L. (1998). Initial trust formation in new organizational relationships. *Academy of Management Review*, *23*(3), 473–490.

Merrill, M. D. (2000). Knowledge objects and mental models. In *Advanced Learning Technologies, 2000. IWALT 2000. Proceedings. International Workshop on* (pp. 244–246). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=890621

Meyerson, D., Weick, K. E., & Kramer, R. M. (1996). Swift trust and temporary groups. *Trust in Organizations: Frontiers of Theory and Research*, *166*, 195.

Miller, C. C. (2016). The Long-Term Jobs Killer Is Not China. It's Automation. - Google Search. Retrieved May 16, 2017, from https://www.nytimes.com/2016/12/21/upshot/the-long-term-jobs-killer-is-not-china-its-automation.html?_r=0

Mohammed, S., & Angell, L. C. (2004). Surface-and deep-level diversity in workgroups: Examining the moderating effects of team orientation and team process on relationship conflict. *Journal of Organizational Behavior*, *25*(8), 1015–1039.

Montano, D. E., & Kasprzyk, D. (2015). Theory of reasoned action, theory of planned behavior, and the integrated behavioral model. *Health Behavior: Theory, Research and Practice (*. Retrieved from https://books.google.com/books?hl=en&lr=&id=9BQWCgAAQBAJ&oi=fnd&pg=PA95&dq=theory+of+reasoned+action&ots=ecPb9cvTa_&sig=8UwxCDjHpzWgCW85kQDVpipj_JI

Monteiro, R. B., & Vieira, V. A. (2016). Team potency and its impact on performance via self-efficacy and adaptability. *BAR-Brazilian Administration Review*, *13*(1), 98–119.

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.

Morris, S. A., Marshall, T. E., & Rainer Jr, R. K. (2002). Impact of user satisfaction and trust on virtual team members. *Information Resources Management Journal (IRMJ)*, *15*(2), 22–30.

Mugge, R., Schoormans, J. P., & Schifferstein, H. N. (2009). Emotional bonding with personalised products. *Journal of Engineering Design*, *20*(5), 467–476.

Mukherjee, K. (2010). A dual system model of preferences under risk. *Psychological Review*, *117*(1), 243.

Mutlu, B., Osman, S., Forlizzi, J., Hodgins, J., & Kiesler, S. (2006). Task structure and user attributes as elements of human-robot interaction design. In *Robot and Human Interactive Communication, 2006. ROMAN 2006. The 15th IEEE International Symposium on* (pp. 74–79). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=4107788

Nakajima, H., Yamada, R., Brave, S., Morishima, Y., Nass, C., & Kawaji, S. (2003). The functionality of human-machine collaboration systems-mind model and social behavior. In *Systems, Man and Cybernetics, 2003. IEEE International Conference on* (Vol. 3, pp. 2381–2387). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1244240

Nass, C., & Lee, K. M. (2001). Does computer-synthesized speech manifest personality? Experimental tests of recognition, similarity-attraction, and consistency-attraction. *Journal of Experimental Psychology: Applied*, *7*(3), 171.

Newell, J., Maruping, L., Riemenschneider, C., & Robert, L. (2008). Leveraging E-Identities: The Impact of Percieved Diversity on Team Social Integration and Performance. Retrieved from http://aisel.aisnet.org/icis2008/46/

Nichols, G. (2016). Before heading to Mars, NASA's Valkyrie humanoid lands at MIT. Retrieved May 19, 2016, from http://www.zdnet.com/article/before-heading-to-mars-nasas-valkyrie-humanoid-lands-at-mit/

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). Piscataway, NJ, USA: IEEE Press. Retrieved from http://dl.acm.org/citation.cfm?id=2447556.2447563

Nomura, T., Kanda, T., & Suzuki, T. (2006). Experimental investigation into influence of negative attitudes toward robots on human–robot interaction. *Ai & Society*, *20*(2), 138–150.

Oleson, K. E., Billings, D. R., Kocsis, V., Chen, J. Y., & Hancock, P. A. (2011). Antecedents of trust in human-robot collaborations. In *Cognitive Methods in Situation Awareness and Decision Support (CogSIMA), 2011 IEEE First*

International Multi-Disciplinary Conference on (pp. 175–178). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=5753439

Paolacci, G., & Chandler, J. (2014). Inside the turk understanding mechanical turk as a participant pool. *Current Directions in Psychological Science*, *23*(3), 184–188.

Paolacci, G., Chandler, J., & Ipeirotis, P. G. (2010). Running experiments on amazon mechanical turk. *Judgment and Decision Making*, *5*(5), 411–419.

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

Pearce, C. L., Gallagher, C. A., & Ensley, M. D. (2002). Confidence at the group level of analysis: A longitudinal investigation of the relationship between potency and team effectiveness. *Journal of Occupational and Organizational Psychology*, *75*(1), 115–119.

Pelled, L. H., Eisenhardt, K. M., & Xin, K. R. (1999). Exploring the black box: An analysis of work group diversity, conflict and performance. *Administrative Science Quarterly*, *44*(1), 1–28.

Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. In *Communication and persuasion* (pp. 1–24). Springer. Retrieved from http://link.springer.com/chapter/10.1007/978-1-4612-4964-1_1

Phillips, E., Ososky, S., Grove, J., & Jentsch, F. (2011). From Tools to Teammates Toward the Development of Appropriate Mental Models for Intelligent Robots. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 55, pp. 1491–1495). SAGE Publications. Retrieved from http://pro.sagepub.com/content/55/1/1491.short

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

Powell, A., Piccoli, G., & Ives, B. (2004). Virtual teams: a review of current literature and directions for future research. *ACM Sigmis Database*, *35*(1), 6–36.

Powers, A., & Kiesler, S. (2006). The advisor robot: tracing people's mental model from a robot's physical attributes. In *Proceedings of the 1st ACM SIGCHI/SIGART conference on Human-robot interaction* (pp. 218–225). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=1121280

Rae, I., Takayama, L., & Mutlu, B. (2012). One of the gang: supporting in-group behavior for embodied mediated communication. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 3091–3100). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=2208723

Rae, I., Takayama, L., & Mutlu, B. (2013). In-body experiences: embodiment, control, and trust in robot-mediated communication. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 1921–1930). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=2466253

Randell, R., Greenhalgh, J., Hindmarsh, J., Dowding, D., Jayne, D., Pearman, A., … Kotze, A. (2014). Integration of robotic surgery into routine practice and impacts on communication, collaboration, and decision making: a realist process evaluation protocol. *Implementation Science*, *9*(1), 52.

Reeves, B., & Nass, C. (1996). *How people treat computers, television, and new media like real people and places*. CSLI Publications and Cambridge university press. Retrieved from http://www.humanityonline.com/docs/the%20media%20equation.pdf

Richter, L. A., & Salvendy, G. (1995). Effects of personality and task strength on performance in computerized tasks. *Ergonomics*, *38*(2), 281–291.

Robert Jr, L. P., & You, S. (2015). Subgroup Formation in Teams Working with Robots. In *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems* (pp. 2097–2102). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=2732791

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). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=2441818

Robert, L. P., Denis, A. R., & Hung, Y.-T. C. (2009). Individual swift trust and knowledge-based trust in face-to-face and virtual team members. *Journal of Management Information Systems*, *26*(2), 241–279.

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., Jr. (2016). Monitoring and Trust in Virtual Teams. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing* (pp. 245–259). New York, NY, USA: ACM. https://doi.org/10.1145/2818048.2820076

Robert, L. P., & Sykes, T. (2017). Extending the Concept of Control Beliefs: Integrating the Role of Advice Networks, *28*(No. 1), 84–96.

Robert, L. P., & You, S. (2013). Are you satisfied yet? Shared leadership, trust and individual satisfaction in virtual teams. Retrieved from https://www.ideals.illinois.edu/handle/2142/39060

Robert, L. P., & You, S. (2014). Human-Robot Interaction in Groups: Theory, Method, and Design for Robots in Groups. In *Proceedings of the 18th International Conference on Supporting Group Work* (pp. 310–312). New York, NY, USA: ACM. https://doi.org/10.1145/2660398.2660426

Robert, L. P., & You, S. (2015). Subgroup Formation in Teams Working with Robots. In *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems* (pp. 2097–2102). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=2732791

Rouse, W. B., & Morris, N. M. (1986). On looking into the black box: Prospects and limits in the search for mental models. *Psychological Bulletin*, *100*(3), 349.

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.

Sanders, T., Oleson, K. E., Billings, D. R., Chen, J. Y., & Hancock, P. A. (2011). A Model of Human-Robot Trust Theoretical Model Development. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 55, pp. 1432–

1436). SAGE Publications. Retrieved from http://pro.sagepub.com/content/55/1/1432.short

Sarker, S., & Valacich, J. S. (2010). An alternative to methodological individualism: a non-reductionist approach to studying technology adoption by groups. *Mis Quarterly*, *34*(4), 779–808.

Schaefer, K. E., Sanders, T. L., Yordon, R. E., Billings, D. R., & Hancock, P. A. (2012). Classification of robot form: factors predicting perceived trustworthiness. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 56, pp. 1548–1552). SAGE Publications. Retrieved from http://pro.sagepub.com/content/56/1/1548.short

Schaubroeck, J., Lam, S. S., & Peng, A. C. (2011). Cognition-based and affect-based trust as mediators of leader behavior influences on team performance. *Journal of Applied Psychology*, *96*(4), 863.

Schifferstein, H. N., & Zwartkruis-Pelgrim, E. P. (2008). Consumer-product attachment: Measurement and design implications. *International Journal of Design*, *2*(3), 1–13.

Schippers, M. C., Den Hartog, D. N., Koopman, P. L., & Wienk, J. A. (2003). Diversity and team outcomes: the moderating effects of outcome interdependence and group longevity and the mediating effect of reflexivity. *Journal of Organizational Behavior*, *24*(6), 779–802. https://doi.org/10.1002/job.220

Schoorman, F. D., Mayer, R. C., & Davis, J. H. (1996). Empowerment in veterinary clinics: The role of trust in delegation. In *11th annual meeting of the Society for Industrial and Organizational Psychology, San Diego, CA*.

Schoorman, F. D., Mayer, R. C., & Davis, J. H. (2007). An integrative model of organizational trust: Past, present, and future. *Academy of Management Review*, *32*(2), 344–354.

Scissors, L. E., Gill, A. J., Geraghty, K., & Gergle, D. (2009). In CMC we trust: The role of similarity. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 527–536). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=1518783

Scott, C. R. (1997). Identification with multiple targets in a geographically dispersed organization. *Management Communication Quarterly*, *10*(4), 491–522.

Shah, J., Wiken, J., Williams, B., & Breazeal, C. (2011). Improved Human-robot Team Performance Using Chaski, a Human-inspired Plan Execution System. In *Proceedings of the 6th International Conference on Human-robot Interaction* (pp. 29–36). New York, NY, USA: ACM. https://doi.org/10.1145/1957656.1957668

Shin, S. J., Kim, T.-Y., Lee, J.-Y., & Bian, L. (2012). Cognitive team diversity and individual team member creativity: A cross-level interaction. *Academy of Management Journal*, *55*(1), 197–212.

Sidorova, A., Evangelopoulos, N., Valacich, J. S., & Ramakrishnan, T. (2008). Uncovering the intellectual core of the information systems discipline. *Mis Quarterly*, 467–482.

Singh, R., Wegener, D. T., Sankaran, K., Singh, S., Lin, P. K., Seow, M. X., … Shuli, S. (2015). On the importance of trust in interpersonal attraction from attitude similarity. *Journal of Social and Personal Relationships*, *32*(6), 829–850.

Sirkin, H. L., Zinser, M., & Rose, J. (2015). Industries and Economies Leading the Robotics Revolution. *Www.bcgperspectives.com*. Retrieved from https://www.bcgperspectives.com/content/articles/lean-manufacturing-innovation-industries-economies-leading-robotics-revolution/

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.

Srinivasan, S.-S., Maruping, L. M., & Robert, L. P. (2012). Idea Generation in Technology-Supported Teams: A Multilevel Motivational Perspective. In *System Science (HICSS), 2012 45th Hawaii International Conference on* (pp. 247–256). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6148637

Stanovich, K. E., & West, R. F. (2000). Individual Differences in Reasoning: Implications for the Rationality Debate? Retrieved from http://www.rfwest.net/Site_2/Welcome_files/Stanovich-IndDifReas-Gilo02.pdf

Streukens, S., Wetzels, M., Daryanto, A., & De Ruyter, K. (2010). Analyzing factorial data using PLS: Application in an online complaining context. In *Handbook of Partial Least Squares* (pp. 567–587). Springer. Retrieved from http://link.springer.com/chapter/10.1007/978-3-540-32827-8_25

Suh, K.-S., Kim, H., & Suh, E. K. (2011). What if your avatar looks like you? Dual-congruity perspectives for avatar use. *MIs Quarterly*, *35*(3), 711–729.

Sung, J.-Y., Grinter, R. E., Christensen, H. I., & Guo, L. (2008). Housewives or technophiles?: understanding domestic robot owners. In *Proceedings of the 3rd ACM/IEEE international conference on Human robot interaction* (pp. 129–136). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=1349840

Tajfel, H., & Turner, J. C. (2004). The Social Identity Theory of Intergroup Behavior. Retrieved from http://psycnet.apa.org/psycinfo/2004-13697-016

Takayama, L., Groom, V., & Nass, C. (2009). I'm sorry, Dave: i'm afraid i won't do that: social aspects of human-agent conflict. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 2099–2108). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=1519021

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). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=1349827

Tanenbaum, J. G., Williams, A. M., Desjardins, A., & Tanenbaum, K. (2013). Democratizing technology: pleasure, utility and expressiveness in DIY and maker practice. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 2603–2612). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=2481360

Tannenbaum, S. I., Mathieu, J. E., Salas, E., & Cohen, D. (2012). Teams are changing: are research and practice evolving fast enough? *Industrial and Organizational Psychology*, *5*(1), 2–24.

Tapus, A., & Mataric, M. J. (2008). Socially Assistive Robots: The Link between Personality, Empathy, Physiological Signals, and Task Performance. In *AAAI Spring Symposium: Emotion, Personality, and Social Behavior* (pp. 133–140). Retrieved from http://www.aaai.org/Papers/Symposia/Spring/2008/SS-08-04/SS08-04-021.pdf

Tapus, A., Ţăpuş, C., & Matarić, M. J. (2008). User—robot personality matching and assistive robot behavior adaptation for post-stroke rehabilitation therapy. *Intelligent Service Robotics*, *1*(2), 169–183.

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.

Teasley, S., Covi, L., Krishnan, M. S., & Olson, J. S. (2000). How does radical collocation help a team succeed? In *Proceedings of the 2000 ACM conference on Computer supported cooperative work* (pp. 339–346). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=359005

Tepper, B. J., Moss, S. E., & Duffy, M. K. (2011). Predictors of abusive supervision: Supervisor perceptions of deep-level dissimilarity, relationship conflict, and subordinate performance. *Academy of Management Journal*, *54*(2), 279–294.

Thrun, S. (2004). Toward a framework for human-robot interaction. *Human–Computer Interaction*, *19*(1–2), 9–24.

Timmerman, T. A. (2000). Racial Diversity, Age Diversity, Interdependence, and Team Performance. *Small Group Research*, *31*(5), 592–606. https://doi.org/10.1177/104649640003100505

Trzcielinski, S., & Karwowski, W. (2012). *Advances in Ergonomics in Manufacturing*. CRC Press.

Tsui, A. S., Egan, T. D., & O'Reilly III, C. A. (1992). Being different: Relational demography and organizational attachment. *Administrative Science Quarterly*, 549–579.

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.

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. Retrieved from http://psycnet.apa.org/psycinfo/1987-98657-000

van der Land, S. F., Schouten, A. P., Feldberg, F., Huysman, M., & van den Hooff, B. (2015). Does Avatar Appearance Matter? How Team Visual Similarity and Member–Avatar Similarity Influence Virtual Team Performance. *Human Communication Research*, *41*(1), 128–153.

Van der Land, S., Schouten, A. P., van den Hooff, B., & Feldberg, F. (2011). Modeling the metaverse: a theoretical model of effective team collaboration in 3D virtual environments. *Journal For Virtual Worlds Research*, *4*(3). Retrieved from https://journals.tdl.org/jvwr/index.php/jvwr/article/viewArticle/6126

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 Dick, R., Van Knippenberg, D., Hägele, S., Guillaume, Y. R., & Brodbeck, F. C. (2008). Group diversity and group identification: The moderating role of diversity beliefs. *Human Relations*, *61*(10), 1463–1492.

van Emmerik, I. H., & Brenninkmeijer, V. (2009). Deep-level similarity and group social capital: Associations with team functioning. *Small Group Research*, *40*(6), 650–669.

Van Knippenberg, D., De Dreu, C. K., & Homan, A. C. (2004). Work group diversity and group performance: an integrative model and research agenda. *Journal of Applied Psychology*, *89*(6), 1008.

Vance, A., Elie-Dit-Cosaque, C., & Straub, D. W. (2008). Examining trust in information technology artifacts: the effects of system quality and culture. *Journal of Management Information Systems*, *24*(4), 73–100.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425–478.

Wainer, J., Feil-Seifer, D. J., Shell, D. A., & Mataric, M. J. (2007). Embodiment and human-robot interaction: A task-based perspective. In *Robot and Human interactive Communication, 2007. RO-MAN 2007. The 16th IEEE International Symposium on* (pp. 872–877). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=4415207

Webber, S. S. (2008). Development of cognitive and affective trust in teams a longitudinal study. *Small Group Research*, *39*(6), 746–769.

Webber, S. S., & Donahue, L. M. (2001). Impact of highly and less job-related diversity on work group cohesion and performance: A meta-analysis. *Journal of Management*, *27*(2), 141–162.

Wegge, J., Roth, C., Neubach, B., Schmidt, K.-H., & Kanfer, R. (2008). Age and gender diversity as determinants of performance and health in a public organization: the role of task complexity and group size. *Journal of Applied Psychology*, *93*(6), 1301.

Whyte, G. (1998). Recasting Janis's groupthink model: The key role of collective efficacy in decision fiascoes. *Organizational Behavior and Human Decision Processes*, *73*(2), 185–209.

Wieselquist, J., Rusbult, C. E., Foster, C. A., & Agnew, C. R. (1999). Commitment, pro-relationship behavior, and trust in close relationships. *Journal of Personality and Social Psychology*, *77*(5), 942.

Wikipedia. (2017, May 19). Robot. In *Wikipedia*. Retrieved from https://en.wikipedia.org/w/index.php?title=Robot&oldid=781170436

Williams, M. (2001). In whom we trust: Group membership as an affective context for trust development. *Academy of Management Review*, *26*(3), 377–396.

Wilson, J. R., & Rutherford, A. (1989). Mental models: Theory and application in human factors. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *31*(6), 617–634.

Windeler, J. B., Maruping, L. M., Robert, L. P., & Riemenschneider, C. K. (2015). E-profiles, conflict, and shared understanding in distributed teams. *Journal of the Association for Information Systems*, *16*(7), 608.

Wolf, F. A., Way, L. W., & Stewart, L. (2010). The efficacy of medical team training: improved team performance and decreased operating room delays: a detailed analysis of 4863 cases. *Annals of Surgery*, *252*(3), 477–485.

Woods, S., Dautenhahn, K., Kaouri, C., Boekhorst, R., & Koay, K. L. (2005). Is this robot like me? Links between human and robot personality traits. In *Humanoid Robots, 2005 5th IEEE-RAS International Conference on* (pp. 375–380). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1573596

Woods, S., Dautenhahn, K., Kaouri, C., te Boekhorst, R., Koay, K. L., & Walters, M. L. (2007). Are robots like people?: Relationships between participant and robot personality traits in human–robot interaction studies. *Interaction Studies*, *8*(2), 281–305.

Wu, K., Zhao, Y., Zhu, Q., Tan, X., & Zheng, H. (2011). A meta-analysis of the impact of trust on technology acceptance model: Investigation of moderating influence of subject and context type. *International Journal of Information Management*, *31*(6), 572–581.

Yaari, M. E. (1987). The dual theory of choice under risk. *Econometrica: Journal of the Econometric Society*, 95–115.

Yagoda, R. E., & Gillan, D. J. (2012). You want me to trust a ROBOT? The development of a human–robot interaction trust scale. *International Journal of Social Robotics*, *4*(3), 235–248.

Yanco, H. A., & Drury, J. L. (2004). Classifying human-robot interaction: an updated taxonomy. In *SMC (3)* (pp. 2841–2846). Retrieved from http://www.researchgate.net/publication/220755236_Classifying_human-robot_interaction_an_updated_taxonomy/file/9c9605229dde7b60e0.pdf

Yanco, H. A., Norton, A., Ober, W., Shane, D., Skinner, A., & Vice, J. (2015). Analysis of Human-robot Interaction at the DARPA Robotics Challenge Trials. *Journal of Field Robotics*, *32*(3), 420–444.

You, S., & Robert Jr, L. (2016). Curiosity vs. Control: Impacts of Training on Performance of Teams Working with Robots. In *Proceedings of the 19th ACM Conference on Computer Supported Cooperative Work and Social Computing Companion* (pp. 449–452). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=2869121

You, S., & Robert, L. (2016). Curiosity vs. Control: Impacts of Training on Performance of Teams Working with Robots. In *Proceedings of the 19th ACM Conference on Computer Supported Cooperative Work and Social Computing Companion* (pp. 449–452). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=2869121

You, S., & Sundar, S. S. (2013). I feel for my avatar: embodied perception in VEs. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 3135–3138). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=2466428

Zaheer, A., McEvily, B., & Perrone, V. (1998). Does trust matter? Exploring the effects of interorganizational and interpersonal trust on performance. *Organization Science*, *9*(2), 141–159.

Zawieska, K., & Duffy, B. R. (2014). Human-Robot Exploration. In *Robot and Human Interactive Communication, 2014 RO-MAN: The 23rd IEEE International Symposium on* (pp. 808–813). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6926352

Zellmer-Bruhn, M. E., Maloney, M. M., Bhappu, A. D., & Salvador, R. B. (2008). When and how do differences matter? An exploration of perceived similarity in teams. *Organizational Behavior and Human Decision Processes*, *107*(1), 41–59.

Zhang, Y., & Huxham, C. (2009). Identity Construction and Trust Building in Developing International Collaborations. *The Journal of Applied Behavioral Science*, *45*(2), 186–211. https://doi.org/10.1177/0021886309333327

Ziemke, T. (2003). What's that thing called embodiment. In *Proceedings of the 25th Annual meeting of the Cognitive Science Society* (pp. 1305–1310). Citeseer. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.529.2280&rep=rep1&type=pdf