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A Meta-Analysis of Factors Influencing the Development of Human-Robot Trust

by Peter A. Hancock, Deborah R. Billings, Kristin E. Oleson, Jessie Y. C. Chen, Ewart De Visser, and Raja Parasuraman

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Peter A. Hancock, Deborah R. Billings, and Kristin E. Oleson
University of Central Florida

Jessie Y. C. Chen
Human Research and Engineering Directorate, ARL

Ewart De Visser and Raja Parasuraman
George Mason University

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*University of Central Florida, Institute for Simulation & Training, 3100 Technology Pkwy., Orlando, FL 32826
†George Mason University, 4400 University Drive, Fairfax, VA 22030

14. ABSTRACT
The effects of human, robot, and environment-related factors impacting perceived trust in human-robot interaction (HRI) were evaluated and quantified using meta-analytic procedures. To date, reviews of trust in HRI have been qualitative or descriptive. Our quantitative review provides a fundamental empirical foundation to advance both theory and practice. Meta-analytic methods were applied to the available literature on trust and HRI. A total of 29 empirical studies were collected, of which 10 met the selection criteria for correlational analysis and 11 for experimental analysis. These provided 69 correlational and 47 experimental effect sizes. The overall correlational effect size for trust was $\bar{r}$ = +0.26 with an experimental effect size of $\bar{d}$ = +0.71. Moderator effects were examined for human, robot, and environmental characteristics, as well as submoderating effects of the robot (performance and attribute-based characteristics). Robot performance and attributes were the largest contributors to the development of trust in HRI. Environmental factors played a moderate role. Presently, there was little evidence for effects of human-related factors. The findings provide quantitative estimates of human, robot, and environmental factors influencing HRI trust. Furthermore, the effect size estimates are useful in establishing design and training guidelines with reference to robot-related factors of HRI trust. In this way, improper trust calibration can be mitigated by manipulating robot design. Many future research needs are identified.

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trust, human-robot interaction, meta-analysis

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1. Introduction

Technological advancements have made human-robot interaction (HRI) a continuously evolving field. Robots can extend human sensory, psychomotor, and cognitive capabilities and compensate for certain intrinsic human limitations (Riley et al., 2010). Consequently, they can provide important roles in helping mentally or physically challenged individuals live more independently and improve their quality of life (Heerink et al., 2010). Robots can also be used for a variety of tasks that pose safety risks to people. They can operate in areas that are unreachable by or intolerable for humans; perform activities that would impose extremely high levels on human workload; and carry out actions requiring complex tactical skills and information integration (Hinds et al., 2004; Parasuraman et al., 2009). Because of the increasing capabilities of robots, various military agencies are investigating the usefulness of employing them in risky and uncertain environments.

The roles that humans play in HRI are also more diverse as robots become increasingly proficient in performing various tasks. Wang (2007) outlines five different roles that humans can assume in HRI:

1. Humans can act in supervisory roles where they monitor a robot and intervene when necessary.
2. Humans can become operators and interact directly with a robot on a continuous basis to manipulate the behaviors and actions of the robot.
3. Humans can play the role of a mechanic or programmer, working to modify the software and hardware of a robot.
4. Humans can act as peers where they work interdependently with a robot to achieve a mutual goal.
5. Humans may simply be bystanders. In other words, humans may not be part of a human-robot team, yet they can still affect how the robot or team accomplishes its task by observing or interfering with the actions of the team.

The role that a human assumes in HRI may influence how that individual perceives a robot.

Robots used in military operations are often perceived as tools manipulated by humans and needed to accomplish specific discrete functions (Chen et al., 2010). Yet there is significant interest in pursuing the possibility that robots might provide a higher function, as full-fledged team members. This type of human-robot collaboration is often referred to as a mixed initiative team (Ogreten et al., 2010) where robots and humans work side by side as teammates, each contributing something vital to the success of the team. Basic research on the development of such peer relationships between humans and robots is largely lacking (Chen et al., 2010), although there are efforts that address the formation of human-computer teams (Nass and Moon, 2000; Nass et al., 1994; Nass et al., 1996).

Regardless, the military is taking steps to increase the use of robots and to increase research in this field. In 2001, the U.S. Congress mandated that one-third of all combat ground vehicles will be unmanned by 2015, and the military continues to actively develop future robotic systems to deploy by land, sea, and air (Chen et al., 2010; Stormont, 2008). In fact, over the past 20 years, the military's budget for robot-related research has gone from approximately $40 million to almost $1 billion annually (National Research Council, 2005). Clearly, the military has invested substantially in the development and utilization of robotic assets in mixed teams. While this increased integration and teaming of human and robots may lead to improved team capabilities in battlefield situations, it may also create difficult challenges that need to be overcome before human-robot teams can work effectively (Adams et al., 2003). Consequently, creating a robotic "teammate," where the robot works alongside a human as a partner, is becoming the "holy grail" of HRI research (Groom, 2008).

1.1 Human-Robot Partnerships

Effective human-robot partnerships are especially vital to success in dangerous military combat missions, often due to the increased stress and cognitive workload demands that are placed on the exposed warfighter (Hancock and Warm, 1989; Parasuraman et al., 2009). The U.S. military is taking steps to ensure the use of robots in these contexts and to encourage research in this field. However, research in this area is often focused on the robot itself and its specific engineering characteristics and capabilities, not necessarily the human needs and expectations of its potential teammates and commanders. Such an emphasis on the autonomous capabilities of robots, rather than on the interaction between humans and robots, is consistent with a technology-centered approach to design that has frequently been seen in the general area of automation. As research on human-automation interaction has shown, automation does not simply replace human work, but rather changes it (Parasuraman and Riley, 1997; Woods, 1996). Likewise, the introduction of robots fundamentally changes the way that humans perform a task (Goodrich and Schultz, 2007). Robots allow humans to perform difficult tasks or tasks that they were incapable of completing prior to using robots; thus, human efforts and processes involved in the tasking inevitably change when robots are introduced. While the technical capabilities of robots do indeed need further development, a robot's ability to efficiently interact with humans must also be improved before effective teaming can occur (Groom, 2008).

In future military contexts, warfighters will be required to interact with a diverse inventory of robots on a regular basis, particularly in dynamic and stressful environments (Chen and Terrence, 2009). Already, robotic systems have demonstrated their usefulness in decision-making, communication, and combat efficiency; they also enhance warfighter situation awareness and reduce uncertainty in volatile situations (Adams et al., 2003). However, the assumption that introducing robots into human teams will result in better performance, as compared to when the team or robot operates independently, is not always justified. The military relies on the abilities of individuals to quickly form teams that work toward a shared goal and perform critical tasking effectively, yet this is not an automatic process (Salas and Bowers, 1995). Therefore, adding a robot to a human team does not necessarily mean that the team will function effectively from the start. Research continues to address challenges, such as creating and validating metrics for the evaluation of a wide spectrum of HRI issues (Steinfeld et al., 2006); designing human-robot interfaces to facilitate interaction, operator understanding, and situation awareness (Keyes et al., 2010); translating qualities of good human teammates into features of the robot; and encouraging human trust in robots (Adams et al., 2003; Groom and Nass, 2007). One of the most significant challenges for human-robot teams is the development of appropriate levels of trust in robots (Desai et al., 2009; Groom and Nass, 2007).

1.2 Human-Robot Trust

Trust is an emergent property of the interaction between entities, yet trust is not just limited to this type of human-machine relationship. Although at first trust may appear to be a relatively simple construct, as it is part of our daily language and used in a variety of contexts, a closer look reveals a high level of complexity. Trust has been defined extensively in many domains, such as human interpersonal trust (Mayer et al., 1995; Rempel et al., 1985; Rotter, 1971), human-automation trust (Lee and See, 2004; Madhavan and Wiegmann, 2007; Moray et al., 2000), and trust in software agents (Patrick, 2002), to name only a few. However, no consensus definition currently exists in cognitive science or across other areas (Adams et al., 2003). While we look to address this definitional issue in future work, the present focus is on quantitative evaluation, not on philosophical dispute and discourse. For our present purposes, we adopt the definition offered by Lee and See (2004), namely, “the attitude that an agent will help achieve an individual’s goals in a situation characterized by uncertainty and vulnerability” (p. 54).

Beginning in the 1980s, research has examined trust in human-machine systems (including human-automation and human-computer trust), but very little research has specifically addressed trust in human-robot relationships independent of the other human-entity relationships (Park et al., 2008). Trust in HRI is very much related to trust in automation in general, which has been studied with respect to its performance influences (Chen et al., 2010; Lee and See, 2004; Parasuraman et al., 2008; Sheridan, 2002). Robots differ from most other automated systems in that they are mobile, are often built in a fashion that approximates human or animal form, and are often purpose-designed to effect action at a distance. Such differences could suggest that human trust may differ for robots and automation, although this would need to be demonstrated empirically; few if any such comparisons have been conducted. Some researchers suggest that robotics has added a degree of uncertainty and vulnerability that automation does not have and, therefore, should be studied independent of automation (Desai et al., 2009). Alternatively, one can begin with the view that human-robot trust and human-automation trust do not differ significantly but allow for the possibility for differences as new evidence is obtained.

The vast literature on human-automation trust provides a fertile ground for understanding a number of factors influencing how humans trust other external agents. The human-robot trust literature is more restricted, but nevertheless sufficient numbers of studies have been conducted to warrant a meta-analysis in order to identify the major factors currently involved.

In order for a human-robot team to accomplish its goal, humans must trust that a robotic teammate will protect the interests and welfare of every other individual on the team. An individual's trust of robots will be particularly critical in high-risk situations (such as combat missions) if humans and robots are to succeed as effective teammates (Groom and Nass, 2007). Trust is important in these contexts because it directly affects the willingness of people to exchange information, follow the suggestions, or use information obtained by the robotic system (Freedy et al., 2007). It can also affect the decisions that humans make in uncertain or risky environments (Park et al., 2008). For example, the less an individual trusts a robot, the sooner that he or she will intervene as it progresses toward task completion (de Visser et al., 2006; Steinfeld et al., 2006). Some accounts from warfighters in the field demonstrate the ease with which trust often develops between robots and humans in stressful environments. For example, one explosive ordnance disposal (EOD) unit named their robot "Sgt. Talon," gave it promotions, and even "Purple Hearts" for its stellar bomb disposal performance (Garreau, 2007). Other warfighter accounts, however, illustrate the difficulties in trusting robots in these situations. For instance, the SWORD (Special Weapons Observation Reconnaissance Detection) system was developed and deployed in Iraq in 2007 to support combat operations (Ogreten et al., 2010). SWORD, although fully operational, was never used in the field because warfighters did not trust it to function appropriately in dangerous situations.

As illustrated by these accounts, varying levels of trust in robots currently exist across the HRI domain. Inappropriate levels of trust may have negative consequences, such as over-reliance on and misuse of the system (in cases of extremely high levels of trust), or disuse of the system entirely (in cases of very low trust [Lee and See, 2004; Parasuraman and Riley, 1997]). Both of these undermine the value of the system. Trust also influences neglect tolerance, defined as the decline in semi-autonomous robot performance as human attention is directed to other tasks and/or as the task complexity increases (Goodrich et al., 2003). When people place a high amount of trust in a robot and do not feel compelled to actively manage it, they may ignore the robot for long periods of time. Consequently, neglect tolerance should be appropriate to the capabilities of the robot and the level of human-robot trust. Too much neglect can make it difficult for the individual to regain situation awareness after redirecting attention back toward the robot.

A key issue in human-robot relationships, therefore, is trust calibration, namely, a balance between the extremes of distrust—where human operators do not use, turn off, or even consciously disable (e.g., Sorkin, 1988) automated systems that can help them—and over-reliance and complacency, in which automation is not effectively monitored and raw information sources are ignored (Parasuraman and Manzey, 2010). Trust calibration refers to the match between a human's perception of a system's capabilities and the actual capabilities of the system (Lee and See, 2004). If perceived capabilities match the actual capabilities, trust is expected to be calibrated appropriately. Trust calibration can benefit HRIs in many ways, including mitigating neglect tolerance. For instance, if human teammates know that a robot has trouble navigating around particular obstacles, they could specifically direct their attention to the robot when it enters particularly difficult terrain. Conversely, one consequence of poor trust calibration is overtrust, leading to misuse of the system (Parasuraman and Riley, 1997). For example, humans may trust a robot to perform a task that it was never designed to do, potentially leading to complete mission failure. Poor trust calibration may also cause distrust, leading to disuse of the system (Lee and See, 2004). For example, even though warfighters have access to robots that can potentially assist them in completing dangerous tasks, they may choose not to use a particular robot because of their belief that the robot will not function effectively in critical situations (as illustrated by the SWORD example). Thus, the assessment and utility of trust calibration is a necessary requirement.

1.3 Identification of Possible Antecedents of Trust

To identify potential factors of trust development in HRI, existing literature on trust in automation and trust specifically in robots (both theoretical and empirical) was reviewed, and subject matter experts (SMEs) were consulted. The literature suggests that several factors play important roles in trust development. Some factors involve the human directly, while others focus on aspects of the robot. Other factors deal with various aspects of the team environment. SME input confirmed these potential factors and contributed other suggestions as well.

1.3.1 Factors Associated With the Human Element in HRI

Several human-related factors, or personal characteristics and experiences, were identified as potential antecedents of trust in HRI. For instance, research has found that humans who have high self-confidence are less likely to develop trust in robotic systems, whereas humans with low self-confidence are more likely to trust a robot more than they should (Freedy et al., 2007; Ogreten et al., 2010, citing Lee and Moray, 1994). In addition, propensity to trust (i.e., the tendency for some individuals to trust someone or something else) may impact trust in robots (Adams et al., 2003). In particular, Lee and See (2004) reported that highly trusting people may be more likely to trust automation more appropriately, and that prior interactions with the system may influence trust. Personality characteristics may also influence trust in HRI. Research has demonstrated that extroverts tend to trust more than introverts (McBride and Morgan, 2010). Literature also revealed that an individual's familiarity, training, and understanding of a robot's functionality may impact trust (Ogreten et al., 2010). Individuals exhibiting high levels of expertise are less likely to blindly trust a system, whereas individuals with low levels of expertise are more willing to trust the system (McBride and Morgan, 2010). In summary, a wide range of individual ability-based and personality-based factors were identified that potentially affect trust development in HRI (figure 1).

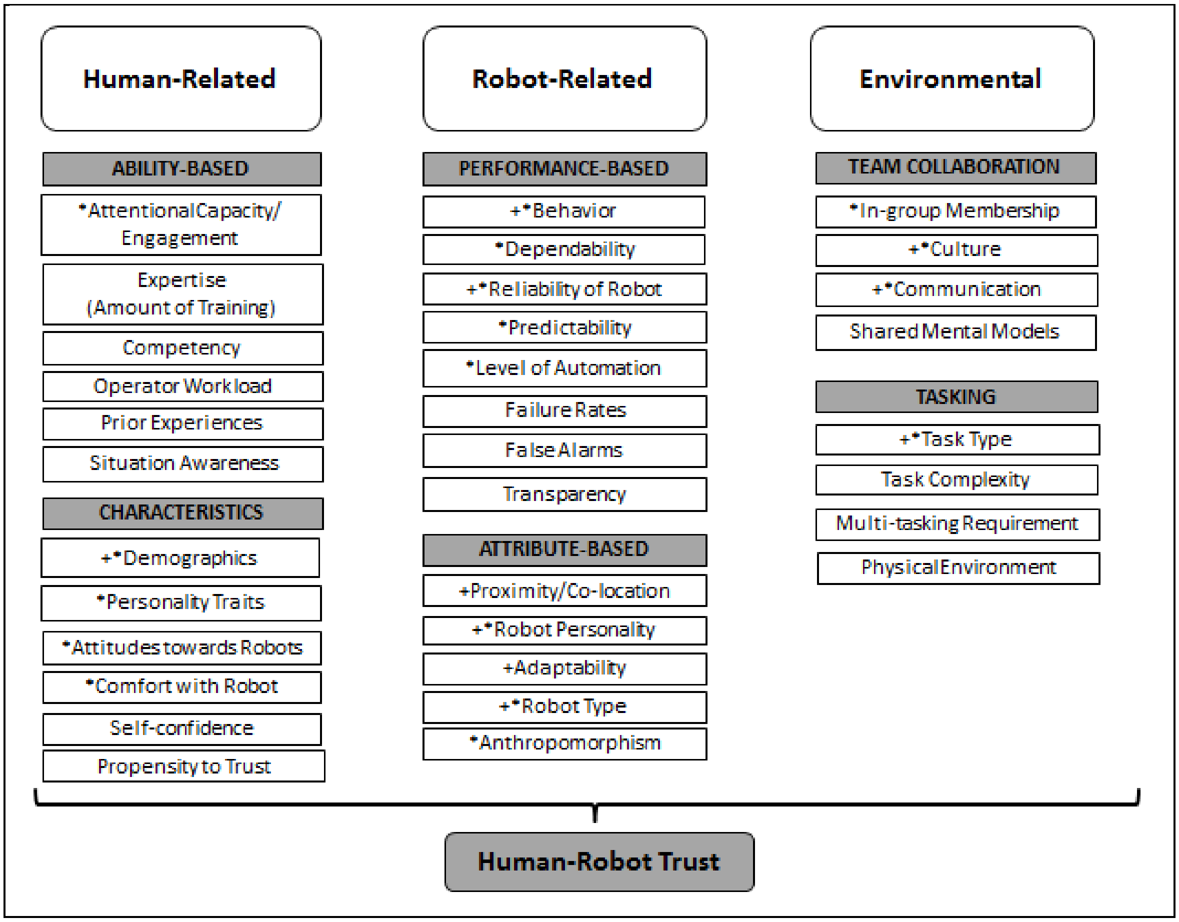

Figure 1. Factors of trust development in HRI. Factors included in the correlational analysis are starred (*), and factors included in the experimental analysis are crossed (+).

1.3.2 Factors Associated With the Robot

Literature also suggests that robotic system characteristics can influence a human's level of trust in the robotic element. System performance characteristics (e.g., consistency, dependability, predictability, and reliability) may have substantial influence on trust (Ogreten et al., 2010). For example, when an individual is not able to predict what an automated or robotic system is supposed to do, trust decreases; therefore, the predictability of the system is an important factor in trust development and maintenance (Lee and See, 2004; Ogreten et al., 2010, citing de Brun et al., 2008). Reliability of the system is also critical in HRI trust; when reliability decreases (and errors increase), trust in the system decreases (Lee and See, 2004; de Vries et al., 2003; Dzindolet et al., 2003). Another example of a potential factor impacting trust is an individual's proximity to a robot; Bainbridge et al. (2008) suggest that co-location or close proximity to robotic systems leads to a greater degrees of trust. Finally, research has demonstrated that robot personality can affect trust. People tend to trust a polite robot, which can compensate for low reliability or the robot's actual capabilities (Parasuraman and Miller, 2004). These highlighted examples from the literature suggest that robot-related factors play a critical role in HRI trust.

1.3.3 Factors Associated With the Environment in Which HRI Occurs

Other potential factors impacting trust in HRI are directly related to the environment in which HRI occurs. For example, the cultural context and norms of the environment where humans interact with robots can affect trust levels (Lee and See, 2004). Empirical research has found that culture accounts for significant differences in trust ratings for robots; some collectivist cultures have higher trust ratings than individualistic cultures (Li et al., 2010). Our SMEs also indicated that team collaboration issues (e.g., communication, shared mental models) and tasking characteristics (e.g., task type and multitasking requirements) may impact trust in HRI.

1.4 Current Research

Trust is dynamically influenced by factors within the robotic system itself, the surrounding operational environment, and the nature and characteristics of the respective human team members (Park et al., 2008). Each of these factors can play an important role in trust development. To date, reviews of trust in HRI have been qualitative and descriptive, and existing experiments largely attempt to extrapolate the optimum degree of trust for a given outcome (e.g., team performance, reliance on the robot). In doing so, a degree of inappropriate trust (i.e., excessive trust or too little trust) is also identified for each potential outcome of HRI, such as over- or under-reliance and poor team collaboration. Factors impacting the development of trust in HRI also need to be considered, as they will contribute to a more complete understanding of trust calibration.

Therefore, the goal of the current research was to perform a comprehensive objective and quantitative review of identified antecedents of trust in human-robot teams. Meta-analytic methods were applied to the extant literature on trust and HRI with the aim of quantifying the effects of differing dimensions on human-robot trust. Determining their relative impact on trust will not only provide an indication of current trends in the human-robot trust research, but it will also lead to the identification of areas critical for future study. Consequently, our quantitative review contributes an empirical foundation upon which to advance both theory and practice.

2. Analytical Method

2.1 Sample of Studies

A formal literature search was conducted using library databases (including PsycINFO, PsycARTICLES, PsycBOOKS, ACM digital library, Applied Science and Technology, IEEE, ScienceDirect, and ProQuest Dissertations & Theses). U.S. Army Research Laboratory technical reports were also examined for relevance. In addition, we used a number of Web-based search engines, e.g., Google and its derivative Google Scholar, to seek further references not discovered by the initial formal scan. The primary search terms included *human-robot interaction*, *robot*, and *trust*. After the initial listing of articles was obtained, reference lists were checked to determine whether any other related studies could be included. In a concurrent process, SMEs were consulted for reference to articles that had not been identified by the prior, formal search procedure. Following this initial procedure, we examined the collected literature and identified potential factors associated with the development of trust. SMEs also provided guidance in identifying factors influencing trust in human-robot relationships.

2.2 Three-Factor Classification Scheme for Antecedents of Trust

After identifying various possible antecedents of trust from the theoretical and empirical literature and SME input, we developed a classification scheme for human-robot trust factors to guide our meta-analysis. This organization was influenced in part by prior research suggesting that robot characteristics (e.g., performance and attributes) and human characteristics (e.g., knowledge, skills, abilities, and attitudes) should be considered in the development of human-machine teams (Chen et al., 2010). In addition, prior research suggested that elements in the environment were also important to assess (Park et al., 2008). Consequently, studies included in the meta-analysis were classified into three broad categories based on the experimental manipulation in the study. These categories included robot-related, human-related, and environmental factors impacting trust.

Robot-related factors of trust incorporate performance- and attribute-based characteristics of the robot. Performance-based antecedents include robot behavior, dependability, reliability, predictability, level of automation, failure rates, and the number of false alarms. Attribute-based antecedents include anthropomorphic features, robot personality, robot type, robot adaptability, and proximity. Human-related factors of trust refer to aspects of the human teammate that include abilities and personality. Ability-based factors include demographics, prior experiences, engagement, expertise, competency, compliance with the robot, operator workload, and situation awareness. Personality-based factors include self-confidence, propensity to trust, comfort with robots, attitudes toward robots (biases), and personality traits. Finally, environment-related factors of trust incorporate team cooperation characteristics (in-group membership, culture of the team and environment, and shared mental models across teammates) and tasking characteristics (task type, task complexity, and user multitasking requirement). These categorizations enabled a quantitative review of the predictive strength of these respective trust factors in human-robot teams. See figure 1 for factors identified as potential antecedents of human-robot trust based on a literature review and SME guidance. Starred factors (*) represent those included in the correlational analysis, while crossed factors (+) represent those included in the experimental analysis. Several factors identified in theoretical literature and through SME input were not found in existing correlational or experimental analyses due to the limited empirical research in the area of HRI.

Next, based on these identified factors, we conducted specific literature searches in the aforementioned databases using the primary search terms *robot* and *trust* combined with these secondary terms: *prior experience, attentional capacity, expertise, competency, personality,* *attitudes, propensity to trust, self-confidence, false alarm, failure rate, automation, anthropomorphism, predictability, proximity, robot personality, multitasking, workload, task load, culture, shared mental models,* and *situation awareness.* When these elicitation processes no longer yielded new citations, we compiled the final listing of articles.

2.3 Criteria for Study Inclusion

All studies were inspected to ensure that they fulfilled the following four criteria for inclusion in the meta-analysis:

1. Each study had to report an empirical examination of trust in which trust was a directly measured outcome of an experimental manipulation. Studies in which trust served as the experimental manipulation were excluded.

2. The empirical examination of trust was directed toward a robot. Thus, for instance, studies on human-automation trust focusing on a decision-aid were excluded because the emphasis of such research is on the decision-aid and not a robot, which, as discussed before, can differ in many ways from automated systems in terms of such factors as mobility, sensor and effector capabilities, etc.

3. The study had to incorporate human participants who either viewed or participated directly in interactions with a robot through physical, virtual, or augmented means.

4. Each study had to include sufficient information to determine effect size estimates.

Initially 168 articles on human-robot trust were collected; however, some were immediately omitted due to failure to meet the criteria for inclusion in the meta-analysis. First, 78 articles investigating trust in something other than a robot (e.g., human, automation, or computer trust) were excluded. Second, 42 nonempirical articles were excluded from the analysis. Of these nonempirical articles, 8 discussed programming/building a robot, 22 introduced factors involved in HRI, 4 focused on robot tasking, and 8 discussed theoretical underpinnings for trust in a robot. A total of 29 empirical articles of the initial 168 articles collected were excluded for the following reasons: 23 did not include trust as a dependent variable, or measure trust at all, and 6 did not have sufficient information to calculate effect size. In addition, several articles reported data from the same study and data set. For these, we only included one of the articles as a representation of that data. See appendix A for a complete list of retrieved references not included in the analysis. It is important to note that rejecting primary studies in a meta-analysis is a common occurrence and is necessary to ensure meaningful results when combining effect sizes across studies.

Nineteen articles, reports, dissertations, and conference proceedings fulfilled the identified criteria for inclusion. The articles were published between 1996 and 2010 and contained correlational data, experimental data, or both. Of these, 10 papers containing 69 correlational effect sizes and 12 papers containing 47 experimental effect sizes met selection criteria for inclusion. Literature meeting these inclusion criteria are identified in the reference listing of this report by either an asterisk (*) or a cross (+) appearing in front of the first author's name (American Psychological Association, 2001). The asterisk represents those studies included in the correlational analysis, and the cross represents those studies included in the experimental analysis.

2.4 Coding of Studies

We coded available study characteristics from each experiment, including but not limited to the following: dependent variable(s), independent variable(s), statistical analysis used, test values, degrees of freedom, means, standard deviations, alpha level, and statistical significance. If more than one variable was manipulated in a study, each independent variable was coded and analyzed separately. We also coded several additional variables, including the following: (1) type of robotic platform used, (2) participant population, (3) participant mean age, and (4) participants' gender.

2.5 Statistical Calculations

The data were analyzed using PASW Statistics 18 (IBM SPSS, Inc., 2009). Effect sizes and variance estimates were calculated. For a detailed description of calculations, see appendix B.

2.5.1 Effect Size

The studies included in effect size calculation contained both correlational and group design data; therefore, the use of multiple meta-analytic methods (correlation and Cohen's *d*) was necessary. The correlational effects represent an association between trust and the given factor. Cohen's *d* indicates the standard difference between two means in standard deviation units. From these we can gather correlational and causal inferences between trust and any given factor. Through both types of meta-analytic effects, the more positive the effect represents more trust. Findings were interpreted using Cohen's (1988) established ranges for small ($d \leq 0.20$; $r \leq 0.10$), medium ($d = 0.50$; $r = 0.25$), and large ($d \geq 0.80$; $r \geq 0.40$) effect sizes.

2.5.2 Variance Estimates

Several variance estimates were calculated. First, variability of the effect sizes themselves (s^2_g) and variability due to sampling error (s^2_e) were estimated. Next, these two values were used to compute the residual variance (s^2_δ). A large (s^2_δ) is an indication that the effect sizes may be heterogeneous and therefore one or more variables are likely to be moderating the magnitude of that particular effect. A final check for homogeneity of variance $\left({s_e^2}/{s_g^2}\right)$ was calculated (proportion of total variance accounted for by sampling error). Hunter and Schmidt (2004) suggest that an outcome here of 0.75 or greater suggests that the remaining variance is due to a variable that could not be controlled and represents homogeneity of variance. However, large residual variance and small homogeneity of variance may be due to a small number of sample studies, as is evident in some of the following results.

3. Results

3.1 Correlational Analysis

For the 10 papers included in the correlational analysis, there were 69 correlational effect sizes. Detailed information about these papers, along with the factors addressed in each one, can be found in appendix C.

For the studies reporting correlational data, the present meta-analytic results indicated that there was a moderate global effect between trust and all factors influencing HRI ($\bar{r}$ = +0.26; see table 1). That the identified confidence interval does not include zero confirms that this identified relationship is consistent and substantive. The subsidiary analysis between trust and human, robot, and environmental factors individually indicated only small effects for the human dimensions ($\bar{r}$ = +0.09) and also the environmental characteristics ($\bar{r}$ = +0.11), and because the confidence intervals for human and environmental factors included zero, our current state of knowledge suggests that the human and the environment are not strongly associated with trust development in HRI at this point in time. We should, however, emphasize that these results derive from only a limited number of studies and thus may change with future evaluations.

Robot-related characteristics were found to be moderately associated with trust in HRI ($\bar{r}$ = + 0.24) in line with the level of the global effect. Robot influences were able to be parsed into two subcategories: robot performance-based factors (e.g., reliability, false alarm rate, failure rate) and attribute-based factors (e.g., proximity, robot personality, and anthropomorphism). With respect to the influence of the robot, it was determined that performance factors were more strongly associated ($\bar{r}$ = +0.34) with trust development and maintenance. However, in contrast, robot attributes had only a relatively small associated role ($\bar{r}$ = +0.03). Such moderators for human and environmentally related factors were not examined, as there were insufficient samples to run meta-analytic procedures on each of these submoderators.

Table 1. Formal human-robot trust meta-analysis results using correlational data.

Category	k	$\bar{r}$	s_r^2	s_e^2	s_ρ^2	s^2_e / s^2_p	95% CI	N
Global	10	+0.26	0.14	0.01	0.13	0.05	+0.21<δ<+0.31	1228
Trust factors	—	—	—	—	—	—	—	—
Robot	8	+0.24	0.21	0.01	0.20	0.05	+0.16<δ<+0.31	882
Human	7	+0.09	0.14	0.02	0.13	0.11	0.00<δ<+0.19	727
Environment	4	+0.11	0.11	0.01	0.10	0.08	+0.02<δ<+0.20	645
Robot factors	—	—	—	—	—	—	—	—
Attribute	5	+0.03	0.08	0.02	0.07	0.22	-0.09<δ<+0.15	686
Performance	5	+0.34	0.43	0.01	0.42	0.03	+0.25<δ<+0.43	607

k = number of studies.
N = sample size.
s^2_r estimates the variability of the effect sizes themselves.
s^2_e estimates the variability due to sampling error.
s^2_p is an estimate of the residual variance.
(s^2_e / s^2_p) is a calculation of homogeneity of variance.

3.2 Experimental Analysis

The 12 papers included in the experimental analysis yielded 47 experimental effect sizes. Of these papers, two reported different pertinent statistics from the same data set (Kiesler et al., 2008; Powers et al., 2007). Consequently, both articles were required to calculate the effect size for that particular study. These two papers both contributed information relating to the same effect size, which is reflected in our data analysis (*k* = 11, rather than *k* = 12). These papers, along with the factors addressed in each one, can be found in appendix D.

This experimental analysis was conducted on research reporting group differences. The results for the meta-analytic approach using Cohen's *d* produced a similar pattern to that for the correlational studies. These results, shown in table 2, indicated there was a large global effect concerning trust and HRI ($\bar{d}$ = +0.71). As the confidence interval here excluded zero, we can assume this is a substantive and consistently large effect. The subdivision of this global effect into robot, human, and environmental characteristics indicated that the robot ($\bar{d}$ = +0.67) had the greatest effect. There was a moderate effect for environmental factors ($\bar{d}$ = +0.47) but only very small effects for human factors ($\bar{d}$ = –0.02). Robot factors were again parsed into the two previously identified submoderating categories, attributes and performance. Robot performance factors ($\bar{d}$ = +0.71) were the largest identifiable influences on HRI trust, whereas robot attributes ($\bar{d}$ = +0.47) had a smaller but still sizeable influence on trust development. It is important to note, however, that the performance factors are based upon two studies that may bring into question the stability of the effect. However, each study has a sizeable effect supporting this finding. The attribute factors are based upon eight studies, pointing to stronger stability of the effect. The submoderators for human and environmentally related factors were not examined, as

Table 2. Formal human-robot trust meta-analysis results using Cohen's *d*.

Category	**k**	$\bar{d}$	s_g^2	s_e^2	s_δ^2	s^2_e / s^2_g	**95% CI**	**N**
Global	11	+0.71	0.26	0.09	0.16	0.36	$+0.53 < \delta < +0.89$	1567
Trust factors	—	—	—	—	—	—	—	—
Robot	8	+0.67	0.15	0.07	0.08	0.48	$+0.48 < \delta < +0.85$	1119
Human	2	-0.02	(Kidd, 2003) g = +0.01; (Scopellit et al., 2005) g = –0.88					202
Environment	5	+0.47	0.21	0.07	0.13	0.36	$+0.23 < \delta < +0.71$	609
Robot factors	—	—	—	—	—	—	—	—
Attribute	8	+0.47	0.25	0.07	0.19	0.27	$+0.28 < \delta < +0.65$	1119
Performance	2	+0.71	(Ross, 2008) g = +0.71; (Tsui et al., 2010) g = +0.74					554

k = number of studies.
N = sample size.
s^2_g *estimates the variability of the effect sizes themselves.*
s^2_e *estimates the variability due to sampling error.*
s^2_δ *is an estimate of the residual variance.*
(s^2_e / s^2_g) *is a calculation of homogeneity of variance.*

there were insufficient data to run the meta-analysis (i.e., too few effect sizes were available to examine these factors individually). In all of the categories in which there were sufficient data to identify effects, none of the confidence intervals for the experimental work included zero. Therefore, these findings infer a degree of confidence that these are each consistent and real effects.

4. Discussion

Trust is a crucial dimension in maintaining effective relationships with robots. The presence, growth, erosion, and extinction of trust have powerful and lasting effects on how each member of any shared relationship behaves currently and will behave in the future. Presently, we see technology (and the present panoply of robots) as largely insensate and without individual motive force. While we are often frustrated with technological shortcomings and failures and express our frustration either vocally or motorically, at heart we know we are dealing with the residual effects of a remote human designer. The intention of a robot is a reflection of the intention of its designer. However, we stand on the verge of a sufficiently impactful change that our attribution of intentionality to all technology and the nascent robotic children will soon not be misplaced (and see Epley et al., 2007; Moravec, 1988). Here, the issue of trust will be as influential in development as in our own human relationships, if not more so.

Trust is only one of a number of critical elements essential to human-robot collaboration, but it continues to be a growing concern as robots advance in their functionality. This is especially the case in military and emergency contexts in which a warfighter's or operator's own life and the lives and safety of others depend on successful interaction. The current research represents one of the first systematic efforts to quantify effects concerning human trust in robots. Our results reveal that robot characteristics, and in particular, performance-based factors, are the largest influence on perceived trust in HRI. Trends in the literature suggest that higher trust is associated with higher reliability (for example, see Ross, 2008). Further, the type, size, proximity, and behavior of the robot also impact trust (for examples, see Bainbridge et al., 2008; Tsui et al., 2010). Environmental factors were also found to be moderately influential on trust development, although extensive inferences about a variety of other moderating effects could not be drawn due to the insufficiency of the currently available empirical data. Limited evidence for human-related factors was found. The present findings, however, should not be taken to imply that human characteristics (i.e., individual differences) in HRI are not necessarily important. Rather, the small number of studies found in this area suggests a strong need for future efforts on human-related, as well as environment-related, factors.

Although human-automation interaction in general has been researched at length (Dzindolet et al., 2003; Lee and See, 2004; Madhavan and Wiegmann, 2007; Sheridan, 2002; Sheridan and Parasuraman, 2006), sparse empirical research has been conducted in a number of specific and important areas associated with human-robot trust. For instance, as noted there is a dearth of studies on the human-related characteristics, including prior level of operational experience, attentional capability, the amount of training received, self-confidence, the propensity to trust, existing attitudes toward robots, personality traits, operator workload, and situation awareness, to name only a few central characteristics. Gaps in the understanding of the various environmental characteristics include culture (of team, individual, and environment), shared mental models, multitasking requirements, task complexity, and task type. We also have limited empirical evidence on the effects of robot false alarms and failures. Resolution in these areas is crucial to provide a depth of understanding on trust in HRI.

Our meta-analytic findings have implications for both research and practice. In terms of research, as we build functional models of HRI, we will need to understand and quantify the various influences and derive information on factors which we have shown that, to date, are completely missing. Without a larger and active empirical attack, our knowledge will remain precarious and based often on either anecdotal or engineering-centered case studies. With regard to practical implications, the major lesson learned is that a robot's performance and attributes should presently be considered the primary drivers of trust. Understanding exactly how these factors impact trust will be critical for trust calibration. For example, we are aware of a number of instances in the military where robots have looked to be deployed, but because of the intrinsic trust question, they have never been taken "out of the box" (often due to a bad reputation preceding the system or its perceived complexity of operation). Consequently, if the perceived risk of using the robot exceeds its perceived benefit, practical operators almost always eschew its use. Hence, training that encourages trust in specific robots is necessary from the point of design inception to the eventual field use.

The type of trust measure used is relevant to the present conclusions. Our meta-analysis found that current trust in HRI is derived almost exclusively via subjective response, measured one time after a specific interaction. However, physiological indicators, such as oxytocin-related measures, and objective measures, such as trust games measuring actual investment behavior, are used frequently in the human-interpersonal trust literature (for examples, see Chang et al., 2010; Keri et al., 2009). These measures should be explored in the context of human-robot trust to augment the present perceptual assessments and identify potential inconsistencies between measures. Discrepancies between an individual's self-report (i.e., perception) and their behavior (i.e., observable reaction) is an issue that has been a topic of concern in psychology for a number of decades (see Hancock, 1996; Natsoulas, 1967). An individual can report that he (or she) will trust their robot, but existing research leads us to believe that this statement-action relationship is not always perfect (Chen and Terrence, 2009). Therefore, empirical research that includes both subjective and objective measurements can provide a more complete portraiture of the genesis and persistence of trust. However, it is important to note that the existing HRI empirical studies do not actually ask for people to trust a robot, where they must become vulnerable, or place their lives in the hands of a machine. Instead, people are asked if they *would* trust a robot in certain risky and uncertain situations. In other words, the trust measures in these studies tend to be a statement of belief or observation of an action in a simulated scenario. Consequently, all of the empirical data collected so far is only weakly diagnostic of what warfighters do in the real world and how trust develops in those situations.

A comparison of perceptions and actual robot capabilities is also needed. A team of people can each have differing perceptions of the intent, performance, and actions of a robotic entity, but indeed they may not all match the true capabilities of the robot. These differences in perceptions may be mitigated to an extent by employing training methods that adequately prepare an individual for interacting with the robot.

5. Summary and Conclusion

Numerous avenues of research need to be pursued to fully comprehend the role that trust plays in HRI, as well as the factors that influence trust in robots. Even so, our current findings indicate that the more important element of trust is robot-related. Fortunately, these factors (e.g., robot performance, robot attributes) can be directly manipulated by designers (under the constraints of technological capabilities). In this way, we are able to predict to some degree the development of trust in human-robot partnerships in currently existing systems.

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Appendix A. References Not Included in the Meta-Analysis

This appendix is in its original form, without editorial change.

Trust in Entity other than a Robot

Computer Trust

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Appendix B. Detailed Description of Data Analysis

The data were analyzed using PASW Statistics 18.[1] Although PASW is not designed to run meta-analyses automatically, meta-analysis syntax can be entered to enable this operation. The researchers chose to use PASW over other statistical programs for several reasons. First, this statistical package can deal with the problem of independence of effect sizes with minimal loss of information. Second, PASW has the ability to adjust metrics of within-group statistics to match the metrics of the between-group statistics. Therefore, PASW offers flexibility that other meta-analysis programs are not capable of.

The first step to conducting a meta-analysis through PASW was to compute effect sizes for all within- and between-group studies. Therefore, each study's effect size was calculated using standard formulas (see Hedges and Olkin, 1985; Hunter and Schmidt, 2004; Morris and Deshon, 2002). Within-group statistics were converted to a common metric so that both between-group and within-group statistics were in the same units.

Using the calculated effect sizes, the correlational and experimental meta-analyses were then conducted. Effect sizes were weighted via the reciprocal of the variance (Hedges and Olkin, 1985). Variance estimates were computed, including the proportion of observed variance due to sampling error, residual variance, and homogeneity of variance. The 95% confidence interval and the total N associated with the average weighted effect sizes were also calculated. These values can be found in appendices C and D.

[1]IBM SPSS, Inc. *PASW Statistics 18.0*; Chicago, IL, 2009.

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Appendix C. Empirical Studies Included in Correlational Analysis

This appendix is in its original form, without editorial change.

Author(s) and Date	Measure of Trust	Main Moderator	Sub-Moderator	Antecedent	Effect Size	Correlation
Biros, Daly, & Gunsch (2004)	Self-report questionnaire (Likert scale)	Robot	Performance	Predictability	1.08	0.48
		Robot	Performance	Reliability	1.40	0.57
		Robot	Performance	Level of Automation	1.87	0.68
		Robot	Performance	Predictability	1.83	0.68
		Robot	Performance	Dependability	1.89	0.69
Evers, Maldanado, Brodecki, & Hinds (2008)	Self-report questionnaire (Likert scale)	Environment	Team Collaboration	Culture	0.32	0.16
		Environment	Team Collaboration	In-group Membership	0.14	0.07
		Environment	Team Collaboration	In-group Membership	0.35	0.17
		Human	Characteristics	Demographics	-0.08	-0.04
		Human	Characteristics	Comfort with Robot	1.54	0.61
		Human	Characteristics	Comfort with Robot	0.41	0.20
		Robot	Attribute	Anthropomorphism	0.54	0.26
Kidd & Breazeal (2004)	Self-report questionnaire	Robot	Attribute	Robot Personality	-1.09	-0.48
		Environment	Team Collaboration	Communication	0.63	0.30
		Robot	Attribute	Robot Personality	0.68	0.32
		Robot	Attribute	Robot Personality	1.22	0.52
		Robot	Performance	Reliability	-0.98	-0.44
		Environment	Team Collaboration	Communication	-0.35	-0.17
		Human	Ability	Attentional Capacity/Engagement	-0.30	-0.15

Author(s) and Date	Measure of Trust	Main Moderator	Sub-Moderator	Antecedent	Effect Size	Correlation
Li, Rau, & Li (2010)	Adapted version of SHAPE Automation Trust Index (SATI)	Robot	Attribute	Robot Personality	1.96	0.70
		Human	Ability	Attentional Capacity/Engagement	1.65	0.64
		Human	Characteristics	Personality Traits	2.44	0.77
		Human	Ability	Attentional Capacity/Engagement	0.70	0.33
		Environment	Team Collaboration	Culture	-0.73	-0.34
		Robot	Attribute	Anthropomorphism	-0.16	-0.08
		Environment	Tasking	Task Type	0.12	0.06
Looije, Neerincx, & Cnossen (2010)	Self-report survey, based on items in Social Behavior Questionnaire (SBQ)	Human	Characteristics	Personality Traits	1.50	0.60
		Human	Characteristics	Personality Traits	0.75	0.35
		Human	Characteristics	Personality Traits	1.32	0.55
		Robot	Performance	Behaviors	0.41	0.20
Mutlu, Yamaoka, Kanda, Ishiguro, & Hagita (2009)	Self-report questionnaire (Likert scale)	Human	Ability	Attentional Capacity/Engagement	-0.37	-0.18
Rau, Li, & Li (2009)	Receptivity/ trust subscale of the Relationship Communication scale	Robot	Attribute	Robot Personality	2.11	0.73
		Human	Characteristics	Attitudes towards Robots	1.93	0.70
		Human	Characteristics	Attitudes towards Robots	0.53	0.25

Author(s) and Date	Measure of Trust	Main Moderator	Sub-Moderator	Antecedent	Effect Size	Correlation
Ross (2008)	Self-report questionnaire	Robot	Attribute	Anthropomorphism	-0.14	-0.07
		Robot	Attribute	Anthropomorphism	0.20	0.10
		Robot	Attribute	Anthropomorphism	0.08	0.04
		Robot	Attribute	Anthropomorphism	0.04	0.02
		Robot	Attribute	Anthropomorphism	0.06	0.03
		Robot	Attribute	Anthropomorphism	-0.61	-0.29
		Robot	Attribute	Anthropomorphism	0.35	0.17
		Robot	Attribute	Anthropomorphism	0.16	0.08
		Robot	Attribute	Anthropomorphism	0.26	0.13
		Robot	Attribute	Anthropomorphism	-0.04	-0.02
		Robot	Attribute	Anthropomorphism	0.08	0.04
		Robot	Attribute	Anthropomorphism	-0.10	-0.05
	Self-report questionnaire	Robot	Attribute	Robot Type	-0.20	-0.10
		Robot	Attribute	Robot Type	-0.58	-0.28
		Robot	Attribute	Robot Type	0.20	0.10
	Self-report questionnaire	Robot	Performance	Reliability	0.14	0.07
		Robot	Performance	Reliability	0.16	0.08
		Robot	Performance	Reliability	-0.41	-0.20
		Robot	Performance	Reliability	0.65	0.31
		Robot	Performance	Reliability	0.14	0.07
		Robot	Performance	Reliability	0.32	0.16

Author(s) and Date	Measure of Trust	Main Moderator	Sub-Moderator	Antecedent	Effect Size	Correlation
Ross (2008)	Self-report questionnaire	Robot	Performance	Reliability	-0.04	-0.02
		Robot	Performance	Reliability	-0.37	-0.18
		Robot	Performance	Reliability	-0.95	-0.43
	Self-report questionnaire	Robot	Performance	Level of Automation	0.37	0.18
		Robot	Performance	Level of Automation	0.52	0.25
Tenney, Rogers, & Pew (1998)	Self-report questionnaire	Robot	Performance	Level of Automation	3.37	0.86
Wang, Rau, Evers, Robinson, & Hinds (2010)	Self-report questionnaire	Environment	Team Collaboration	Culture	-0.14	-0.07
		Environment	Team Collaboration	Communication	0.41	0.20
		Environment	Team Collaboration	In-group Membership	0.80	0.37
		Human	Characteristics	Attitudes towards Robots	-1.22	-0.52
		Environment	Team Collaboration	In-group Membership	1.04	0.46
		Human	Characteristics	Attitudes towards Robots	-0.35	-0.17
		Human	Characteristics	Attitudes towards Robots	0.77	0.36
		Human	Characteristics	Attitudes towards Robots	0.30	0.15

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Appendix D. Empirical Studies Included in Experimental Analysis

This appendix appears in its original form, without editorial change.

Author(s) and Date	Measure of Trust	Main Moderator	Sub-Moderator	Antecedent	Effect Size	Main Finding
Bainbridge, Hart, Kim, & Scassellati (2008)	Self-report questionnaire	Robot Robot	Attribute Attribute	Proximity Proximity	1.13 0.93	Physical presence afforded higher trust in a robot.
de Ruyter, Saini, Markopoulous, & van Breemen (2005)	Self-report questionnaire	Robot	Attribute	Robot Personality	-0.43	Social intelligence of robot matters. People trusted a socially unintelligent robot more in this task.
Evers, Maldonado, Brodecki, & Hinds (2008)	Self-report questionnaire (Likert scale)	Environment Robot Robot Robot Robot Robot	Team Collaboration Attribute Attribute Attribute Attribute Attribute	Culture Robot Type Robot Type Robot Type Robot Type Robot Type	0.29 .12 1.20 1.15 1.18 1.06	The type of partner matters in determining degree of trust. U.S. participants reported higher trust of robot than Chinese participants. Further, both U.S. & Chinese participants trusted the robot over the human.
Heerink, Krose, Evers, & Wielinga (2010)	Self-report questionnaire	Robot Environment	Attribute Team Collaboration	Adaptability Communication	0.35 0.04	Trust increases when a human has the ability to adapt the level of the robot's automation. People trusted a less social robot.
Kidd (2003)	Self-report questionnaire	Human	Characteristics	Demographics	0.01	Gender of human does not appear to affect trust ratings.
		Environment	Tasking	Task Type	0.52	Task type impacts trust level. Participants reported higher trust in a collaborative task than information gathering task.
		Robot	Attribute	Proximity	0.37	Co-located robot affords higher trust ratings than one viewed remotely.

Author(s) and Date	Measure of Trust	Main Moderator	Sub-Moderator	Antecedent	Effect Size	Main Finding
Powers, Kiesler, Fussell, & Torrey (2007)/Kiesler, Powers, Fussell, & Torrey (2008)	Self-report questionnaire	Robot	Attribute	Proximity	1.45	Higher trust ratings in the co-located robot.
Rau, Li, & Li (2009)	Receptivity/ trust subscale of the Relationship Communication scale	Environment	Team Collaboration	Culture	1.70	Trust in robot is different across different cultures. Chinese participants reported higher levels of trust in the robot than German participants.
Ross (2008)	Self-report questionnaire	Robot	Performance	Reliability	1.10	High reliability leads to higher trust. While there is no significant difference when using multiple robots, different robots have slightly higher trust ratings than using multiple same robots or humans.
		Robot	Performance	Reliability	0.75	
		Robot	Performance	Reliability	0.29	
		Robot	Performance	Reliability	1.12	
		Robot	Performance	Reliability	0.58	
		Robot	Performance	Reliability	0.76	
		Robot	Performance	Reliability	0.76	
		Robot	Performance	Reliability	-0.08	
		Robot	Performance	Reliability	1.12	
		Robot	Attribute	Robot Type	0.13	
		Robot	Attribute	Robot Type	-0.04	
		Robot	Attribute	Robot Type	0.10	
Scopelliti, Giuliani, & Formana (2005)	Self-report questionnaire	Human	Characteristics	Demographics	-0.93	Age is important in trust. Young adults trust robots more than older adults.
		Human	Characteristics	Demographics	-1.33	
		Human	Characteristics	Demographics	-0.39	

Author(s) and Date	Measure of Trust	Main Moderator	Sub-Moderator	Antecedent	Effect Size	Main Finding
Tsui, Desai, & Yanco (2010)	Self-report questionnaire	Robot	Attribute	Robot Type	-0.72	People tend to trust a human operator more than a robot acting without an apparent operator.
		Robot	Attribute	Robot Type	-0.78	
		Robot	Attribute	Robot Type	-0.94	
		Robot	Attribute	Robot Type	0.42	Type of robot and size of robot affects trust.
		Robot	Attribute	Robot Type	0.29	
		Robot	Attribute	Robot Type	0.10	
	Self-report questionnaire	Robot	Performance	Behaviors	0.23	Overall participants trust slower robotic behaviors more than faster ones.
		Robot	Performance	Behaviors	1.41	
		Robot	Performance	Behaviors	0.19	
		Robot	Performance	Behaviors	1.54	
		Robot	Performance	Behaviors	1.30	
		Robot	Performance	Behaviors	-0.26	
Wang, Rau, Evers, Robinson, & Hinds (2010)	Self-report questionnaire	Environment	Team Collaboration	Culture	0.19	Trust in robot is different across cultures. U.S. reported greater levels of trust than Chinese participants. Culture can also impact trust related to different types of communication (implicit / explicit).
		Environment	Team Collaboration	Communication	0.06	
		Environment	Team Collaboration	Communication	0.20	
		Environment	Team Collaboration	Communication	0.18	

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