A Review on Trust in Human-Robot Interaction

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Abstract—Due to agile advancements in the autonomy of robotic systems, prospective robotic agents are intended to play the role of teammates and partners with humans to perform operations rather than tools that are replacing humans or helping humans in specific tasks. This notion of “partnering” with robots raises new challenges for the human–robot interaction (HRI), which gives rise to a new field of research in HRI, namely Human-Robot Trust. Where humans and robots are working as partners, the performance of work can be diminished if humans do not trust robots appropriately. Considering the impact of human-robot trust observed in different HRI fields, many researchers have investigated the field of human-robot trust and examined various concerns related to the human-robot trust. In this work, we review the past works on human-robot trust based on the research topics and discuss selected trends in this field. Based on these reviews, we finally propose some ideas and areas of potential future research at the end of this paper.

Index Terms—human-robot interaction, human-robot trust, modeling trust in HRI, trust calibration in HRI, trust measurement, factors affecting trust in HRI, trust repair in HRI, trust definition in HRI, multidimensional nature of trust in HRI

I. INTRODUCTION

Trust is one of the essential elements in the development of any constructive relationship. Trust is not limited to only inter-personal interactions, and it can affect different forms of interaction, including relationships among human individuals and robots. We can mention trust as an overarching concern that affects the effectiveness of a system, especially in terms of safety, performance, and use rate [1]. Having this concern in mind, trust has become a critical element in the design and development of automated systems [2]. Autonomous systems are being designed and developed with increased levels of independence and decision-making capabilities, and these capacities will be efficient in uncertain situations [3].

Human–robot trust is an important branch of human–robot interaction (HRI) which has recently gained increasing attention among scholars in many disciplines, such as Computer Engineering [4], Psychology [5], Computer Science [6] and Mechanical Engineering [7]. Trust is a significant factor that needs to be taken into considerations when robots are going to work as teammates in human–robot teams [8], where robots are designed to be used as autonomous agents [9], or where robots are going to be used in a complex and dangerous situation and take the place of the human in the high-risk tasks [4][10]. In many cases, trust is the main factor determining how much a robotic agent would be accepted and used by the human [11]. A human would not use or rely on an automated system if they believe that system is not trustworthy [12].

In this work, we review the past works on human-robot trust based on the research topics and discuss selected trends in this field. Based on these reviews, we finally propose some ideas and areas of potential future research at the end of this work. The overall purpose of this document is to explore different studies concentrated on trust in HRI and review these studies. The selected trends of human-robot trust that are going to be discussed in this work are as follow: first, we review different definitions of trust and talk about the multidimensional nature of trust in HRI, then we will talk about factors affecting trust in HRI and classify those factors, after that we will talk about trust repair and trust calibration and finally, we will talk about modeling trust and trust measurement techniques. Based on the reviews and comparison of the available works on trust in HRI, shortcoming and challenges of studying trust in HRI that has not been answered yet and more avenues of research need to be concentrated on them, are mentioned in the conclusion and future work section.

II. DEFINITION OF TRUST IN HRI

From the psychology point of view, trust is a mental state of a human [22]. Numerous researchers have extensively explored the notion of trust for decades. Trust is not limited to just interpersonal interaction. It underlies different forms of interaction, such as banks’ interactions with customers,
governments with citizens, employers with employees, etc., [23]. Therefore, we can say trust can affect human-robot interaction, as it can affect the human user or collaborator’s willingness to assign a task, share information, cooperate with, provide support, accept results, and interact with a robot [24].

As trust is one of the necessities for building a successful human-robot interaction, we need to study trust and factors affecting the formation and loss of trust to create methodologies for modeling, measuring, and calibrating trust. The first step toward studying trust is having a clear definition of trust. However, despite the broad efforts and a considerable number of studies concentrating on trust, yet there is no unique definition for trust, as the definition of trust concept is heavily dependent on the context in which trust is being discussed [25]. There are many different definitions for trust by different researchers in human-robot trust field, for instance, in [26] trust is defined as “the reliance by one agent that actions prejudicial to the well-being of that agent will not be undertaken by influential others”.

The issue for making a unique definition for trust within the context of HRI comes primarily from a variety of applications, and situations that robots are used, around which trust needs to be defined, explored, and measured as a variable. Different applications, different robotic agents, different human operators, and different operation situations would provide different challenges for defining trust for every specific context in HRI that robots are used. For example, in robotic applications that trust needs to be explored in the context of user-safety and high-risk situation such as emergency evacuation [4], the definition of trust might differ substantially from the situation in which trust is explored in the context of border tracking robots [27].

One of the most thorough definitions of trust, which is deployed by many other studies concentrated on human-robot trust, is by Lee and See [11]. They define trust from the perspective of automation. This definition was generated by reviewing many other studies concentrated on defining trust and was complementary to many other works. They define trust as “the attitude that an agent will help achieve an individual’s goals in a situation characterized by uncertainty and vulnerability”. This definition of trust is accepted and used by many studies on trust in HRI. Wagner et al. [23] also provided a comprehensive definition for trust: “a belief, held by the trustor, that the trustee will act in a manner that mitigates the trustor’s risk in a situation in which the trustee has put its outcomes at risk”. They also provided a model for determining if an interaction demands trust or not. All these definitions have two things in common, one is: “whether robot’s actions and behaviors correspond to human’s interest or not?”, and two is: “human has something to lose.” To address this concern in each robotic application, trust needs to be defined based on human interest in that domain.

III. MULTIDIMENSIONAL NATURE OF TRUST IN HRI

In recent years due to the advancements of robotics, robots are being used very close contact with humans in a variety of settings, ranging from homes [28] and schools [29] to the workplace [30]. Robots are no more used as tools that their only contribution is to perform repetitive physical tasks. With the advances in the realm of robotic and human-robot interaction, robots are increasingly used as social agents in a variety of social applications [31]. Therefore, to investigate the nature of trust in human-robot interaction, one should move from the domain of human-automated trust into the domain of human-human trust [32].

Works in the domain of human-automated trust emphasize the performance of automated systems. In the literature on trust in automation, the main focus is on improving human users’ trust in automation by modifying the performance of the system based on human expectation or matching a human user’s expectations of a system with information about the system performance. Automated systems are motiveless, and there is no mention of any concerns about being deceived, betrayed, or exploited by the system. In sum, trust in automated systems is highly correlated with the system performance, and the only worries concern the systems’ reliability and ability [3]. However, the emphasis of the works in the domain of human-human trust is on moral trust. The question is whether a human agent will take advantage of another human’s vulnerability either unconsciously because of a lack of ability or consciously because of a lack of moral integrity [32].

A modern conceptualization of human-robot trust which is not limited to the traditional interpretation of human-automation trust and better matches the current understanding of human-robot trust, is provided by Ulman et al. [32]. They reviewed the literature and performed empirical work, finally they suggested that trust is multidimensional, incorporating both performance aspects (i.e., central in the human-automation literature) and moral aspects (i.e., central in the human-human trust literature). These two trust aspects break into two sub-factors (i.e., Reliable and Capable within Performance, and Sincere and Ethical within Moral). A multidimensional conceptualization of trust in HRI can be applied to any robotic applications which demands trust in robots. However, only some of the trust dimensions may be relevant for any given robotic application or interaction type.

Based on the multidimensional nature of the trust in human-robot interaction, Park et al. [33] divide the human-robot trust into two categories, performance-based trust, and relation-based trust. Performance-based trust mainly emphasis on reliability, capability, and competency of the robot at any given task, without demanding to be monitored by a human supervisor. A robot that garnered the performance-based trust of a human’s trust is a proper choice to perform a critical factory job with zero interaction with humans. However, relation-based trust implies the acceptance of a robot as a trusted social agent. A robot should have some features such as being sincere and ethical to the person with whom it interacts. A robot that is granted relation-based trust is a good choice for robotic uses that involve close interaction with a human. This type of trust is less studied in the past, but it is becoming increasingly relevant by the advancements in social robots, and
therefore more researches will be concentrated on factors that may influence this type of trust.

IV. FACTORS AFFECTING TRUST

Most of the current researches in the human-robot trust are concentrated on factors affecting trust (e.g., trust gain, trust loss and trust repair in human after robot’s faulty behavior or trust violation). The top factors affecting human-robot trust can be considered an extension to the factors affecting human-automation trust. Lee et al. [1] provided a complete review of the factors affecting trust in human-human interaction and generalize these factors by theoretical and empirical examination to factors affecting trust in human-automation interaction (HAI). There are also many other studies reviewing and analyzing factors affecting trust in HAI [3, 34, 44]. However, robots differ from other forms of automation in many cases. First, robots are mobile, and this mobility can cause injury to the human when they are working in the same field. Second, robots can work remotely, and they can go out of control. Third, robots are designed in many different shapes, which sometimes people are not familiar with those, and it affects the whole trust process as well [6]. Therefore, although there are many similarities among factors affecting trust in human-automation and human-robot interaction, factors affecting trust in human-robot interaction need to be investigated separately.

To identify the elements that affect trust between humans and robots, researchers design experiments in which humans interact with robots in different scenarios. Researchers manipulate factors in the experiment that want to examine their effect on trust. There are numerous studies in the field of HRI that study the effects of different factors on trust. Hancock et al. [5] provided a meta-analysis of factors affecting trust in human-robot interaction and classify these factors in three classes: Human-related factors (i.e., ability-based, characteristics); Robot-related factors (i.e., performance-based, attribute-based); and Environment-related factors (i.e., team collaboration, tasking). In this study, we will review and classify recent studies on modeling trust in human-robot interaction and factors affecting trust with a similar classification basis as [5] with some changes in categories and subcategories. In this work, factors affecting trust in human-robot interaction are classified into three categories: 1- Robot-related factors (i.e., robot-performance, robot’s appearance, robot’s behaviors, and physical presence of the robot), 2- task and environment-related factors, 3- human-related factors. Table I shows our classification of factors affecting trust.

1) Robot-Related Factors: These factors are directly related to the design and construction of the robots, and by changing the design and construction of the robot, trust in robots can be increase or decrease. Robot-related factors have the most significant effect on the trust in human-robot interaction [5]. This justifies the significant number of researches in the human-robot trust field, concentrating on robot-related factors. In this study, we classify robot-related factors under four sub-categories: performance-related factors, behavior-related factors, appearance-related factors, and a single feature: robot physical presence.

(a) Performance-Related Factors: There are many empirical and analytical studies over performance-related factors affecting trust in human-robot interaction. Performance-related factors determine the quality of the performed operation by the robot from the human operator’s point of view. Of these factors we can mention reliability, faulty behavior, frequency of fault occurrence [35], timing of error [36], transparency, feedback [37, 38], level of situation awareness [39], false alarms [40], and level of autonomy [41].

(b) Appearance and Personality-Related Factors: People consider a personality for robots based on robots’ appearance and behavior while interacting with them. Some features in robot appearance such as anthropomorphism [38], robot’s gender [42], harmony of robot’s activity with it’s appearance [43], and robot’s similarity (e.g., the same/different gender) by two deep level human-robot similarity (e.g., similar/different work style) [44] affect trust in human-robot interaction.

(c) Behavior-Related Factors: Advancements in robotic systems in recent years and increased autonomy of robots caused people to consider them more like teammates to tools, and increase the intelligence of robots altered the form of human-robot interacting to a more naturalistic interaction [21]. Approaching a more human-like interaction with robots cause people to consider the intention for robot’s behavior. Some of the robot’s behaviour such as robot’s likeability (e.g., gaze behaviors and greeting) [35, 38], proximity (e.g., physical and physiological proximity) [45, 47], engagement [43], confess to the reliability [38, 48], and harmony of robot personality with the task (e.g., introverted robotic security guard and an extroverted robotic nurse) [42] can affect formation and maintenance of trust. There are some other behaviors such as apologies after failure, making excuses and explanations after failure or dialogues [35, 38, 49, 50] can affect trust repair after failure. Some studies on the effect of robot’s behavior on trust also showed that the harmony of behaviors with robot’s activity (i.e., introverted robotic security guard and an extroverted robotic nurse) could affect humans’ trust toward robotic agent [42].

(d) Robot’s Physical Presence: Robot’s co-location with participants in an experiment causes people to trust the robot better than when the robot is virtually present (i.e., telepresence throw video display) in the experiment. Studies on the effects of robot physical presence on trust showed that people are more willing to trust robots and comply with their commands and even irrational commands when robots are physically present [38, 51].
V. TRUST MEASUREMENT IN HUMAN-ROBOT INTERACTION

As mentioned in the previous section, researchers design experiments in which humans interact with robots in different scenarios to identify the elements that affect trust between humans and robots. Researchers manipulate factors in the experiment that want to examine their effect on trust. Latter, they need to assess experiment participants' gain or loss of trust in the presence of those manipulated factors, so they need to apply the trust measurement technique to evaluate trust at the end of these experiments. In human-robot trust research, there are two main methods for measuring trust, subjective trust measurement and objective trust measurement. In the rest of this section, we will review these methods, their benefits and limitations, different strategies for deployment of these methods in various studies, and examples of studies that have used these methods for measuring trust in human-robot interaction.

1) Subjective Trust Measurement: The first and most dominant method for trust measurement in HRI is subjective trust measurement. This trust measurement technique involves assessing experiment participants’ answers to questionnaires designed to gauge a people’s trust in automated agents or specifically to the robots [57]. The main advantage of subjective trust measurement methods is the ease of use, as in these methods, information is derived from the source directly. However, there are several potential issues with these trust measurement methods; those two are noted here. First, participants of the experiments may consciously or unconsciously align their answers to the demands of the experimenters in the study. Second, peoples’ states of trust attribution to a robot in a specific situation may differ heavily from the actual behavioral responses of those people to a robot in risky situations. Individuals report more attributed trust to a robot in impractical situations than they actually would do in real-world scenarios where there is vulnerability and risk [53]. Although by the use of subjective trust measurement methods, trust can be assessed at various times during a study, trust measurement in HRI is mainly dominated by post-hoc questionnaires. This makes the subjective trust measurement methods more prone to error. They only allow for measurement of trust at a singular moment, which contradicts with varying nature of trust and limits the understanding of the dynamics of trust-building [58].

There are some trust scales or questionnaires for trust assessment developed and validated by experts to be used in HRI research. Of those we can mention, Human-Robot Trust Scale [59], Trust in Automation Scale [60], Human-Robot Interaction Trust Scale [61], and Human-Computer Trust Instrument [62]. Many of the studies in HRI use these validated questionnaires. However, some studies create non-validated ad-hoc questionnaires for a single research study. The validation qualification is very important and shows the applicability of those methods in other research and the comparability of the research results with other research results [59].

2) Objective trust measurement: These trust measurement methods are based on analyzing how experiment participants interact with the robots, rather than relying on participants’ speculation about themselves. The main advantage of these methods is that they are not prone to errors related to biased answers by participants and variation between stated trust and behavioral trust in real-world scenarios [57]. However, these methods also have some drawbacks. The first and most important drawback of objective trust measurement methods is that a researcher who uses this method for measuring trust should operationalize behaviors of people and decides that certain behaviors represent trust or distrust. Therefore, when using objective trust measurement, researchers must demonstrate people’s behavior as a reflection of their trust attitude toward the robot [58]. However, a person’s behaviors might sometimes vary from their attitudes about trust. From the teamwork view, people’s attitudes, behaviors, and cognitions are known to be distinct from each other [63].

Objective trust measurement methods are used less frequently in human-robot trust studies than subjective trust measurement methods. There are four different categories of objective trust measurement methods [64]. We will explain these four categories below:

1) Task Intervention: For trust measurement in this method, researchers assign a robot to perform a task normally done by a human and ask participants to interact with the robot during this task. Trust measurement is performed by monitoring the number of times the human participant intervenes in the robot’s task by changing the robot’s working mood from autonomous to control mood or the number of times the human participant preventing the robot from doing the task and start doing the task by themselves. Of the researches that used this trust measurement method, we can mention [65][66].

2) Task delegation: This objective trust measurement method is based on assigning a robot to perform a task that is
TABLE I
FACTORS AFFECTING DEVELOPMENT OF TRUST IN HUMAN–ROBOT INTERACTION

| 1. Robot-Related | (a) Performance-Related | (c) Appearance-Related | 3. Task & Environment-Related |
|------------------|-------------------------|------------------------|-------------------------------|
|                   | Dependability, reliability and error [4],[35],[38],[52] | Similarity with operator [44] | Nature of task [41],[42] |
|                   | Autonomy level [41],[53] | Gender [42],[44] | Physical presence of robot in task site [38],[51] |
|                   | Situation awareness, feedback and Transparency [38],[39],[48],[52] | Harmony of appearance with task [43] | In-group membership [8],[54] |
|                   | (b) Behavior-Related | Anthropomorphism [38] | Task site [41] |
|                   | Dialogues [36] | 2. Human-Related | Revocability [37] |
|                   | Proximity [45],[47] | Personality [37] | Risk [4],[41],[44] |
|                   | Likeability and friendliness [45] | Culture [55] | Workload, complexity and required level of multi-tasking [35] |
|                   | Personality (harmony with task) [42] | Understanding of the system [21] | |
|                   | Confess to reliability [38],[48] | Demographics [46],[56] | |
|                   | Apology for failure [38],[49],[50] | Subjective feeling [40],[46] | |
|                   | Engagement [43] | Experience with robots [56] | |

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normally done by a human. However, in this method, at the end of the task, participants are asked to choose to assign one robot among multiple robots, or to choose from a robot or a human to perform a second task. This objective trust measurement method is also used by many researchers in HRI field [67],[68].

3) Behavioral Change: This objective trust measurement method is based on observing or measuring participants’ behavior when they are naturally interacting with different robots. In this trust measurement method, trust is measured differently based on the nature of the interaction for each different study [69],[70].

4) Following advice: In this objective trust measurement paradigm, experiment participants are assigned to perform a task with the help of a robot, the robot can only give suggestions or offer advice to the participants, and participants have the option of whether or not to follow the robot advice. Trust is measured by monitoring how much participants conform with the robot’s advice, and suggestion [71],[72].

VI. TRUST VIOLATION AND TRUST REPAIR

Even the robots with the most precise design will sometimes fail or make an error while performing their tasks. Researches have shown that even one mistake from the robot’s side can cause a loss of trust by human users [73]. Many researchers have investigated the effect of faulty behavior of robots on human trust [57],[52]. Some researchers also investigated the effect of some special features of an error on trust such as error type [57], timing and magnitude of the error [74], frequency of the error occurrence [55], and revocability of the error [37]. There are also researches on the effect of the error on trust in some special circumstances such as high-risk time-critical situations [4],[74]. When an error from the robot side occurs, possible negative effects of that error on human trust need to be mitigated. This is where trust repair comes into play. Trust repair in HRI can be defined as efforts for rebuilding trust when a robotic agent violates the trust of the human user or cooperator. But what causes the occurrence of trust violations, and how can trust be repaired after trust violation? Not enough research has been done in the area of trust repair after trust violation in the field of HRI [58].

From the engineering perspective, robots are machines and do not intend their behaviors, and they behave the way they are designed to do. However, most of the studies on trust repair in human-robot interaction use the same strategies as those of inter-human trust repair. Some of the strategies used in human-robot trust repair are apologies, promises, compensation, showing vulnerable behavior, making excuses or explanations and dialogues, showing awareness of its error and expression of regret [36],[49],[50],[73],[75],[76]. The results of these studies show that taking robots as intentional agents from the psychological perspective can make users attribute sufficient beneficence to the robot’s motives and can help trust repair [77]. Robinette et al. [73] also investigated that trust repair efforts such as promising to perform better, apologizing for mistakes, and convincing a human user to trust a robot by providing additional information after a failure can work, if the timing for these actions is right.

Tolmeijer et al. [77] provided a taxonomy of different error or failure types that can occur during human-robot interaction and influence human users’ trust toward the robot. Four error types that are mentioned in this work are 1- system error, 2- design error, 3- expectation error, and 4- user error. In this work, some mitigation strategies based on the error type are also proposed, namely fixing the error, and redesigning interaction in case of system error or designing error, providing an explanation, and providing training in case of user and
VII. Trust Modeling

Inappropriate trust can be problematic in any form of human-robot collaboration. Both under-trust and over-trust to a robotic system might be problematic and costly. Appropriate levels of trust need to be formed among humans and the robotic agent to safely and effectively use robots by a human. That is why trust needs to be modeled, measured, and calibrated during human-robot interaction.

Trust in HRI has a lot in common with trust in HAI, studied at length. Muir et al. [78] found the available definitions for trust between humans inconsistent with the nature of HAI based on the multidimensional construct of trust. She defined one of the first trust models for HAI. This model was based on the model of human expectation of automation proposed by Barber et al. [79]. Three elements of expectation defined by Barber’s model were included in Muir’s trust model: the fundamental expectation of persistence, technical competence (skill, rule, and knowledge-based behavior), fiduciary responsibility (intention, power, and authority). Lee and Moray [80] built upon Muir’s strategy for modeling trust, identifying independent variables that influence trust, and introducing another trust model. Later, other researchers have modeled the operator’s trust in automation, considering more factors affecting trust [1-81, 82]. These models were finally classified into five groups [83]: regression-based models [78-80], time series models [84], qualitative models [85], argument based probabilistic models [86], and neural net models [82].

Although there are many similarities between trust in human-robot interaction and trust in human-automation interaction, and there are great similarities among factors affecting trust in automation and human-robot interaction. However, models generated for modeling trust in human-automation interaction are inconsistent with the needs of human-robot interaction. According to Desai et al. [87] “these models do not consider some factors that appear while working with robots such as situational awareness, the usability of the interface, physical presence of robots (co-located with human or remotely-located), limitations and complexities of the operating environment, workload, task difficulty, etc. which influence HRI considerably”. Desai et al. [87] introduced a schematic of a model considering some factors affecting human-robot trust (e.g., interface usability, user-related factors, and environment-related factors) in conjugate with factors affecting human-automation trust. Latter, Yagoda et al. [61] introduced one of the first models for trust in human-robot interaction. This model was generated based on the different dimensions of a human-robot interaction task and validity assessment of each of these directions by subject matter experts (SMEs) in the human-robot interaction field. Desai et al. [6] also were one of the pioneers in modeling trust in HRI. They generated a more detailed model for trust in human and autonomous robot teleoperation. This model used the Area Under Trust Curve (AUTC) measure to account for an individual’s entire interactive experience with the robot. In this model, many factors affecting trust in robots were included (i.e., situation awareness, task difficulty, feedback, long-term interaction, age, and timing of reliability drop).

The tasking of evolving robotic world is transitioning from strict teleoperation to tasking in which the robots play the role of a team member or a partner in a dyadic or group working. There is a strong correlation between the level of trust in human-robot teammates with the performance of the robotic agent’s work, and it also impacts their interaction quality [1-6]. According to Xu et al. [88], high levels of trust among human-robot teammates often demonstrate great synergy in which matched decision-making capabilities of the human member in the team complements the exhaustive controlling and executing capabilities of the robotic agent. In contrast, a low level of trust among human-robot teammates might cause humans to refuse to delegate tasks to the robotic agent or sometimes decide to disable the robotic agent [88]. As there is a high correlation between trust and performance of the work in human-robot collaboration, trust can be modeled based on the performance [7-89] and modifying the performance of the collaboration based on the human expectations to convince human to show the act of trust toward robotic agent. There are also some trust models based on the performance of robotic operation, which is not aimed to modify the performance but also for detecting robotic agents that are not reliable and assigning less critical tasks to them or disregard them while assigning tasks to robotic agents in multi-robot tasks [90]. On the other hand, the human-robot collaboration’s performance can also be modeled based on the trust [24, 91], these models are used to modify the root’s trust-related behavior in order to manage and optimize the overall performance of the collaboration.

A prevalent class of human-robot collaborations is supervisory collaboration. There are two roles for an individual in the human-robot teams, supervisor (human) and worker(robot), where the supervisor delegate tasks to the worker and oversee the performance of the operation. Supervisor also has the authority to take control of the robot when the robot is doing something in the wrong way and correct the robot’s mistake. The model of trust for supervisory collaboration, which is presented in [89], is based on the trust in human-human collaboration, generates a quantity showing the compatibility of robot performance with human expectation, and let the robot modify its performance to fulfill human expectations and improve trust. Latter, this trust model was improved [92] and more factors affecting trust in supervisory collaboration, such as failure rate in the autonomous agent and the rate of supervisor intervention, were involved in designing the trust model. Online Probabilistic Trust Inference Model (OPTIMo) [92] is another model of trust in human-robot supervisory collaboration which the same research group introduced. This model formulates Bayesian beliefs over human’s trust status in each moment based on the performance of the robot on the task over time to generate an estimate of the real-time human’s trust in the robot.

Modeling trust in human-robot collaboration is mainly used to notify automation whenever the human operator loses trust
to let the automation correct its performance. However, human over-reliance needs to be considered in modeling trust and responding by the robot. When trust can be modeled and measured in a real-time manner in human-robot collaboration, it can help the robot repair trust whenever the human starts under-trusting the robot [27]. A real-time model of trust (trust-POMDP) for human-robot peer-to-peer collaboration is introduced in [66], which integrates measured trust in the robot’s decision-making. The trust-POMDP model closes the loop between measured trust by the real-time trust model and robot decision-making process to maximize collaboration performance. This model grants a robot the ability to influence human trust systematically to reduce and increase trust in over-reliance and under-reliance situations, respectively.

Hancock et al. [5] provided a meta-analysis of a significant number of factors affecting trust in human-robot interaction. They evaluate and quantify the effects of human-based, robot-based, and environmental-based factors on trust in human-robot interaction and provide quantitative measurement for the effect of each of these class of factors. They develop a model of human-robot team trust, based on their findings in meta-analysis [5]. In addition to the effect of three classes of factors affecting trust, which they introduced in their meta-analysis, they considered the effects of training implications and designing implications on their final model of trust [92].

Subjective trust measurement techniques are recently being used in companion with objective trust measurement techniques in some of the studies on modeling trust in human-automation interaction and human-robot interaction. Subjective trust measurement techniques are deployed to increase the accuracy and robustness of trust measurements. Chen et al. [66] uses machine learning methods to reason for human behavior based on robot behavior and modify robot behavior based on human expectation. There are some studies in human-automation trust, human-computer interaction, and human trust to artificial intelligence that use psycho-physiological measurements for trust modeling [94, 96]. Khalid et al. [97] introduced a model for trust modeling in human-robot interaction, which uses facial expressions, voice features, and extracted heart rate features in combination with self-reported trust of human to model trust. They classify human trust in a robot into low, natural, and high trust levels using a Neuro-fuzzy trust classifier.

VIII. TRUST MODEL: INPUTS AND OUTPUTS

Trust models formulate the effect of factors on the formation and variation of trust in robots. Trust models use factors affecting trust to estimate trust. Since these factors vary in different domains and environments, input factors to the trust models vary based on the application domain. For example, Robinette et al. [98] models trust in emergency evacuation based on the situational risk (e.g., amount of danger perceived by the human in the environment around him) and agent risk (e.g., agent’s behavior and appearance) to model perceived trust by the human and the human’s decision to trust the robot’s guidance or not. In contrast, [89] proposes a trust model for a supervisory collaboration and formulates trust as a function of the robot’s success and failure in performing the task. The output of this trust model is closing the loop between human trust and robot function by adjusting the robot’s action to improve the collaboration efficiency. Finally, [61] proposes a more general trust model based on team configuration, task, system, context, and team process to scale trust for trust measurement.

Many of the studies on modeling trust in HRI consider the performance of collaboration as one of the main input elements for their model [7, 27, 91]. Most of these models consider the effect of performance in conjugate with some other factors. For instance, the OPTIMO probabilistic trust model [27] uses rates of robot’s failures and human interventions in conjugate with task performance as inputs to the model to estimate the human’s degree of trust in a robotic teammate. Meanwhile, [91] uses the operator’s perception of system capabilities, past experience, and training to assess initial trust. Trust gets updated in a loop based on system performance, cognitive workload, and frequency of changes from teleoperation to autonomous operation. This trust model’s output is a measure of gain and loss of trust and the impact of these trust changes on collaboration performance. Sadrfaridpour et al. [2] models trust based on human performance (i.e., muscles fatigue and dynamics of recovery), robot performance (i.e., speed of robot doing the specific task), workload, and human expectation of task performance. The output of this model is feedback to the robot to adjust its performance according to operator desires.

IX. CONCLUSION AND FUTURE WORK

To perform any research on trust in human-robot interaction, we need to define trust clearly. Some of the available definitions of trust that many researchers use are taken from other fields, especially from HAI [1]. Recent studies on the nature of trust in human-robot interaction showed that trust has a multidimensional nature [32]. Based on this multidimensional nature, any form of trust in robots can be categorized into two categories: performance-based trust, which is mostly based on the factors affecting trust in HAI, and relation-based trust, primarily based on factors affecting trust in human-human interaction. Therefore, we can conclude that trust definitions, which are defined based on the needs of trust in HAI, cannot be inclusive enough to be used in the domain of human-robot trust, and a more inclusive definition for trust, encompassing all aspects of human-robot trust is needed HRI researches.

There are numerous studies on trust violation and trust repair in HRI, most of those study the effects of trust violation and trust repair on a singular moment, and they did not investigate the dynamics of trust loss and trust repair after a specific interaction [36, 49, 50, 75]. However, trust is seen as something that changes over time based on different factors in an interaction. Therefore, the long-term effect of failure and trust repair strategies are understudied. Studies exploring the evolving nature of trust based on the different types of failures and different types of trust repair strategies are missing in the literature. For example, there are no answers to these...
questions: how does trust loss as the effect of robot failure change with the user’s increasing familiarity with a robotic agent? Or how do trust repair strategies help trust repair in long-term interaction where an error has occurred several times and efforts have been made to restore trust several times?

Most of the existing trust models in HRI are developed for a specific form of human-robot interaction, specific task type, or a specific type of robotic agent. For example, in [25], a model of trust is specified for evacuation robots; in [35], the trust model is specified on robots with shared control, and in [27] the generated model is usable for supervisory collaboration. As present trust models are domain or task specified, they can not be used in other robotic domains, and the result of those can not be compared with each other. Therefore, we can not evaluate any of these trust models. HRI fields lack a general trust model that can be applied to different robotic tasks and domains. Such a model will eliminate the need for creating new trust models for newly emerging tasks.

Trust is a subject of interest for research in many other fields such as psychology, sociology, and even physiology. In these fields, other indicators of trust are used for trust measurement. For example, some studies use physiological indicators, such as oxytocin-related measures [99]-[101], and objective measures, such as trust games that assess actual investment behavior [102]-[103]. These methods for trust measurement can be used for measuring trust in human-robot interaction. These trust measurement methods can provide an accurate assessment of trust that does not suffer from the many error probabilities that current trust measurement methods used in human-robot interaction studies suffer from. These measurement methods can also help formulate trust and generate trust models independent of the countless parameters that affect trust.
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