Timescales Matter: A Teamness Perspective on Modeling Trust in Human-Robot Team Interactions

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ABSTRACT

Designing robots for trustworthiness is often justified by its purported benefits to overall human-robot team performance. However, there is mixed empirical evidence for how such design approaches truly support robust human-robot teaming through building trust. This may be due to the incongruence between interaction-focused robot trustworthiness designs and the proliferation of trust modeling techniques that are most appropriate for broader teaming and trusting timescales. We offer an appraisal of current methodological and analytical approaches for modeling trust within finer interaction timescales relative to emergent cognitive properties of human-robot teams. We then identify challenges that the trust research community must address in order to produce more precise frameworks for modeling trust, towards more effective human-robot interaction design paradigms.

CCS CONCEPTS

• **Human-centered computing → Interaction design theory, concepts and paradigms**.

KEYWORDS

Human-Robot Interaction, Human-Robot Teaming, Trust, Teamness

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1 INTRODUCTION

There are increasingly numerous ways that people and robots can interact to jointly achieve goals beyond what each could achieve on their own. This growth in robot interaction capabilities, fueled by rapid advances in artificial intelligence and machine learning algorithms, has made it so that human-robot teams (HRTs) are now thought to be on the horizon [35]. In HRTs, robots not only perform programmed actions based on preset cues or provide insights to guide human decision-making, but also independently enact plans and decisions to varying extents [14].

A big motivation for the development of HRTs is the potential of robot teammates to adaptively perform tasks in risky situations in which human teammates' lives can be endangered by certain tasks, such as urban search and rescue in debris-littered environments [4]. However, in other prospective HRT scenarios like joint combat involving human soldiers and robotic confederates, ineffective human-robot teaming can risk disasters that imperil lives beyond those within the teams involved. Thus, safe and effective HRTs require robot teammates that can adaptively interact with human counterparts with respect to changing team task contexts. Because this has been approached through the use of increasingly inscrutable underlying robot frameworks [39], designing for trustworthiness has become a paramount goal of recent HRT research. However, the relationship between trust-oriented robot interaction designs and effective human-robot teaming is unclear.

In this paper, we discuss a disparity between the growing breadth of research in trustworthy HRT designs and the dearth of theory-grounded approaches for validating their utility in HRTs. We then discuss the gaps and challenges in moving towards trust models based on the team-level cognitive phenomena that arise across various trust timescales.

2 TRUST & HUMAN-ROBOT TEAMNESS

Trust, or the willingness to rely on another agent amid risks [32], is crucial in situations where teamwork is essential for achieving critical goals in risky environments. Lee and See's [26] seminal model posits that people's trust in an automated agent like a robot is based on their understanding of its intended purpose, underlying processes, and expected level of performance. There are many similarities between interpersonal and human-robot trust [30], including how people also judge a robot's trustworthiness in light of human social norms and expectations, in addition to knowledge of its reliability [34, 38]. As such, much research over the last three decades has focused on how a robot's social interactive capabilities can adequately inform people of its trustworthiness.

Current approaches to support trust in HRTs includes equipping robots with humanlike verbal speech patterns, voices, and intonations [6, 46]; the ability to apologize or redirect blame after making errors [3, 13, 44]; and non-verbal displays of human-like emotion, including gestures and laughter [36, 37, 40]. There is an abundance of trust-oriented robot design paradigms and measures that impact perceptions of robot teammate trustworthiness [13, 22]. However, it is unclear whether the facilitation of trustworthy perceptions through prosocial robot interaction abilities truly impacts human-robot team performance [41]. This ambiguity is reflected in the observed lack of trustworthiness-oriented human-robot interaction design paradigms validated with respect to their impacts on team processes and performance [43].

Interactive team cognition theory [11] posits that team-level sociocognitive phenomena arise from the succession of individual interactions taken towards shared goals. These phenomena include group decision-making processes and social dynamics, many of which are also related to trust in HRTs [45]. The extent to which these team-level cognitive properties are distinct from those of individual human and robot team members (i.e., a team's "teamness") depends on various dimensions of interdependence of these individual human-robot interactions [10]. Although teamness is a newly-introduced construct, its performance-related dimensions have been successfully modeled in HRTs with respect to team speech patterns [17] and recurrence of physiological signals [18]. Therefore, adopting teamness-oriented approaches may hold promise for reappraising the effectiveness of trustworthiness-oriented HRT interaction designs [8].

3 ACCOUNTING FOR TIMESCALES IN HUMAN-ROBOT TEAM TRUST MODELS

Modeling trust with respect to teamness requires identifying trust phenomena and the timescales over which they manifest to inform precise trust-and-performance models. For instance, people use their knowledge of these informational dimensions in three stages [26]: at first, people rely on faith-based assumptions regarding general system reliability; as their interaction histories accrue with a robot, trusting decisions become based on situational dependability, and then on the immediate predictability. Depending on how interactions take place sequentially, people may rely on analytical perceptions of a robot's overall reliability more than social perceptions, or vice versa [2, 5, 23]. Chiou and Lee's [5] relational model identifies three timescales at which trust may manifest distinctly depending on sequences of human-robot interactions: *interactions*, which occur over milliseconds to a few seconds and span minute information exchanges or decisions; *situations*, which comprise a finite set of interactions corresponding to immediate goals, spanning minutes to a few hours; and *relationships*, which comprise successive situations spanning hours and beyond.

Interactive team cognitive phenomena are best observed in the context of individual interactions [11, 20]. However, the various measures have been used to model trust over time are often collected and analyzed only with respect to situation-level timescales. Questionnaires are the most prevalent in the recent literature [25], which meta-analyses support the validity of for measuring overall trends in trusting perceptions between situation-level timescales of interaction [22, 41]. However, questionnaires are limited by inherent logistical limitations and validity issues associated with repeated administrations between only a few interactions [42, ch. 2]. There have been recent attempts to use questionnaires for modeling interaction-level trust dynamics by administering single-item abbreviations of established trust scales after individual interactions with a robot (e.g., [47]). However, caution should be exercised when using truncated surveys, as they are rarely validated with respect to broader trust questionnaires, in addition to having general issues of internal consistency reliability [16].

Behavioral indicators of trust are often considered as context-sensitive alternatives to questionnaire-based methods [25]. Commonly used examples include reliance upon robot teammates to perform a task or compliance with a robot teammate recommendation [33]. An oft-cited benefit for using behavioral measures is that they can be gathered unobtrusively and repeatedly over sustained periods [10]; nonetheless, they are still typically reported as situation-level aggregates, e.g., [9, 12, 21]. This may be due to the limited use of dynamically-sensitive analytical techniques in the HRT literature, which recent empirical models of trust at interaction-level timescales have employed, e.g., [15, 17, 18].

In sum, there exist several behavioral and questionnaire-based trust measures that can be gathered at interaction-level timescales, but an overreliance on aggregation analytical approaches may have prevented more precise understanding of how trusted robots support teaming through interactions. This lag has coincided with similar methodological gaps in dynamically modeling other team cognitive phenomena, such as team workload [19] and situation awareness [29]. However, there are are many candidate methodological frameworks compatible with current measurement techniques used in the trust literature, with some already in limited use. These include dynamical systems analysis [1, 20, 48], semantic and sentiment analyses [28], and the use of machine learning models capable of handling time-series data [27]. More widespread appreciation for and usage of similar timescale-flexible methods like these is needed towards developing more robust trust measurements, and, subsequently, more meaningful HRT interaction designs.

4 CHALLENGES & FUTURE DIRECTIONS FOR TIMESCALE-FLEXIBLE TRUST MODELS

We acknowledge some theoretical and methodological challenges in moving towards HRT trust models at the interaction-level timescales. For one, although Chiou and Lee [5] specify the durations that interaction, situation, and relationship trusting timescales typically span, the boundaries between these timescales are not clearly defined. For example, an HRT under stress may send a quick succession of messages between a person and their robot teammate, displaying drastic shifts in trust dynamics not commonly observed in routine team situations, e.g., [7]. It is possible that other teaming frameworks, such as temporal coordination phases [31], may be more informative than durations or raw action counts for distinguishing which situations certain interactions belong to, and so on. However, in larger HRTs, trust within subgroups may overlap and unfold simultaneously, making unobtrusive measurements hard to interpret in real-time for robot teammates to use effectively. Empirical demonstrations of trust models that are scale-flexible with respect to time and group size, e.g., [24] are still forthcoming in the literature and may be useful once formalized.

More broadly, analyzing trust at interaction-level timescales may involve large corpora of data, which can be resource-intensive and difficult to manually perform quality control over. This may require certain levels of aggregation and limit the sensitivity of interaction-level analytical techniques. Ultimately, and somewhat ironically, big data from interaction-level trust models may require the use of inscrutable machine learning models and dissuade HRT trust researchers from investigating trust at scale. Research community-driven efforts will be needed to innovate solutions for investigating the mechanistic complexities of trust and HRT interactions.

5 CONCLUSION

Trust and team processes unfold and are observable in the various timescales at which human-robot teams interact. As robot teammates become increasingly central in risk-prone work environments, more nuanced HRT design paradigms require more precise approaches to studying trust and teamness dynamics over these teaming timescales. Achieving this precision entails reexamining current trust measurement methods and analysis techniques while answering practical questions about adapting the existing HRT trust research traditions. Recent empirical studies that demonstrate the utility of dynamic and contextual trust models can serve as a starting point toward this endeavor, and are ripe for discussion within the trust research community.

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