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Position Paper: Trust, Teamwork and Digital Twins

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Position Paper: Trust, Teamwork and Digital Twins

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Abstract

We explore how team trust psychology can help us understand human interactions with digital twins. We first discuss trust from a psychological perspective and examine trust in human—human and human—AI dyads. Here, Artificial Intelligence (AI) broadly refers to intelligent agents, including autonomous systems. Next we discuss aspects of trust that emerge in teams. In the final section, we summarise the roles humans and digital twins have been reported to assume in their interactions and consider how the factors of interdependence, distinct roles and shared goals may impact the performance of work teams involving a digital twin.

CCS Concepts

• **Human-centered computing**; • **Security and privacy** → *Vulnerability management*; • **Computer systems organization** → *Embedded and cyber-physical systems*;

Keywords

Trust, Team Trust, Digital Twin

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1 Introduction

Trust in a Digital Twin (DT) has been identified as an important factor in their acceptance and practical implementation [40, 72]. This is reflected in the view that real-world use of DTs arises from the interaction of cyber, physical and social systems [2]. In this paper, we focus on the psychology of trust and teamwork in human interactions with DTs. Implicit in this is the assumption that as DTs are increasingly adopted, they will become part of human teams. For example, consider DT use within a fleet of vehicles: how might performance vary depending on whether the DT is monitored by the driver, the fleet manager, the manufacturer, the insurer, an external agency, or some combination of these actors to form a team?

Our analysis is divided into three parts. First, we examine several facets of the psychology of trust: trust between two humans, trust between a human and an AI and trust within human-human and human-DT teams. Second, we review the different generic roles that humans and DTs will play in performing a task. Finally, we examine how team structure might impact the implementation of a DT.

2 Trust

2.1 Human - Human Trust

Understandings and conceptualisations of interpersonal and organisational trust have expanded significantly over time. However, the concept of trust is inherently complex with no agreed upon definition. Trust has been studied in a wide range of fields and disciplines, each conceptualising trust in a different way. For example, economists have viewed trust as calculative or institutional whilst sociologists have viewed trust as socially embedded properties in relationships with people.

Contemporary psychological approaches to trust revolve around two seminal papers on interpersonal trust. Mayer et al. [47] placed emphasis on the willingness for parties to be vulnerable to the actions of the other, and the risk that comes along with this vulnerability. Mayer et al. also identified three factors that contribute to the trustworthiness of a trustee: ability, benevolence (the extent to which the trustee's intents and motivations are aligned with the trustor), and integrity (the extent to which the trustee is adhering to the same principles as the trustor). Mayer et al. argue that integrity will be the most important and salient factor early on in the trust formation process until enough information can be gathered on the trustee's benevolence, at which point the benevolence factor will grow in importance. McAllister [48] conceptualised trust as positive expectations and a willingness to act upon another party's words, decisions, or actions. McAllister distinguished between two distinct types of trust: cognition-based trust, based on rational assessments of reliability and dependability, and affect-based trust, based on reciprocated emotional care and concern. McAllister framed cognition-based trust as an antecedent of affect-based trust, and subsequent work by McAllister et al. [49] viewed both cognition-based and affect-based trust as antecedents of a willingness to be vulnerable.

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Despite a large discourse on a single definition of trust, Hoff and Bashir [35] point out that nearly all definitions of trust in the literature have three components: there is a truster to give trust, a trustee to accept trust, and there is something at stake; the trustee has some incentive to perform the task; and there is a possibility that the trustee will fail to perform the task, inviting uncertainty and risk.

2.2 Human – AI Trust

Despite the parties involved in human-automation trust differing compared to interpersonal trust, some of the concepts of interpersonal trust still apply. Human-automation trust still represents attitudes tied towards specific situations with an exchange marked by uncertainty. Past research has suggested that people form relationships when interacting with computers and robots in a similar manner to relationships formed with other humans [56, 63] and also apply social norms such as politeness and gender stereotypes to computers [57]. Early work by Lee and Moray [41] argued that human-automation trust depends on the performance, process, and purpose of an automated system. This maps very similarly onto the components of interpersonal trust identified by Mayer et al. [47], with performance being comparable to ability and process being comparable to integrity. A recent literature review of work on both interpersonal and human-automation trust found support for Mayer et al's interpersonal trust components in both literatures, with many of the terms used to describe factors of trust in other papers being semantically equivalent [8]. Automation transparency in particular has been found to be a very significant factor, with studies suggesting that higher levels of transparency lead to higher trust in a system [32, 53, 80].

The closed-loop system of trust in automation has been extended by Hoff and Bashir [35] into a three-layer framework that breaks trust down into dispositional, situational, and learned factors, each influencing trust over time. Dispositional trust represents an operator's overall tendency to trust automation across situations, independent of context or specific automated systems. Examples of dispositional factors include culture, age, gender, and personality. Situational trust represents trust dependent on the specific context of the interaction. This is split further into external variability (situational factors tied to the environment) and internal variability (situational factors tied to context-dependent characteristics of the operator). Examples of external variability include the type and complexity of the system, task difficulty, workload, task framing, the organisational setting, and perceived risks and benefits. Examples of internal variability include self-confidence, subject matter expertise, mood/affect, and attentional capacity. Learned trust is trust built on past experiences of a specific automated system (initial learned trust) or a current interaction (dynamic learned trust). A number of studies have suggested that past experience with an automated system or a similar technology leads to a greater tendency to trust or rely on that system [29, 33] and reliance on an automated system increases over the course of an interaction [34]. However, some studies have also found that negative past experiences can result in less reliance in automated systems [4], and that trust degrades faster when an automated system makes noticeable errors [45]. Dynamic learned trust is essentially trust calibration, which has been developed further into full models of how positive and negative outcomes in trust relationships can increase or decrease trust over time (see [19] for more detail).

2.3 Trust in Humans versus Trust in AI

One of the key differences between interpersonal and human-automation trust is the way in which trust is formed. Mayer et al. [47] argue that interpersonal trust is initially based on the perceived integrity of the trustee. As interpersonal trust develops into a longer-term trust relationship, benevolence becomes the core basis of trust because an alignment of goals ensures that the trustor and trustee are working to achieve the same thing in the long term [42]. The opposite effect has been found for the trust formation process in human-automation relationships. Research has suggested a tendency to initially assign positive evaluations towards unfamiliar objects and this positivity bias has also been found towards automation systems [22], suggesting that human-automation trust is initially based on faith and benevolence. However, system errors cause this initial trust to dissolve, and eventually lead to human-automation trust relationships to be based on the ability of the system [46].

In comparing interpersonal trust to human trust in AI, there are also differences in the effect of breaches of trust (i.e., trust violations). Research indicates that trust violations have a more pronounced impact on trustworthiness assessments when they involve automated systems compared to when humans are involved [3, 22]. It is believed that this effect arises from individuals anticipating consistent, high-level performance from automated systems [21, 60]. As trustors identify these initial errors, they realise that systems are fallible and that their performance may be unreliable, which impairs assessments of trustworthiness [22]. In contrast, trustors may not hold the same expectation for human agents, resulting in milder consequences for breaches of trust [46]. However, with regards to trust violations tied to ethical considerations, individuals may have heightened negative responses toward humans compared to AI. According to [39], this phenomenon may be rooted in a lack of awareness regarding the potential for system outputs to reflect unfair biases and the perception that automated systems are less able to have intentional capacity that are ethical or social in nature [5, 6]. As argued by Butler and Miller [7], the key factor contributing to this social risk premium is the reluctance stemming from concerns about the potential malicious intentions of other humans, which is grounded in their ability to engage in intentional actions. However, in the context of AI, research indicates that individuals perceive AI agents differently [9]. They believe that AI agents lack self-driven goals [37], possess lower intentional capacity [31], and consequently, exhibit less self-interest and greater impartiality [10]. Indeed, in research by [9], delegating tasks to AI was perceived to be more controllable and less risky than delegating to a human agent, resulting in greater delegation rates.

3 Team Trust

In research concerning trust in teams, the theoretical perspectives of interpersonal trust from [47] and [48] have been extended to understand trust at the team level. Conceptually, team trust has been characterised as a form of trust that is collectively shared among all members of the team [27]. However, the emergence of trust within teams consisting of more than two individuals is regarded as a more intricate phenomenon when compared to the development of trust within dyadic relationships. The concept of a "team" is versatile and spans various social and organisational contexts. Regardless of the setting in which a team operates, it is essentially a collective of individuals engaged in adaptive, interdependent, and dynamic interactions aimed to achieve a common and valued objective [67].

Team trust can be conceptualised as a dynamic, shared state that emerges at the team level. It encompasses team members' belief in each other's competence, positive expectations regarding motivations, and a collective willingness to be vulnerable, grounded in the mutual understanding that teammates will act in the team's best interest [16, 25]. Current theory regarding team trust highlights that it grows and transforms through the combination and compilation of interpersonal interactions and group dynamics [16, 25, 50].

3.1 Factors Influencing Trust in Human Teams

In their review of trust in teams, Costa et al. [16] distinguish between individual-level factors, team-level factors and contextual factors. We summarise these below.

3.1.1 Individual-level Factors. Individual-level factors can exert an influence on trust within teams through two distinct mechanisms. The first mechanism, grounded in emergent state theory (Marks et al., 2001), posits that individual-level factors impact interpersonal trust among team members. This, in turn, causes the emergence of shared trust at the team level as a result of their interactions [51, 71]. The second mechanism draws from composition models of aggregation [38]. This theory argues that factors at the individual level can aggregate to give rise to a shared team-level variable. However, it's important to note that the application of aggregation models, which extend the influence of individual factors to represent a team-level variable like trust, is applicable primarily when the individual-level factors show substantial consensus or similarity within the group [38]. It has been proposed that both mechanisms are capable of impacting trust within teams and can operate simultaneously [16].

Examples of individual-level factors include trustor characteristics and trustee characteristics [16]. As a trustor characteristic, propensity to trust - the personal trait of how much trust an individual shows regardless of situation - has been shown to influence the development of trust within teams. As teams progress and foster trusting relationships, other trust-related factors become more abundant and exert a greater influence [73].

Besides the individual attributes of the person extending trust (trustor), the characteristics of the individual being trusted (trustee) also play a crucial role in shaping trust at the team level. Drawing upon the trust framework introduced by Mayer [47], the fundamental dimensions of trustworthiness—ability, benevolence, and integrity significantly impact team trust. In the context of temporary work teams, it has been observed that ability and integrity hold the most significant influence over trust [65]. Given that forming a judgement on benevolence often necessitates the establishment of emotional bonds over an extended duration, benevolent traits of a trustee tend to hold greater importance in fostering team trust within teams that endure over a longer time span [43].

3.1.2 Team-level Factors. Team level factors can influence trust within teams by shaping the overall team dynamics and atmosphere. While specific to the broader context of the team, rather than the interpersonal relationships between team members, these factors also indirectly affect interpersonal dynamics [16]. Examples of factors that affect the social and structural orientation of a team include team composition, degree of virtuality, and team leadership.

Team composition relates to how a team is structured and the composition of its members. Studies investigating the impact of demographic variety on team trust have demonstrated that elements like nationality, age, and functional experience tend to be linked to decreased levels of trust within the team and how team members perceive each other's trustworthiness [13, 17, 77]. However, it must also be recognised that team diversity can yield positive outcomes such as increased innovation and broader perspectives to solutions [66]. Implementing strategies that promote trust-building and facilitate the establishment of interpersonal bonds among team members can effectively support trust formation within diverse teams [58].

Team virtuality is characterised as a spectrum representing the extent to which work is conducted through technology when team members are physically separated across locations [61]. Compared to face-to-face teams, virtual teams require more time to establish trust [61]. Based on Media Richness Theory [18], face-to-face interactions are better in conveying complex messages and efficient feedback compared to interactions that take place in a virtual environment [36].

3.1.3 Contextual-level Factors Related to the Organisation. Because numerous teams function within larger organisations, it is important to acknowledge that contextual factors at the organisational level can impact trust within teams [16]. Pertaining to the organisation itself, these factors encompass the organisational structure and the prevailing organisational culture within which a team functions.

Organisational structure encompasses the formal arrangement for the allocation, grouping, and coordination of work assignments [70]. When work tasks are distributed and assembled based on the competencies, inclinations, and capabilities of its members, this can enhance the cohesion among team members. Trust may also be fostered when members are aligned with a suitable structure that aligns with their abilities and interests [70]. Related to the structural context of an organisation, [55] found that organisations characterised by high levels of formality were perceived as less supportive of interpersonal and team trust when compared to those that encourage more participation.

3.2 Human-AI Teams

A review of whether machines are conceived as tools or teammates found that Human-AI Team (HAT) research has focused on the simplest scenario where a single human collaborates with one AI agent [64]. However, as the number of agents increases, both human and AI, the social dynamics become more complex [44]. In larger teams where one AI collaborates with multiple humans, the AI may function more as a tool than a full-fledged teammate due to challenges posed by numerous human interactions. Therefore, care is needed when designing team size and structure [68].

One critical aspect of establishing a successful HAT where the AI is seen as a teammate relies on establishing a common goal that is valued by all team members, both human and AI [11, 15, 52]. The aim is to foster a sense of "teamness" [54]. However, instilling confidence in human team members that an AI is equally committed to this shared goal can be challenging, especially when the consequences of failure may primarily affect humans. This difference in stakes can undermine a sense of "teamness" and increase the risk of conflicts due to the lack of a reciprocal exchange structure [12].

Interdependency, where the outcomes of one team member are directly influenced by another, whether human or AI, is a key factor in the success of HATs [75]. This interdependence fosters collaboration, which is a cornerstone of effective HATs. Similar to human teams, successful HAT outcomes tied to interdependency can lead to tangible rewards for humans. Collaboration can be incentivized, but it can also naturally occur when AI helps reduce the cognitive load on human teammates [23].

Distinct roles and functions are crucial for the smooth functioning of HATs. Assigning roles based on each team member's strengths, similar to human team dynamics [20, 69], enhances synergy. For example, an AI might handle data cleaning, while a human teammate specializes in data analysis, leveraging their respective strengths. Role differentiation is beneficial, but not mandatory; well-defined roles, even if not entirely unique, can be sufficient. Co-creation is an example where roles are defined but not necessarily distinct [59]. However, the successful delegation of tasks from humans to AI can be challenging to implement [28, 62], and humans may be hesitant to accept a humanized AI as a leader [79].

4 Digital Twins and Trust

4.1 Proposed Roles for Digital Twins

Although there is no universally accepted definition for "Digital Twin" [14, 30], the shared characteristics of definitions across the literature include the integration of various data sources, allowing for a virtual representation of a physical object or process [24]. In their Level of Digital Twin Framework, Agrawal et al. [1] recognise that the extent of automation of a DT influences the role of human support needed. As the automation level of a DT increases, it results in reduced reliance on human intervention. To describe these levels Agrawal et al. [1] introduce a taxonomy consisting of four conceptual categories outlining the roles of DTs, encompassing the roles of observer, analyst, decision maker, and action executor. When DTs are not completely automated, depending on level of automation, human agents will share the roles of observer, analyst, decision maker, and action executor.

Another view of the roles of humans and DTs was provided by Wilhelm et al. [76], who reviewed recent literature to see what roles humans and DTs had taken in published reports. They summarized that humans had taken the roles of operation, decision, supervision and implementation, while DTs had taken the roles to inform, support, decide and act. Notable in this summary of roles is the duplication between human and DT roles. In addition, the human role of supervision is passive, where the human is not responsible for a decision but only for verification.

4.2 Trust in Human-DT Teams

The implementation of DT in the human-DT network given by Agrawal et al. [1] still leaves room for human-human interactions between each of the roles and the trust relationships that come along with these interactions. In a traditional system that does not contain a DT, interpersonal trust relationships are formed at each stage of the decision making process (i.e., relationships between observer-analyst, analyst-decision maker, and decision maker-action executor). All of these relationships develop and form based on the aforementioned interpersonal trust factors, such as Mayer et al.'s ability, benevolence, and integrity factors [47] and McAllister's cognition and affect based trust [48]. It would be expected that the direction of trust is based on the order of operations, with parties that rely on work from another party taking the role of the trustor in that relationship. However, research into coworker dyads has suggested that perceived benevolence and integrity of both parties influences how trust is formed between a trustor and trustee [78]. Ferrin et al. [26] describe a spiralling effect of trust in interpersonal dyads, in which party A assesses party B as trustworthy and displays more trusting behaviours towards party B, which is then subsequently recognised by party B, causing party B to trust party A more. In the context of Agrawal et al.'s model [1], this may be seen through the analyst trusting the observer and their work, and the observer trusting that the analyst will also use their work in an effective way, forming this bidirectional trust relationship.

5 Discussion

In this position paper, we presented the concepts of trust, trust in teams, and the proposed roles of digital twins. In our discussion, we focus on themes that we believe deserve further attention for the deployment of DTs in human teams.

Theme 1: Team Member Interdependence. Team performance benefits when each member either has a distinctive function that avoids overlap of roles or there is co-creation of roles. The team members rely on each other in an interdependent manner. The literature on proposed roles for DTs reveals that there can be a lack of distinct roles for a DT, with humans and DTs often sharing a role. Of course, one defense of this is that we should view the DT as a tool rather than a team mate, but this would reduce efficiency of the DT. How to achieve co-creation between a DT and human team members is also an open question. Additionally, given an organization comprising a more complex structure, questions will ultimately arise over ambiguity on how to assign responsibility to the DT.

Theme 2: Shared Goals. Team performance benefits when members share common goals, and this has multiple dimensions. First, a DT lacks a sense of agency comparable to the human concept of 'having skin in the game,' which can hinder trust. Second, in humans, trust has both cognitive and affective components. This means that even if there is cognitive trust in a DT's performance, there may still be a disconnect in the human user's emotional comfort with the DT's role and decisions.

Theme 3: Dynamic Trust. Trust is a dynamic property and trust towards DTs will vary over time and over the network of individuals that rely on the DT to achieve a shared goal. With AI, users often exhibit early over-reliance, followed by a rapid loss of trust when the system underperforms. Therefore, it is crucial to carefully calibrate trust in the Digital Twin (DT). This calibration becomes even more complex when it occurs within a larger organization.

6 Conclusions

We argue that digital twins can be thought of as part of a human team. Considering trust and how it influences performance can qualitatively inform better design of digital twins and their interfaces with humans as well as potentially fit into quantitative models [74]. As their deployment broadens these issues are likely to rise in significance and it is timely to consider these aspects.

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