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ScienceDirect

Procedia Computer Science 221 (2023) 710–717

Procedia Computer Science

www.elsevier.com/locate/procedia

Information Technology and Quantitative Management (ITQM 2023)

The Effect of Trust-based Management Strategy on Performance of Human-Machine Collaborative Team: A Dynamic Computational Model

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Abstract

In human-machine collaborative teams, trust has an important effect on team performance. However, precisely how trust and trust-based management strategy influence team performance have remained elusive. This paper develops a method of trust-based team management to understand which managerial strategy has what impact on performance, and to discern decision alternatives. The method concentrates on providing a dynamic model of trust considering trust relationship initialization, updating trust based on experience and determining what trust should have an effect on. The model is used to explain how the trust-based management strategy caused the team to evolve in particular directions rather than others. Some prescriptions are put forward for the proper management of team. We argue that a human-machine collaborative team is a multi-agent system and team members are autonomous agents. Three computational experiments are conducted under different internal and external conditions for the artificial team, yielding the following results. (1) Under different difficulty of tasks, trust may produce either positive or negative effect on performance. (2) Trust-based management strategy dose has effect on performance under difficult task. (3) The results demonstrate the different effect of three trust-based management strategies on performance. The study method and findings presented herein are appropriate for other studies focusing on dynamic effects on team, laying the foundations for new ideas for studying team building and team development.

Keywords: Trust; Human-machine collaborative team; Knowledge transfer; Agent-based modeling

1. Introduction

Faced with the increasing demands of complex competitive environments, organizations are looking to collaboration and teamwork as means of resolving challenges, both large and small, across hierarchical levels and cultures [1]. In particular, the human-machine collaborative team has become a new fundamental form for organizations [2]. One key component in ensuring effective team functioning is to make full use of knowledge among team members that consist of both human and machine [3]. Knowledge transfer offers a mean to make knowledge exchanged and shared among members [4, 5]. Most important for fostering knowledge transfer between team members, and the related team performance, is the existence of a climate of trust [6]. Thus, team performance

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1877-0509
10.1016/j.procs.2023.08.042

can be affected by individual decisions as to whether, with whom, and on what terms to put in trust and transfer knowledge.

Trust has been identified as an important component of teamwork [7]. Indeed, researchers have proposed that it plays a critical role in the development of effective teamwork processes and in the team's successful performance [8]. Trust may help to liberate team members to act in ways beneficial to the team's performance, such as seeking help and feedback from others, proposing innovative solutions to problems, engaging in boundary-spanning behavior on the team's behalf, and voicing concerns before they develop into crises [9]. Trust may help to unlock members' potential by instilling greater self-confidence in their abilities to perform effectively, in addition to creating conditions in which members feel comfortable expressing differences in ways that enable the team to better learn from experiences and to identify more creative task strategies [10]. However, some research has shown that trust can have limited benefits [11] or even negative consequences [12, 13]. Therefore, different trust-based management strategies should be considered carefully, such as what intensity the strategy is, how long the strategy lasts and when the strategy intervenes.

However, there is very little research that concurrently examines both trust's dynamic process and the effect of trust-based management strategy on performance. It is challenging to obtain individual-level data on knowledge, trust and knowledge transfer and extremely difficult to gain access to sites for conducting field experiments. And it is also impossible to obtain of the consequence of different trust-based management strategies conducted in the same team or replicate past results. Thus, how trust between team members might actually be built or declines along with team's development and what effect the trust-based management strategies have on performance are still unclear [14]. Formalization in a model allows us to conduct experimentation that is simply impossible in the field, interacting known variables to derive inconspicuous propositions [15]. Modeling may be especially suitable because empirical work in this area, as meticulous as it may be, suffers from severe data limitations [16].

Our primary research objectives are to explain how trust operates at the individual level of analysis, how it is related to knowledge transfer, and, particularly, the mechanisms by which this inherently individual-level phenomenon translates into a team-level outcome: performance. Furthermore, how to leverage trust in management activities and what advantage the trust-based management strategy can provide for performance is also studied. This paper presents a model of trust's development and decline and investigates the trust-based management strategies' effect on performance. The team, modeled as an artificial team, is viewed as a Multi-Agent System [17] and team members (both human and machine) are viewed as autonomous and adaptive agents [18]. The artificial teams are regarded as possible alternatives of real teams. We employ a computer as an experimental laboratory for investigating team activities, such as knowledge transfer, that are influenced by trust. We aim to reveal the mechanisms of how team performance is influenced by different trust-based management strategies.

2. Trust Modeling

Based on the existing results and conclusion of empirical research on trust [19, 20], trust springs and develops in knowledge transfer and, in turn, influences this process. In other words, trust involves both formation and effect during the development of human-machine collaborative team. What's more, the formation and effect of trust is a dynamic process, which means that members' trust adjust autonomously and adaptively according to the environment in knowledge transfer. Thus, our trust model contains four processes: (1) generation, (2) update, (3) accumulation, and (4) effect. We take the n-th interaction between A_i and A_j for example to discuss the formation process of A_i's trust for A_j.

2.1. Generation of Trust

In knowledge transfer, a knowledge supplier's trust for knowledge requester forms on the expectation. This expectation is denoted $EP_n(A_i, A_j)$ and is defined as

$$EP_n(A_i, A_j) = \frac{K_n^{\text{give}}(A_i, A_j)}{K_n^{\text{need}}(A_j)}, \text{ when } A_i \text{ gives knowledge to } A_j \tag{1}$$

where $K_n^{\text{give}}(A_i, A_j)$ denotes the knowledge amount that A_i gives to A_j, and $K_n^{\text{need}}(A_j)$ denotes the knowledge amount that A_j needs $[0 \leq K_n^{\text{give}}(A_i, A_j) \leq K_n^{\text{need}}(A_j), 0 < K_n^{\text{need}}(A_j) \leq 1, 0 \leq EP_n(A_i, A_j) \leq 1]$.

This expectation will convert to current trust, which represents the trust given the most recent interaction and which eventually contributes to the accumulation of trust. Negative expectation converts to negative current trust, whereas positive expectation converts to positive current trust [13]. The current trust $CT_n(A_i, A_j)$ is defined as

$$CT_n(A_i, A_j) = \begin{cases} \log_{0.5}^{2-2EP_n(A_i,A_j)}, 0 \leq EP_n(A_i, A_j) < 0.5 \\ \log_{2}^{2EP_n(A_i,A_j)}, 0.5 \leq EP_n(A_i, A_j) \leq 1 \end{cases} \tag{2}$$

2.2. Update of Trust

When an individual signals expectation toward another individual, and another reciprocates the expectation, trust spirals upwards. When expectations are not reciprocated, trust spirals downwards and may even reach the point of distrust [21]. This reciprocal expectation generated by A_i for A_j is denoted as $RE_n(A_i, A_j)$, defined as:

$$RE_n(A_i, A_j) = \frac{K_n^{\text{get}}(A_i, A_j)}{K_n^{\text{need}}(A_i)}, \tag{3}$$

where $K_n^{\text{get}}(A_i, A_j)$ denotes the amount of knowledge that A_i gets from A_j, and $K_n^{\text{need}}(A_i)$ denotes the amount of knowledge that A_i needs.

A_i updates their expectation as follows:

$$\begin{aligned} &EP_n(A_i, A_j) = EP_{n-1}(A_i, A_j) + \frac{RE_n(A_i, A_j) - EP_{n-1}(A_i, A_j)}{2}, \\ &\text{when } A_i \text{ gets knowledge from } A_j \end{aligned} \tag{4}$$

where $EP_n(A_i, A_j)$ denotes the n-th affective expectation of A_i for A_j, and $EP_{n-1}(A_i, A_j)$ denotes A_i's $(n-1)$-th expectation for A_j. Initially, $CT_0(A_i, A_j) = 0$, so we set $EP_0(A_i, A_j)$= 0.5. If $RE_n(A_i, A_j) < AE_{n-1}(A_i, A_j)$, then affective expectation decreases; if $RE_n(A_i, A_j)$=$EP_{n-1}(A_i, A_j)$, then expectation remains constant; and if $RE_n(A_i, A_j)$>$EP_{n-1}(A_i, A_j)$, then expectation increases. $EP_n(A_i, A_j)$ also converts to current trust, as per equation(2).

2.3. Accumulation of Trust

Trust accumulates by means of current trust which develops with the variation of expectation. Thus, trust accumulates from previous trust and current trust [22]. $Tr_n(A_i, A_j)$ denotes the trust accumulated by A_i for A_j up to n-th interaction and is defined as

$$Tr_n(A_i, A_j) = \begin{cases} Tr_{n-1}(A_i, A_j) + \left[1 - Tr_{n-1}(A_i, A_j)\right] CT_n(A_i, A_j), \\ \qquad \text{when} \quad \mathrm{Tr_{n-1}(A_i, A_j) > 0} \\ Tr_{n-1}(A_i, A_j) + \left[1 + Tr_{n-1}(A_i, A_j)\right] CT_n(A_i, A_j), \\ \qquad \text{when} \quad \mathrm{Tr_{n-1}(A_i, A_j) \leq 0} \end{cases}, \tag{5}$$

where $Tr_{n-1}(A_i, A_j)$ denotes the affective trust accumulated by A_i in A_j up to the $(n-1)$-th interaction. $Tr_0(A_i, A_j)$=0.

2.4. Effect of Trust

Individuals are more willing to transfer knowledge to those for whom he has a high level of trust given that those members are expected to reciprocate and can make a better knowledge transfer in the future. Therefore, trust affects the amount of knowledge transferred between individuals. When A_i gives K_h type of knowledge to A_j, the knowledge amount $K_n^{\text{give}}(A_i, A_j)$ is defined as follows:

$$K_n^{\text{give}}(A_i, A_j) = \left[k_h(A_i) - k_h(A_j)\right] \frac{1 + Tr_{n-1}(A_i, A_j)}{2}, \tag{6}$$

Only when $k_h(A_i) > k_h(A_j)$ the knowledge transfer can happen.

3. Experiments and Results

According to existing study, trust may produce not only positive effect but also negative effect on performance. The different results are due to different study conditions. We strive to figure out on which condition trust may produce positive effect or negative effect. Furthermore, we try to illustrate whether team will get rid of conditions with negative effect through trust-based management strategy. Thus, we design three experiments to study the the issues above.

3.1. Study 1: Static trust on performance

We design two types of artificial teams for comparative analysis. The only difference between two teams is whether trust exists and functions between team members. Thus the difference in performance of the two teams may help us better explain the positive or negative effect and corresponding conditions. One type is "equivalent exchange" artificial team (EE-team for short) in which agents don't own trust attribute. The other type is "trust" artificial team (Tr-team for short) in which agents own trust attribute. We also design two knowledge-transfer mechanism: equivalent-exchange mechanism and trust mechanism. In former mechanism, the knowledge transfer process is not affected by trust. The amount of knowledge that an agent gives must equal the amount that he gets; only in this situation can the knowledge transfer occur. In latter mechanism, the knowledge transfer process is affected by trust. The agent is not constrained by the equivalent exchange for each knowledge transfer. The agent will reciprocate based on the long-term relationship with others. In our experiments, EE-team and Tr-team adopted equivalent-exchange knowledge-transfer mechanism and trust knowledge-transfer mechanism respectively. By comparing the experimental results of these two types of teams, we can examine the possible relationship between trust, knowledge transfer and team performance.

3.1.1. Method

We simulate the task performing process of 50 teams. The agents' knowledge is in [0, 1] and heterogeneous within and among each team. Each team performs two kinds of tasks: simple (the knowledge range of task's each dimension is in [0, 0.5]) and difficult [0.5, 1]. Each kind consists of 100 tasks. After a team performed a task, the team is reset to the initialized state. In other words, the experiment is conducted from static perspective and members' knowledge and trust are not accumulated. Four initialized trust range is set in [-1, -0.5], [-0.5,0], [0, 0.5], [0.5,0] for four Tr-teams(Tr-team 1-4). The outputs are task-completion rate. Each result is the average value of 20 replications.

3.1.2. Results

Fig. 1 shows the task-completion rate between EE-team and Tr-team under simple and difficult task. The initial trust of Tr-team 1 to 4 is in range [-1, -0.5], [-0.5,0], [0, 0.5], [0.5,0] respectively.

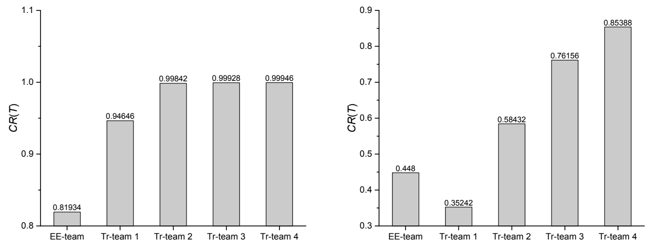

Fig. 1. (a) simple task (b) difficult task.

As shown in (a) of Fig. 1, the performance difference between Tr-team and EE-team is obvious under simple task. The performance of Tr-team is better than that of EE-team over the four initial trust range. This indicates that trust has effect on team performance and generate positive effect under simple task.

As shown in (b) of Fig. 1, the performance difference between Tr-team and EE-team is obvious under difficult task. The performance of EE-team is better than that of Tr-team 1 and worse than that of the other three Tr-teams. This indicates that trust has effect on team performance and generate negative effect under difficult task.

Findings of study 1:. These two main results indicate that trust dose has effect on performance and it may generate not only positive effect but also negative effect on performance.

3.2. Study 2: Dynamic trust on performance

As discussed in study 1, the study 2 make a further research from dynamic perspective.

3.2.1. Method

The experiment settings are the same with study 1 except for task and initial trust. In study 2, the tasks are performed continuously by 100 batch and the initial trust is 0 between each agent. In other words, the experiment is conducted from dynamic perspective and members' knowledge and trust are accumulated. The outputs are task-completion rate. Each result is the average value of 20 replications.

3.2.2. Results

When performing simple tasks, team trust is positive at the beginning of task batch and keeps increasing with performing of task(left panel of Fig. 2). The performance of Tr-team is better than that of EE-team over the whole task batch(middle panel of Fig. 2). When performing difficult tasks, team trust is negative at the beginning of task batch, then declines rapidly and finally is steady at a low value with performing of task(left panel of Fig. 3). The performance of Tr-team is worse than that of EE-team over the whole task batch(middle panel of Fig. 3).

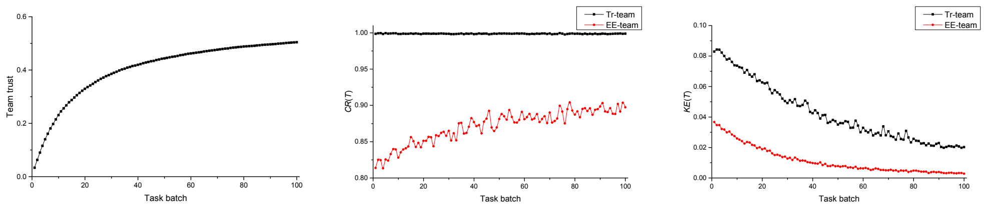

Fig. 2. Team performance under simple task.

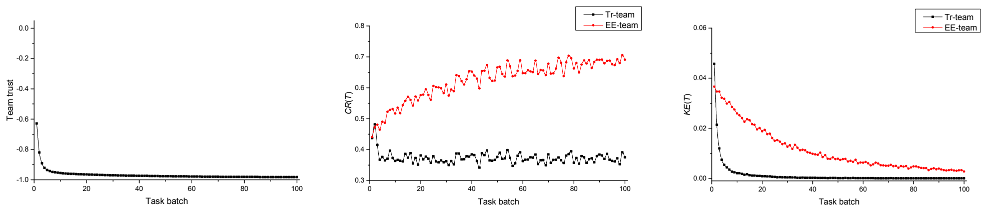

Fig. 3. Team performance under difficult task.

We can infer that the variety of performance under different task difficulties may be caused by trust. This phenomenon can be explained through knowledge transfer efficiency. Knowledge transfer efficiency of Tr-team is higher than that of EE-team over the whole task batch under simple task(see right panel of Fig. 2); while the result is opposite under difficult task(see right panel Fig. 3). Thus higher knowledge transfer efficiency of Tr-team compared with EE-team guarantees better performance and lower knowledge transfer efficiency leads to worse performance. It is easy to image some virtuous cycle of mutually reinforcing effects, where high knowledge transfer efficiency bolsters positive trust, which in turn increases knowledge transfer efficiency, ultimately performance; and some vicious cycle of mutually weakening effects, where low knowledge transfer efficiency leads to negative trust, which in turn decreases knowledge transfer efficiency, ultimately performance.

Findings of study 2. The results are consistent with known empirical evidence and theoretical assertions [14, 16, 23], thus adding to the validly of the model. The more important thing is that the results generate from dynamic perspective. We also find that, under simple task, trust may produce positive effect on performance and, under difficult task, trust may produce negative effect on performance.

3.3. Study 3: Trust-based management strategy on performance

As discussed above, Tr-team underperforms EE-team under difficult tasks. Thus, some management strategies on adjusting trust could be conducted to rescue the team from this terrible development state. Study 3 investigated whether different trust-based management strategy may have different effect on performance. The investigation was analyzed through Tr-team's dynamic development process.

3.3.1. Method

Study 2 takes the same Tr-team in study 1 for research and the Tr-team performs the same difficult task as in study 1. Study 2 takes implement intensity (denote as II), lasting period(denote as LP) and intervening point(denote as IP) as three kinds of management strategies. Three levels of implement intensity are defined: weak (trust between each agent was raised by 0.2, $II = 0.2$), moderate ($II = 0.5$), strong ($II = 0.8$). Three norms of lasting period were defined: short (lasting 1% task batch, $LP = 1\%$), medium ($LP = 5\%$), and long ($LP = 25\%$). Three patterns of intervening point are defined: early (starts at 25th task batch of total 100, 25%, $IP = 25\%$), middle ($IP = 50\%$), late ($IP = 75\%$). The experimental outputs are task-completion rate and average task-completion rate. Each result is the average value of 20 replications. Analysis are conducted on the resulting performance data of Tr-teams.

3.3.2. Results

Fig. 4 shows the task-completion rate under different combination of implement intensity, lasting period and intervening point. The left panel of Fig. 4 shows the task-completion rate of different levels of implement intensity strategies across lasting period and intervening point. The middle panel of Fig. 4 shows the task-completion rate of different lasting period strategies across implement intensity and intervening point. The right panel of Fig. 4 shows the task-completion rate of different intervening point strategies across implement intensity and lasting period. Each panel contains 9 cells. Each cell represents the task performing process for 100 tasks under a given strategy pattern.

Fig. 4. Team performance under difficult task.

Findings of study 3. When one strategy varies and the other two are fixed,

(1) Stronger implement intensity produces higher performance when lasting period and intervening point are fixed.
(2) Longer lasting period produces higher performance when implement intensity and intervening point are fixed.
(3) The variation of intervening point leads to different performance when implement intensity and lasting period are fixed.

When two strategies vary and another one is fixed,

(1) The performance gradually increases as implement intensity becomes stronger and lasting period becomes longer when intervening point is fixed.
(2) The performance increases first and then decreases as implement intensity becomes stronger and lasting period becomes shorter when intervening point is fixed.

(3) The performance increases first and then decreases as intervening point becomes later and lasting period becomes longer when implement intensity is fixed.
(4) The performance increases as intervening point becomes earlier and lasting period becomes longer when implement intensity is fixed.
(5) The performance increases as intervening point becomes earlier and implement intensity becomes stronger when lasting period is fixed.
(6) The performance is contingent as intervening point becomes later and implement intensity becomes stronger when lasting period is fixed.

The findings above indicate that trust-based management strategies do have effect on performance and the effect varies across different combinations of strategies.

4. Conclusion

In this paper, we examine knowledge transfer to explicate a mechanism for the connection between trust, trust-based management strategy and team performance in human-machine collaborative team. We model human-machine trust from interaction perspective, and focus on decision in knowledge transfer. Trust forms in the knowledge transfer and in turn influences this process. We regarded team as MAS and team member as autonomous agents. We built three trust-based management strategies: implement intensity, lasting period and intervening point. Through three computational experiment studies, we suggest that trust not only has an impact on performance, and it may produce either positive or negative effect. Under simple tasks, trust and performance forms virtuous cycle. While under difficult tasks, trust and performance forms vicious cycle. Trust-based management strategy can be helpful under difficult tasks. Our research can not only demonstrate how performance varies as one strategy changes but also how performance varies when two or more strategies changes simultaneously.

We believe that our paper carries several implications for both scholarship and practice. Our modeling method is particularly suitable for tracking trust over time and assessing the performance under different trust-based management strategies. This approach can generate complex interactions and behavior patterns. As a result, we can observe, analyze and understand multi-agent systems such as teams through emergences.

To conclude, our research makes several contributions to research on the effect of trust on team performance. This paper attempts to investigate different trust-based management strategies' effect on team performance. The main idea is to model trust from dynamic perspective and systematically apply computational experiments to achieve the decision support for managers. Furthermore, we hope to enrich our research by further considering the cost of management strategy and detailing levels of strategy, and exploring the optimal strategy and precise decision support for teams with different trust states and different situations.

Acknowledgements

This work was partly supported by the National Natural Science Foundation of China under Grant No.72231010.

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