<u>Reviewer 1</u>

[Comment R1.1] *The authors proposed a trust model to estimate human trust during human-autonomous teams' systems. The manuscript addresses a relevant topic, and it is very well-structured. The main limitation is the sample size. The study was developed only with 6 healthy male participants.*

[Reply to R1.1] The authors thank the reviewer for the comment. "The major limitation of this study is our participant pool; only male participants were involved in our experiments. For future works, we will enlarge the participant pool and consider gender balance to conduct a more comprehensive research. Furthermore, we will develop trust modelling to assess the trust of robot agents and then create a mutual trust model to provide more informatic reasoning for interaction in HAT systems."

[**Comment R1.2]** Lines *31-32: The authors mentioned: "Previous studies proposed trust-based approaches to explore either human or teammate trust for the optimization of interactions among agents in specified tasks". However, they could consider a recent paper (published in the current year) about this issue: https://doi.org/10.3390/robotics11030059*

[Reply to R1.2] The authors thank the reviewer for the comment. We have cited the suggested paper in Section 1. Introduction and added more publications in Section 2. Related work. Please refer to the revised sentences as follows.

In Section 1. Introduction, "Previous studies proposed trust-based approaches to explore either human or teammate trust for the optimization of interactions among agents in specified tasks [5, 11–20]."

In Section 2. Related work, "Several studies have modelled human trust by analyzing human physiological signals and behaviors. Sadrfaridpour et al. proposed a mutual trust model between human and autonomous agents to coordinate collaboration [14]. The authors defined human performance based on muscle fatigue and the recovery dynamics of the human body when performing repetitive tasks, and the performance of autonomous agents was evaluated using the difference between human and autonomous agents' behaviors. Mahani, Jiang and Wang applied a Bayesian mechanism to predict human-to-autonomy trust based on human trust feedback to each individual robot and human intervention [16]. With the aid of a data-driven approach, Hu et al. proposed a human trust model that categorized an individual's trust and untrust with electroencephalography (EEG) signals and galvanic skin response (GSR) data [15]. Similar work is also presented in [34]; the researchers exploited human cognitive states extracted from EEG data to model human workers' trust in Collaborative Construction Robots. In addition, the pupillary response is observed to be an effective index for human trust estimation. Lu and Sarter exploited eye-tracking metrics to infer human trust in real time [17]. Alves et al. [18] consider kinesic courtesy cues from human to machine as an important factor in establishing human trust in HAT collaboration. Apart from pure human factors, some works consider human behavior and machine performance when modeling the mutual trust between human users and machines. By inspiration of human social behavior, Jacovi et al. [19] proposed a formalization method to model mutual trust between a human user and a machine. Additionally, some researchers proposed computational trust models for HAT systems. In [11], the model of pupil dilation is extended as a computational trust model to facilitate interaction between humans and robots. The computational model of human-robot mutual trust presented in [20] considers multiple pieces of information in physical human-robot collaboration, such as robot motion, robot safety, robot singularity, and human performance."

[Comment R1.3] *The discussion section shall be improved, comparing the authors' results with previous studies. And the limitations of the current study have to be discussed, pointing future work*.

[Reply to R1.3] The authors thank the reviewer for the comment. We have revised Section 6. Discussion and Section 7. Conclusion, accordingly. Please refer to the revised sections as follows.

In Section 6. Discussion, "In addition to Scenario_2, the collaboration controlled by our proposed model also shows greatly improves in the more complicated scenarios. The performance of Participant 2 in Scenario_3 indicates that the human decision was estimated to be trustworthy to make the shortest choice of path through the aid of our evaluation model on real-time human states, which did achieve an optimal decision on the route to save a lot of time to complete the task. Similarly, in Scenario_4, Participant 1 and Participant 2 were successfully evaluated as a trustworthy agent, although Participant 1 could choose the better path. The experimental results in Scenario_3 and Scenario_4 suggest that the fusion weights trained with the Q-learning algorithm in Scenario_1 can be directly applied to more complicated scenarios without retraining. The fusion weights were trained with collected cross-subject human data and can be used in real-time scenarios, which implies that the FIS can overcome the subject difference in human data and compute proper rewards for the Q-learning algorithm to tune the fusion weights."

In Section 7. Conclusion, "This study proposed an adaptive trust model considering multiple real-time human cognitive states. The proposed trust model leverages a fusion mechanism to combine various types of information, namely, the human attention level, stress index, and human perception. To verify the performance of the proposed trust model, we deployed four environmental settings, including different types of obstacles and different numbers of robot agents. We compare the performance made by the HAT with those made by pure human agents and those made by robot agents. The comparison results show that the HAT team with the proposed trust model can improve the efficiency of the given task by at least 13% in different scenario settings; The HAT team coordinated by the proposed trust model can complete the given task faster than others. Our results also suggest that the trust value generated based on these three pieces of evidence can reflect the performance of a human agent more accurately, which contributed to an improvement of efficiency for the cooperation between human and autonomous robot agents in all test scenarios. These results demonstrate that the proposed model can adapt to various human performance levels and generate reliable trust values via the reinforcement-learning algorithm. The major limitation of this study is our participant pool; only male participants were involved in our experiments. For future works, we will enlarge the participant pool and consider gender balance to conduct a more comprehensive research. Furthermore, we will develop trust modelling to assess the trust of robot agents and then create a mutual trust model to provide more informatic reasoning for interaction in the HAT systems."

Reviewer 2

[Comment R2.1] *It would be good to add clear point-by-point the main contributions at the end of the Introduction section.*

[Reply to R2.1] The authors thank the reviewer for the comment. We have added our main contributions point-by-point in the introduction section. Please see the revised contributions as follows.

"The main contributions of this research are three-fold:

- This paper proposes a trust model to estimate human trust value in real-time. The proposed trust model was applied to a ball-collection task with robot agents, which presents uses of the proposed trust model in the human-autonomous teaming framework.
- The proposed trust model considers multiple pieces of information from a human agent, e.g., attention level, stress index and situational awareness, by leveraging a fuzzy fusion model. In this research, the attention level and the stress index are evaluated based on pupil response and heart rate variability, respectively; situational awareness is measured from the environment through visual perception.
- We further use a Q-learning algorithm with a fuzzy reward to adaptively learn the fusion weight of the fusion model. The fuzzy reward is generated by a TSK-type fuzzy inference system, which facilitates the defending reward for complex scenarios and is able to handle the uncertainty from human information."

[Comment R2.2] *It would be good to add the remainder of this paper.*

[Reply to R2.2] The authors thank the reviewer for the comment. We have added the remainder of this paper in the introduction section. Please see the revised contributions as follows. "This paper is organized as follows. Section 2 introduces related works of human trust modelling. Section 3 describes the proposed Multi-Human-Evidence Based Trust Evaluation Model. This section firstly describes the details of trust evaluation metrics, followed by the details of the Trust Metric Fusion Model and the Reinforcement Learning Algorithm. Section 4 presents the experimental methods, including scenario design, human agent setup and recording, and Experimental procedures. Section 5 presents the experimental results. Section 6 shows the discussion based on the experimental results. Finally, Section 6 presents conclusions."

[Comment R2.3] *Fig 1-3, 5-6, 8-9 are very small. Please increase it.*

[Reply to R2.3] The authors thank the reviewer for the comment. We have improved the quality of all figures.

[Comment R2.4] *It would be good to mention about SGTM Neural-Like Structure and T-Controller in the Section 2.2.2.*

[Reply to R2.4] The authors thank the reviewer for the comment. We have cited the suggested paper in the Section 3.2.2 (Section 2.2.2 in the previous version). Please see the revised sentences as follows. "This section presents the FIS used to produce fuzzy rewards for RL to learn fusion weights and adjust the Q-learning reward. The FIS is composed of a zero-order Takagi-Sugeno-Kang (TSK) fuzzy system [39–41], …"

[Comment R2.5] *The conclusion section should be extended using: 1) numerical results obtained in the paper; 2) limitations of the proposed approach; 3) prospects for future research.*

[Reply to R2.5] The authors thank the reviewer for the comment. We have revised the conclusion accordingly. Please see the revised version as follows.

"This study proposed an adaptive trust model considering multiple real-time human cognitive states. The proposed trust model leverages a fusion mechanism to combine various types of information, namely, the human attention level, stress index, and human perception. To verify the performance of the proposed trust model, we deployed four environmental settings, including different types of obstacles and different numbers of robot agents. We compare the performance made by the HAT with those made by pure human agents and those made by robot agents. The comparison results show that the HAT team with the proposed trust model can improve the efficiency of the given task by at least 13% in different scenario settings; The HAT team coordinated by the proposed trust model can complete the given task faster than others. Our results also suggest that the trust value generated based on these three pieces of evidence can reflect the performance of a human agent more accurately, which contributed to an improvement of efficiency for the cooperation between human and autonomous robot agents in all test scenarios. These results demonstrate that the proposed model can adapt to various human performance levels and generate reliable trust values via the reinforcement-learning algorithm. The major limitation of this study is our participant pool; only male participants were involved in our experiments. For future works, we will enlarge the participant pool and consider gender balance to conduct a more comprehensive research. Furthermore, we will develop trust modelling to assess the trust of robot agents and then create a mutual trust model to provide more informatic reasoning for interaction in the HAT systems."

[Comment R2.6] *Some of references are outdated. Please fix it using 3-5 years old papers in high-impact journals.*

[Reply to R2.6] The authors thank the reviewer for the comment. We have added eight recent publications from high-impact journals and discussed them in Section 2. Related Works.

"Several studies have modelled human trust by analyzing human physiological signals and behaviors. Sadrfaridpour et al. proposed a mutual trust model between human and autonomous agents to coordinate collaboration [14]. The authors defined human performance based on muscle fatigue and the recovery dynamics of the human body when performing repetitive tasks, and the performance of autonomous agents was evaluated using the difference between human and autonomous agents' behaviors. Mahani, Jiang and Wang applied a Bayesian mechanism to predict human-to-autonomy trust based on human trust feedback to each individual robot and human intervention [16]. With the aid of a data-driven approach, Hu et al. proposed a human trust model that categorized an individual's trust and untrust with electroencephalography (EEG) signals and galvanic skin response (GSR) data [15]. Similar work is also presented in [34]; the researchers exploited human cognitive states extracted from EEG data to model human workers' trust in Collaborative Construction Robots. In addition, the pupillary response is observed to be an effective index for human trust estimation. Lu and Sarter exploited eye-tracking metrics to infer human trust in real time [17]. Alves et al. [18] consider kinesic courtesy cues from human to machine as an important factor in establishing human trust in HAT collaboration. Apart from pure human factors, some works take both human behavior and machine performance into consideration when modeling the mutual trust between human users and machines. By inspiration of human social behavior, Jacovi et al. [19] proposed a formalization method to model mutual trust between a human user and a machine. Additionally, some researchers proposed computational trust models for HAT systems. In [11], the model of pupil dilation is extended as a computational trust model to facilitate interaction between humans and robots. The computational model of human-robot mutual trust presented in [20] takes into account multiple pieces of information in physical human-robot collaboration, such as robot motion, robot safety, robot singularity, and human performance. Although all of the above studies provide valuable perspectives on human trust modelling, some trust models consider subjective feedback or the historical behavior of humans, which is not reliable enough and may lead to bias in the evaluation of present status and condition. Other approaches that generate trust based on a single human cognitive state might also result in miscalibration of trust in complex scenarios. Thus, this study attempted to remedy the lack of multievidence in current trust models by modelling information from multiple sources that can be optimized without prior knowledge and provides a comprehensive evaluation of human trust."

Reviewer 3

[Comment R3.1] *What the paper is missing is a separate section on related work. Even though the introduction presents some existing work, this is not adequate. A separate related work section is required that discusses the related work and how the proposed work is differs/compares with the related work.*

[Reply to R3.1] The authors thank the reviewer for the comment. We have added a separate related work section as Section 2 in the current version, in which we compare many different human trust models and algorithms to emphasize our motivations and innovation of the proposed models.

"Several studies have modelled human trust by analyzing human physiological signals and behaviors. Sadrfaridpour et al. proposed a mutual trust model between human and autonomous agents to coordinate collaboration [14]. The authors defined human performance based on muscle fatigue and the recovery dynamics of the human body when performing repetitive tasks, and the performance of autonomous agents was evaluated using the difference between human and autonomous agents' behaviors. Mahani, Jiang and Wang applied a Bayesian mechanism to predict human-to-autonomy trust based on human trust feedback to each individual robot and human intervention [16]. With the aid of a data-driven approach, Hu et al. proposed a human trust model that categorized an individual's trust and untrust with electroencephalography (EEG) signals and galvanic skin response (GSR) data [15]. Similar work is also presented in [34]; the researchers exploited human cognitive states extracted from EEG data to model human workers' trust in Collaborative Construction Robots. In addition, the pupillary response is observed to be an effective index for human trust estimation. Lu and Sarter exploited eye-tracking metrics to infer human trust in real time [17]. Alves et al. [18] consider kinesic courtesy cues from human to machine as an important factor in establishing human trust in HAT collaboration. Apart from pure human factors, some works take both human behavior and machine performance into consideration when modeling the mutual trust between human users and machines. By inspiration of human social behavior, Jacovi et al. [19] proposed a formalization method to model mutual trust between a human user and a machine. Additionally, some researchers proposed computational trust models for HAT systems. In [11], the model of pupil dilation is extended as a computational trust model to facilitate interaction between humans and robots. The computational model of human-robot mutual trust presented in [20] takes into account multiple pieces of information in physical human-robot collaboration, such as robot motion, robot safety, robot singularity, and human performance. Although all of the above studies provide valuable perspectives on human trust modelling, some trust models consider subjective feedback or the historical behavior of humans, which is not reliable enough and may lead to bias in the evaluation of present status and condition. Other approaches that generate trust based on a single human cognitive state might also result in miscalibration of trust in complex scenarios. Thus, this study attempted to remedy the lack of multievidence in current trust models by modelling information from multiple sources that can be optimized without prior knowledge and provides a comprehensive evaluation of human trust."

[Comment R3.2] *The authors may want to discuss about computational trust models, please see, for example, Tjøstheim, T. A., Johansson, B., & Balkenius, C. (2019, September). A computational model of trust-, pupil-, and motivation dynamics. In Proceedings of the 7th International Conference on Human-Agent Interaction (pp. 179-185). Also, the authors mention trust and trustworthiness without defining these and how they are related with each other in the context of their work, please see, for example, Pavlidis, M., Mouratidis, H., Islam, S., & Kearney, P. (2012, May). Dealing with trust and control: a meta-model for trustworthy information systems development. In 2012 Sixth International Conference on Research Challenges in Information Science (RCIS) (pp. 1-9). IEEE.*

[Reply to R3.2] The authors thank the reviewer for the comment. We have added the suggested paper in Section 1. Introduction and Section 2. Related Works.

In Section 1. Introduction, "Previous studies proposed trust-based approaches to explore either human or teammate trust for the optimization of interactions among agents in specified tasks [5, 11–20]."

In Section 2. Related work, "Additionally, some researchers proposed computational trust models for HAT systems. In [11], the model of pupil dilation is extended as a computational trust model to facilitate interaction between humans and robots. The computational model of human-robot mutual trust presented in [20] takes into account multiple pieces of information in physical human-robot collaboration, such as robot motion, robot safety, robot singularity, and human performance."

[Comment R3.3] *In terms of the experimental evaluation the authors could discuss if there were any threat to the validity and how these were mitigated.*

[Reply to R3.3] The authors thank the reviewer for the comment. We actually faced difficulty dealing with human data collected from multiple participants. The behaviors and reactions could be very different from subject to subject, which caused unstable rewards for the Q-learning algorithm. We, therefore, use a TSK-type fuzzy inference system (FIS) to overcome the subject differences. The FIS leverages fuzzy logic to implement set-to-set mapping that can reduce the impact of uncertainty from the inputs. Please see the revised discussion as follows.

"The test results shown in Table 2 suggest that the fusion weights trained with the Q-learning algorithm in Scenario_1 can be directly applied to more complicated scenarios without retraining. The fusion weights were trained with collected cross-subject human data and can be used in real time scenarios, which implies that the FIS can overcome the subject difference in human data and compute proper rewards for the Q-learning algorithm to tune the fusion weights."

Article

Modelling the trust value for human agents based on real time human states in human-autonomous teaming systems

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Abstract: The modelling of trust values on agents is broadly considered fundamental for decision-making in human-autonomous teaming (HAT) systems. Compared to the evaluation of trust values for robotic agents, the estimation of human trust is more challenging due to trust miscalibration issues, including undertrust and overtrust problems. As a subjective perception, the human trust could be altering along with dynamic human cognitive states, which makes trust values hard to calibrate properly. Thus, in an attempt to capture the dynamics of human trust, the present study evaluated the dynamic nature of trust for human agents through real time multievidence measures, including human states of attention, stress and perception abilities. The proposed multievidence human trust model applied an adaptive fusion method based on fuzzy reinforcement learning to fuse multievidence from eye trackers, heart rate monitors and human awareness. In addition, fuzzy reinforcement learning was applied to generate rewards via a fuzzy logic inference process that has tolerance for uncertainty in human physiological signals. The results of robot simulation suggest that the proposed trust model can generate reliable human trust values based on the real time cognitive states in the process of ongoing tasks. Moreover, the human-autonomous team with the proposed trust model improved the system efficiency by over 50% compared to the team with only autonomous agents. These results may demonstrate that the proposed model could provide insight into the real time adaptation of HAT systems based on human states and thus might help develop new ways to better enhance future HAT systems.

Keywords: Trust modelling, Information fusion, Human-autonomous teaming

Citation: Lin, C. T.; Fan, H. Y.; Chang, Y. C.; Ou, L.; Liu, J.; Wang, Y. K. and Jung, T. P. Modelling the trust value for human agents based on real time human states in human-autonomous teaming systems. *Technologies* **2022**, *1*, 0. https://doi.org/

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1. Introduction

The emerging cooperation of artificial intelligence and advanced automation systems provides an opportunity to ease the requirements of human labour and minimize risk in various tasks. In many instances, human and autonomous agents are coupled in a human-autonomous teaming (HAT) system to address complex problems, where the tasks could be either unreachable or dangerous for humans or not suitable for autonomous agents with conventional automation [1–5]. Such problems often contain a series of factors that may easily cause mistakes and result in a high cost, including but not limited to the areas of navigation, patrolling, medical health insurance, rescue, and scientific research [6–9].

As a critical factor in coordinating agents or allocating tasks, the evaluation of trust values for human agents becomes an essential issue in the cooperation of human and autonomous agents [10]. Previous studies proposed trust-based approaches to explore either human or teammate trust for the optimization of interactions among agents in specified tasks [5,11–20]. The trust in autonomous agents can be well-modelled based on their previous experience, states, and actions, where humans can judge the trustworthiness of autonomous agents by observing their actions, e.g., whether they can act as expected. Additionally, measuring human cognitive states may benefit the identification of under what circumstances and contexts autonomous agents' performance can be higher or lower than expected [21,22]. However, it is challenging to fairly measure an individual's states, as cognitive states, such as mental stress and attention, are easily affected by human behaviors, which could lead the human cognitive states to change from time to time[5,23]. Therefore, in an attempt to properly evaluate the trustworthiness of human agents, this study captured the human state in real time and investigated the distributed human trust dynamics in a HAT system. We considered human trust to be affected by human psychological state and situational awareness as factors that indicated individuals' bias when making decisions during human-autonomous interactions. This definition aligns with the concept proposed by Guo et al [24] and Azevedo-Sa et al [25].

In this study, we introduced a fusion mechanism in the proposed trust model to estimate human trust values by fusing multiple pieces of information from human agents. To obtain an adaptive fusion mechanism for the human trust model, we leveraged a reinforcement learning (RL) algorithm to learn fusion weights from an external reward via a simulation-based training process. One advantage of using RL is that it can learn without prior knowledge, which avoids bias based on forepassed data [26,27]. However, a mathematical equation to describe reward values is still difficult to define for a system with multiple sources with RL. Moreover, uncertainty and noise are additional issues, as external or ineffective information could confuse rewards with reinforcement learning. To overcome these issues, we applied the fuzzy inference system (FIS) in our model. FIS is well known as an effective method to generate rewards for complex scenarios and deal with uncertainty from the environment. Several recent studies present the implementation of FIS-based reward structures for different complex scenarios [28–30]. Evidence shows that with the aid of its membership functions and If-Then-Rule structure, FIS has an inherent capability to overcome uncertainty and noise from the environment [23,31–33]. Thus, we used FIS in this study to generate rewards for the proposed trust model to overcome the above issues.

To verify the effectiveness of the proposed trust model, we use a robot simulator to design a ball-collection task scenario that includes a HAT team working together. The HAT team involves a human agent who has to cooperate with one or two robot agents to collect the balls with collision-free movements while performing the task. The human agent's sight is restricted; the environment can only be observed through a fixed monitoring camera in the simulator. The robot agents can determine whether follows the commands from human or not based on the human trust values evaluated by the proposed trust model. We use a training scenario to learn the fusion method with the Q-learning algorithm and test it in three test scenarios with different settings. We further compare the performance of the HAT, only human agents and only robot agents. The comparison results demonstrate that the proposed trust model can improve the coordination in the HAT teams with different human participants in all test scenarios, which also suggests that the proposed model can adapt to various human performance levels and generate reliable trust values via the Q-learning algorithm.

The main contributions of this research are three-fold:

- This paper proposes a trust model to estimate human trust value in real time. The proposed trust model was applied to a ball-collection task with robot agents, which presents uses of the proposed trust model in the human-autonomous teaming framework.
- The proposed trust model considers multiple pieces of information from a human agent, e.g., attention level, stress index and situational awareness, by leveraging a fuzzy fusion model. In this research, the attention level and the stress index are evaluated based on pupil response and heart rate variability, respectively; situational awareness is measured from the environment through visual perception.

- We further use a Q-learning algorithm with a fuzzy reward to adaptively learn the fusion weight of the fusion model. The fuzzy reward is generated by a TSK-type fuzzy inference system, which facilitates the defending reward for complex scenarios and is able to handle the uncertainty from human information.

This paper is organized as follows. Section 2 introduces related works of human trust modelling. Section 3 describes the proposed Multi-Human-Evidence Based Trust Evaluation Model. This section firstly describes the details of trust evaluation metrics, followed by the details of the Trust Metric Fusion Model and the Reinforcement Learning Algorithm. Section 4 presents the experimental methods, including scenario design, human agent setup and recording, and Experimental procedures. Section 5 presents the experimental results. Section 6 shows the discussion based on the experimental results. Finally, Section 6 presents conclusions.

2. Related Works

Several studies have modelled human trust by analyzing human physiological signals and behaviors. Sadrfaridpour et al. proposed a mutual trust model between human and autonomous agents to coordinate collaboration [14]. The authors defined human performance based on muscle fatigue and the recovery dynamics of the human body when performing repetitive tasks, and the performance of autonomous agents was evaluated using the difference between human and autonomous agents' behaviors. Mahani, Jiang and Wang applied a Bayesian mechanism to predict human-to-autonomy trust based on human trust feedback to each individual robot and human intervention [16]. With the aid of a data-driven approach, Hu et al. proposed a human trust model that categorized an individual's trust and untrust with electroencephalography (EEG) signals and galvanic skin response (GSR) data [15]. Similar work is also presented in [34]; the researchers exploited human cognitive states extracted from EEG data to model human workers' trust in Collaborative Construction Robots. In addition, the pupillary response is observed to be an effective index for human trust estimation. Lu and Sarter exploited eye-tracking metrics to infer human trust in real time [17]. Alves et al. [18] consider kinesic courtesy cues from human to machine as an important factor in establishing human trust in HAT collaboration. Apart from pure human factors, some works consider human behavior and machine performance when modeling the mutual trust between human users and machines. By inspiration of human social behavior, Jacovi et al. [19] proposed a formalization method to model mutual trust between a human user and a machine. Additionally, some researchers proposed computational trust models for HAT systems. In [11], the model of pupil dilation is extended as a computational trust model to facilitate interaction between humans and robots. The computational model of human-robot mutual trust presented in [20] considers multiple pieces of information in physical human-robot collaboration, such as robot motion, robot safety, robot singularity, and human performance. Although all of the above studies provide valuable perspectives on human trust modelling, some trust models consider subjective feedback or the historical behavior of humans, which is not reliable enough and may lead to bias in the evaluation of present status and condition. Other approaches that generate trust based on a single human cognitive state might also result in miscalibration of trust in complex scenarios. Thus, this study attempted to remedy the lack of multievidence in current trust models by modelling information from multiple sources that can be optimized without prior knowledge and provides a comprehensive evaluation of human trust.

3. Multi-Human-Evidence Based Trust Evaluation Model

This section introduces the proposed trust evaluation framework used to generate the human trust values based on real time human cognition signals. The objective of the proposed framework is to enable autonomous agents to be aware of the real time human states and, therefore, to make a decision of the proper action based on the current human conditions. Through generating a single trust value without historical data, the proposed model could reduce the complexity of the cooperation task and surely eliminate the bias from previous behavior. Fig. 1 shows the structure of our model. The proposed model combines multiple human evidence to estimate a single human trust value. The evidence contains three human states, including attention level, stress index and human perception. The information fusion block is responsible for combining the three pieces of evidence with sorting and weight learning via fuzzy Q-learning. The final output of the framework is the human trust value. Note that the human trust value is produced in real time, although the learning of the fusion weights requires offline training. Details of the components of the framework are presented in the following subsections.

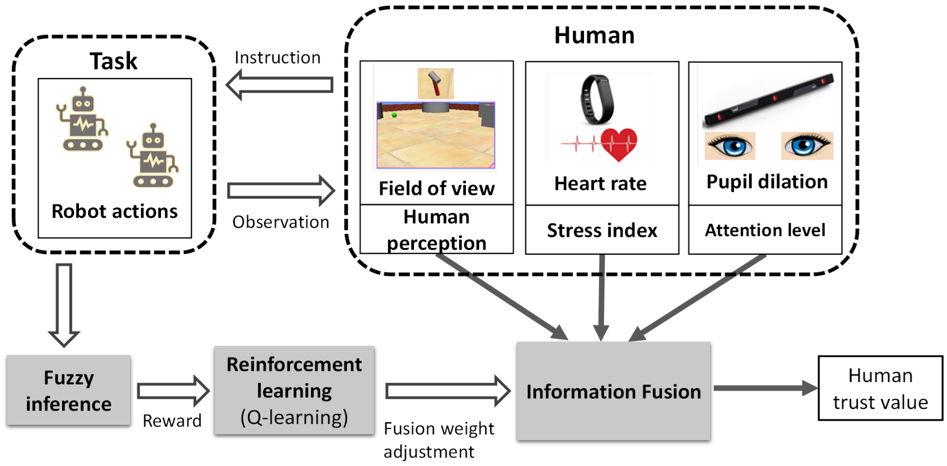


Figure 1. Structure of the proposed model.

3.1. *Trust Evaluation Metrics*

3.1.1. Attention level

As one of our three evaluation metrics for human performance, the attention level is calculated based on pupil response. Evidence from researchers has shown that the dynamics of the pupil response are an effective characteristic for estimating the human state of concentration or distraction[35]. The attention level is computed based on equation (1) proposed by Hoeks and Levelt [35]:

$$y(t) = h(t) * x(t), \tag{1}$$

where $y(t)$ is the pupillary response, $h(t)$ is a system constant called the impulse response, $x(t)$ is the attention level and $*$ is the convolution operator. The variables y, h, and x indicate the functions for the independent variable, time t.

The impulse response $h(t)$, derived from the approach introduced by Hoeks and Levelt [35], is set to represent the relation between attention and the pupillary response. The computing equation of impulse response $h(t)$ is presented in (2).

$$h(t) = s \times (t^n) \times e^{\left(\frac{-n \times t}{t_{\max}}\right)}, \tag{2}$$

where n is the number of layers that is set to 10.1, $t_{\max} = 5000$ ms is the maximum response time of participants, $s = \frac{1}{10^{33}}$ is a constant used to scale the impulse response, and t is the response time, which are the same settings as in the cited equation [35].

3.1.2. Stress index

It has been well accepted that the stress level of individuals can affect the corresponding performance in a task. Thus, we also calculated human stress as one metric used for human trust evaluation. In this paper, we used heart rate variability (HRV) as the stress index of the participants. HRV is computed based on the measurement of the duration from a series of continuous heart cycles, known as the interbeat interval (IBI), which is used to evaluate the human body's autonomic regulation. A normal heart rate is in the range of 60-70 beats/min, which is controlled by the parasympathetic nervous system. During a cognitive state with stress, human sympathetic nervous system activity increases, which affects the duration of IBI and heart rate. To quantitatively evaluate the stress level, we applied geometric methods to analyze the distribution and shapes of the IBI. The stress index (SI) was computed with the IBI data by means of Baevsky's equation in (3) [36].

$$SI = \frac{AMo}{2 \times Mo \times MxDMn}, \tag{3}$$

where AMo is the pattern amplitude expressed as a percentage, Mo is the mode that represents the most frequently occurring RR interval (the interval between successive heartbeats), and $MxDMn$ is the variation range, which reflects the variability degree of the RR interval, as shown in Fig. 2. The mode of Mo is simply taken as the median of the RR intervals, and AMo is the height of the histogram of the normalized RR interval (the width is 50 msec). $MxDMn$ represents the difference between the shortest and longest RR intervals for each participant.

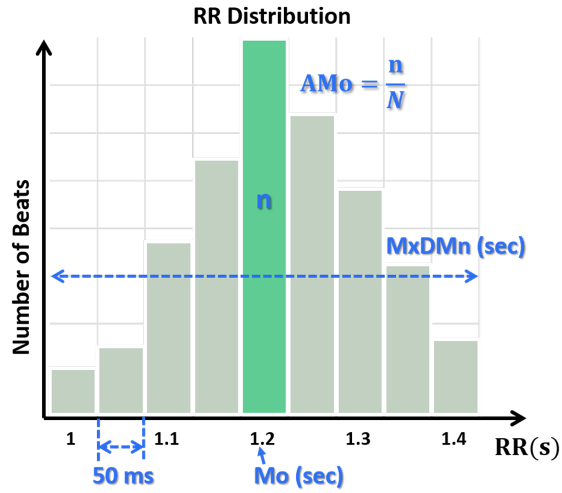


Figure 2. Histogram of RR distribution for Baevsky's stress index, in which n is the number of beats, N is successive beat intervals, AMo is the height of the histogram of the normalized RR interval, $MxDMn$ represents the difference between the shortest and longest RR intervals, and Mo is the median of RR intervals.

3.1.3. Human perception

Human perception measures confidence in the decision-making of the human agent based on the situational awareness of the human in a HAT environment through visual perception. The simulation task applied in this study is a target (ball)-collection task. As shown in Table 1, based on human perceptions of the autonomous agent and target, four situations could occur during the task. The first situation is that the human can see both the autonomous agent and target; the second and third are the human only observes either the target or the agent, respectively; and last, the human can see neither the autonomous agents nor the target. We use four factors, including the indexes to indicate position ($S1$), orientation ($S2$), distance ($S3$) and view angle ($S4$), to estimate the human perception ability, where the human perception evaluation level equals $f(S1) + f(S2) + f(S3) + f(S4)$. More details of our experiment and indexes are elaborated in Section 4

Table 1. Four situations of human perception

	Human perception
First situation	Agent + Target
Second situation	No Agent + Target
Third situation	Agent + No Target
Fourth situation	No Agent + No Target

3.2. *Trust Metric Fusion Model*

The fusion model combines three pieces of evidence from real time human states to produce a trust value. The function is defined as $F : [0,1]^n \rightarrow [0,1]$, through which multiple values located in the interval $[0,\ 1]$ are mapped to a single final value. We use the Hamacher product [37] to implement the fusion for the proposed trust model. The Hamacher product is a nonlinear transformation operation that uses confidence values from detectors to produce the final confidence for the fusion. If the evaluated single input values improve, the final trust value will increase such that $F(0,\ 0,\ \ldots,\ 0) = 0$ and $F(1,\ 1,\ \ldots,\ 1) = 1$. When all the evaluated single input values are zero, the final trust value falls to the minimum; in other words, the human is completely untrustworthy. However, if all the values of the evaluated input are 1, the upper limit of the trust value is 1. Assuming that the fusion result $F(\boldsymbol{E})$ satisfies the constraint $\min\left(E^1,\ E^2,\ \ldots,\ E^n\right) \leq F(\boldsymbol{E}) \leq \max\left(E^1,\ E^2,\ \ldots,\ E^n\right)$, we can define an aggregation function as follows:

$$F(\boldsymbol{E}) = \sum_{i=1}^{n} f(E_i - E_{i-1}, w_i), \tag{4}$$

where $\boldsymbol{E} = (E_1,\ E_2,\ \ldots,\ E_n) \in [0,\ 1]^n$ is an increasing permutation of evaluations such that $0 \leq E_1 \leq E_2 \leq \ldots \leq E_n$, $\boldsymbol{w} = [w_1,\ w_2,\ \ldots,\ w_n]$ is the fusion weight vector, and $w_1 + \ldots + w_n = 1$.

We use the Hamacher product to fuse each pair of evidence. The Hamacher t-norm involves the use of a fuzzy measure [35]. Therefore, the fusion model that produces the trust value based on the three pieces of evidence is defined as follows:

$$F_h(\boldsymbol{E}) = \frac{g(\boldsymbol{E}) \times w_i}{g(\boldsymbol{E}) + w_i - g(\boldsymbol{E}) \times w_i}, \tag{5}$$

where $F_h(\boldsymbol{E})$ represents the human trust value, and $g(\boldsymbol{E}) = \sum_{i=1}^{n} (E_i - E_{i-1})$. The fusion weights $\boldsymbol{w} = [w_1,\ w_2,\ w_3]$ are learned by Q-learning based on the collected human state data, including pupil, HRV and human perception signals. In addition, we used the min-max normalization for the pupil and HRV data to normalize the value in the range of $[0, 1]$.

3.2.1. Reinforcement learning

This section discusses the Q-learning method used to update the fusion weights. As a model-free, off-policy reinforcement learning method, Q-learning tracks what has been learned and finds the best course of action for the agent to gain the greatest reward [38,39]. As discussed above, the final trust value is calculated by multiplying the evaluated values of three human states by the corresponding weights and then summing the results. The weights represent the relative importance of each individual evaluation, and the vector of weights is initialized randomly. Thus, since Q-learning is able to transfer functions or reward functions with random factors [40], we applied its algorithm to determine which weight vector is used to fuse the estimated trust values from a random perspective. The equation to update the Q-value with action i and state s in each step is shown below:

$$Q(s,\ i) \leftarrow Q(s,\ i) + \alpha \times \left(w(s,\ i) \times \nabla + \gamma \times \sum_{j=1}^{n} \left(w(s',\ j) \times Q(s',\ j) \right) - Q(s,\ i) \right) \tag{6}$$

where α is a fixed value used as the learning rate that satisfies the condition $0 < \alpha \leq 1$, $w(s,\ i)$ represents the value of the weight in state s and action i, the parameter γ is a temporal discount factor that satisfies the condition $0 < \gamma \leq 1$, s' is the state after performing the action under state s, and ∇ is the reward. Here, we set α to 0.1 and γ to 0.2. Additionally, we update the weight vector based on the Q-values after updating the Q-tables. Two conditions are used when applying the value of weight $w(s,\ i)$: 1) The summation of $w(s,\ i)$ is normalized to 1. 2) Parameter δ is within the range $(0,\ 1]$.

Formula (7) shows the weight updating rule:

$$w'(s,i) \leftarrow w(s,i) + \begin{cases} (1 - w(s,i)) \times \delta \times \left(\frac{1}{1+e^{-a \times Q(S,i)+b}} \right), if\ i = \arg\max_j Q(s,j) \\ (0 - w(s,\ i)) \times \delta \times \left(\frac{1}{1+e^{-a \times Q(S,i)+b}} \right), otherwise. \end{cases} \tag{7}$$

Then, we normalize the weight value in (8) so that $\sum_{i=1}^{n} w(s,\ i) = 1$:

$$w(s,\ i) \leftarrow \frac{w'(s,\ i)}{\sum_{j=1}^{n} w'(s,\ j)}, \tag{8}$$

3.2.2. Fuzzy reward

This section presents the FIS used to produce fuzzy rewards for RL to learn fusion weights and adjust the Q-learning reward. The FIS is composed of a zero-order Takagi-Sugeno-Kang (TSK) fuzzy system [41–43], which can be defined as

$$\begin{aligned} R_I : If\ x_1(k)\ is\ A_{i1}\ And\ \ldots\ And\ x_n(k)\ is\ A_{in} \\ Then\ y_1(k)\ is\ a_i, \end{aligned} \tag{9}$$

where $x_1(k), \ldots, x_n(k)$ represents the input variables at time k, $A_{i1}, \ldots, A_{in}$ are the fuzzy sets, and a_i represents the singleton consequence. Moreover, $\mu_{A_{ij}}$ is the membership value of A_{ij}, and Φ_i is the firing strength of rule R_i. We use algebraic multiplication to implement the fuzzy AND operation. Then, Φ_i with input data set $\vec{x}(k) = [x_1(k), \ldots, x_n(k)]$ can be described as

$$\Phi_i(\vec{x}(k)) = \prod_{j=1}^{n} \mu_{A_{ij}}(x_j(k)) \tag{10}$$

Supposing the FIS consists of r rules, the output of the FIS $y(k)$ can be calculated by the weighted average defuzzification method in (11).

$$y(k) = \frac{\sum_{i=1}^{r} \Phi_i(\vec{x}(k)) a_i}{\sum_{i=1}^{r} \Phi_i(\vec{x}(k))} \tag{11}$$

To properly score the relationship between the generated trust value and human performance, we used the fuzzy reward to feed back the score to the proposed trust model to tune the fusion weights. We defined four rules for reward evaluation based on human performance for the Q-learning algorithm. There are two input variables for each fuzzy rule: human reaction time τ_h and human trust value F_h. Here, the reaction times are divided into fast and slow camps, and the trust values also contain high and low levels. Thus, four combinations exist. The rules are defined as follows.

R_1: If $\tau_h(k)$ is A_{fast} and $F_h(k)$ is B_{high}, then $r(k) = 1$.

R_2: If $\tau_h(k)$ is A_{slow} and $F_h(k)$ is B_{low}, then $r(k) = 1$.

R_3: If $\tau_h(k)$ is A_{fast} and $F_h(k)$ is B_{low}, then $r(k) = -1$.
R_4: If $\tau_h(k)$ is A_{slow} and $F_h(k)$ is B_{high}, then $r(k) = -1$.
where A_{fast} and A_{slow} are fuzzy sets describing fast and slow human reaction times, respectively. Specifically, under R_1, humans make decisions faster and are trustworthy, the trust value of the fusion result is high, which represents a positive result, and the reward value of R_1 is 1. Under R_2, humans are slow to make decisions and thus untrustworthy. In addition, the fusion result of the trust value is low. The two input variables of R_2 both show a consistently negative result, so the reward value of R_2 is 1. However, if the trend is inconsistent, as in R_3 and R_4, the reward is -1.

The membership value of A_{fast} and A_{slow} is computed by the membership function, as follows

$$\mu_{A_{fast}} = \begin{cases} f\left(\tau_h \middle| m_{fast}\ ,\ \sigma_{fast}\right), & \tau_h > m_{fast}, \\ 1, & otherwise \end{cases} \tag{12}$$

and

$$\mu_{A_{slow}} = \begin{cases} f(\tau_h | m_{slow}\ ,\ \sigma_{slow}), & \tau_h > m_{slow}, \\ 1, & otherwise \end{cases} \tag{13}$$

where $f(x|m,\sigma) = exp\left[-\frac{(m-x)^2}{\sigma^2}\right]$,$B_{high}$ and B_{low} are the fuzzy sets describing high and low human trust values, respectively. The membership value of B_{high} and B_{low} is computed by the membership function as follows:

$$\mu_{B_{high}} = \begin{cases} f\left(F_h \middle| m_{high}\ ,\ \sigma_{high}\right), & F_h > m_{high}, \\ 1, & otherwise \end{cases} \tag{14}$$

and

$$\mu_{B_{low}} = \begin{cases} f(F_h | m_{low}\ ,\ \sigma_{low}), & F_h > m_{low}, \\ 1, & otherwise \end{cases} \tag{15}$$

where m_{high} and m_{low} of the reaction time are calculated using the average reaction time and standard deviation of reaction times from all participants. The slow reaction time is defined as the time values that are twice the standard deviation more than the average reaction time, and the fast reaction time is twice the standard deviation less than the average reaction time. Fig. 3 shows a schematic diagram of the four rules.

4. Methods

4.1. Participants

Six healthy male participants aged 21 to 24 years old participated in this study. Following an explanation of the experimental procedure, all participants were provided an informed consent form and signed before participating in the study. This study obtained the approval of the Institute's Human Research Ethics Committee of National Chiao Tung University, Hsinchu, Taiwan. None of the participants reported a history of psychological disorder, which might have affected the experimental results.

4.2. Scenario Design

The built simulation scenario of ball collection is designed by a professional robot simulator, Webots 8.6.2 (Cyberbotics Ltd., Lausanne, Switzerland). As shown in Fig. 4, the environment is fenced with several balls and obstacles inside. A human agent and a robot agent are expected to work together to collect the balls without collision between the robot and the wall or the obstacles. Humans can only observe the whole environment with restricted sight through a monitoring camera located at the left-top corner of the scenario. Based on the observation, the human can instruct the robot to search for the ball, and the robots are also allowed to explore the environment by themselves when there is no instruction from the human or the human trust values are not high enough to be trusted.

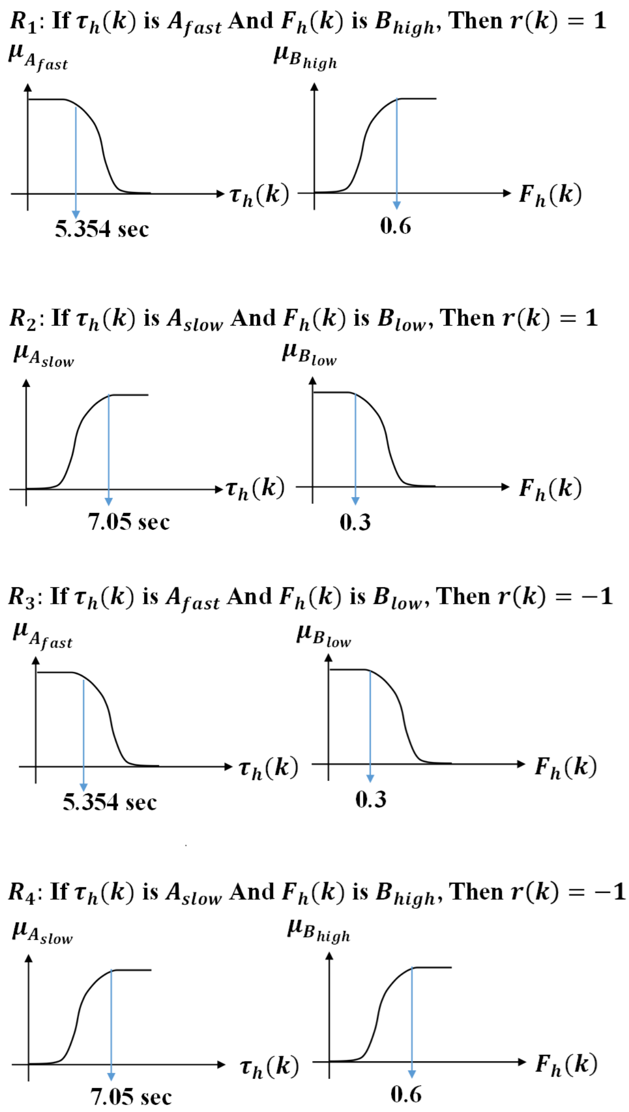


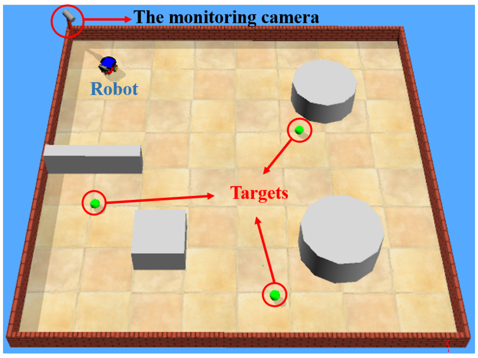
Figure 3. Four rules of the fuzzy neural network.

4.3. Human agent setup and recording

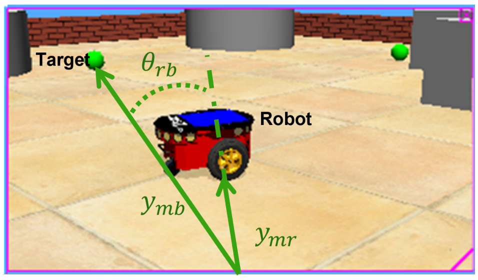
The design of the whole scenario is affected by not only the autonomous agents' actions but also human physiological factors. Here, we use two instruments, eye-tracking and a heart rate monitoring watch, to measure the human physiological state in real time, as shown in Fig. 1. The eye-tracking data were recorded by the Tobii Pro X2-30 screen-based eye tracker (Tobii AB Corp., Stockholm, Sweden). We corrected the pupil data and gaze location from each participant to monitor their concentration level and fixation pathways. The heart rate data were recorded via the Empatica-E4 wristband (Empatica Inc., Cambridge, United States). We used the real time heart rate from each participant to estimate the current stress level for the human agent while performing the task.

The ability of human perception was identified through the monitoring camera used to provide sight of the scenario situation for the human agent, as presented in Fig. 4a. Following our definition of human perception in Section Trust Evaluation Metrics, we categorized human perception into four classes (see Table 1). The real time perception ability is calculated according to the following formula:

$$E^a = k_1 \times \left(1 - \frac{y_{mr}}{y}\right) + k_2 \times \left(1 - \frac{y_{mb}}{y}\right) + k_3 \times \left(1 - \frac{\theta_{rb}}{\pi}\right), \tag{16}$$



(a) Scenario with one robot and three balls.



(b) Participant's view via the monitoring camera during the experiment.

Figure 4. Scenario for training data collection (Scenario_1).

where E^a is the value of current perception ability, k_1,k_2,k_3 are predefined weights, y_{mr} is the distance between the monitoring camera and the robot, y_{mb} is the distance between the monitor and ball, θ_{rb} is the deviation value between the robot and ball, and y is the farthest distance that can be measured by the monitoring camera, as shown in 4b.

We set k_3 as the largest weight because it represents the situation in which the robot and ball can both be perceived, in which humans have the best chance of completing the task successfully. k_2 is given the second-highest weight that represents the situation in which the human knows the exact position of the ball, although the robot is not visible. Finally, k_1 has the smallest weight, which indicates the situation in which the human does not know the location of the ball, although the robot is visible. Every situation is transformed into a corresponding evaluation value, which ranges in value between 0 and 1. Here, if the human cannot see the ball or robot, the corresponding terms are set to zero in the equation. Then, if neither the robot nor ball can be seen, the third term in the equation is set to 0. Furthermore, if an object does not exist in some conditions, the value of that item is also set to 0.

4.4. Experimental procedures

During the experiment, participants sat in front of the computer screen while conducting the task. A calibration for the eye tracker was performed by each participant first. Next, we introduced the operation and process of the whole experiment, including how the robot is controlled and various other considerations in the experiment. While conducting the ball-collection task, participants used two keys on the keyboard to control the clockwise or anticlockwise rotation of the robot following our instructions. The balls were scattered around the environment, including in visible or blinded areas. The participant can only monitor the scenario from a fixed perspective as mentioned above, and an example of the participant's view via the monitoring camera is shown in Fig. 4b. The task would be completed once all the balls have been found by the robot.

For the cooperative work between human and robot agents, we define the process of their interaction in each trial. First, the human has eight seconds to set the facing direction for the robot through rotation control. Then, the robot moves in that direction the human agent has selected for 15 seconds. To discard the direction setting for the robot, the human agent is allowed to select robot self-exploration. The robot may move for more than fifteen seconds if it detects a target by itself during self-exploration. A schematic diagram of each trial is shown in Fig. 5. Here, t_p represents the time that the human controls the direction of the robot, $t_{p_{\max}}$ represents the maximum time for the human to control the robot, and t_r represents the time that the robot acts and follows the command from the human.

5. Results

This section describes the results of our simulation experiment with our proposed trust model in the human-autonomous cooperation task scenario. We first discuss the training

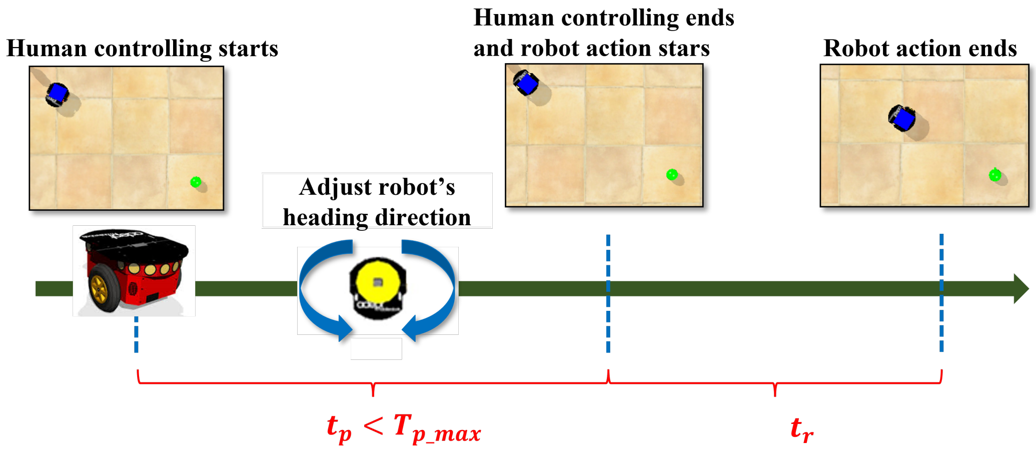


Figure 5. Robot and human interaction in each trial.

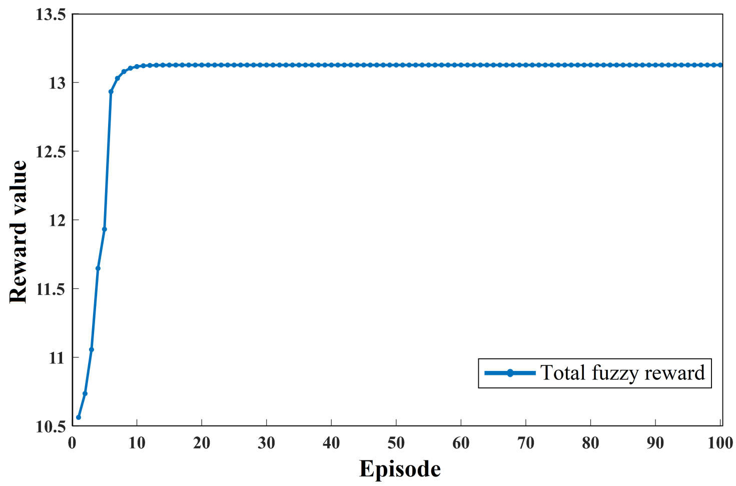


Figure 6. Convergence of the fuzzy reward during the training process of the fusion mechanism.

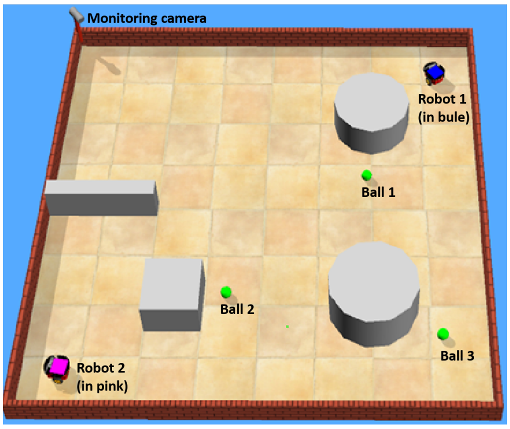
results by presenting the convergence of the fuzzy reward and its standard deviation. Then, we provided our testing results based on three different scenarios with our trained trust model.

5.1. Training results

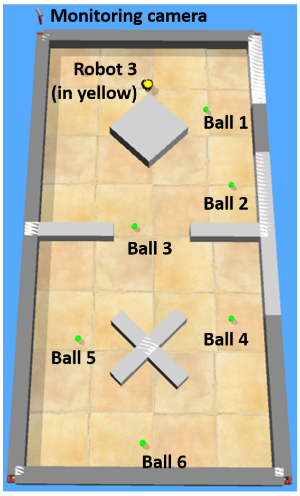
The training process inputs the data collected in Fig. 4 into the Q-learning. In (6), we set the learning rate, α, to 0.1 and the discount factor, γ, to 0.2. These settings are commonly applied to various scenarios with the fuzzy neural network to obtain the reward value [43–45]. We implemented 100 episodes to train our model to eliminate the impact of the unstable reward in the first ten episodes. The visualized convergence result of the reward values from each episode is shown in Fig. 6. The data recorded in Fig. 5 were used to train the reinforcement learning method, including three pieces of human evidence signals and the reaction time of humans t_p. The training results combined cross-subject data. One of the best-performing weights with the best reward values is $[w_1, w_2, w_3] = [0.2440, 0.3688, 0.3872]$.

5.2. Testing results

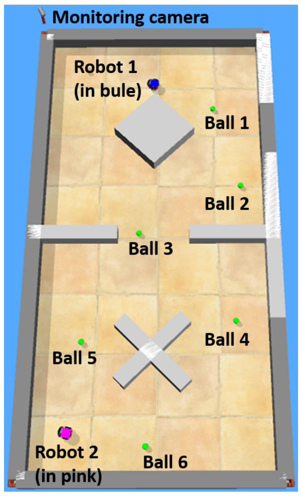
We used the trained weights to fuse the three human states. The fusion results from all six participants are used to assess the human trust value, which ranges from 0 to 1. Then, we conducted the tests in one training (Scenario_1) and three test scenarios (Scenario_2–4). Fig. 7 presents the three test scenarios, which we refer to as Scenario_2, Scenario_3 and Scenario_4. Tables 2 and 3 provide all the test results. We statistically analyzed the



(a) Small scenario with two robots and three balls. (Scenario_2)



(b) Large scenario with one robot and six balls. (Scenario 3)



(c) Large scenario with two robots and six balls. (Scenario_4)

Figure 7. Scenarios for testing.

execution time of three task-performing modes, including human instruction (robot follows human instruction only to find the targets), collaboration of human and robot agents (HAT) and robot random search in Table 2. The results contain both the completion time and decision time. Additionally, the number of operations in the collaboration and human instruction modes are presented in Table 3.

Overall, the completion time under the collaboration mode is always the shortest compared to the other two modes for all participants. Specifically, in Scenario_1 shown in Table 2, Participant 5 spent the shortest time completing the task in collaboration mode, and the proportion of manipulation by humans was also the highest, which indicates that a high level of trust was evaluated for this participant while conducting the ball-collection task.

In Scenario_2, Participant 3 took the longest time to complete the task in collaboration mode. However, the proportion of manipulations by humans was also the highest in this case. This may be because Participant 3 maintained a high level of trust but failed to control the robot well, which led to a longer time required to complete the task. In Scenario_3, the second participant took the shortest time to achieve the task in collaboration mode, and the robot was involved in the least amount of autonomous control. This result may suggest that the second participant was trustworthy and able to identify the shortest path to save a considerable amount of time during the experiment. In Scenario_4, the result of decisions indicate that Participants 1 and 2 controlled the robot all by themselves without

Table 2. Completion time under Scenario_1-4, HAT represents experiments with control switching between the human and robot.

Evaluation of completion time		Participant					
		1	***2***	***3***	***4***	***5***	***6***
Scenario	**Setting**	**Time (sec)**					
Scenario_1	human instruction	223	175	194	196	177	216
	HAT	194	138	171	140	131	143
	random search	287					
Scenario_2	human instruction	165	181	168	121	132	129
	HAT	117	119	123	98	100	90
	random search	185					
Scenario_3	human instruction	408	428	407	469	427	450
	HAT	372	343	371	403	380	359
	random search	573					
Scenario_4	human instruction	209	237	248	229	222	242
	HAT	178	208	195	201	197	213
	random search	330					

Table 3. Number of decisions made in Scenarios_1–4.

Evaluation of number of decisions made		Participant					
		1	***2***	***3***	***4***	***5***	***6***
Scenario	**Setting**	**Number of decisions**					
Scenario_1	human instruction	6	6	6	6	6	6
	human/robot	4 / 2	4 / 2	4 / 2	4 / 2	5 / 1	4 / 2
Scenario_2	human instruction	6 / 6	5 / 6	6 / 6	4 / 5	4 / 6	4 / 5
	human/blue	4 / 2	4 / 1	5 / 1	3 / 1	3 / 1	2 / 2
	human/pink	2 / 4	3 / 3	4 / 2	3 / 2	5 / 1	2 / 3
Scenario_3	human instruction	12	12	13	12	12	11
	human/robot	9 / 3	9 / 3	7 / 6	7 / 5	8 / 4	6 / 5
Scenario_4	human instruction	5 / 7	6 / 7	6 / 8	6 / 7	6 / 7	8 / 7
	human/blue	3 / 2	3 / 3	2 / 4	2 / 4	4 / 2	4 / 2
	human/pink	7 / 0	7 / 0	5 / 3	5 / 2	4 / 3	4 / 3

a robot intervention, and the completion time varied greatly. This may suggest that both participants were trustworthy, but the first participant could identify a better path than the second.

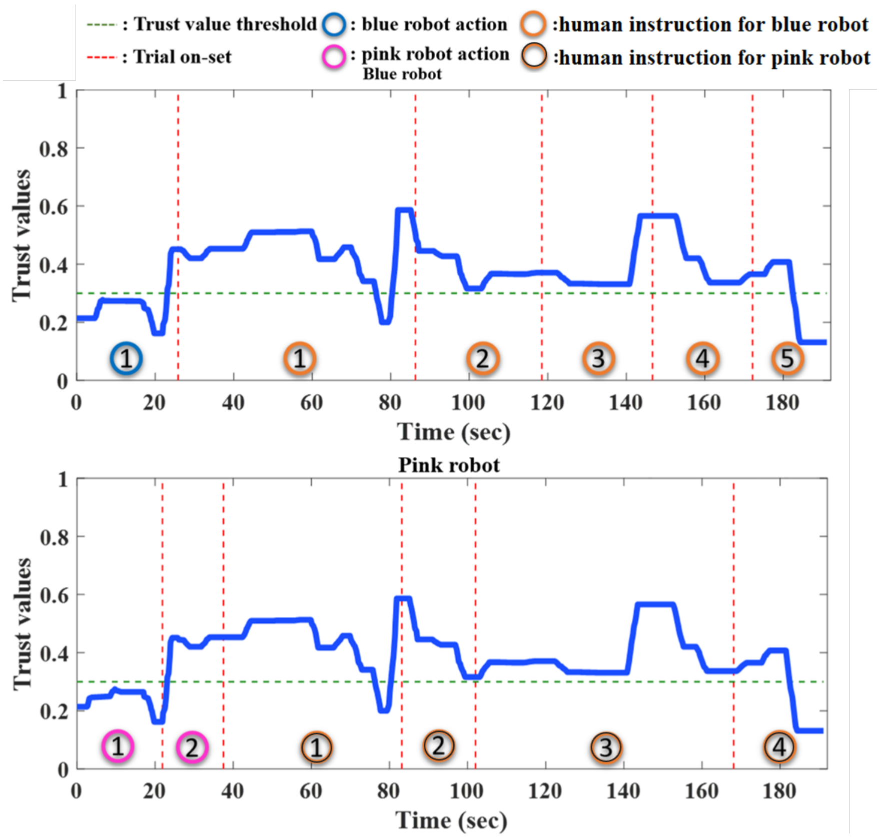
6. Discussion

This section discusses the improvement of efficiency among the three modes (robot random search, human instruction and collaboration/HAT) and explores the reasons for the improved efficiency. The magnitude of the improvement for each scenario is shown in Table 4.

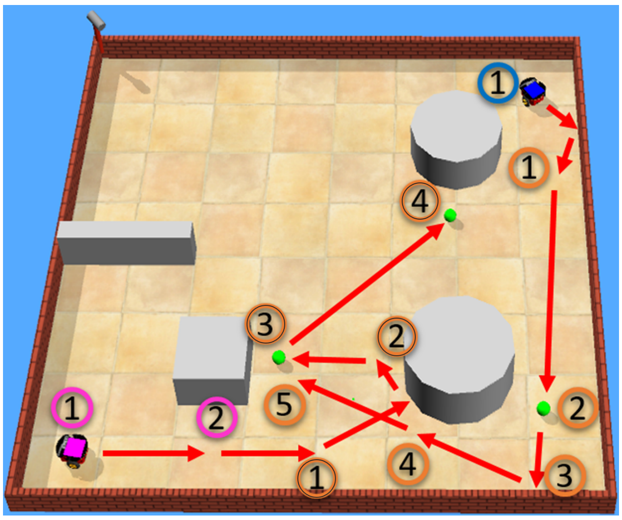
In Scenario_2, Participant 3 conducted the task with the largest number of decisions made by humans and the longest completion time, and in contrast, Participant 6 had the largest number of decisions made by two robots and the shortest completion time. The two robots follow Participant 3's instructions nine times in 12 trials, which is 75% of decisions made by the human, and follow Participant 2's instructions seven times in 11 trials, which is 63.6% of decisions made by the human. Whereas, Participant 6 made decisions four times for the two robots in nine trials, which is 44.4% of decisions made by the human. To visualize how these two participants conducted the tasks, we present the robot paths and control decisions in Figs. 8 and 9 for each participant, respectively. As revealed in Fig. 8, Participant 3 controlled the pink robot in the third trial but did not adjust it to the right direction, which caused the pink robot to take a long detour to find the ball and wasted a substantial amount of time. In contrast, the pathways of robots in Fig. 9 indicate that Participant 6 could well control both robots and guide them a shorter route to find the balls. Moreover, as the greatest improvement achieved between human instruction and HAT, we also visualized the task route of Participant 2, as shown in Fig. 10. In the human instruction condition, Participant 2 failed to adjust the robot to the right direction in the fifth trial, which resulted in a miss-out of the targets for the robot. However, in the collaboration condition, because of the lower trust value in the fifth trial for Participant 2 than the threshold value, the pink robot did not receive human instructions and proceeded forward to collect the ball. In other words, along with the successful awareness of human states, the robot made the decision itself and achieved better performance through an efficient evaluation of human states by our model.

In addition to Scenario_2, the collaboration controlled by our proposed model also shows greatly improves in the more complicated scenarios. The performance of Participant 2 in Scenario_3 indicates that the human decision was estimated to be trustworthy to make the shortest choice of path through the aid of our evaluation model on real-time human states, which did achieve an optimal decision on the route to save a lot of time to complete the task. Similarly, in Scenario_4, Participant 1 and Participant 2 were successfully evaluated as a trustworthy agent, although Participant 1 could choose the better path. The test results shown in Table 2 suggest that the fusion weights trained with the Q-learning algorithm in Scenario_1 can be directly applied to more complicated scenarios without retraining. The fusion weights were trained with collected cross-subject human data and can be used in real time scenarios, which implies that the FIS can overcome the subject difference in human data and compute proper rewards for the Q-learning algorithm to tune the fusion weights.

In summary, the proposed multi-evidence-based trust evaluation model could generate a trust-considering value for human agents that reflects the dynamics of human states in real time. The comparison among robot random search, human instruction only and collaboration modes demonstrate that the collaboration between human and autonomous robots controlled by the proposed trust model has adaptability and robustness for the ball-collection task under different levels, which greatly improves the task completion time compared to the other two modes.

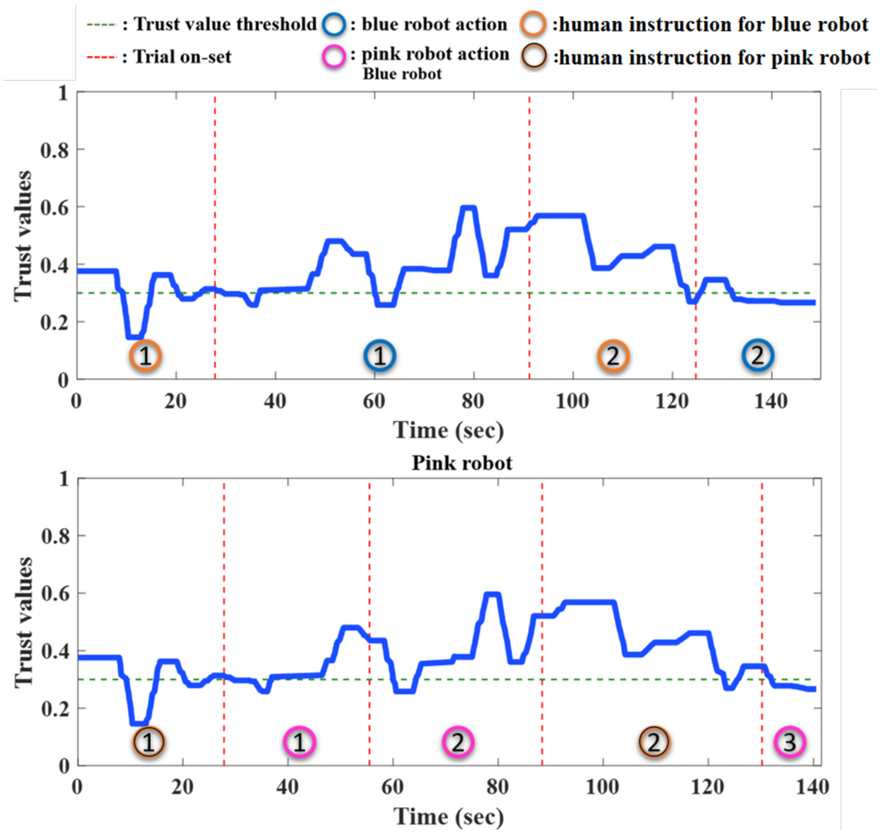


(a) Control switch between human and robot.

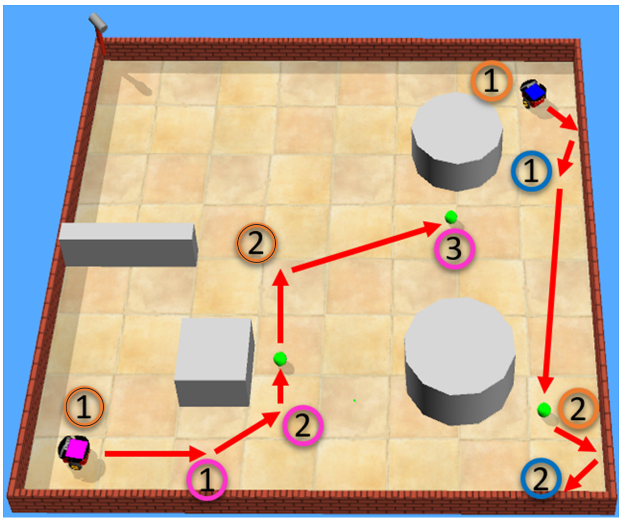


(b) Robot path trajectory.

Figure 8. Experimental results made by Participant 3.

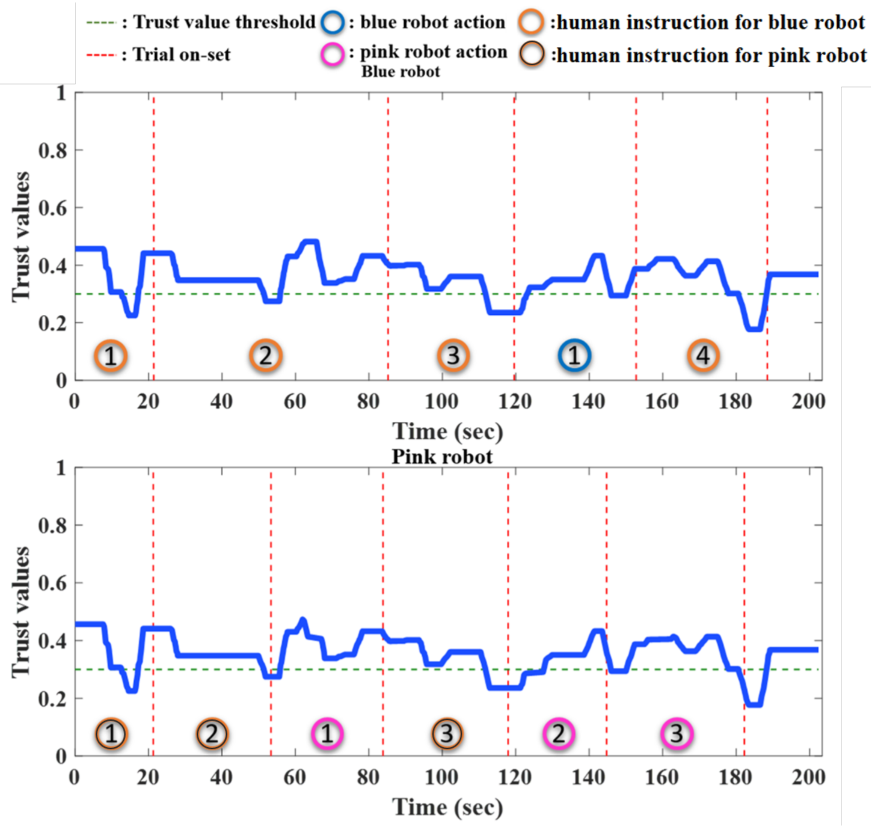


(a) Control switch between human and robot.

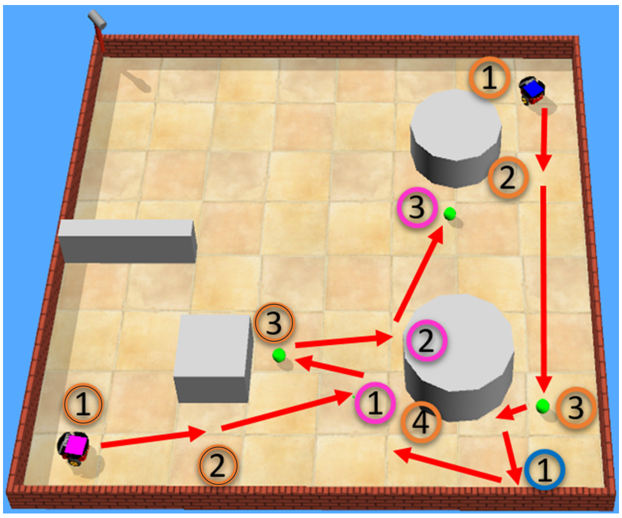


(b) Robot path trajectory.

Figure 9. Experimental results made by Participant 6.



(a) Control switch between human and robot.



(b) Robot path trajectory.

Figure 10. Experimental results made by Participant 2.

Table 4. Comparison of the improvement rate in Scenarios_1–4. HAT represents experiments with control switching between the human and robot, H represents experiments with only human instructions, and RS represents experiments with only robot random search

Scenario	Setting	Participant						
		1	2	3	4	5	6	Avg
		Improvement rates						
Scenario_1	H vs. RS	22.29	39.02	32.4	31.71	38.33	24.74	31.42
	HAT vs. RS	32.4	51.92	40.42	51.22	54.36	50.17	46.75
	HAT vs. H	13.01	21.14	11.86	28.57	25.99	33.79	22.39
Scenario_2	H vs. RS	10.81	2.16	9.19	34.59	28.65	30.27	19.28
	HAT vs. RS	36.76	35.68	33.51	47.02	45.95	51.35	41.71
	HAT vs. H	29.09	34.25	26.79	19.01	24.24	30.23	27.27
Scenario_3	H vs. RS	28.8	25.31	28.97	18.15	25.48	21.47	24.69
	HAT vs. RS	35.08	40.14	35.25	29.67	33.68	37.35	35.19
	HAT vs. H	8.82	19.86	8.85	14.07	11.01	20.22	13.81
Scenario_4	H vs. RS	36.67	28.18	24.85	30.61	32.73	26.67	29.95
	HAT vs. RS	46.06	36.97	40.91	39.09	40.3	35.45	39.79
	HAT vs. H	14.83	12.24	21.37	12.22	11.26	11.98	13.98

7. Conclusions

This study proposed an adaptive trust model considering multiple real-time human cognitive states. The proposed trust model leverages a fusion mechanism to combine various types of information, namely, the human attention level, stress index, and human perception. To verify the performance of the proposed trust model, we deployed four environmental settings, including different types of obstacles and different numbers of robot agents. We compare the performance made by the HAT with those made by pure human agents and those made by robot agents. The comparison results show that the HAT team with the proposed trust model can improve the efficiency of the given task by at least 13% in different scenario settings; The HAT team coordinated by the proposed trust model can complete the given task faster than others. Our results also suggest that the trust value generated based on these three pieces of evidence can reflect the performance of a human agent more accurately, which contributed to an improvement of efficiency for the cooperation between human and autonomous robot agents in all test scenarios. These results demonstrate that the proposed model can adapt to various human performance levels and generate reliable trust values via the reinforcement-learning algorithm. The major limitation of this study is our participant pool; only male participants were involved in our experiments. For future works, we will enlarge the participant pool and consider gender balance to conduct a more comprehensive research. Furthermore, we will develop trust modelling to assess the trust of robot agents and then create a mutual trust model to provide more informatic reasoning for interaction in the HAT systems.

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