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A Human-Machine Trust Model and Trust Calibration Method for Decision-Aid Systems

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Abstract: With the development of AI technology, decision-aid systems are widely applied. The trust level between humans and decision aids has a great impact on the overall performance of the system. Current research on human-machine trust has deficiencies in trust modeling and trust calibration, especially lacking quantitative characterization of human trust levels. In response to this, this paper proposes a human-machine trust evaluation model and a transparency-based trust calibration method for decision-aid systems. Firstly, a dynamic evolution model of human-machine trust is constructed, with machine performance and past trust as influencing factors. Secondly, the meaning of trust calibration is elaborated, the impact of transparency on the trust model is analyzed, and a transparency-based trust calibration method is proposed. Through the simulation experiment of a tumor prediction medical assistance system, the rationality of the proposed trust model and the effectiveness of the calibration method are verified.

Key Words: Human-machine system, trust model, decision-aid system, trust calibration

1 Introduction

With the rapid development of AI technology, decision-aid systems empowered by AI have been applied more and more widely[1][2]. AI can acquire a certain degree of autonomy through learning from the surrounding environment and is capable of performing some advanced cognitive tasks such as decision-making [3][4]. In situations where humans are unable to obtain accurate information or find it difficult to make correct decisions, decision-aid systems provide suggestions to human users, who then make the final decisions. For example, in some rescue scenarios, it is necessary to determine whether there are trapped people in a post-disaster area. However, human users usually cannot directly go to rescue because of the complexity of the environment. Through sensor data such as visual images transmitted by rescue equipment, the decision on whether there are trapped people in this area is conveyed to human users, and then the human users can further carry out rescue work. Besides the above scenarios, decision-making assistance systems are very common in various fields, such as medical care, autonomous driving, industry, national defense, and military, etc. The interaction process between the decision-aid system and human users is shown in Figure 1.

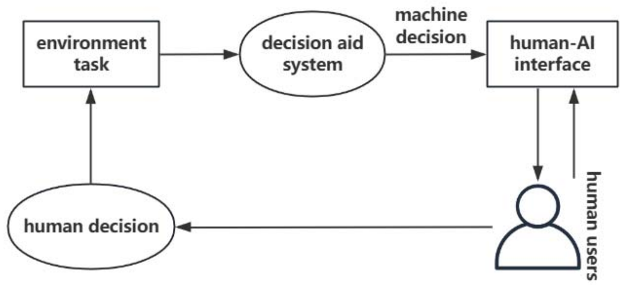

Fig. 1: Interaction process between humans and decision-aid systems

When using a decision-aid system, the level of trust that humans have in it is of great importance and will affect the overall performance of the system [5][6]. Trust is defined as the subjective perception of humans towards the objective capabilities of machines, reflecting the cognitive relationship between humans and machines. If the trust level that humans have in the system is inappropriate, that is, either lacking trust or overtrust, it will prevent the system from achieving its best performance and may even lead to system failure and bring about safety issues [7]. For example, in the case of an intelligent driving system, if a human driver overtrusts the decisions made by the driving assistance system and fails to take over when the system makes a wrong decision in an emergency situation, a car accident may occur. Another example is that if humans lack trust in it, they may interfere with the machine even when it is not necessary. In either case, it deviates from the original intention of the design of the intelligent assistance system. Therefore, an appropriate level of trust is crucial for decision-aid systems.

Obtaining an appropriate level of trust contains two parts. Firstly, it is necessary to quantify and model trust so as to obtain the dynamic value of trust. Secondly, when the trust level is inappropriate, trust calibration should be carried out to restore trust to an appropriate level. Currently, there are some related studies[8]. In terms of trust quantification models, they can mainly be divided into two major categories. The first category is the probability model type. For example, trust is modeled as a POMDP (Partially Observable Markov Decision Process) model [9], where trust is regarded as a state variable with two states, high or low, and the probability model of trust transition is studied. However, this method often makes it difficult to understand the evolution of trust over time. The other category is the time-series model

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type [10]. The factors influencing trust evolution are quantified and modeled as difference sequences that evolve over time. This method better reflects the evolution law of trust, but it is often specific to certain scenarios and lacks generality. Regarding trust calibration, since the trust model is immature, there is even less work on trust regulation. Most of the trust regulation studies are mainly for specific scenarios and are mainly in the form of experiments [11][12]. They adjust human trust through feedback, lacking the support of theoretical models.

In response to the above issues, this paper will propose a human-machine trust evolution model for decision-aid systems and, on this basis, a transparency-based trust calibration method. Firstly, taking system performance and past trust as important factors influencing trust evolution, a time-series trust evolution model will be constructed. The system performance specifically refers to the decision-making performance of the decision-aid system. Furthermore, on the theoretical basis of the constructed computable trust model, the transparency of the system is adjusted to affect the relevant parameters in the model when the trust level is inappropriate, thereby changing the level of human trust and achieving the goal of trust calibration.

The structure of this paper is as follows: In Section 2, a dynamic model will be established for the trust evolution of the decision-aid system. In Section 3, a transparency-based trust calibration method is proposed. In Section 4, the effectiveness of the trust model and the trust calibration method is verified through simulation experiments. In Section 5, the full text is summarized.

2 Trust Modeling for Decision-Aid Systems

This chapter mainly introduces the trust modeling process for decision-aid systems. Firstly, a trust dynamic evolution model with system performance and past trust as the main influencing factors is proposed. Secondly, the meaning of the system performance of the decision-aid system is clarified. Finally, the parameters in the model are determined by the least squares method.

2.1 Trust Model Evolving over Time

Define the trust value of the human user at time t as:

$$T(t) = T(k), t \in [t_k, t_{k+1}), k \geq 0 \tag{1}$$

where k represents the interval of trust update for the human user, t_k is the moment when the human user's trust is updated. $T(t) \in [0, 1]$ is the trust level of the human user at time t. This deeply implies that, in practice, the trust of the human user doesn't change at any time but changes at some specific moments. For the decision-aid system, t_k refers to the moment when a decision needs to be made currently.

In order to study the evolution of the law of trust, we make the following assumptions: The trust level $T(k)$ of a person in the system at moment k is mainly influenced by two factors. One is the trust level at the previous moment $T(k-1)$; the other is the performance of the system during the period from $k-1$ to k.

Define the system performance from moment $k-1$ to moment k as $P(\Delta k)$, the dynamic model of trust evolving over time is described as:

$$\begin{cases} T(k) = \alpha T(k-1) + (1-\alpha)P(\Delta k), k > 0 \\ T(t) = T(k), t \in [t_k, t_{k+1}), k > 0 \end{cases} \tag{2}$$

where $\alpha \in (0, 1)$ refers to the human factor. This is due to the individualized differences brought about by the different genders, ages, occupations, and personalities of human users. Even with the same performance of the machine, the impact on the change of trust level varies from person to person. It needs to be determined through parameter identification methods in the subsequent steps.

In addition, it should be noted that in practice, when the human user perceives the system's performance as being correct or incorrect, the corresponding changes in the trust level, whether it rises or falls, are not the same. Generally speaking, the magnitude of the decline is usually greater. Discuss the parameter α in two cases:

$$\alpha = \begin{cases} \alpha^+, & P(\Delta k) \geq T(k-1); \\ \alpha^-, & P(\Delta k) < T(k-1). \end{cases} \tag{3}$$

When the machine's performance is greater than the trust level at the previous moment, the trust level rises; conversely, when the machine's performance is less than the trust level at the previous moment, the trust level drops, and the magnitudes of the trust changes are respectively related to the coefficients α^+ and α^-.

The amount of trust change from moment $k-1$ to moment k is obtained from formula (2) as follows:

$$\Delta T = T(k) - T(k-1) = (1-\alpha)(P(\Delta k) - T(k-1)) \tag{4}$$

We can notice that:

$$\alpha = \begin{cases} \alpha^+, & \Delta T \geq 0; \\ \alpha^-, & \Delta T < 0. \end{cases} \tag{5}$$

2.2 System Performance for Decision-Aids

We have presented a quantitative model of the evolution of trust levels over time for decision-aid systems. However, the specific meaning of the system performance in the model was not indicated. In this part, a more detailed discussion of the system performance in the model will be carried out in light of the characteristics of the decision-aid system.

For a decision-aid system, the main indicator for evaluating its performance is whether the decision is correct or not. That is, when the system makes a correct decision at moment k, $P(\Delta k) = 1$; when the system makes a wrong decision, $P(\Delta k) = 0$. If the decision is of a continuous type, consider the gap between the decision and the optimal decision as the criterion for evaluating the quality of the decision.

For binary decisions, if we further consider that different types of decision errors of the system have different impacts on the system, then:

$$P(\Delta k) = \begin{cases} 1 & \text{decision correct} \\ c1 & \text{Decision error type 1} \\ c2 & \text{Decision error type 2} \end{cases} \tag{6}$$

2.3 Determination of Parameters

The parameter α in the model reflects the extent to which the trust levels of different users are affected by machine performance and trust in previous moments. In order to determine the parameter α in the model, it is necessary to obtain it using the parameter identification method before applying the model. It is assumed that during the actual task process, the human factors in the model are determined and do not change over time. The method of least squares is used for fitting. The basic principle of the least squares method is to find the best function match for the data by minimizing the sum of the squares of the errors, and it is widely used in linear problems.

The main steps are as follows:

Step 1. Rewrite the original equation as:

$$T(k) - P(\Delta k) = \alpha(T(k-1) - P(\Delta k)) \tag{7}$$

Define the following variables:

$$y := T(k) - P(\Delta k) \tag{8}$$

$$x := T(k-1) - P(\Delta k) \tag{9}$$

Transform the problem into fitting the parameter α in the equation $y = \alpha x$.

Step 2. Given a set of data $(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)$, define the objective function as:

$$S(\alpha) = \sum_{i=1}^{n} (y_i - a x_i)^2 \tag{10}$$

Since the parameter α is divided into two cases, namely α^+ and α^-, the data will be classified into two categories accordingly. One category is the positive samples n^+, that is (x^+, y^+), and the other category is the negative samples $n^- = n - n^+$, that is (x^+, y^+), which are used to fit α^+ and α^- respectively.

Step 3. In order to find the value of α that minimizes $S(\alpha)$, we take the derivative of $S(\alpha)$ with respect to α for both the positive samples and the negative samples, respectively, and set the derivative equal to zero: $\frac{dS(\alpha)}{d\alpha} = 0$.

Step 4. Solve this equation to obtain the best-fitting values of α, respectively:

$$\hat{\alpha}^+ = \frac{\sum_{i=1}^{n^+} x_i^+ y_i^+}{\sum_{i=1}^{n} (x_i^+)^2} \tag{11}$$

$$\hat{\alpha}^- = \frac{\sum_{i=1}^{n^-} x_i^- y_i^-}{\sum_{i=1}^{n} (x_i^-)^2} \tag{12}$$

By using the above least squares method, the human parameter α can be fitted through the collected data.

3 Trust Calibration Method for Decision-Aids

In this chapter, the meaning and importance of trust calibration are first elaborated. Furthermore, by analyzing the factors that affect trust calibration, the adjustable parameters in the model are determined. Finally, from the perspective of system transparency, a trust calibration method based on transparency is proposed, which enables the adjustment of trust values when trust imbalance occurs.

3.1 Definition of Trust Calibration

Through the trust dynamic evolution model established in the previous section, we can estimate the user's trust level in the decision-aid system in real time according to the performance of the system. However, the user's trust level may not match the actual capabilities of the system, which will lead to a decline in system performance and even cause safety problems. At this point, trust calibration is needed. Define the objective ability of the system as C_m. For a decision-aid system, the objective ability of the system is:

$$C_m = P_a \tag{13}$$

where P_a represents the pre-specified decision accuracy rate of the system. Generally, users will be informed of this information before using the system, and we assume that this value does not change as the task progresses.

Based on the above definitions, the definitions of over-trust and lack of trust can be obtained as follows:

$$\begin{cases} \frac{T(k)}{C_m} > 1 & \text{over-trust} \\ \frac{T(k)}{C_m} = 1 & \text{appropriate trust} \\ \frac{T(k)}{C_m} < 1 & \text{lack of trust} \end{cases} \tag{14}$$

Then the definition of trust calibration is as follows: When there is lack of trust or over-trust, adjust the trust level $T(k)$ so that $\frac{T(k)}{C_m} = 1$.

It is also necessary to determine the timing of trust calibration. Trust calibration needs to be carried out when the trust level $T(k)$ at moment k satisfies the following conditions:

$$\frac{T(k)}{C_m} < \beta^- \tag{15}$$

or

$$\frac{T(k)}{C_m} > \beta^+ \tag{16}$$

where $\beta^+ > 1, 0 < \beta^- < 1$ are the upper and lower thresholds for trust calibration, respectively. In practice, they are generally given according to the task requirements or user experience.

3.2 Trust Calibration Based on Transparency

The transparency of a system refers to how the system presents its output, whether the output meets expectations, and whether the system follows predefined rules [13]. Existing relevant research has confirmed that continuously updated system transparency information can improve trust calibration and enhance the performance of human-machine teams [14]. However, there is also related research indicating that an excessive increase in transparency or frequent switching can increase human workload and have a negative impact [15]. Therefore, it is necessary to first determine the relationship between transparency and the trust level.

The transparency of the system will affect the extent of the change in the trust level caused by the good or bad performance of the machine. In other words, it will affect the human factor α in the model proposed previously. Specifically, the user parameters satisfy a mapping relationship of different transparencies, that is:

$$\alpha = f(tp) \tag{17}$$

where tp represents the transparency of the system, and f represents the mapping relationship between transparency and user parameters. For a decision-aid system, the transparency is mostly in discrete cases of different levels. The more information the system conveys to the user during decision-making, the higher the transparency. Through the data obtained by users training in advance under different transparency levels, the human parameters in the model are fitted to obtain the mapping relationship.

When $T(k)$ satisfies the trust calibration conditions, by adjusting the transparency tp of the system, the value of the human factor α is changed so that the following conditions are met:

$$\alpha^* = \arg\min_{\alpha} \left| \frac{T(k,\alpha)}{C_m} - 1 \right| \tag{18}$$

α^* corresponds to the value of the human factor that makes the human trust level match the objective ability of the system most appropriately.

Finally, the process of the trust calibration method based on transparency is as follows:

Step 1. Determine whether the trust level $T(k)$ at the current moment satisfies the conditions for trust calibration.

Step 2. If the timing for trust calibration is met, then according to (18), select the appropriate system transparency level tp and adjust the human parameter α in the trust evolution model accordingly; if not, skip this step.

Step 3. Continue with the trust evolution at the next moment $k+1$.

4 Simulation Verification

In this section, a tumor prediction medical assistance system in the medical field will be taken as a simulation example to verify the rationality of the proposed trust model and the effectiveness of the trust calibration method.

4.1 Simulation Environment

After being trained with deep learning, this tumor detection aid system can make a decision based on the input images: whether the patient has a tumor. Then, the doctor makes the final diagnosis according to the system's suggestion. For this medical assistance system, if the doctor over-trusts it, the risk of misdiagnosis will increase; conversely, if the doctor under-trusts it, the medical treatment efficiency will be lowered, and medical resources will be wasted.

Specifically, this model was trained using the MRI dataset on Kaggle. 85% of the data was used as the training set, and the remaining 15% was used as the test set. The ResNet50 network was used for training, and the accuracy rate of the final model was 82.5%, that is, the objective ability of the machine is:

$$C_m = P_a = 0.825 \tag{19}$$

Meanwhile, the system is designed with three different transparency levels. Low transparency tp_l The system only provides the final decision result, that is, whether the patient has a tumor or not, without providing any other relevant information. Medium transparency tp_m: On the basis of providing the final decision result, the system gives the confidence level of that decision. High transparency tp_h: Besides providing the final decision result and the confidence level, when the decision result is that the patient has a tumor, the system will also give an additional text reminder.

4.2 Acquisition of Experimental Parameters

When conducting the experiment, it is first necessary to determine the human factor parameters α^+ and α^- in the model. For the three different transparencies, two typical users are involved, namely the more conservative user H_c and the more radical user H_r. The radical user is more inclined to believe the decisions made by the machine, while the conservative user tends to be skeptical. Each time, the experimental data should have no less than 100 groups for both positive and negative samples. The process of obtaining the human factor parameters is shown in Figure 2.

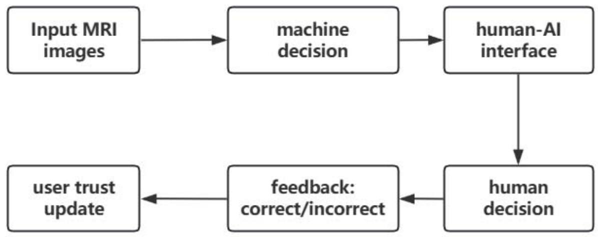

Fig. 2: Process of obtaining human parameters

The initial trust values of the users are set as follows: $T_{Hr}(0) = 0.8$,$T_{Hc}(0) = 0.6$. If the system makes a correct decision, then $P(\Delta k) = 1$; otherwise, $P(\Delta k) = 0$. By repeating this process, collecting data, and using the least squares method for fitting, the human factor parameters of the two types of users under the three transparency levels are finally obtained, as shown in the following table:

Table 1: Human factors under different conditions

transparency	tp_l		tp_m		tp_h	
human factors	α^+	α^-	α^+	α^-	α^+	α^-
H_c	0.764	0.740	0.635	0.765	0.624	0.775
H_r	0.563	0.811	0.425	0.876	0.462	0.865

4.3 Rationality of the Trust Model

After obtaining the human factor parameters through identification, another 40 groups of data sets were selected to conduct experiments under medium transparency levels. The ground trust values of both conservative users and radical users are obtained through the following questionnaire: What do you think is the probability of AI making the right decision? We use the probability that humans believe AI decisions are correct to reflect subjective understanding of the system and represent the true value of human trust. On the other hand, the estimated trust value is calculated by the dynamic model after obtaining the human parameters. The initial trusts were set as $T_{Hr}(0) = 0.8$, $T_{Hc}(0) = 0.6$ respectively. The comparison between the trust evolution situation obtained through model fitting and that obtained from the actual reports of users is shown in Figure 3.

In Figure 3, the red and blue colors respectively represent the trust change situations of the conservative user and the radical user. The solid lines and the dashed lines respectively represent the trust obtained through model fitting and the trust reported by the users themselves. It can be seen that the obtained trust evolution model is close to the trust values actually reported by human users and has the same change

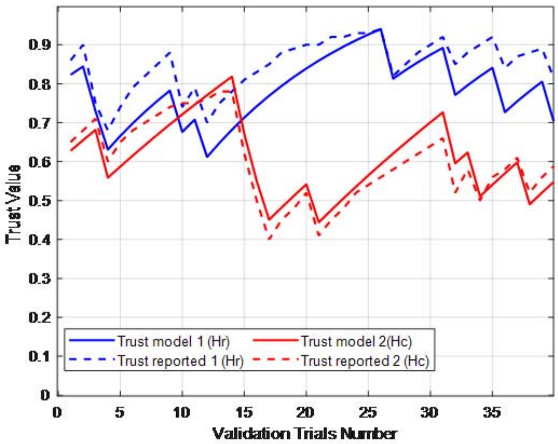

Fig. 3: Trust level of H_r and H_c

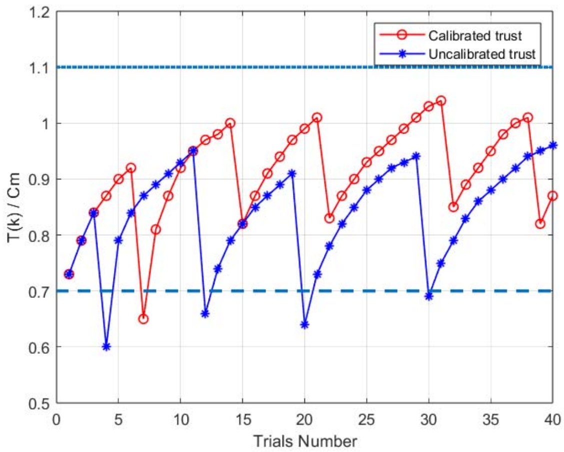

Fig. 4: Trust evolution for conservative users

trend, indicating that the constructed trust model can, to a certain extent, reflect the real situation of the change in user trust. Moreover, it can be observed that the radical user is more inclined to trust the decisions made by the decision assistance system compared to the conservative user, and the opposite is true for the conservative user, which is consistent with the assumptions made before the experiment.

4.4 Effectiveness of the Trust Calibration Method

First, set the upper and lower thresholds for trust calibration. Select $\beta^+ = 1.1$ and $\beta^- = 0.7$. The experiment also involves two typical users with different personalities, H_c and H_r. To facilitate the research of trust calibration for the two trust imbalance phenomena, lack of trust and over-trust, we conduct experiments on the two users separately.

For the conservative user H_c, an initial trust of $T_{Hc}(0) = 0.6$ was selected, and the initial system transparency level was set to low transparency tp_l. The experiment was divided into a contrast experiment with the trust calibration mechanism added and one without considering the trust calibration mechanism. Each experiment was also carried out with 40 groups, and the trust levels reported by the user were recorded respectively. For the experiment with trust calibration added, when the trust level reached the threshold condition, the transparency was switched accordingly to achieve trust calibration. With the simulation trials as the x-axis and $\frac{T(k)}{C_m}$ as the y-axis, the evolution of the trust level is shown in Figure 4:

In Figure 4, 0.7 and 1.1 are the upper and lower limits for trust calibration, respectively. The red line represents the trust level after calibration, while the blue line represents the trust level without calibration. It can be seen that the conservative user is more prone to the phenomenon of lack of trust. When the machine makes the first incorrect decision, the conservative user lacks trust in both conditions. Through the trust calibration mechanism, when there is a lack of trust, the transparency of the system is correspondingly increased, thus augmenting the amount of information accessible to the user. The increase in the trust level after calibration is higher than that in the case without calibration. Moreover, compared with the uncalibrated trust, the calibrated trust value is maintained at a more appropriate level, indicating that adjusting the transparency can effectively alleviate the lack of trust.

The same comparative experiment was carried out for the radical user. An initial trust of $T_{Hr}(0) = 0.8$ was selected, and the initial system transparency level was set to high transparency tp_h. Similarly, each experiment was conducted with 40 groups, and the trust levels reported by the user were recorded respectively. With the simulation trials as the x-axis and $\frac{T(k)}{C_m}$ as the y-axis, the evolution of trust level is shown in Figure 5:

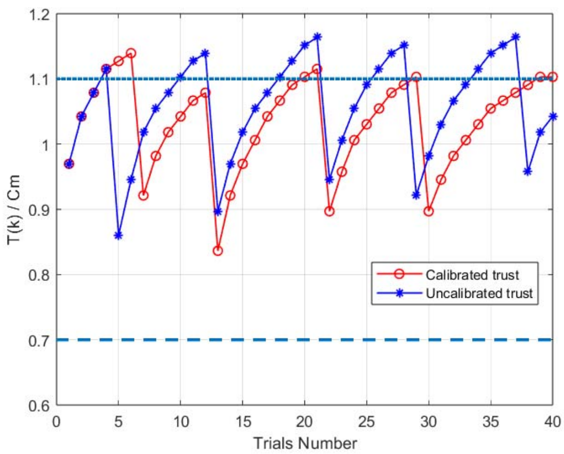

Fig. 5: Trust evolution for radical users

It can be observed that the radical user is more likely to experience over-trusting. Under the condition that the machine makes correct decisions consecutively several times, over-trusting occurred at the moment of $k = 4$ in both experiments. Through the trust calibration method, when over-trusting emerges, the transparency of the system is reduced, thereby decreasing the amount of information accessible to the user. The increase in the trust level after calibration is slightly smaller than that in the case without calibration, and the calibrated trust level is within a more appropriate trust range compared with the uncalibrated one. This indicates that adjusting the transparency can effectively alleviate over-trusting.

Through the simulation analysis of the above two situations, the effectiveness of the proposed transparency-based trust calibration method has been verified. Both the lack of trust and over-trust situations have been alleviated to a certain extent. However, for the over-trust situation, since the machine's performance is mostly correct, the radical user will still tend to experience over-trust. Moreover, due to the limitation of only three transparency levels, it cannot be guaranteed that over-trust will not occur. Further research is needed in the future to propose more powerful trust calibration methods.

5 Conclusion

In response to the issues of the lack of a quantitative trust model and corresponding trust calibration methods in decision-aid systems, this paper first proposes a human-machine trust dynamic evolution model for decision-aid systems, taking system performance and trust at past moments as important factors influencing the evolution. Furthermore, aiming at the possible trust imbalance problems of over-trust or lack of trust, a trust calibration method based on system transparency is designed. The medical diagnosis assistance system is selected for simulation verification. Through experiments on two types of people with different typical personalities, the rationality of the proposed model is verified. Moreover, through the proposed trust calibration method, the phenomenon of trust imbalance is effectively alleviated.

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