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Mental Health Education Model Based on Matrix Decomposition

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Abstract

The exploration on whether it is possible to use the psychological trust relation in the rough open psychological system when the conditions for the use of factor analysis and the multiple regression method are not satisfied, is fundamentalally one of the most complicated social-psychological relations. It involves many factors such as hypothesis, expectation, behavior, and environment. Hence, accurate quantified representation and prediction are tricky. Combined with the cognitive behavior in the human society, a matrix decomposition mental health education model that conforms to the human cognitive habit is proposed: (1) Through the historical evidence window-based adaptive credibility decision, not only the common subjective judgment of weight in the present models can be overcome, but the reliability prediction issue when the direct evidence is insufficient can be resolved; (2) The DTT (direct trust tree) mechanism is used to search and aggregate the global psychological feedback information, to reduce the consumption of the negative psychological factors, enhance the scalability of the psychological system in the large scale psychological system; (3) We introduced the concept of the induced ordered average weighted (abbreviated as IOWA) operator and established an IOWA operator-based psychological trust prediction model to address the poor dynamic adaptability of conventional prediction models. From the results of tests, it can be seen that the model proposed in this paper has greater dynamic adaptability and higher prediction precision than the existing models.

Keywords: *Psychological System; Matrix Decomposition; Mental Health Education Model; Induced Ordered Weighted averaging Operator;*

1. Introduction

Regarding the construction of a dynamic model for predicting psychological trust relations, it is not only a fundamental research subject on “psychological trust management [1-3]” theories and technologies but also a key scientific question to be answered first. In recent years, some scholars studied the psychological trust model in the grid, pervasive computing, P2P, Ad hoc, and other open environments, where multiple mathematical methods and tools are used to demonstrate the complexity, dynamics, and uncertainty of psychological trust relations. Finally, a prediction model is established to show psychological trust relations [4-6]. Undoubtedly, the achievements of these studies have effectively driven the development of theoretical research on measuring the dynamic psychological trust relations, greatly enriched people's further understanding of the connotation of the dynamic psychological trust relation.

To solve the security issue of the mental health service, the concept of "Psychological Trust Management [7]" was put forward. The mechanism of psychological trust management is introduced into the psychological system for the first time.

In recent years, the dynamic psychological trust relations in many distributed applications have been studied by some scholars. Various mathematical approaches and tools are used to establish the model for predicting psychological trust relations, with typical examples as follows: PTM (pervasive trust management) [8] adopts the improved theory of evidence (D-S) to conduct modeling on the psychological trust relation and makes the psychological trust evaluation using the

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probability-weighted averaging method. In the vector mechanism-based psychological trust model [9], the vector computing mechanism is introduced to describe the psychological trust relations. The model makes mathematical quantification for some uncertain factors. Based on the semi-ring algebra theory [10], the psychological trust issue is defined as a path issue of directed graph G (V, E) in the psychological trust model. In the literature [11], psychological trust relations are modeled based on the entropy concept in the information theory. In the literature [12], Power-Trust, a P2P reputation system with robustness and scalability, is developed, which has greatly enhanced the precision of global reputation aggregation. In the literature [13], a psychological trust relation evaluation model for the P2P file sharing psychological system is proposed. The overall psychological credibility is obtained by risk-based direct psychological trust and recommendation-based psychological trust feedback coupling. In the literature [14], PSM, an aggregation method for psychological trust information based on personal similarity is proposed to address the problem of the mean algorithm, which fails to meet the dynamic requirement of the psychological trust. The PSM algorithm can adapt to the malicious feedback of key points properly due to the simple adaptive time window. However, it cannot reflect the dynamic changing trend of psychological trust relations effectively. As a result, the precision of psychological trust evaluation is impacted. In the literature [15], a psychological trust measurement model in the P2P environment is studied. Four parameters (that is, recent psychological trust, long-term psychological trust, punitive factor, and recommended psychological trust) are introduced to show the psychological credibility of key psychological points by mathematical statistics.

To address the above issues, we combined the psychological, cognitive process with the behavior habit of human society on the psychological trust relations to predict the dynamic psychological trust relations by cognitive computing. The conventional model for psychological trust relation prediction is modified to overcome the problems of current models. In Section 1, the study progress of some related work is introduced. In Section 2, the construction of a dynamic model for predicting psychological trust relations by cognitive computing is discussed in detail. In Section 3, the feasibility and validity of the proposed model are verified through simulation tests. In Section 4, the paper is summarized, and the subsequent research plan is described.

2. Mental health education model based on matrix decomposition

2.1 Historical Evidence Window-based Calculation of the Adaptive Overall Psychological Trust

Definition 1. Let P_1, P_2, …, P_N represent the N entities with the interaction behavior in the psychological system, in which an entity can be an element in any mental network, such as a user (critical psychological point), a software service (resource), psychological network equipment, or a dataset. Let Ω = {P1, P2, ..., PN} be a real domain. In any psychological system Ω with the set S, $S \subset \Omega$, and element $o, o \subset \Omega$, there is $\forall s \in S$ where s → o is implemented by operations. S represents a subject domain. Set o represents an object domain, which is expressed as O.

The service requester (abbreviated as SR) falls into O, and the service provider (SP) falls into S.

Based on psychological, cognitive habits, it is their direct experience and judgment that people trust. For those who already have rich direct experience to judge the psychological trust for others, they do not need to consult a third party for advice. Based on this cognition, a new method for calculating psychological trust based on historical evidence window is proposed in this paper:

Definition 2. The overall credibility (abbreviated as OTD), denoted as $\Gamma(P_i,P_j)$, refers to the credibility evaluation of $\forall P_j$ on P_j as a whole based on the interaction history with$\exists P_j$, in which, $P_i \in$S, $P_j \in O$. The direct credibility (abbreviated as DTD) is denoted as $\Gamma_D(P_i,P_j)$, and the indirect credibility

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(abbreviated as ITD) is denoted as Γ_I (P_i,P_j):

$$\Gamma\left(P_i,P_j\right)=\begin{cases}\Gamma_D\left(P_i,P_j\right), & if\ h\geq H\\ \Gamma_D\left(P_i,P_j\right), & if\ h=0\\ \dfrac{1}{1+\beta\left(P_j\right)}\times\Gamma_D\left(P_i,P_j\right)+\dfrac{\beta\left(P_j\right)}{1+\beta\left(P_j\right)}\times\Gamma_I\left(P_i,P_j\right), & if\ 0\leq h\leq H\end{cases} \quad (1)$$

Where h represents all historical evidence (samples) for the interaction between P_i and P_j of the psychosocial system. H represents the maximum historical records in the credibility prediction set by the psychosocial system, that is, historical evidence window. Function $\beta(P_j)\in[0,1]$ indicates the active entity degree of service requester P_j. The active entity degree has reflected the active and stable degree of the entities in the psychological network. human cognition suggests that more providers of feedback indicates a larger number of other entities (providers of feedback) with successful interaction records. The higher the active degree is, it also shows that the higher the feedback credibility P_j has.

A key issue in the study of dynamic psychological trust management is how to gather the feedback psychological trust information in an effective way. In this paper, the DTT (direct trust tree) mechanism proposed by the research group is adopted to carry out the search and aggregation of the global feedback psychological trust information, so as to reduce the psychological negative factor consumption.

As pointed out in the previous analysis, most of the existing psychological trust prediction models adopt the method of direct and indirect psychological trust weighted averaging to calculate credibility. The classification weight adopts the subjective methods (expert opinion, or average weight). The prediction results thus obtained have relatively huge subjective elements. It can affect the scientific nature of decisions and lack flexibility. When determined, the weight can hardly be adjusted dynamically by the psychological system in practice. Hence, the prediction model lacks adaptability. Due to $\beta(P_j)\in[0,1]$, the direct psychological trust (1 + β (Pj) always has a weight lower than the indirect $\beta(P_j)$/+(1+$\beta(P_j)$. In the calculation of the other overall credibility in this paper, the maximum weight $1/(1+\beta(P_j))$ is assigned to the direct psychological credibility of SP in the formula. That is, the service provider always trusts its direct judgment first. However, function β (Pj) is used to determine the weight of the psychological credibility $\beta(P_j)/(1+\beta(P_j))$ in feedback automatically. Hence, the general psychological trust calculation in this paper is an adaptive method for determining the classification weight through the psychological system based on the mathematical model. The formula for function β (Pj) is defined as follows:

$$\beta\left(P_j\right)=\frac{1}{2}\left[\Phi\left(L_{P_j}\right)+\Phi\left(n_{total}\right)\right]$$

Where $\Phi\left(x\right)=1-\dfrac{1}{x+\delta}$, L_{P_j} represents the number of feedbacks, n_{total} represents the number of all entities with interaction with P_j observed by the psychological system. The adjustment constant δ of $\Phi\left(x\right)$ is an arbitrary constant > 0 for controlling the velocity of $\Phi\left(x\right)$ when it approaches 1. A greater value of δ indicates a faster speed at which $\Phi\left(x\right)$ approaches 1. Eq. (2) shows that the entity active degree $\beta\left(P_j\right)$ is jointly determined by variables L_{P_j} and n_{total} . A larger number of other entities trading with the entity indicates higher $\beta\left(P_j\right)$. Meanwhile, more feedback providers

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indicate higher $\beta\left(P_j\right)$. The number of variables L and n_{total} represents the active level of entities in the psychological network. For example, L_{P_j} =55, n_{total} =15, δ=0.2, then $\beta\left(P_j\right)$=0.95.

The proposed OTD calculation method is superior to conventional OTD calculation methods: (1) It better conforms to the human psychological cognition and daily behavior habits: To minimize the risk, people will not consider the advice of a third party unless their knowledge (evidence) is not enough to determine the credibility of others. (2) In a large scale psychological system, it often needs to search for the providers of recommendation in the whole psychological network through broadcasting to obtain the accurate ITD, leading to substantial psychological system overhead. The proposed OTD calculation method can lower the volume of ITD calculation, thereby effectively reducing the computational complexity and overhead of the psychological system. (3) It can solve the problem of evaluating credibility with insufficient direct and indirect evidence.

2.2 Feedback Psychological Trust Aggregation Mechanism Based on DTT

After analysis of the recommendation behavior of human society, we can easily find the following common sense: People are more willing to believe the recommendation information provided from someone they know, and less likely to believe the recommendation from a stranger. Hence, the fundamental psychological cognitive process can be reflected in the aggregation algorithm of the feedback psychological trust. We put forward the concept of direct trust tree (referred to as DTT for short)t, and establish a new scalable psychological feedback trust information aggregation algorithm based on DTT. The algorithm first constructs DTT based on the direct trust relation between the critical psychological points. It then uses DTT to perform psychological feedback trust information search, while introducing two parameters, quality factor, and distance factor, to adjust the scale of the aggregation computation automatically at the same time. Since the construction of DTT is established entirely according to the psychological historical data interaction between the critical psychological points, no excessive time/space overhead or JION/LEAVE message control is required for the maintenance of the ordinary tree topology. Fig. 1 (a) shows the construction method for two subcritical psychological points of critical psychological point P_0 , P_1 and P_2 are two critical psychological points that have integration behavior with P_0, then P_1 and P_2 become the neighbor critical psychological points on DTT. The direct trust of P_0, to P_1 and P_2 constructs the weight of the directed tree. Similarly, P_1 and P_2 have their own neighbor critical psychological points, and so forth, then a weighted directed tree can be constituted.

Definition 3. IDT, also known as feedback credibility (referred to as FTD for short), mainly calculates OTD (P_i trusts P_j , P_j trusts P_k , then P_j trusts P_k) based on the psychological trust transitivity, so we call ITD a feedback psychological trust value provided by a third party. In a certain interactive process, entity P_i needs to assess the entity P_j's feedback credibility. Let the set of the providers of feedback be $\left\{W_1,W_2,...,W_L\right\}$. FTD aggregation function is defined as follows

$$\Gamma_I\left(P_i,P_j\right)=\begin{cases}\left.\sum_{k=1}^{L}\left(\varpi\left(W_k\right)\times\Gamma_I\left(P_k,P_j\right)\right)\middle/\sum_{k=1}^{L}\varpi\left(W_k\right)\right., & L\neq 0\\ 0, & L=0\end{cases} \quad (3)$$

In the Eq., L represents the number of the

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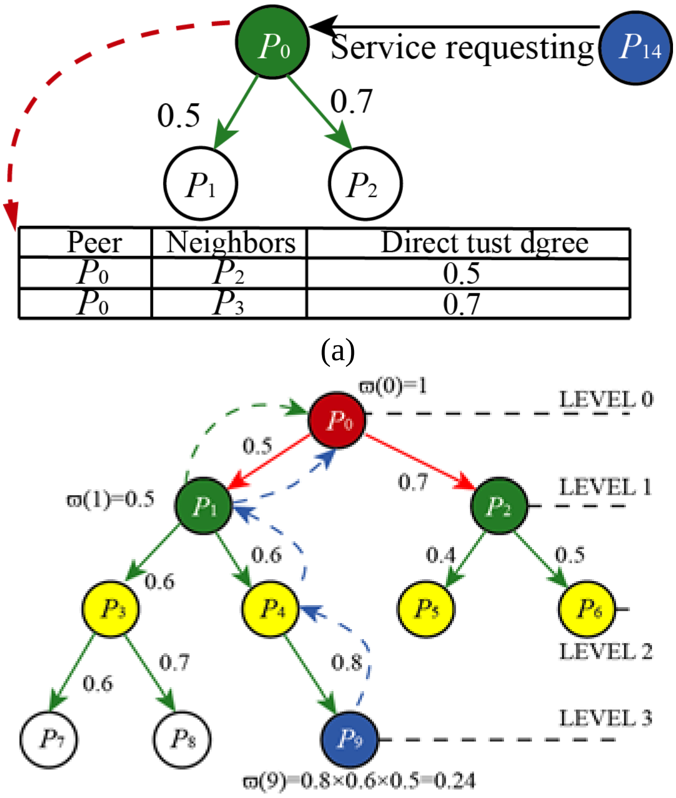
providers of feedback, and $\varpi(W_k)$ represents the weighted factor of the provider of feedback.



(b)

Fig 1. Example of FTD calculation based on DTT

FTD cannot adopt a simple weighted averaging approach, the *LEVEL* of different providers of feedback is different, some providers of feedback are neighbors (*LEVEL* = 0), and some are not (*LEVEL* $\neq$ 0). In Definition 4, we use $\varpi(W_k)$ to weight each of the feedback information. According to the *LEVEL* of each provider of feedback, the definition of $\varpi(W_k)$ is given as follows:

$$\varpi(W_k)=\begin{cases}1, & LEVEL=0\\ \prod_{m=0}^{l}\Gamma_D(P_m,P_n), & LEVEL>0\end{cases} \quad (4)$$

In the Eq., $\Gamma_I(P_k,P_j)$ represents the DTD of P_m to its successor critical psychological point P_n on the psychological trust path from P_0 to P_k, and l represents the layer that the critical psychological point W_k is located. Fig. 1 shows an example of the calculation of DTT-based FTD. Fig. 1 (a) shows the construction principle of the first layer DTT of the critical psychological point P_0, P_1 and P_2 stand for the neighbor critical psychological points of P_0 (that is: P_0 used to have interactive behavior with P_1, P_2, and in the local database of P_0, the psychosocial trust value of P_1 and P_2 is recorded, we call P_0 as the neighbor critical psychological point of P_1 and P_2, similar to the "Acquaintance" in the human society), and P_1 and P_2 also have neighbor critical psychological points, in this way, we can build a DTT tree of the critical psychological point P_0 layer by layer. Since the construction of the DTT is completely maintained by the psychological trust value based on the historical interaction in the local database, the construction of the DTT does not need the JION and LEAVE control messages as required to maintain the structure of the other trees. It can be seen that DTT is a logical data structure established on the basis of the application layer, and the maintenance of the DTT can be achieved with relatively little mental overhead (mainly the overhead to maintain the data sheet for the neighbor critical psychological points).

3. Simulation test and its results analysis

The simulation test is the most extensively used evaluation method for psychological trust models. Computer is used to simulate the interaction between the application scenario and the entity. And the effect of the psychological trust model in solving the practical issue can be evaluated from multiple perspectives. With the increase in the studies of the distributed psychological trust model, test simulation has become the primary evaluation method to evaluate psychological trust models. In this paper, a simulated Peer-to-Peer psychological network environment is implemented through the NetLogo platform to analyze the IOWA model and algorithm performance. NetLogo provides an open simulation platform with its own model database. The users can change the settings of various

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conditions to understand the concept of the modeling by simulating a Multi-Agent complex open psychological system. As a powerful tool used by researchers, it can help modelers instruct thousands of "Independent" agents in parallel operation, which is especially applicable for the complex psychological system that evolves over time.

3.1 Test Setup

Table 1 shows part of the test parameters for the test simulation.

The scenario parameters include:

◊ The type of critical psychological point (entity) in the simulation test:

1) An entity has three roles independent of each other. An entity can be used as SP, SR, and FR. An entity can be a good SP, or a malicious RP. Various identities are independent of and not interfering with each other.

2) FR include four types:

①Subject class H, where real feedback can always be provided;

②Subject class M, where opposite evaluation is always conducted on other subjects;

③Subject class E, where expanded evaluation $\Gamma + \Delta(1-0.5)$ is always conducted (In the simulation test, take $\Delta = 0.5$) on other subjects based on the expansion factor Δ ;

④Subject class C, where the other subjects in the group are classified as 1, and the other subjects as 0.

3) SP includes three types based on the level of service quality: ① GS can always provide reliable services; ② BS always rejects services provided; ③ RS provides GS and BS services with dynamic changes over time.

◊ The dynamics characteristics of the psychological system are mainly demonstrated by physical behavior dynamics of entities in the psychological system. For example, the services provided by SP can dynamically change between the GS, BS and RS. FR can change dynamically in four identities. The entities can also exit and randomly participate in the test. The test reflects the dynamics of the psychological system in three parameters, with the following scenario settings:

1) Let the service request frequency be SRF (0≤SRF≤1), when ($\lceil radom(D+1) \rceil / D$ <SRF(D∈[1…N]), the critical psychological point issues a service request. A higher SRF indicates more frequent service requests, which suggests that the psychological system is busy and dynamic. In the test, SRF is a constant set in the psychological system.

2) Let the service dynamic frequency be SCF (0≤SCF≤1). It indicates the instability of the service provider or resource in the psychological system. A higher SRF indicates more frequent dynamic switching of SP between SP, GS, and RS. In the test, SRF is a constant set in the psychological system.

3) Let the community frequency be SDF (0≤SDF≤1). It indicates the psychological network community uncertainty. In the test, SDF is a constant set in the psychological system. There are SDF × N unstable subjects in the psychological system, and they can exit or particupate the test at any time.

Table 1. Simulation test parameters description

Parameters	Possible values	Description
N	100000	The total number of peers
S	2000	The total running time-steps
H	4	The value of history evidence window
max-*LEVEL*	3	The parameter in DTT
α	0.5-1	The parameter in Algorithm 1

3.2 Precision Evaluation of Forecast Model

Impacted by multiple uncertainties, forecast error is inevitable. Precision refers to the conformity between the measured and real values. It is often measured by error, that is, a smaller error indicates a higher precision; and vice versa. Let A_{t+1} be the actual psychological trust value at the time $t+1$,

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F_{t+1} be the predicted psychological trust value at the time $t+1$. The following is the indexes used in the simulation test to measure the prediction precision of the algorithm:

1) Mean absolute deviation (abbreviated as MAD)

$$MAD = \frac{\sum |e_t|}{m} \tag{5}$$

Where e_t represents the prediction error at the time t, $e_t = A_{t+1} - F_{t+1}$, m is same in Eq. (8) and Eq. (9). MAD measures the absolute error of each predicted value compared with the true value over the entire prediction period (positive or negative, deviation considered only). MAD can adequately represent prediction accuracy but not prediction unbiasedness.

2) Mean absolute percentage error (referred to as MAPE for short)

$$MAPE = \frac{1}{m}\sum \left|\frac{e_t}{A_{t+1}}\right| (\times 100\%) \tag{6}$$

Where e_t represents prediction error at the time t, $e_t = A_{t+1} - F_{t+1}$, m is same in Eq. (8) and Eq. (9). To determine the precision of a predicted value, we need to obtain error e_t and true value A_{t+1}. In the simulation test, the psychological trust degree $\Gamma_D^{(t+1)}\left(P_i, P_j\right)$ of the next timestamp is calculated by Netlogo as the true value of A_{t+1}. Table 1 shows that in the fundamental environment settings, relatively stable community environment (*M*+*E*+*C*=20%, and psychological system with only a small part of the critical psychological points are malicious critical psychological points. SRF=40%, the psychological system is a moderately busy psychological system. SCF = 20%, 80% of SP always provide stable service. SRF = 20%, 80% of entities in the psychological system cannot participate in or exit the psychological system freely, affected by changes in the potential parameter α on the prediction precision of the algorithm. The simulation results are shown in Table 2.

The test results in Table 2 suggest that when the potential parameter α =0.8, the MAD and MAPE corresponding to the IOWA psychological trust prediction model are lower than the other α values in a relatively stable community environment. Hence, α =0.8 is taken as the fundamental value of the potential parameter in the following comparative test.

Table 2. Test results of different parameters α prediction precision

	α=0.5	α=0.6	α=0.7	α=0.8	α=0.9	α=1.0
MAD	0.24808	0.17246	0.130945	0.125950	0.126256	0.126923
MAPE (%)	18.35	17.69	14.72	13.06	13.25	13.64

As can be seen in Fig. 2, the test results of several psychological trust models are compared in a stable community environment. In the simulation test, *M*+*E*+*C*=20% is used, which suggests that only a small proportion (20%) of the critical psychological points in the psychological system are malicious. It also fundamentally complies with the characteristics of an actual psychological network. The reason is that in a practical psychological network, most entities are honest, and only a small part are malicious (20%). In a practical psychological network environment, most service providers can provide a stable service. Fig. 2 (a) suggests that in these 4 models, the average absolute deviation MOW in the IOWA Trust Model is the lowest, with a mean of 0.126, whereas the MAD in the Peer-Trust Model is the highest, with a mean of 0.185. The MAD in the PET Model and the Dy-Trust Model is between the IOWA Trust Model and the Peer-Trust Model, with means of 0.128 and 0.148, respectively. As MAD measures the deviation of a model, a closer value to 0 indicates higher precision of the predicted results. Hence, in the four prediction models, IOWA Trust Model has the optimal precision, whereas Peer-Trust Model has relatively low precision. In Fig. 2 (b), the average absolute error percentages MAPE of the four prediction

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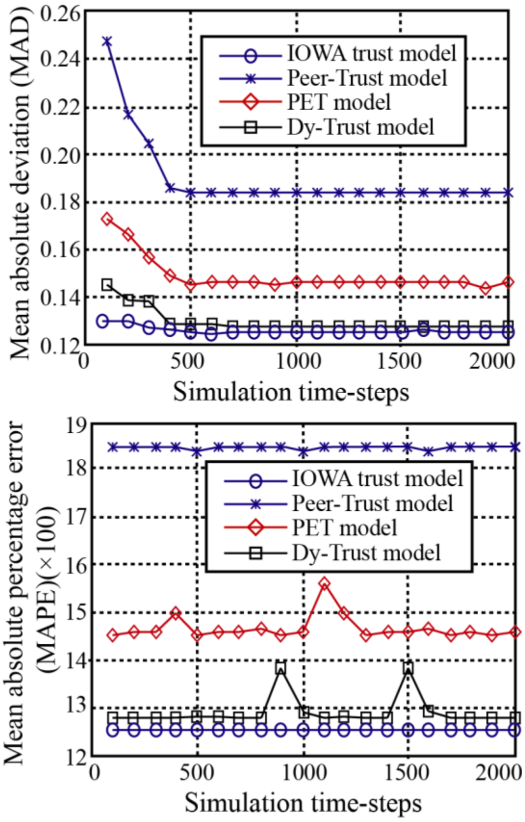
models are compared. The test results essentially comply with those in Fig. 2 (a). The MAPE in the IOWA Trust Model is the lowest, whereas the predicted MAPE in the Peer-Trust Model is the highest. It further demonstrates that IOWA Trust Model has the best prediction precision among the four models.



(a)

(b)

Fig 2. Prediction model precision evaluation test results

3.3 Model Dynamic Adaptability Evaluation

Dynamic adaptability is the ability of the psychological system to provide reliable services under the dynamic influence of various uncertain factors. A dynamic adaptability model with strong dynamic adaptability can continue to provide stable services in the complex dynamic environment and can resist malicious attack and prevent the occurrence of cooperative deception. The dynamic feature in the open psychological system is mainly reflected in the dynamic change of the physical behavior of the entities in the psychological system and the dynamic change of the whole psychological network environment. For example: The services provided by the service provider SP can change dynamically in GS, BS, and RS; the critical psychological point of the provider of feedback FR can change dynamically in four identities; any entity in the entire psychological network can also leave or join the psychological system randomly. The test reflects the dynamics of the psychological system through the three parameters. As shown before, to describe the dynamic change of the psychological system in the simulated test environment, we use three parameters: SRF, SCF, and SDF to carry out the scene simulation, which can be realized through the corresponding random function mechanism.

In the simulation test, we adopt a real-time forecast tracking signal (abbreviated as FTS) to detect the dynamic adaptability of the psychological system. The so-called forecast tracking signal refers to the ratio of the rolling and mean absolute deviation of the prediction error. The calculation method for FTS is as follows:

$$FTS = \frac{RFSE}{MAD} = \frac{\sum_{t} e_t}{MAD} = \frac{\sum_{t=1}^{n} \left(A_t - F_t \right)}{MAD}$$

In which, RFSE (running sum of forecast errors) represents the sum of the errors (error roll) detected in real time, and MAD is the mean absolute deviation (referred to as MAD for short) in Eq. (9). If the prediction model is still valid in a dynamically changing environment, the FTS should be close to 0. Hence, the value of FTS can be used to illustrate the dynamic adaptability of the model. In the scenario simulation environment with various dynamic parameters, the smaller FTS shows that the model has good dynamic adaptability.

Same as in the first group of tests, the types of the feedback subjects FR in this group of simulation test are set as $H80\%$,$M10\%$,$E5\%$ and $C5\%$, respectively. Such value taking is also fundamentally consistent with the characteristics of an actual psychological network. The reason is that in an actual

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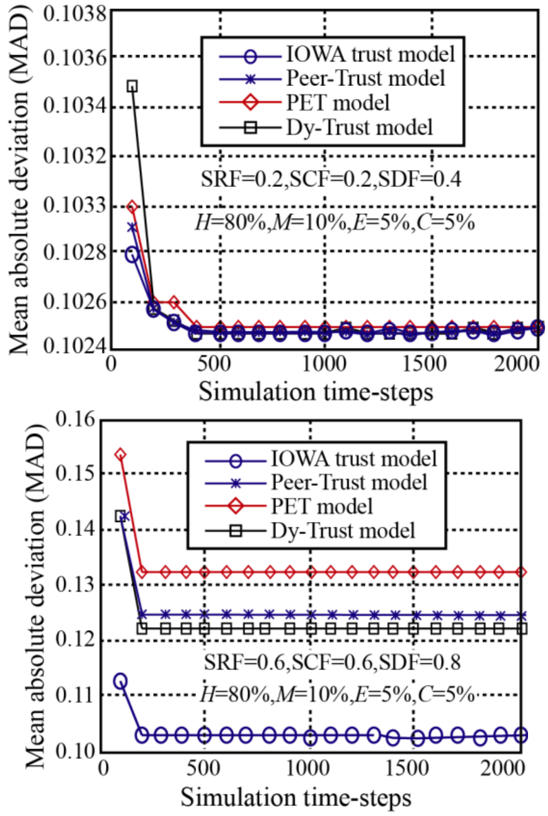
psychological network, most of the subjects are honest subjects (H = 80%), and only a small part of the subjects are malicious subjects (M + E + C = 20%). Firstly, the dynamic adaptability of the model in a psychological network environment with relatively small dynamic changes is observed (as shown in Fig. 3 (a)). SRF value is taken as 20%. It suggests that the psychological system is not very busy. 80% of the critical psychological points are in the idle state. The comparison results of Fig. 3 (a) indicates that the FTSs in the four models are close to each other in a stable environment, which is 0.1024 and 0.1026. It suggests that in a psychological network environment with relatively small dynamic changes, all the four models can provide stable and credible relation prediction services with FTS approaching 0. Fig. 3 (a) also shows that the four models have good dynamic adaptability in the scenario set in the test. The test results in Fig. 3 (b) are the FTS comparative results of the four models in a highly dynamic network environment. In the simulation test, the scenario model setting is as follows: SRF=0.6, indicating that the psychological system is a relatively busy psychological network; SCF = 0.6, indicating that 60% of the service provider's critical psychological points are dynamic critical psychological points. They change their service strategy periodically, and the services provided by 60% of the critical psychological points frequently switch between GS, BS, and RS; SDF = 0.8, indicating that the psychological network is an unstable environment, and 80% of the critical psychological points can join or leave the psychological network freely. The test results in Fig. 3 (b) show that with the increase in the integration business volume of the psychological system and the high fluctuation in the environment, the FTS of the model proposed in this paper is significantly lower than that of the other three models, about 1% ~ 5% lower in average. It indicates that under the scenario set in the test, the model proposed in this paper still has very robust service capability and dynamic adaptability. While the FTS of the PET model is the largest, indicating that the dynamic adaptability of PET model is the weakest among the four models, which is mainly caused by the inadequate depiction of the time decay of the PET model to the psychological PET trust.



(a)

(b)

Fig 3. Model dynamic adaptability evaluation test results

4. Conclusion

The mental health education model aims to explore the human thinking mechanism, especially the mechanism of human information processing, and provide new system architecture and technical methods for designing an AI system. Since human cognitive activities are complicated and diverse, it is challenging to build a mental health education model that can encompass everything. It is usually considered that each cognitive function complies with structural principles based on the modular assumption, and each mental health education model can represent only one (or a few) aspects of cognitive characteristics. To address the poor adaptability of conventional prediction models to

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dynamic changes due to irrational distribution in the classification weight of direct and feedback psychological trust, inadequate representation of the model time decay to the dynamic psychological trust relation in matrix decomposition psychological health education models, and predict psychological trust relations by cognitive computing modeling, we proposed a matrix decomposition mental health education model based on cognitive computing. The historical evidence window-based overall credibility decision method is developed. It can not only overcome the subjective judgment for determining the weight used in the present models but also address reliability prediction issue with inadequate direct evidence. The concept of IOWA is introduced to establish a direct psychological trust prediction model based on IOWA operator to address insufficient dynamic adaptability in conventional prediction models.

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