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REGULAR CONTRIBUTION

A familiarity-based trust model for effective selection of sellers in multiagent e-commerce systems

Jie Zhang · Ali A. Ghorbani · Robin Cohen

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Abstract In electronic marketplaces, trust is modeled, for instance, in order to allow buying agents to make effective selection of selling agents. Familiarity is often considered to be an important factor in determining the level of trust. In previous research, familiarity between two agents has been simply assumed to be the similarity between them. We propose an improved familiarity measurement based on the exploration of factors that affect a human's feelings of familiarity. We also carry out experiments to show that the trust model with our improved familiarity measurement is more effective and more stable.

Keywords Trust · Familiarity · Multiagent systems · E-commerce

1 Introduction

The Internet and other computer networks are changing the conventional way of doing business, leading to the enterprise of electronic commerce. Organizations bring their business on-line. Buyers can make orders directly through network connections from anywhere in the world. These changes provide many benefits, i.e., high business efficiency, reduced operation costs, attracting new customers, accessing more opportunities, convenient shopping, etc [13]. They also offer opportunities for electronic commerce to become increasingly popular and to exist worldwide [17]. For example, electronic commerce in Canada has grown from \$5.7 billion to over \$28 billion from 2000 to 2004 [21]. As also pointed by Noce and Peters [21], electronic commerce keeps growing as many organizations realize the benefits of e-commerce.

Trust plays an important role in e-commerce [12,22]. It provides a form of social control and allows agents in e-marketplaces reason about reliability, capability and honesty of others, in order to choose the best possible business partners. Trust also encourages honest behavior. It is found that the rate of successful transactions on e-commerce systems enforced by trust management remains very high [23]. Using real world applications as examples, Resnick et al. [23] point out that trust is an important key to the successes of the e-commerce systems such as eBay and Amazon. One challenge that arises is to ensure that organizations participating in e-commerce have sufficient trust in order to bring their businesses online. The first step of undertaking the challenge is to study how trust can influence Internet users' decisions and how their trust on the organizations can be built. We are especially interested in the relationship between familiarity and trust and how familiarity can help to make effective selection of business partners through trust.

Researchers have explored the relationship between trust, familiarity and investment. It has been shown that individuals often prefer familiar investments, and fear change and the unfamiliar [3]. This phenomenon shows the effects of familiarity on financial decisions through trust. Gefen [9] studies familiarity and trust in the context of e-commerce based on survey data from 217 potential users of Amazon.com, an e-commerce site on the Internet. The results show that although trust and familiarity are different, trust is significantly affected by familiarity. Gefen also emphasizes the importance of familiarity because it is a building block and a

J. Zhang (✉) · R. Cohen
School of Computer Science, University of Waterloo, Waterloo, Canada
e-mail: j44zhang@uwaterloo.ca

A. A. Ghorbani
Faculty of Computer Science, University of New Brunswick, New Brunswick, Canada

precondition of trust. Minsky [18] distinguishes two kinds of trust, familiarity-based trust and regularity-based trust. Familiarity-based trust is trust based on personal familiarity, whereas regularity-based trust is based on the recognition that the trusted party belongs to a class or a community. Although the focus of Minsky's work is regularity-based trust in e-commerce, he also concludes that familiarity-based trust and regularity-based trust are complementary and regularity-based trust often relies on certain familiarity-based trust.

In order to assist individual users and business organizations in conducting both B2B and B2C e-commerce, researchers in artificial intelligence have been designing intelligent agents to perform the tasks of buying or selling, on behalf of their human clients [16,26]. While these agents assist in offloading the processing required by people in order to find the best business partnerships, it then becomes critical for these agents to make effective decisions. Only when this is done will users and businesses have the confidence to allow agents to reason on their behalf. We then face a different challenge in addressing trust—having agents model the trustworthiness of other agents in the marketplace as an influence in these agents' decision making.

A new trust model has been proposed to effectively formalize agents' trust in multiagent e-commerce systems (see [4]). The concept of trust is viewed as a combination of self-esteem, reputation, and familiarity. Trust is formalized through a concept graph map, which also indicates that the two major factors, reputation and self-esteem, are determined by roles based on the underlying values. Carter and Ghorbani propose that the formalization of familiarity can contribute to the formalization of trust. However, familiarity is simply assumed to be the similarity of the underlying value-systems of the two individuals. On the other hand, Luhmann [15] defines familiarity as a complex understanding, which is often based on previous interactions, experiences, and learning of others. This research suggests that it is desirable to develop a richer model of familiarity, thus enabling agents to learn more about other agents in the multiagent e-commerce system, leading to a more rapid determination of desirable business partners and ultimately resulting in a more stable marketplace.

In this paper, we develop a richer representation of familiarity inspired by a variety of human factors that affect the feeling of familiarity derived from analyses done by many researchers in the fields of psychology and sociology. These factors are prior experience, repeated exposure, the level of processing, and the forgetting rate [29]. We build a hierarchy of all the factors, and map them to the properties of multiagent e-commerce systems. We then propose a way of measuring the familiarity value between two agents and continuously updating the value based on those factors. Once familiarity has been effectively modeled, we discuss how to represent trust using this improved familiarity measurement.

We then argue for the effectiveness of this trust model, for buying and selling agents operating in an e-commerce environment. In particular, we explore how a buyer can use this familiarity-based model of trust in order to make effective selection of selling agents with which to do business. We demonstrate that the multiagent e-commerce system using the trust model is able to assist buyers in selecting the most trustworthy selling agents to do business with. We further analyze the stability of the system. In our case, this is derived from the ranking of selling agents performed by all buying agents reflecting their level of trust in those selling agents. A high stability implies that sellers will not change much in their ranking within the system. We carry out experiments to compare the stability of the system that uses the trust model with the improved familiarity measurement and that with the fixed familiarity value. Experimental results show that the stability of the system is increased by 33.47% through the application of the improved familiarity measurement. The higher stability is also explained by two phenomena: when buying agents rank selling agents, these sellers in the system can find their position in the trustworthiness ranking more quickly; and they will more likely retain correctly the appropriate rankings.

The rest of the paper is organized as follows. In Sect. 2 we briefly explain the familiarity-based trust model. In Sect. 3 we describe in detail all the major factors affecting familiarity, and formalize the way of measuring and updating familiarity. We provide examples to step through our improved familiarity measurement, compare our measurement with the similarity-based measurement, and demonstrate effects of familiarity parameters in Sect. 4. We then discuss the simulation of the e-commerce based multiagent system that is used to objectively examine the trust model in Sect. 5. Experimental results are presented and discussed in Sect. 6. Finally, the conclusions of the present study and future work are presented in Sect. 7.

2 The trust model

Carter and Ghorbani [4] have established a new model of trust formalization for agent societies with the primary goal of clarifying the concept of trust. This work is carried out based upon their previous research of formalizing reputation within the confines of an information sharing multiagent society [5]. The new model proposes that trust is a combination of self-esteem, reputation, and familiarity within a multiagent system context. The set of dependencies amongst those concepts are further discussed through the concept graph illustrated in Fig. 1. The concept graph denotes that trust can be defined as being dependent on an agent's reputation. Reputation, in turn, is dependent on the roles that are used to define it, such as a seller and a buyer. Reputation of an agent occurs

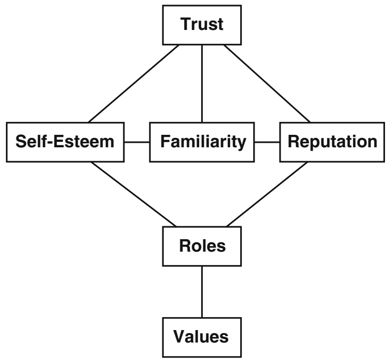

Fig. 1 Concept graph of trust [4]

on a personal and social basis. Personal reputation that an agent has of another agent is based on the enforcement of role ascription of the formal agent onto the latter one. Social reputation is ascribed by society based on a set of commonly agreed upon roles. Trust can also be defined as being dependent on self-esteem. Self-esteem acts as an assessment of the trustworthiness of an agent in its own trusting mechanism. Finally, as with people, trust between two agents is also dependent on familiarity between them.

Roles act as a manifestation of values. Different roles have been chosen based on the agent type. In a multiagent e-commerce system, an agent can be seen as a seller or a buyer. Different values are also defined for this trust model. The values of responsibility, independence, obedience, benevolence and capability are embedded directly within the role of a buying agent. Independence implies self-reliance. For instance, a independent buying agent should rely on itself about assessing the trustworthiness of other agents. Benevolence indicates a buying agent's willingness of helping another buying agent (for example, in providing information about selling agents). A selling agent must value honesty and obedience. A honest selling agent will not misrepresent the quality of its products, therefore will not lie about the prices of the products. Obedience of a buying or selling agent implies that the requests of the agent's owner (buying or selling a product) always have higher priority over other agents' requests (asking for recommendations). These values enable a non-trivial update of trust. This is similar in spirit to the cognitive attribution process proposed by Falcone and Castelfranchi [8]. They claim that update of the trust agent a_i has of agent a_j from a_i's direct experience with a_j should be based on not only the amount of a_j's success and failure, but also other cognitive attributes, for instance, a_i's reliance on a_j.

The concepts discussed above are linked to the idea of fulfillment. The model proposes that an agent's trust is ascribed based on the degree of role fulfillment assessed in accordance with the goals and ideals of other agents. In this sense, it is similar to the Socio-cognitive model of trust proposed by Castelfranchi and Falcone [6]. For example, they claim that in order for an agent a_i to trust another agent a_j, a_i must have some goal, and must believe that a_j is willing to do what a_i needs and is capable of doing so. In order to formalize trust, the measurement of each role's degree of role fulfillment has been established [4]. For example, a selling agent's honesty can be measured as the ratio of the number of honest reports of product quality to total number of reports. The independence of an agent can be measured based on the ratio of the number of requests issued by that agent that are deemed necessary to the total number of its requests.

3 Familiarity measurement

In the work of Carter and Ghorbani [4], they propose that the formalization of familiarity can contribute to the formalization of trust. However, the familiarity between two agents is roughly the similarity between them based on the argument that familiarity is a result of similarity in the underlying value-systems of the two individuals. Similarity of two agents is measured based on the Hamming distance of their value hierarchies, each of which is a vector of value importance. As an example, the vector $H = \{4, 3, 2, 1\}$ represents the importance of four predefined values. It indicates that the value corresponding to the fourth element is the most important while the element in the first position is the least important. The vector of value importance is fixed for each agent. Therefore, the similarity value of two agents is also fixed for them.

As stated in [15], familiarity should be a complex understanding, often based on previous interactions, experiences, and learning of others. Experience is also often conceptualized as familiarity. For example, in their study of customer familiarity and its effects on satisfaction and dissatisfaction, Söderlund and Gunnarsson [25] measure a customer's familiarity with an airline based on the number of times the customer has made trips with this airline. Loken and Ward [14] also measure familiarity as frequency of encounter.

In multiagent e-commerce systems, agents make effective decisions on behalf of human users, based on their learning of the environment and of the other agents. Since these agents act on behalf of humans, it is useful to explore factors that affect human familiarity, when equipping agents with methods for measuring trustworthiness of other agents. In addition, we are interested in mapping those factors to the properties of multiagent e-commerce systems. By doing so, we will propose an improved familiarity measurement for the buying and selling agents of those electronic marketplaces.

3.1 Factors affecting familiarity

Some factors to include in our model of familiarity are motivated by research on familiarity in the fields of psychology and sociology [19,27,28]. Yonelinas [28] reviewed 30 years of studies of two types of memories: recollection and familiarity. He examined the models and methods that have been developed to measure recollection and familiarity. The focus of his work was to review how differently each factor can affect recollection and familiarity. He concluded that there are some factors affecting familiarity, such as the forgetting rate and the level of processing. Whittlesea [27] carried out experiments based on human's memory of four-letter words. Although experimental results show that feelings of familiarity can be aroused in the absence of prior experience, he did point out that prior experience can produce feelings of familiarity. Experiments on recognizing people's faces were carried out by Moreland and Zajonc [19] to explore the relationship between familiarity, similarity and attraction. In this work, they defined familiarity in terms of actual frequency of exposing objects, which implies that repeated exposure can increase familiarity. In summary, the major factors affecting a human's feelings of familiarity are prior experience, repeated exposure, level of processing, and forgetting rate. Exploration of each factor is further described separately as follows:

- Prior experience:[1] Prior experience produces feelings of familiarity [27]. The source of prior experience is not necessarily the object itself, but the meaning of it or an object which semantically relates to the current object. As also stated in [28], familiarity relies on memory of prior experience. For example, it arises when processing of an object is attributed to prior experience with the object or similar objects.
- Repeated exposure: The methods used for experiments in [19] imply that repeated exposure will increase the feeling of familiarity. The repeated exposure in their experiments is represented as the frequency with which the same photograph of a person's face is shown.
- Level of processing: The amount of familiarity that can be gained from processing is associated with the level of the processing [28]. Deep processing (processing the meaning) leads to greater increase in familiarity than shallow processing (processing the perceptual aspects). For example, the process of a word's meaning can increase familiarity more than that of judging whether the word is in upper or lower case.
- Forgetting rate: Both immediate delays and long-term delays decrease familiarity [28]. As an example, the results of experiments on item recognition conducted by Hockley in [10] show that across 32 intervening items in a continuous recognition test, familiarity for single items decreases significantly.

[1] Note that in our work experience and knowledge are two exchangeable terms, because it is reported by several studies that familiarity is positively associated with knowledge [24]. Söderlund [24] also uses experience as one kind of measure for knowledge.

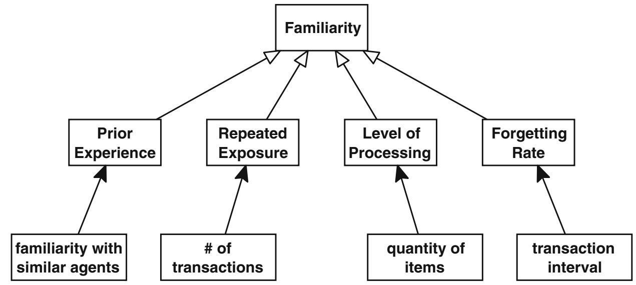

Fig. 2 Mapping human factors to properties of multiagent e-commerce systems

The four major factors affecting familiarity (prior experience, repeated exposure, level of processing and forgetting rate) can be mapped to properties of multiagent e-commerce systems as shown in Fig. 2. For a buying agent and a selling agent in the system that have not encountered each other, the buying agent's prior experience with the selling agent is based on its familiarity with other similar selling agents. Repeated exposure is represented by how many transactions have been established between the two agents. The feeling of familiarity will be increased after each transaction established by two agents. The more times agents interact with each other and establish transactions, the more familiar they will be with each other. Level of processing is determined by the quantity of items bought in each transaction. A greater number of items involved in the transaction implies a deeper level of processing, which will lead to a greater increase in familiarity. The forgetting rate is calculated based on the interval between the last transaction and the current transaction, and the character of the system. The longer the interval between the transactions of agents, the greater the decrease in the feeling of familiarity.

3.2 The improved familiarity measurement

Having explored the factors affecting agents' familiarity and mapped the factors to the properties of multiagent e-commerce systems, we propose an improved familiarity measurement. The improved familiarity measurement consists of two stages. Before a buying agent b establishes the first transaction with a selling agent s, its prior experience with s is based on its initial familiarity value with s. The initial familiarity value b has with s is determined based on its familiarity with other selling agents that are similar to s. In the second stage, the familiarity value between these two agents will then be updated before each transaction. It will be decreased or increased based on three factors, including repeated exposure, level of processing, and forgetting rate.

3.2.1 Initializing the familiarity value

Besides the selling agent s, we suppose that there are n other selling agents $\{s_1, s_2, \ldots, s_n\}$ in the multiagent e-commerce system. Let $F(b, s_i)$ represent the familiarity that s has with one of the selling agent s_i $(1 \leq i \leq n)$ and $S(s, s_i)$ represent the similarity between s and s_i. Similarity between two agents is determined based on the Hamming distance of their value hierarchies, each of which is a vector of value importance, as follows:

$$S(s, s_i) = 1 - \frac{H(\tau_s, \tau_{s_i})}{N}, \tag{1}$$

where τ_s and τ_{s_i} are the value hierarchies of s and s_i respectively, and N is the total number of values each seller has. The Hamming distance of the two value hierarchies is the total number of values that have different importance.

If the buying agent b has not encountered s before, its initial familiarity value with s can be determined by how much it is familiar with other selling agents that are similar to s. We believe that the agents that are more similar to s can affect b's feeling of familiarity with s more heavily. Thereby, we use a weighted average function to compute the initial familiarity value as follows:

$$F_0(b, s) = \sum_{i=1}^{n} \left[F(b, s_i) \frac{S(s, s_i)^2}{\sqrt{\sum_{i=1}^{n} S(s, s_i)^2}} \right], \tag{2}$$

where $F \in [0, 1]$ and $S \in [0, 1]$.

Inspired by the work of Söderlund and Gunnarsson [25] that uses experience to measure familiarity, we also believe that the familiarity value increases with the increase of experience following the trend of a logic function, such that familiarity value increases rapidly with the increase of experience when experience is little but slowly when experience is great. The value of familiarity can be calculated from the experience that the buying agent b has with the selling agent s as follows:

$$F_c(b, s) = \frac{2}{1 + e^{-E_c(b,s)}} - 1, \tag{3}$$

where $F_c(b, s)$ and $E_c(b, s)$ represent the familiarity value and the experience value that the agent b has from the perspective of the agent s before the current, c, transaction, respectively. Note that $E \in [0, +\infty]$.

The prior experience the buying agent b has with the selling agent s is associated with its initial familiarity value with s. According to Eq. 3, the prior experience E_0 can be calculated as follows:

$$E_0(b, s) = -\ln\left(\frac{2}{F_0(b, s) + 1} - 1\right). \tag{4}$$

Equation 3 will be also used when updating familiarity from experience.

3.2.2 Updating the familiarity value

We first update the buying agent's experience. Since the familiarity value is affected by the previous level of processing and the forgetting rate, a simple formula for updating the buyer's experience is as follows:

$$E_c(b, s) = E_p(b, s) + L_p(b, s) - G_p(b, s), \tag{5}$$

where $E_p(b, s)$ and $E_c(b, s)$ represent the experience values that buying agent b has with the selling agent s before the previous and the current transactions, respectively. $L_p(b, s)$ is the level of processing of agents b and s during the previous transaction, and $G_p(b, s)$ represents the forgetting value between the previous and the transactions. When the current transaction is the first transaction between b and s, $E_p(b, s)$ is the same as $E_0(b, s)$, which can be determined by Eqs. 2 and 4. In this case, $L_p(b, s)$ and $G_p(b, s)$ both are equal to 0.

Bahrick [1] observes students' learning of Spanish with different levels of training. He uses a variety of criteria to score students' learning, such as number of Spanish courses taken. The scores increase exponentially with the increase in the level of training, which implies that the learning curve should be similar to an exponential curve. We formulate the learning rate as follows:

$$\gamma_p = 1 - e^{-Q_p/l}, \tag{6}$$

where Q_p represents the quantity of the items in the previous transaction and l represents the learning coefficient. The value of l may differ for different systems. It can be determined by analyzing how much the number of items in a transaction can increase the buyer's experience. Learning is also affected by the previous experience that the buyer b has with s. Thus, the previous level of processing the buying agent b has of the selling agent s can be calculated by:

$$L_p(b, s) = E_p(b, s)\gamma_p, \tag{7}$$

where $E_p(b, s)$ is the previous experience that b has with the seller s.

After the previous transaction, the buying agent b starts forgetting. The forgetting value of agent b and agent s can be calculated as follows:

$$G_p(b, s) = (E_p + L_p)r_p = E_p(2 - e^{-Q_p/l})r_p, \tag{8}$$

where r_p is the forgetting rate for the previous transaction. It is similar to formulation proposed in [11] that the forgetting value is also based on the experience that b has with the selling agent s up to the moment when the transaction is completed. The more experience the buying agent b has with the selling agent s, the more b will forget in the same period of time. As discovered by Ebbinghaus in 1885 [7], forgetting has an exponential nature. Thus, the forgetting rate can be roughly described by the following formula:[2]

$$r_{\mathrm{p}} = 1 - \mathrm{e}^{-\triangle t_{\mathrm{p}}/m}, \tag{9}$$

where m represents the memory coefficient, and $\triangle t_{\mathrm{p}}$ represents the time difference between the current transaction and the previous transaction of agents b and s. Note that although it slightly changes for different agents, m differs largely for different agent societies with different characteristics. Similarly, we can determine its value by analyzing how much experience will be decreased in a time period.

Finally, the current experience that agent b has with agent s is updated as follows:

$$E_{\mathrm{c}}(b, s) = E_{\mathrm{p}}(b, s)(2 - \mathrm{e}^{-Q_{\mathrm{p}}/l})\mathrm{e}^{-\triangle t_{\mathrm{p}}/m}. \tag{10}$$

The updated familiarity value that the buying agent b has with the selling agent s can be calculated from b's updated experience with s through Eq. 3.

4 Examples

In this section, we first use a simple example to go through each step of our measurement to demonstrate how to measure a buying agent's familiarity with a selling agent. We also compare our improved familiarity measurement with the similarity-based measurement. Finally, we present a more elaborate example to demonstrate the effects of different parameters used in our improved familiarity measurement.

4.1 Measuring familiarity

Let's consider a system involving one buying agent b and four selling agents $\{s_1, s_2, s_3, s_4\}$. We want to measure the familiarity value b has with s_1. Agent b has not met agent s_1 before, but it has previously encountered the three other selling agents. We assume that the familiarity values that b has with s_2, s_3 and s_4 are as follows:

$$F(b, s_2) = 0.7$$
$$F(b, s_3) = 0.4$$
$$F(b, s_4) = 0.2.$$

We also assume that each seller has ten different kinds of values $\{v_1, v_2, \ldots, v_{10}\}$. The importance of each value can be chosen from $\{1, 2, 3, 4, 5\}$, where the smaller numbers represent that the corresponding values are more important. In this case, "1" indicates that the corresponding value is the most important, and "5" indicates that the corresponding value is the least important. The value hierarchies of the four sellers representing the importance of each value are listed in Table 1. From the value hierarchies of sellers, we can calculate the similarity values between the seller s_1 and the three other selling agents based on the Hamming distances of their value hierarchies, using Eq. 1 as follows:

Table 1 Value hierarchies of sellers

v_i	v_1	v_2	v_3	v_4	v_5	v_6	v_7	v_8	v_9	v_{10}
s_1	1	2	3	4	5	1	2	3	4	5
s_2	1	2	4	3	1	2	3	4	5	2
s_3	1	2	3	5	4	2	3	4	5	2
s_4	1	2	3	4	1	2	3	4	5	2

$$S(s_1, s_2) = 1 - \frac{H(\tau_{s_1}, \tau_{s_2})}{N} = 1 - \frac{8}{10} = 0.2$$
$$S(s_1, s_3) = 0.3 \quad S(s_1, s_4) = 0.4.$$

The initial familiarity b has with s_1 then can be calculated by Eq. 2 as follows:

$$F_0(b, s_1) = \frac{0.7 \times 0.2^2 + 0.4 \times 0.3^2 + 0.2 \times 0.4^2}{\sqrt{0.2^2 + 0.3^2 + 0.4^2}} = 0.18.$$

From the initial familiarity value, we can calculate prior experience b has with s_1 using Eq. 4 as follows:

$$E_0(b, s_1) = -\ln\left(\frac{2}{0.18 + 1} - 1\right) = 0.36.$$

We assume that buying agent b conducts a transaction with agent s_1. In this transaction, they exchanged three items. We assume that the time interval between the first transaction and the second transaction is 10 days. We also assume that agent b has the learning coefficient of 10 ($l = 10$) and the memory coefficient of 100 ($m = 100$). We can update the experience agent b has with s_1 using Eq. 10:

$$E_1(b, s_1) = 0.36 \times (2 - \mathrm{e}^{-3/10})\mathrm{e}^{-10/100} = 0.41.$$

Finally, the current familiarity value b has with s_1 can be calculated from Eq. 3 as follows:

$$F_1(b, s_1) = \frac{2}{1 + \mathrm{e}^{-0.41}} - 1 = 0.2$$

which indicates that the familiarity value has been increased up to the moment of the second transaction.

[2] This is also similar in spirit to the forgetting factor introduced in [11], such that the forgetting factor can be calculated as $\mathrm{e}^{-1/m}$.

4.2 Comparison of familiarity measurements

In this example we have the buying agent b measure two different selling agents s_5 and s_6. s_5 is a honest selling agent. It will always truthfully represent the quality of its products and offer true prices for the buying agent's requests. s_6 is a dishonest selling agent, and it will always misrepresents the true quality of its products. Therefore, the buying agent b will always choose s_5 to do business with. To simplify the example, we assume that b purchases three items from s_5 on each day, from day 1 to day 5. We also assume that the initial familiarity values between b and the sellers both are 0.18, which is the similarity between b and the sellers. We set the learning coefficient l to be 10 and the memory coefficient m to be also 10. We update the familiarity between b and the two sellers before each day. Note that the familiarity value has not been changed before the first day because the buyer has not done business with any of the sellers and there is no forgetting either. The familiarity values between b and the two selling agents before each other days (from day 2 to day 6) are listed in Table 2.

From Table 2, we can see that the familiarity between b and s_5 has been increased before each day because of learning, whereas the familiarity between b and s_6 has been decreased because of forgetting. Therefore, the difference between familiarity values of s_5 and s_6 has been enlarged (from 0.07 to 0.41). However, the familiarity values measured as similarity between b and the two selling agents will stay the same, which is based on the Hamming distance between their value hierarchies.

4.3 Varying various familiarity parameters

We provide here an extended example to demonstrate the effects of different parameters used in our improved familiarity measurement. In this example, we have three buying agents b_1, b_2 and b_3 measure their familiarity with the same selling agent s. We assume that each buyer b_j ($j \in \{1, 2, 3\}$) has a different initial familiarity value ($F_0(b_j, s)$) with the seller s. Based on the initial familiarity values, we calculate the prior experience each buyer has with s using Eq. 4, as listed in Table 3.

We assume that each buyer purchases some number of items from the seller s. Here, we demonstrate how different numbers of items Q_0 in their transactions and different values of the learning coefficient l will affect the learning rate γ_0. As listed in Table 4, a larger number of items involved in the transaction will produce a higher learning rate. In addition, for the same number of items, the smaller value of learning coefficient will also produce the higher learning rate. For continuing our demonstration, we set $l = 10$ for each buyer and assume that each buyer purchases six items in the transaction. Therefore the learning rate of each buyer is 0.45. The previous level of processing each buyer has of the selling agent s can be calculated as follows:

$$L_0(b_1, s) = E_0(b_1, s)\gamma_0 = 0.1 \times 0.45 = 0.05$$
$$L_0(b_2, s) = E_0(b_2, s)\gamma_0 = 0.4 \times 0.45 = 0.18$$
$$L_0(b_3, s) = E_0(b_3, s)\gamma_0 = 0.85 \times 0.45 = 0.38.$$

We can see that the more previous experience that the buyer has with the seller s also produces the higher level of processing.

We also assume that there is a time interval between the first transaction and the second transaction each buyer has with the seller s. We demonstrate how different time intervals $\triangle t_0$ and different values of memory coefficient m can affect a buyer's forgetting factor r_0. As can be seen from Table 5, for the same memory coefficient, when the time interval is longer the forgetting factor will also be larger. For the same time interval, the forgetting factor will become larger when the memory coefficient is smaller. We set $m = 100$ and $\triangle t_0 = 9$ for the buyers b_1 and b_2. According to Table 5, the forgetting factor of b_1 and b_2 is 0.09. We also set $m = 100$ and $\triangle t_0 = 22$ for the buyer b_3. The forgetting factor of b_3 is then 0.2. The forgetting values the buyers have of the seller s can be calculated as follows:

Table 2 Familiarity values of s_5 and s_6

Day	2	3	4	5	6
$F(b, s_5)$	0.23	0.28	0.35	0.43	0.52
$F(b, s_6)$	0.16	0.15	0.13	0.12	0.11
$F(b, s_5) - F(b, s_6)$	0.07	0.13	0.22	0.31	0.41

Table 3 Prior experience b_j has with s

b_j	b_1	b_2	b_3
$F_0(b_j, s)$	0.05	0.2	0.4
$E_0(b_j, s)$	0.1	0.4	0.85

Table 4 Learning rate for different values of Q_p and l

Q_0	3			6		
l	10	20	30	10	20	30
γ_0	0.26	0.14	0.1	0.45	0.26	0.18

Table 5 Forgetting factor for different values of Q_p and l

$\triangle t_0$	9			22		
m	40	80	100	40	80	100
r_0	0.2	0.11	0.09	0.42	0.24	0.2

$$G_0(b_1, s) = (E_0 + L_0)r_p = (0.1 + 0.05) \times 0.09 = 0.01$$
$$G_0(b_2, s) = (0.4 + 0.18) \times 0.09 = 0.05$$
$$G_0(b_3, s) = (0.85 + 0.38) \times 0.2 = 0.25.$$

From the values of $G_0(b_1, s)$ and $G_0(b_2, s)$, we can see that the more experience the buyer has with the seller, the larger forgetting value it has of the seller, for the same forgetting factor.

We summarize the amount of each buyer's learning and forgetting in Table 6. Using Eq. 5, we can update the experience the buyers have with s as follows:

$$E_1(b_1, s) = E_0 + L_0 - G_0 = 0.1 + 0.05 - 0.01 = 0.14$$
$$E_1(b_2, s) = 0.53 \quad E_1(b_3, s) = 0.98.$$

Finally, the current familiarity values the buyers have with the seller can be calculated using Eq. 3, as follows.

$$F_1(b_1, s) = 0.07$$
$$F_1(b_2, s) = 0.26$$
$$F_1(b_3, s) = 0.45.$$

We also list the familiarity and experience values in Table 7. Comparing the initial familiarity and experience values with the updated familiarity and experience values, the amount of increased experience the buyers b_2 and b_3 have with s is the same, such that $E_1 - E_0 = 0.13$. However, the amount of increased familiarity value the buyer b_2 has with s (0.06) is larger than that b_3 has with s (0.05). This indicates that the increase of familiarity value is larger with the increase of experience when experience is little but smaller when experience is great, for the same amount of increase in experience.

5 The simulated multiagent e-commerce system

The trust model with the improved familiarity measurement is now examined within the context of an e-commerce framework. The e-commerce based multiagent system (shown in Fig. 3) is composed of buying (b) agents and selling (s) agents that wish to conduct business, and a market manager (denoted by a pentagon) and a mystery shopper (denoted with a cross symbol) agents.

Table 6 The amount of forgetting and learning

b_j	b_1	b_2	b_3
Q_0	6	6	6
l	10	10	10
γ_0	0.45	0.45	0.45
$L_0(b_j, s)$	0.05	0.18	0.38
$\triangle t_0$	9	9	22
m	100	100	100
r_0	0.09	0.09	0.22
$G_0(b_j, s)$	0.01	0.05	0.25

Table 7 Comparing initial and updated familiarity and experience

b_j	b_1	b_2	b_3
$E_0(b_j, s)$	0.1	0.4	0.85
$E_1(b_j, s)$	0.14	0.53	0.98
$E_1 - E_0$	0.04	0.13	0.13
$F_0(b_j, s)$	0.05	0.2	0.4
$F_1(b_j, s)$	0.07	0.26	0.45
$F_1 - F_0$	0.02	0.06	0.05

Selling agents set prices according to supply and demand functions and quote prices to customers. The selling agents know each other's true selling prices, but are not restricted to quoting the true prices. Each seller is assigned a reputation by a buyer based on the buyer's perception of the fulfillment of the values outlined in Sect. 2.

Buying agents in the agent society form the majority of the population of the multiagent system. They are responsible for fulfilling requests by end-users. End-users supply the quantity of items and the expectation of how much each will cost. Buying agents use both factors to construct measurements of expectation and cost-efficiency fulfillment. After the potential sellers are established, a buying agent must visit the selling agent that currently has highest rank on the list of desirable sellers. The expectation is that once a buyer has increased its familiarity with this desirable seller, the seller will remain highly ranked in the society. The rating of desirability for each seller s from the perspective of buyer b is decided by a shopping factor $\delta(b, s)$ as follows:

$$\delta(b, s) = \frac{T(b, s)}{d(b, s)} \tag{11}$$

$$d(b, s) = |x_b - x_s| + |y_b - y_s|. \tag{12}$$

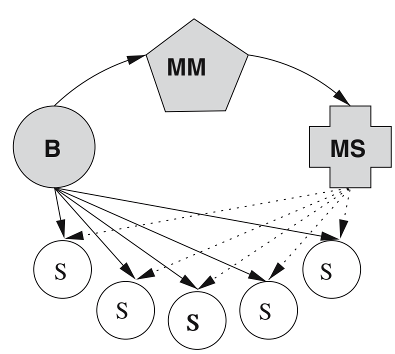

Fig. 3 The multiagent e-commerce system

Here, $T(b, s)$ denotes the trustworthiness of the selling agent s from the perspective of buying agent b based on the trust model. $d(s, b)$ denotes the physical distance between seller s and buyer b. Carter and Ghorbani [4] calculate $T(b, s)$ as follows:

$$T(b, s) = w_1 F(b, s) + w_2 R_\mathrm{p}(b, s) + w_3 R_\mathrm{s} \tag{13}$$

where w_1, w_2 and w_3 are weights of familiarity, personal reputation and social reputation values, respectively, and they sum to one. $F(b, s)$ represents the familiarity of the buying agent b with the selling agent s. We use the improved familiarity measurement to calculate $F(b, s)$. $R_\mathrm{p}(b, s)$ denotes the personal reputation buyer b has of seller s. It is evaluated based on buyer b's direct observations of the seller's degree of role fulfillment. R_s represents the seller's social reputation. It can be acquired by averaging the trust value each buyer has of the seller.

The buying agent engages in a transaction with the selling agent and receives a price quote for the item along with the quotes of fellow competitors. The agent considers the information it has received. Based on a suspicion value, an agent decides whether or not to trust the information provided by the current seller. The suspicion value is measured based on the seller's reputation variance [2]. If the seller's reputation is reduced to a significant degree, the agent will become suspicious of the information provided by the seller. The agent will then return to the request state and engages the next seller on the stack. Otherwise, the agent trusts the currently available information and does not need to visit any more sellers.

The market manager agent is responsible for overseeing the market and enforcing rules to curb macroeconomic behavior of the system. Buying agents that generate an unacceptably large suspicion, report their findings to the market manager agent. When the market manager's profile of a given seller generates enough internal suspicion about the seller, an undetectable mystery shopper is released into the environment to approach the seller. The seller is unable to recognize a mystery shopper. In the case of deceit, the mystery shopper will be lied to and the market manager's suspicions will be confirmed. In such a case, the market manager then reduces the social reputation of the selling agent by decreasing the value fulfillment of honesty. Such reductions take the form of interactions rather than speculations within a buying agent, as the buying agent can always trust the market manager.

6 Analysis

In the previous section, the design of the proposed simulation was presented. This section is devoted to the analysis of the simulated multiagent system that uses the familiarity-based trust model to model trust. The simulation and analysis are based on the trust model introduced in this work using the values and formulas discussed in [4]. The values held by the agents are those already outlined in Sect. 2. Both the two kinds of familiarity measurements, the improved familiarity measurement and the fixed familiarity value calculated by the similarity of two agents, are implemented and embedded in the trust model of the simulation. For later reference, two notions are defined as follows:

- TMIFM: the system using the trust model with the improved familiarity measurement to model trust.
- TMFFV: the system using the trust model with fixed familiarity values to model trust.

We first analyze the effectiveness of the trust model with our improved familiarity measurement. Our model is able to always keep the most trustworthy sellers on the top of buyers' ranking list; therefore it can assist buying agents in selecting the most trustworthy selling agents to do business with. We then compare the stability of the model with the two kinds of familiarity measurements. The stability of the system is considered with respect to trustworthiness rankings. It is increased by 33.47% through the improved familiarity measurement.

6.1 Effectiveness

In this analysis, we further extend the example in Sect. 4.2 to show the effectiveness of the trust model with our improved familiarity measurement. Similarly, we have a honest selling agent and a dishonest one. Eventually, the honest selling agent will have higher chance to do business with buying agents. We measure the familiarity between each of the two selling agents and buying agents on each day. The results are shown in Fig. 4. The familiarity of the two selling agents in TMFFV remains the same. The familiarity of the honest selling agent in TMIFM increases exponentially, whereas the familiarity of the dishonest selling agent in TMIFM decreases exponentially.

Based on the results of specific selling agents shown in Fig. 4, we can analyze the effectiveness of the trust model with our improved familiarity measurement, by extending to the more general case when formalization of trust makes use of our improved familiarity measurement. Buying agents in TMIFM first of all select the most trustworthy selling agents to do business with. The familiarity buyers have with these desirable sellers will also be increased according to our familiarity measurement, which will increase their trustworthiness. At the same time, the untrustworthy selling agents will have less chance to be selected by buyers. The familiarity buyers have with these undesirable agents will also decrease because of forgetting, which will decrease their

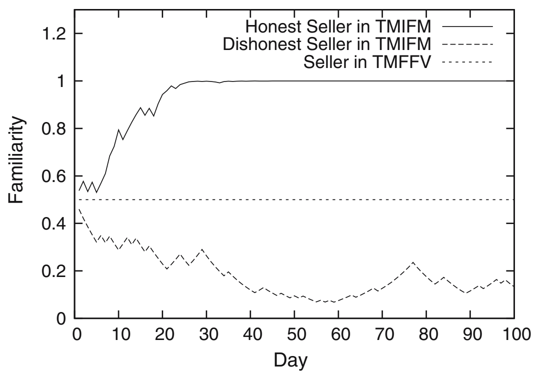

Fig. 4 Familiarity of sellers in TMIFM and TMFFV

trustworthiness. As a result, the gap between trustworthy and untrustworthy selling agents will be enlarged. In brief, the multiagent system that uses the trust model with the improved familiarity measurement keeps the most trustworthy selling agents on the top of the ranking list. Therefore, it is able to assist buyers in selecting the most trustworthy selling agents to do business with.

6.2 Stability

We present as well a comparison of the stability of the system with two kinds of familiarity measurements. Within this work, stability is connected to the idea of ranking. Each selling agent maintains a certain social reputation within the system. These agents can be ranked in ascending order of social reputation. A sample result of ranking is given in Table 8.

The ranking of sellers may shift on a daily basis as presented in Table 8. Stability refers to the degree of change in sellers ranking. A high stability implies that agents will not change much in their rankings. Due to the random nature of the simulation, descriptive statistics must be used to measure the stability in order to eliminate as much randomness as possible in the data. Stability is measured through an examination of the average variance of the selling agents' ranks on a daily basis, as calculated by the formula as follows:

$$\overline{v} = \frac{\sum_{i=1}^{n} v_i}{n}, \tag{14}$$

Table 8 Sample result of ranking

Day	Seller 1	Seller 2	…	Seller m
1	1	5		4
2	2	3		4
3	1	6		3
…				
n	3	5		4

where $\overline{v}$ represents the average variance of the selling agents' ranks and v_i represents the variance of ranking of agent i on a daily basis. Lower values of $\overline{v}$ reflect higher stability.

The comparative stability of TMIFM and TMFFV is presented in Table 9 and Fig. 5. On average, the average variance of TMIFM is 33.47% lower than that of TMFFV, which means that the former is more stable than the latter. Note that the average values in Table 9 are calculated after setting aside the highest and lowest values.

The result can be further illustrated by analyzing the change of rank of any given selling agent as shown in Figs. 6 and 7. From the two figures, it is obvious that the variance of the rank in TMIFM is lower than that in TMFFV. Therefore, TMIFM is more stable than TMFFV.

Experimental results show that the system that uses the trust model with the improved familiarity measurement has higher stability. The reason for this can be explained by analyzing two phenomena in both of the two systems, TMIFM and TMFFV. One phenomenon is that agents are pushed faster to their correct position in trustworthiness in TMIFM compared with TMFFV, which can be seen in Figs. 6 and 7.

Table 9 Comparison of stability of TMIFM and TMFFV

Test #	TMIFM	TMFFV	Percentage difference (%)
1	3.92	5.77	32.06
2	5.61	7.91	29.08
3	6.11	10.12	39.62
4	5.36	8.62	37.82
5	4.00	4.96	19.35
6	3.94	5.61	29.77
7	4.39	7.75	43.35
8	5.11	9.51	46.27
9	4.47	6.10	26.72
10	6.35	7.00	9.29
Average	4.73	7.11	33.47

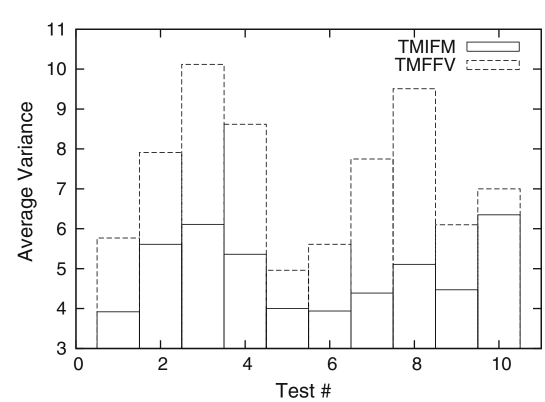

Fig. 5 Comparison of stability of TMIFM and TMFFV

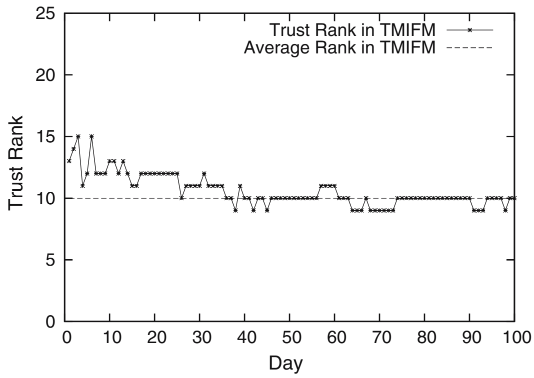

Fig. 6 Change of rank of any given agent in TMIFM

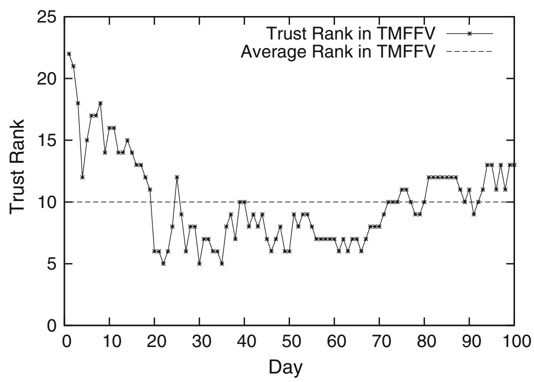

Fig. 7 Change of rank of any given agent in TMFFV

The agent in TMIFM nearly reaches the average line earlier (approximately on day 25) than in TMFFV (approximately on day 40). This happens because the improved familiarity measurement increases the speed of pushing the agent to its preferred position. Compared to the familiarity values of selling agents in TMFFV, familiarity of agents in TMIFM will also be increased/decreased (can be seen from Fig. 4). Therefore, trust values of agents in TMIFM will increase or decrease more rapidly than that in TMFFV.

Another phenomenon is that once agents have been given a position, they remain close to that position. This phenomenon can also be seen in Figs. 6 and 7. From day 25 on, the rank of the agent in TMIFM stays close to the average line, whereas the rank of the agent in TMFFV keeps changing. This phenomenon is also explainable. The selling agents with higher/lower rank have more/less possibility of being selected to establish transactions with buying agents in both TMIFM and TMFFV. The familiarity that buying agents have with these desirable sellers will be increased, and that with undesirable sellers will also be decreased, as illustrated in Fig. 4. Consequently, the familiarity difference of them and the difference in trust values will be enlarged. The desirable selling agents and the undesirable ones will be pushed further in TMIFM than in TMFFV. Therefore, both the selling agents with higher rank (trust values) and those with lower rank (trust values) will more likely stay in their preferred positions in TMIFM.

7 Conclusions and future work

In this paper, we propose an improved familiarity measurement by exploring the factors mainly affecting familiarity. The four factors included in our model are prior experience, repeated exposure, level of processing, and forgetting rate. Those human factors are mapped to the properties of multi-agent e-commerce systems. Note that these factors are motivated by psychological research and as such should provide a good basis for satisfying human users employing agents who model familiarity in this way. We then devised a convenient way to measure and update the familiarity value. The improved familiarity measurement has been integrated into a new trust model. The trust model with the improved familiarity measurement has been examined within the context of the e-commerce framework. We carry out experiments to demonstrate that the trust model with our improved familiarity measurement is more effective for assisting buying agents in selecting the most trustworthy selling agents to do business with. Different experiments are also carried out to compare the stability of the system that uses the trust model with the improved familiarity measurement and that exploited the fixed familiarity value. Experimental results show that the stability has been increased by 33.47% through the improved familiarity measurement.

Our research contributes to the development of electronic marketplaces where human users can feel more secure. The users' trust of their buying agents increases as these agents make effective recommendations of selling agents. An important factor in the selection of a selling agent is its trustworthiness and our research assists in improving the determination of that trustworthiness. This is achieved by incorporating the important consideration of familiarity and by modeling familiarity more accurately.

In multiagent e-commerce systems, selling agents may attempt to raise prices in order to maximize profits. In future work, we will examine how the trust model with the improved familiarity measurement can effectively cope with such dishonest behavior. The effectiveness of the model can be measured by how much the acceleration of inflation can be prevented. The inflation rate can be determined by net aggregate demand and net aggregate supply.

For future work, we will also carry out experiments to compare our model with competing models, such as the beta reputation system [11] and the computational model [20]. The performance of the models could be evaluated, for instance, based on how effectively they can assist buyers in selecting the most trustworthy sellers to do business with.

Furthermore, scalability of a trust model is also crucial. We will conduct experiments to analyze the scalability of the trust model with the improved familiarity measurement over changes in the agent population. We will examine how changes in the agent population will affect stability of the system that uses the trust model. We are encouraged by results presented in [4] that prove the model of Carter and Ghorbani to be scalable over changes in agent population. Our model is an extension of this one, with an improved familiarity measurement. In addition, we know that the improved familiarity measurement is linear in the sense that it updates agents' familiarity values before each transaction. Therefore, our model should also scale well.

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