



## A Reputation Model for Evaluating the Trustworthiness of Agents in E-commerce Multi-Agent Environments

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**Abstract:** This paper aims to enhance trust in e-commerce multi-agent systems by presenting a model to evaluate reputation of provider agents. In this case, we study the most representative trust models in multi-agent systems, which provide different methods for calculating reputation. According to these analysis criteria, a new approach is presented to compute the reputation of provider agents. To evaluate the proposed reputation model, the experimentation was carried out in two stages. First, the average accuracy of model in computing the reputation was evaluated by simulating the proposed approach in a multi-agent environment. Second, the performance of the model was compared with a multi-agent environment which does not apply the proposed model. The experimental results show that the proposed reputation model can evaluate the reputation of providers accurately, and the comparison demonstrates that the proposed model can significantly choose the trustworthy provider agent than the randomly approach without using the proposed model. The ultimate goal of this study is to present a model for computing the reputation of provider agents, and selecting the trustworthy provider based on this computation. We believe that the proposed model will be beneficial to enhance trust in e-commerce environments.

[Kharkwal G, Mehrotra P, Rawat YS. **Taxonomic Diversity of Understorey Vegetation in Kumaun Himalayan Forests.** *Life Sci J* 2021;13(2):50-58] (ISSN:1097-8135). <http://www.lifesciencesite.com>.

8. doi: [10.7537/marswro130221.08](https://doi.org/10.7537/marswro130221.08).

**Keywords:** E-commerce; Multi-agent; Reputation; Trust

### 1. Introduction

The multi-agent systems in an e-commerce environment organize and constrain the actions that the agents can perform at a given time (Tampitsikas, Bromuri, Fornara, & Schumacher, 2012). In particular, intelligent software agents apply information to organize and filter data to meet the user's needs (Khan, Hashmi, Alhumaidan, & Zafar, 2012). It should be considered that many of the methodologies proposed based on the concept of multi agent systems are mainly for developing agent based business applications. It means that the main motivation for these methodologies is to design and develop the business application that is used in the real environment (Mirzaie & Fesharaki, 2012). But e-commerce has increased the likelihood or negative consequences of some risks that already exist in the offline environment and created some risks that are completely new (Zendehdel & Paim, 2012). So, the generation of economic activities via electronic transactions which is based on multi-agent systems require the presence of a system of trust and distrust in order to ensure the fulfillment of a contract (Walter, Battiston, & Schweitzer, 2008; Zhou, 2009),

to minimize the uncertainty associated with interactions in open distributed systems.

In an e-commerce multi-agent environment vital information can be leaked and lost easily without an appropriate solution to support the security of a system (Jung, Kim, Masoumzadeh, & Joshi, 2012; Zacharia, Moukas, & Maes, 2000). While the agents have partial knowledge of their environment and peers, trust plays a vital role to safeguard these interactions (Huynh, Jennings, & Shadbolt, 2004; Maximilien & Singh, 2001). Thereby, management of trust will determine the effectiveness of services marketing efforts (Öztüren, 2013). Many researchers have argued that trust is essential for understanding interpersonal behavior and economic exchanges (Luhmann, 2000; McKnight & Chervany, 2002; Taleghani, 2011), especially through multi-agent systems.

In fact, the most important factor, regarding the trust refers trust of belief (Raisian et al., 2014), it means that a first agent asks a responsible second agent to execute a task, so a belief that the second agent will complete the task is generated. The lack of assurance that a task will be completed is a big problem in task delegation; hence there is a need for

mechanisms which can minimize the risks of unaccomplished tasks (Botêlho, Enembreck, Ávila, De Azevedo, & Scalabrin, 2011; Fullam et al., 2005; Griffiths, 2005) and select the most promising agent. When an agent has to select the most promising agents, it should be capable of allocating a proper weight to the reputation in order to determine the trust (D. Rosaci, 2011). Trust and reputation vectors combine to compute a novel trust factor computation for resource selection (Kumar & Sumathi, 2013). In fact, trust is a reflection of the reputation of an entity which it has been built over time based on the entity's history of behavior, and may be reflecting a positive or negative assessment (Al-Hmouz, Momani, & Takruri, 2013). In particular, reputation is a total measure of trust by other agents in a network of a service provider (Nusrat & Vassileva, 2012). Several researchers have presented trust and reputation models to provide good level of trust in multi-agent environments, but these were not considering the all variables which are necessary for computing the reputation value of agents. Thus, it is the aim of this paper to present a reputation model based on computing the necessary variables which can support a selection of trustworthy agent and enhance trust in e-commerce multi-agent environments.

The rest of the paper is organized as follows: Section Two describes reputation and multi-agent systems, Section Three described the related models. The proposed approach presents in Section Four. This is then followed by evaluation of the proposed model with two stages of experimentations in Section Five, then the experimental results represents in Section Six. Finally, Section Seven contains the discussions.

## 2. Reputation and Multi-agent Systems

Agents are “sophisticated computer programs that act autonomously on behalf of their users, across open distributed environments to solve a growing number of complex problems” (Aref, 2003; Czibula, Czibula, Cojocar, & Guran, 2008; Quteishat, Peng Lim, Tweedale, & Jain, 2009; Ramchurn, Huynh, & Jennings, 2004; Suriyakala & Sankaranarayanan, 2007). In fact, agents can be a human, information systems or any entity (Roadprasert, Chandarasupsang, Chakpitak, & Yupain, 2014). Nature has shown that complex collective behaviors can be made possible by very simple interactions among large number of agents which are relatively unintelligent (Camazine, 2003; Yeom, 2013). Agents who migrate among hosts can be supported by a multi-agent technology (Jiang, Xia, Zhong, & Zhang, 2005). Multi agent system is a rapidly growing field of distributed artificial intelligence that has gained significant position

because of its ability to solve complex real world problems (Aslam et al., 2012).

On the other hand, agent parties in the online environment, should be on safe and secure environment, with minimal risk, and maximal trust (Najafi, 2012). So, trust is a vital feature in the design and analysis of secure distribution systems (Saravanan & Chitra, 2013) such as multi-agent systems. In fact, establishment of trust between stranger agents promises to extend a successful transaction to a much broader range of participants in an multi-agent environment (Yu, Winslett, & Seamons, 2002). According to Gambetta (Gambetta, 2000), “trust (or symmetrically, distrust) is a particular level of the subjective probability with which an agent assesses that another agent or group of agents will perform a particular action”. Trust in multi-agent environments can be derived from direct interactions or recommendations (Manikandan & Manimegalai, 2013). Generally, evaluating trust value of each agent is associated with measuring the reputation of that agent among the network. Reputation is a collective positive evaluation of an agent based on satisfying previous interactions carried out by many agents, while the agent has a self-interested behavior in multi-agent systems.

## 3. Related Works

In this section, we describe two related works which proposed different approach for computing trust and reputation of agents.

### 3.1 Formal Trust Model

Formal Trust Model (Wang & Singh, 2007) presented by Wang and Singh is based on the probability theory. This model divides the outcomes of interactions into positive (satisfying) and negative (dissatisfying) outcomes of past interactions, respectively. The model also combine the trust values from multiple sources (Hang, Wang, & Singh, 2008; Wang & Singh, 2010). This model calculates the trust of each agent according to the posterior probability of satisfying and unsatisfying interactions.

Moreover, this model measures the probability of uncertainty based on two elements, positive and negative outcomes, for combining the trust values from multiple sources (Hang et al., 2008; Wang & Singh, 2010)

### 3.2 TRR

An integrated reliability-reputation model for the agent societies (TRR) (Domenico Rosaci, Sarnè, & Garruzzo, 2011) presented by Rosaci et al. combined reliability and reputation in a synthetic trust model. This model solves one issue which existed in measuring the reputation of agents by

considering the trustworthiness of an agent that rates the other agents.

In fact, in this model the reputation of each agent in a multi-agent environment is computed based on the ratings given by other agents who have had previous interactions with it. In this case, the ratings reported by highly trustworthy agents should have higher values than the ratings reported by agents with lower trustworthy. In addition, the model presents the particular reliability model independently; it means that each agent has its own reliability model. Finally, the trust value of each agent is evaluated as a weighted mean between reliability and reputation.

#### 4. The Proposed Model

In this section we present a new method for calculating reputation of each provider agent and selecting the most trustworthy provider agent. In this case, first the requester agent sends a query to their neighborhood agents who had experienced with the providers, as an advisor agent, and asks them, if they are familiar with the identified providers which they can provide its needed services, then suggest the trustworthy provider and identify the number and also rating of satisfying previous interactions that they had with these providers, as:

- i) The ID of the requester agent that has issued the query (*Req*)
- ii) The kind of services which the requester needs (*S*)
- iii) The ID of providers that claims they can provide the services (*Pro*)
- iv) Identify the number and the overall rating of satisfying previous interactions with providers (if any)

A sample query and the responses of the recommenders to this query are, as follows:

(*A, S, Pro<sub>1</sub>, Pro<sub>2</sub>, Pro<sub>3</sub>, Number of Previous Satisfying Interactions: , Rate of Previous Satisfying Interactions:* )

After collecting the responses, then requester calculates the reputation of each provider to select the most trustworthy one.

#### 4.1 Computing Reputation

For computing the reputation of each provider we consider four main variables which are essential in computing the reputation of each provider, as; i) the weight of advisor who rates the providers, ii) the satisfying rates that advisors give to a specific provider, iii) the number of previous interactions that each advisor had with each rated provider, and v) finally the number of advisors who rates each provider. Thereby, we present the initial reputation formula for each agent as:

$$r_{A \rightarrow a_i} = \frac{\sum_{a_i \in A} (\sigma_{Req \rightarrow a_i} \times \omega_{a_i \rightarrow Pro} \times \lambda_{a_i \rightarrow Pro})}{\sum_{a_i \in A} (\sigma_{Req \rightarrow a_i})} \quad (1)$$

where  $A = \{a_1, a_2, \dots, a_n\}$  is the advisors that rates the providers,  $\sigma_{Req \rightarrow a_i} \in [0,1]$  is the weight that requester considers for the advisor agent,  $a_i$ , according to their previous interaction, and  $\omega_{a_i \rightarrow Pro}$  is the total satisfaction value which advisor agent,  $a_i$ , gives to provider agent, *Pro*, according to their previous interactions,

$$\lambda_{a_i \rightarrow Pro} = \frac{\sum_{l \in \delta} l_{a_i \rightarrow Adv}}{\sum_{l \in \text{interaction}} i_{a_i \rightarrow Adv}} \quad \text{denotes the}$$

proportion of the number of satisfying interactions to the total number of previous interactions between advisor,  $a_i$  and the provider agent, *Pro*. In fact, satisfaction value for rating each provider is considered according to their previous interaction as a numerical between 0 and 1.

Moreover, the number of advisors,  $N$ , which sends their ratings affects the accuracy of the reputation value. As the number of advisors that participate in computing reputation of a specific provider agent grows, the reputation value becomes more accurate. Hence, the final formula for computing the reputation of each provider is:

$$R_{Req \rightarrow Pro} = \frac{\sum_{n \in M} n}{M} \times r_{A \rightarrow Pro} \quad (2)$$

where  $\sum_{n \in M} n$  is the total number of advisors that rates and participates in computing the reputation value of provider agent, *Pro*,  $M$  is the total number of advisors rates to providers, and  $r_{A \rightarrow Pro}$  is the reputation value of a specific provider agent, *Pro*, obtained by equation (1).

Finally the requester makes a decision based on the obtained reputation value for each provider, and it selects the provider that achieved the highest value of reputation.

#### 4.2 Example

To demonstrate how our proposed approach computes reputation of each provider and selects the trustworthy one, this section presents a simple example that go through each step of this approach.

Assuming a requester agent, *Req*, that needs to make a decision for interaction with one of the providers who claim that they can provide the needed services. But the requester has no or limited experience with that providers, so it seeks the advisor agents,  $Adv_1$ ,  $Adv_2$  and  $Adv_3$ , which it had previous interactions

with them, to recommend a trustworthy provider. For instance the requester considers the following weights for each advisor according to its previous interactions that it had with each of the advisor,  $Adv_1$ ,  $Adv_2$  and  $Adv_3$ , as shown in Table 1.

Table 1. Weighting of each advisor by requester

Advisors	$Adv_1$	$Adv_2$	$Adv_3$
Requester	0.3	0.8	0.5

Thus, the requester agent,  $Req$ , sends a query to advisor agents,  $Adv_1$ ,  $Adv_2$  and  $Adv_3$ , and asks them to identify the number of satisfying previous interactions and also rate them according to their previous interactions, if they had any experienced. Then, the requester collects the all responses and calculates reputation of each provider according to responses of the advisors. Table 2, illustrates the sample of collected data from responder advisors.

Table 2. Collected data from responder advisors

Advisors	Number of satisfying Interactions		Rating of satisfying Interactions	
	$Pr_{O_x}$	$Pr_{O_y}$	$Pr_{O_x}$	$Pr_{O_y}$
$Adv_1$	3	2	0.6	0.8
$Adv_2$	1	-	0.7	-
$Adv_3$	3	6	0.8	0.5

As illustrated in Table 2, there are two providers,  $Pr_{O_x}$  and  $Pr_{O_y}$  that advisors rated. Although, the advisor,  $Adv_2$ , did not rate the provider,  $Pr_{O_x}$ , because it had no previous interactions with that provider. Then the requester computes the reputation of each provider,  $Pr_{O_x}$  and  $Pr_{O_y}$ , according to equations (1) and (2), as follows:

$$r_{A \rightarrow a_i} = \frac{\sum_{a_i \in A} (\sigma_{Req \rightarrow Adv_i} \times \omega_{Adv_i \rightarrow Pr_{O_x}} \times \lambda_{Adv_i \rightarrow Pr_{O_x}})}{\sum_{a_i \in A} (\sigma_{Req \rightarrow Adv_i})}$$

$$= \frac{(0.3 \times 0.6 \times 3) + (0.8 \times 0.7 \times 1) + (0.5 \times 0.8 \times 3)}{0.3 + 0.8 + 0.5} = 2.487$$

Since all advisors,  $Adv_1$ ,  $Adv_2$  and  $Adv_3$ , rated the provider,  $Pr_{O_y}$ , by considering the equation (2), the final value of reputation for provider,  $Pr_{O_y}$ , is:

$$R_{Req \rightarrow Pr_{O_x}} = \frac{\sum_{n \in M} n}{M} \times r_{A \rightarrow Pr_{O_x}} = \frac{3}{3} \times 2.487 = 2.487$$

On the other hand the reputation of provider,  $Pr_{O_y}$ , is measured as:

$$r_{A \rightarrow a_i} = \frac{\sum_{a_i \in A} (\sigma_{Req \rightarrow Adv_i} \times \omega_{Adv_i \rightarrow Pr_{O_y}} \times \lambda_{Adv_i \rightarrow Pr_{O_y}})}{\sum_{a_i \in A} (\sigma_{Req \rightarrow Adv_i})}$$

$$= \frac{(0.3 \times 0.8 \times 2) + (0.5 \times 0.5 \times 6)}{0.3 + 0.8 + 0.5} = 1.237$$

By considering two advisors  $Adv_1$  and  $Adv_3$  which rated the provider,  $Pr_{O_y}$ , the final value of reputation for  $Pr_{O_y}$  is calculated by using the equation (2), as:

$$R_{Req \rightarrow Pr_{O_y}} = \frac{\sum_{n \in M} n}{M} \times r_{A \rightarrow Pr_{O_y}} = \frac{2}{3} \times 1.237 = .825$$

Thereby, according to reputation values of  $Pr_{O_x}$  and  $Pr_{O_y}$ , the requester selects the  $Pr_{O_x}$  which has higher value of reputation.

### 5. Experimentation

In this section, a simulation of multi-agent environment is constructed as a controlled experiment by using MATLAB (R2012a). Then the average accuracy of proposed reputation model is examined in two stages; in the first stage, the average accuracy of calculating reputation is examined. In this case, the reputation of providers in average times of total iteration is calculated. The expectation is that the average accuracy of the reputation values for the trustworthy providers is higher than untrustworthy ones. In the second stage, the average accuracy of selecting the trustworthy provider, by using the proposed reputation model, is compared with the selecting the provider randomly without computing the reputation. In this stage, the average accuracy of the model is calculated as the average times of choosing trustworthy providers in total iterations with various numbers of trustworthy and untrustworthy providers. The expectation is that the performance of the proposed reputation model in selecting the trustworthy provider is better than the performance of random selection without evaluating the reputation of providers. In order to mimic a multi-agent environment to evaluate the models, the simulation environment is constructed according to the following settings:

i) Composition: The analysis is performed for three distributions with different percentage of trustworthy and untrustworthy providers, as shown in Table 3. In addition, to test the scalability of our approach, further experiments are done with different

numbers of agents in three groups, as shown in Table 3.

Table 3. Parameters of experimentation

No of	Dis1	Dis2	Dis3
Trustworthy providers	25	50	75
Untrustworthy provider	75	50	25
No. of	G1	G2	G3
Requester	1	1	1
Advisor	2	5	3
Provider	2	4	16
Total	5	10	20

Dis: Distribution

G: Group

ii) Structure: Our experiments are designed by the reference of Zhang and Cohen's simulations (2008) and Joshua Gorner, et al. (2013). According to these methods, the requester, advisors, and providers are selected randomly and also the agents rate each other arbitrarily as satisfying rates, for each time of simulation. Moreover, the total number of interactions in this simulation is 500.

iii) Behavior: First the requester sends a query to its neighbors. When neighbors who are the advisor agents receive a query, they will reply it based on their vectors to the providers. Then, requester records the responses of the queries and evaluates the reputation of each provider. In each time of running, the community of the agents updates their neighbors.

## 6. Results

The first experimental configuration is contained 5 agents with distribution, Dis1, in which the majority (75%) of providers are randomly selected as trustworthy ones and (25%) are untrustworthy. The average accuracy of the proposed reputation model is examined in each 50 iteration reach, as shown in Figure 1.

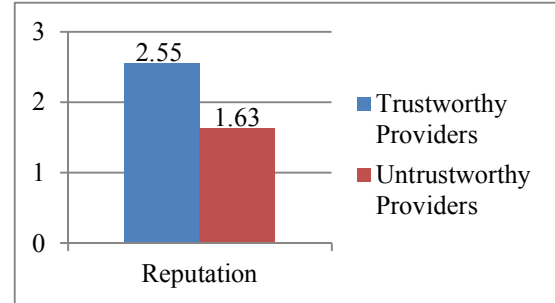


Figure 1. Comparison of the average accuracy of the reputation, with distribution, Dis1, and group G1

As shown in Fig 1, the average accuracy of the reputation values for trustworthy agents is higher than untrustworthy ones. Then, we extended the size of network to 10 and then 20 agents with the same sensitiveness distribution setting. The summary of experimental results for all experimental results is illustrated in Table 4.

Table 4. Summary of the results for all experimental settings

Distribution: Dis1 (25% Trustworthy, 75% Untrustworthy)		
	Reputation	Group
Trustworthy provider	2.55	G1
Untrustworthy provider	1.63	
Distribution: Dis2 (75% Trustworthy, 25% Untrustworthy)		
	Reputation	Group
Trustworthy provider	2.40	G1
Untrustworthy provider	1.63	
Distribution: Dis3 (75% Trustworthy, 25% Untrustworthy)		
	Reputation	Group
Trustworthy provider	2.35	G1
Untrustworthy provider	1.97	
Distribution: Dis1 (25% Trustworthy, 75% Untrustworthy)		
	Reputation	Group
Trustworthy provider	2.18	G2
Untrustworthy provider	1.52	
Distribution: Dis2 (50% Trustworthy, 50% Untrustworthy)		
	Reputation	Group
Trustworthy provider	1.98	G2
Untrustworthy provider	1.70	
Distribution: Dis3 (75% Trustworthy, 25% Untrustworthy)		

	Reputation	Group
Trustworthy provider	2.43	G2
Untrustworthy provider	1.81	
Distribution: Dis1 (25% Trustworthy, 75% Untrustworthy)		
	Reputation	Group
Trustworthy provider	2.21	G3
Untrustworthy provider	1.69	
Distribution: Dis2 (50% Trustworthy, 50% Untrustworthy)		
	Reputation	Group
Trustworthy provider	2.32	G3
Untrustworthy provider	1.77	
Distribution: Dis3 (75% Trustworthy, 25% Untrustworthy)		
	Reputation	Group
Trustworthy provider	2.60	G3
Untrustworthy provider	1.89	

Table 4 has nine stages of simulation with three distributions of trustworthy and untrustworthy provider agents along with three groups of agents for 500 iterations.

As shown in Table 4, in all stages of simulation the average reputation values of trustworthy agents is higher than untrustworthy ones. This result can approve our expectation about the accuracy of the proposed model.

In the second stage of experimentation, the performance of proposed reputation model is compared with random selection of providers. Figure 2, shows the comparison of the proposed model with choosing providers randomly, without calculating their reputation, for 5 agents with distribution, **Dis1**.

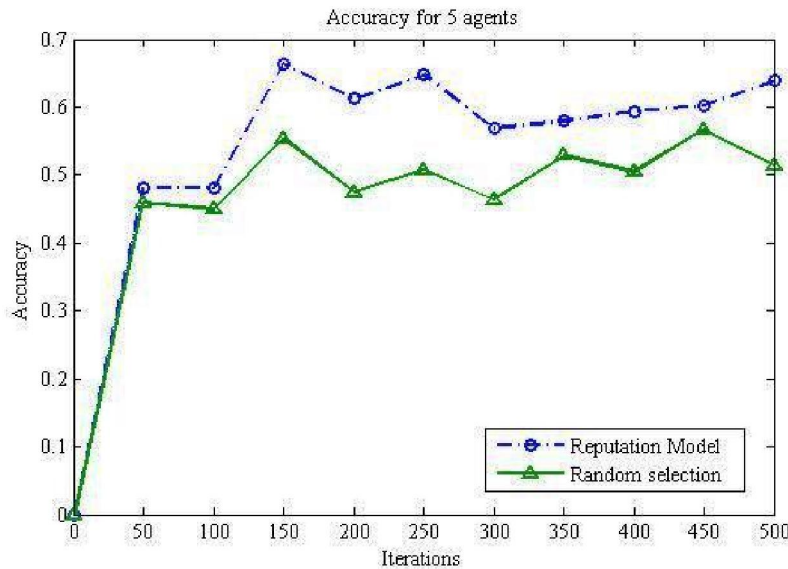


Figure 2. Comparison of the average accuracy of the proposed approach with the random approach for **Dis1**, and group **G1**

Figure 2 illustrates that the proposed model can select the trustworthy providers better than random approach in all iteration. In addition, the summary of experimental results for 10 and 20 agents is illustrated in Table 5.

Table 5. Summary of the results for comparison of the proposed reputation model and the random selection

Distribution: Dis1 (25% Trustworthy, 75% Untrustworthy)				
Model	250 iteration	500 iteration	Average iteration	Group
Reputation model	0.612	0.638	0.533	G1

Random selection	0.508	0.514	0.456	
Distribution: Dis2 (50% Trustworthy, 50% Untrustworthy)				Group
Reputation model	0.609	0.583	0.585	G1
Random selection	0.481	0.522	0.535	
Distribution: Dis3 (75% Trustworthy, 25% Untrustworthy)				Group
Reputation model	0.645	0.671	0.625	G1
Random selection	0.555	0.537	0.571	
Distribution: Dis1 (25% Trustworthy, 75% Untrustworthy)				Group
Reputation model	0.680	0.662	0.649	G2
Random selection	0.552	0.531	0.527	
Distribution: Dis2 (50% Trustworthy, 50% Untrustworthy)				Group
Reputation model	0.588	0.602	0.567	G2
Random selection	0.553	0.573	0.514	
Distribution: Dis3 (75% Trustworthy, 25% Untrustworthy)				Group
Reputation model	0.684	0.641	0.630	G2
Random selection	0.652	0.623	0.612	
Distribution: Dis1 (25% Trustworthy, 75% Untrustworthy)				Group
Reputation model	0.620	0.623	0.617	G3
Random selection	0.500	0.510	0.503	
Distribution: Dis2 (50% Trustworthy, 50% Untrustworthy)				Group
Reputation model	0.561	0.587	0.550	G3
Random selection	0.478	0.532	0.486	
Distribution: Dis3 (75% Trustworthy, 25% Untrustworthy)				Group
Reputation model	0.631	0.626	0.613	G3
Random selection	0.575	0.581	0.578	

In overall the comparison of the proposed model with random selection of provider according to Table 5 denotes that the proposed approach had the better performance in selecting the trustworthy provider with different numbers of agents.

Moreover, Figure3 represents the comparison of average accuracy for experimental results which obtained from the second stage of experimentation in different groups of agents, as depicted in Table 5.

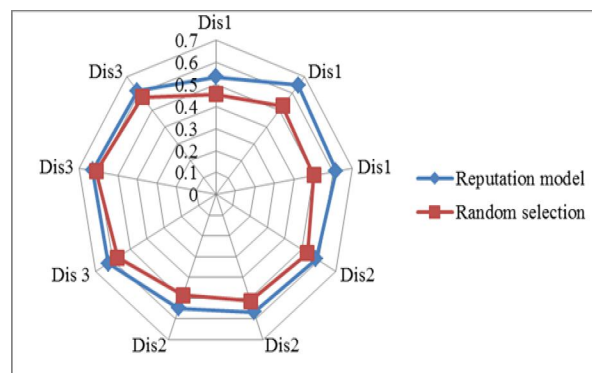


Figure 3. Comparison of the average accuracy of selecting the trustworthy providers

The experimental results clearly approves that the proposed approach has significant performance in all groups with different distribution of the trustworthy and untrustworthy providers. As shown in Figure 3 the proposed model has a better performance in all distributions, especially in, Dis 1, with majority number of untrustworthy providers (75%), this results show that the proposed model has a significant performance when the multi-agent

environment is very unsafety and it contains more untrustworthy providers than the trustworthy ones.

Thereby, the overall results denote that he proposed reputation model can accurately calculate reputation of provider agents in different distribution and different numbers of agents. Moreover, the performance of the proposed model in selecting the trustworthy agents is significantly better than the random election, across all groups, because this

proposed model evaluates vital variables which are essential for computing the reputation.

## 7. Discussions

This paper determined a new approach for selecting the most trustworthy provider agent by computing the reputation of each provider. In this case, we first analyzed several trust and reputation models and methods for computing reputation. Based on study of these models, we proposed a new model for calculating the reputation value of each provider considering the advisor's opinions. Finally, the proposed reputation model was evaluated in two stages of experimentations. In the first stage, the average accuracy of the proposed approach was examined, and then in the second stage the performance of the proposed approach in selecting the most trustworthy provider agents compared with selecting the provider randomly without using the proposed model. The experimental results showed that the proposed reputation model can compute reputation of each provider accurately. In addition, the comparison results illustrated that the performance of the proposed model in selecting the trustworthy providers is significantly better than the random selection without using the proposed model. Thereby, using the proposed reputation model can enhance trust in multi-agent systems, especially in e-commerce environments, and support the requester to experience a successful interaction with the trustworthy provider.

## Acknowledgements:

Foundation item: The National Project of India (No.: RP002B-13ICT). Authors are grateful to University of Malaya for financial support to carry out this work.

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