	-Consistent consultation and assistance should be accommodated. -Action to report should be taken in the event of an unethical practice
Privacy [21], [24]	- The need to ensure that there is no disclosure of private information which may be exploited by irresponsible parties. - The protection of consumer rights by granting an agreed period of time to make decision/make payments.
Leniency [15], [16], [21], [25]	- The alleviation of product price according to one's capability to pay and the ability to negotiate price. - Debtors are given a specified period within which they should settle their debts with the creditors - Forgiveness of mistakes

C. *Social Network Theory*

Social Network Analysis (SNA) is a structural analysis method which uses the application of graph theory. The nature of relationships in graph theory is used by analysts and is illustrated in various types of major problems. Social Network Analysis is used to identify structures in a system based on the relationship between users. Some of the advantages of SNA include: (i) the movement of social network analysis in the form of groups; (ii) the focus on group interaction rather than individual behavior; (iii) the fact that the smaller the group that interacts, the more accurate the outcome of the analysis. The network is commonly used to exemplify complex systems which comprise of entities represented by nodes that interact with each other Rombach et. al. [26]. When a network is represented using a graphic representation, all the connections between the nodes are paired and represented as the edge or side. Such representation has spawned many studies in the field of social science (e.g., sale and purchase interactions in the community), nature (e.g., linkages between plants and water that are mutually needed) and networks (e.g., relationships in the network which may consist of computers, routers, and switches).

Network analysis is formed through structure, function, and interaction. The relationship between the networks is considered as a source, and the structure is the transaction channel for the source. This relationship is measured by density, distance, frequency and other measures. Access in relationships is examined either from one network to another network type or individual access within the network itself. The measure for analyzing the dynamic relationship status in networks and groups is known as centralization. Centralization is a structural indicator of a network, group, and an individual or a node that is relevant. Sub-groups consist of small groups of networks, individual features, and group status, as well as the whole network.

A cohesive sub-group is a subset of network nodes that have a strong, direct, frequent, deep, or positive relationship. Some concepts have been introduced to formalize algorithms represent cohesive groups such as cliques, n-cliques, n-clans, n-clubs, k-plexes, k-core, lambda sets, and most of them with complexity or degree of difficulty NP (non-deterministic polynomial hard), and k-core algorithm is the most efficient [27]. Thus, the k-core algorithm is chosen as a social network analysis technique to see the relationship between users, particularly to identify a cohesive sub-group that conspires to construct false feedback.

Previous studies have shown that SNA has been used to detect frauds. Lin and Khomnotai [28] stated that in order to utilize the network position, each node represents the user and each link represents the feedback. However, in this study, every link has a weighting value derived from the user's feedback in the reputation system. Since sellers and buyers give feedback by placing the weight, hence a non-directional graph is suitable to be used for the representation. Network analysis found that k-core algorithms use nondirectional graphs which identify a cohesive sub-group that is present in a particular network. The k-core algorithm is an operation or a step-by-step that is constructed to identify nodes or entities in that cohesive sub-group. The cohesive sub-group that needs to be identified in this research is a sub-group that conspires or colludes to commit fraud by providing useful feedback to each other in an attempt to enhance their positive reputation as a good user.

The k-core algorithm is the best method to detect problems involving fraud by way of conducting random search processes, as well as sharing information through social networks. Due to the rewarding opportunities that await users when the reputation score turns positive, the cohesive group will seek to commit fraud by raising the reputation score to be positive even though it is not appropriate to do so.

Lin and Khomnotai [28] mentioned that there are various approaches to differentiate between dishonest and honest users in bidding through social network analysis. Feedbacks on social networks have shown that k-core algorithms and SNA are a combination of mediums that can be used to detect fraudulent schemes in social networks. Analysis from the sociological and methodological viewpoints in social network analysis can provide the basis for analyzing group structure, as well as the relationship and status of individual position within the group. The gathering of feedback from consumers about their experience may help other potential users to choose reliable products and users [28].] Fraud is a time-dependent phenomenon, and design the trust model such that a subject's characteristics and fraud probability can change over time [4], [29].

Some studies used a reputation model and agent-based management schemes [4] and social network analysis [29]. The research conducted by Lin et. Al [3] also incorporated the reputation system with network analysis by suggesting a solution which consists of five steps, i.e. (i) using web crawling agents to collect real auction data and using k-core algorithm to detect group frauds; (ii) determining the process of data cleaning and discarding any irrelevant data; (iii) using Page-Rank algorithm to search for critical accounts in the group; (iv) developing a feedback method for the assessment of fraudulent reputation in the auction, this method is an extension of the Page-Rank algorithm and combines web structure concepts and risk assessments; (v) using the Adaptive Neuro-Fuzzy Inference System (ANFIS) as an experiment for the study.

Table 3 refers to the summary of the comparison between the eBay reputation system and lelong.my. eBay developed one of the first feedback mechanisms, allowing buyers and sellers to trade under pseudonyms rather than their real-world names. Through eBay's existing policy, every user is not allowed to exchange feedbacks just for increasing their positive score. Also, eBay also does not allow other parties to ruin the feedback that users have made. According to [30], with the existence of this policy, it is not surprising that eBay has become a prosperous community that is trusted by society. Poee [31] mentioned that the new user would start a zero feedback (0) and have a specific icon displayed beside the name within the first 30 days of membership. The eBay reputation system had many deficiencies before 2007 [31]. However, in 2007, eBay introduced a new version of the reputation system by developing four new components to ensure that feedbacks from the reputation system are more transparent.

As explained by [32], the four extra questions are: (i) Are items delivered as stated? (ii) How is the communication between users? (iii) How long is the delivery time? (iv) Are the delivery and handling charges satisfactory? On top of that, eBay also uses positive (1), negative (-1) and neutral (0) scales. Disappointed buyers often do not leave feedback and buyers can be deterred from truthful reporting by the threat of retaliatory feedback [30]. Since 98% of positive/negative feedback is positive, average feedback scores appear to have relatively little information content. Nevertheless, eBay's reputation system seems to have worked well enough to screen out most of the horrible actors and deter highly fraudulent behavior.

Lelong.my is a major e-auction company in Malaysia. In line with the research conducted, Lelong.my is the most popular business auction in Malaysia today. Besides that, Lelong.my has succeeded in generating more than hundreds of thousands ringgit as its monthly income. Table 3 presents the characteristics of eBay and Lelong.my reputation systems.

TABLE III
REPUTATION SYSTEM CASE STUDY

Case Study	**Characteristics**
eBay [32]	1. One-way feedback 2. Using the scales of; Negative (−1) Neutral (0) Positive (+1) 3. Advantage; The focus on giving of scores which makes it easy to detect positive percentages. 4. Disadvantage; One-way feedback cannot detect conspiring cohesive groups.
Lelong.my (www.lelong.my) [33]	1. Two-way feedback 2. Feedback by the representation of percentages i Feedback scores: 4092+ ii Positive feedback: 99.98% iii Total products: 377 3. Using the scales of; i. Good ii. Poor iii. Neutral 3. Advantage; Easy to detect the percentage of positive feedback in the reputation system 4. Disadvantage; Two-way feedback but no function for the buyer's feedback section. The seller's feedback is only useful for the assessment of future buyers and cannot be used to detect the conspiracy of cohesive groups.

According to [34], based on the year 2016 report released by the Internet Crime Complaint Centre (IC3), 298,728 complaints were received, with a total victim loss of $1.33 billion. The highest reported crime for the year 2016 is related to non-payment/non-delivery (81,029 victims) which is followed by a personal data breach (27,573 victims). The total number of complaints received since the year 2000 is 3,762,348. IC3 receives approximately 280,000 complaints each year, or more than 800 per day. In distinguishing between both the credible users and the untrusted ones, a feedback model trust in a reputation system is required. Trust can be increased if the users practice ethics in transactions. As stated by Rice [23], the relevant Islamic business ethics which needs to be practiced during a trade is fulfilling responsibility and upholding trust in business relationships. Rice [23] quoted the Qur'anic verse (04:58) which means "Allah commands you to deliver trusts to those worthy of them."

III. RESULTS AND DISCUSSION

The proposed trust model is developed to improve the trust model implemented in [4]. It is based on Islamic business ethical codes which can be mapped to the three generic trust attributes namely ability, benevolence, and integrity. The value of the rating score is taken into account in producing a measurement for the trust model as emphasized by Jayasinghe et. Al. [35]. Table 5 shows the mapping of 3 selected trust attributes to 9 Islamic business ethical codes and the corresponding feedback questions. Each question is scored using 3 Likert scales following eBay system namely score 1 (agree), 0 (neutral) and -1 (disagree). Algorithm Islamic Business Ethics (IBE) calculates a buyer's or seller's score using the following formula:

$$IBEScore_U = totalRate - totalMinMarks/totalMarks * 100 \quad (1)$$

where
$totalMarks = totalMaxMarks - totalMinMarks$
$totalMaxMarks = +9$ and $totalminMarks = -9$,
Hence, $totalMarks = (+9) - (-9) = 18$
$totalRate = \sum_{i=1}^{i=9} x_i$
where x_i = mark for each question

Equation (1) is used to calculate the IBEScore for a buyer or seller. A buyer/seller is considered not ethical if he gets at least 5 negative feedbacks out of 9 feedbacks. For example, the best feedbacks a buyer/seller can get in the worst-case scenario is 5 negative and 4 neutral feedbacks (-1,-1,-1,-1,-

1,0,0,0,0) for all 9 questions. His IBEScore = -5 – (-9)/18*100 which is 22.2. On the other hand, a buyer/seller is considered ethical if he gets at least 5 positive feedbacks out of 9 questions. The worst a buyer/seller can get in the best-case scenario is 5 positive and 4 neutral feedbacks (+1,+1,+1,+1,+1,0,0,0,0) and his IBEScore = +5-(-9)/18*100 which is 77.7. In general, the IBEScore will determine his adherence to Islamic business ethics. If he gets IBEScore larger or equal to 77.7, he can be considered adhering to Islamic business ethics and may assume to be trusted. The user status is determined as follows:

$$status = \begin{cases} Unethical\ hence\ untrusted, & 0 < IBEScore \leq 22.2 \\ Neutral, 22.2 < IBEScore < 77.7 \\ Ethical\ until\ proven\ otherwise, 77.7 \leq IBEScore \leq 100 \end{cases}$$

Determining a user's IBEScore is only the first step. This is because the IBEScore is totally based on users' feedback. Users can still cheat in the process of giving feedback. Users who fall under the category "Ethical (assumed trusted) until proven otherwise" will be further evaluated using the k-core algorithm. We have adopted the k-core algorithm into our algorithm for determining a user's trustworthiness.

The k-core algorithm proceeds as follows:

Initialize an output list *L*.

1. Compute a number d_v for each vertex *v* in graph *G*, the number of neighbors of *v* that are not already in *L*. Initially, these numbers are just the degrees of the vertices.
2. Initialize an array *D* such that *D[i]* contains a list of the vertices *v* that are not already in *L* for which $d_v = i$.
3. Initialize *k* to 0.
4. Repeat *n* times:
   a. Scan the array cells *D [0]*, *D [1]*, until finding an *i* for which *D[i]* is nonempty.
   b. Set *k* to max(*k*,*i*)
   c. Select a vertex *v* from *D[i]*. Add v to the beginning of *L* and remove it from *D[i]*.
   d. For each neighbor w of *v* not already in *L*, subtract one from d_w and move *w* to the cell of *D* corresponding to the new value of d_w.

At the end of the algorithm, *k* contains the degeneracy of *G* and *L* contains a list of vertices in an optimal order. The *i-cores* of G are the prefixes of *L* consisting of the vertices added to *L* after *k* first takes a value greater than or equal to *i*.

We have a total of 348 transactions simulated from 23rd June 2016 to 23rd June 2017. To demonstrate we have chosen data generated via feedback giving simulation in 24 hours (dated 20th June 2017). Fig. 1 depicts a graph which represents a network of potentially trusted 17 buyers and sellers whose IBEScores equivalent or more than 77.7 from the user's feedback in an e-auction reputation system. Four users (A301, A302, A303, and A305) have been identified to have strong connections in a cohesive group.

To determine whether these users can genuinely be trusted or otherwise, we first run the k-core algorithm to identify members of a cohesive group and discovered a cohesive group with 2-core as the highest *k* which comprised of users A301, A302, A303 and A305 as its members. Another cohesive group with 1-core has all the users as its members. A user might belong to more than one cohesive group. Fig. 3 shows the results of k-core algorithm execution which list a user's id, followed by his k-core value and other members of the cohesive group. Note that members (vertex) which are highly cohesive will have higher k-core value.

To calculate a user's cohesive score, we take into consideration several parameters namely the average IBEScore of buyer-seller (in a buyer-seller feedback relationship), the duration of feedback given (to see its relevance based on how recent the feedback is), the frequency of feedbacks between buyer-seller, user's k value and the highest k-value in a cohesive group.

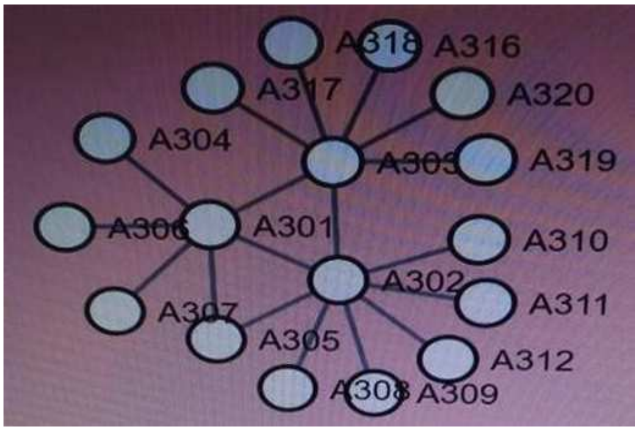

Fig.1 Graph Representing Users Assumed Trusted

Table 4 shows the corresponding points for each parameter's value.

TABLE IV
COHESIVE SCORE PARAMETER-POINT MAPPING

Parameters	Values	Point
Buyer-seller IBEScore average	> 92.0	3
	84.1 – 92.0	2
	77.0 – 84.0	1
IBEScore age (days ago)	0-73	5
	74 - 146	4
	147 - 219	3
	210 - 292	2
	> 292	1
Buyer-seller feedback frequency	1 - 5	5
	6 - 10	4
	11 -15	3
	16 - 20	2
	> 20	1

TABLE V
COHESIVE SCORE-STATUS

Range score	Status
0<= CohesiveScore<= 33.34	Low cohesiveness: Trusted
33.34< CohesiveScore < 66.67	Medium cohesiveness: Neutral
66.67<= CohesiveScore <= 100	High cohesiveness: Untrusted

Equation 2 is used to calculate the cohesive score for a vertex or user. Higher cohesive score implies the strong bond between suspected users; hence if a transaction cohesive score >= 66.67, it is regarded as untrusted. The calculation is rounded up to 2 decimal point. We calculate each cohesive score for every feedback given by a buyer to seller and vice versa, before finally determine a user's trust score. To demonstrate, Table 6 shows detail data for user A301.

$$CohesiveScore_U = (IBEScoreAve_{point} * IBEScoreAge_{point} * freq_{point}/75) * (kvalue_{Partner}/highest\ kvalue) * 100 \quad (2)$$

```
A301 2 A301 A302 A303 A305
A302 2 A301 A302 A303 A305
A303 2 A301 A302 A303 A305
A304 1 A301 A302 A303 A304 A305 A306 A307 A308 A309 A310 A311 A312 A316 A317 A318 A319 A320
A305 2 A301 A302 A303 A305
A306 1 A301 A302 A303 A304 A305 A306 A307 A308 A309 A310 A311 A312 A316 A317 A318 A319 A320
A307 1 A301 A302 A303 A304 A305 A306 A307 A308 A309 A310 A311 A312 A316 A317 A318 A319 A320
A308 1 A301 A302 A303 A304 A305 A306 A307 A308 A309 A310 A311 A312 A316 A317 A318 A319 A320
A309 1 A301 A302 A303 A304 A305 A306 A307 A308 A309 A310 A311 A312 A316 A317 A318 A319 A320
A310 1 A301 A302 A303 A304 A305 A306 A307 A308 A309 A310 A311 A312 A316 A317 A318 A319 A320
A311 1 A301 A302 A303 A304 A305 A306 A307 A308 A309 A310 A311 A312 A316 A317 A318 A319 A320
A312 1 A301 A302 A303 A304 A305 A306 A307 A308 A309 A310 A311 A312 A316 A317 A318 A319 A320
A316 1 A301 A302 A303 A304 A305 A306 A307 A308 A309 A310 A311 A312 A316 A317 A318 A319 A320
A317 1 A301 A302 A303 A304 A305 A306 A307 A308 A309 A310 A311 A312 A316 A317 A318 A319 A320
A318 1 A301 A302 A303 A304 A305 A306 A307 A308 A309 A310 A311 A312 A316 A317 A318 A319 A320
A319 1 A301 A302 A303 A304 A305 A306 A307 A308 A309 A310 A311 A312 A316 A317 A318 A319 A320
A320 1 A301 A302 A303 A304 A305 A306 A307 A308 A309 A310 A311 A312 A316 A317 A318 A319 A320
```

Fig. 2 K-core Results for Users With IBEScore > 77.7

TABLE VI
DETAIL DATA EXAMPLE: USER A301

Seller Id	Buyer Id	Buyer score	Seller score	Timestamp	IBE average	IBEage (days)	Frequency
A301	A302	100	94.44	6/20/2017 14:27	97	1	3
A301	A302	88.89	94.44	6/20/2017 14:28	92	1	
A301	A302	94.44	94.44	6/20/2017 14:29	94	1	
A301	A303	94.44	94.44	6/20/2017 14:30	94	1	3
A301	A303	94.44	94.44	6/20/2017 14:31	94	1	
A301	A303	88.89	100	6/20/2017 14:32	94	1	
A301	A304	94.44	100	6/20/2017 14:33	97	1	2
A301	A304	94.44	94.44	6/20/2017 14:34	94	1	
A301	A305	88.89	94.44	6/20/2017 14:35	92	1	2
A301	A305	88.89	94.44	6/20/2017 14:36	92	1	
A301	A306	88.89	94.44	6/20/2017 14:37	92	1	3
A301	A306	88.89	100	6/20/2017 14:38	94	1	
A301	A306	88.89	94.44	6/20/2017 14:39	92	1	
A301	A307	94.44	100	6/20/2017 14:40	97	1	3
A301	A307	94.44	94.44	6/20/2017 14:41	94	1	
A301	A307	94.44	100	6/20/2017 15:42	97	1	

For example in the first line of Table 6, the IBEaverage for A301 and A302 is 97.0 hence the IBEScoreAverage_point (from Table 7) given is 3, IBEage is 1 and IBEScoreAge_point given is 5, freq is 2 and frequency_point is 5, k-value Partner is 1 (for A302, as computed and shown in Fig. 2) and highest k-value (for A301) is 2. Then we can calculate CohesiveScore for a specific transaction between A301 and A302 as follows:

$$CohesiveScore_{A301} = (3 * 5 * 5/75) * (2/2) * 100 = 100$$

Table 7 shows detail data of all transactions involved in the calculation to derive trustworthiness status for each user. Note that results from Table 7 show that the trust status for all feedbacks given by the members of the 2-core cohesive group to each other is untrusted.

$$TrustScore_U = (trustedNo/relationNo) * 100 \quad (3)$$

Next, equation. Three is used to calculate the trust score of a user which considers the number of trusted feedbacks out of all feedbacks involving the user. This value is mapped to the star rating based on the following ranges:

$$StarRating = \begin{cases} 0, & 0 \\ 1, & 1-19 \\ 2, & 20-39 \\ 3, & 40-59 \\ 4, & 60-79 \\ 5, & 80-100 \end{cases}$$

TABLE VII
COHESIVE SCORE AND TRUST STATUS FOR EACH RELATIONSHIP FOR 2 CORE GROUP MEMBERS

Seller ID	**Buyer Id**	**IBEaverage Point**	**IBEage Point**	**Frequency Point**	**Partner's K-Core**	**Highest *K***	**Cohesive Score**	**Trust Status**
A301	A302	3	5	5	2	2	100	U (Untrusted)
A301	A302	2	5	5	2	2	66.67	U(Untrusted)
A301	A302	3	5	5	2	2	100	U(Untrusted)
A301	A303	3	5	5	2	2	100	U(Untrusted)
A301	A303	3	5	5	2	2	100	U(Untrusted)
A301	A303	3	5	5	2	2	100	U(Untrusted)
A301	A304	3	5	5	1	2	50	N(Neutral)
A301	A304	3	5	5	1	2	50	N(Neutral)
A301	A305	2	5	5	2	2	66.67	U(Untrusted)
A301	A305	2	5	5	2	2	66.67	U(Untrusted)
A301	A306	2	5	5	1	2	33.34	T(Trusted)

A301	A306	3	5	5	1	2	50	N(Neutral)
A301	A306	2	5	5	1	2	33.34	T(Trusted)
A301	A307	3	5	5	1	2	50	N(Neutral)
A301	A307	3	5	5	1	2	50	N(Neutral)
A301	A307	3	5	5	1	2	50	N(Neutral)
A302	A303	3	5	5	2	2	100	U(Untrusted)
A302	A303	3	5	5	2	2	100	U(Untrusted)
A302	A303	3	5	5	2	2	100	U(Untrusted)
A302	A303	3	5	5	2	2	100	U(Untrusted)
A302	A305	3	5	5	2	2	100	U(Untrusted)
A302	A305	3	5	5	2	2	100	U(Untrusted)
A302	A305	3	5	5	2	2	100	U(Untrusted)
A302	A308	2	5	5	1	2	33.34	T(Trusted)
A302	A308	3	5	5	1	2	50	N(Neutral)
A302	A308	3	5	5	1	2	50	N(Neutral)
A302	A308	3	5	5	1	2	50	N(Neutral)
A302	A309	3	5	5	1	2	50	N(Neutral)
A302	A309	3	5	5	1	2	50	N(Neutral)
A302	A309	3	5	5	1	2	50	N(Neutral)
A302	A309	3	5	5	1	2	50	N(Neutral)
A302	A310	3	5	5	1	2	50	N(Neutral)
A302	A310	3	5	5	1	2	50	N(Neutral)
A302	A310	3	5	5	1	2	50	N(Neutral)
A302	A310	3	5	5	1	2	50	N(Neutral)
A302	A311	3	5	4	1	2	40	N(Neutral)
A302	A311	3	5	4	1	2	40	N(Neutral)
A302	A311	3	5	4	1	2	40	N(Neutral)
A302	A311	3	5	4	1	2	40	N(Neutral)
A302	A311	3	5	4	1	2	40	N(Neutral)
A302	A311	3	5	4	1	2	40	N(Neutral)
A302	A311	3	5	4	1	2	40	N(Neutral)
A302	A311	3	5	4	1	2	40	N(Neutral)
A302	A312	3	5	5	1	2	50	N(Neutral)
A302	A312	3	5	5	1	2	50	N(Neutral)
A302	A312	2	5	5	1	2	33.34	T(Trusted)
A303	A316	3	5	5	1	2	50	N(Neutral)
A303	A317	3	5	5	1	2	50	N(Neutral)
A303	A318	3	5	5	1	2	50	N(Neutral)
A303	A319	3	5	5	1	2	50	N(Neutral)
A303	A320	3	5	5	1	2	50	N(Neutral)

Table 8 shows the star rating of the 2-core cohesive group members.

TABLE VIII
COHESIVE SCORE AND TRUST STATUS

User Id	Trusted No	Relation No	Trust Score (%)	No Star
A301	2	16	12.50	1
A302	2	30	6.67	1
A303	0	12	0	0
A305	0	5	0	0

In order determine whether these users can genuinely be trusted or otherwise, we first run the k-core algorithm to identify members of a cohesive group and discovered a cohesive group with 2-core as the highest *k* which comprised of users A301, A302, A303 and A305 as its members. Another cohesive group with 1-core has all the users as its members. A user might belong to more than one cohesive group. As shows the results of k-core algorithm execution which list a user's id, followed by his k-core value and other members of the cohesive group.

To calculate a user's cohesive score every feedback is evaluated by considering three parameters namely, IBEScore average given by the buyer to seller and vice versa, the IBEScore's age (how long ago was the feedback given) and the frequency of feedback given between a buyer and seller. Each parameter value is given a point. The user's partner's k-core also is taken into consideration.

Based on the trust score result the model allocates star rating to the user. User A301 trust score almost doubles from A302's although two members (A301 and A302) are given a 1star rating, from the detail results,. On the other hand, users A303 and A305 do not deserve any star since neither the feedback they gave nor received can be trusted. Our model shows that users who conspire to give false feedback can be identified. This could help new users to avoid doing business with untrusted users.

IV. CONCLUSION

The trust model for e-auction reputation system proposed in this paper was to complement our previous work [4, 5, 30] which have incorporated several features towards the establishment of a Sharia-based e-auction. Supporting literature also highlights the relationship between trust and ethics, and became the premise for introducing Islamic business ethic score (IBEscore) in the design of the feedback system to measure user's adherence to Islamic business ethical codes. Since feedback system is vulnerable to manipulation we adapted k-core algorithm to identify existence of cohesive group of users and demonstrated the use of parameters namely IBEscore average, IBEScore's age and the frequency of feedback given between a buyer and seller, as well as the k-core value to determine whether a user lied when giving feedbacks to trading partners. We have shown that when the identified cohesive group members gave false feedback to one another, the proposed trust model can determine the trustworthiness of a user through his trust score. Some recommendations for further research are to work further on trust update algorithms that take into account the dynamics of trust as well as to engineer existing k-core algorithms to scale to large graphs of billions of edges in life auction system.

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