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Multi-Dimensional Trust Quantification by Artificial Agents Through Evidential Fuzzy Multi-Criteria Decision Making

SANG-WOONG LEE[1], (Senior Member, IEEE), SADAF HUSSAIN[2], GHASSAN F. ISSA[3], SAGHEER ABBAS[2], TAHER M. GHAZAL[3,4], (Member, IEEE), TANWEER SOHAIL[5], MUNIR AHMAD[2], (Member, IEEE), AND MUHAMMAD ADNAN KHAN[1]

[1]Pattern Recognition and Machine Learning Laboratory, Department of Software, Gachon University, Seongnam 13557, South Korea
[2]School of Computer Science, National College of Business Administration and Economics, Lahore 54000, Pakistan
[3]School of Information Technology, Skyline University College, Sharjah, United Arab Emirates
[4]Center for Cyber Security, Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia, Bangi, Selangor 43600, Malaysia
[5]Department of Mathematics, University of Jhang, Jhang 35200, Pakistan

Corresponding author: Muhammad Adnan Khan (adnan@gachon.ac.kr)

ABSTRACT Increasing man-machine trust has burgeoned during the last few decades. The growing interest in trust-building has led to the study of the non-dichotomous nature of trust. Trust as social behavior is an integral part of effective team building. The major focus has been offered to study how humans build trust towards machines, whereas few attempts have been made to study the reverse. Studies have shown that trustworthiness perceptions initialize trust behavior whereas trust behavior influences subsequent trustworthiness perceptions. This paper presents the design and comparative analysis of evidential fuzzy multi-criteria decision-making (EFMCDM) based on multi-dimensional trust quantification schemes to quantify trust level with the human agent in a collaborative environment.

INDEX TERMS Trust, trustworthiness, MCDM, EFMCDM, multi-agent system.

I. INTRODUCTION

A. TRUST

Trust is being defined as the willingness of a party to become vulnerable towards the action of another party with the expectation that the other party will perform the action that is important for the first party, without monitoring or controlling the other party [1]. A lack of trust exists when one party does not have faith in the competencies of another or questions the motivation of the other to take the promised action seriously [2]. Trust can be seen as a relationship between two or more individuals in which one perceives that the others are involved, are competent, will complete their fair share of the work, and will make an honest effort to meet commitments. Trust is important in teams because it lowers transaction costs [3]. Individuals, who do not trust fellow team members, are more likely to monitor or double-check each other's work to ensure the quality of the team's output. This self-protective activity increases the amount of time and resources needed to complete a project.

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While trust is important in all teams, it is crucial in virtual teams where members generally do not meet face-to-face. In virtual teams, trust becomes an important component in preventing psychological distance and it increases confidence in relationships by promoting open information exchange. Trust is often referred to as the glue that holds the virtual team together. Trust has been considered as a determinant of effectiveness in collaborative tasks in teams [4]. Output produced by a well-functioning team should be superior to the output of any individual. Individuals who trust each other usually will be more contented with the team experience. Better team recital and satisfaction is subsequent of mutual trust relationship.

In collaborative teams; for an agent either human or artificial agent, it is likely to be self-interested and may be unreliable. Such properties may come from the fact that the agent needs to cooperate to achieve its personal goals more than a common goal. In relevant situations despite the uncertainty of the system interaction an artificial agent cannot afford to be non-interactive since its goals are unachievable without external help. Therefore, the agent needs to rely on the other agent (human) to cope up with the difficulties of goal achievement. In this context, several formalisms can be used to describe man-machine collaborative teams, among several approaches; probability theory has been found and adopted widely to model trust. This is since probability represents systems with high uncertainty and risk. The probabilistic approach may refer to three different sets of tools [5]:

1) STATISTICAL INFERENCE

Statistical inference is a process of modeling and estimating probability function to a random process. Statistical modeling is based on defining a function that could be used to represent the system, whereas the inference resides on the estimation of that function.

2) PROBABILITY THEORY

Probability theory is a mathematical domain that combines the tools used to study probability as mathematical objects and the relationship and properties of these objects. The major objective of probability theory is the concept of random variables and stochastic processes.

3) DECISION THEORY

The decision process ads applicative decision making on probability theory. Decision problem definition clarifies the tools to be used in statistical inference while estimating the probability function of the system. Associating decision theory to the field of application of trust leads to defining trust models representing the system. Set of properties of the system as evaluation of trust, together with the statistical inference process in understanding trust actions are delineated through a critical understanding of its antecedents [1]. Davis *et al.* depicted trustworthiness as one of the predictors of trust intentions and trust actions [1]. Trustworthiness is an information-oriented perception of a trustee. In either case, the possibility for inaccuracies exists; however, the perceptions may impact behaviors irrespective of their accuracy. The trustor especially gets influenced to develop a desire to trust in the early stages, whereas trust beliefs and trust actions impact the trust process in later stages of interaction [6], [7]. This work adopts an approach to consider familiarity of the trustee as trustor's effect, trustworthiness as trust beliefs, and trust actions over time which is consistent with Jones and Shah [7]. In most cases, decision theory provides a way to estimate the probability of the system based on previous interactions.

In this work, we associate probability theory with the field of application of trust. Defining trust model in our view amounts to identifying a probability model representing the system, the set of properties of the system as mathematical objects of trust, together with the statistical inference process, that, in most cases, will provide a way to estimate the trust probability of the system, with random variables.

B. ANTECEDENTS OF TRUST

Understanding trust actions are delineated through a critical understanding of its antecedents [1]. Mayer et al model depict trustworthiness as one of the predictors of trust intentions and trust actions. Trustworthiness is an information-oriented perception of a teammate. In either case, the possibility for inaccuracies exists; however, the perceptions may impact behaviors irrespective of their accuracy. Especially the trustor gets influenced to develop a desire to trust in the early stages, whereas trust beliefs and trust actions impact the trust process in the later stages of interaction [6], [7]. This work adopts an approach to consider familiarity of the trustee as trustor's effect, trustworthiness as trust beliefs, and trust actions over time which is consistent with Jones and Shah [7].

1) TRUSTWORTHINESS

Trustworthiness is the trustor's perception of the trustee which is an important antecedent of trust [8]. Perceived trustworthiness has been theorized as the perception of trustors regarding the competence of trustee's competence, benevolence, and integrity. These perceptions ascribe motives to the trustee's motivation for action [9]. Therefore, the trustworthiness perception of the trustor is a function of the interaction of trustor and trustee as the trustor processes trustee's information. Trustworthiness perception is the credited beliefs of the trustor which are not necessarily factual since the perceptions may or may not be accurate. The trustworthiness beliefs become more accessible as the relationship develops as more information is available. Through mature interactions, the trustor is more likely to depend on the behavior of the trustee rather than dispositional factors [7], [10]. Research has revealed that the trust behaviors from one individual cause trust behavior from the other; which in turn highlights the trustworthiness of others [11]. The initial trustworthiness perception has a significant influence on later trust behaviors in dyads.

2) FAMILIARITY

Trust has an essential aspect in multi-agent collaborative environments [12]; therefore the knowing the trust antecedents is crucial to obtainers, benefactors and intermediaries. Research has shown that in parallel to trustworthiness perception familiarity also has a distinctive influence on trust-building mechanisms [13]. The general premise is that the familiarity of the trustee is based on preceding interactions and experiences [14]. Familiarity serves as a precondition for the trust that makes an individual develop confidence in each other's trustworthiness [15]. It allows relatively safe Expectations about future behavior and absorbs the residual risk. [15]. Consequently, trustee's familiarity is an trust antecedent that aids to provide the context to clarify future expectations that are based on previous interactions. [13]. Several empirical studies have revealed that the trustor's satisfaction during previous interactions determines his trust in the trustee [16], [17]. Satisfaction during the previous course of interactions not only affects the trust level but also induces better usage and familiarity [18]. During the cultivation of trust, familiarity is imperative since trust is only possible within the familiar world [19]. The relationship between familiarity and trust is best that in or devil when they behave in accordance to trust positive expectations about them. [20]. Experimental surveys also show that familiarity of trustee significantly affects online trust as it determines behavioral intentions of the client to enquire and buy the product online [20].

This paper focuses on a brief review of current trust estimation techniques in human-agent societies and the development of trust quantification mechanisms using multi-criteria decision-making. Preceding sections of the paper are organized as follows. Section II provides a brief background on trust theory, focuses on the previous attempts made to develop a trustworthy human-agent relationship and the applications of MCDM in problem solutions relating specifically to cognitive phenomena. Section III, introduces the proposed fuzzy MCDM based model of trust. The fuzzy inference approach as a structural mechanism for trust decision-making is also cast-off in section III. In order to demonstrate the process of choosing a trust level for the collaborator, the proposed approaches were empirically evaluated and compared in section IV. Section IV discusses the results of the proposed trust quantification system. Finally, section V concludes the current work.

II. LITERATURE REVIEW

Enabling the agent to establish interactions with the human considering a similar level of complexity and multidimensionality has been one of the challenges of contemporary human-agent interaction. The objective has been entertained by an interdisciplinary approach to develop robotic agents capable to establish a trustworthy relationship with their teammates [21]. Reference [22] have simulated human decision-making in robotic agents using developmental theories and from this perspective, the authors tried to highlight the process involved in the establishment of the relationship between human and agent to understand agent response to human behavior under relational context [23], [24].

Trust is dynamic development based on nature of interaction and is subjected to variations operationalized in the study [25], the study of trust is conducted in three phases: trust acquisition, trust loss, and trust restoration. In psychology, trust is described as ''a psychological attitude that is multidimensional in nature involves belief and expectation about the trustee's reliability resulted from social experiences including uncertainty and risk'' [26], [27]. Trust for unknown people can be envisioned by passively witnessing their behaviors with consequences on our own decisions [28]. Trust has a multidimensional nature that can be built on either objective factors or emotional, irrational attitudes towards the partner [29] emotional trust is considered as independent of objective information under total on a certain situation where the trusted partner is not evaluated on objective elements. Therefore in certain situations, the trustee is always accurate until proven otherwise. Emotional trust is successively built during the constant endorsement of trustee's reliability through expected responses. [30]. According to this perspective confirmation of trustor's choices reflect the level of trust acquisition and acceptance as trustworthy [31], [32] highlight the importance of the construction of interpersonal trust while developing new relationships. Previous relational histories also shape human trust relationships originating with primary caregivers proceeding to the significant effective relationship [33]. Sometimes under uncertain situations, trustor's decision to place trust in the case of an unfamiliar person depends on the trustee's general attachment [34]–[36]. Similarly, an individual's cognitive capability is important to be developed, especially for the trustee's epistemic reliability. One can reason about the perspective of others through his cognitive skills. In this regard theory of mind, development enables an individual to conceptualize the mental state of another [37].

Relative to human-agent interactions, different investigations have been made through studies under trust in agent or system involving adult participants, these studies were based on either explicit measurement (self-reporting) or implicit trust measurement [38]. Explicit measurements of trust were subject to the idiosyncratic attitude of human which is usually based on beliefs and not on actual interaction experience, whereas implicit measurement of trust generally enrolled hypothesis postulation based on specific environmental and theoretical conditions [39].

A. EVIDENCE THEORY-BASED TRUST MODEL

Trust is considered as a concept describing the dependability and reliability of agents in collaborative environments that develops a sense of improving quality of collaborative interactions [40]. Trust assessment models have been categorized and studied in four major domains:

1. As logical models where an agents develops trust relationship based on mathematical logic
2. Social cognitive models, taking inspiration from human psychology to develop and foster trust relationship by assessing trustworthiness of the trustee.
3. Organizational models that apprehend trust through personal relationships in a system
4. Numerical models developing trust on mathematical probabilities [41], [42].

The work in this paper implements trust assessment based on social cognitive and numerical models where the trustworthiness of human is assessed on numerical modeling by collecting human's information as personality traits as potential information of trustee. Such sort of trust assessment falls under direct trust [43].

Various methodologies have been employed that collect information under numerical models, among them one effective methodology is Theory of Evidence that have grounds in belief functions or Dempster-Shafer theory (DST) [43], [44] where collaborative agents develop basic probability assignment (BPAs) representing source of information from other agent. Numerous approaches have been found in trust assessment among collaborative agents where DST has been hired [45] is utilized to implement distributed management in electronic commerce. The method may be based on both direct and indirect reputation where the need of indirect trust is faded out when direct trust is obtained. In the meantime, direct application of Dempster's combination rule is used to integrate materials. Virtual temporary system implementing swift trust based on DST has also been observed in the literature [46]. Evidence base methods have special tendency in trust transitivity in describing relationships considering uncertainty by developing transition model considering trust features and relationship types [47]. Authors in [48] used DST to handle network security problem in wireless sensor networks.

Trust modeling based on evidential theory has both advantages and disadvantages. When generating BPAs the characteristic of vanishing evidence reliability is not well emphasized, also for conflicting evidences, evidence based theories are not directly applicable. In recent attempts, entropy based models have been proposed to handle conflicting evidences in multi agent collaborative systems [49], [50]. It has been observed in data fusion models that assigned weights are directly proportional to entropy of evidence [49], [51], [52].

B. MOTIVATION OF THE REASEARCH

Previous works have identified the influencing factors inspiring the trust process – herein termed as antecedents of trust. To the best of our knowledge, for trust decisions, no attempt has been made to consider trustworthiness perceived and the familiarity of the trustee as trust antecedents. Therefore, the current research considers two very important trust antecedents, each having support from previous research. The trust antecedents deliberated in this research include personality traits oriented trustworthiness [47] and familiarity of trustee [53], to quantify the trust level of human collaborator.

III. PROPOSED SYSTEM

A. EFMCDM BASED TRUST ASSESSMENT MODEL

The agent has been designed and developed to make a trust decision in accordance with two parameters; the trustworthiness of the human collaborator and the level of familiarity the agent have developed towards him. The criteria to make a final decision regarding trust are implemented with the help of evidential fuzzy multi-criteria decision-making (EFMCDM) [54].

Multi-criteria decision making appears to be one of the widely used decision making methodologies. The purposed method for final trust estimation uses a novel approach to MCDM with a flavor of evidential fuzziness, evidential fuzzy multi-criteria decision making EFMCDM integrating multi criteria decision making with Dempster Shafer's theory with belief entropy. Figure 1 gives the details of the method adopted in EFMCDM technique. Each criterion is modeled as evidence alternative constructing the frame of discernment. EFMCDM generates suitable basic probability assignments (BPAs) to the criteria by considering both subjective

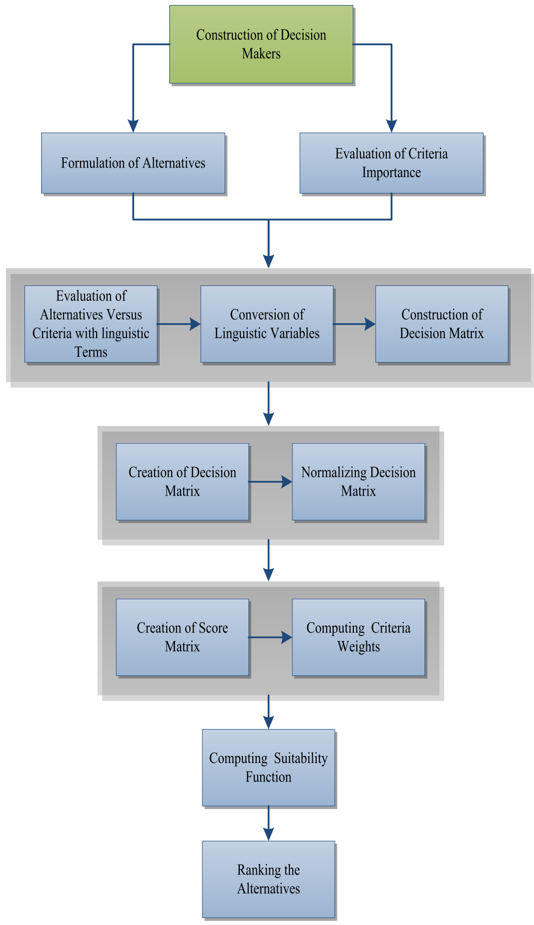

FIGURE 1. **Proposed EFMCDM based trust decision model.**

and objective weights assignment to criteria. These alternatives are rank to determine optimal alternatives. EFMCDM is capable of modeling uncertainty helpful in decreasing uncertainty resulted as subjective human cognition thereby improving decision making.

B. FUZZY INFERENCE BASED TRUST ASSESSMENT MODEL

Zadeh [55], 1965 introduced the fuzzy set theory that transforms linguistic variables to discrete numerical variables during the decision making process.

The lack of diffusion in the allocation of importance weights of criteria and ratings of alternative based on evaluation criteria has overcome with the definition of fuzzy set, developed into EFMCDM. The EFMCDM problems is adopted to measure the trust perception of artificial agent towards human and follows the procedure elaborated in [54].

Definition 1 (Fuzzy Set [55]):

Let $\mu_{\tilde{M}}(x)$ be the continuous mapping from R to the closed interval [0, 1]. A Fuzzy Member is defined as a fuzzy set such that

$$\tilde{M} = \{(x), \mu_{\tilde{M}}(x), x \in R\}$$

Definition 2 (Trapezoidal fuzzy number [56]):

Let $r_1, r_{2,}, r_3, r_4 \in R$ and $r_1, < r_{2,} \le r_3, < r_4$; a trapezoidal fuzzy number is defined as $\mathbb{A} = r_1, r_{2,}, r_3, r_4$ and its membership function as:

$$\mu_{\tilde{\mathbb{A}}}(x) = \begin{cases} \frac{x - r_1}{r_2 - r_1}, & x \in [r_1, r_2] \\ 1, & x \in [r_2, r_3] \\ \frac{r_4 - x}{r_4 - r_3}, & x \in [r_3, r_4] \\ 0, & \text{otherwise} \end{cases}$$

Definition 3 (Dempster-Shafer Theory (DST) [57], [58]):

Dempster Shafer of the theory of evidence and belief estimation is extensively being used in various application tools due to the flexibility and efficiency in uncertainty modeling. DST uses mass functions specifically modeled by complex numbers, called complex basic belief assignment that carries ability to express uncertain information.

The theory E has wide application in numerous areas including fault diagnosis [48], [59], risk analysis [60], multi-agent systems [61], [62], human reliability analysis [63], and pattern analysis [64].

Let $\theta = \{e_1, e_2, e_3 \ldots, e_n\}$ be the collection of events and the power set of θ represented by $2^\theta = \{\emptyset, \{e_1\}, \{e_2\}, \{e_3\}, \ldots, \{e_n\}, \ldots, \{e_1, e_2, e_3, \ldots, e_i\}, \ldots, \theta\}$, for any $b \in 2^\theta$, b is called proposition.

Definition 4 (Mass Function):

The mass function m is expressed as a mapping from 2^θ to [0, 1] in frame of discernment θ, defined as,

$$m : 2^\theta \to [0, 1],$$

and satisfies the condition,

$$m(\theta) = 0 \quad \text{and} \sum_{\theta \notin c \subseteq b} m(b) = 1$$

m is also known as basic probability assignment (BPA) and b will become a focal element of mass function when $m(b) > 0$.

Definition 5 (Belief and Plausibility Functions):

The belief function $Bel : 2^\theta \to [0, 1]$ for a preposition $b \in 2^\theta$ is defined as:

$$Bel(b) = \sum_{\theta \notin c \subseteq b} m(c)$$

whereas, the plausibility function $Pl : 1 - Bel(\bar{b})$ as:

$$Pl(b) = \sum_{c \cap b \neq \emptyset} m(c)$$

Bel (b) and Pl (b) are the lower and upper limit functions of b respectively, and $Pl(b) \geq Bel(b)$

Definition 6 (Dempster's Rule of Combination):

On a frame of discernment θ, let $\mathfrak{p}_1$ and $\mathfrak{p}_2$ be two independent BPAs, Dempster's rule of combination is denoted by:

$$\mathfrak{p} = \mathfrak{p}_1 \oplus \mathfrak{p}_2$$

$$\mathfrak{p}(a) = \begin{cases} \frac{1}{k} \sum_{b, c \in 2^\theta | b \cap c = a} \mathfrak{p}_1(b)\, \mathfrak{p}_2(c), & a \neq 0 \\ 0, & a = 0 \end{cases}$$

k is conflict coefficient between $\mathfrak{p}_1$ and $\mathfrak{p}_2$. Dempster's combination rule is beneficial when $k < 1$.

$$k = \sum_{b, c \in 2^\theta | b \cap c = 0} \mathfrak{p}_1(b)\, \mathfrak{p}_2(c), \quad a \neq 0$$

Definition 7 (Belief Entropy):

Belief entropy is generalized form of Shannon's entropy [65] that offers an operative measurement of uncertain information for the basic probability assignments (BPAs) [66]. Let in terms of BPA, c be the proposition $\mathfrak{p}$ in θ. The belief entropy $E_d(\mathfrak{p})$ of BPA $\mathfrak{p}$ is written as:

$$E_d(\mathfrak{p}) = -\sum_{c \subseteq \theta} \mathfrak{p}(c) \log \frac{\mathfrak{p}(c)}{2^{|c|} - 1}$$

|c| is the cardinality of proportion; c.

C. PROBLEM STATEMENT

An agent's trust towards human is classified under levels, where each level (rangine from the lowest trust "t_1" to the very high trust level "t_7") describes the extent to which agent computes its trust towards human.

The 7 possible mutually exclusive alternatives for the trust levels t; be the frame of discernment,

$$\text{Trust Levels (T)} = \{t_1, t_2, t_3, t_4, t_5, t_6, t_7\}$$

where t_i, $i = 1, 2, \ldots, 7$ denoted the trust levels of human collaborators. The three decision-makers DM;

$$DM = \{DM_1, DM_2, DM_3\}$$

C be the set of decision criteria;

$$\text{Criteria for Decision Making (C)} = \{\tau, f\}$$

where,

$$\tau = \text{trustworthiness of the human agent}$$

And

$$f = \text{familiarity of the human agent}$$

Table 1, Table 2, and Table 3 represents sets of linguistic variables, used for fuzzy importance weights assessment of trustworthiness τ and familiarity f; and the fuzzy ratings for the alternatives allotted for decision. The fuzzy values, utilizing these tables construct decision matrix.

These tables are used to construct the decision matrix with fuzzy values.

The decision matrix of the fuzzy importance weights, for some random criterion is given by the decision-makers can be constructed in table-4 and table-5:

Decision matrix for fuzzy importance weights for one of the possible combination of criteria values given by the decision makers is provided under table – 5. In the meantime decision matrices for initial trust level rating for one of the possible combinations with respect to decision makers is shown in table – 6 and processed with fuzzy weights during successive steps.

TABLE 1. Linguistic terms for trust level towards human with corresponding fuzzy values.

	Importance	Abbr.	Fuzzy Number
t_1	Very Low	*VL*	(0.0, 0.0, 0.05,0.15)
t_2	Low	*L*	(0.05,0.15, 0.2, 0.3)
t_3	Fairly Low	*FL*	(0.2, 0.3, 0.35, 0.40)
t_4	Fairly Medium	*FM*	(0.35, 0.40, 0.45, 0.55)
t_5	Fairly High	*FH*	(0.45, 0.55, 0.60, 0.65)
t_6	High	*H*	(0.60, 0.65, 0.70, 0.80)
t_7	Very High	*VH*	(0.70, 0.80, 1.0, 1.0)

TABLE 2. Linguistic terms for human trustworthiness with corresponding fuzzy ranges.

Importance	Abbr.	Fuzzy Number
Highly Deceptive	*HD*	(0.0, 0.0, 0.1, 0.2)
Deceptive	*D*	(0.1, 0.2, 0.35, 0.40)
Partial Trustworthy	*PT*	(0.35, 0.40, 0.55, 0.60)
Trustworthy	*T*	(0.55, 0.60, 0.75, 0.80)
Highly Trustworthy	*HT*	(0.75, 0.80, 1.0, 1.0)

TABLE 3. Linguistic terms for the familiarity with corresponding fuzzy ranges.

Importance	Abbr.	Fuzzy Number
Highly Unfamiliar	*HU*	(0.0, 0.0, 0.1, 0.2)
Unfamiliar	*U*	(0.1, 0.2, 0.35, 0.40)
Partial Familiar	*PF*	(0.35, 0.40, 0.55, 0.60)
Familiar	*F*	(0.55, 0.60, 0.75, 0.80)
Highly Familiar	*HF*	(0.75, 0.80, 1.0, 1.0)

TABLE 4. The importance weight of the criteria evaluated by decision-makers with linguistic values.

Decision Makers	Criteria (Trustworthiness)	Criteria (Familiarity)
D1	T	HF
D2	HT	PF
D3	T	HF

Table-6 presents the decision matrix for importance weights, $\tilde{w}_{jk}(k = 1, 2, 3)$ and $(j = 1, 2)$ for the jth criterion for kth decision-maker. On the other hand, decision matrices of initial trust level ratings are depicted in table-7.

Generalization of fuzzy values for the weighted trust levels and decision matrix for the weighted fuzzy rating are given in table – 7.

Generation of the fuzzy values of the weighted trust level rating kth decision-maker can be constructed. Fuzzy values of weighted trust levels are aggregated and the decision matrix of weighted trust levels is constructed in table – 8.

The aggregated fuzzy values of trust levels are normalized and are shown in table – 9, whereas fuzzy values of trust level rating is aggregated and the aggregated decision matrix is given in table – 10. Fuzzy values of weighted trust level

TABLE 5. The rating of trustworthiness concerning the decision-makers evaluated criteria.

D1	τ	f
t_1	T	PF
t_2	HD	HF
t_3	D	PF
t_4	PT	F
t_5	D	PF
t_6	HT	HF
t_7	HT	PF
D2	τ	f
t_1	D	F
t_2	τ	PF
t_3	D	HF
t_4	HD	F
t_5	T	HF
t_6	D	HF
t_7	PT	HF
D3	τ	f
t_1	PT	U
t_2	D	HF
t_3	HT	F
t_4	D	PF
t_5	HT	PF
t_6	D	F
t_7	PT	HF

ratings are aggregated is constructed as shown in Table 9 and are normalized in table 10 respectively.

The fuzzy values of initial trust level ratings are then aggregated. The aggregated decision matrix is constructed in table 11 showing the initial trust level ratings. Whereas the fuzzy values for defuzzified normalized aggregates of weighted trust level to obtain crisp values are described in table 12 and are normalized in table 13.

Table 13 depicts the crisp values of defuzzified aggregated fuzzy values of initial trust level and table 14 shows the normalized defuzzified value of initial trust levels.

The uncertainty degree calculation for the criterion (τ and f) gives,

$$\mathrm{Ed}(\tau) = 2.7641$$
$$\mathrm{Ed}(\mathrm{f}) = 2.3758$$

Similarly, normalization of uncertainty degree of criteria gives,

$$\bar{\mathrm{U}}(\tau) = 0.4828$$
$$\bar{\mathrm{U}}(\mathrm{f}) = 0.5172$$

The BPAs of the Trust $T_i(i = 1, 2, \ldots, 7)$ and θ concerning the criterion $C_j(j = 1, 2)$ as shown in the table.

The finalized order ranking of trust level based on beliefs of the criterion (τ, f) is shown in table 16. The optimal decision

TABLE 6. Decision matrix for criteria's fuzzy importance weights.

Decision Makers	Criteria (Trustworthiness)				Criteria (Familiarity)			
D1	0.55	0.60	0.75	0.80	0.75	0.80	1.00	1.0
D2	0.75	0.80	1.00	1.00	0.35	0.40	0.55	0.6
D3	0.55	0.60	0.75	0.80	0.75	0.80	1.00	1.0

TABLE 7. Decision matrices of initial trust level rating.

D1	τ				*f*			
t_1	0.303	0.360	0.563	0.640	0.263	0.320	0.550	0.600
t_2	0.000	0.000	0.075	0.160	0.563	0.640	1.000	1.000
t_3	0.055	0.120	0.263	0.320	0.263	0.320	0.550	0.600
t_4	0.193	0.240	0.413	0.480	0.413	0.480	0.750	0.800
t_5	0.055	0.120	0.263	0.320	0.263	0.320	0.550	0.600
t_6	0.413	0.480	0.750	0.800	0.563	0.640	1.000	1.000
t_7	0.413	0.480	0.750	0.800	0.263	0.320	0.550	0.600
D2	τ				*f*			
t_1	0.075	0.160	0.350	0.400	0.193	0.240	0.413	0.480
t_2	0.413	0.480	0.750	0.800	0.123	0.160	0.303	0.360
t_3	0.075	0.160	0.350	0.400	0.263	0.320	0.550	0.600
t_4	0.000	0.000	0.100	0.200	0.193	0.240	0.413	0.480
t_5	0.413	0.480	0.750	0.800	0.263	0.320	0.550	0.600
t_6	0.075	0.160	0.350	0.400	0.263	0.320	0.550	0.600
t_7	0.263	0.320	0.550	0.600	0.263	0.320	0.550	0.600
D3	τ				*f*			
t_1	0.193	0.240	0.413	0.480	0.075	0.160	0.350	0.400
t_2	0.055	0.120	0.263	0.320	0.563	0.640	1.000	1.000
t_3	0.413	0.480	0.750	0.800	0.413	0.480	0.750	0.800
t_4	0.055	0.120	0.263	0.320	0.263	0.320	0.550	0.600
t_5	0.413	0.480	0.750	0.800	0.263	0.320	0.550	0.600
t_6	0.055	0.120	0.263	0.320	0.413	0.480	0.750	0.800
t_7	0.193	0.240	0.413	0.480	0.563	0.640	1.000	1.000

TABLE 8. The fuzzy values of the weighted trust level ratings.

D	τ				*f*			
t_1	0.0750	0.2533	0.4417	0.6400	0.075	0.240	0.438	0.600
t_2	0.0000	0.2000	0.3625	0.8000	0.123	0.480	0.768	1.000
t_3	0.0550	0.2533	0.4542	0.8000	0.263	0.373	0.617	0.800
t_4	0.0000	0.1200	0.2583	0.4800	0.193	0.347	0.571	0.800
t_5	0.0550	0.3600	0.5875	0.8000	0.263	0.320	0.550	0.600
t_6	0.0550	0.2533	0.4542	0.8000	0.263	0.480	0.767	1.000
t_7	0.1925	0.3467	0.5708	0.8000	0.263	0.427	0.700	1.000

choice is t_7 which is that depicts the strongest belief of agent towards trusting the human.

The EFMCDM generates the following ranking order of the alternatives as follows and selects the optimal alternative T_7.

$$Bel\,(t_7) > Bel\,(t_6) > Bel\,(t_5) > Bel\,(t_3) > Bel\,(t_2) > Bel\,(t_1) > Bel\,(t_7)$$

D. PROPOSED FUZZY SYSTEM FOR TRUST QUANTIFICATION

The proposed fuzzy system for the problem stated under section III is constituted of two fuzzy variables as input. The member functions are practically distributed over a range [0, 1] for trustworthiness and familiarity. The five MFs for trustworthiness input as Highly Deceptive (HD) 0 to 0.2, Deceptive (D) 0.15 to 0.4, Partially Trustworthy (PT) 0.35

TABLE 9. The aggregated decision matrix for weighted trust level ratings.

D	τ				f			
t_1	0.094	0.317	0.552	0.800	0.075	0.240	0.438	0.600
t_2	0.000	0.250	0.453	1.000	0.123	0.480	0.768	1.000
t_3	0.069	0.317	0.568	1.000	0.263	0.373	0.617	0.800
t_4	0.000	0.150	0.323	0.600	0.193	0.347	0.571	0.800
t_5	0.069	0.450	0.734	1.000	0.263	0.320	0.550	0.600
t_6	0.069	0.317	0.568	1.000	0.263	0.480	0.767	1.000
t_7	0.241	0.433	0.714	1.000	0.263	0.427	0.700	1.000

TABLE 10. The aggregated decision matrix after normalization.

D	τ				f			
t_1	0.10	0.40	0.55	0.80	0.10	0.40	0.55	0.80
t_2	0.00	0.27	0.40	0.80	0.35	0.67	0.85	1.00
t_3	0.10	0.40	0.57	1.00	0.35	0.60	0.77	1.00
t_4	0.00	0.20	0.33	0.60	0.35	0.53	0.68	0.80
t_5	0.10	0.53	0.70	1.00	0.35	0.53	0.70	1.00
t_6	0.10	0.40	0.57	1.00	0.55	0.73	0.92	1.00
t_7	0.35	0.53	0.70	1.00	0.35	0.67	0.85	1.00

TABLE 11. The aggregated decision matrix.

D	τ	f
t_1	0.441	0.338
t_2	0.426	0.593
t_3	0.488	0.513
t_4	0.268	0.478
t_5	0.563	0.433
t_6	0.488	0.627
t_7	0.597	0.597

TABLE 12. The defuzzified value $\bar{Def}(x_{ij}^{\bar{\bar{w}}})$.

D	τ	f
t_1	0.135	0.094
t_2	0.130	0.166
t_3	0.149	0.143
t_4	0.082	0.133
t_5	0.172	0.121
t_6	0.149	0.175
t_7	0.182	0.167

TABLE 13. Crisp values of defuzzified aggregated fuzzy values $\bar{Def}(x_{ij}^{\bar{\bar{w}}})$.

D	T	f
t_1	0.463	0.463
t_2	0.367	0.717
t_3	0.517	0.679
t_4	0.283	0.592
t_5	0.583	0.646
t_6	0.517	0.800
t_7	0.646	0.717

TABLE 14. Normalized defuzzified value of initial trust levels.

D	τ	f
t_1	0.137	0.100
t_2	0.109	0.155
t_3	0.153	0.147
t_4	0.084	0.128
t_5	0.173	0.140
t_6	0.153	0.173
t_7	0.191	0.155

to 0.6, Trustworthy (T) 0.55 to 0.80, and Very Trustworthy (VT) 0.75 to 1. The five fuzzifier MFs for familiarity input are termed as Highly Unfamiliar 0 to 0.2, Unfamiliar 0.15 to 0.4, Partially Familiar 0.35 to 0.6, Familiar 0.55 to 0.80, and Highly Familiar 0.75 to 1. The seven MFs of Trust_Level being Very Low, Low, Medium Low, Medium, High, and Very High.

Fuzzy sets are vividly represented in figure (a-c) illustrating the MFs. In universe of discourse, MFs for fuzzy set

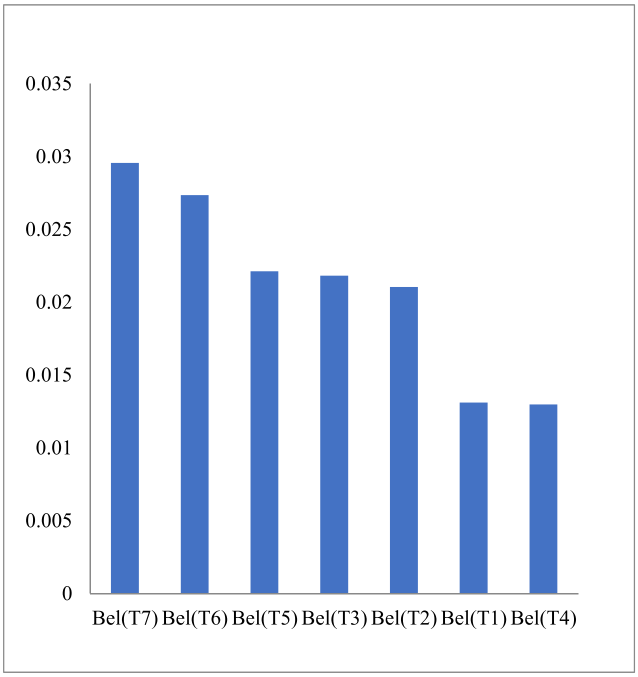

FIGURE 2. Sensitivity analysis of the subjective weights of the criteria.

Trustworthiness and Familiarity are defined as $\mu : X \rightarrow [0, 1]$. Following functions are used to build MFs

Trustworthiness : $(\mu_{trustworthiness(\mathfrak{T})})$

$$\mu_{trustworthiness,HD}(\mathfrak{T}) = \left\{max\left(min\left(1, \frac{0.15-\mathfrak{T}}{0.05}\right), 0\right)\right\}$$

$$\mu_{trustworthiness,D}(\mathfrak{T}) = \left\{max\left(min\left(\frac{\mathfrak{T}-0.15}{0.05}, 1, \frac{0.4-\mathfrak{T}}{0.05}\right), 0\right)\right\}$$

$$\mu_{trustworthiness,PT}(\mathfrak{T}) = \left\{max\left(min\left(\frac{\mathfrak{T}-0.35}{0.05}, 1, \frac{0.6-\mathfrak{T}}{0.05}\right), 0\right)\right\}$$

$$\mu_{trustworthiness,\mathfrak{T}}(\mathfrak{T}) = \left\{max\left(min\left(\frac{\mathfrak{T}-0.55}{0.1}, 1, \frac{0.8-\mathfrak{T}}{0.1}\right), 0\right)\right\}$$

$$\mu_{trustworthiness,VH}(\mathfrak{T}) = \left\{max\left(min\left(\frac{\mathfrak{T}-0.75}{0.1}, 1\right), 0\right)\right\}$$

Familiarity : $(\mu_{Familiarity(f)})$

$$\mu_{Familiarity,HU}(f) = \left\{max\left(min\left(1, \frac{0.15-f}{0.05}\right), 0\right)\right\}$$

$$\mu_{Familiarity,U}(f) = \left\{max\left(min\left(\frac{f-0.15}{0.05}, 1, \frac{0.4-f}{0.05}\right), 0\right)\right\}$$

$$\mu_{Familiarity,PF}(f) = \left\{max\left(min\left(\frac{f-0.35}{0.05}, 1, \frac{0.6-f}{0.05}\right), 0\right)\right\}$$

$$\mu_{Familiarity,F}(f) = \left\{max\left(min\left(\frac{f-0.55}{0.1}, 1, \frac{0.8-f}{0.1}\right), 0\right)\right\}$$

$$\mu_{Familiarity,HF}(f) = \left\{max\left(min\left(\frac{f-0.75}{0.1}, 1\right), 0\right)\right\}$$

Trust_Level : $(\mu_{Trust(T)})$

$$\mu_{Trust,VL}(T) = \left\{max\left(min\left(1, \frac{0.1-T}{0.1}\right), 0\right)\right\}$$

$$\mu_{Trust,L}(T) = \begin{cases} \frac{T-0.1}{0.1}, & if\ T \in [0.1, 0.2] \\ \frac{0.3-T}{0.1}, & otherwise \end{cases}$$

$$\mu_{TrustML}(T) = \left\{max\left(min\left(\frac{f-0.15}{0.05}, 1, \frac{0.4-f}{0.05}\right), 0\right)\right\}$$

$$\mu_{Trust,M}(T) = \begin{cases} \frac{T-0.4}{0.1}, & if\ T \in [0.4, 0.5] \\ \frac{0.6-T}{0.1}, & otherwise \end{cases}$$

$$\mu_{Trust,MH}(T) = \left\{max\left(min\left(\frac{f-0.35}{0.05}, 1, \frac{0.6-f}{0.05}\right), 0\right)\right\}$$

$$\mu_{Trust,H}(T) = \begin{cases} \frac{T-0.7}{0.1}, & if\ T \in [0.7, 0.8] \\ \frac{0.9-T}{0.1}, & otherwise \end{cases}$$

$$\mu_{Trust,VJ}(T) = \left\{max\left(min\left(\frac{f-0.75}{0.1}, 1\right), 0\right)\right\}$$

Here, composition of fuzzy proposition is constructed of atomic fuzzy propositions using the connectives "and". The following fuzzy propositions hold for "τ" and "f":

FP1 = (τ is "Highly Deceptive" and f is "Familiar")

Moreover the t-norm function for layer-1 is defined as:

$$t : [0, 1] \times [0, 1] \times [0, 1] \times [0, 1] \rightarrow [0, 1] \tag{1}$$

Eq. (1) transforms the membership functions of fuzzy sets "τ" and "f" among membership function of the intersection of "τ" and "f" that is:

$$t[\mu_\tau(\tau), \mu_f(f)] = \min[\mu_\tau(\tau), \mu_f(f)] \tag{2}$$

Eq. (2) can be written in terms of t-norm as:

$$\mu_{\tau \cap f}(\tau, f) = t[\mu_\tau(\tau), \mu_f(f)] \tag{3}$$

From Eq. (2) & (3)

$$\mu_{\tau \cap f}(\tau, f) = \min\left[\mu_\tau(\tau), \mu_f(f)\right]$$

Few rules for the fuzzy inference system are provided as under.

IF (Trustworthiness is "*Highly Deceptive*" and *f* is

TABLE 15. The basic probability assignments for the trust level.

BPAs	Criterion	
	τ $mC_j(t_i) = \bar{D}ef(\overline{\widetilde{x_{ij}^w}}) * (1 - \bar{U}_j)$	f $mC_j(f_i) = \bar{D}ef(\overline{\widetilde{x_{ij}^w}}) * (1 - \bar{U}_j)$
$m(t_1)$	0.054	0.056
$m(t_2)$	0.053	0.099
$m(t_3)$	0.060	0.085
$m(t_4)$	0.033	0.080
$m(t_5)$	0.070	0.072
$m(t_6)$	0.060	0.104
$m(t_7)$	0.074	0.099
$m(\theta)$	0.596	0.404

TABLE 16. Alternatives for the belief values of the.

Bel(t_7)	Bel(t_6)	Bel(t_5)	Bel(t_3)	Bel(t_2)	Bel(t_1)	Bel(t_7)
0.029561041	0.027348411	0.022124056	0.021813557	0.021041796	0.013104	0.0129797

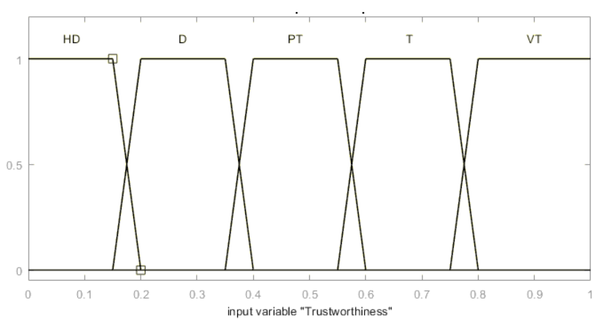

FIGURE 3. Membership functions graphs for τ.

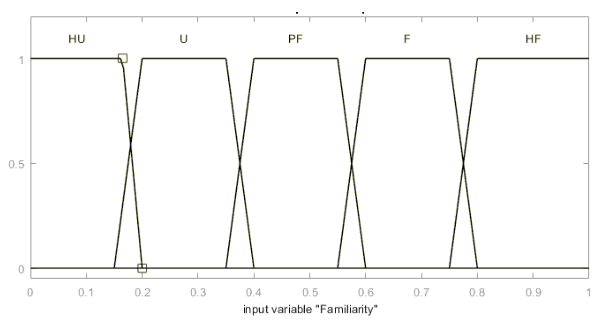

FIGURE 4. Membership functions graphs for familiarity.

"*Familiar*") THEN Trust_Level is "*Very Low*"
IF (Trustworthiness is "Trustworthy" and f is "*Partially Familiar*") THEN Trust_Level is "*High*"

.
.
.

IF (Trustworthiness is "Very Trustworthy" and f is "*Highly Familiar*") THEN Trust_Level is "Very *High*"

These fuzzy IF-THEN rules are interpreted as a fuzzy relation Q32 with the membership function are written as:

$$\mu Q_{32}(\tau, f) = \min[\mu_{FP1}(\tau), \mu_{FP2}(f)]$$

Fuzzy IF-THEN rules are the constituents of the fuzzy rule base. The fuzzy rule base is the major component of the fuzzy system because all other components are used to implement these rules realistically and proficiently. Fuzzy rule base comprises the following fuzzy IF-THEN rules, where rules for layer 1 are denoted by r^e where, $1 \leq e \leq 32$:

r^1 = IF (τ is "Highly Deceptive" and f is "Familiar") THEN Trust_Level is "Very Low"
r^2 = IF (τ is "Trustworthy" and f is "Partially Familiar") THEN Trust_Level is "High"

.
.
.

r^{32} = IF(τ is "Very Trustworthy" and f is "Highly Familiar") THEN Trust_Level is "Very High"

Ru^e and ru^f represents any fuzzy IF-THEN rule, then

$$r^e = \tau^e \times f^e \rightarrow T^e$$

Then

$$\mu_{\tau \cap f}(\tau, f) = \mu_\tau(\tau) \cap \mu_f(f)$$

TABLE 17. Results comparison between EFMCDM and fuzzy inference system.

Decision Makers	Criteria: Trustworthiness (τ)	Criteria: Familiarity (f)	General Belief	Fuzzy Linguistic Value
D1	HT	HF	Bel(t_7) = Very High 0.024206689	Very High
D2	T	HF		Very High
D3	T	F		High
D1	PT	PF	Bel(t_6) = High 0.034999268	Fairly Medium
D2	PT	F		Fairly High
D3	T	HF		High
D1	T	HF	Bel(t_5) = Fairly High 0.024638268	Fairly High
D2	T	PF		Fairly High
D3	HT	F		High
D1	T	HF	Bel(t_4) = Fairly Medium 0.022124056	Fairly High
D2	HT	PF		Fairly Medium
D3	T	HF		High
D1	D	F	Bel(t_3) = Fairly Low 0.031766465	Low
D2	PT	U		Fairly Low
D3	T	PF		Low
D1	HD	HU	Bel(t_2) = Low 0.03833001	Very Low
D2	PT	HU		Low
D3	D	HU		Low
D1	D	U	Bel(t_1) = Very Low 0.023975965	Very Low
D2	HD	U		Very Low
D3	PT	PF		Fairly Familiar

Accepting the first view of a set of rules, the rules are interpreted as a single fuzzy relation Q_{32}

$$Q_{32} = \bigcup_{e=1}^{32} r^e$$

The combination in equation 8 is called the Mamdani combination. Let "in" and "out" be arbitrary fuzzy sets and be the input and output to the fuzzy inference Engine respectively. Then, by viewing Q_{32} as a single fuzzy IF-THEN rule and using the generalized modus ponens [67], we obtain the output of the fuzzy inference engine as

$$\mu_{VL \cap L \cap ML \cap M \cap MH \cap VH}(\text{out}) = \sup_{I \in (\tau, f)} t\left[\mu_I(\tau, f), \mu_{Q_{32}}(\tau, f, T)\right]$$

Here,

$$Y_1 = \mu_{out}(VL, L, ML, M, MH, VH)$$

Mamdani composition based inference is used here we obtain the product inference engine as

$$\mu_{out}(\text{TrustLevel}) = \max_{1 \le I \le 32}\left[\sup_{I \in (\tau, f)}\left(\prod_{k=1}^{32}\left(\mu_{\tau_k, f_k}(\tau, f)\right)\right)\right]$$

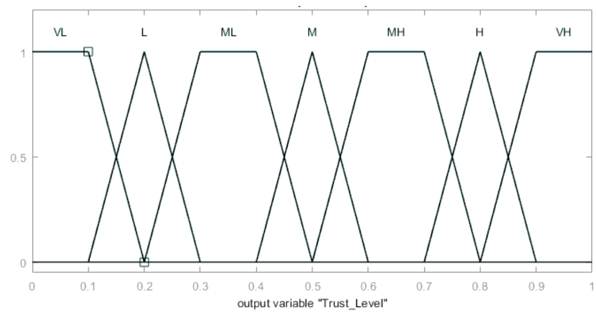

FIGURE 5. Membership functions graphs for trust level.

The center of gravity defuzzifier specifies the o∗ as the center of the area covered by the membership function out, that is,

$$o^* = \frac{\int \text{out}\,\mu_{out}(\text{out})\,d\text{out}}{\int \mu_{out}(\text{out})\,d\text{out}}$$

The crisp output values for the trustworthiness dimensions are calculated in eq. 26, provided the fuzzy set of familiarity and trustworthiness of human collaborator.

IV. RESULT AND DISCUSSION

The ranking order of the trust level alternatives obtained by EFMCDM method chooses the optimal alternative t_7 that depicts "Very High" trust level quantified by the agent towards human. The ranking is further elaborated with respect to decision makers. The subjective belief according to the criteria for trustworthiness and familiarity, given in the following table, the initial weights assignment by decision maker D_1 is "Highly Trustworthy" and "Highly Familiar" and for D_2 it is "Trustworthy" and "Highly Familiar", generating a belief to have a Very High trust level. Similarly with D_3's allocations for trustworthiness and familiarity the belief is produced towards human being for being "High". The general belief or the objective belief of all three decision makers towards a particular human being has been quantified as "Very High", which coincides with the subjective believes of the decision makers.

The alternatives' belief values of are produced showing the results in table 17.

Consequently, under different sets of criteria weights, the ranking orders of the alternatives are offered in table 17. The belief values of alternatives are found to be stable against variations in criteria weights. Moreover, it has been observed that optimal choice is always a choice close to the subjective believes of decision makers, irrespective of the relative importance weights of the criteria.

V. CONCLUSION

Human agent collaborative environments are getting more complex and demanding. Both humans and agents are often oriented towards subjective goals and may act maliciously. Agents are required to quantify trust towards humans in the same way human do; hence they are required to possess capabilities and sophisticated decision making to develop trust assessments towards human teammate. Trust quantification is increasingly important to address the issue of mutual understanding of intentions between humans and agents to achieve a common goal. The current work proposed a new formulation of trust based on the principles of evidential fuzzy multi criteria decision making (EFMCDM) approach and introduced a fuzzy inference method in order to evaluate and score among human's trust levels. Evidential Fuzzy Multi criteria decision making has advantage in trust quantification. Since evidential method for fuzzy MCDM is based on integration of Dempster-Shafer theory with belief entropy. EFMCDM method not only considers the subjective weights measured by belief entropy, utilized to obtain the BPAs of criteria. The results are compared and are found to be consistent with those of fuzzy inference system. In future we plan to incorporate more trust antecedents and factors influencing trust mechanism and implementation through more robust techniques of deep learning.

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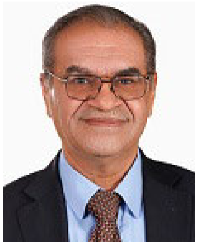
SANG-WOONG LEE (Senior Member, IEEE) received the B.S. degree in electronics and computer engineering and the M.S. and Ph.D. degrees in computer science and engineering from Korea University, Seoul, South Korea, in 1996, 2001, and 2006, respectively. From June 2006 to May 2007, he was a Visiting Scholar with The Robotics Institute, Carnegie Mellon University. From September 2007 to February 2017, he was a Professor with the Department of Computer Engineering, Chosun University, Gwangju, South Korea. He is currently a Professor with the School of Computing, Gachon University, Seongnam, South Korea. His current research interests include face recognition, computational aesthetics, machine learning, medical imaging analysis, and AI-based applications.

SADAF HUSSAIN received the master's degree in physics from U.E.T., Lahore, Pakistan, the master's degree in computer science from Iqra University, Lahore, and the M.Phil. degree in computer science from G.C. University Lahore. She is currently pursuing the Ph.D. degree in computer science with the School of Computer Science, NCBA&E, Lahore. She has extensive experience in the development and teaching of computer science to undergraduate students and college students. She is working at the Lahore Garrison Education System. Her research interests include cognitive computing, soft computing, and artificial intelligence.



GHASSAN F. ISSA received the M.S. and Ph.D. degrees in computer science/artificial intelligence from Old Dominion University, VA, USA, in 1987 and 1992, respectively. He was a Faculty Member and the Department Chair of computer science at the Pennsylvania College of Technology, PA, USA, from 1992 to 1995. He also worked as the Dean of computer science at Applied Science University, Amman, Jordan, from 2003 to 2005, and the Dean of information technology at the University of Petra, Amman, from 2008 to 2018. He is currently a Professor and the Dean of the School of Information Technology, Skyline University, Sharjah, United Arab Emirates. He is a Professor of computer science. His research interests include AI and machine learning with work on deep neural networks fine-tuning, learning by analogy, and associative classification algorithms.

SAGHEER ABBAS received the M.Phil. degree in computer science from the School of Computer Science, NCBA&E, Lahore, Pakistan, and the Ph.D. degree from the School of Computer Science, NCBA&E, in 2016. He is currently working as an Associate Professor at the School of Computer Science, NCBA&E. He has been teaching graduate and undergraduate students in computer science and engineering for the past eight years. He has been teaching graduate and undergraduate students in computer science for the past 12 years. He is guiding five Ph.D. scholars and six M.Phil. scholars. He has published more than 95 research articles with cumulative JCR-IF more than 180 in international journals as well as reputed international conferences. His research interests primarily include cloud computing, the IoT, intelligent agents, image processing, and cognitive machines, with various publications in international journals and conferences.

TAHER M. GHAZAL (Member, IEEE) received the B.Sc. degree in software engineering from Al Ain University, in 2011, the M.Sc. degree in information technology management from The British University in Dubai associated with The University of Manchester and The University of Edinburgh, in 2013, and the Ph.D. degree in IT/software engineering from Damascus University, in 2019. He is currently pursuing the Ph.D. degree in information science and technology with Universiti Kebangsaan Malaysia. He has more than ten years of extensive and diverse experience as an Instructor, a Tutor, a Researcher, a Teacher, an IT Support/Specialist Engineer, and a Business/Systems Analyst. He worked in engineering, computer science, ICT, and the Head of the STEM and Innovation Departments. He was also involved in quality assurance, accreditation, and data analysis, in several governmental and private educational institutions under KHDA, Ministry of Education, and Ministry of Higher Education and Scientific Research, United Arab Emirates. His research interests include the IoT, IT, artificial intelligence, information systems, software engineering, web developing, building information modeling, quality of education, management, big data, quality of software, and project management. He is actively involved in community services in the projects and research field.

TANWEER SOHAIL received the M.Sc. degree (Hons.) in mathematics from Government College University Lahore and the Ph.D. degree from the University of Science and Technology of China, China, by obtaining a scholarship from the Chinese Academy of Science and The World Academy of Sciences. He has worked at the University of Sargodha, Gujranwala Campus, as the Director of QEC. He is currently working as an Assistant Professor with the Department of Mathematics, University of Jhang, Jhang. He has seven years of teaching experience at undergraduate and graduate levels. He has supervised many students at the undergraduate level. His research interests include algebraic topology, algebra, knot theory, soft computing probability theory, and its application.

MUNIR AHMAD (Member, IEEE) received the Master of Computer Science degree from the Virtual University of Pakistan, in 2018. He is currently pursuing the Ph.D. degree in computer science with the School of Computer Science, National College of Business Administration and Economics. He has spent several years in industry. He is working as the Executive Director/Head of the IT Department, United International Group, Lahore, Pakistan. He has vast experience in data management and efficient utilization of resources at multinational organizations. His research interests include data mining, big data, and artificial intelligence. He has conducted many research studies on sentiment analysis and utilization of AI for prediction on various healthcare issues.

MUHAMMAD ADNAN KHAN received the B.S. and M.Phil. degrees from the International Islamic University, Islamabad, Pakistan, by obtaining a scholarship award from the Punjab Information and Technology Board, Government of Punjab, Pakistan, and the Ph.D. degree from ISRA University, Islamabad, by obtaining a scholarship award from the Higher Education Commission, Islamabad, in 2016. He is currently working as an Assistant Professor with the Pattern Recognition and Machine Learning Laboratory, Department of Software, Gachon University, Republic of Korea. Before joining Gachon University, he has worked in various academic and industrial roles in Pakistan. He has been teaching graduate and undergraduate students in computer science and engineering for the past 12 years. He is guiding five Ph.D. scholars and six M.Phil. scholars. He has published more than 200 research articles with cumulative JCR-IF more than 335 in reputed international journals as well as international conferences. His research interests primarily include machine learning, MUD, image processing and medical diagnosis, and channel estimation in multi-carrier communication systems using soft computing.