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Trust identification through cognitive correlates with emphasizing attention in cloud robotics

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ABSTRACT

Attention and Trust remain the crux of robotic sensory perception when associated with cloud robotics. It involves tasks that compete for attention from several stimuli taken by the robot itself upon its selective attention mode, focuses its attention on the task with higher precedence, and filters out the rest to be performed later. The robot could unload storage-extensive and computation extensive jobs towards the cloud while keeping trust establishment in control. Factors leading to these robots' availability, confidentiality, data protection, and isolation security trigger attention. Trust involving suppliers and users is intended to attain safety measures that endorse various cloud suppliers' status and accessible services. It takes several input stimuli from the robot, i.e., confidence, experience, and emotion, and gives output as trust level to pay attention during social interactions among robots. Input parameters are mapped into fuzzy sets, taking a range of input and output membership functions. The fuzzifier and defuzzifier are designed according to the proposed scheme. The developed system, named Trust Annotator, is tested and analyzed using MATLAB R2021a. Mamdani model is conferred, which yielded some unusual yet promising outcomes. These outcomes show conformity between the designed and simulated systems.

1. Introduction

With other rapid advancements in technology in everyday life, social robots have also paved their way in predominating our society by offering enhanced capabilities through much accurate natural language processing and image processing. Owing to this fact, these robots have widely been deployed from the industrial to the commercial sector, thus broadening their application areas from laboratory to routine life [1–3]. Since an extensive knowledge base contributes to better cognitive capabilities, these robots can benefit from cloud technologies having access to more powerful computation, storage, and other shared services offered by the centralized data centers, leading to the cost-effectiveness of having lightweight, compact but more intelligent robots [4].

Attention and Trust in cloud robotics are used in several intelligent machines to perform insistent, tedious tasks. Such preprogrammed robots have always been flourishing in their accomplishments due to their precision, survival (endurance), and cognitive capabilities, i.e., attention and Trust. These cognitive capabilities manifest on close-grained information required for visual direction (like in cocktail party phenomenon) [5–7].

A trust-based approach could be enforced to compete with privacy vulnerability in a universal computing environment. Any application or service incorporated in cloud robotics needs to

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own full trust values judged by all individual parameters [8]. An identity management system guards the allotment of identities and protects them—a security concern for authentication checks. The authorization is a two-way treaty. Data service privacy and secrecy are required while moving from one cloud to another [2]. The communication medium should be secure enough to incorporate a private, confidential conversation as virtualization (simulating or emulating on a computer or using cloud computing) gives rise to the hypervisor, thus protecting such obstacles or risks [4].

Many enterprises and businesses are moving towards producing human-centric systems, keeping human needs as their objectives. Critical socioeconomic impacts have been brought to human lives over the past few decades. The inducement of Trust in cloud robotics helps robots have Trust in humans to carry out only those commanded by a trustable human being [5]. Even in domestic circumstances, a social humanoid robot must not carry out all the assigned tasks as some of them may be hazardous to the people living in the house or to himself. In addition, developing Trust in cloud robotics can also diminish confidentiality and privacy issues as desired information would be given only to the trusted person or machine [6].

To handle these machines, the primary stint is to cope with the sizeable quantity of facts continuously received via more than one sensor [7,8]. There are stern difficulties of redundant data control in robots' visible belief [9]. Consequently, modeling primates-like visual interest mechanisms for the robot is becoming more popular among many robotic researchers [10]. A visual interest model allows the robots to selectively and autonomously pick a "behaviorally applicable" section of visible information for additional processing [11].

With the utilization of cloud foundation and its convention set of IoT, assets can give robots and mechanization framework [12]. The operation of robots and robotization frameworks depends upon information through the system to help [13]. We can enhance robot and computerization framework utilizing cloud either by giving access to datasheets, production models, benchmark, recreational instruments, open rivalry for the plan and framework or open-source programming can also contribute for the said cause [14].

Fuzzy Logic is an advanced Boolean logic form where the values always lie between 0 and 1. The truth is deemed entirely true and completely false (including extreme values). The said technique is vital in demonstrating human-like behavior or decision-making by the non-human agents for mechanization purposes in which robotics and automation are prominent prospects [15]. Typically, the robots sense various environmental information through their sensors which act as inputs to the fuzzy system, then the Fuzzification process converts crisp inputs into fuzzy values, and finally, we get crisp output through the Defuzzification process [9,10,16]. The following model below represents the working of the Fuzzy Logic in Fig. 1. In this paper, the robot's Trust has been gained through three input parameters: confidence, experience, and emotion, given to the Fuzzy Inference System.

A set of requirement specifications is treated as objects and meets the fuzzy membership properties. The membership Expectation of the represented items of the fuzzy set varies (E). Assume that set 'X' contains several elements, each of which must be symbolized by the interval [0, 1]. If any Robot's Trust Level 'Y' is a member of set 'X,' then Equation (1) denotes this mapping:

$$E_X(Y) \in [0,1] \tag{1}$$

also, for the ' m' number of items, they can be characterized in the form of Equation (2):

$$X = \left[\frac{E_X^{(y_1)}}{x_1} + \frac{E_X^{(y_2)}}{x_1} + \cdots + \frac{E_X^{(y_m)}}{x_m}\right] = \sum_{j=1}^{m} \frac{E_X^{(y_j)}}{x_j} \tag{2}$$

where $y_1, y_2, \ldots, y_m$ are members of X and $E_X^{(y_1)}, E_X^{(y_2)}, \ldots, E_X^{(y_m)}$ are the membership degrees of $Y_1, Y_2, \ldots, Y_m$.

Fuzzy measure (E) is an extension of likeness on a space 'Y' is a mapping from subsets of Y into the unit interval E: 2Y → [0, 1] such that E(Y) = 1, E(Y) = 0, and if $X \subset D$ then $E(X) \leq E(D)$.

Fuzzification is the technique of making the crisp input values to the comparable membership function to acquire the fuzzy measure of that corresponding value. Fuzzification of user input variables for creating fuzzy inference systems relies heavily on the usage of fuzzy linguistic variables [17]. As a result, defuzzification converts the aggregated fuzzy value into a precise quantity for user comprehension. Any element $\times \in X\Omega$ that has a grade of membership greater than or equal to the value 'E' belongs to 'X'.

Assume E is a fuzzy measure on 'Y,' the Sugeno integral of a function g: Y [0, 1] in terms of fuzzy measure. Equation (3) is used to define E:

$$g(y)dE = \max 1 \leqslant j \leqslant m(\min(\ g(y_j, E(X_j)))) \tag{3}$$

where $g(y_1)$, $g(y_2)$, $g(y_3)$, … , $g(y_m)$ are the ranges and they are defined as $g(y_1) \leq g(y_2) \leq g(y_3) \leq \cdots \leq g(y_m)$.

The fuzzy decision tree combines decision tree concepts with the capacity to process fuzzy systems' ambiguity and imprecision. Furthermore, fuzzy decision trees inherit the necessary qualities of decision trees, such as low computing cost and the ability to express information graphically or as a collection of rules. In three ways, a fuzzy decision tree differs from a typical decision tree: it uses splitting criteria based on fuzzy limitations, it uses alternative inference processes, and the fuzzy sets that represent Trust Level information must be defined [18].

The attributes are chosen based on their information gain, which reduces the amount of data required in the decision table to classify the Trust Level. Equation (4) gives the predicted information needed to classify the Trust Level in the dataset DT:

$$\mathrm{T}(D_T) = -\sum_{j=1}^{m} Pb_j \log_2 Pb_j \tag{4}$$

Pbj is the probability that an arbitrary Trust Level in DT fits class C_j and is projected by adding the Trust Level entropy. Assume that the Trust Level in C_j have m distinct values, $\{c_1, c_2, \ldots, c_s\}$, Trust Level in C_j can be used to partition D_T into m partitions or subsets, $\{D_1, D_2, \ldots, D_s\}$ where $D_1(k = 1, s)$ comprises those Samples (S) in D_T. Then the Entropy (En) of Trust Level C_i is given by Equation (5):

$$En(C_i) = \sum_{k=1}^{s} \frac{S_{1j} + S_{2j} + S_{1sj}}{S} T(S_{1j} + S_{2j} + S_{1sj}) \tag{5}$$

The branching attribute is chosen based on the Trust Level, resulting in the most information gain. Equation (6) expresses the information gain for a given subset D_s:

$$T(D_{1j} + D_{2j} + D_{1sj}) = -\sum_{j=1}^{m} Pb_{jk} \log_2 Pb_{jk} \tag{6}$$

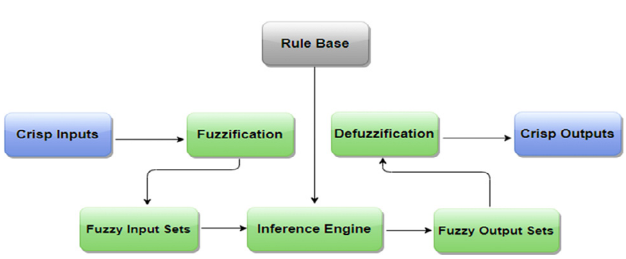

Fig. 1. Fuzzy logic model.

Finally, the information gain of Trust Level C_j is given by; Gain (Cj) = $T(D_T) - En(C_j)$

The details of the proposed work have been discussed in the coming sections of the paper. The literature study has been carried out in section 2. The methodology of the proposed work is elucidated in section 3. The results obtained through the work proposed are presented and analyzed in section 4, followed by the concluding remarks in section 5.

2. Related work

In this section, different proposed works from various authors have been studied to know the applications of social robots and the contribution of fuzzy Logic to optimize cognitive capabilities in one way or another.

2.1. Risk assessment in parallel robot for elbow and wrist rehabilitation using fuzzy logic

The application of robots in medicine and healthcare comprises several types, i.e., surgery, rehabilitation, telepresence, sanitation, etc. As it is a susceptible application area, it needs extra attention to be drawn. The main concern regarding robots in medicine and healthcare is their safe use, both for patients and agents. The authors have assessed the risk of using robotic systems for wrist and elbow rehabilitation, particularly from the safety point of view [11]. The results are further analyzed through Fuzzy Logic to know the extent of the safety. This innovative method for risk assessment was then tested successfully on 18 patients for the trials, validating the safety concerns.

2.2. Visual tracking using closed-words

In this study, the authors have provided a robust motion detection algorithm for the robot, which detects motion rate using a background subtraction technique [19]. It captures the static image, and whenever it detects any change, it subtracts the current image from the previously captured image to analyze the difference. It gives object blobs compared to the last image frame in which the object was detected. In this way, motion can be detected from the background [20].

2.3. Advanced controllers using fuzzy logic

A self-tuning fuzzy regulator wherein the control rules, the enrollment work, or the scaling factors are self-balanced. Among them, the control rules and the scaling factors assume significant jobs. So the authors have utilized an ongoing tuning for yield scaling factors. Its primary points of interest over a general FLC are more grounded control ability, expanded adaptability, and heartiness. The PI-type fuzzy regulator generally gives excellent; consistent state execution yet has transient execution, not all that great. The authors have followed a technique in [21] to get significant transient and consistent state execution. The technique is that, initially, the framework has a substantial positive speeding up, so the scaling variable is increased to such an extent that the ascent and settling times are decreased. Close to the set moment that the framework has a negative speed up, the scaling variables are diminished with the end goal of diminished or dispensed overshoot. While controlling a plant, a talented human administrator controls the procedure input (i.e., regulator yield) based on blunder 'e' and changes in mistake 'Δe' to limit the blunder inside the base time. Fuzzy logic control is an information-based framework. The yield SF should be resolved cautiously for the fruitful and compelling FLC [21,22].

2.4. New controller for mobile robots using fuzzy and genetic algorithm

The fuzzy regulator permits the robot to improve its movement and arrive at the last objective. Specifically, when the robot meets a deterrent during its shifting, the fuzzy regulator enters an office that permits the robot to stay away from the hindrance straightforwardly and familiarly. The boundaries utilized as contributions to the fuzzy regulator are data originating from natural sensors from the portable robot's gadgets, and they empower it to recreate the general condition [23]. Specifically, as contributions of the regulator, the researchers utilized these accompanying factors [24]:

Distance obstacle Δx demonstrates the separation and the level pivot between the versatile robot and the impediment.

Distance obstacle Δy demonstrates the separation and the vertical hub between the versatile robot and the snag.

Both distance obstacles Δx and Δy are considered in correlation with a fixed deterrent [25].

2.5. Application of fuzzy Logic in autonomous robots

The utilization of fuzzy procedures in achieving autonomy has gotten across the board in recent years and various fields of applied autonomy, such as to conduct structure, coordination of conduct, observation, limitation, and so on. The centrality of the commitments was at its peak till the end of the 1990 s, where the fundamental point in mechanical autonomy was the execution of essential practices. In recent years, the deliberation in autonomy implementation moved to build robots that work independently in natural conditions. The actual effect of fuzzy methods in the mechanical technology network is not as profound as it was in the beginning phases to apply autonomy or what it is worth for in other application regimes. However, new rising regimes in mechanical technology, for example, human and humanoid communication, or settled ones, for example, discernment, are genuine instances of new expected domains of uses where hybridized fuzzy methodologies, will without a doubt, be fitted for showing their ability to manage such perplexing and dynamic situations [26].

2.6. Framework for culture aware robots based on fuzzy logic

Cultural variation, i.e., the coordination of a robot's practices to its client's cultural standards and inclinations, is a notable fundamental necessity for achieving any assistive application. Nonetheless, culture-subordinate robot practices are regularly verifiably set by architects, accordingly, not taking into account a programmed and straightforward variation to various societies [27]. A strategy for the plan of culture-mindful robots that can adjust their conduct to adjust to a given culture is presented [28]. Planning from cultural components to related restrictions of robot practices depends on semantic factors to encode heterogeneous cultural elements in a uniform formalism and on fuzzy guidelines to encode subjective relations among various factors [29]. It is shown in two reasonable contextual analyses [30].

3. Materials and methods

3.1. Proposed work

The proposed technique environs that a robot's Trust relies on three fundamental cognitive factors: confidence level, emotions of the interacting machine, and the experience with another machine. To emphasize attention based on Trust, Mamdani Fuzzy Inference System (MFIS) Module named as Trust Annotator is being designed and implemented in the cloud, which could leverage the use of centralized knowledge base as well as the local rule bases of the regions from where the robots are accessing the centralized MFIS module as depicted in Fig. 2.

The MSIF module is employed to determine the trust level in robots via Machine-to-Cloud (M2C) communication to gain attention for social interactions in Machine-to-Machine (M2M) communication in cloud robotics. The proposed scenario algorithm is as under, where S is the region obtained for serving robotic agents during a time interval t.

Algorithm: For Development of Trust and Emphasizing Attention in M2M Communication

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Goal: To make robotic agents more socially able by seeking attention through the Trust level.
Step 1: Initializing cloud monitoring cycle over different regions
Step 2: Declaration of input parameters and output signal for the MSIF:
$Ex \leftarrow$ Experience
$E \leftarrow$ Emotion
$C \leftarrow$ Confidence
$T \leftarrow$ Trust level
Step 3: Return S for t
Step 4: MSIF module $\leftarrow$ robotic agent from S
Step 5: Sensing of input stimuli for Ex, E, and C by robotic agent
Step 6: Sharing information via M2C communication during t
Step 7: Returning T value for the agent
Step 8: M2M communication based on the value of T
Step 9: Update the centralized knowledge base
Step 10: $t \leftarrow t + 1$
Repeat step 3.

At a certain time, a new regional set of robotic agents are procured to establish a Machine-to-Cloud communication link from where a certain agent accesses the MFIS module before social interaction with other agents. The MFIS module contributes to the interaction's attention-seeking phase by inducing cognitive capabilities by developing Trust based on the agent's cognitive, sensory inputs, hence, dealing with the severe difficulties and issues in maintaining confidentiality and privacy.

In coming subsections, the Trust Annotator module's methodology presented in Fig. 1 is elucidated in which Mamdani Inference Model has been exploited. Its intuitiveness is crucial for choosing this model, which generates a control system that employs sets of linguistic rules from a more interpretable rule base, easily obtained through experienced human operators. Due to this fact, they are pertinent to expert systems where human-like knowledge is required. Crisp values are like binary values assigned to any (input stimuli) statement answer but always exist between 0 and 1. More superficially, It is defined as either the value is true or false, varying like binary values. But in the case of fuzzy, we would take the intermediate value (any real-numbers between 0 & 1). Obtained crisp values of input stimuli are given to a fuzzifier that transfers to the inference engine in the form of fuzzy input sets, and over there, defined rules get applied. As a result, fuzzy output sets are obtained that get defuzzified in the defuzzifier and transferred as crisp outputs to the user.

3.2. Fuzzifier

The given crisp values for input stimuli are associated with the fuzzifier with a definite level and produce linguistic values for every entered variable [31]. The inference engine simulates the human decision in fuzzy Logic with fuzzy standards, consequence, and inference [32]. For three input variables and the output, Triangular membership functions created using MATLAB R2021A are shown in Figs. 3a, 3b, 3c, and 3d.

These triangular member functions can be mathematically written as piece-wise functions, denoted by μ defining different ranges between 0 and 100 for each. So, the piece-wise functions are $\mu_{low}(x)$, $\mu_{medium}(x)$ and $\mu_{high}(x)$ represented through Equation

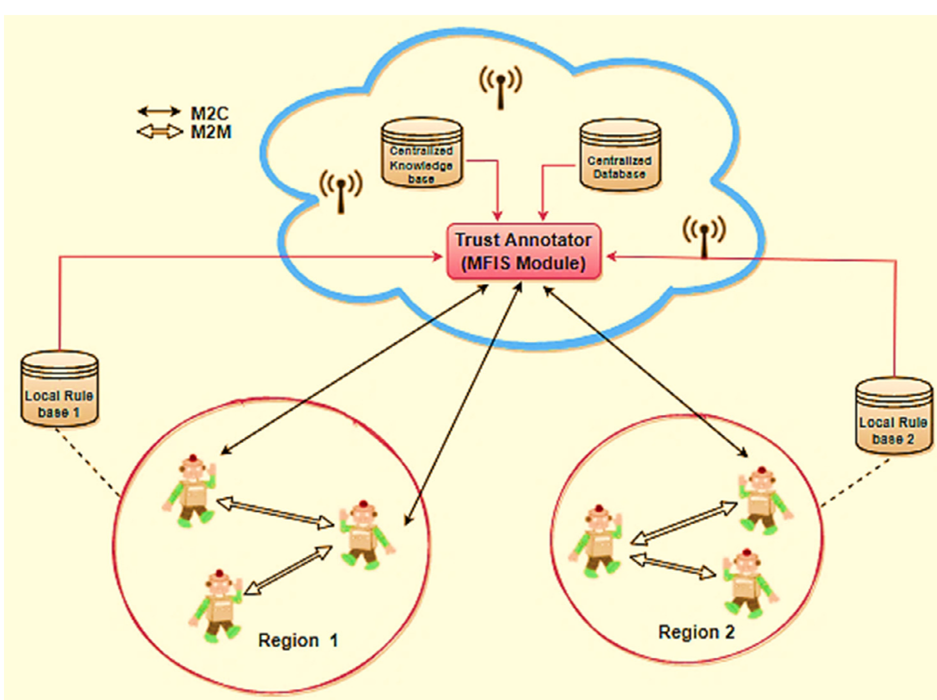

Fig. 2. Trust Development Among Cloud Robotics using Mamdani-Type Fuzzy Inference System.

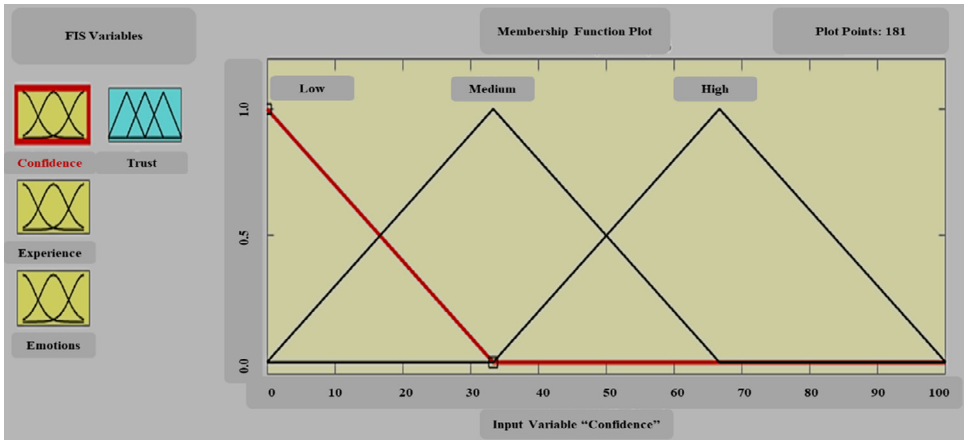

Fig. 3a. Membership functions for Input "Confidence"

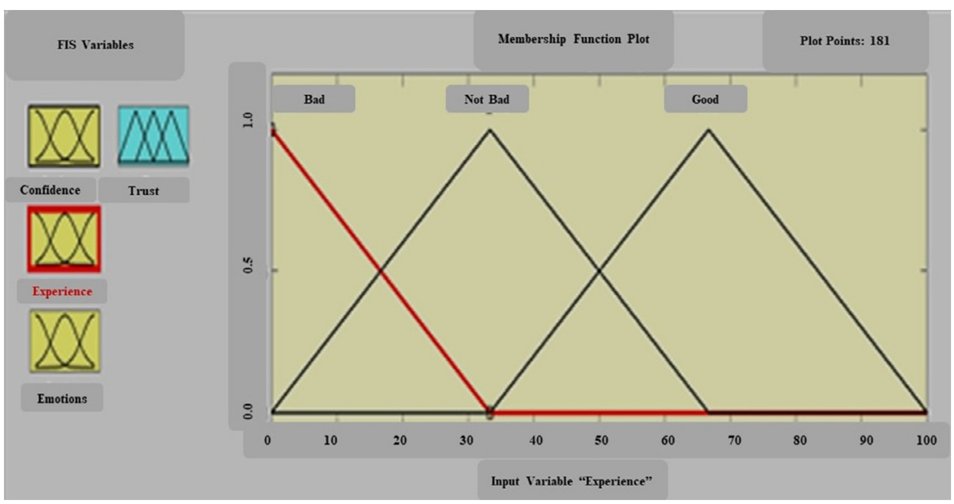

Fig. 3b. Membership functions for Input "Experience"

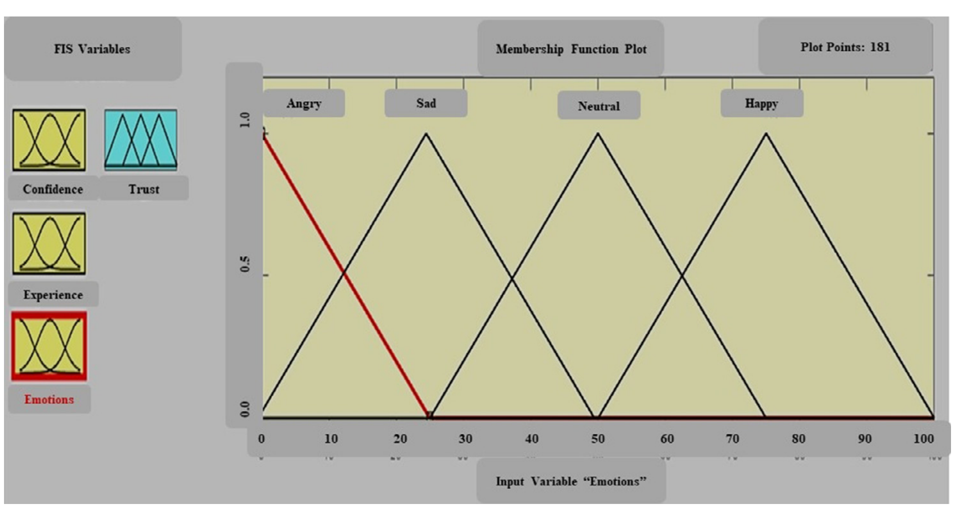

Fig. 3c. Membership functions for Input "Emotions"

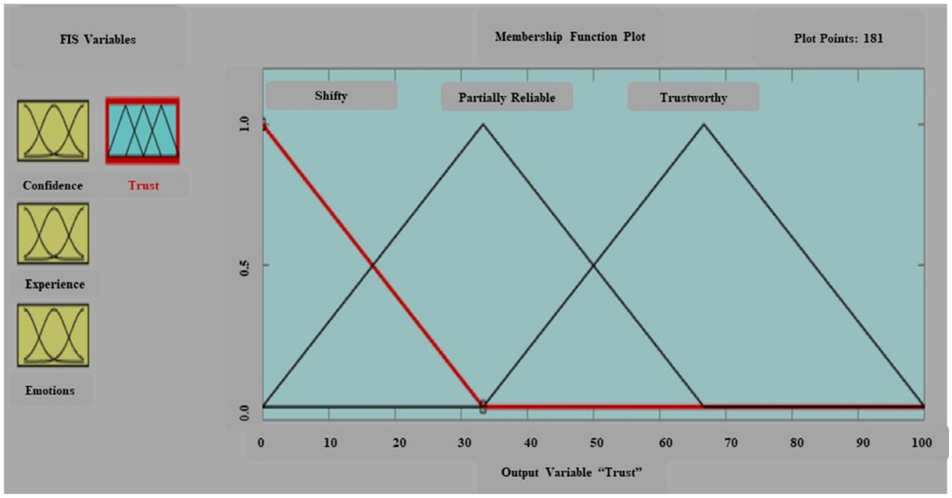

Fig. 3d. Membership Functions for Output "Trust"

(7), Equation (8) and Equation (9) for the 'Confidence' input where $\times \in \{C\}$.

$$\mu low(x) = \begin{cases} 0 & x \le 0 \\ (33.33 - x)/(33.33 - 0) & 0 \le x \le 33.33 \end{cases} \quad (7)$$

$$\mu med(x) = \begin{cases} (x - 0)/(33.33 - 0) & 0 \le x \le 33.33 \\ (66.66 - x)/(66.66 - 33.33) & 33.33 \le x \le 66.66 \end{cases} \quad (8)$$

$$\mu high(x) = \begin{cases} (x - 33.33)/(66.66 - 0) & 33.33 \le x \le 66.66 \\ (100 - x)/(100 - 66.66) & 66.66 \le x \le 100 \end{cases} \quad (9)$$

Likewise, the membership functions for Experience input have the same defined ranges, so the piece-wise functions μ_{bad}(x), $\mu_{not\text{-}bad}$(x) and μ_{good}(x) represented through Equation (10), Equation (11) and Equation (12) is similar to those mentioned above where $\times \in \{Ex\}$.

$$\mu bad(x) = \begin{cases} 0x \le 0 \\ (33.33 - x)/(33.33 - 0)0 \le x \le 33.33 \end{cases} \quad (10)$$

$$\mu not - bad(x) = \begin{cases} (x - 0)/(33.33 - 0)0 \le x \le 33.33 \\ (66.66 - x)/(66.66 - 33.33)33.33 \le x \le 66.66 \end{cases} \quad (11)$$

$$\mu good(x) = \begin{cases} (x - 33.33)/(66.66 - 0)33.33 \le x \le 66.66 \\ (100 - x)/(100 - 66.66)66.66 \le x \le 100 \end{cases} \quad (12)$$

The third input parameter, Emotion, has four membership functions μ_{angry}(x), μ_{sad}(x), $\mu_{neutral}$(x), and μ_{happy}(x), with different ranges defined between 0 and 100. So, the piece-wise functions are represented through Equation (13), Equation (14), Equation (15), and Equation (16), where $\times \in \{E\}$.

$$\mu angry(x) = \begin{cases} 0x \le 0 \\ (25.0 - x)/(25.0 - 0)0 \le x \le 25.0 \end{cases} \quad (13)$$

$$\mu sad(x) = \begin{cases} (x - 0)/(25.0 - 0)0 \le x \le 25.0 \\ (50.0 - x)/(50.0 - 25.0)25.0 \le x \le 50.0 \end{cases} \quad (14)$$

$$\mu neutral(x) = \begin{cases} (x - 25.0)/(50.0 - 25.0)25.0 \le x \le 50.0 \\ (75.0 - x)/(75.0 - 50.0)50.0 \le x \le 75.0 \end{cases} \quad (15)$$

$$\mu happy(x) = \begin{cases} (x - 50.0)/(75.0 - 50.0)50.0 \le x \le 75.0 \\ (100 - x)/(100 - 75.0)75.0 \le x \le 100 \end{cases} \quad (16)$$

And similar is the case with the output variable Trust having $\mu_{unreliable}$(x), $\mu_{partially\text{-}reliable}$(x) and μ $t_{rustworthy}$(x) where $\times \in \{T\}$ within the defined range 0–100 and are represented through Equation (17), Equation (18), and Equation (19).

$$\mu unreliable(x) = \begin{cases} 0x \le 0 \\ (33.33 - x)/(33.33 - 0)0 \le x \le 33.33 \end{cases} \quad (17)$$

$$\mu partially - reliable(x) = \begin{cases} (x - 0)/(33.33 - 0)0 \le x \le 33.33 \\ (66.66 - x)/(66.66 - 33.33)33.33 \le x \le 66.66 \end{cases} \quad (18)$$

$$\mu reliable(x) = \begin{cases} (x - 33.33)/(66.66 - 0)33.33 \le x \le 66.66 \\ (100 - x)/(100 - 66.66)66.66 \le x \le 100 \end{cases} \quad (19)$$

Hence the total number of membership functions for inputs is 10, and that for output is 3. The input membership functions and their linguistic values, ranges of occupied regions, and rule mappings are given in Table 1 and Table 2. After every sampling period, the algorithm takes Confidence, Experience, and Emotion to measure the trust level by applying Fuzzy Logic [33].

Three different fuzzifiers are needed for the fuzzification process, which takes three variables. The model of such a fuzzifier is demonstrated in Fig. 4.

Using the predefined values of inputs, positive outcomes of three fuzzifiers are listed in Table 3. These outcomes are obtained using the fuzzified model for confidence, emotion, and experience intakes.

3.3. Implication engine (Inference)

This engine, consisting of six AND operators, selects the most negligible value intake for the output. The Maximum-Minimum arrangement is applied to get the resultant values by accepting six intakes from the fuzzifier [34]. Total active rules can be calculated as k*m*n, where k, m, and n are the levels taken for each input, respectively. The three input variables described here consisted of two three's and one four membership functions. Altogether, these rules become 36 in number. In the current situation, for specific values of three variables, merely eight rules are needed, which are designed as under through Equation (20) to Equation (27):

Table 1
Membership functions and linguistic values of input variables in all fuzzified regions.

Input Variables	Membership Functions	Linguistic Variables	1st Region	2nd Region	3rd Region	4th Region
Input 1 = Confidence	Low	q1	q1[−33.33, 33.3]			
	Medium	q2		q2[0, 66.66]		
	High	q3			q3[33.33, 100]	
Input 2 = Experience	Bad	q4	q4[−33.33, 33.33]			
	Not Bad	q5		q5[0, 66.66]		
	Good	q6			q6[33.33, 100]	
Input 3 = Emotion	Angry	q7	q7[-25, 25]			
	Sad	q8		q8[0, 50]		
	Neutral	q9			q9[25,75]	
	Happy	q10				q10[50,100]

Table 2
Rule mapping with occupied regions.

No.	Region occupied Input 1 = Confidence	Input 2 = Experience	Input 3 = Emotion	Rules an[b] = Member's rate
1	1st	1st	1st	q1[−33.33, 33.33] ^ q4[−33.33, 33.33] ^ q7[-25,25] = P1
			2nd	q1[−33.33, 33.33] ^ q4[−33.33, 33.33] ^ q8[0,50] = P2
			3rd	q1[−33.33, 33.33] ^ q4[−33.33, 33.33] ^ q9[25,75] = P3
			4th	q1[−33.33, 33.33] ^ q4[−33.33, 33.33] ^ q10[50,100] = P4
2	1st	1st	1st	q1[−33.33, 33.33] ^ q5[0, 66.66] ^ q7[-25,25] = P5
			2nd	q1[−33.33, 33.33] ^ q5[0, 66.66] ^ q8[0,50] = P6
			3rd	q1[−33.33, 33.33] ^ q5[0, 66.66] ^ q9[25,75] = P7
			4th	q1[−33.33, 33.33] ^ q5[0, 66.66] ^ q10[50,100] = P8
3	1st	1st	1st	q1[−33.33, 33.33] ^ q6[33.33, 100] ^ q7[-25,25] = P9
			2nd	q1[−33.33, 33.33] ^ q6[33.33, 100] ^ q8[0,50] = P10
			3rd	q1[−33.33, 33.33] ^ q6[33.33, 100] ^ q9[25,75] = P11
			4th	q1[−33.33, 33.33] ^ q6[33.33, 100] ^ q10[50,100] = P12
4			1st	q3[33.33, 100] ^ q6[33.33, 100] ^ q7[-25,25] = P33
			2nd	q3[33.33, 100] ^ q6[33.33, 100] ^ q8[0,50] = P34
			3rd	q3[33.33, 100] ^ q6[33.33, 100] ^ q9[25,75] = P35
			4th	q3[33.33, 100] ^ q6[33.33, 100] ^ q10[50,100] = P36

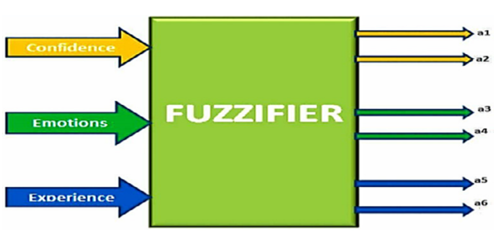

Fig. 4. Fuzzifier block.

Table 3
Fuzzified results.

Inputs	Values	Selected Region	Calculated Fuzzy Set
Confidence	J = 17	1st Region	q1=(50–17)/50 = 0.66
			q2 = 1-q1 = 1–0.66 = 0.34
Experience	J = 49	2nd Region	q3=(50–49)/50 = 0.02
			q4 = 1-q3 = 1–0.02 = 0.98
Emotion	J = 70	3rd Region	q5=(100–70)/66.6 = 0.45
			q6 = 1-q5 = 1–0.45 = 0.55

$$P_1 = q_1^{[1]} q_3^{[1]} q_5^{[3]} = 0.66^0.02^0.45 = 0.02 \quad (20)$$

$$P_2 = q_1^{[1]} q_3^{[1]} q_6^{[4]} = 0.66^0.02^0.55 = 0.02 \quad (21)$$

$$P_3 = q_1^{[1]} q_4^{[2]} q_5^{[3]} = 0.66^0.98^0.45 = 0.45 \quad (22)$$

$$P_4 = q_1^{[1]} q_4^{[2]} q_6^{[4]} = 0.66^0.98^0.55 = 0.55 \quad (23)$$

$$P_5 = q_2^{[2]} q_3^{[1]} q_5^{[3]} = 0.34^0.02^0.39 = 0.02 \quad (24)$$

$$P_6 = q_1^{[2]} q_3^{[1]} q_6^{[4]} = 0.34^0.02^0.61 = 0.34 \quad (25)$$

$$P_7 = q_2^{[2]} q_4^{[2]} q_5^{[3]} = 0.34^0.98^0.39 = 0.34 \quad (26)$$

$$P_8 = q_2^{[2]} q_4^{[2]} q_6^{[4]} = 0.34^0.98^0.61 = 0.34 \quad (27)$$

3.4. Rule selector

Rule selector obtains crisp values of confidence, emotion, and experience. Singleton values are given out of resultant functions under algorithmic rules applied to the designed system. Eight rules are required to conform to singleton values G1, G2, G3, G4, G5, G6, G7, and G8, each for three input variables, as listed in Table 4 below.

With every region having three fuzzy variables, the rule base accepts three crisp input values to allocate the cosmos of discourse into regions, rules get applied, and singleton values are given out as output agreeing to every output variable. The fundamental block of the rule base is presented in Fig. 5.

3.5. Defuzzifier

Crisp value productivities are provided in the defuzzification process after approximating its intakes. To every single of the three defuzzifiers, sixteen inputs are given; Eight values of P1, P2, P3, P4, P5, P6, P7, P8 from the implication engine's productivities, and eight values G1, G2, G3, G4, G5, G6, G7, and G8 as shown in Fig. 6 below. The defuzzifier rounds off to crisp value employing the following mathematical expression denoted by D, where i = 1 to 8.

Table 4
Singleton values of predefined rules against inputs.

No.	Inputs			Output		
	Confidence	Experience	Emotion	Trust	Singleton value	The output of Singleton value
1	Low	Bad	Angry	t1	G1	25% Trust
2	Low	Bad	Sad	t2	G2	25% Trust
3	Low	Bad	Neutral	t3	G3	25% Trust
4	Low	Bad	Happy	t4	G4	25% Trust
5	Low	Not Bad	Angry	t5	G5	25% Trust
6	Low	Not Bad	Sad	t6	G6	25% Trust
7	Low	Not Bad	Neutral	t7	G7	50% Trust
8	Low	Not Bad	Happy	t8	G8	50% Trust
33	High	Good	Angry	t33	G33	75% Trust
34	High	Good	Sad	t34	G34	100% Trust
35	High	Good	Neutral	t35	G35	100% Trust
36	High	Good	Happy	t36	G36	100% Trust

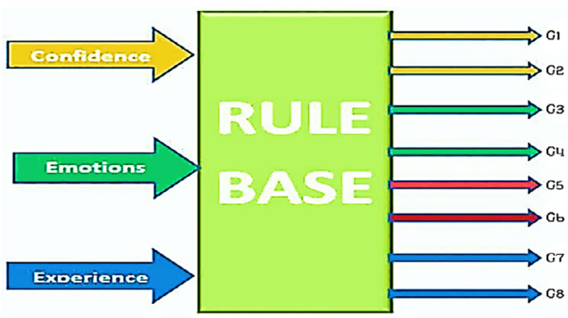

Fig. 5. Rule base (key block).

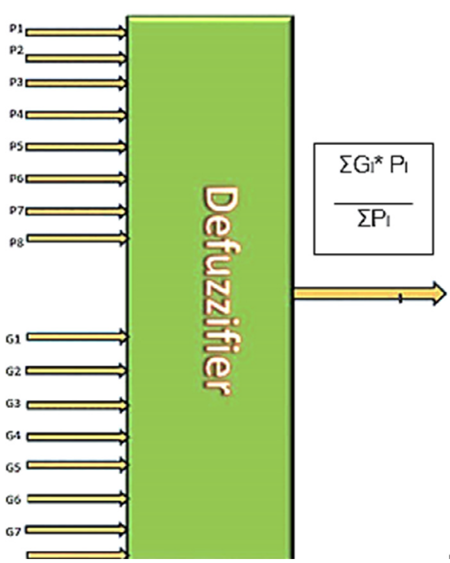

Fig. 6. Defuzzifier block.

4. Results and discussion

The Trust Annotator MFIS is discussed in this section by comparing the designed values with the simulated ones in MATLAB R2021A. Table 5 lists the inference engine's designed values, then propagated to the defuzzifier to obtain crisp output values.

Table 5
Designed values for Trust.

I	Pi	Gi	Pi*Gi
1	0.02	0	0
2	0.02	0	0
3	0.45	0	0
4	0.55	0.25	0.137
5	0.02	0	0
6	0.02	0.50	0.01
7	0.34	0.50	0.17
8	0.34	0.75	0.255

According to the results of the designed values of the inference engine through Equation (28) to Equation (30):

$$\sum P_i = 0.02 + 0.02 + 0.45 + 0.551 + 0.02 + 0.02 + 0.34 + 0.34 = 1.761 \tag{28}$$

The summation of the products of inference engine's productivities and that from the rule base is:

$$\sum P_i G_i = 0.572 \tag{29}$$

Then,

$$V_c = \sum P_i G_i / \sum P_i = 0.308 = 30.8\% \tag{30}$$

Here, Vc determines the crisp value for the output variable. The outcomes are then originated conferring to the MATLAB R2021A simulation. These outcomes are compared and are found precisely according to the designed system. The provided value for confidence is 17 that falls in the 1st region; for the experience, it is 49, which again falls in the 1st region; and for emotion, it is 70 that falls in the 3rd region. According to this range scheme, these eight rules are applied for MATLAB R2021A simulation. Using MATLAB R2021A Rule viewer, the implemented values are identified as represented in Fig. 7.

Table 6 shows the comparative outcomes of the system's designed value and its corresponding simulated value, which is considerably good.

We have performed exhaustive experiments for better performance representation in this study. The presented results are optimized as we have verified these results after varying the number of fuzzy sets and shape of the fuzzy sets, but we get the best results with the presented configuration. The evaluated and simulated results are close enough to be considered promising, with an error rate of 8.0 %. In this proposed model, Trust relies on the chosen attributes of confidence, emotion, and experience altogether. How-

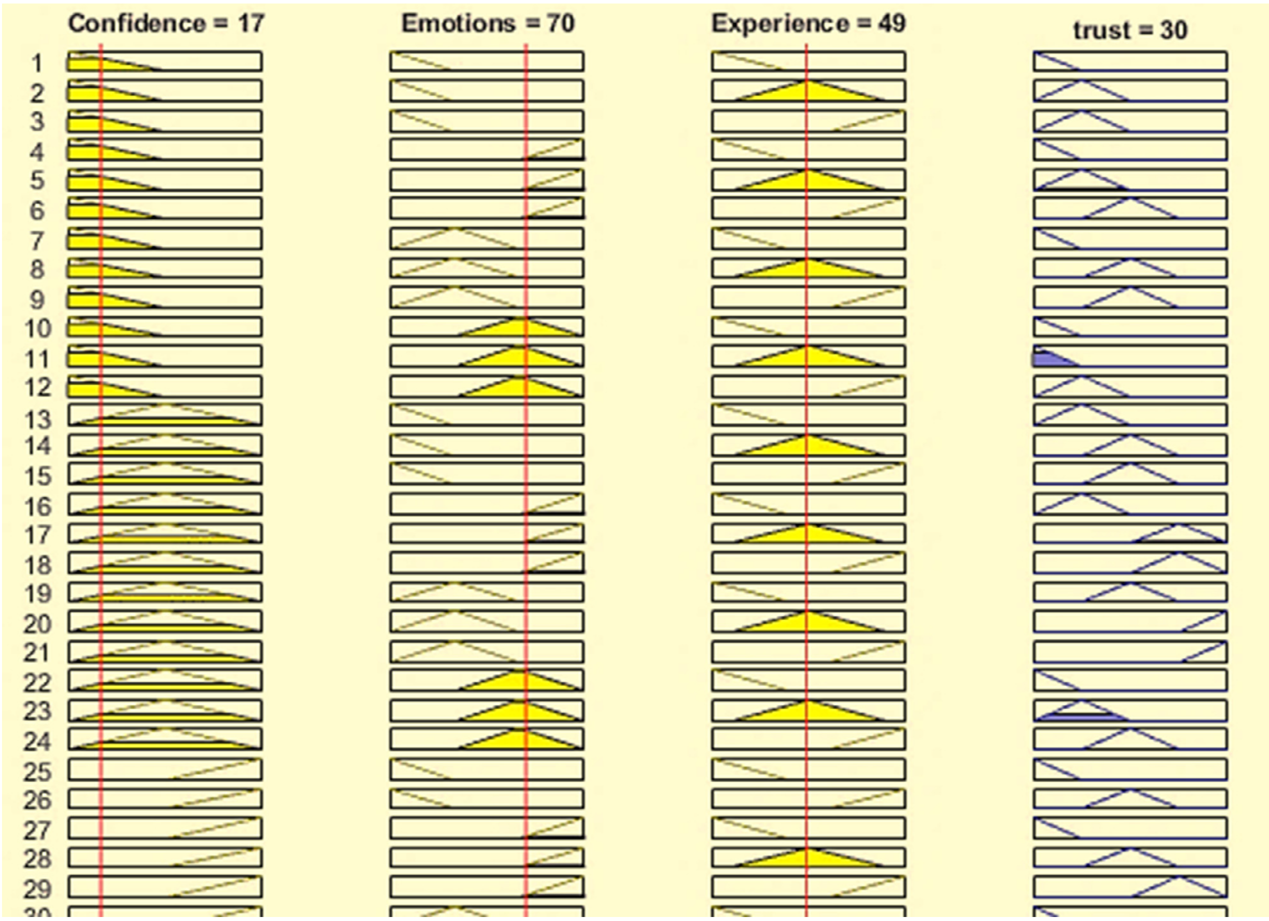

Fig. 7. MATLAB R2021a rule viewer.

Table 6
Support vector machine characterization.

Analysis	Outcome Values
Designed System Value	30.8
MATLAB R2021A Simulated System Value	30
Error Percentage	8.00%

ever, the dependency of Trust on these factors can be visualized more precisely and effectively utilizing surface graphs. Figs. 8(a), 8(b), and 8(c) represent the plots between Trust and its cognitive factors, i.e., confidence, emotion, and experience.

The visualizations from these graphs show that the level of Trust varies gradually with the variations in its cognitive factors' values. However, the dependency of Trust is less inclined towards the confidence and experience of the robots. Whereas the third input parameter, i.e., emotion, has a far critical impact on drawing attention based on Trust in contrast with the other two factors, i.e., if it is happy along with not-bad to a good experience with the interacting robot only then, it builds full Trust (see Fig. 8(c)). On the contrary, if the interacting robot's experience is somewhere between not-bad and bad, but the confidence is medium to high, it can still consider it trustworthy with a 75–100% trust level (see Fig. 8(a)). Likewise, if the emotion is neutral and happy and the confidence level is higher, the Trust Level is 75–100% (see Fig. 8(b)). Keeping in view the impact of the robot's emotion from the above statements, this particular cognitive factor's significance plays a significant part in reinforcing cognitive capabilities.

5. Conclusion

The MFIS named Trust Annotator is proposed in this paper, a cloud-based FLC system for developing Trust among robots during social interactions. After so many iterations and configurations, the system is designed for ideal outcomes and then tested using MATLAB R2021a. The designed and simulated system results for the developed Trust Annotator are quite an in accordance. The designed model can be protracted for any range of sensory inputs and outcomes. The application of developing Trust in cloud robotics using attention level has a broader scope. It covers the problems of privacy and access control and safeguards all beings in the natural environment. The proposed system, being a more precise way of developing Trust, using the comparison of attention and emotion, can lead to a better interpretation in human-robot companionship. In future with the proposed systems' help, we can put another step to hold a more sociable agent, increasing productivity and efficiency by emotional empathy prediction to cater Robot-to-Robot or Robot-to-Human mutual interaction precisely in a socially dynamic environment.

a

b

c

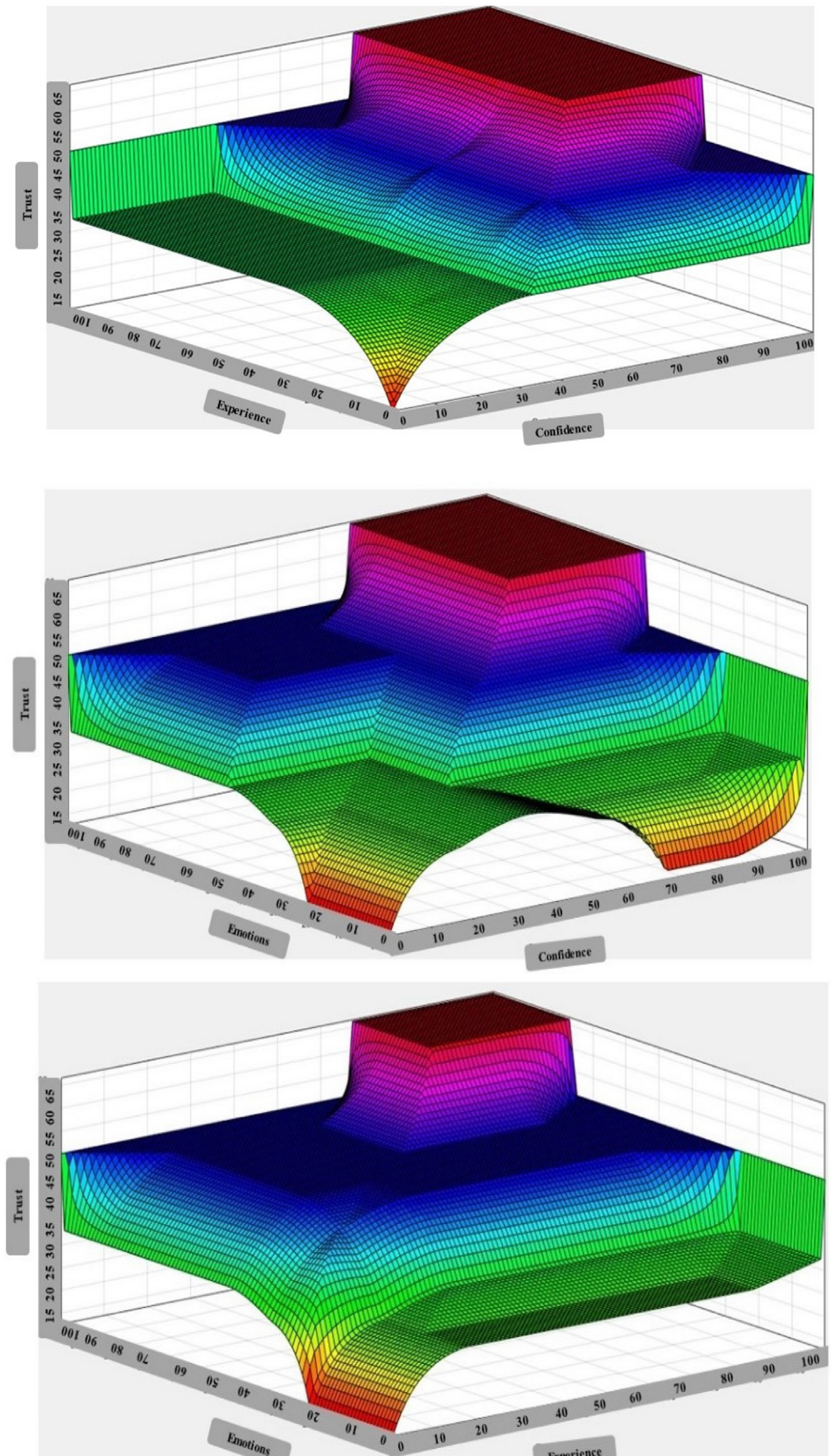

Fig. 8. a. The Plot Between Confidence, Emotions, and Trust; b. The Plot Between Emotions, Experience, And Trust; c. The Plot Between Confidence, Experience, And Trust.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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