Modeling A Fuzzy Expert System for Predicting Behavioral Intention of Customers through Parallel Prediction of Perceived Values and Customer Satisfactions in Restaurants

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Abstract: Fuzzy logic has emerged as one of the leading methods in the field of linguistic uncertainty modeling, parallelly with the technological advancement of artificial intelligence. Application of the fuzzy logic extends to establish an optimal balance between human reasoning and output prediction in recommendation systems for the food industry, restaurants, university subject rankings, university rankings, etc. This paper focuses on the modeling of the recommendation process for the flourishing restaurant industry. The prevalence of fraudulent reviews poses a significant challenge in ascertaining the genuine intentions of customers, thereby impeding the process of obtaining accurate service evaluations. Soft computing techniques offer a promising solution to this problem, as they can analyze authentic customer feedback and generate reliable evaluations. The objective of this study is to predict customers' intensions in terms of recommendation score for a fine dining experience. A fuzzy-based model has been proposed to develop the recommendation system. To facilitate a comparative analysis and to identify the optimal approach, different membership functions and defuzzification methods are employed along with correlational behavior among various input subsets. Results have shown that even though the recommendation scores are same for some input subsets, the correlations among the corresponding inputs reflects various membership strength levels.

Keywords: Fuzzy logic, FIS, Recommendation system, Perceived value, Customer satisfaction, Facility comfort, Food quality, Cleanliness, Customer intension

1 Introduction

In the age of an excess of various web services, it is difficult to imagine their service quality without any recommendation system [1]. Recommendation systems are the algorithms designed to suggest relevant items beneficial to both users and service providers as it reduces the transaction costs associated with selecting and finding items from any web service. It aids in increasing sales, making sound decisions in online transactions, and rearranging the user's experience with web services [2].

There are various techniques for making recommendations, such as content-based filtering, collaborative filtering, hybrid filtering, and so on [3]. Collaborative filtering is the most commonly used technique because it recommends items by identifying other users who have similar interests. In content-based filtering, a user profile is created based on the access history and data provided by the user upon which the suitable contents are suggested [4]. Content-based filtering, collaborative filtering, and other approaches are combined in hybrid filtering strategies [5]. Some recommendation systems also follow binary method [6], which lies on filtering the contents and performing condition check, such as if the value becomes 1, the item will be suggested; otherwise not. However, none of the above strategies consider the intermediate values ranging from 0 to 1 defining the closeness of the content which are being suggested. Fuzzy logic (FL) system mainly models this concept and bridge the gaps between mathematics and the impreciseness of human linguistic perceptions [7]. Design of complex systems has been simplified by leveraging the explicability of the FL system. Moreover, the prediction models involving Artificial Neural Network (ANN), Machine Learning (ML), Transformer Learning (TL), or Large Language Modeling (LLM) [8][9] involve large dataset requiring greater storage, longer learning time, and huge processing capabilities with high computational complexity. Over these intricacy, various types of FIS architectures are convenient, light, and the most convenient way to predict a target result, resembling the behavior of human reasoning and thinking processes [10][11].

For the evaluation of the customer's performance expectancy, this study proposes a parallel fuzzy architecture where the classical input data are fuzzified and used for subsequent processing. The rules base knowledge is designed by applying the Mamdani fuzzy inference system (MFIS) that contributes to the output fuzzy sets. This fuzzy output sets are de-fuzzified by applying a suitable de-fuzzification process converting the output set into crisp value. For this study several de-fuzzification methods are applied (CoA, BoA, MoM, LoM, and SoM). The main contribution of this study is to propose a parallel architecture of FIS model to analyze the customer satisfaction and the perceived value with the aim of determining customers' intension. The article also provides a comparative analysis among the five de-fuzzification methods. For this study, it is observed that the most reliable results are generated for the CoA defuzzification approach.

2 Related Works

Fuzzy-based recommendation system is a popular strategy which is reflected in many decision support systems. One of the examples is to assist students in choosing their major at university level where a clustering-based technique can be applied to determine the students' preferred majors [12]. The application of the similar system is also can be seen in some works to improve ubiquitous hotel recommendations for online applications. A FUTCHR system interpreted as "*fuzzy ubiquitous traveler clustering and hotel recommendation*" is proposed in recent research where the system generates the groups of travelers based on their choice and historical data. This cluster information leads to provide the solution for the recommendation system where a fuzzy mixed binary-nonlinear programming model is introduced [13].

Application of fuzzy system also can be found in recommending framework that helps users to monitor their calories based on the BMI and to provide food suggestions based on the habit and preferences. The study also introduced an Android application to provide the services with extra facilities of using pedometer to track steps or workouts [14]. Another interesting application of the fuzzy expert system is to recommend common research topics, relevant research gaps, etc. intelligently where the analysis pf papers can be performed based on key features, evaluation strategies, datasets used, and relevant application areas [1]. Possible threat prediction and support system for protected regions, for example air defense system, also can be incorporated efficiently using fuzzy rule-based system. The system can use some parameters like object's distance, secondary radar input, speed of the flying object, etc. to tracked and categorize the object as a decision support system for anti-missile launching [15].

Numerous applications in medical decision support system are also reported in the past literatures. One of the recent works implemented a prediction system for intravenous fluid resuscitation (IFR) rate for burn patients where percentage of total body surface area burned (%TBSA) and hourly urine output (HUO) are taken as inputs [16]. The proposed model employed a Mamdani fuzzy inference system (MFIS) using clinical burn protocols where different membership functions (MF) and de-fuzzification methods are tested and analyzed. Comparative analysis of the study claims that the Gaussian (Π) membership function with centroid of area (CoA) method provides the most accurate predictions.

Predicting the impact of supply chain performance on customer perceived value can also be modeled using MFIS, with the input parameters as the indicators of the Supply Chain Operations Reference (SCOR) [17]. Constructing a decision model for the performance analysis of online stores based on the performance influencing factors (system quality, information quality, and service quality) sometimes reflects the successful use of the FIS model [18][19]. A relevant study proposed a multi-criteria decision-making methodology called VIUE (Value, Impact, Urgency, Emotional) for prioritizing and personalizing customer interactions in contact centers. The research extends the traditional ITIL approach by incorporating additional pertinent factors like customer value, emotional nature of the interaction, waiting times, and contact center workload. The methodology leverages linguistic 2-tuple models to handle subjective assessments and the Analytic Hierarchy Process (AHP) to determine criteria weights dynamically [20].

Drawing from the existing literature, it becomes apparent that the FIS model claims notable success in the implementation of prediction and decision support systems [12][21]. Moreover, the majority of literature highlights the efficacy of the simple MFIS model, demonstrating acceptable prediction efficiency. This article contributes to this body of knowledge by outlining the design of an MFIS architecture tailored specifically for predicting perceived value in customer satisfaction, thereby facilitating the maintenance of high-quality services in the restaurant industry.

3 System Design and Modeling

To predict the recommendation status more effectively, a FL architecture is designed, as presented in Figure 1, depending on the perceived value and customer satisfaction as inputs. In this design open-loop parallel architecture is considered where the first one involves in determining the customer perceived value based on the quality of food served, the comfort facilities available, and the time taken for serving the food (time of order to the time of serving). The second model is responsible to determine the customer satisfaction based on the food quality, comfort facilities, and cleanliness of the facility. Each of the FL models convert the crisp inputs into fuzzy input sets based on the designed membership functions based on the selected fuzzy values. Here the triangular membership functions are used within the defined Universe of Discourse (UoD). By utilizing the IF-THEN-ELSE rules of fuzzy knowledge base, the FIE generates relevant fuzzy sets which latter aggregated and converted into classical output. The antecedents and the consequences of a FIS are mainly the linguistic variables making the system useful for designing a complex system. Table 1 presents the overall scenario of the proposed system.

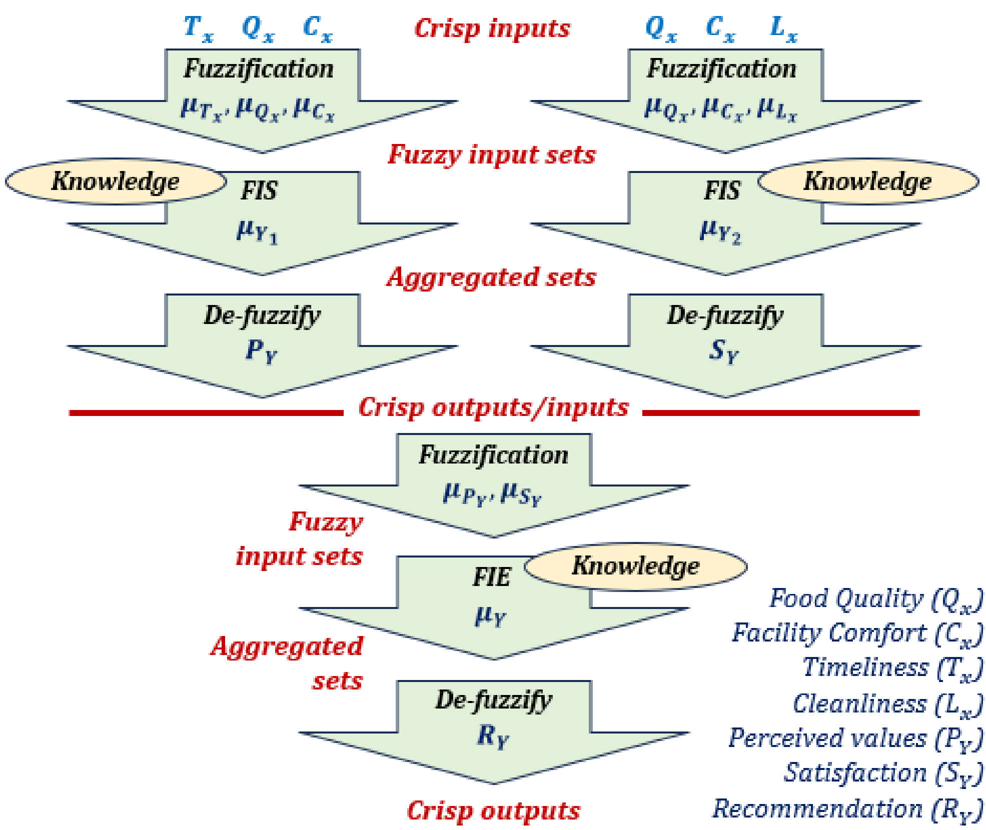

Fig. 1 Conceptual design of the parallel fuzzy architecture

Table 1. Properties of the designed fuzzy model

Fuzzy properties	**Description**
Method	Madman Rule Base FIS
Food quality (Q_x) Facility comfort (C_x) Timeliness (T_x) Cleanliness (L_x) Perceived values (P_Y) Satisfaction (S_Y) Recommendation (R_Y)	Fuzzy set in terms of linguistic variables
AND operation	Min operation
OR operation	Max operation
Implication	Min operation
Aggregation	Max operation
De-fuzzification	Centroid of Area (CoA)

At first the fuzzy variable (linguistic variable) is converted into set-of-terms (fuzzy values) through syntax rules. The set of terms then are transformed into MFs based on semantic rules. This strategy mainly converts the fuzziness of words/phrases into fuzzy numbers in terms of fuzzy subset. The steps are shown in Figure 2. The Mamdani FIS Implication operation is demonstrated in Figure 3 that follows the fuzzy knowledge-based (rule-based) structure; for example, "$IF\ x_1\ is\ A_{11}\ AND\ x_2\ is\ A_{21}\ THEN\ y_1\ is\ B_1$" and "$IF\ x_1\ is\ A_{12}\ AND\ x_2\ is\ A_{22}\ THEN\ y_2\ is\ B_2$" where x_1 and x_2 are two classical inputs; A_{11}, A_{12}, A_{21}, and A_{22} are the MFs of two input UoDs; B_1 and B_2 are the MFs of output UoD; and y_1 and y_2 are the crisp output. After designing the rule-base, the de-fuzzification methods are applied to obtain the crisp values.

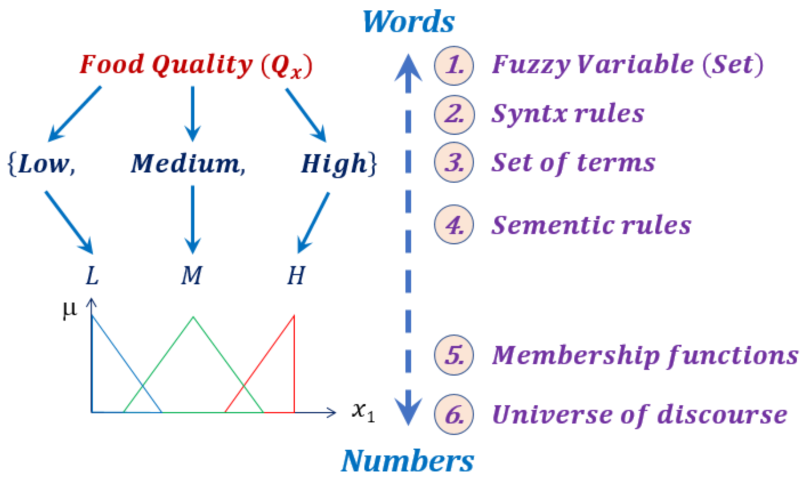

Fig. 2 Conversion of linguistic terms into fuzzy numbers

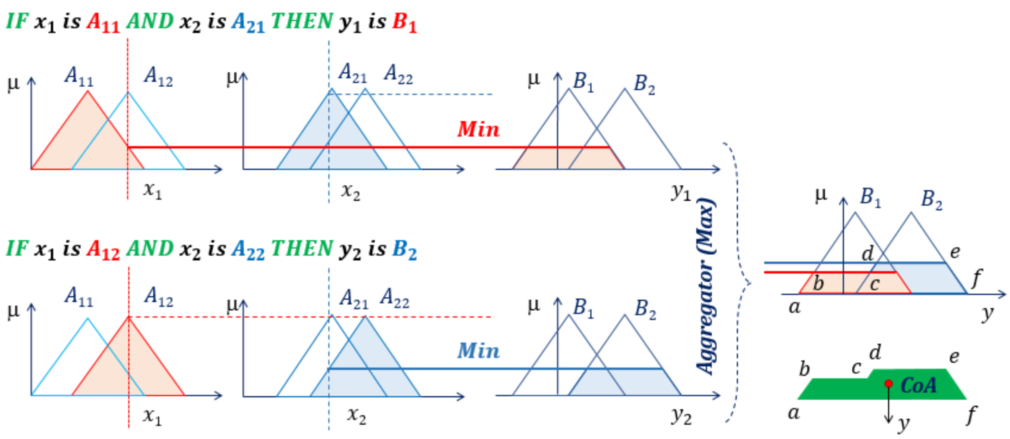

Fig. 3 Mamdani FIS-block architecture concept

Mathematical expression of a triangular MF is shown in Equation (1) where $\mu_A(x)$ is the membership value; a, b, c are the boundary of a triangular MF, and x is the crisp input on the UoD [22][23].

$$\mu_A(x) = \begin{cases} 0 & for\ x \leq a \\ \frac{(x-a)}{(b-a)} & for\ a < x \leq b \\ \frac{(c-x)}{(c-b)} & for\ b < x \leq c \\ 0 & for\ x > c \end{cases} \tag{1}$$

3.1 Development of Fuzzy System

To design the fuzzy expert system, it is important to recognizing the input and output linguistic terms and their associated values as depicted in Table 2 and Table 3. Identification of fuzzy sets through the membership functions is the next step. To evaluate the performance expectancy, the task of this study is subdivided into two, determining the impact of service qualities on a) consumer perception and b) customer satisfaction.

Table 2. Input-output specifications for Perceive Value

Input/output	Fuzzy variables	Fuzzy values
Inputs	Food Quality	High, Low, or Medium
	Facility Comfort	Poor, Acceptable, or Amazing

	Timeliness	Poor, Medium, or Fast
Output	Perceived Value	Very low, Low, Medium, High, or Very high

Table 3. Input-output specifications for Customer Satisfaction

Input/output	Fuzzy variables	Fuzzy values
Inputs	Food Quality	High, Low or Medium
	Facility Comfort	Poor, Acceptable or Amazing
	Cleanliness	Poor, Acceptable or Amazing
Output	Customer Satisfaction	Satisfied, Neutral, Dissatisfied

According to the analysis of a recent study conducted by Tuncer *et al.* [22], the three factors to analyze the *Perceived Values* are, a) *Food Quality* with three fuzzy values as *High* (6-10), *Medium* (2-8) and *Low* (0-2); b) *Facility Comfort* with three fuzzy values as *Amazing* (6-10), *Acceptable* (2-8), and *Poor* (0-4); and c) *Timeliness* with the fuzzy values as *Fast* (6-10), *Medium* (2-8), and *Poor* (0-4). The fuzzy variable, *Perceived Value*, is also responsible for the measurement of customer's behavioral intention. So, the variable is modeled with five fuzzy values with range of 0-10 distributed as *Very low* (0-2), *Low* (1-5), *Medium* (3-7), *High* (5-9), and *Very High* (8-10).

To predict the *Customer Satisfaction*, three variables are imperative, a) *Food Quality* with three fuzzy values as defined earlier; b) *Facility Comfort* with three fuzzy values same as previous, and c) *Cleanliness* with three fuzzy values as *Amazing* (6-10), *Acceptable* (2-8), and Poor (0-4). The variable, *Customer Satisfaction*, having UoD ranging from 0 to 10 with three linguistic terms as *Satisfied* (0-4), *Neutral* (2-8), and *Dissatisfied* (6-10) is also responsible for the measurement of customer's behavioral intention.

According to the study, Customer satisfaction and perceived value both have positive impacts on the customer intension [22]. Sometimes there might be some cases where the food quality and the price of the food does not match. Rather they may be unreasonable. In that case the perceived value of a customer changes that influence the level of recommendation. Customers might be satisfied with the food quality or the place but the perceived value may restrict them to recommend the restaurant with a good score. Similarly, prolonged food serving time may raise dissatisfaction in customers' mind which may impact on the recommendation score. The parameter specifications of the fuzzy model for predicting possible recommendation score (behavioral intention) is presented in Table 4.

Table 4. Input-output specifications for Behavioral Intention

Input/output	Fuzzy variables	Fuzzy values
Input	Perceived Value	Very low, Low, Medium, High, Very high
	Customer Satisfaction	Satisfied, Neutral, Dissatisfied
Output	Intension of customer	Will not Recommend (WnR), Less Possibility of Recommendation (LPR), Will Recommend (WR)

3.3 Formulation of Fuzzy Knowledge-base

Fuzzy rules are formulated separately for the three FIS models. For perceived value prediction, the three fuzzy-variables each containing three fuzzy-values formulating the fuzzy knowledge-base with twenty-seven ($3 \times 3 \times 3$) rules. For example:

***If** Food Quality is "High" **AND** Facility Comfort is "Amazing" **AND** Timeliness is "Fast" **THEN** Perceived Value is "Very High"*

Similarly, the three fuzzy-variables each having three fuzzy-values for the prediction of customer satisfaction, a knowledge-base is formatted with twenty-seven ($3 \times 3 \times 3$) rules. For example:

***If** Food Quality is "High" **AND** Facility Comfort is "Amazing" **AND** Cleanliness is "Amazing" **THEN** Customer is "Satisfied"*

For the final prediction of customer intension (recommendation score), the two fuzzy-variables having five and three fuzzy-values contribute to design a total of fifteen rules (3×5). For example:

***If** Customer Satisfaction is "Neutral" **AND** Perceived Value is "Medium" **THEN** Customer intention is "Less possibility to recommend"*

Corresponding matrices to formulate the knowledge-base are presented in Table 5, Table 6, and Table 7.

Table 5. Fuzzy Rules for Perceived values

Food Quality	**Facility Comfort**		
	Poor	**Acceptable**	**Amazing**
	1. Timeliness: Poor		
Low	*Very Low*	*Very Low*	*Low*
Medium	*Low*	*Low*	*Medium*
High	*Medium*	*Medium*	*High*
	2. Timeliness: Medium		
Low	*Low*	*Medium*	*Medium*
Medium	*Low*	*High*	*High*
High	*Medium*	*High*	*Very High*
	3. Timeliness: Fast		
Low	*Low*	*Medium*	*Medium*
Medium	*Medium*	*High*	*Very High*
High	*Medium*	*Very High*	*Very High*

Table 6. Fuzzy Rules for Customer satisfaction

Food Quality	**Facility Comfort**		
	Poor	**Acceptable**	**Amazing**
	1. Cleanliness: Poor		
Low	*Dissatisfied*	*Dissatisfied*	*Dissatisfied*
Medium	*Dissatisfied*	*Dissatisfied*	*Neutral*
High	*Neutral*	*Neutral*	*Satisfied*
	2. Cleanliness: Acceptable		
Low	*Dissatisfied*	*Neutral*	*Neutral*
Medium	*Dissatisfied*	*Satisfied*	*Satisfied*
High	*Neutral*	*Satisfied*	*Satisfied*
	3. Cleanliness: Amazing		
Low	*Dissatisfied*	*Neutral*	*Neutral*
Medium	*Neutral*	*Satisfied*	*Satisfied*
High	*Neutral*	*Satisfied*	*Satisfied*

Table 7. Fuzzy Rules for Customer intension

Customer Satisfaction	Perceived Values				
	VL	L	M	H	VH
Dissatisfied	*WnR*	*WnR*	*WnR*	*LPR*	*LPR*
Neutral	*WnR*	*WnR*	*LPR*	*WR*	*WR*
Satisfied	*LPR*	*LPR*	*WR*	*WR*	*WR*

VL=Very Low; L=Low; M=Medium; H=High; VH=Very High;
WnR=Will not Recommend; WR=Will recommend;
LPR=Low Possibility of Recommendation

3.4 Rule Aggregation and Defuzzification

Aggregation process helps to obtain the output fuzzy-subset based on the contributed results of each individual rule. The aggregation procedure is followed by the defuzzification steps through which an understandable crisp output is produced. This study uses five different types of de-fuzzification methods to compare the demeanor of the results.

Centroid of Area (CoA) method is the most widely used de-fuzzification strategy, also known as the "Centroid" method [24][25]. The mathematical expression of CoA presented in Equation 2. The next popular approach for de-fuzzification is to use Bisector of Area (BoA) method which mainly divides the fuzzy output-set into two equal regions [25][26]. Mathematical expression of BoA method is shown in Equation 3. The Mean of Maximum (MoM) method is another approach of de-fuzzification where output is the mean value of the element with the largest membership-values ($\mu_A(x) = max$). The other two approaches are Largest of Maximum (LoM) and Smallest of Maximum (SoM). The LoM is the maximum value on the x-axis of a UoD for $\mu_A(x) = max$. Opposing, the SoM is the minimum value on the x-axis of a UoD for $\mu_A(x) = max$. Necessary mathematical expressions are shown in Equation (5) and Equation (6) [27][28].

$$CoA(x) = \int_{min}^{max} x\, \mu_A(x)dx \Big/ \int_{min}^{max} \mu_A(x)dx \tag{2}$$

$$BoA(x) = x^* \;\; if \;\; \int_{min}^{x^*} \mu_A(x)dx = \int_{x^*}^{max} \mu_A(x)dx \tag{3}$$

$$MoM(x) = \int_{(x|\mu_A(x)=max)} x\, dx \Big/ |(x|\mu_A(x) = max)| \tag{4}$$

$$LoM(x) = \max(x) \;\; for \;\; \mu_A(x) = max \tag{5}$$

$$SoM(x) = \min(x) \;\; for \;\; \mu_A(x) = max \tag{6}$$

4 Implementation and Results

The perceived value and customer satisfaction are evaluated parallelly based on the food quality, facility comfort, timeliness, and cleanliness as inputs. After defuzzification of the both models, the results become the inputs of the final FIS model to determine the intention of a customer for possible recommendation. Figure 3 visualizes the example inputs and outputs of the FIS model for the processing of Perceived-values for the input scores as $Food\ Quality\ (Q_x)\ = 6.0$, $Facility\ Comfort\ (C_x) = 5.0$, and $Timeliness\ (T_x) = 7.0$. The output scores for five de-fuzzification methods CoA, BoA, MoM, LoM, and SoM are predicted as 7.0, 7.0, 7.0, 8.35, and 5.65, respectively. The corresponding scenario is demonstrated in Figure 4. For the variations of inputs, the de-fuzzified outputs for five de-fuzzification methods are presented in Table 8.

Similarly, for the prediction of Satisfaction score, a parallel FIS model is designed. The output membership activities of the customer satisfaction based on the inputs as $Food\ Quality\ (Q_x) = 6.0$, $Facility\ Comfort\ (C_x) = 5.0$, and $Cleanliness\ (L_x) = 7.0$ are demonstrated in Figure 5. The results of the five defuzzification methods CoA, BoA, MoM, LoM, and SoM are depicted as 8.23, 8.24, 8.60, 10.0, and 7.20, respectively. The overall scenario also tested for ten various inputs to observe the various de-fuzzified outputs. The results are presented in Table 9.

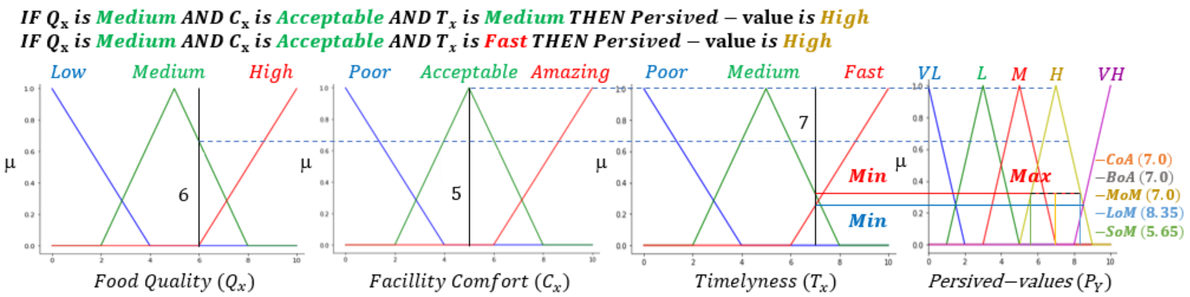

Fig. 4 Demonstrating a scenario with various outputs for Perceived-value prediction with three inputs, $Food\ Quality\ (Q_x)\ = 6.0$, $Facility\ Comfort\ (C_x) = 5.0$, and $Timeliness\ (T_x) = 7.0$

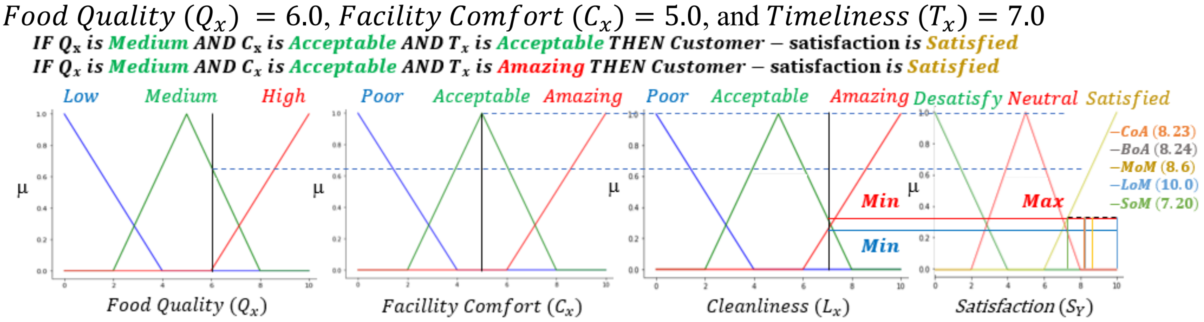

Fig. 5 Demonstrating a scenario with various outputs for predicting Customer Satisfaction with three inputs, $Food\ Quality\ (Q_x)\ = 6.0$, $Facility\ Comfort\ (C_x) = 5.0$, and $Cleanliness\ (L_x) = 7.0$

Table 8. De-fuzzified values for various inputs in predicting Perceived-values

Q_x	C_x	T_x	CoA	BoA	LoM	MoM	SoM
0.5	6.0	0.5	2.99	3.0	3.0	3.0	3.0
0.5	0.5	0.5	0.68	0.61	0.0	0.0	0.0
1.0	2.0	1.0	0.77	0.75	1.0	0.0	0.0
2.0	2.0	4.0	0.77	0.75	1.0	0.0	0.0
2.5	3.0	1.0	2.39	2.44	4.0	3.0	2.0
4.0	4.0	4.0	7.00	7.0	7.0	7.0	7.0
5.88	9.44	0.5	5.00	5.0	5.0	5.0	5.0
6.0	0.5	0.5	2.99	3.0	3.0	3.0	3.0
7.5	10.0	0.5	6.4	5.75	7.0	6.8	4.0
10.0	10.0	10.0	9.33	9.41	10.0	10.0	10.0

Table 9. De-fuzzified values for various inputs of predicting Customer Satisfaction

Q_x	C_x	L_x	CoA	BoA	LoM	MoM	SoM
0.5	0.5	0.5	1.36	1.21	0.0	0.0	0.0
0.5	6.0	0.5	1.44	1.32	1.0	0.5	0.0
1.0	2.0	1.0	1.5	1.5	2.0	1.0	0.0

2.0	2.0	4.0	1.5	1.5	2.0	1.0	0.0
2.5	3.0	1.0	1.67	1.62	2.0	1.0	0.0
4.0	4.0	4.0	8.55	8.67	10.0	9.5	7.0
5.88	9.44	0.5	4.99	5.0	5.0	5.0	5.0
6.0	0.5	0.5	1.44	1.325	1.0	0.5	0.0
7.5	10.0	0.5	6.28	6.25	10.0	7.0	4.0
10.0	10.0	10.0	8.87	8.828	10.0	10.0	10.0

Based on the outputs of the above scenarios, it is observed that the de-fuzzification methods, LoM, MoM, and SoM, produce 0.0 values in some cases which are unreliable. The LoM and SoM only focus on the extreme values, the largest and smallest, and completely ignore the shape of the fuzzy set which leads to a significant loss of information. The MoM averages the points where the membership values reach to the maximum and ignores the rest of the fuzzy set, thus has a significant loss of information. For the designed model, the last three de-fuzzification methods may cause instability as a slight change in the input fuzzy sets may lead to an abrupt change in the output. Moreover, the methods could be ambiguous if the highest level of membership values are spread over a wide range.

In most of the practical applications, the most reliable de-fuzzification method is CoA which reflects the centroid point of the fuzzy set providing a balance output by considering all the elements of the entire output fuzzy set. On the other hand, for this design, the BoA method could be highly sensitive to the output shape if the MF is not symmetric, producing deviation of the central tendency of the fuzzy set. Moreover, BoA method sometimes become computationally intensive for a large and complex shape of the output fuzzy set. Thus, the CoA method is chosen in this parallel design of the FIS models.

Based on the aforementioned setups, the outputs of the CoA method are applied to determine the final result of Customer Intension (recommendation score, R_Y). The final reflection of the example scenario for the inputs as $Customer\ satisfaction$ ($S_Y = 8.23$), and $Perceived - values$ ($P_Y = 7.0$), the R_Y scores are determined by using the five de-fuzzification methods as $CoA = 8.50$, $BoA = 8.49$, $MoM = 9.10$, $LoM = 10.0$, and $SoM = 8.19$, for comparative analysis, as depicted in Figure 6. Finally, based on the overall analysis, CoA method is recommended. The 3D plot of the input perceived values (P_Y) and customer satisfaction (S_Y), and the output, customer intention (R_Y) is shown in Figure 7.

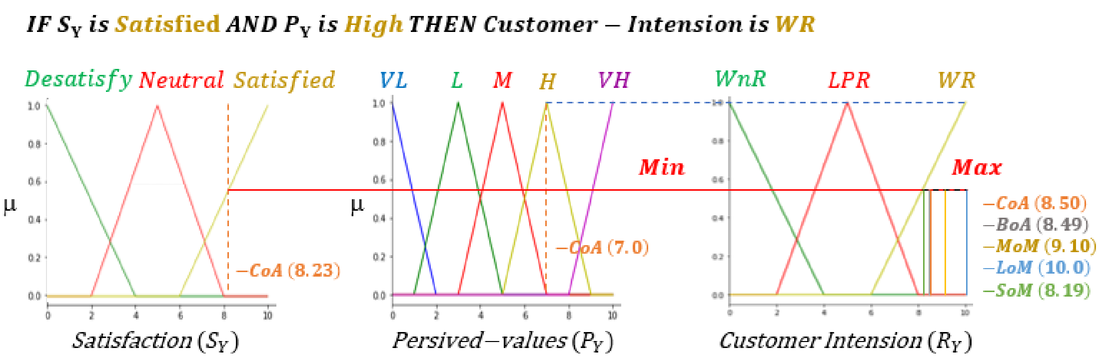

Fig. 6 Demonstrating the prediction of Customer Intension with two inputs (output of the previous parallel FIS), $Customer\ satisfaction\ (S_Y) = 8.23$, and $Persived - values\ (P_Y) = 7.0$

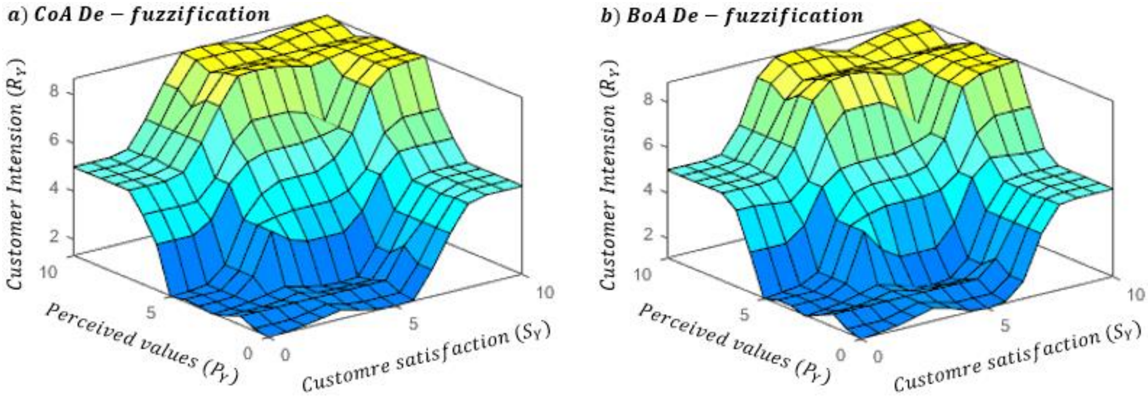

Fig. 7 Surface plot of customer intention (R_Y) based on perceived values (P_Y) and customer satisfaction (S_Y) for a) CoA De-fuzzification, and b) BoA De-fuzzification

Fuzzy relation operation ($R(Subset_A \times Subset_B)$) helps in mapping input fuzzy sets to output fuzzy sets through the rule-base to determine the optimal operating condition and provide a comprehensive explanation on partial input data. For example, to determine the co-relation between partial data set for inputs S_Y and P_Y, as shown in Equation (7) and Equation (8), the correlation matrix presented in Equation (9) explains that highest degree of membership is 0.95. This also indicates that the highest membership strength is produced for the corresponding output MF ($R_{Y\,(WR)}$) only for the crisp input 5.1 for $S_{Y\,(neutral)}$ and crisp input 6.90 for $P_{Y\,(High)}$.

$$S_{Y\,(Neutral)} = \left\{\frac{0.33}{3.0} + \frac{0.66}{4.0} + \frac{0.96}{5.1} + \frac{0.73}{5.8} + \frac{0.16}{7.5}\right\} \tag{7}$$

$$P_{Y\,(High)} = \left\{\frac{0.50}{6.0} + \frac{0.75}{6.5} + \frac{0.95}{6.9} + \frac{0.80}{7.4} + \frac{0.55}{7.9}\right\} \tag{8}$$

$$R_{(S_Y,P_Y)}\left(\mu_{S_Y\,(Neutral)} \wedge \mu_{P_Y\,(High)}\right) = \begin{array}{c} \\ 3.0 \\ 4.0 \\ 5.1 \\ 5.8 \\ 7.5 \end{array} \begin{array}{c} \begin{array}{ccccc} 6.00 & 6.50 & 6.90 & 7.40 & 7.90 \end{array} \\ \begin{bmatrix} 0.33 & 0.33 & 0.33 & 0.33 & 0.33 \\ 0.50 & 0.66 & 0.66 & 0.66 & 0.55 \\ 0.50 & 0.75 & 0.95 & 0.80 & 0.55 \\ 0.50 & 0.73 & 0.73 & 0.73 & 0.55 \\ 0.16 & 0.16 & 0.16 & 0.16 & 0.16 \end{bmatrix} \end{array} \tag{9}$$

Co-relational behavior with membership strength also can be observed through the graphs presented in Figure 8. According to the designed model, for the perceived-values (P_Y) ranging from 8.5 to 10.0 (MF as VH), while Satisfaction input is 5 (MF as $Neutral$), the crisp value results (Recommendation scores for MF as WR) shows slightly nonlinear pattern varies from 8.2 to 8.7. At the same time, the membership strengths of crisp outputs show linearly increasing characteristics (0.25 to 1.0), as demonstrated in Figure 8(a). For P_Y score as 8.5 and S_Y score as 5, although the R_Y score is 8.2, the membership score is very low as $R_{(S_Y \times P_Y)}(5, 8.5) = 0.25$, reflecting a weak correlation between the inputs. On the other hand, for $P_Y = 9.7$ and $S_Y = 5$, the $R_Y = 8.67$ (MF as WR) with the $\mu_{\text{strength}} = 0.75$, describing the strong correlation between the input states.

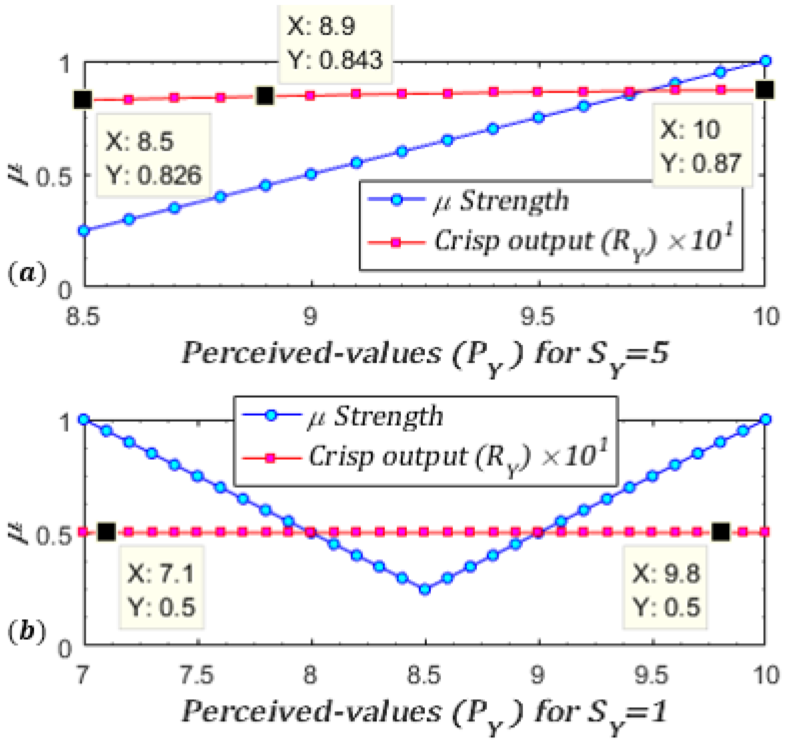

Fig. 8 Recommendation scores and corresponding membership strengths for, (a) $Neutral - VH - WR$ relations, and (b) $Desatisfied - H\&VH - LPR$ relations

The $Desatisfied - H\&VH - LPR$ relational characteristics are represented in Figure 8(b) where Satisfaction score is 1.0 and Perceived-values scores varies from 7.0 to 10.0. Results show that the crisp output (Recommendation score) remains unchanged ($R_Y = 5.0$) while the membership scores ($\mu_{strength}$) show V-shaped linear pattern. The demeanor reflects that the lowest correlation between the two inputs (at this condition) are observed at $P_Y = 8.5$. The correlations are getting stronger for spreading the perceived-values from the center.

5 Conclusion and Future Work

Finding a great place to eat has become a form of entertainment for many people. Often, individuals rely on reviews from others who have visited a particular venue and shared their opinions. However, with the overwhelming number of reviews available, it can be challenging to judge a place accurately. To address the situation, this study presents a FIS model that analyzes customer sentiment to recommend dining spots. The proposed system reduces the burden of sifting through numerous posts and ratings. Additionally, the work evaluates the recommendation system from two perspectives, one: the overall worthiness of a place in terms of consistent price and quality, and two: the level of customer satisfaction based on the service received. In this parallel architecture model, five de-fuzzification methods are studied to enhance the accuracy of the recommendations score. Finally, based on the result analysis, CoA method is recommended to ensure the central tendency of fuzzy sets.

The final results clearly indicate that both customer satisfaction and perceived value positively influence a customer's intention to recommend or give a good review. A person may be fully satisfied with a service, but any inconsistency between the service provided and the perceived value may reduce the likelihood of recommending the place. This work presents a potential solution for a recommendation system by assuming certain values that impact these factors. For computational simplicity, only the parameters with the highest impact on the fine dining experience were considered. As the future direction of this study, some additional variables like cost, aesthetics, and other aspects could be considered to observe the changes in the outcome. The model can be applied for other relevant areas of recommendation, for example online meal delivery services, fast food businesses, etc. Last ut not the least, incorporating the Artificial Neuro FIS (ANFIS) model [29][30] may improve the overall system efficiency and performances.

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