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# Customer classification: A Mamdani fuzzy inference system standpoint for modifying the failure mode and effect analysis based three dimensional approach

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ABSTRACT

Customer categorization using a three dimensional loyalty matrix, based on failure mode and effect analysis (FMEA), is an innovative approach for customer classification but is vulnerable to FMEA limitations. The main purpose of this research is to utilize a multi input single output Mamdani fuzzy inference system (FIS) to cope with the traditional FMEA inherited shortcomings. Besides, the classification logic and classes of the Loyalty Matrix methodology have been adopted for the purpose. We have also identified four potential market scenarios and evaluated the performance of the proposed methodology within these contexts. Correspondingly, four tailored FIS's consisting of a total of 108 fuzzy rules have been developed. Empirical results indicate that the new approach successfully resolved serious issues such as data uncertainty, weight ignorance, the same output value computation from different input values and the discontinued output.

## 1. Introduction

Of the paramount characteristics ubiquitous amongst almost all thriving enterprises is offering class specific value prepositions to each category of customers. Such a strategy is usually initiated with customer classification, a concept evolving to be integral to marketing and being applied by numerous firms to meet customer needs more appropriately (Floh, Zauner, Koller, & Rusch, 2014). Customer classification is also a prerequisite for targeting the best customer segment (Madzík & Shahin, 2020) and predicting the customer churn (Abbasimehr, Setak, & Soroor, 2013). Literature review indicates that a considerable number of such classification efforts have been made through the lens of the customer loyalty level.

Loyalty is a strong commitment to consistently re-purchase or re-patronize a preferred product or service in the future, which, as a result, leads to repetition of buying the same set of the brand, in spite of the fact that situational impacts and marketing attempts may potentially result in switching behavior (Oliver, 1999, p. 34). This definition elucidates the fact that loyalty serves as a shield protecting sellers against their rivals (Mascarenhas, Kesavan, & Bernacchi, 2006), and (truly) loyal customers are committed to keep re-purchasing regardless of circumstance (Narayandas, 2005). Moreover, such customers are greatly cooperative and willing to provide positive word of mouth and recommendation (Tanford & Baloglu, 2013).

While there is not a universal approach for measuring loyalty, literature shows several methods employed for the purpose, such as Net Promoter Score (Reichheld, 2003), Loyalty Ladder (Narayandas, 2005; Mascarenhas et al., 2006), Bandyopadhyay and Martell's (2007) framework for consumer brand loyalty classification, and Loyalty Matrix used by Tanford and Baloglu (2013). In a recent study, Madzík & Shahin (2020) places a more explicit emphasis on including behavioral factors of loyalty as necessary supplements to the attitudinal one. In other words, inspired by the Risk Priority Number (RPN) calculation from multiplication of three risk factors in Failure Mode and Effect Analysis (FMEA) – a well-known technique in risk assessment and quality management – they proposed computing the Loyalty Priority Number (LPN) from the product of three loyalty dimensions: customer purchase value (V), purchase frequency (F) and loyalty (L). The LPN was, in turn, utilized as an overarching index for customer classification. However, the multiplication formula of basic FMEA, adopted in the Madzík & Shahin's (2020) Three Dimensional Customer Classification (TDCC) methodology, has widely been criticized in literature. The TDCC limitations,

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together with their corresponding FMEA roots (Liu, Liu, Liu, & Mao, 2012; Liu, Liu, & Liu, 2013; Geramian, Mehregan, Garousi Mokhtarzadeh, & Hemmati, 2017; Geramian, Abraham, & Ahmadi Nozari, 2019; Geramian, Shahin, Minaei, & Antony, 2020), are summarized in Table 1.

Since these issues are of a FMEA nature, the present research utilizes the most popular approach for modifying the traditional FMEA shortcomings, this time, to resolve the TDCC limitations. This popular solution is the expert system and artificial intelligence approach of Fuzzy Inference System or FIS (Liu et al., 2013; Geramian et al., 2017, 2019, 2020). FIS is capable of resolving almost all of the abovementioned issues (Geramian et al, 2017, 2019, 2020). Moreover, as ratings of TDCC loyalty dimensions are determined through respondents' judgment and prone to uncertainties hidden in human judgments, application of the fuzzy sets theory (Zadeh, 1965), in general, and FIS fuzzification (Geramian et al, 2017, 2019, 2020) and fuzzy numbers (Shahin, Barati, & Geramian, 2017), in particular, are of tremendous advantages in this regard. With respect to the fact that TDCC is of three inputs (loyalty dimensions) and one output (LPN), along with a questionable or unknown inputs to output relationship, we draw on a Multi Input Single Output (MISO) FIS of the Mamdani type (Mamdani & Assilian, 1975; Geramian et al, 2019; 2020). Using a type 1 fuzzy system – versus more enhanced versions such as the type 2 fuzzy logic – the present study will act as an initial step in application of fuzzy inference in the TDCC problem. Therefore, it is mainly application oriented, by nature.

As a result, the objective of the present research is *to utilize the Mamdani MISO FIS methodology to modify TDCC*. For this purpose, first we identify four potential market types, as contextual scenarios, which customer classification analysts may encounter. Then, corresponding to them, four tailored FIS's based on TDCC are developed. It is noteworthy that classes/categories of the proposed approach are designed on the basis of the Loyalty Matrix methodology used by Tanford and Baloglu (2013). Implementation of the developed approach in the identified scenarios facilitated highlighting outperformance of FIS based TDCC over basic TDCC from several aspects.

Academically, this study will equip the customer classification function of customer relationship management with the expert and intelligent system of FIS. To the best of the authors' knowledge, the present study is the first research applying the fuzzy logic and, in particular, the Mamdani MISO FIS, to modify the FMEA based customer classification. In other words, such application will bring a higher level of accuracy to this specific manner of the classification problem through modifying the drawbacks of its underlying method – the traditional FMEA. As a result, integration of both the behavioral and attitudinal dimensions into a single classification oriented index will be carried out much more reliably.

Practically, it will shed light on the fact that the context matters when classifying customers. Identifying the potential contextual factors, this paper will draw a comprehensive picture of market scenarios that practitioners may face. Besides, it will provide four FIS's, with each being tailor made to classify customers in a specific scenario. Accordingly, this research proposes a viable methodology that helps companies tailor their offerings and marketing strategies towards each specific customer class.

**Table 1**
Limitations of Three Dimensional Customer Classification (TDCC) and their corresponding FMEA based roots.

| FMEA root | Resultant TDCC limitation | Description and example |
|---|---|---|
| The same RPN may be derived from various mixtures of risk factors, risk implications of every combination may be substantially different though. | A set of loyalty dimensions with completely different values and, thus, totally deferring loyalty implications, may lead to the same LPN. | Suppose$(V = 1, F = 3, L = 10)$and$(V = 10, F = 3, L = 1)$, as two different combinations of the three loyalty dimensions; according to the Loyalty Matrix view adopted by Tanford and Baloglu (2013), the first one represents a latent customer, but the second one is a spurious customer. Nevertheless, according to TDCC, both have the same LPN, 30, and, as a result, are classified into the same class, Random. This shows that TDCC lacks discriminability between classes in such cases. |
| There exist lots of duplicate values for RPN. | There are many duplicated LPN values. | LPN = 24, for instance, is duplicated 21 times (for differently loyal customers). |
| Relative weight or importance of risk factors are neglected and assumed to be the same, which may not necessarily be the case in reality. | Relative importance weights of loyalty dimensions are considered and assumed to be equal, that may not be true in practice. | Each of the three dimensions have the same implicit weight of unity: $10(\times 1) \times 3(\times 1) \times 1(\times 1) = 30$ |
| RPN is computed through multiplication of risk factors, which is open to doubt and question. | Obtaining the LPN scores through product of loyalty dimensions is questionable. | |
| RPN is not an index of continual values, suffering from many gaps. | LPN index could not provide a continuous trend for the level of loyalty. | There exists no LPN with values including, but not limited to, 11, 46 and 733. In the 1 to 1000 range of LPN, only 120 values are unique. |

## 2. Background

### 2.1. Loyalty based customer classification approaches

By measuring the extent to which a customer is willing to recommend a given company to others, Reichheld (2003) developed Net Promoter Score as a basis for customer categorization. The measure is computed via subtracting the percentage of detractors from that of promoters and used to classify customers into detractors, passively satisfied and promoters. Narayandas (2005) categorizes the customers' loyalty behaviors in the business market setting into a hierarchy of levels called Loyalty Ladder. Each behavior rung of the ladder entails a specific cost to be managed and represents a specific amount of revenue. With regard to the customers' position on the ladder and the cost level, Narayandas (2005) shows that customers are classified into four categories, including commodity buyers, underperformers, partners and most valuable customers. Building on some earlier studies, Bandyopadhyay and Martell (2007) proposed a conceptual framework to classify consumer brand loyalty. Their framework consists of a two level attitudinal loyalty part – weak and strong – and a three level behavioral loyalty one – *single users*, *multiple users* and *non users*. They found that the difference between attitudinal loyalty in the second two behavioral categories are more striking than that between single users and multiple users. They also found that even non user customers could be potential consumers in future. Mascarenhas et al. (2006) addressed the causal relation between total customer experience and lasting customer loyalty and derived a multi dimension Loyalty Ladder. The ladder not only implies the hierarchy proposed by Narayandas (2005), but also is a function of three primary variables of total customer experience, including engaging experiences, provider interaction and value differentiation. Loyalty Matrix is another customer classification approach. Tanford and Baloglu (2013), for instance, investigated applicability of a previous four cell loyalty matrix in the hospitality context. The matrix is yielded by crossing a horizontal behavioral axis and a vertical attitudinal one, as the two dimensions of loyalty, and consists of *true loyalty*, *low loyalty*, *latent loyalty* and *spurious loyalty* categories of potential customers. True and low loyalty categories are characterized respectively by high and low levels of both of the dimensions. The latent loyal customers are high in attitudinal aspects but low, behaviorally. In contrast, the spurious ones demonstrate strong loyalty behaviors while having poor attitudes toward loyalty.

As mentioned earlier, Madzík & Shahin's (2020) research is one of the most recent papers in the area. The study, in fact, borrowed the FMEA multiplication mechanism for calculating RPN from risk factors (Ghoushchi, Yousefi, & Khazaeili, 2019) to aggregate three loyalty dimensions into a single index for customer classification, called LPN. Since our study builds on this previous research, its general procedure is concisely explained in Section 3.

The literature on customer classification is also characterized by several other recent studies. Considering preferences of different customer classes, Jing, Yao, Gao, Li, Peng, and Jiang (2021) identified overall satisfaction and the optimum alternative in the problem of conceptual scheme selection. They used techniques, such as the interval valued intuitionistic fuzzy set and rough set. Rahim, Mushafiq, Khan, and Arain (2021) employed the RFM – Recency, Frequency and Monetary – method to classify and model customer behaviour in the retail industry, as well as Multi Layer Perceptron (MLP), Support Vector Machine (SVM) and decision tree classification to validate their approach. Their experiments indicated a considerable customer classification rate. Increasing the accuracy of customer classification, Wang, Niu, and Tan (2021) developed a feature selection algorithm on the basis of the bacterial colony approach, which was implemented together with the K Nearest Neighbour method. Results indicated that their proposed approach was more viable in comparison to several extant techniques for feature selection. Song, Liu, Liu, and Niu (2021) developed a multi objective feature selection method for customer segmentation on the basis of hydrological cycling optimization – a meta heuristic algorithm, with findings indicating its outperformance regarding some improved qualities, such as computation stability and diversity of search. Tsai, Merkert, Tsai, and Lin (2021) utilized some existing theories, such as the social exchange, to propose a preferred customer methodology based on the taxonomy method. Implementation of their approach in business to business markets of air express resulted in determining various customer categories.

### 2.2. Fuzzy inference system applications

Mamdani FIS has widely been applied in such various contexts as failure analysis (Geramian et al., 2017, 2020; Yazıcı, Gökler, & Boran, 2020), educational performance evaluation (Cervero, Castro-Lopez, Álvarez-Blanco, Esteban, & Bernardo, 2020), performance degradation diagnosis (Kang, Kim, Heo, & Song, 2017), customer perceived value analysis (Zanon, Arantes, Calache, & Carpinetti, 2020) and so forth. More relevant applications of the approach are elaborated on below.

MahmoumGonbadi, Katebi, and Doniavi (2019) used FIS for customer prioritization in the queue system problem. They proposed a two stage fuzzy expert system, at the first stage of which customers were initially prioritized using a FIS and based on four criteria such as customer loyalty. The output of this stage and waiting time were used to obtain final priorities of customers by means of another FIS, at the second stage. They also demonstrated the outperformance of their methodology over FIFO (First in First out) and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) methods in two scenarios and five system statuses. Ghani, Bajwa, and Ashfaq (2018) applied FIS for the purpose of customer loyalty measurement. In fact, once they applied a sentiment analysis and obtained the sentiment scores of a product based on the users' comments on Facebook and the Amazon website, they converted the scores into customer loyalty. FIS also was employed for simultaneous prioritization and classification of both customers and suppliers in a surgical instrument supply chain by Imran, Agha, Ahmed, Sarkar, and Ramzan (2020). Indeed, after identifying the metrics of sustainability dimensions and determining the most important ones using Analytical Hierarchical Process (AHP), they developed two FIS's: the first one for mapping evaluation of metrics to sustainability dimension scores; and the second one for converting the dimension scores to priority indices. The calculated values of priority indices were further utilized for the classification purpose.

In addition, there exists a vast range of sophisticated applications of the fuzzy system, such as in (i) Castillo, Melin, Ramírez, and Soria (2012), that employed a Mamdani FIS to integrate results of three classifiers, including Fuzzy K Nearest Neighbors and two multi layer neural networks, for heart related arrhythmia classification; (ii) Castillo, Cervantes, Soria, Sanchez, and Castro, (2016), where the generalized type 2 fuzzy logic, concepts of control and granular computation were integrated in the case of an aircraft overall flight control; (iii) Ontiveros-Robles and Melin (2020), developing a computer aided system using both the general type 2 fuzzy logic and embedded type 1 fuzzy memberships in diagnosis problems; and (iv) Ontiveros-Robles, Castillo, and Melin (2020), that proposed application of non singleton inputs in general type 2 fuzzy systems implemented for the purpose of classification.

Moreover, the relevant literature involves diverse applications and/or enhancement of fuzzy systems. For instance, Tavana, Mousavi, Nasr, and Mina (2021) modified the fuzzy weighted influence non linear gauge system and applied this modified version to decision on NASA advanced technologies. Montazeri-Gh and Yazdani (2020) applied interval type 2 fuzzy logic systems to a fault detection and identification problem in the case of a gas turbine. Juang, Chang, and Hung (2021) adopted fuzzy rules in an approach to track hand palms with three dimensions, implemented in a system imitating a robot upper body. Xue, Ding, Zhang, Wu, and Wang (2021) applied a range of tools and techniques, such as the picture fuzzy set and Best Worst Method (BWM), to fault monitoring and operation safety evaluation.

## 3. Theoretical foundations

### 3.1. Three dimensional customer classification

Madzík & Shahin (2020) developed TDCC, the general mechanism of which is based on the traditional FMEA. FMEA is an analytic approach for definition, identification and elimination of potential and/or known failures, errors and so forth from design, service, process and system, prior to the items reaching the customer (Stamatis, 1995; Liu et al., 2012). In traditional FMEA, risk of failures is prioritized through the RPN index, calculable via Eq. (1) (Qin, Xi, & Pedrycz, 2020).

$$RPN = S \times O \times D \tag{1}$$

Where $S, O$ and $D$ are three risk factors which can be rated regarding the failure effect severity, failure occurrence and probability of failure non detection, respectively.

By identifying the similarities summarized in Table 2, Madzík & Shahin (2020) proposed prioritization and classification of customers, again, through a multiplication formula, Eq. (2).

$$LPN = V \times F \times L \tag{2}$$

Where $V, F$ and $L$ are three loyalty dimensions, each with the domain $[1, 10]$, and $LPN$ is a function of them, with the range $[1, 10]$. In fact, they developed the LPN index to classify the customers into four classes, namely Random, Bronze, Silver and Gold.

**Table 2**
Similar components between FMEA and TDCC.

| FMEA | TDCC |
|---|---|
| 1. Risk | 1. Loyalty |
| 2. Risk Priority Number (RPN) | 2. Loyalty Priority Number (LPN) |
| 3. Severity (S) | 3. Customer purchase value (V) |
| 4. Occurrence (O) | 4. Purchase frequency (F) |
| 5. Detection (D) | 5. Loyalty (L) |

### 3.2. Multi input single output Mamdani FIS

The MISO Mamdani FIS (FIS) is useful for input to output relationship mapping where there are data uncertainty, more than one inputs, an output and an unknown relationship between inputs and the output. Such conditions can be found, for instance, in the case of FMEA (Geramian et al., 2017). A typical FIS procedure consists of four stages (Geramian et al., 2019, 2020): First, in the fuzzification stage, crisp inputs are converted into fuzzy inputs, and their membership degrees in Membership Functions (MFs) or linguistic variables, such as high and very high, are determined. MFs can be of triangular, trapezoidal and/or Gaussian shapes, for example.

Second, in the fuzzy rule base stage, the rules for mapping the relationship between inputs to the output are defined by knowledgeable experts. Rules are building blocks of a rule base, with each rule consisting of an *if-then* format. In other words, conjunction of the if part or antecedent – using, for instance, an AND method such as Product or Minimum – leads to a specific then part – or consequence. For example, in a problem with three inputs designed with $n_1, n_2$ and $n_3$ number of MFs, the entire number of needed rules is $n_1 \times n_2 \times n_3$.

Third, in the fuzzy inference and aggregation stage, the defined rules are fed with inputs and then evaluated through, for example, a Product or Minimum method. Afterwards, the evaluation results for all rules are aggregated, e.g., via a Maximum or Sum method.

The aggregation output is defuzzified, later, in the fourth stage – defuzzification – by means of a method, such as Bisector, Centroid, Largest of Maximum (LoM), Middle of Maximum (MoM) and Smallest of Maximum (SoM).

## 4. Proposed approach: FIS based three dimensional customer classification

Our proposed methodology has a framework (Fig. 1) inspired by the fuzzy FMEA methodology (Geramian et al. 2019, 2020). In Fig. 1., as the direct relationship between the loyalty dimensions (V, F and L) and LPN is questionable in TDCC, it is depicted using a dotted arrow between crisp values of these inputs and the output value, which is indicated using the Defuzzified form of a Fuzzy LPN (Defuzzified FLPN).

Instead, a mapping between them can be established through FIS, indirectly (Sections 4.2-4.5). Additionally, review of some previous studies, indicated in Section 4.1, brought us to the conclusion that there are different scenarios or types of markets in which loyalty dimensions are not equally important. The proposed framework, therefore, includes a scenario identification stage as well, which influences the content of two other stages, that is, fuzzification and fuzzy rule base.

### 4.1. Scenario identification

According to Narayandas (2005), while consumer markets typically have many customers, business markets are of fewer ones. However, although the value of transactions is usually lower in the former, it is higher in the latter. Therefore, it appears that loyalty behavioral dimensions – the frequency and value of purchase (V and F) – are not equally important in the business and consumer markets.

In addition, it seems that in monopolistic markets, where customers have few alternatives and, thus, are trapped by exit barriers, the behavioral dimensions of loyalty are much more important than the attitudinal one – loyalty (L) (Reichheld, 2003). The logic behind this is that although a set of customers may not have a positive attitude towards a company, they have to buy only from that company. That is why the attitudinal dimension may not matter in a monopolistic setting. This is in contrast to mechanisms of competitive markets, where customers can easily churn between various companies (Amin et al., 2019) and the attitudinal dimension may even be of higher importance.

Accordingly, a crossed form of the business versus consumer and monopoly versus competition categories led us to design four scenarios (Fig. 2) including monopoly-business (Scenario 1), competition-business (Scenario 2), monopoly-consumer (Scenario 3) and competition-

| | Monopoly | Competition |
|---|---|---|
| Business | Scenario 1 $V \succ F \succ L$ | Scenario 2 $L \succ V \succ F$ |
| Consumer | Scenario 3 $F \succ V \succ L$ | Scenario 4 $L \succ F \succ V$ |

**Fig. 2.** Identified four scenarios along with importance orders of loyalty dimensions.

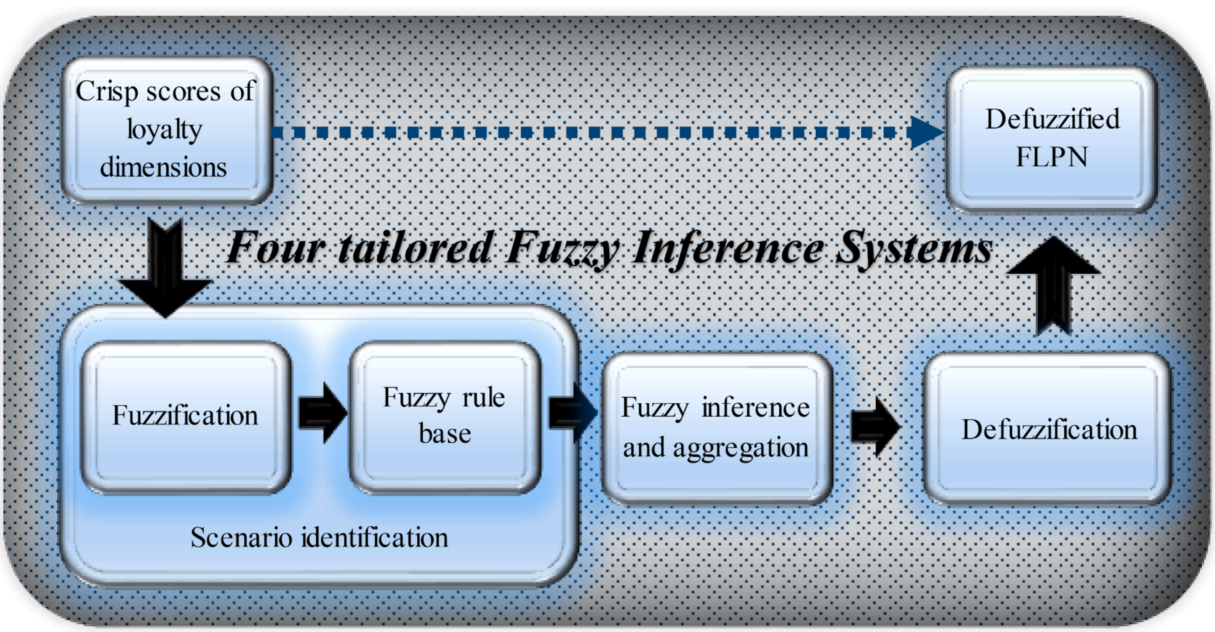



**Fig. 1.** Proposed framework.

consumer (Scenario 4) markets, each with a specific importance order of the three loyalty dimensions. In order to consider these specific importance orders, four different FIS's are developed, correspondingly, in Sections 4.2-4.5, with FIS i being designed for Scenario i, for $i = 1,2,3,4$.

### 4.2. Fuzzification

In a fuzzy FMEA problem, there are three fuzzy input variables including Severity (S), Occurrence (O), Detection (D) and one fuzzy output, fuzzy RPN (FRPN). However, the FIS based TDCC problem includes three fuzzy input variables including customer purchase value (V), purchase frequency (F) and loyalty (L), as well as a fuzzy output variable, that is, fuzzy LPN (FLPN). The input vectors are presented in Eqs. (3) to (5).

$$Value_{vector} = \left\{ \begin{array}{l} V, [1,\ 10], \{L, M, H\}, \\ \{\mu_L(v), \mu_M(v), \mu_H(v)\} \end{array} \right\} \tag{3}$$

$$Frequency_{vector} = \left\{ \begin{array}{l} F, [1,\ 10], \{L, M, H\}, \\ \{\mu_L(f), \mu_M(f), \mu_H(f)\} \end{array} \right\} \tag{4}$$

$$Loyalty_{vector} = \left\{ \begin{array}{l} L, [1, 10], \{L, M, H\}, \\ \{\mu_L(l), \mu_M(l), \mu_H(l)\} \end{array} \right\} \tag{5}$$

Where $V, F$ and $L$ are of the change domain of $[1, 10]$. For simplification, all these input variables are designed using the same set of MFs,$\{L, M, H\}$, with the elements denoting Low, Medium and High, respectively. The corresponding membership degrees include$\{\mu_L(k), \mu_M(k), \mu_H(k)\}$, for crisp values$k = v, f, and\, l$, and are real numbers within $[0, 1]$.

As with the LPN values, the higher the fuzzy output FLPN value is, the more important the relevant customer would be. Since MFs of FLPN should represent customer classes, we define them using the Loyalty Matrix categories – true loyalty, low loyalty, latent loyalty and spurious loyalty – instead of those proposed by Madzík & Shahin (2020). The reason is that the former set of classes highlights both behavioral and attitudinal strength within each class (Tanford & Baloglu, 2013), which provides better insights for customer relationship management. However, the applied fuzzy output categories are somewhat different in the competition and monopoly scenarios in question.

#### 4.2.1. Fuzzy output design for competition related scenarios

MFs of the fuzzy output in competition scenarios are designed to be the same as the four categories in Loyalty Matrix. Eq. (6) shows the fuzzy output FLPN in Scenarios 2 and 4.

$$FLPN_{vector} = \left\{ \begin{array}{l} FLPN, [1,\ 1000], \{low, spurious, latent, true\}, \\ \{\mu_{low}(lpn), \mu_{spurious}(lpn), \mu_{latent}(lpn), \mu_{true}(lpn)\} \end{array} \right\} \tag{6}$$

Where$FLPN$ changes in the $[1,\ 1000]$ range, with MFs being low, spurious, latent and true. The corresponding membership degrees include $\left\{\mu_{low}(lpn), \mu_{spurious}(lpn), \mu_{latent}(lpn), \mu_{true}(lpn)\right\}$, for the crisp value $lpn$, and are real numbers belonging to $[0, 1]$.

#### 4.2.2. Fuzzy output design for monopoly related scenarios

As mentioned earlier, Loyalty (L) – as the attitudinal dimension – is of the lowest importance in the case of purely monopolistic markets. Therefore, this dimension, which acts as a partition between the spurious and true classes as well as the latent and low classes, is missing in such markets. This fact led us not to include latent and spurious MFs in the monopoly related scenarios. Instead, in order to retain the fuzzy nature of the relevant FIS's, they are replaced with two other MFs, called partially true and partially low. The fuzzy output of Scenarios 1 and 3, are depicted by Eq. (7).

$$FLPN_{vector} = \left\{ \begin{array}{l} FLPN, \{1, 2, \ldots 1000\}, \{low, partiallylow, partiallytrue, true\}, \\ \{\mu_{low}(lpn), \mu_{partiallylow}(lpn), \mu_{partiallytrue}(lpn), \mu_{true}(lpn)\} \end{array} \right\} \tag{7}$$

In order to achieve a smoother mapping surface, the input and output variables are designed using the Gaussian shape MFs. For simplification and comparability, inputs and the output of all of the four FIS's are designed by the same shapes and parameters, except for the mentioned difference between the labels of output MFs in competition and monopoly scenarios (Fig. 3).

### 4.3. Fuzzy rule base

This is the stage where the different importance orders of the loyalty dimensions in various scenarios (Fig. 2) are considered through defining four differing rule bases. These rule bases, in turn, lead to developing four different FIS's. As the antecedent part has three factors (V, F and L), each with three MFs (L, M and H), each of the rule bases consists of $27(3 \times 3 \times 3)$rules. In total, we defined$108(4 \times 27)$rules for all the four FIS's. By way of brief comparison, one of the rules, which is defined with the same antecedent part – but different consequent part – in the four FIS's is highlighted in Eqs. (8) to (9). Despite the mentioned differences in the outputs of monopoly and competition scenarios, all of the four FIS's are of the same general architecture (Fig. 4). In this study, components of the antecedent part are combined using Minimum, as an AND method.

$$\begin{array}{l} InFIS's1\mathrm{and}3 : If < (VisL) and (F\, is\, L) and (L\, is\, H) > \\ \quad then < Defuzzified\ FLPN\ is\ Low > \end{array} \tag{8}$$

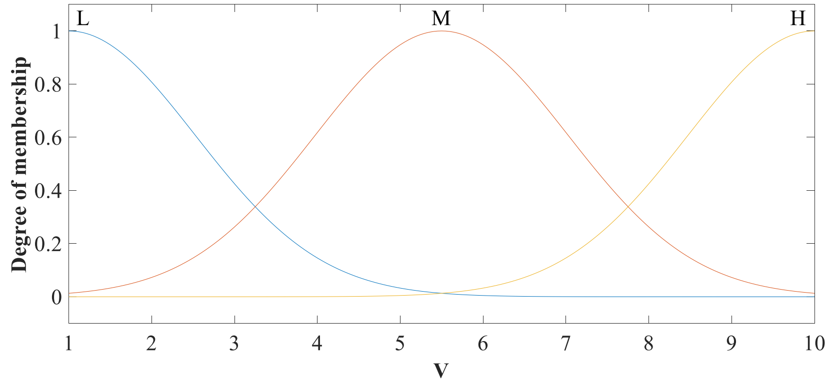
$$\begin{array}{l} InFIS's2\mathrm{and}4 : Rule : If < (VisL) and (FisL) and (LisH) > \\ \quad then < DefuzzifiedFLPNisLatent > \end{array} \tag{9}$$

We defined the rules according to a Loyalty Matrix based classification logic which is also customized to specific needs of the scenarios. For example, on one hand, according to a pure Loyalty Matrix logic, a combination of low behavioral loyalty and high attitudinal loyalty dimensions results in the relevant customers being classified in the latent class (Tanford & Baloglu, 2013). On the other hand, in a monopolistic market scenario, attitudinal loyalty is not of a significant impact on customer classification decisions. Therefore, the FIS 1 rule, depicted in Eq. (8), shows that the high (H) level of attitudinal loyalty (L) cannot lead to a Defuzzified FLPN more than Low – in a combination with the Low (L) level of the two behavioral dimensions. Nevertheless, in a competitive market scenario, where the L dimension is of a high influence, the same antecedent or if part leads to the latent class (Eq. (9)).

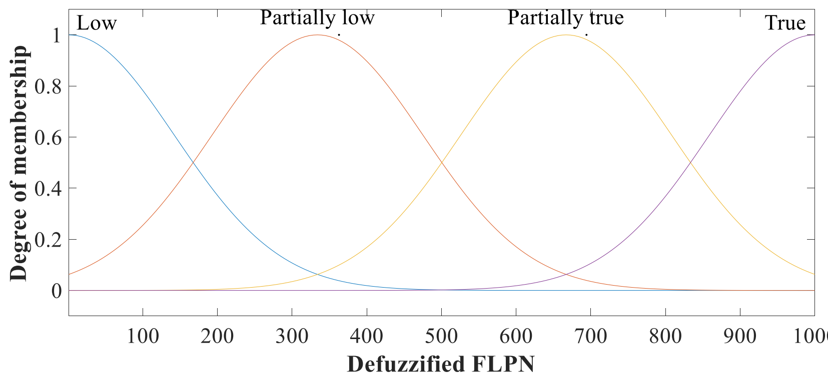
According to Fig. 2, the dimension L is of the lowest importance in Scenarios 1 and 3 (the monopolistic ones). It is also the case for dimensions F and V respectively in Scenarios 2 and 4. In accordance with these, we take into account the extreme status – zero impact on determining the consequent output MF – for them in the mentioned scenarios. Indeed, we do so to better highlight the significance of weighting through the rule definition capability of FIS.

After defining the rules, we managed to obtain mapping relationships amongst each two inputs and the output in the form of surface plots. Surface plots of FIS's 1 to 4 are illustrated in Figs. 5 to 8. Since L – the attitudinal dimension – is of lowest importance in the monopolistic scenarios, the slope pertaining to this dimension is zero in both Scenarios 1 and 3 (Figs. 5 and 6). With respect to the behavioral dimensions, as V is much more important than the variable F in a business (versus consumption) scenario, the slope of V is higher than F in FIS 1 (versus FIS 3) – compare the (a) components in Figs. 5 and 6.

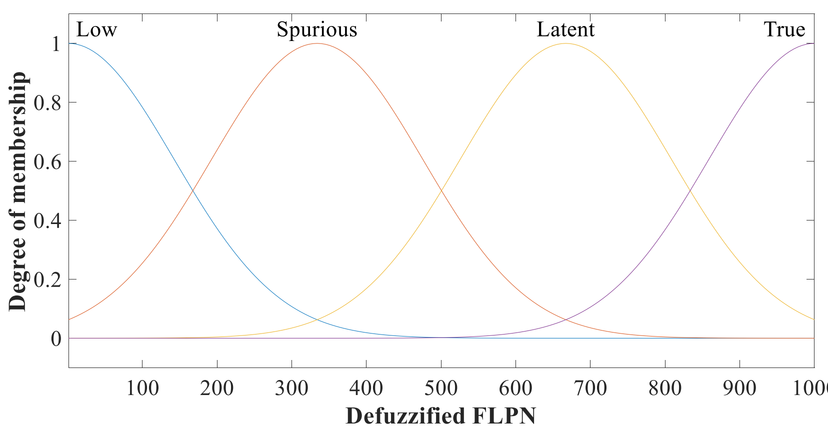
By contrast, regarding the fact that L is important in competition scenarios, it is not of the zero slope in FIS's 2 and 4 (Figs. 7 and 8). However, as mentioned earlier, FIS's 2 and 4 were designed in such a way to represent the extreme status of lowest importance respectively




(a) Three membership functions of the fuzzy input variable V (similar to those of F and L) in FIS's 1 to 4




(b) Four membership functions of the fuzzy output variable Defuzzified FLPN in monopoly-based scenarios: Scenarios 1 and 3




(c) Four membership functions of the fuzzy output variable Defuzzified FLPN in competition-based scenarios: Scenarios 2 and 4

**Fig. 3.** Fuzzy inputs and output of FIS's 1 to 4.

for F and V. That is why the F and V variables are of zero slopes in FIS's 2 and 4 (Figs. 7 and 8), respectively.

### 4.4. Fuzzy inferenced and aggregation

The defined rules are fed with inputs, and each rule is evaluated through the Minimum implication method, Eq. (10), in this study.

$$\mu(R^j) = Min(\alpha^j, \mu_{output\ MF^j}) \quad (10)$$

With $\alpha^j$ denoting the output of AND method on the jth rule antecedent components, and $\mu_{output\ MF^j}$ representing MF of the jth rule output ($j = 1, 2, \ldots n_V \times n_F \times n_L$). Afterwards, the $\mu(Rj)$ values for all rules were aggregated via the Maximum operator, Eq. (11).

$$\mu_{FLPN} = Max\{\mu(R^1), \quad \mu(R^2), \quad \ldots \quad \mu(R^{n_V \times n_F \times n_L})\} \quad (11)$$

### 4.5. Defuzzification

The value derived from Eq. (11) is of a fuzzy nature. Becoming easily understandable, it is deffuzzified using the Centroid method, Eq. (12).

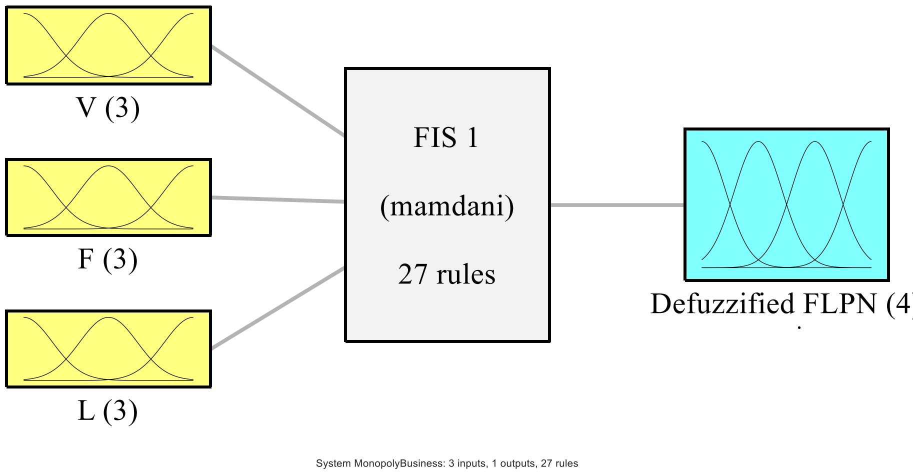



**Fig. 4.** Architecture of FIS 1, including the three fuzzy inputs, 27 rules and one fuzzy output, which is the same as the other three FIS's.

$$Defuzzified\ FLPN = \frac{\int_{-\infty}^{+\infty} \mu_{FLPN}(y) \times y \times dy}{\int_{-\infty}^{+\infty} \mu_{FLPN}(y) \times dy} \quad (12)$$

With y denoting the input variable of aggregated MFs.

## 5. Application of the approach

In order to investigate applicability and effectiveness of the proposed methodology, it is applied in the context of some scenarios by considering several assumptive customers, each being characterized by three assumptive values for the loyalty dimensions. This provided us with the chance of implementing our proposed approach in comparison to TDCC, followed by findings and discussion.

### 5.1. Assumptive customers and data

Evaluating performance of the new approach, we considered five assumptive customers,$Ci,\ i = 1, 2, \ldots, 5$, as well as a set of assumptive loyalty dimension scores (V, F and L) for each one (the first four columns of Table 3).

### 5.2. Findings

In order to provide a comparative evaluation, both the base approach and proposed methodology were implemented using the same set of data indicated in Section 5.1.

#### 5.2.1. Results of the base approach

First, TDCC was implemented using the assumptive scores. Indeed, having been calculated through multiplication of scores of the three loyalty dimensions, LPN values were used to determine customer classes – regarding the within $[0, 1000]$ quartile where they were located (Madzík & Shahin, 2020). The LPN values also contribute to ranking the assumptive customers. These obtained results are summarized in the last three columns of Table 3).

#### 5.2.2. Results of the modified approach

Next, we fed the four tailored FIS's developed in Sections 4.2-4.5 with the same crisp values. In other words, once the crisp data were fuzzified in the fuzzification step, the defined rules of each FIS were activated to a specific extent. Subsequently, these evaluated rules were aggregated and the resultant fuzzy output was defuzzifed. Defuzzified FLPN values of the four FIS's were utilized as a basis for determining priorities (rankings) and classes of the assumptive customers. These yielded results are summarized in Tables 4 and 5.

### 5.3. Discussion

Since relative importance of the loyalty dimensions are not taken into account by TDCC, this approach ignored the importance orders mentioned in Fig. 2. Consequently, it led to the same set of customer classes in several cases – the sixth column in Table 3 – regardless of the four market scenarios. This fact shows that TDCC lacks discriminability between the potential markets.

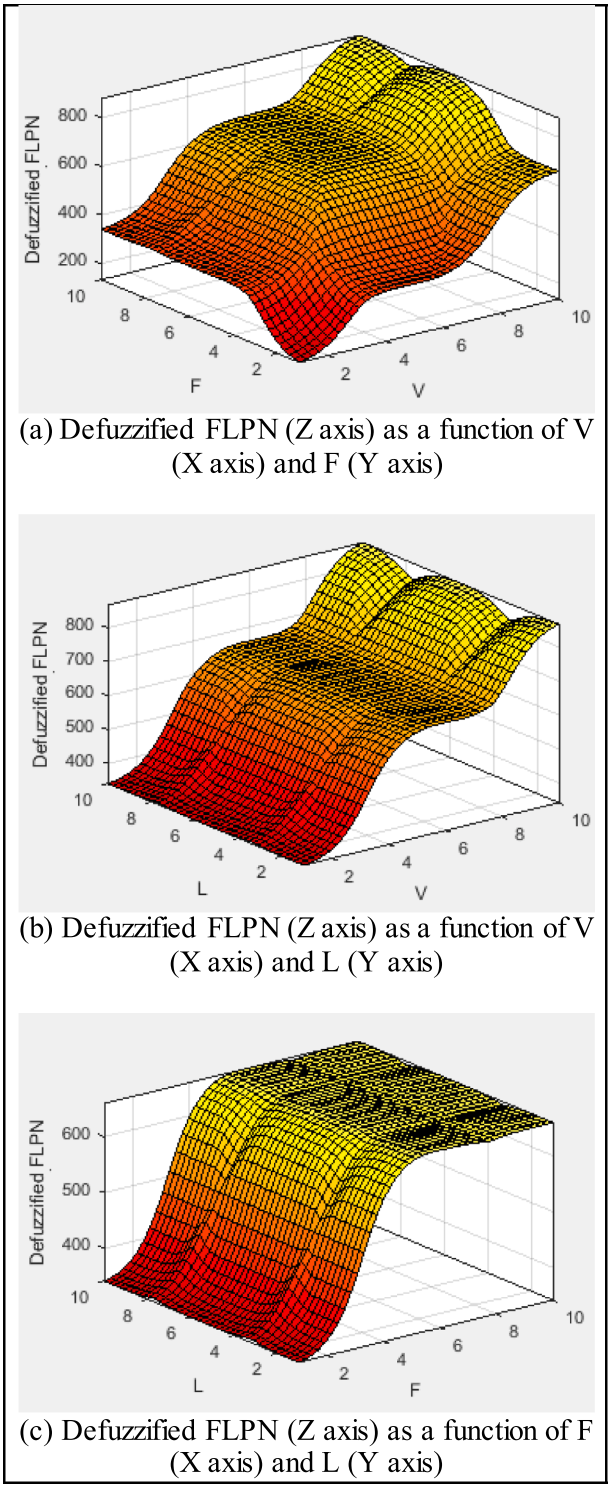
By contrast, results of implementing the new approach (Tables 4 and 5) indicate that it successfully resolved the issue. For instance, customer C2, whom was classified in the same category – Random – by TDCC in all (or regardless) of the scenarios, has been located in the partially low, latent, partially low and true classes by FIS based TDCC respectively in Scenarios 1 to 4. This is the capability that we call 'between scenario discriminability'.

Also, Table 6 shows that the four tailored FIS's provide scenario specific customer priorities, in comparison to the one prioritization set provided by TDCC.

Besides these, our proposed approach is of the following advantages over the basic TDCC:

- Table 3 indicates that, through TDCC, customers C1 and C5, with completely different scores of $V(10\ \text{versus}\ 3)$ and $F(3\ \text{versus}\ 10)$received the same LPN, 30. However, as these two loyalty dimensions are of different weights in business and consumer market scenarios, the two customers received different Defuzzified FLPN within each of the corresponding scenarios. For instance, FIS 1, which puts more emphasis on V compared to the F dimension, characterized customer C1 with a higher Defuzzified FLPN (672) than C5 did (464). This is a solution for the problem of identical LPN derived from different sets of loyalty dimension scores – which we call 'within scenario discriminability'.
- Since different weights of loyalty dimensions are considered in the new approach, it is expected that it significantly reduces the duplicate values observed in the output variable of TDCC, as well.
- The FIS based TDCC does not use the questionable multiplication formula for input to output mapping.
- In contrast to LPN, Defuzzified FLPN proved to be a continuous output variable, which can be observed through the surface plots (Fig. 5). The plots also indicate that Defuzzified FLPN is an ascending function of the inputs – except for L, which was purposely set to be of a zero impact regarding the specific need of the scenario. This ascending trend shows that the FIS 1 rules (and similarly, those of the other three FIS's) were defined accurately (Geramian et al., 2020).

Admittedly, though, MFs used in this research are of type 1 or of

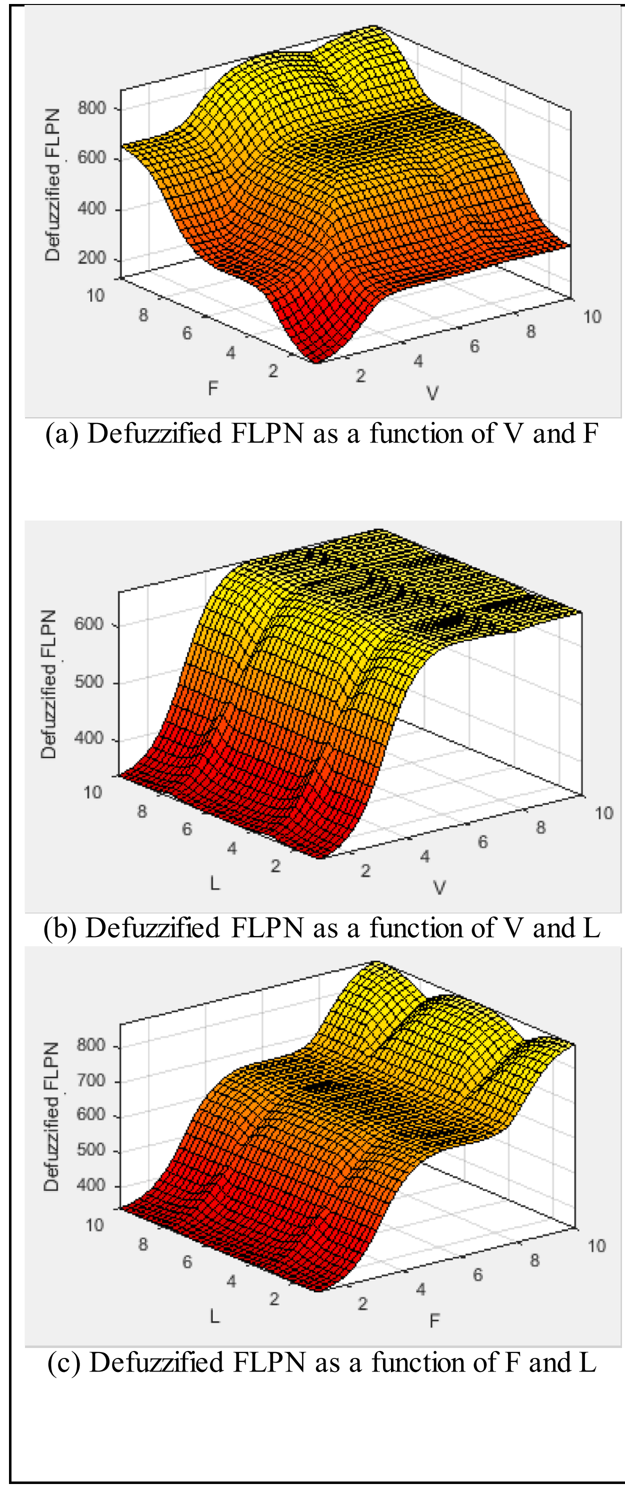


(a) Defuzzified FLPN (Z axis) as a function of V (X axis) and F (Y axis)

(b) Defuzzified FLPN (Z axis) as a function of V (X axis) and L (Y axis)

(c) Defuzzified FLPN (Z axis) as a function of F (X axis) and L (Y axis)

**Fig. 5.** Surface plots of FIS 1, relating to monopoly-business scenario.



(a) Defuzzified FLPN as a function of V and F

(b) Defuzzified FLPN as a function of V and L

(c) Defuzzified FLPN as a function of F and L

**Fig. 6.** Surface plots of FIS 3, relating to monopoly-consumer scenario.

certain numeric values, which, compared to type 2 fuzzy sets, are not capable of directly tackling uncertainties in rules, measurement and exact membership function definition (Castillo et al., 2016).

## 6. Practical implications

This study sheds light on the fact that marketing managers should carry out the customer classification task with respect to the context – market type – they are planning for; otherwise, they may end up with misleading results. In competitive markets, managers should pay much more attention to attitudinal loyalty factors. In such contexts, a given company's customers with only high behavioral loyalty – purchase value or frequency – indication may easily stop buying from the company because they are of high switching power there. Accordingly, attitudinal loyalty appears to act as a momentous deciding factor in their purchase decisions.

In contrast, companies operating in monopolistic markets do not have to focus on the attitudinal dimensions a lot. In fact, regarding the

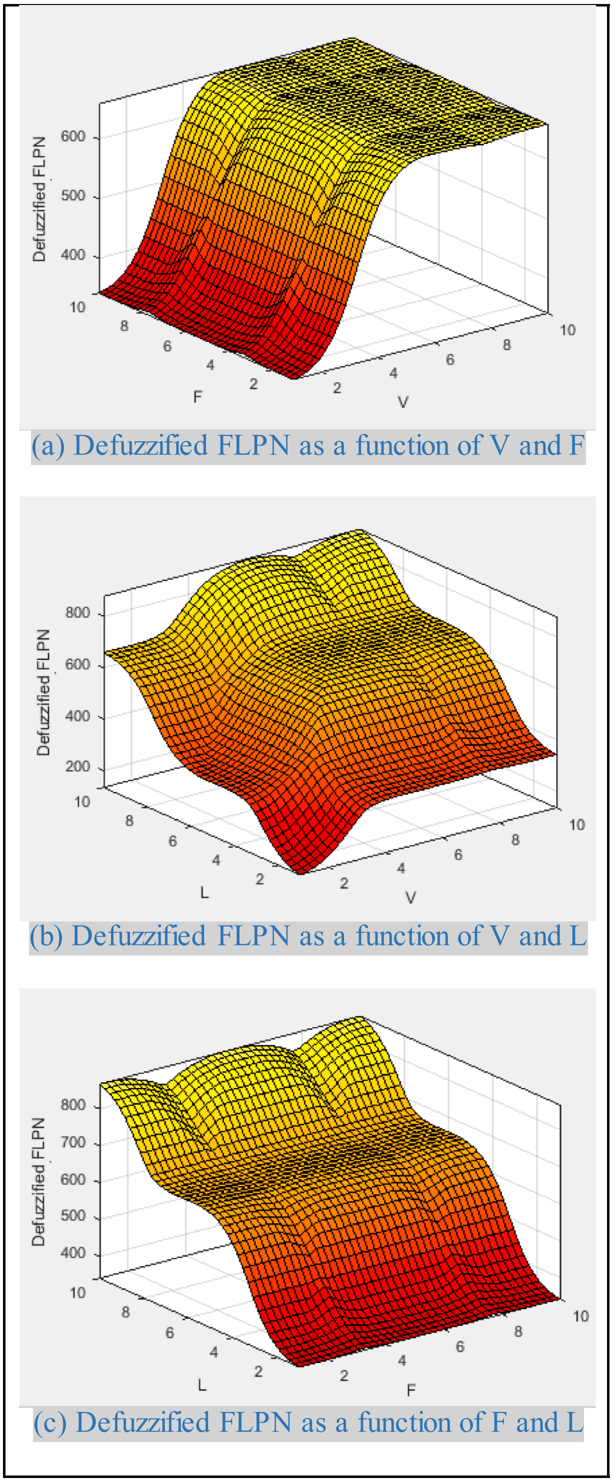



**Fig. 7.** Surface plots of FIS 2, relating to competition-business scenario.

weak switching power of customers, customers' loyalty driven behaviors are the only essential things they are looking for.

Managers also need to operationalize these marketing considerations during their customer classification efforts. For this purpose, they can adopt the FIS based TDCC, an approach capable of taking into consideration various importance weights of the loyalty dimensions. It facilitates incorporating practitioners' knowledge and experience within its fuzzy rule bases. It is also a user friendly methodology in that it can take the judgement about levels of loyalty dimensions simply through the natural language – such as high, medium, etc. Moreover, it is a powerful

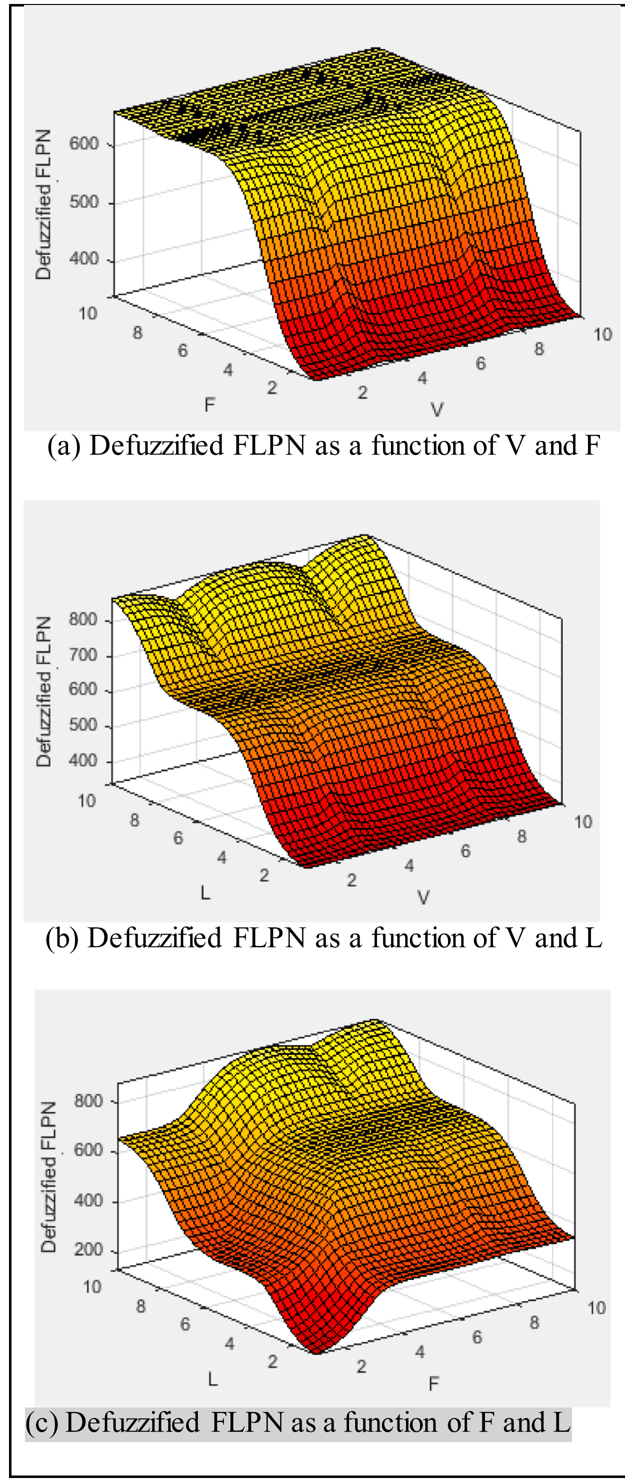



**Fig. 8.** Surface plots of FIS 4, relating to competition-consumption scenario.

**Table 3**
Assumptive customers, scores of loyalty dimensions, and results derived from implementation of TDCC.

| Customer | V | F | L | LPN | Class | LPN based ranking |
|---|---|---|---|---|---|---|
| C1 | 10 | 3 | 1 | 30 | Random | 3 |
| C2 | 1 | 6 | 10 | 60 | Random | 2 |
| C3 | 10 | 10 | 10 | 1000 | Gold | 1 |
| C4 | 1 | 2 | 2 | 4 | Random | 4 |
| C5 | 3 | 10 | 1 | 30 | Random | 3 |

**Table 4**
FIS's 1 and 3 (tailored for monopolistic scenarios, 1 and 3) results.

| Customer | FIS 1 for Scenario 1: Monopoly business market | | | FIS 3 for Scenario 3: Monopoly consumer market | | |
|---|---|---|---|---|---|---|
| | Defuzzified FLPN | Priority | Class* | Defuzzified FLPN | Priority | Class |
| C1 | 672 | 2 | Partially true | 464 | 3 | Partially low |
| C2 | 342 | 4 | Partially low | 350 | 4 | Partially low |
| C3 | 878 | 1 | True | 878 | 1 | True |
| C4 | 180 | 5 | Low | 180 | 5 | Low |
| C5 | 464 | 3 | Partially low | 672 | 2 | Partially true |

* The classes were identified based on the consequence part of the rule which was activated or fired more.

**Table 5**
FIS's 2 and 4 (tailored for competitive scenarios, 2 and 4) results.

| Customer | FIS 2 for Scenario 2: Competition business market | | | FIS 4 for Scenario 4: Competition consumer market | | |
|---|---|---|---|---|---|---|
| | Defuzzified FLPN | Priority | Class | Defuzzified FLPN | Priority | Class |
| C1 | 346 | 3 | Spurious | 289 | 4 | Spurious |
| C2 | 659 | 2 | Latent | 874 | 2 | True |
| C3 | 878 | 1 | True | 878 | 1 | True |
| C4 | 180 | 5 | Low | 238 | 5 | Low |
| C5 | 289 | 4 | Spurious | 346 | 3 | Spurious |

**Table 6**
TDCC prioritization versus the four set of tailored prioritizations by FIS based TDCC.

| Scenario No. | Four set of scenario specific priorities derived from FIS based TDCC | The same priorities derived from TDCC |
|---|---|---|
| 1: monopoly-business market | $C3 \succ C1 \succ C5 \succ C2 \succ C4$ | $C3 \succ C2 \succ C1 = C5 \succ C4$ |
| 2: competition-business market | $C3 \succ C5 \succ C1 \succ C2 \succ C4$ | $C3 \succ C2 \succ C1 = C5 \succ C4$ |
| 3: monopoly-consumer market | $C3 \succ C2 \succ C1 \succ C5 \succ C4$ | $C3 \succ C2 \succ C1 = C5 \succ C4$ |
| 4: competition-consumer Market | $C3 \succ C2 \succ C5 \succ C1 \succ C4$ | $C3 \succ C2 \succ C1 = C5 \succ C4$ |

technique in dealing with data ambiguities in ratings of the loyalty dimensions. Future users of the proposed method should select and tailor the best FIS with respect to the specific market scenario they will face. Also, they should periodically update the fuzzy rule base on the basis of the most recent situation emerging in their market.

## 7. Conclusions

In the present research, we modified TDCC, an approach recently developed to classify customers, by means of the MISO Mamdani FIS and, in part, Loyalty Matrix. Benefits of such modification are extensive: tackling human judgment uncertainties extant within input data; providing both within and between scenario discriminability; considering relative importance weights of the loyalty dimensions; facilitating a relaxation of the questionable multiplication formula; introducing a gap free output variable, Defuzzified FLPN; and reducing the number of duplicate values in the output variable.

One of the most considerable findings of this study is that customers should not be classified regardless of the market types. We considered those types of markets in the form of potential scenarios which firms may encounter. In the light of its comprehensive scenarios, the present research is expected to open a new window on more future empirical research in a wide range of markets.

However, the loyalty dimensions, in the proposed methodology, were assumed to be independent; the fuzzy input variables were designed only by three MFs; levels of FIS operators – AND, implication, aggregation and defuzzification – were not set, systematically; and a basic version of the fuzzy logic – that is, the type 1 FIS – was applied. Therefore, future studies will have the opportunity to focus on potential interactions amongst the three loyalty dimensions; on more number of input MFs, as a method to increase the capability of handling uncertainties; a systematic way to determine FIS operators through relevant mechanisms previously developed in the FIS literature; and on application of a recent extension of the fuzzy logic such as type 2.

## 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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## References

Abbasimehr, H., Setak, M., & Soroor, J. (2013). A framework for identification of high-value customers by including social network based variables for churn prediction using neuro-fuzzy techniques. *International Journal of Production Research., 51*(4), 1279–1294.

Amin, A., Al-Obeidat, F., Shah, B., Adnan, A., Loo, J., & Anwar, S. (2019). Customer churn prediction in telecommunication industry using data certainty. *Journal of Business Research., 94*, 290–301.

Bandyopadhyay, S., & Martell, M. (2007). Does attitudinal loyalty influence behavioral loyalty? A theoretical and empirical study. *Journal of Retailing and Consumer Services, 14*(1), 35–44.

Castillo, O., Cervantes, L., Soria, J., Sanchez, M., & Castro, J. R. (2016). A generalized type-2 fuzzy granular approach with applications to aerospace. *Information Sciences., 354*, 165–177.

Castillo, O., Melin, P., Ramírez, E., & Soria, J. (2012). Hybrid intelligent system for cardiac arrhythmia classification with Fuzzy K-Nearest Neighbors and neural networks combined with a fuzzy system. *Expert Systems with Applications., 39*(3), 2947–2955.

Cervero, A., Castro-Lopez, A., Álvarez-Blanco, L., Esteban, M., & Bernardo, A. (2020). Evaluation of educational quality performance on virtual campuses using fuzzy inference systems. *Plos One, 15*(5), Article e0232802.

Floh, A., Zauner, A., Koller, M., & Rusch, T. (2014). Customer segmentation using unobserved heterogeneity in the perceived-value–loyalty–intentions link. *Journal of Business Research., 67*(5), 974–982.
Geramian, A., Abraham, A., & Ahmadi Nozari, M. (2019). Fuzzy logic-based FMEA robust design: A quantitative approach for robustness against groupthink in group/team decision-making. *International Journal of Production Research., 57*(5), 1331–1344.
Geramian, A., Mehregan, M. R., Garousi Mokhtarzadeh, N., & Hemmati, M. (2017). Fuzzy inference system application for failure analyzing in automobile industry. *International Journal of Quality & Reliability Management., 34*(9), 1493–1507.
Geramian, A., Shahin, A., Minaei, B., & Antony, J. (2020). Enhanced FMEA: An integrative approach of fuzzy logic-based FMEA and collective process capability analysis. *Journal of the Operational Research Society., 71*(5), 800–812.
Ghani, U., Bajwa, I. S., & Ashfaq, A. (2018). A fuzzy logic based intelligent system for measuring customer loyalty and decision making. *Symmetry., 10*(12), 761.
Imran, M., Agha, M. H., Ahmed, W., Sarkar, B., & Ramzan, M. B. (2020). Simultaneous Customers and Supplier's Prioritization: An AHP-Based Fuzzy Inference Decision Support System (AHP-FIDSS). *International Journal of Fuzzy Systems., 22*(8), 2625–2651.
Ghoushchi, S. J., Yousefi, S., & Khazaeili, M. (2019). An extended FMEA approach based on the Z-MOORA and fuzzy BWM for prioritization of failures. *Applied Soft Computing., 81*, 105505. https://doi.org/10.1016/j.asoc.2019.105505
Jing, L., Yao, J., Gao, F., Li, J., Peng, X., & Jiang, S. (2021). A rough set-based interval-valued intuitionistic fuzzy conceptual design decision approach with considering diverse customer preference distribution. *Advanced Engineering Informatics., 48*, 101284. https://doi.org/10.1016/j.aei.2021.101284
Juang, C. F., Chang, C. W., & Hung, T. H. (2021). Hand Palm Tracking in Monocular Images by Fuzzy Rule-based Fusion of Explainable Fuzzy Features with Robot Imitation Application. *IEEE Transactions on Fuzzy Systems*.
Kang, Y. K., Kim, H., Heo, G., & Song, S. Y. (2017). Diagnosis of feedwater heater performance degradation using fuzzy inference system. *Expert Systems with Applications., 69*, 239–246.
Liu, H.-C., Liu, L., & Liu, N. (2013). Risk evaluation approaches in failure mode and effects analysis: A literature review. *Expert Systems with Applications., 40*(2), 828–838.
Liu, H.-C., Liu, L., Liu, N., & Mao, L.-X. (2012). Risk evaluation in failure mode and effects analysis with extended VIKOR method under fuzzy environment. *Expert Systems with Applications., 39*(17), 12926–12934.
Madzík, P., & Shahin, A. (in press). Customer categorization using a three-dimensional loyalty matrix analogous to FMEA. International Journal of Quality & Reliability Management.
MahmoumGonbadi, A., Katebi, Y., & Doniavi, A. (2019). A generic two-stage fuzzy inference system for dynamic prioritization of customers. *Expert Systems with Applications., 131*, 240–253.
Mamdani, E. H., & Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Man-Machine Studies., 7*(1), 1–13.
Mascarenhas, O. A., Kesavan, R., & Bernacchi, M. (2006). Lasting customer loyalty: A total customer experience approach. *Journal of Consumer Marketing., 23*(7), 397–405.
Montazeri-Gh, M., & Yazdani, S. (2020). Application of interval type-2 fuzzy logic systems to gas turbine fault diagnosis. *Applied Soft Computing., 96*, 106703. https://doi.org/10.1016/j.asoc.2020.106703
Narayandas, D. (2005). Building loyalty in business markets. *Harvard Business Review., 83*(9), 131–139.
Oliver, R. L. (1999). Whence consumer loyalty? *Journal of Marketing., 63*(4_suppl1), 33–44.
Ontiveros-Robles, E., & Melin, P. (2020). Toward a development of general type-2 fuzzy classifiers applied in diagnosis problems through embedded type-1 fuzzy classifiers. *Soft Computing., 24*(1), 83–99.
Ontiveros-Robles, E., Castillo, O., & Melin, P. (2020). An approach for non-singleton generalized Type-2 fuzzy classifiers. *Journal of Intelligent & Fuzzy Systems., 39*(5), 7203–7215.
Qin, J., Xi, Y., & Pedrycz, W. (2020). Failure mode and effects analysis (FMEA) for risk assessment based on interval type-2 fuzzy evidential reasoning method. *Applied Soft Computing., 89*, 106134. https://doi.org/10.1016/j.asoc.2020.106134
Rahim, M. A., Mushafiq, M., Khan, S., & Arain, Z. A. (2021). RFM-based repurchase behavior for customer classification and segmentation. *Journal of Retailing and Consumer Services., 61*, 102566. https://doi.org/10.1016/j.jretconser.2021.102566
Reichheld, F. F. (2003). The one number you need to grow. *Harvard Business Review., 81*(12), 46–55.
Shahin, A., Barati, A., & Geramian, A. (2017). Determining the critical factors of radical innovation using an integrated model of fuzzy analytic hierarchy process-fuzzy Kano with a case study in Mobarakeh steel company. *Engineering Management Journal., 29*(2), 74–86.
Song, X.i., Liu, M. T., Liu, Q., & Niu, B. (2021). Hydrological cycling optimization-based multiobjective feature-selection method for customer segmentation. *International Journal of Intelligent Systems., 36*(5), 2347–2366.
Stamatis, D. H. (1995). *Failure mode and effect analysis: FMEA from theory to execution*. New York: ASQC Press.
Tanford, S., & Baloglu, S. (2013). Applying the loyalty matrix to evaluate casino loyalty programs. *Cornell Hospitality Quarterly., 54*(4), 333–346.
Tavana, M., Mousavi, H., Khalili Nasr, A., & Mina, H. (2021). A Fuzzy Weighted Influence Non-linear Gauge System with Application to Advanced Technology Assessment at NASA. *Expert Systems with Applications., 182*, 115274. https://doi.org/10.1016/j.eswa.2021.115274
Tsai, M.-C., Merkert, R., Tsai, M.-T., & Lin, S.-C. (2021). Towards a taxonomy-based preferred-customer model for suppliers in air cargo express service markets. *Journal of Air Transport Management., 90*, 101962. https://doi.org/10.1016/j.jairtraman.2020.101962
Wang, H., Niu, B., & Tan, L. (2021). Bacterial colony algorithm with adaptive attribute learning strategy for feature selection in classification of customers for personalized recommendation. *Neurocomputing., 452*, 747–755.
Xue, H., Ding, D., Zhang, Z., Wu, M., & Wang, H. (2021). A fuzzy system of operation safety assessment using multi-model linkage and multi-stage collaboration for in-wheel motor. *IEEE Transactions on Fuzzy Systems*.
Yazıcı, K., Gökler, S. H., & Boran, S. (in press). An integrated SMED-fuzzy FMEA model for reducing setup time. Journal of Intelligent Manufacturing.
Zadeh, L. A. (1965). Fuzzy sets. *Information & Control., 8*(3), 338–353.
Zanon, L. G., Munhoz Arantes, R. F., Calache, L. D. D. R., & Carpinetti, L. C. R. (2020). A decision making model based on fuzzy inference to predict the impact of SCOR® indicators on customer perceived value. *International Journal of Production Economics., 223*, 107520. https://doi.org/10.1016/j.ijpe.2019.107520