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Using Fuzzy Logic to Make Decisions Based on the Data From Customer Relationship Management Systems

Agnieszka Bojanowska[1*], Monika Kulisz[2]

[1] Department of Marketing, Faculty of Management, Lublin University of Technology, ul. Nadbystrzycka 38D, 20-618 Lublin, Poland

[2] Department of Organization of Enterprise, Faculty of Management, Lublin University of Technology, ul. Nadbystrzycka 38D, 20-618 Lublin, Poland

* Corresponding author's e-mail: a.bojanowska@pollub.pl

ABSTRACT

The purpose of the article is to propose a fuzzy logic solution for decision-making based on data from CRM (Customer Relationship Management) systems to evaluate banking customer attractiveness. The article is based on theory about management IT systems, especially the CRM type. Based on the literature research, nine identified factors were proposed that can influence whether the relationship with the customer will be profitable for the bank. Factors that affect banking customer attractiveness are considered, including the share of the customer's wallet and the customer's tendency to express a positive opinion of the bank. The data allowing for the identification of these factors is collected in the bank's IT systems, among other CRMs. Based on the research, a model prepared in Simulink using a Mamdani-type Fuzzy Inference System was made. It is a decision model that provides a result in the form of a binary value of 0 or 1, where 1 means it is worth investing in a customer, while 0 means it is not. After considering the subjective opinions, competence and experience of specialists as well as confronting them with the results from the developed model, it can be confirmed that the model works as expected.

Keywords: fuzzy logic, AI, CRM systems, customer loyalty.

INTRODUCTION

The paper's authors assumed the goal of revealing the possibility of applying fuzzy logic to decision-making based on data from customer relationship management (CRM) systems, using the banking industry as an example. Currently, in order to establish a proper relationship with the customer, it is necessary not only to collect and process his data, but also to use appropriate software for this purpose. Data must be processed using the latest technological solutions to maintain pace with increasing competition in every market, including banking. There is a wide range of CRM application software, packaged differently by different vendors, and with varying degrees of integration [1]. Pan and Lee give a high level CRM application classification into information integration, customer analysis, campaign management, real time decision-making and personalised messaging [2]. CRM application software includes: customer profitability analysis, churn analysis, campaign management, customer profiling, propensity scoring, personalisation, call centre technology, channel integration software, contact management, general analytical and data warehouse tools, and sales force automation [3-6]. It is considered that the intelligent application of CRM software can yield improvements in business performance [7]. The implementation of specialized software in the business supports the processes related to production and employees' activities, and those providing quick access to the necessary information between branches. The need for better business management and closer interaction with customers via the

Internet underpins modern CRM systems development [8]. Currently, CRM is increasingly benefiting from artificial intelligence. AI plays a fundamental role because AI solutions applied to CRM enable companies to better assimilate and analyse customer data [9]. It's even said that CRM is evolving from a data driven strategy to an AI-driven strategy [10]. Ledro et al. propose model serves as a guideline tool for executives and managers to plan an appropriate and consistent strategy for AI implementation in CRM and improve efficiency in the information management of Big Data, technology investigation of AI and ML techniques and AI-driven business transformation [11]. Until now, for example, machine learning solutions are being used in CRM. CRM systems use machine-learning models to analyze customers' personal and behavioral data to give organization a competitive advantage by increasing customer retention rate [12]. For example, it was noted that companies have difficulties leveraging existing data when they attempt to make inferences about customers at the beginning of their relationship and developing a probabilistic machine learning modelling framework that leverages the information collected at the moment of the acquisition was proposed [13].

Fuzzy logic, which the authors of this article decided to apply to customer relationship management problems, has its origins in fuzzy sets. As fuzzy sets were introduced by Zadeh in 1965, they were born closely linked with imprecise predicates, that is, with names of non-precisely defined classes of objects. Even more, most of the applications of Zadeh's ideas are made with properties the objects do verify to some degree between the two classical extremes 0 and 1, respectively [14]. In 1975, Zadeh introduced a fuzzy logic system [15]. Fuzzy logic is the study and computational management of imprecision and non-random uncertainty, both with the highest accuracy and precision possible in each case, that fuzzy logic is not fuzzy in itself [16]. Fuzzy logic is an extension of classical reasoning to reasoning that is closer to humans. It introduces values between the standard 0 and 1; it 'fuzzes' the boundaries between them by giving the possibility for values from between this interval to exist (e.g.: almost false, half true) [17]. Fuzzy logic is used in a wide range of applications, such as control systems, image processing, natural language processing, medical diagnosis, and artificial intelligence [18]. In business and science, fuzzy logic finds applications in many, remote fields, such as geology [19], machine control systems [20, 21], management [22], and medicine [23]. Fuzzy logic is used virtually everywhere where the use of classical logic poses a problem due to the difficulty of notating the process mathematically or when it is impossible to calculate or retrieve the variables needed to solve the problem [24]. Among the determinants of a profitable bank-customer relationship are precisely such variables, which are qualitative and therefore difficult to quantify. They should be reduced to quantifiable data, but this often brings interpretive difficulties and ambiguities.

Modern banking is struggling with a number of difficulties resulting, for example, from the post-pandemic economic collapse. The paradigms that determine the shape of the bank-customer relationship are changing. The correlations between the factors influencing this relationship and the result in terms of profitable customer relationship building are worth identifying. This profitable relationship is based on what the customer's value is to the bank. As Kumar et al. state, the challenge for a company today is to implement an optimal blend of differential levels of customer treatment to maximise profits, which is made possible by collecting and processing data in CRM systems. Undoubtedly, one of the tools used to identify the value or profitability of customers is Customer Lifetime Value (CLV) [25, 26]. CLV is sometimes defined differently, and consequently, different computational models are adopted. For example, Berger and Nasr consider CLV to be the net profit or loss to the company from a customer over the entire life of transactions of that customer with the company [27]. CLV is also sometimes perceived as expected profits from customers, exclusive of costs related to customer management [28]. Most CLV models stem from the basic equation, although we have many other CLV calculation models having various realistic problems. The basic model form based on the proposed definition is as follows:

$$CLV = \sum_{i=1}^{n} \frac{(R_i - C_i)}{(1+d)^{i-0,5}} \qquad (1)$$

where: i – the period of cash flow from customer transactions, Ri – the revenue from the customer in period i, Ci – the total cost of generating the revenue Ri in period i, n – total number of periods of projected life of the customer under consideration; d – the discount rate (usually the weighted average cost of capital for the selected company is taken, or for comparative analysis the average market value is taken, about 10%) [29].

Therefore, to calculate the customer's value, data such as the retention period, or the customer's share of wallet are relevant [30]. It is also important to position the customer in the life cycle (whether it is a new customer, a repeat customer, or an outgoing customer) and their brand loyalty [31]. Information for calculating CLV is provided by CRM systems that collect, gather, process and analyze data. According to the authors, it is possible to apply fuzzy logic solutions to model the customer potential evaluation for a bank, which involves CLV assessment by banks. The data relevant to the CLV calculation is, as it were, the initial point that inspired the paper's authors to identify variables that can provide input in a fuzzy logic model to determine the bank customer's attractiveness.

LITERATURE REVIEW REGARDING THE VARIABLE SELECTION ASPECT OF THE FUZZY LOGIC MODEL

In order to apply the fuzzy logic tool to the issue described, it is necessary to properly select the input criteria for the model. Due to this reason, a literature analysis was conducted on the factors affecting customer attractiveness in the bank-customer relationship. Building customer relationships requires using various tools but also determining how to identify the best and most lucrative customers for the company. This is also the case for banking institution customers. Using modern technologies, Customer Relationship Management is becoming a method to maintain existing structure and development of high quality customer base. It involves the development of a marketing strategy through a better understanding of the entire customer base, understanding the needs and attitudes of customers, as well as more efficient consideration of profitability and added value that each customer has for the bank [32]. Literature reviews allow us to conclude that there are several important factors that make the bank-customer relationship profitable for both the bank and the customer. These will be described below, whereas Table 1 lists sources that indicate the relevance of the given factors to customer relationship formation in the banking sector and data acquisition for CRM systems.

Customer contact is essential for the relationship to be proper and lead to profit. Therefore, when exploring the bank-customer relationship, it is important to consider the frequency of visits to the website, mobile app and bank branch. Thereby, the quality of pull communication can be assessed. However, this type of communication is initiated by the customer and has a remarkable role in evaluating the customer's activity towards the company. The key to successful pull communications is identifying what information people need or desire, now or in the future [42]. Banks use multi-channel distribution, therefore special attention should be paid to which communication channels customers use. The more often they approach the bank on their own initiative, the more chances they have to propose a new offer or product. The data obtained from all customer contact points, if well managed, can support companies

Table 1. Compilation of factors that affect customer attractiveness to the bank, along with literature sources that indicate the relevance of the given factors to customer relationship formation in the banking sector and data acquisition for CRM systems

No.	Factor	Literature that refers to the factor
1	Frequency of visits to the website	[33]
2	App visit frequency	[34]
3	Frequency of visits to a bank branch	[35]
4	Retention period	[36]
5	Number of products per customer	[37]
6	Disseminating a positive opinion about the bank by the customer	[38]
7	Brand loyalty	[39]
8	Share of wallet	[40]
9	Customer income	[41]

in generating personalised marketing responses, creating new ideas, tailoring products and services and, thus, delivering high customer value and gaining competitive advantage [43]. Banks are eager to engage customers in mobile banking because it is an economical solution and the customer is actually logged in to the application all the time. It is possible to track its activities and often its location as well. It brings tremendous amounts of data to the customer relationship management system that can be used to shape the relationship further. According to Elhajjar and Ouaida the marketing campaigns should stimulate the users' curiosity to discover mobile banking and to approach the audience cleverly, by telling them how up-to-date they will become when adopting mobile banking or they would lag behind their peers [34].

Another extremely important factor for the bank to evaluate this customer is their retention period. It can be directly related to the CLV (Customer Lifetime Value) index calculation, since the length of time a customer remains is among the components of this index. CLV can be defined as the present value of all future profits obtained from a customer over his or her relationship with a company [44]. According to Ho et al. one of the variables considered under CLV is churn probability, which is the customer's probability of terminating his/her relationship with the company in a given time period [45]. Kumar et al. also consider customer lifespan as an important variable [25]. The CLV value is also influenced by brand loyalty (in the context of maintaining brand purity), as well as the customer's dissemination with a positive opinion of the bank, which stems from customer loyalty. Helgesen noted that customer loyalty affects most of the other variables mentioned in this study and therefore is a predictor of CLV [46].

The important issue for the bank is whether customers consider it their home bank. In such a situation, they are more likely to be loyal and to duplicate their purchasing decisions without leaving for the competition. This can be checked by, among other things, determining how many products a customer has with a particular bank. This value is used at least to assess a customer's creditworthiness. Banks are more willing to lend money to the customers who have a stronger relationship with them through multiple products. This is due to the greater customer credibility and the possibility of mutual trust in the relationship. Machine learning solutions are now being used to support credit scoring [47], which increases data quality and reduces the risk assigned to a given customer.

For the profit generated in the bank, especially from B2B relations, share of wallet is important. Research indicates that in particular, the initial satisfaction level and the conditional percentile of change in satisfaction significantly correspond to changes in share of wallet [40]. They indicate that the volume of customers' transactions within a firm has little correlation with the volume of their transactions with the firm's competitors and a small percentage of customers account for a large portion of all the external transactions, suggesting the considerable potential to increase sales if these customers can be correctly identified and incentivized to switch [48]. Share of wallet is the most critical behavior-related marketing performance metric and when several stores offer similar products/services, share of wallet is the key outcome indicating loyalty from a customer's perspective [49]. Another factor that affects a customer's attractiveness to the bank is the income generated by the customer. The larger it is, the more profit the customer can bring to the bank. Studies conducted, for example, by Homburg and Giering in 2000 [50] showed that income is the moderation variable of satisfaction effect on loyalty. According to Engel et al. [51] customer characteristics such as different incomes will lead to other demands and tastes so these affect the products and services consumed. Therefore, customer income has a noticeable impact on customer loyalty and relationship building [52]. In banking, customer income is particularly important considering bank risk minimization.

The purpose of the research conducted was to create an algorithm based on fuzzy logic for decision-making based on data from customer relationship management (CRM) systems for assessing banking customer attractiveness, in order to obtain information from the output of the algorithm on whether it is worth investing in a customer relationship or not. The first stage of the research was the appropriate selection of input criteria for modelling, which validity is presented in the introduction, followed by the creation of a Mamdani-type Fuzzy Inference System and, in the final stage, the creation of a decision model that has a binary value of 0-1 in the output, where 1 means that it is worth investing in the customer, while 0 means that it is not worth it. Customer relationship management systems process ever-increasing amounts of data. It is increasingly difficult to obtain information from these data that can be used to make management decisions. Creators of CRM software are constantly looking for new solutions and opportunities. Few studies have so far considered the possibility of using fuzzy logic in CRM. This connection does not always seem obvious. Both practitioners and theoreticians do not always see the possibilities arising from it. Therefore, the authors of the article decided to bridge this gap.

MATERIALS AND METHODS

For the conducted research, the authors proposed the use of fuzzy logic, which was implemented in the Matlab - Simulink environment, version 2023a using the Fuzzy Logic Designer toolbox. The scheme of the conducted research is shown in Figure 1.

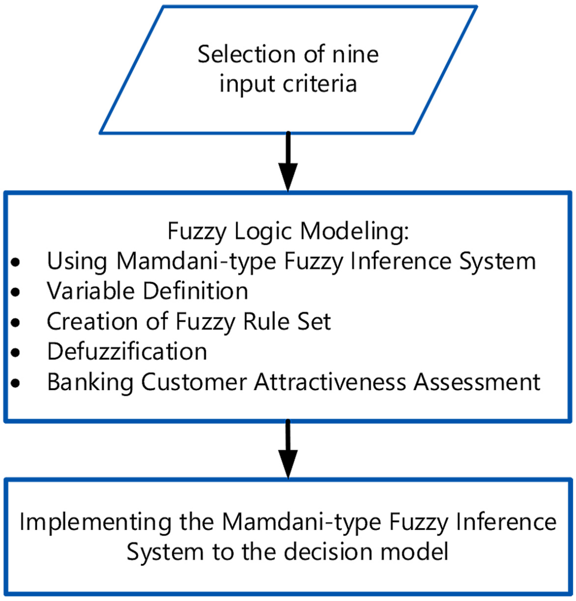

Figure 1. Research scheme

Mamdani-type Fuzzy Inference System was chosen. Based on the above-mentioned literature review, nine criteria were selected as input factors for the algorithm under construction:

1. Frequency of visits to the website.
2. App visit frequency.
3. Frequency of visits to a bank branch.
4. Retention period.
5. Number of products per customer.
6. Disseminating a positive opinion about the bank by the customer.
7. Brand loyalty.
8. Share of wallet.
9. Customer income.

An assessment of banking customer attractiveness was defined as the output variable as the importance of investing in the client, whether or not it is worth investing in the customer relationship. The fuzzy logic model is presented in Figure 2. Based on subjective evaluation, experts' knowledge and experience, fuzziness was applied to input and output variables. A Gaussian function was used to determine the input data, while a triangular function was used for the output data. The Gaussian function was adopted for the input data to facilitate a smooth and gradual transition between different membership levels. In many instances, data from CRM systems might exhibit dispersion and not necessarily show clear boundaries between categories. The Gaussian function offers flexibility, allowing for a more accurate representation of real-world data. The mathematical form of the Gaussian function is:

$$f(x) = e^{-\frac{(x-c)^2}{2\sigma^2}} \quad (2)$$

where: c – represents the centre of the function, and σ denotes.

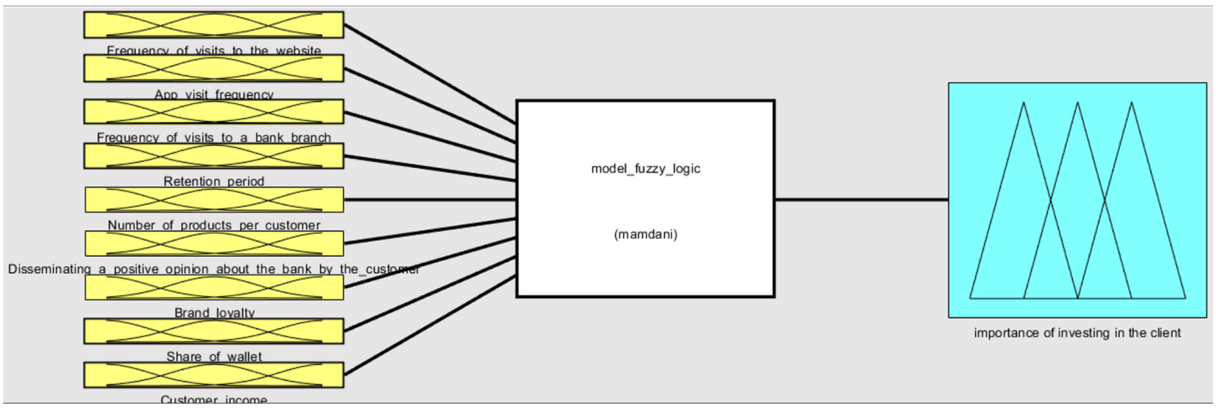

Figure 2. Fuzzy logic model

The triangular function was chosen owing to its simplicity and interpretability. When evaluating the attractiveness of a banking customer, our primary interest lies in the membership to one of the three categories (low, average, high). The triangular function provides distinct boundaries between these categories and is intuitive for individuals who are not well-versed in fuzzy logic. The mathematical representation of the triangular function is:

$$f(x;a,b,c) = \begin{cases} 0 \; for \; x \le a \; and \; x \ge c \\ \frac{x-a}{b-a} \; for \; a \le x \le b \\ \frac{c-x}{c-b} \; for \; b \le x \le c \end{cases} \quad (3)$$

where: a, b, and c – represent the left, middle, and right vertices of the triangular function respectively.

Table 2 presents a three-stage scale and a two-stage scale for these variables. A three-point scale was adopted for the output variable: low, average and high. The membership function example for the variable Frequency of visits to the website is shown in Figure 3. The input data has been normalized.

Based on the aggregation of fuzzy rule sets, the attractiveness of bank customers is assessed. The impact of given criteria on the attractiveness of bank customers is evaluated using a set of fuzzy IF-THEN rules. These rules are based on experts' subjective judgment, knowledge and expertise. The rules have been developed in such a way that significant dependencies between input criteria are taken into account. 56 such fuzzy rules were created. Only 6 of the following are examples of fuzzy rules with their weights found in the knowledge base:

1. IF "Frequency_of_visits_to_the_website" is low AND "App_visit_frequency" is low AND "Frequency_of_visits_to_a_bank_branch" is low THEN "importance of investing in the client" is low; weight: 0.2
2. IF "Frequency_of_visits_to_the_website" is high AND "Frequency_of_visits_to_a_bank_branch"

Table 2. Adopted scale for variables in the model

Variable	Unit	Scale		
		Low/Little	Average/Medium	High/Much
1. Frequency of visits to the website 2. App visit frequency 3. Frequency of visits to a bank branch	Number of entries per year	up to 2	3-4	over 4
4. Retention period	In years	up to 2	3-4	over 5
5. Number of products per customer	Quantity	up to 2	3	over 4
6. Disseminating a positive opinion about the bank by the customer	Yes/No	no	-	yes
7. Brand loyalty	Yes/No	no	-	yes
8. Share of wallet	%	under 20	20–40	over 40
9. Customer income	in PLN/month	up to 4000	4000–8000	over 8000

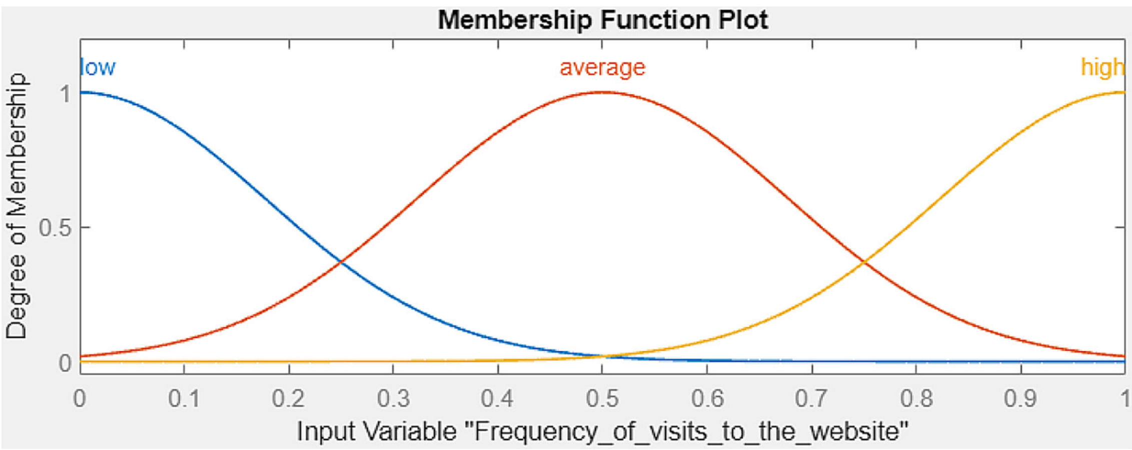

Figure 3. Membership function example for variable frequency of visits to the website

is high AND " Retention_period " is high THEN "importance of investing in the client" is high; weight: 0.5

3. IF "Frequency_of_visits_to_the_website" is high AND " Retention_period " is high AND "Number_of_products_per_customer" is much THEN "importance of investing in the client" is high; weight: 0.6
4. IF "Frequency_of_visits_to_the_website" is low AND " Retention_period " is low AND "Number_of_products_per_customer" is little THEN "importance of investing in the client" is low; weight: 0.9
5. IF "Frequency_of_visits_to_the_website" is high AND "Number_of_products_per_customer" is much AND "Disseminating_a_positive_opinion_about_the_bank_by_the_customer" is yes THEN "importance of investing in the client" is high; weight: 1
6. IF "Frequency_of_visits_to_the_website" is low AND "Number_of_products_per_customer" is little AND "Disseminating_a_positive_opinion_about_the_bank_by_the_customer" is no THEN "importance of investing in the client" is low; weight: 0.8

For modelling, the centroid-centre of gravity method was chosen as the defuzzification method.

RESULTS AND DISCUSSION

An example of fuzzy driver operation for a selected tested client is shown in Figure 4. In the figure, the inference rules are shown in the rows and the model variables are shown in the columns, with the first nine columns being the input variables and the last column being the output variable. Due to the limitations of the rule display window, only the first 16 of the 56 rules fit in the figure. The total estimated result is displayed in the upper right corner of the screen. This form also allows you to visualize (and, if necessary, analyze) the performance of individual fuzzy reasoning rules by interacting the corresponding membership functions with the entered parameters. In this case, the output received a value of 0.829. Considering the subjective evaluation, experts' knowledge and experience, it was determined that if the value is above 0.6 it means that it is worth investing in the customer relationship, in the case of a value below 0.6 it is not worth investing in such a relationship. Therefore, in the case of the customer shown in Figure 4, it would be necessary to decide that it is worth investing in the relationship with the customer.

The prepared Mamdani-type Fuzzy Inference System was implemented into the model prepared in Simulnik. The output of the model is a decision whether it is worth investing in customer relations (value "1") or not (value "0"). To obtain the binary value 0-1 in the model, the fcn function was used, which interrupts the output data of the Mamdani type Fuzzy Inference System as follows: for a value greater than 0.6, it generates a "1" value, and for values equal to or less than 0.6, it generates a "0" value. Input data to the model is entered in the form of a vector of data corresponding to a given customer. The model's appearance is shown in Figure 5. The model's performance results are shown in Table 3. Considering the subjective evaluation, experts' knowledge and experience, and comparing them with the results obtained from the developed model, it can be concluded that the model works properly. In the context of CRM, fuzzy logic is taken into account

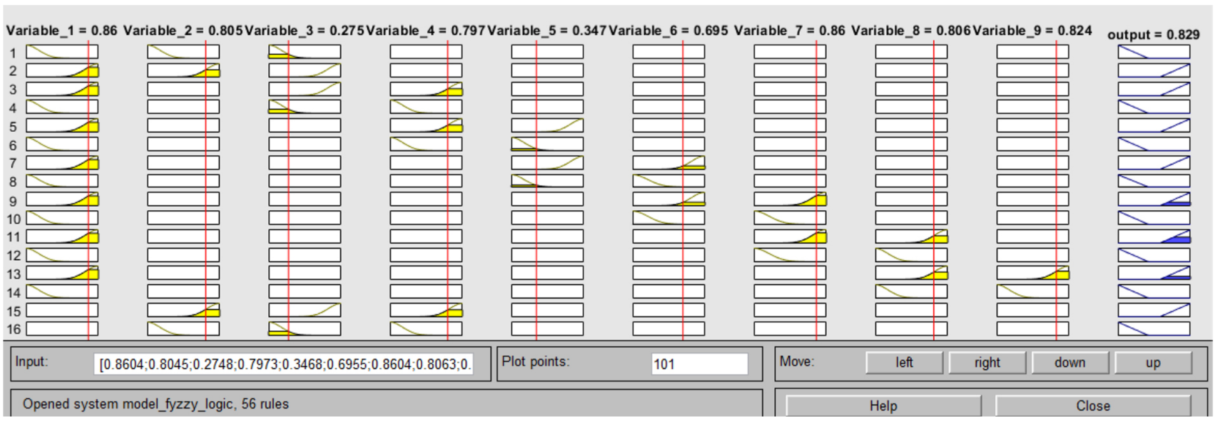

Figure 4. Fragment of the rules operation window and the final result

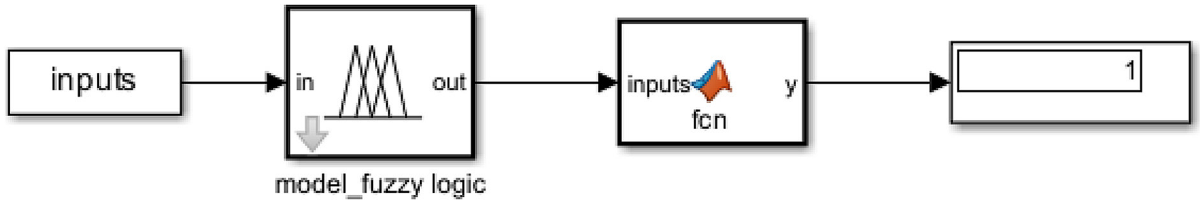

Figure 5. Fuzzy logic model in Simulink

Table 3. The model's performance results

No.	Variable	Customer									
		1	2	3	4	5	6	7	8	9	10
1	Frequency of visits to the website	15	16	30	22	15	78	17	19	21	15
2	App visit frequency	300	350	350	60	132	154	253	360	250	189
3	Frequency of visits to a bank branch	2	5	10	12	6	9	14	20	15	12
4	Retention period	7	2	3	4	8	10	5	14	15	3
5	Number of products per customer	1	5	2	1	2	3	2	4	2	1
6	Disseminating a positive opinion about the bank by the customer	yes	no	yes	no	yes	no	yes	yes	yes	no
7	Brand loyalty	yes	no	yes	no	yes	no	yes	yes	yes	no
8	Customer income	10%	45%	30%	25%	28%	11%	5%	28%	15%	7%
9	Client income	6000	12500	2560	4580	7800	5410	10000	15000	9000	8900
Results of the fuzzy logic driver		0.8607	0.5233	0.8076	0.4485	0.8530	0.5939	0.8424	0.8425	0.5545	0.2128
Output – Is it worth investing in the customer relationship (1- worth it, 0 - not worth it)		1	0	1	0	1	0	1	1	0	0

in the literature, e.g. in an article Shafia et al. who aims to provide a framework for evaluating the impact of implementing customer relationship management (CRM) based on the balanced scorecard (BSC) [53]. Fuzzy logic is also used for customer segmentation, which is important both in the context of CRM and marketing. The data of customers in this context are various and often fuzzy. For identifying the right customers and applying effective marketing activities it is necessary to build customer segments. In this approach compensatory fuzzy logic is used for customer segmentation based on user preferences [54].

The scientific literature finds a number of fuzzy logic applications, among others, to improve customer classification based on a three-dimensional loyalty matrix using the Mamdani-type Fuzzy Inference System. The empirical results presented in Geramian & Abraham indicate that the described approach effectively deals with a number of significant problems, such as uncertainty in the data, unknown weights, calculation of the same output value based on different input values, and the discontinued output [55]. Yasar & Korkusuz Polat, meanwhile, discuss the use of fuzzy logic in the context of Marketing 4.0. They propose a model based on fuzzy logic to identify weak points of contact along the customer path and monitor customer purchase rates and brand advocacy. The authors argue that by using fuzzy logic, an artificial intelligence technology, weaknesses in the 5A customer path can be identified in advance, allowing brand managers to develop appropriate strategies to increase customer loyalty [56]. Fuzzy logic can be a powerful decision-making tool for assessing customer loyalty and attractiveness, among other things. It enables appropriate use of the data collected in CRM systems and, through them, a more complex understanding of customer behavior. It can also help identify areas for improvement in marketing strategies. However, the effectiveness of fuzzy logic applications depends on the specific context and the quality of the input data. The application of fuzzy logic to assess banking customer attractiveness provides new opportunities for customer portfolio management and CRM system usage. Fuzzy logic, unlike traditional evaluation methods, allows for more flexible and accurate modelling of the uncertainty and ambiguity inherent in assessing customer attractiveness. Therefore, allowing them to better understand and assess whether it is worth investing in a relationship with a particular customer or whether it is not profitable from the banking establishment's perspective.

However, despite its many advantages, the fuzzy logic application is not without its challenges. It requires advanced data analysis and specialized knowledge, which potentially can be a barrier to some application areas. Furthermore, as with any method, fuzzy logic cannot completely eliminate risk, and its effectiveness depends on the quality and accuracy of the input data. Moreover, they depend on the appropriate formulation of fuzzy rules, which are based on the expert's knowledge and experience [56].

In the future, fuzzy logic application based on data from computer systems, among others, in assessing banking customers' attractiveness can be further developed and improved [57, 58].

CONCLUSIONS

The article aimed to propose a fuzzy logic solution for decision-making based on data from CRM systems to assess banking customer attractiveness. Considering the subjective assessments, specialists' knowledge and experience, and comparing these elements with the results generated by the developed model, it can be confirmed that the model is working properly.

The article shows the possibility of applying fuzzy logic to make decisions about customers using selected factors in the form of data downloaded from CRM systems. Companies use many IT solutions in their operations, but the appropriate use of the data they collect and process can increase their competitiveness. Every enterprise, not only banks, is constantly confronted with the choice of which customers are worth investing in and which are not. The proposed solution allows the right management decision to be made based on data that the company already has or can easily obtain from IT systems. Certainly, it is possible to expand the proposed considerations in further research and publications. The considerations shown in the article are intended to demonstrate the applicability of fuzzy logic solutions to management problems.

Like any research, this one too has its limitations. This is, for example, the selection of factors based on a literature review rather than practical research in banking companies. However, the article's authors trust that the theoretical selection of factors coincides with practice. The solutions presented in the article have both practical and theoretical implications. Banking companies and all others that collect and process customer data can use them. The article shows a practical solution that can assist in managerial decision-making. At a time when IT systems in enterprises process a huge data amount, automation or partial automation of the decision-making process will certainly be extremely helpful. This article brings theoretical implications and shows some mechanisms and opportunities for further research on artificial intelligence solutions in business.

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