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Decision Intelligence to Enhance Bank Profitability through Customer Promotion Path Design

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ABSTRACT

Studying the behavior of a bank's customers over time to determine and monitor their position in a customer segmentation system (CSS) could be the basis for producing and proposing some paths to promote the customers to a preferred level in the CSS. It is mutually beneficial for both the bank and the customers. On the one hand, the bank increases its revenue by growing sales; on the other hand, the customers benefit from incentive allocation. In this research, with the help of the new concept of Decision Intelligence (DI) along with the machine learning modeling approach, customized paths were extracted that led to improving the level of the customers in the bank's CSS. These paths are designed according to the specific circumstances of each customer and the scope of its business, which ensures its feasibility. The proposed method was implemented for 422,264 customers in a private bank, and the results show that this method has been successful in achieving successfully achieved the predefined goals.

Keywords

Customer segmentation; Decision intelligence; Machine learning; Customized banking.

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1. Introduction

Over the decades, organizations have focused only on their products and brands. However, the focus has been on establishing and maintaining an effective exclusive relationship with customers in recent years (Prasad and Aithal 2017; Mosa et al. 2023). The reason for this can be considered as the need to move to a higher level of customer service in competitive business environments. In this new level of service, the design and presentation of a product or service are tailored to the needs and position of any customer. Therefore, gaining knowledge from customers and identifying homogeneous groups of customers to design and offer appropriate products, services, and incentives to maintain and promote customer loyalty and profitability are current issues of both researchers and organizations, especially the marketing departments of organizations, including banks. Homburg et al. (2008) published a comprehensive survey on different customer prioritizing criteria and methods in marketing. In this regard, some newly published papers can be mentioned too; Gao et al. (2020) used Behavior Mining to establish a personalized recommendation system. Using precision marketing, Zhu and Gao (2019) provided a method based on big data analysis for personalized marketing. In 2020, Behera et al. presented a personalized recommender system based on data analytics. Gayathri and Arunodhaya (2021) presented a method for Personalized Marketing using K-means and Apriori Algorithms. Eslami et al. (2024) studied unveiling IoT customer behavior by segmentation to get insights to enhance IoT-CRM strategies. Adeniran et al. (2024) used segmentation methods to detect customer behavior in a customized manner. However, due to market dynamics, static cognition and segmentation cannot be sufficiently responsive. So, studying the behavioral patterns of customers over time and predicting trends can be very effective in maintaining or promoting the customers at a desired level of loyalty and profitability. In fact, instead of assigning one segment to each customer in terms of loyalty or profitability, the status of the customer in terms of loyalty and profitability is determined in the form of a trajectory over a relatively long period. These trajectories can generate some "paths" through which the customers can improve their position in the organization's customer segmentation system (CSS). It should be noted that due to resource constraints, providing incentives to all customers is not possible or even logical. Therefore, organizations almost use available resources for superior or potentially superior customers in the CSS. Improving the customer level in the CSS has economic returns for the organization by selling more products or services and also for the customer by benefiting from special privileges and rewards of loyal and profitable customers offered by the organization.

Among the methods for customer evaluation and segmentation based on customer lifetime value (CLV), loyalty, and profitability is the RFM analytical approach that uses only three criteria: Recency (R), Frequency (F), and Monetary (M) according to customer interaction with an organization to determine customer position in the CSS. One outstanding advantage of this approach is its reliance on the operational data stored in the organization's databases. So, it eliminates any need to collect new extra information. Therefore, RFM is an easy, low-cost, and fast way to estimate CLV, as well as a widespread basis for customer segmentation. A comparison of several methods of evaluating CLV is given by Borle et al. (2008). It must be noted that due to the type of customer interactions with banks, which distorts the importance of novelty of interaction, the criterion of continuity of interactions (C) is considered in such segmentation.

Regarding marketing context, organizations are faced with a decision-making challenge, including setting a threshold level of usage of products or services to benefit from incentives, which must be addressed specifically for each customer. Given the number of customers in organizations such as banks, where the number easily reaches millions of business and private customers, using a new approach in decision making, namely the Decision Intelligence (DI), has been proposed by Pratt (2019).

Decision intelligence is a new concept that many believe is part of the future of artificial intelligence-related technologies such as Business Intelligence (BI) and Decision Science. DI deals with how to match the technological needs of an organization in the field of Artificial Intelligence (AI) on the one hand and the needs of the organization's decision-making structure on the other hand. So, it enables organizations to make the best operational to strategic decisions by examining the outcome of each action resulting from their decisions in a volatile, uncertain, complex, and ambiguous environment. These decisions range from choosing a market to enter or entering an investment to incorporating a feature into a product or service to decisions in designing an operational process (Hasić et al. 2018; Ma et al. 2018; Moser et al. 2021; Nica et al. 2022, Haider & Tehseen 2022). Organizations will be able to see the results of their actions in advance. Hence, DI is also called Action Intelligence. According to the research conducted by the researcher of this paper, the concept of DI has not been used in the issues of customized banking methods. Therefore, this article can be considered a report on the first efforts in this field.

This research practically provides a method that if a customer wants to know what to do to be upgraded in the bank's CSS in terms of a set of behaviors, the answer is clear in a customized

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manner. As far as we know, this issue has not been covered before in the related literature. The problem of this research includes classifying customers in terms of loyalty and profitability and then determining a customized path for each customer so that the customer gets a promotion in the CSS. It should be noted that these two issues are raised together, and the solution will be generated in an integrated manner. The necessity of solving this problem arises from the fact that organizations need to classify customers so that the resources allocated for promotion can be spent effectively to encourage customers to increase the use of services and products that are available.

On the other hand, customer segmentation doesn't meet all needs because a question always remains with customers and organizations: If a customer wants to move from an existing level to an upper one in a CSS, how do author do it? This question is difficult to answer because customer segmentation criteria generally comprise several factors. Therefore, there are several ways to improve the value of the factors. In banks, for example, customer segmentation may be based on criteria such as CLV, which is calculated or estimated in various ways (including using the RFMC analytical approach used in this study). It is generally a function of the level of customer resources in the types of deposit accounts and the credits. Each of these two groups of products includes a wide range of items that the banks can provide. Also, each customer needs some of them according to the type and scope of his/her business. Therefore, in such circumstances, the question arises: according to the customer's needs and conditions, which products or services and to what extent will improve the customer level in the CSS?

As a significant contribution, this article presents a method that uses the DI approach to determine a customized path for each customer. Through the path, the customer can grow in the CSS. So, the organization and the customer benefit together. In fact, to determine these customized paths, the data in the organization's database, artificial intelligence, and machine learning techniques will be rendered in terms of the DI. Also, the paths should be extracted way so that their implementation by the customers is feasible according to the specific conditions of its business and needs, while the organization benefits in developing the level of interaction with the customers, too.

Section 2 describes the proposed method based on Decision Intelligence and data analysis methods. Section 3 presents the results, followed by Section 4 describing the conclusions.

2. Decision intelligence for problem-solving

2.1. Decision intelligence approach

The problem mentioned in the introduction section will be solved according to the existing complexities and the necessity of generating a customized promotion path in CSS using the DI concept. The basis for the DI is creating a chart called the Causal Decision Diagram, or CDD for short. This diagram shows the process by which each decision or action ends in a result. Drawing this diagram provides a basis for building a model using artificial intelligence or machine learning, considering stored data. This model can be utilized to estimate the outcome of each action. The resulting model is then used reversely to identify the best action to achieve the desired result. Figure 1 shows the key elements of a CDD. According to a CDD, the link between the decisions and the outcomes is modeled mainly through Machine Learning (Pratt, 2019). A CDD shows intermediate elements (under the organization's control) and factors outside the organization's control (external) involved in turning a decision into an outcome. The task of DI is to find out how to influence and then adjust the best level of factors to achieve the goals.

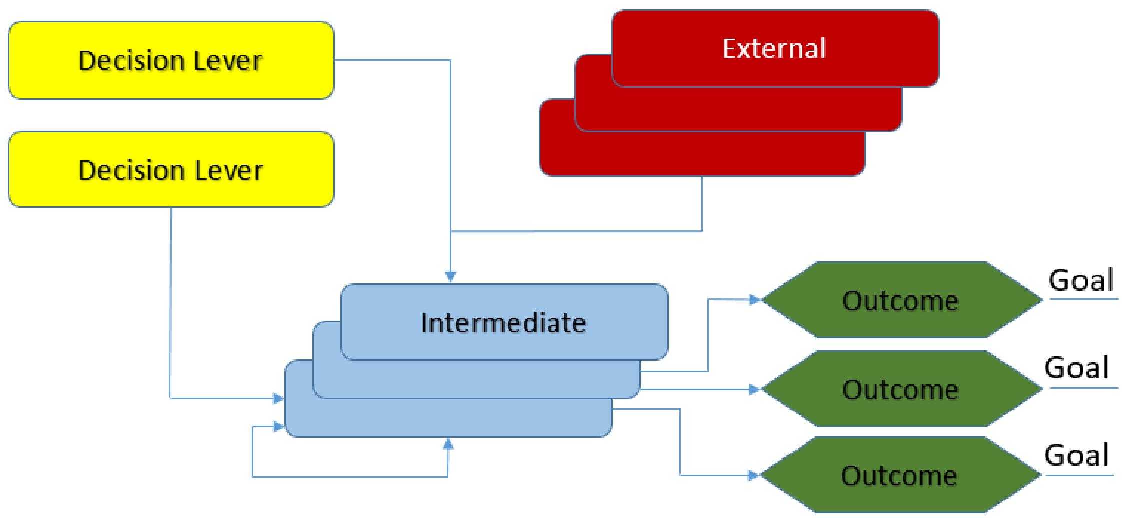

Figure 1. Key elements of a CDD

Figure 2 shows the factors and how the change in the four criteria R, F, M, and C affect the CSS's customer loyalty and profitability level. Considering a banking business, transaction date affects R and C, number of transactions affects F, and account average, loan, letter of guarantee, and letter of credit affect M. Regarding the CDD, in the action section, the threshold in the amount of bank account average, loan, letter of guarantee and letter of credit should be specified to determine the status of each customer in the segmentation system through RFMC-Score. This figure shows how customer interaction with a bank determines the customer segment in the

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CSS based on RFMC-Score. With this chart and modeling its relations, the appropriate interaction thresholds to create the desired change in a particular customer segment can be determined.

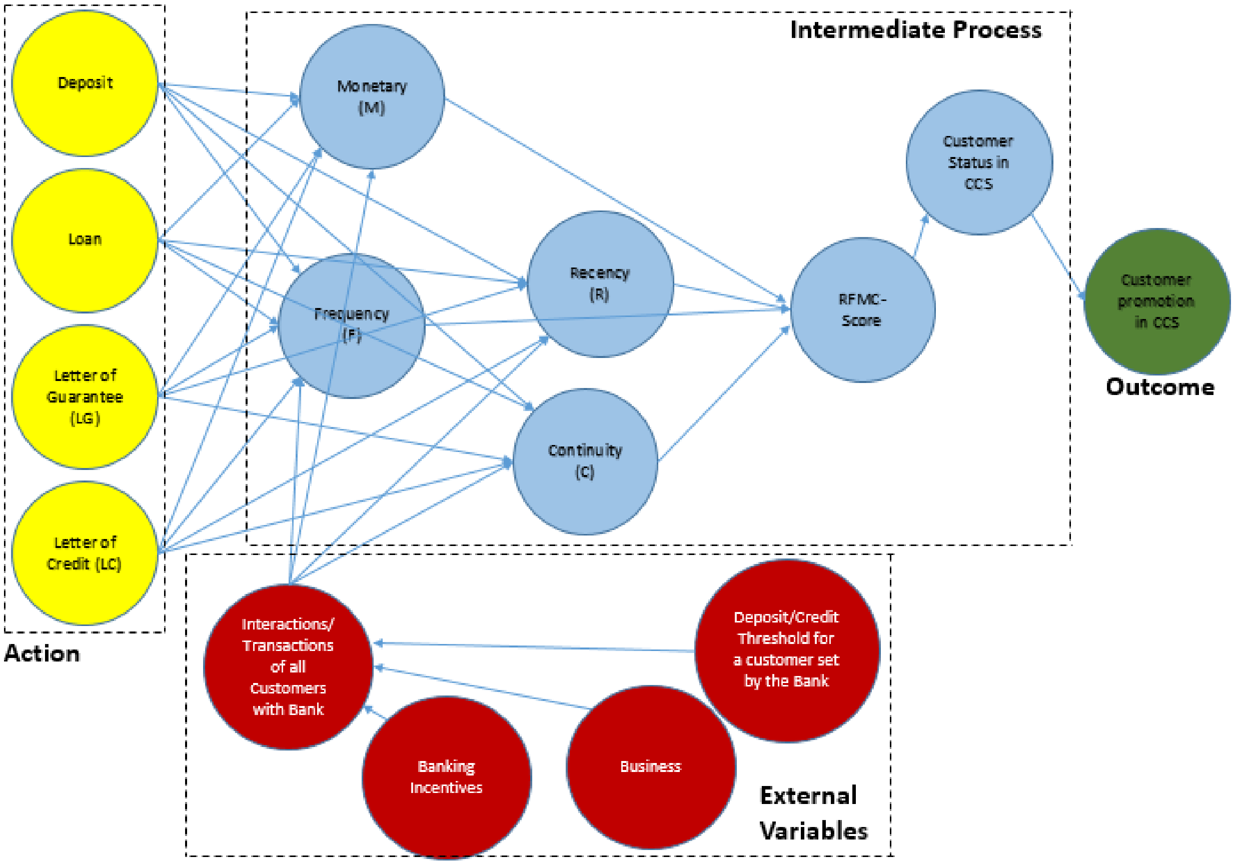

Figure 2. The CDD describes how elements affect customer level in a CCS considering RFMC-Score

It should be noted that any change in the customer segment is related to external factors and the bank's decisions in determining the thresholds. These thresholds are set specifically for each customer and are considered as a target for him/her that achieving it leads to a positive change in the customer's segment. Therefore, if a model that links each action to the result is achieved, it can be possible to determine the best action: the thresholds of the account average, loan, letter of guarantee, and letter of credit required for each customer. These thresholds or target levels will be a roadmap or path for each customer to be promoted to a higher loyalty or profitability segment in the CSS.

2.2. K-Nearest neighbors method

In this research, the similarity structure is obtained through the *k*-nearest neighbors or *k*-NN, one of the well-known methods in the machine learning (Tékouabou Koumétio and Toulni 2021). *k*-NN is often useful for considering more than one neighbor of an instance. Although the technique is more commonly called *k*-Nearest Neighbour Classification, the underlying intuition can be used to construct a similarity system for a group of instances. So, one can call *k*-NN in a machine learning toolkit and easily get *k* nearest neighbors of any instance, which is named here Similarity Structure.

2.3. Problem solving methodology

For generating the customized promotion paths, the customers would first be placed in 4 classes over two six-month intervals using the RFMC-Score criterion. For this purpose, the information previously stored in the bank database is used. All the changes in customer segments over time will be analyzed. Here, two categories of customers will be given special attention; the first category is the customers who have moved from a specific level to a higher level of loyalty and profitability in two tandem intervals. It should be noted that this upgrade in the segment is necessary through increasing the level of product usage, which the bank provides. This category of customers is called Potential Reference Customers (PRC). The second category is the customers who have remained in a constant segment for two tandem intervals. These are called Potential Target Customers (PTC). Then, using the *k*-NN method, *the most similar customers for all PTCs will* be extracted.

The basis for calculating similarity can be the items such as the amount of bank account average, loan, letter of guarantee, letter of credit, number of transactions, and industry or business for a long time. After extracting *k* most similar customers for each PTC, if there are PRCs in the list of similar customers, the most similar one will be selected as the so-called Reference Customer (RC). In this way, the reference is identified only for a subset of PTCs. These subsets are called Target Customers (TC). For each TC, the level of the interactions associated with the assigned RC during the last segmentation time interval is determined as a target. So, if the TC reaches the thresholds, it is considered a customer in the upper segment in the CSS.

Since both the RC and the TC have been in the same segment in the previous period and, on the other hand, based on banking information, have had similar conditions, we can expect them to achieve the target thresholds specified for each TC. The combined use of information about the bank deposit accounts and the volume of use of credit products in the modeling process can ensure that both the TC and the RC have the same type of behavior in using deposit services or credits provided by the bank. This can ensure that the proposed path is appropriate for each TC.

also figure 3 presents the proposed method of problem-solving and shows the software and analytical techniques used in each step.

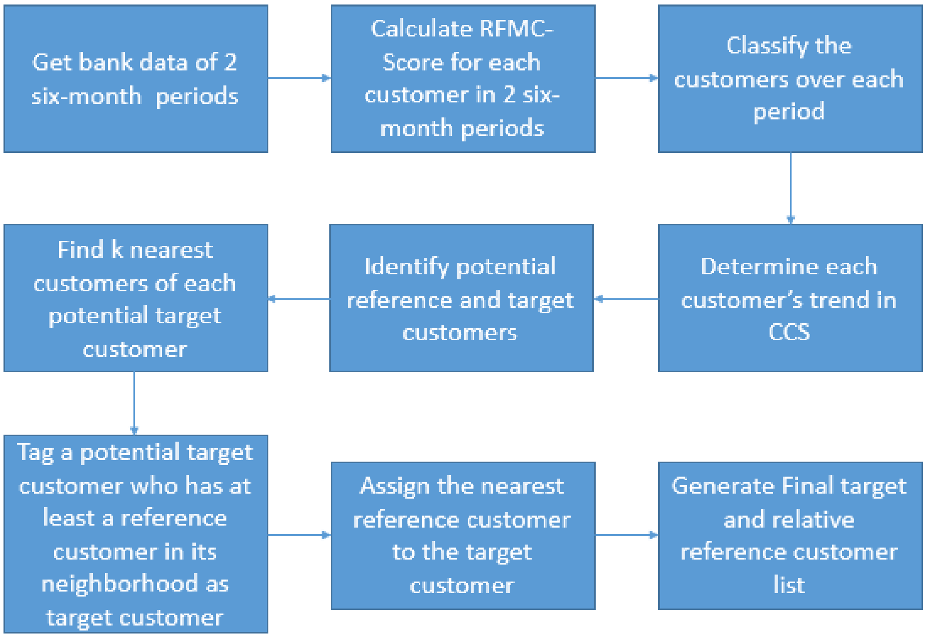

Figure 3. Main steps of the proposed method

3. Experiments

3.1. Data

- The proposed method was used for 422,264 corporates, which are commercial bank customers in three categories: big, medium, and small businesses. Information, including the following items over a 2-year period, was extracted from the bank database for these customers. Monthly average of the four deposits, including current, short-term, long-term, and saving in 2 years (96 variables)
- Amount and count of monthly transactions related to the four deposits over 2 years (192 variables)
- Amount and count of loans received during four 6-month intervals (8 variables)
- Amount and count of LGs received during four 6-month intervals (8 variables)
- Amount and count of LCs received during four 6-month intervals (8 variables)
- Customer category (1 variable)

3.2. RFMC-Score calculation

Segmentation of the customers in terms of profitability and loyalty was implemented with the help of RFMC-Score. For this, Equation (1) was used to integrate the factors R, F, M, and C. Relevant weights have been used based on the results of research by Zaheri et al. (2002) and Khajvand et al. (2011) on determining the relative importance of the factors.

$$\text{RFMC-Score} = 0.1R + 0.1F + 0.7M + 0.1C \quad (1)$$

4. Results

The number of final RCs and TCs in each of the three studied categories when k equals 40 was obtained, as shown in Table 1. It should be noted that to ensure the feasibility of a proposed path, the similarity of an RC to a TC has been prioritized over the number of detected TCs. On the other hand, by changing the parameter k in the k-NN method, the number of final TCs can be controlled so that a higher k value leads to extracting more TCs, and a lower value leads to a smaller number of TCs. However, it should be noted that a high value of k suggests paths that may not be feasible.

Table 1. Frequency of target and reference customers

Customer category	All customers	Reference customers	Target customers
Big	4958	20	424
Medium	23148	238	2730
Small	394158	69	1756

Examples of the references for two target customers are shown in Figures 4 and 5. In Figure 4, for a target customer who, according to their past interaction with the bank, is of a depositor type, the reference customer is assigned intelligently from the same behavior using the proposed method. By comparing historical data of the target and the reference customers, it is clear that both customers in the former three 6-month periods of four examined 6-month periods had experienced similar deposit averages, so they were in the third segment or level in CSS. However, the reference customer increased the deposit average to 16.75 billion in the last 6-month period and entered the fourth segment (the highest segment). Therefore, if the target customer increases its deposit average to this point (16.75) by adding 16.45 billion, it can enter the fourth segment, too. On the other hand, we can expect this increase in the deposit average to be feasible due to the similarity of the situation in the past periods.

In Figure 5, for the target customer, which, according to the historical data, is a creditor-type customer, the reference customer of the same behavioral type is assigned. Regarding this case, the target and the reference customers were in the same situation in the first three 6-month periods and, therefore, were classified in the same segment (the third segment). However, in the last 6-month period, the reference customer increased its total deposit average to 42 billion and, on the other hand, got a loan of 45 billion. Therefore, the target customer can enter the fourth segment (the top segment) by increasing the level of interaction with the bank in terms of total deposit average and consuming loans and/or credits at the mentioned level by depositing 35.6 billion and receiving loans and credits up to the level of 45 billion.

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Moving customers from the lower segment in the bank's CSS to a higher one leads them to benefit from incentives designed for loyal and profitable customers. Therefore, for the customers who have this motivation, with the help of the proposed method, a clear and wholly quantitative and, at the same time, customized path is generated according to its conditions, behavioral type, and business.

Customer	Referenc
Loan_1	0
Loan_2	0
Loan_3	0
Loan_4	0
LG_1	0
LG_2	0
LG_3	0
LG_4	0
Deposit Average_1	3.7
Deposit Average_2	4.5
Deposit Average_3	6.7
Deposit Average_4	16.75
LC_1	0
LC_2	0
LC_3	0
LC_4	0
Transaction Frequency_1	330
Transaction Frequency_2	173
Transaction Frequency_3	149
Transaction Frequency_4	202
Category_1	3
Category_2	3
Category_3	3
Category_4	4

Customer	Target
Loan_1	0
Loan_2	0
Loan_3	0
Loan_4	0
LG_1	0
LG_2	0
LG_3	0
LG_4	0
Deposit Average_1	1.5
Deposit Average_2	1.3
Deposit Average_3	1.2
Deposit Average_4	0.3
LC_1	0
LC_2	0
LC_3	0
LC_4	0
Transaction Frequency_1	228
Transaction Frequency_2	322
Transaction Frequency_3	349
Transaction Frequency_4	146
Category_1	3
Category_2	3
Category_3	3
Category_4	3

Figure 4. Information of a depositor target customer and the determined reference point

Customer	Referenc
Loan_1	0
Loan_2	0
Loan_3	45
Loan_4	0
LG_1	0
LG_2	0
LG_3	0
LG_4	0
Deposit Average_1	3.6
Deposit Average_2	20
Deposit Average_3	21
Deposit Average_4	42
LC_1	0
LC_2	0
LC_3	0
LC_4	0
Transaction Frequency_1	382
Transaction Frequency_2	596
Transaction Frequency_3	681
Transaction Frequency_4	518
Category_1	3
Category_2	3
Category_3	3
Category_4	4

Customer	Target
Loan_1	7.6
Loan_2	6
Loan_3	7.5
Loan_4	7
LG_1	4.4
LG_2	3.7
LG_3	0
LG_4	0
Deposit Average_1	3.4
Deposit Average_2	4.3
Deposit Average_3	6.8
Deposit Average_4	6.4
LC_1	0
LC_2	0
LC_3	0
LC_4	0
Transaction Frequency_1	345
Transaction Frequency_2	401
Transaction Frequency_3	349
Transaction Frequency_4	371
Category_1	4
Category_2	4
Category_3	3
Category_4	3

Figure 5. Information of a creditor's target customer and the determined reference point

Notably one of the main reasons for creating a CCS and then providing the proposed method is budget restrictions to provide incentives to promote the level of all customers. Therefore, the intention is to provide a promotion path for potentially valuable customers. Small values of *k* make the “promotion path” more attainable for a target customer; conversely, the chance of finding such a path will be low. On the other hand, large *k* increases the chance of finding the path but reduces its feasibility. Therefore, this value directly affects the number of customers the promotion path. Therefore, its value is determined based on the amount of the marketing budget. In this article, the number 20 has been chosen, which has led to the number of TCs identified in Table 1.

5. Conclusion

In this paper, the concept of Decision Intelligence (DI) was introduced to generate a customized path through which a customer can make purposeful changes in the level of interaction with a bank to improve the loyalty and profitability segmentation system. For this purpose, a proper CDD diagram was first developed. It demonstrated how each decision or action relates to a result. Then, using the *k*-NN method, the relationship between action and result was modeled to determine the best action to achieve the desired result, which is the positive change in the customer segment leading to determining the target levels for the customer interaction with the bank. The proposed method was used for the data of 422,264 corporate customers of a private bank. Finally, the customers who were prone to upgrade and the target levels were determined for each. In this research, the RFMC-Score criterion was used to classify the customers. Using the proposed method for these customers, 4,910 potential customers were identified to be promoted to a higher level at the Customer Segmentation System, along with targets for each in terms of deposit average and credit. A closer look at the results showed that the proposed method of setting targets for each customer according to the kind of customer behavior in both depositor and creditor worked intelligently. Due to the successful performance of the proposed method for bank customers, it can be utilized by other organizations. Also, using more accurate CLV evaluation criteria and customer segmentation based on such criteria is another research topic that can be mentioned in the context of the DI and the general framework presented in this research.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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