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An Analytical Approach for Churn Prediction: A Study Based on the Gaussian AHP Method

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Abstract

Customer retention has become a critical challenge in the contemporary business environment, particularly in the banking sector, due to increasing competition from fintechs and evolving consumer expectations. This study proposes a methodological framework using the Gaussian-AHP method to rank customers based on their likelihood of churn, using relevant variables for churn prediction. The analysis, conducted on a dataset of 10,127 customers, identified key predictors of churn, including customer inactivity time, number of dependents, and revolving balance. Customers with prolonged inactivity or high revolving balances were more likely to churn, with inactivity time emerging as the most significant factor in the model. Conversely, customers with fewer dependents and lower revolving balances showed a lower probability of churn. These findings suggest that customer engagement and financial behaviors are crucial for retention strategies in the banking sector. The study also highlights opportunities for model enhancement, including the exploration of additional variables and advanced prediction techniques.

Keywords: churn, decision-making, banks, credit.

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1. Introduction

Decision-making in the banking sector has become increasingly challenging due to the growing market competition. The five largest banks in the country, which once had a consolidated market, now face reduced market barriers related to the improved credit offerings from "fintechs" [1]. The entry difficulties in the financial market have decreased due to technological, regulatory, and institutional advancements. These advancements have enabled the emergence of alternative funding sources and freedom in capital flow, reducing information monopoly and creating channels between creditors and debtors [2], [3]. Resolution No. 4,656/18 from the Central Bank [BACEN] introduced two forms of digital companies in the financial sector, providing a solid legal basis for "fintech" operations and stimulating market competition [4].

Today, a bank can obtain various information about its clients, such as demographic, geographic, and purchasing behavior data. New business models will primarily rely on the information from their customer base. In this context, those who possess accurate information about clients and know how to utilize this data effectively stand out. Banks need to acquire skills to develop solutions based on the information they have accumulated from customers over decades [3]. In this situation, companies that possess precise information about customers and master the technique of leveraging this data efficiently shine. Banks must enhance their capabilities to create solutions based on the information amassed over the years. One effective method may be through "churn" analysis, or excessive turnover analysis (churning) [5], [6]. Within this competitive scenario, according to Porter [1], customer bargaining power increases, and according to [7], reducing customer attrition is an effective strategy.

For Gauer [7], in this type of competitive market, focusing on retaining existing customers and avoiding attrition, or "churn," can be an efficient strategy. "Churn" occurs when a customer ends their relationship with a company with which they had some economic involvement, either by opting for a competitor or another product or technology option [8]. A study by Eidelwein [8] and Hadden et al. [9] identified two types of "customer abandonment." One is involuntary "churn," where the breakup comes from the company, such as non-payment or fraud in the service process. In contrast, voluntary "churn" comes from customers, either deliberately when they choose to take advantage of another provider's benefits or accidentally, such as losing a job.

Within the context of decision-making, the "Analytic Hierarchy Process [AHP]" method, conceived by Saaty in 1980, stands out. This method represents a multicriteria analysis approach, allowing for the comparison and weighting of various factors involved in a complex decision-making problem. In other words, AHP provides a systematic framework to evaluate and prioritize the available options, considering multiple criteria and their interrelations. This is particularly useful in situations where there are various aspects to consider and the relative importance of each may vary. By adopting AHP, decision-makers are empowered to weigh the various dimensions involved in a choice more effectively, thus assisting in selecting the most appropriate and informed alternative [10]. The variables chosen for this study can help generate rankings of customers with the lowest probabilities of "churn." AHP has been utilized as part of the methodology to support the decision-making process, such as in constructing consumer preferences regarding different characteristics of food products and segmenting the market according to these preferences [11]. Bahmani et al. [12] discussed the application of AHP in a consumer choice problem, utilizing AHP to evaluate consumer preferences regarding various characteristics of "smartphones," such as design, brand, price, features, and durability.

As a new approach to the AHP method, the Gaussian AHP method stands out for not requiring pairwise evaluations between criteria to obtain a prioritization result of alternatives. While traditional AHP relies on pairwise comparisons and weight assignments through human judgment, Gaussian AHP introduces a more quantitative approach, using numerical data and statistical techniques to determine the weights of the criteria. Moreover, this method is ideal for evaluating many alternatives and criteria, which is a limitation of classic AHP that allows for a maximum of 15 alternatives and/or criteria [13].

In this work, a study was developed to evaluate the ranking of the best customers with the lowest likelihood of attrition through the Gaussian AHP method. This analysis considered quantitative variables from 10,127 customers, either demographic or indicators of purchasing behavior. The AHP-Gaussian methodology became the focal point of the work, testing the model's ability to indicate the best customers and make the best decision.

To this end, this study proposes the use of the Gaussian AHP method as a systematic approach to evaluate and classify customers based on relevant variables for predicting "churn." This method allows for a weighted and careful analysis of the different criteria that influence the likelihood of a customer leaving the financial institution.

2. Methodology

According to [14], the subject is the center of decision-making and the freedom of action, and phronesis is a term for the virtue of practical reasoning. He argues that human action should be defined by itself, characterizing it as a movement whose principle lies within the human being. The rational part of the soul is divided into two faculties: one is scientific, and the other is calculative. It is within this domain that the cognitive capacities of the rational soul or the virtues of thought reside. The first virtue is sophia, which is more intellectual, while the second, more contingent, is phronesis, associated with practical wisdom or discernment. This refers to the ability to deliberate without formulas—a form of practical intelligence that aids in distinguishing between good and bad. It is a wisdom acquired through life experiences, shaped by trial and error.

According to [15] and [16]—the author behind the broad concept of human capital—when making decisions in uncertain situations involving risk, individuals tend to assign value not only to the wealth they possess and expect to gain but also to what he calls moral value or utility. This value is not calculated solely based on monetary terms (the financial value of gains) but rather on its perceived usefulness.

According to [17], the ideal approach is to focus on human beings who desire or fear certain outcomes to varying degrees, rather than on the events themselves. Kahneman [18] and Gallo [15] argue that absolute value (commonly referred to as financial value), which influences an individual's decision-making in risky situations, is not the primary determinant. Instead, subjective value (utility)—the value an individual assigns to each possible outcome—plays a crucial role. Thus, subjective value is not merely the weighted average of its possible financial effects but rather the average of the utility derived from those effects.

According to [19], Frank Knight, in 1921, proposed a distinction between risk and uncertainty. Risk refers to situations in which probabilities can be calculated or known, whereas uncertainty arises when probabilities cannot be determined, a perspective also supported by [20]. In 1955 and 1956, Herbert Simon developed the theory of Bounded Rationality, arguing that individuals seek solutions that satisfy their aspirations and, as a result, simplify their decision-making processes due to human limitations in time and cognitive capacity. Based on this, he suggests that humans rely on shortcuts, known as heuristics, to make decisions, including recognition processes and the selection of alternative choices [21]. The field of research now known as Heuristics and Biases emerged from psychological studies conducted in the 1950s and 1960s, which demonstrated that human judgments are less consistent than mathematical models, such as those based on Bayes' Theorem [22].

Kahneman [18] identified System 1 as the system of biases—one that already possesses data for decision-making, facilitating a series of rapid responses. It is constantly supplied with historical information, helping to recognize patterns to explain situations. This system continuously seeks to form associations between what is unknown and what is already known. For reasoning processes, he introduced System 2, which generates more reliable outcomes. When new information is processed, System 2 aids in critical thinking and reflection, reducing errors. The confirmation bias leads individuals to seek out data that support their preexisting hypotheses. Through various studies on decision-making, Kahneman and Tversky [23] assert that people rely on a limited number of heuristic principles that simplify complex tasks, such as evaluating probabilities and predicting values, into more straightforward judgment operations.

According to Prospect Theory, when individuals feel certain about an outcome, they tend to avoid risks in pursuit of gains but may take greater risks when attempting to avoid losses [24]. From a perspective-based approach, distinct behaviors emerge in response to positive (gain-related) and negative (loss-related) situations, a phenomenon referred to as the reflection effect. In the first scenario, risk aversion is observed and intensified by the certainty effect, as individuals are more attracted to outcomes perceived as guaranteed. Conversely, when losses are at stake, there is a tendency to embrace risk—showing a preference for taking larger, probabilistic losses over accepting a smaller, certain loss with a higher probability. This effect forms the basis of the S-shaped utility curve (Figure 1) proposed by [23].

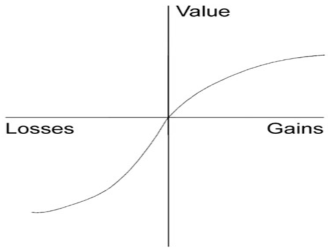

Figure 1. S-curve of the Prospect Theory.

According to [25], what increases or decreases the likelihood of an alternative being chosen is its perceived worth. A risk-based decision can be characterized as a combination of risk and other considerations. In decision-making, risk manifests differently for each individual, varying from person to person and raising the question of how much risk is acceptable. A decision problem is essentially the challenge of making a successful choice, represented by the equation (1):

$$\text{Worth} = f\,(\text{Risk, Other considerations}) \tag{1}$$

In the context of economics and business, risk arises when returns are not guaranteed. According to Yates [25], the key elements of the risk construct are:

- Potential for loss;
- Significance of these losses;
- Uncertainty of these losses.

Decision-making research integrates various fields of study, demonstrating how they are interconnected [26]. As a result, these studies offer solutions applicable across multiple disciplines. Saaty [27] developed the Analytic Hierarchy Process (AHP), a systematic and rational approach to decision-making that enables the selection of the best alternative from a diverse set based on multiple criteria. According to Costa et al. [13], the Gaussian AHP method differs from Saaty's traditional AHP in that it does not rely on pairwise comparisons to determine the weights of criteria. Instead, weights are assigned using a factor known as the Gaussian Factor, which is computed based on quantitative inputs for each criterion under evaluation. Araújo et al. [28] state that Gaussian AHP is a method that ensures equivalence when attributes are incorporated into the decision matrix. While quantitative attributes are independent, qualitative attributes can be methodologically converted into quantitative values. The steps of the Gaussian AHP method are illustrated in Figure 2.

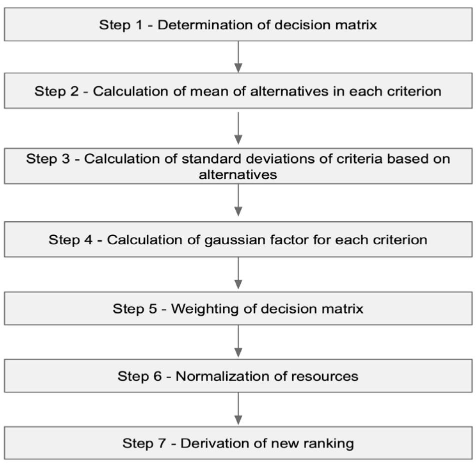

Figure 2. Seven steps gaussian AHP

The arithmetic mean is essential for normalizing the data and defining the weights of the criteria within the Gaussian AHP method, thus enabling a more objective and robust analysis. This measure is applied in Step 2, as shown in Equation (2):

$$\underline{x} = \frac{\Sigma x_i}{n} \tag{2}$$

The standard deviation helps capture data variability and contributes to a more precise determination of criteria weights in decision-making. For the calculation of standard deviation in Step 3 and the Gaussian factor, Equation (3) is used:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \underline{x})^2}{n}} \tag{3}$$

The Gaussian factor is then combined with the normalized means of the criteria to determine the final weights. These weights are used for comparative analysis and decision-making, giving greater importance to criteria that exhibit higher variability in the normalized data. The Gaussian factor is calculated using Equation (4):

$$fgaussian = \frac{\sigma}{\underline{x}} \tag{4}$$

For data collection, the dataset titled "Predicting Credit Card Customer Attrition with M" from [29] was used as the basis for analysis. This dataset consists of information from 10,127 customers of a financial institution, including demographic, behavioral, and transactional variables. To construct the decision matrix for this study, variables were selected based on expert analysis in the field, aiming to identify key factors associated with customer churn.

In the first step of defining the decision matrix, it is necessary to determine whether the selected variables are monotonic benefit (profit-oriented) or monotonic cost (cost-oriented). For this study, the following variables were classified as monotonic cost criteria (i.e., lower values indicate better classification):*Months_Inactive_12_mon,Total_Revolving_Bal.*

The following variables were classified as maximized criteria (higher values indicate better classification): *Dependent_count, Months_on_book, Total_Relationship_Count, Contacts_Count_12_mon, Credit_Limit, Total_Trans_Ct.*

The Gaussian AHP method was applied using the software developed by Gomes et al. [30]. To perform the analysis, the dataset was input as required by the software, ensuring that each variable's monotonicity was correctly identified. Table 1 below describes the selected variables used to construct the decision matrix.

Table 1. Variables in the Decision Matrix

Monotonicity	Variable	Meaning
Monotonic Cost	Months_Inactive_12_mon	Number of months the customer has been inactive in the last 12 months.
	Total_Revolving_Bal	Revolving balance, which represents the amount a customer owes to the financial institution when they choose not to pay the full outstanding balance in a given billing period.
Monotonic Benefit	Dependent_count	Number of dependents.
	Months_on_book	Account tenure
	Total_Relationship_Count	Number of relationships the customer has with the company.
	Contacts_Count_12_mon	Number of contacts the customer had in the last twelve months.
	Credit_Limit	Credit limit.
	Total_Trans_Ct	Total number of transactions on the account.

3. Results and Discussion

The results indicated that specific variables play a crucial role in predicting churn. Notably, it was observed that customer inactivity period, number of dependents, and revolving balance emerged as the primary predictors of churn.

Table 2. Output from the Gaussian AHP Software

Criteria	Means	Standard Deviation	Gaussian Factor	Weights
Months_Inactive_12_mon	9.87E-05	0.00184272	18.66122404	0.714670829
Dependent_count	9.87E-05	0.000315422	3.194282576	0.122331771
Total_Revolving_Bal	9.87E-05	0.000173869	1.760768623	0.067432338
Credit_Limit	9.87E-05	0.000103972	1.052922313	0.040323875
Contacts_Count_12_mon	9.87E-05	4.45E-05	0.450542611	0.017254477
Total_Relationship_Count	9.87E-05	4.03E-05	0.407704959	0.015613919
Total_Trans_Ct	9.87E-05	3.57E-05	0.361903221	0.013859845
Months_on_book	9.87E-05	2.19E-05	0.222286945	0.008512946

Standard deviation is a crucial statistical measure that provides insights into data dispersion around the mean. In the context of the variable Months_Inactive_12_mon (Months of Inactivity in 12 Months), a standard deviation of approximately 0.00184 indicates that the values of this variable are relatively close to the mean. This suggests that most customers have a similar number of months of inactivity, centered around the calculated average.

On the other hand, if the standard deviation were significantly higher, it would indicate greater data dispersion, meaning that customer inactivity periods vary more widely in relation to the mean. A low variability in inactivity months may suggest consistency in customer behavior regarding their banking activity. This could indicate that customers with a specific number of months of inactivity have a more predictable probability of churn, whereas customers with higher variability in inactivity months may be harder to predict in terms of churn.

For instance, in the case of Months_Inactive_12_mon, the Gaussian factor is approximately 18.66. This value highlights the relative importance of this criterion in predicting churn, considering both its mean and standard deviation. A higher Gaussian factor suggests that this criterion significantly influences the classification of customers in relation to *churn*. By incorporating the Gaussian factor into the Gaussian AHP model, weights are assigned to the criteria based on statistical considerations, taking into account not only the mean of the data but also its dispersion. This enhances the model's robustness and its ability to handle variability in the dataset.

The weights are calculated based on Gaussian factors and represent the relative contribution of each variable to the decision-making process. The higher the weight, the greater the influence of the variable in predicting *churn*. For example, the variable *Months_Inactive_12_mon* has a weight of approximately 0.714, indicating its high importance in the decision-making process.

Customers with prolonged inactivity periods or high revolving balances were more likely to leave the financial institution. Table 2 presents all operations involving the Gaussian AHP model. When analyzing the highest-weighted criterion, *Months_Inactive_12_mon* stands out as the most influential. In other words, the number of months a customer remained inactive holds the highest weight. When examining the original dataset and the top ten ranked samples from the Gaussian AHP model, it is evident that all of the top 32 ranked customers had an inactivity period equal to zero.

Table 3. Ranking Gaussian AHP

Rank	Client_num	Months_Inactive_12_mon	Dependent_count	Total_revolving_balance_of_custome	Credit_Limit	Contacts_Count_12_mon	Total_Relationship_Count	Total_Trans_Ct	Months_on_book
1	717103758	0	0	0	18550	2	5	42	55
2	812979408	0	0	0	15142	3	3	41	34
3	714855108	0	0	973	3466	1	6	69	50
4	720769533	0	0	682	1438.3	1	4	63	36
5	827984658	0	3	0	23870	4	3	39	45
6	715405758	0	1	0	10057	4	5	42	42
7	716800908	0	2	0	5137	3	5	49	13
8	796083783	0	2	0	1438.3	6	1	57	49
9	827898033	0	1	0	2912	3	4	54	50
10	755996583	0	2	0	2475	3	5	43	50

11	718297683	0	1	0	4085	3	1	71	50
12	712827258	0	3	0	1438.3	3	5	77	25
13	708801108	0	3	0	1438.3	3	3	38	51
14	826077033	0	2	0	2002	4	1	39	42
15	807136758	0	2	0	1944	2	3	40	53

When examining the second highest-weight criterion, "Dependent_count," meaning the number of dependents a customer has on the account, the top four ranked customers had zero dependents. From the fifth-ranked customer onward, this number does not follow a specific pattern. Looking at the third highest-weight criterion, "Total revolving balance of customer," it is noted that the first and second-ranked customers had no revolving balance, nor did customers ranked from 4th to 19th. However, when compared to the average revolving balance of customers, which is $1,162, the 3rd and 4th-ranked customers had a lower-than-average balance of $973 and $682, respectively. Interestingly, all of the top 15 ranked customers had high account tenure. This indicates that older customers may be more loyal than newer ones.

Given the above, it is possible to note that customers less likely to churn are those who have a higher level of banking activity. However, other criteria that also hold significant weight in the AHP-Gaussian model relate to customer quality. "Total revolving balance of customer," "Total_Trans_Ct," and "Credit_limit" are variables that, together, may serve as credit discrimination factors. This means that these criteria not only identified customers who are actively engaged with the bank and unlikely to churn but also those who may have a lower probability of default.

4. Final Considerations

This study proposed a methodological framework based on the application of the AHP-Gaussian method to generate customer rankings based on churn probability using relevant variables for analysis. Decision-making in the banking sector has become increasingly challenging due to growing competition and the evolution of the financial market, with the rise of fintechs and reduced entry barriers. In this scenario, in-depth customer knowledge and the ability to anticipate behaviors become essential for maintaining competitiveness.

The AHP-Gaussian method proved to be an effective tool for evaluating and classifying customers based on different criteria, providing valuable insights for identifying customers less likely to churn. By analyzing the results, it was observed that variables such as inactivity time, number of dependents, and revolving balance were crucial in identifying these customers. Although the proposed method has demonstrated its effectiveness, there is still room for improvements and refinements. Future studies could explore the inclusion of other relevant variables and validate the model in different contexts and samples. Additionally, applying techniques such as Naïve Bayes could enhance decision-making accuracy. In summary, this study offers a significant contribution to understanding and managing churn in the banking sector, providing a robust, data-driven methodological approach for identifying and retaining customers. By integrating theory and practice, this framework is expected to provide valuable insights for financial institutions in strategic decision-making and customer relationship strategies.

Despite the methodological soundness of the proposed model, its application to a single dataset limits the potential for generalizing the results. Although relevant, the Kaggle dataset may not represent all bank customers' behavioral and socioeconomic diversity. Consequently, the robustness and practical applicability of the model can be improved by replicating the study in multiple databases from different institutions and contexts. In addition, the lack of a comparative analysis with consolidated predictive models, such as decision trees, logistic regression, or neural networks, makes it difficult to assess the superiority of the approach based on Gaussian AHP compared to methods established in the churn prediction literature.

Another point of attention refers to the limitation in the selection of model variables. Although criteria such as inactivity time, number of dependents, and revolving balance have proven to be relevant, the inclusion of more subjective or qualitative variables, such as the level of customer satisfaction, history of complaints, or interactions with the manager, could provide a more comprehensive view of evasion behavior. Furthermore, macroeconomic factors or recent changes in the bank's product offerings can also significantly impact a customer's decision to maintain or terminate their relationship with the institution. Future research should consider expanding the set of variables analyzed and using hybrid methods that combine statistical techniques with artificial intelligence.

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