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A Methodological Framework for Business Decisions with Explainable AI and the Analytic Hierarchical Process

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Abstract: In today's data-driven business landscape, effective and transparent decision making becomes relevant to maintain a competitive advantage over the competition, especially in customer service in B2B environments. This study presents a methodological framework that integrates Explainable Artificial Intelligence (XAI), C-means clustering, and the Analytic Hierarchical Process (AHP) to improve strategic decision making in business environments. The framework addresses the need to obtain interpretable information from predictions based on machine learning processes and the prioritization of key factors for decision making. C-means clustering enables flexible customer segmentation based on interaction patterns, while XAI provides transparency into model outputs, allowing support teams to understand the factors influencing each recommendation. The AHP is then applied to prioritize criteria within each customer segment, aligning support actions with organizational goals. Tested with real customer interaction data, this integrated approach proved effective in accurately segmenting customers, predicting support needs, and optimizing resource allocation. The combined use of XAI and the AHP ensures that business decisions are data-driven, interpretable, and aligned with the company's strategic objectives, making this framework relevant for companies seeking to improve their customer service in complex B2B contexts. Future research will explore the application of the proposed model in different business processes.

Keywords: fuzzy C-means clustering; explainable AI (XAI); SHAP values; LIME; customer service; machine learning (ML); RFID

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1. Introduction

Companies in the Business to Business (B2B) sector increasingly rely on data-driven approaches to enhance their customer support strategies and manage complex client relationships [1]. This study centers on a management software provider that serves technology partners responsible for implementing the software across a diverse array of businesses, varying in both sector and size. These partners, acting as intermediaries, have distinct support needs that require tailored and prioritized strategies to ensure both efficient service delivery and high levels of customer satisfaction.

To address these needs, we propose a comprehensive methodological framework that combines Explainable Artificial Intelligence (XAI) [2], Fuzzy C-means (FCMs) clustering [3], and the Analytic Hierarchy Process (AHP) with 2-tuple integration [4]. Fuzzy C-means is utilized to segment clients based on their interaction patterns and support requirements, accommodating the variability in their behavior and enabling the company to develop targeted support strategies for each segment.

To validate the reliability of this segmentation, a Random Forest model is applied to evaluate the accuracy of the FCMs clustering, while also employing XAI techniques, specifically SHapley Additive exPlanation (SHAP) values [5] and Local Interpretable Model-agnostic Explanation (LIME) [6], to interpret model outputs at both global and local levels. SHAP values clarify the importance of each feature in the overall predictions, while LIME provides case-specific explanations, helping support teams understand the drivers behind individual client classifications.

For prioritization within each cluster, the Analytic Hierarchy Process (AHP), enhanced with a 2-tuple approach, allows for the flexible weighting of key criteria such as interaction frequency, support urgency, and client value. This ensures that support resources are allocated effectively, and decisions align with strategic objectives.

The integration of human and machine learning-based decision making leverages the strengths of both approaches to create a more balanced and effective framework. While machine learning models provide data-driven insights by identifying patterns and trends that may not be immediately evident, human decision making introduces the context, expertise, and strategic alignment that are determinant for nuanced and responsible choices [7]. This synergy allows companies to make informed decisions that rely on quantitative analyses and to act guided by human judgement and prioritizations. The main objective of this work is to establish a methodology that effectively integrates both aspects, ensuring that automated insights are complemented by human interpretation and prioritization. By combining these approaches, organizations can improve the accuracy, transparency, and relevance of their decisions, ultimately leading to more robust and adaptable strategies in various business contexts.

This work provides a structured solution, providing efficient customer segmentation using Fuzzy C-means (FCMs), validating the reliability of the clusters with Random Forest, ensuring interpretability using SHAP and LIME, and prioritizing the actions to be taken for each cluster with the AHP. These aspects through the proposed methodology contribute to improving decision-making processes, offering a transparent, data-driven, and human-centered framework for managing customer service in B2B environments.

This methodology, while applied here in the context of interactions between technology partners and a software provider, is designed to be flexible and extensible to other business processes within the company. Its approach can support strategic decision making across various domains, including marketing processes, employee management, production planning, and beyond. The proposed framework thus addresses methodological needs that are common to businesses in any industry, enabling organizations to make more informed, efficient, and transparent decisions across a range of applications.

The following sections are organized as follows: Section 2 provides a review of the relevant literature on the use of AI and decision-making techniques in customer support management, with a focus on Fuzzy C-means, XAI, and the AHP. Section 3 presents the details of the proposed methodology, outlining the integration of FCMs, XAI, and the AHP in the decision-making process. Section 4 applies this framework to real customer interaction data, showcasing how it optimizes segmentation and prioritization. Finally, Sections 5 and 6 offer discussions on the findings, conclusions, and future research directions.

2. Related Work

To establish a comprehensive account of the work related to the study objective, a structured research process was followed that examined the relevant literature in several key areas. Through this approach, the aim was to investigate previous work and, thus, discover the relevance of the proposed methodology.

The review process begins by exploring studies in the Web of Science (WoS) database that integrate clustering techniques, such as Fuzzy C-means and K-means, with Explainable Artificial Intelligence (XAI) to improve the interpretability of the models. This review aims to understand the role of clustering in improving the explainability of machine learning models.

Next, research on clustering methods, specifically in customer service contexts, is examined to identify how clustering is used to group customers based on their characteristics and needs, optimizing service strategies in B2B environments. The review then focuses on studies that apply XAI in customer service, particularly those that use SHAP and LIME to interpret and explain customer segmentation, which helps companies understand and act on AI-driven recommendations for each segment.

Next, studies on the Analytic Hierarchical Process (AHP) in customer service decision making are reviewed, showing how AHP helps prioritize actions and resource allocation based on specific criteria within each customer segment. Finally, the review includes the author's previous research on RFID and related studies, demonstrating how this previous work aligns with and extends the current literature through the integration of clustering, XAI, and the AHP, thus highlighting the unique contributions of the proposed methodology.

2.1. Clustering and XAI

In recent years, the integration of clustering techniques with Explainable Artificial Intelligence (XAI) has gained significant attention, as organizations and researchers aim to balance model accuracy with interpretability across various applications. Clustering methods like Fuzzy C-means and K-means have traditionally been used to group data into segments based on shared characteristics. However, the addition of XAI techniques enhances the transparency of these clusters, allowing stakeholders to understand and trust the model's segmentation decisions.

The following work provides an in-depth exploration of different approaches to explainability, establishing a framework for evaluating XAI techniques in applications that require transparency, such as customer classification [8].

Another important study delves into the use of LIME for interpreting model predictions [9]. LIME's ability to provide local explanations for individual predictions has proven valuable in making clustering decisions interpretable, especially in contexts where understanding individual data points is essential.

Similarly, the next study compares SHAP and LIME in terms of their effectiveness in interpreting machine learning models. The work is relevant in clustering processes, as SHAP and LIME provide insights into the importance of features for each cluster, helping to build trust in data-driven decisions [10].

Study [11] demonstrates the application of XAI methods to interpret clustering results in human activity data. The study emphasizes the versatility of XAI in clustering, showcasing its potential in domains beyond traditional business applications.

Article [12] focuses on rule-based approaches to explainable AI, which are particularly useful for clustering models as they provide interpretable and actionable insights.

These works highlight advancements in explainable clustering, underscoring the importance of XAI techniques like SHAP and LIME in enhancing the interpretability of clustering results [13]. As organizations increasingly adopt clustering models in areas such as customer, supplier, and internal staff segmentation, these studies support the development of methodologies that ensure transparency and ethics in business decision making.

Figure 1 shows a preliminary review of the research related to clustering and XAI in the Web of Science Core Collection, identifying a total of 121 open-access publications.

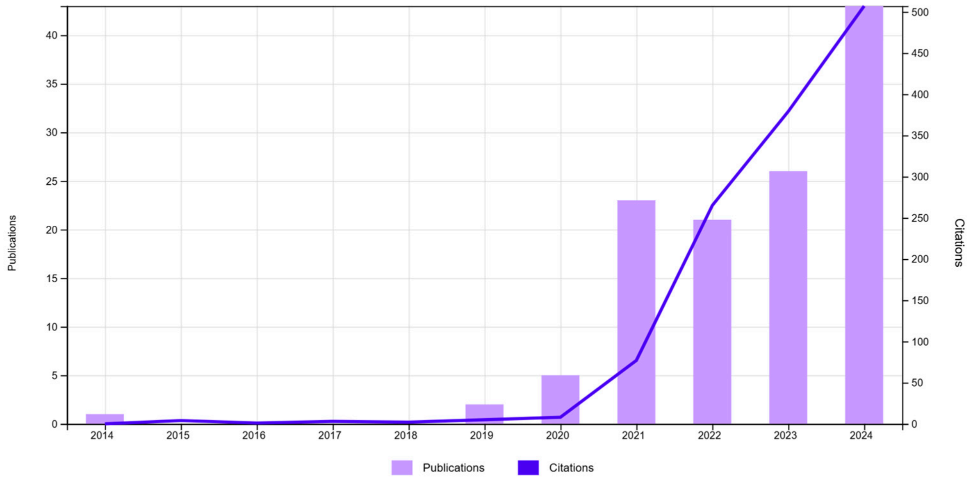

Figure 1. Publications (121) and citations. TS = ("CLUSTERING") AND TS = ("XAI" OR "EXPLAINABLE ARTIFICIAL INTELLIGENCE").

2.2. Clustering and XAI Applied to Customers

Next, the review will concentrate on clustering and XAI applied to customers, in the Web of Science database. The review revealed that there are currently some studies that emphasize the use of XAI and clustering that are specifically targeted at customer applications. This indicates that there is a significant development opportunity in this area, especially within marketing models where customer segmentation and personalized strategies predominate. Furthermore, when the query was expanded to include "Customer Service", no relevant results were found, highlighting the untapped potential for integrating explainable AI and clustering in customer service contexts. This gap suggests a clear path forward for advancing research in business decision making, as the topic remains largely unexplored.

Study [14] investigated the use of XAI in analyzing the potential for customer churn in a B2B model, providing strategies for understanding the most important characteristics that can predict churn and retention.

Study [15] emphasized the use of XAI in understanding customer behavior in the insurance industry, providing insights into why customers choose to buy insurance and enhancing transparency in model predictions.

Study [16] investigated the role of XAI in explaining unsupervised clustering models for customer segmentation, showing how interpretability can help businesses understand customer grouping patterns for better marketing strategies.

Similarly, study [17] applied XAI to churn prediction in the telecommunications sector, supporting customer retention efforts by offering interpretable insights into factors driving customer loyalty.

In the following study, a mathematical model using XAI was proposed for customer segmentation, adaptable to different demographics and industries, allowing for more personalized engagement strategies [18].

Study [19] focused on optimizing costs and profits while meeting customer demand in the development of perishable product deliveries.

Figure 2 shows a preliminary review of the research related to clustering, XAI, and customers in the Web of Science Core Collection, identifying a total of 5 open-access publications.

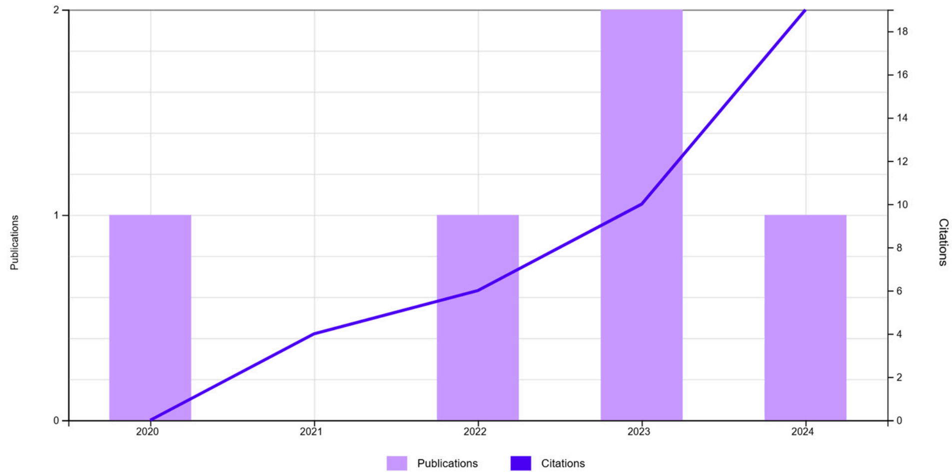

Figure 2. Publications (5) and citations. TS = ("CLUSTERING") AND TS = ("XAI" OR "EXPLAINABLE ARTIFICIAL INTELLIGENCE") AND TS = ("CUSTOMER").

2.3. Customer Service and AHP

The literature review revealed a limited number of studies—only 15—focused on the application of the Analytic Hierarchy Process (AHP) in customer service and support contexts. This scarcity underscores a significant research gap in leveraging the AHP to enhance decision making in customer-focused areas. Among these studies, several emphasize improving customer support through various applications of the AHP.

Study [20] explored the AHP for improving decision-making processes, allowing organizations to allocate resources efficiently. Similarly, ref. [21] demonstrated how the AHP can be applied in complex decision-making scenarios, providing a framework to prioritize actions based on multiple criteria (authors not provided). Another study, [22], used the AHP to handle multi-criteria decision making in resource allocation, relevant to customer service environments with limited resources.

Study [23] focused on using the AHP to interpret customer feedback, enabling targeted improvements in customer satisfaction. Study [24] utilized the AHP to assess customer needs, aligning service provider offerings with customer expectations (authors not provided). Additionally, [25] applied the AHP to prioritize features in software selection, showcasing the AHP's potential for customizability in B2B service contexts.

In [26], the AHP aided in evaluating mobile banking applications, focusing on the features most valued by customers. Study [1] was directly focused on customer service, using the AHP to optimize service aspects that directly influence customer satisfaction. Study [27] applied the AHP in a logistics context, indirectly benefiting customer service through operational efficiency.

Study [28] combined the AHP with multi-attribute decision making, which, while not directly related to customer service, demonstrated the flexibility of the AHP in prioritizing various attributes. In [29], the authors focused on logistics optimization, applying the AHP to improve the customer experience by enhancing service speed and accuracy.

Study [30] utilized the AHP to select business partners, a process that impacts customer service quality indirectly (authors not provided). In [31], the authors used the AHP to evaluate service quality, focusing on enhancing customer satisfaction in supply chain contexts. Furthermore, study [32] applied the AHP for homestay selection, which involves prioritizing customer-preferred features.

Finally, ref. [33] directly addressed customer service by using the AHP to prioritize factors in bonus distribution, ultimately aiming to motivate customer service employees to perform better and improve service quality.

Figure 3 shows a preliminary review of research related to the AHP and customer service in the Web of Science Core Collection, identifying a total of 15 open-access publications.

Figure 3. Publications (15) and citations. TS = ("ANALYTIC HIERARCHY PROCESS" OR "the AHP") AND TS = ("CUSTOMER SERVICE") AND TS = ("DECISION MAKING").

These studies collectively demonstrate the adaptability of the AHP to different aspects of customer service and support, from complaints management to resource allocation and service customization. Despite the demonstrated potential of the AHP in enhancing customer service, the limited number of studies highlights an untapped opportunity for further exploration, particularly in combining the AHP with methodologies like XAI and clustering. This could pave the way for more advanced and explainable decision making frameworks in customer support and management, ultimately bridging the gap between data-driven insights and actionable customer-focused strategies.

3. Methodology

The methodology used in this study is based on the Knowledge Discovery in Databases (KDD) process [34]. It starts with the collection of information from a dataset provided by a company that manufactures ERP solutions, which contains the records of interactions between the company and its customers, mainly technology partners. After data collection, data transformation tasks are performed to prepare the information for modeling.

The first stage of modeling consists of adapting the RFID (recency, frequency, importance, and duration) model to quantify the characteristics of each customer interaction [35]. A fuzzy clustering technique is then applied to segment the customers into clusters, allowing customized actions to be taken for each cluster, based on the importance of the criteria established using the AHP model.

Once the clusters are defined, an accuracy analysis is performed for each cluster using a Random Forest classifier to assess the accuracy of the segmentation. SHAP and LIME are then used to interpret and explain predictions, improving the interpretability of the clustering model both globally and locally.

Finally, the AHP model is used to generate customized recommendations for each cluster, aligning actions with the company's strategic priorities and addressing the specific needs of each customer segment. This approach aims to deliver a tailored customer experience that improves customer satisfaction and optimizes the allocation of customer service resources.

Figure 4 describes the whole process:

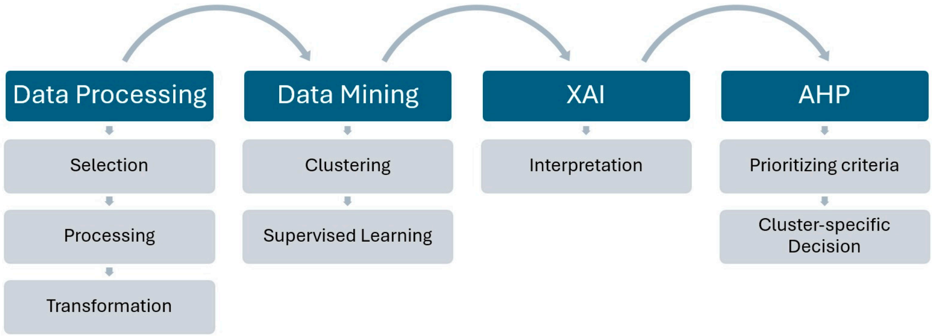

Figure 4. Methodological process.

3.1. Data Processing

The selected dataset originates from the Salesforce CRM, specifically targeting customer interaction records from the customer service system. The objective of this phase is to extract and process the data necessary to construct an RFID model, which evaluates recency, frequency, importance, and duration for each customer interaction. To prepare the data for analysis, several steps were undertaken to compute these features while ensuring data completeness and consistency.

The initial dataset included raw customer interaction logs, and preprocessing tasks were performed to ensure data quality. Incomplete data, such as records with missing values in critical fields like interaction timestamps and customer IDs, were excluded. Additionally, outliers were identified and removed to maintain consistency in the dataset. The raw information was then processed to compute the necessary RFID metrics for further analysis. Each RFID metric was derived as follows:

- Recency R: this represents the time elapsed since the last customer interaction.

$$R_i = T_c - T_{\text{lint},\, i} \tag{1}$$

where T_c is the current date (or dataset reference date), and $T_{\text{lint},\, i}$ is the last recorded interaction date for customer i.

- Frequency F: the total number of interactions a customer has had within a specific time frame:

$$F_i = \sum_{j=1}^{n} Int_{ij} \tag{2}$$

where n is the total number of interactions logged for customer i during the reference period, and Int_{ij} refers to the j-th interaction recorded for customer i within the specified reference period.

- Importance I: The I value represents the average importance level of all the interactions a customer has had with the support service. This is calculated by aggregating the importance values for each interaction, which are categorized using a fuzzy classification model with five linguistic variables: Very High (VH), High (H), Medium (M), Low (L), and Very Low (VL). Each interaction's importance is assigned a fuzzy score, and the final importance for a customer is derived as the mean value of these scores.

$$I_i = \frac{1}{n_i} \sum_{j=1}^{n_i} \sum_{k=1}^{5} \mu_{k,ij} \cdot w_k \tag{3}$$

where I_i represents the average importance for customer i; n_i is the number of interactions for customer i; $\mu_{k,ij}$ is the membership value of interaction j for customer i to fuzzy category k; and w_k is the weight assigned to category k.

- Duration D: This measures the time taken to resolve a customer issue. For each interaction:

$$D_{ij} = T_{\text{cl}, ij} - T_{\text{op}, ij} \tag{4}$$

where $T_{\text{cl}, ij}$ and $T_{\text{op}, ij}$ are the timestamps for when the interaction j for customer i was closed and opened, respectively.

- Feature Scaling

After calculating the RFID metrics, all the features were scaled to a uniform range $[0, 1]$ using the MinMaxScaler:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{5}$$

where x' is the scaled value, x is the original value, and $\min(x),\ \max(x)$ are the minimum and maximum values of the feature, respectively.

3.2. Data Mining

3.2.1. Fuzzy C-means

The first phase of the analysis consists of grouping customers into clusters, using Fuzzy C-means [3]. This clustering technique allows for fuzzy classification, which means that each customer can partially belong to more than one cluster. This approach is ideal in the context of customer care, as it allows for capturing ambiguity in the behaviors of technology partners.

The Fuzzy C-means algorithm minimizes a cost function that allows partial membership to be assigned to each cluster, effectively capturing the variability in customer behavior. The membership function is defined as

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m |x_i - c_j|^2 \tag{6}$$

N is the number of customers, C is the number of clusters, u_{ij} represents the degree of customer ownership i to the cluster j, m is the fuzzy parameter (usually $m = 2$),

x_i is the vector of customer characteristics i, c_j is the cluster centroid j, $\left|x_i - c_j\right|$ is the distance between client i and the centroid of cluster j (usually calculated using the Euclidean distance).

The degree of membership u_{ij} is computed as

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\left|x_i - c_j\right|}{\left|x_i - c_k\right|} \right)^{\frac{2}{m-1}}} \tag{7}$$

Each iteration of the algorithm adjusts the values of u_{ij} and c_j until J_m converges to a minimum, thereby segmenting customers into fuzzy groups.

3.2.2. Random Forest

In the second phase, the Random Forest model is employed to evaluate the accuracy of the clustering model. Specifically, after customers are classified according to the RFID model and assigned to a cluster, Random Forest is used to assess the precision of these assignments. This helps to validate the effectiveness of the clustering process.

The Random Forest algorithm uses multiple decision trees to perform predictions [36]. Each tree is trained on a random sample of the data and produces a prediction based on a series of binary decisions. The final prediction of the forest is determined by the majority vote (for classification problems) or the average (for regression problems) of all the trees.

For a given customer x, the complete Random Forest, RF, predicts the probability of belonging to a specific cluster as

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} h_t(x) \tag{8}$$

where T is the number of trees in the forest, and $h_t(x)$ is the prediction of the $t - th$ tree for customer x.

Each tree, h_t, is built by minimizing an impurity function, such as entropy or the Gini index. For example, the Gini index for a node with K classes is defined as

$$G = 1 - \sum_{k=1}^{K} p_k^2 \tag{9}$$

where p_k is the proportion of observations belonging to class k in the node. This method ensures that the Random Forest model can robustly evaluate the precision of the clustering assignments by analyzing how well the clusters align with the predicted customer segments.

3.3. XAI

Explainability is an important element in any context, and specifically in B2B relationships, where support teams need to understand the predictions made by the model to make informed and personalized decisions in customer management. In this methodology, two explainability models are employed: LIME (Local Interpretable Model-agnostic Explanation) and SHAP (SHapley Additive exPlanation). While LIME focuses on providing localized explanations for specific predictions [37], SHAP offers a global and consistent interpretation of the importance of features in the Random Forest model, creating a comprehensive framework for understanding predictions [38].

3.3.1. SHAP

In this analysis, SHAP values are used to interpret the importance of each characteristic (recency, frequency, significance, and duration) within each cluster. Using SHAP, the distinctive characteristics of each cluster can be better understood by providing aid teams with practical information to adapt strategies and prioritize proactive actions effectively.

SHAP values are derived from the Shapley value concept in cooperative game theory. In this case, the prediction for a customer is considered the outcome of a "game", and each feature is treated as a "player" contributing to the prediction. The Shapley value for each feature quantifies its marginal contribution to the prediction, averaged over all possible feature combinations.

For a customer, x, let $f(x)$ be the predicted probability of needing intensive support. The Shapley value for a feature, ii, is calculated as

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!}[f(S \cup \{i\}) - f(S)] \tag{10}$$

where S is a subset of features, excluding i; N is the total set of features {recency, frequency, importance, and duration}; $f(S \cup \{i\})$ is the model prediction using the features in S plus feature i; and $f(S)$ is the model prediction using only the features in S.

3.3.2. LIME

To explain the prediction for a specific customer using LIME, a local linear model is fitted around the prediction of the complex model for that customer. This linear model approximates the behavior of the complex model about the instance x.

The weighted linear model is fitted by minimizing the following cost function:

$$L(f, g, \pi_x) = \sum_{z \in Z} \pi_x(z)(f(z) - g(z))^2 + \Omega(g) \tag{11}$$

where f is the complex model (Random Forest in this case); g is the local explanatory model (linear); $\pi_x(z)$ is a weighting function that assigns higher importance to instances z closer to x; and $\Omega(g)$ is a regularization term to prevent g from becoming overly complex.

LIME generates an interpretation by fitting g in such a way that it captures the local relationships around x, providing explanations in terms of the input features.

3.4. AHP

The Analytic Hierarchy Process (AHP) is based on constructing pairwise comparison matrices to weigh the relative importance of each criterion. For each cluster, a pairwise comparison matrix, A, is created, where each entry, a_{ij}, represents the relative importance of criterion i compared to criterion j.

The weighing of each criterion is calculated as the principal eigenvalue of the normalized matrix A through the following steps:

Calculate the sum of each column of the matrix A.

Normalize the matrix by dividing each element, a_{ij}, by the sum of its column.

Calculate the weight, w_i, of each criterion as the average of row ii of the normalized matrix.

$$w_i = \frac{1}{n} \sum_{j=1}^{n} \tilde{a_{ij}} \tag{12}$$

where $\tilde{a_{ij}}$ is the normalized element of A, and n is the number of criteria.

The consistency of the comparison matrix is evaluated using the consistency index (CI) and Consistency Ratio (CR) to ensure that the comparisons are coherent. If $CR < 0.1$, the matrix is considered consistent:

$$\begin{array}{c} CI = \frac{\lambda_{\max} - n}{n-1}; \\ CR = \frac{CI}{RI} \end{array} \tag{13}$$

where $\lambda_{\max}$ is the principal eigenvalue of A; and RI is the random consistency index (predefined based on the number of criteria).

In this case, the AHP will be used to weigh and prioritize the actions to be performed for each defined cluster. This allows for tailored decision making that aligns with the specific characteristics and needs of each customer group.

4. XAI–AHP Business Decision Framework for Customer Service Support

4.1. Application: Data Selection, Processing, and Transformation

The methodology outlined in this study facilitates the creation of classification models tailored to specific attributes. In this research, the XAI–AHP Business Decision Framework was implemented in the context of customer support within B2B business models, using attributes extracted from a Salesforce CRM system (2019 version), San Francisco, CA, USA. A summary of these attributes is provided in Table 1.

Table 1. Dataset from Salesforce CRM. Features.

Features	
Account_ID	Customer Code
Case_ID	Incident Identification Code
Date_Opened	Incident Opening Date
Status	Incident Status
Status_Date	Incident Closing Date
Priority	Incident Priority Level
Case_Age	Total Incident Management Hours
Type	Incident Classification Type

In Figure 5, the number of incidents by month in 2023 can be visualized.

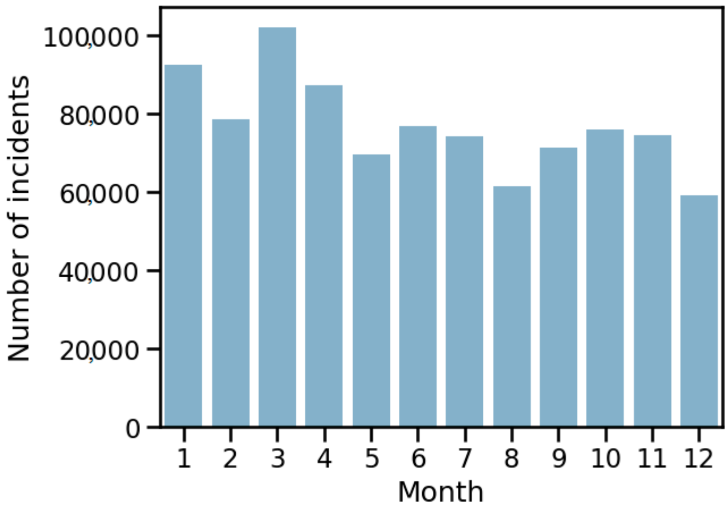

Figure 5. Incidents by month.

From the initial data, calculations were performed to derive the recency, frequency, importance, and duration of customer interactions. The R, F, I, D values were also expressed in 2-tuple format. Table 2 shows the recency, frequency, importance, and duration values for 15 accounts, both in numerical values and in their translation to the 2-tuple domain.

Table 2. Numerical and fuzzy values of Recency, Frequency, Importance, and Duration..

Account_ID	Recency	Frequency	Importance	Duration	Type	R	F	I	D
wReca	179	2	2	0.0	0	(H, −0.124)	(M, 0.009)	(M, 0.025)	(L, 0.077)
wRenT	94	4	2	0.0	0	(H, 0.025)	(H, −0.007)	(M, 0.025)	(L, 0.077)
wReue	230	2	2	0.0	1	(M, 0.048)	(M, 0.009)	(M, 0.025)	(L, 0.077)
wRezt	339	1	2	0.0	0	(M, −0.077)	(L, −0.042)	(M, 0.025)	(L, 0.077)
wRf4A	96	2	2	25.0	0	(H, 0.019)	(M, 0.009)	(M, 0.025)	(H, 0.119)
wRf5G	31	1	2	0.0	0	(VH, −0.089)	(L, −0.042)	(M, 0.025)	(L, 0.077)
wRf6k	326	1	2	6.0	0	(M, −0.063)	(L, −0.042)	(M, 0.025)	(H, 0.026)
wRg8S	305	2	2	17.0	0	(M, −0.038)	(M, 0.009)	(M, 0.025)	(H, 0.062)
wRgDS	340	2	2	23.0	0	(M, −0.078)	(M, 0.009)	(M, 0.025)	(H, 0.094)
wRgcI	222	2	2	0.0	0	(M, 0.059)	(M, 0.009)	(M, 0.025)	(L, 0.077)
wRgdG	289	1	2	0.0	0	(M, −0.016)	(L, −0.042)	(M, 0.025)	(L, 0.077)
wRgda	341	1	3	17.0	0	(M, −0.08)	(L, −0.042)	(VL, 0.035)	(H, 0.062)
wRgdk	278	3	2	20.0	0	(M, −0.004)	(H, −0.095)	(M, 0.025)	(H, 0.077)
wRge9	341	1	2	9.0	0	(M, −0.08)	(L, −0.042)	(M, 0.025)	(H, 0.039)
wRgeJ	157	1	2	9.0	0	(H, −0.087)	(L, −0.042)	(M, 0.025)	(H, 0.039)

The correlation matrix for the values of recency, frequency, importance, and duration, after being scaled to between zero and one [0, 1], is shown in Figure 6.

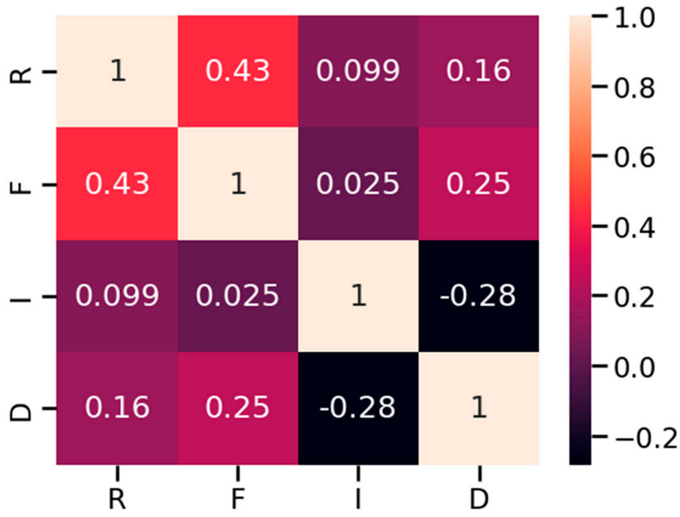

Figure 6. Correlation matrix.

The correlation values reveal generally weak relationships between the variables, with the most notable being between recency and frequency. This indicates that the variables capture distinct aspects of customer behavior, justifying their inclusion in the clustering model. It also seems logical that there is an inverse correlation between importance and duration in the interactions.

4.2. Application: Data Mining

4.2.1. Clustering

Determining the optimal number of clusters is the first step in the analysis process. Two widely used techniques, the Elbow Method [39] and the Silhouette Coefficient [40], were applied to identify the appropriate cluster count for segmenting customers in this study.

The Elbow Method evaluates the sum of the squared distances (inertia) between data points and their assigned cluster centroids as the number of clusters increases. As illustrated in Figure 7, the curve demonstrates a significant reduction in inertia as the number of clusters grows, which gradually levels off, forming an elbow around five clusters.

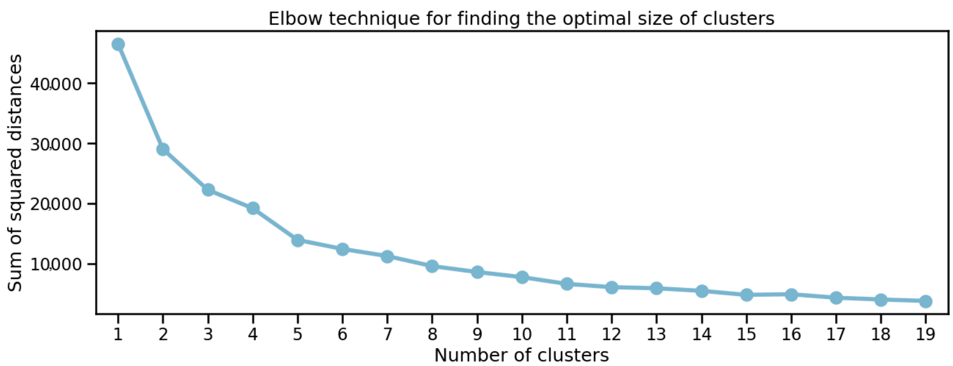

Figure 7. Elbow technique.

The Silhouette Coefficient measures the quality of clustering by comparing the distance of data points within a cluster to the nearest neighboring cluster. Higher silhouette scores reflect better-defined clusters. Figure 8 shows the silhouette scores for different cluster numbers, with the highest score of 0.376 occurring for five clusters. This confirms that the clustering structure is most coherent and distinct at this level.

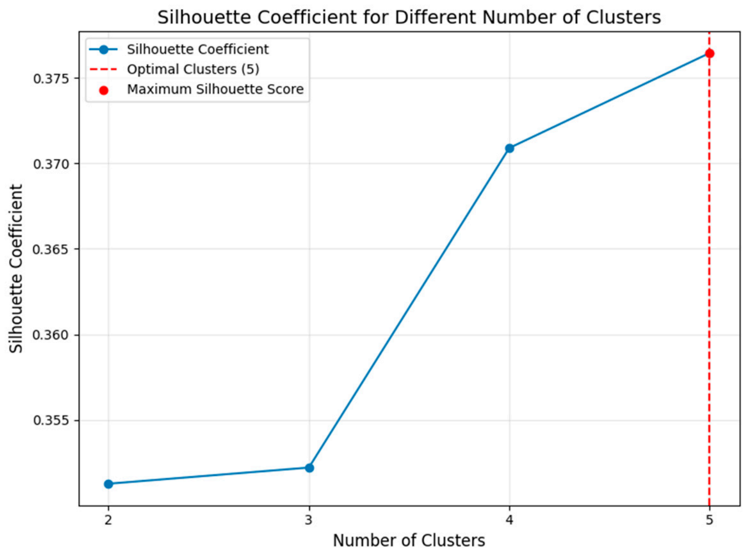

Figure 8. Silhouette Coefficient.

The subsequent step focuses on examining the centroids of the identified clusters to analyze the key characteristics that differentiate each group, as shown in Figure 9.

The centroids represent the average characteristics of each cluster in terms of recency (R), frequency (F), importance (I), and duration (D). The following is a summary of each cluster's profile:

1. Cluster 0: This cluster includes low-engagement clients with sporadic, short interactions. They may benefit from incentives to increase interaction frequency.
    - Recency (0.647): high, indicating interactions occurred a long time ago.
    - Frequency (0.245): low, suggesting infrequent interactions.
    - Importance (0.515): moderate, reflecting average interaction relevance.
    - Duration (0.381): low, indicating minimal support time needed.
2. Cluster 1: This cluster comprises clients who interact briefly and occasionally despite recent activity. They may be new or reach out only for specific needs.
    - Recency (0.179): low, indicating recent interactions.
    - Frequency (0.224): low, suggesting occasional interactions.
    - Importance (0.517): moderate, reflecting average interaction relevance.
    - Duration (0.359): low.
3. Cluster 2: This cluster includes high-demand clients who, despite long periods of inactivity, require frequent and extended support. Regular follow-ups could enhance satisfaction.
    - Recency (0.737): high, indicating long gaps since their last interaction.
    - Frequency (0.789): high, reflecting frequent interactions when active.
    - Importance (0.508): moderate, showing average relevance.
    - Duration (0.829): high, suggesting prolonged support needs.
4. Cluster 3: This cluster represents active and moderately frequent clients requiring short support sessions. They are likely satisfied and engaged.
    - Recency (0.331): moderate, indicating relatively recent interactions.
    - Frequency (0.581): moderate to high, showing consistent engagement.
    - Importance (0.511): moderate, reflecting steady commitment.
    - Duration (0.392): low to moderate.

5. Cluster 4: This cluster involves clients who engage frequently during interactions but have not done so recently. They may need reactivation to maintain regular engagement.
   - Recency (0.744): high, indicating significant time since the last interaction.
   - Frequency (0.753): high, reflecting frequent engagement when active.
   - Importance (0.517): moderate, showing average interaction significance.
   - Duration (0.367): low.

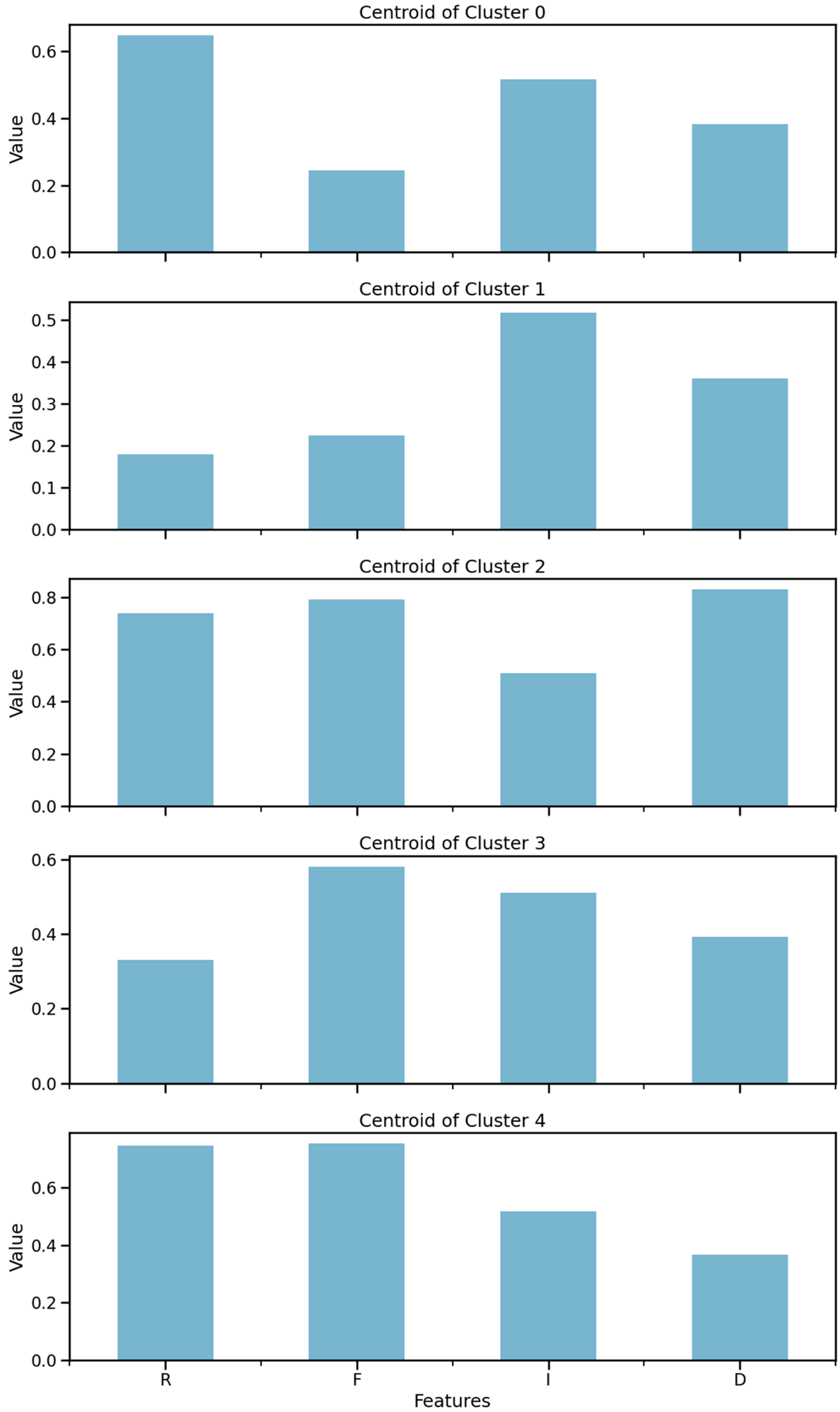

Figure 9. Centroid for each cluster.

These centroids highlight distinct interaction patterns, aiding in tailoring support and retention strategies to meet the needs of each cluster effectively.

Table 3 presents five selected customers from each cluster. The table provides their normalized scores for recency (R), frequency (F), importance (I), and duration (D) within the range [0, 1], the fuzzy cluster (FC) to which they belong, and their degree of membership in each cluster (%).

Table 3. RFID evaluation and Fuzzy C-means membership.

Account	R	F	I	D	FC	% Cluster 0	% Cluster 1	% Cluster 2	% Cluster 3	% Cluster 4
iLPL9	0.621356	0.208160	0.525362	0.327059	0	0.932766	0.023811	0.007794	0.020623	0.015005
iNO6y	0.502784	0.208160	0.525362	0.327059	0	0.671153	0.158169	0.026127	0.097309	0.047242
kLfwz	0.461686	0.208160	0.525362	0.760564	0	0.320229	0.237833	0.137310	0.196442	0.108186
yUY6X	0.743364	0.208160	0.525362	0.327059	0	0.864883	0.037135	0.020170	0.037915	0.039897
VtZGs	0.978908	0.208160	0.525362	0.327059	0	0.530640	0.094895	0.093954	0.108068	0.172443
iLsi8	0.058911	0.208160	0.525362	0.327059	1	0.038821	0.868055	0.012939	0.062500	0.017685
s6XLZ	0.265748	0.208160	0.525362	0.327059	1	0.052124	0.870735	0.009597	0.052765	0.014779
iKtFs	0.317957	0.208160	0.525362	0.327059	1	0.132028	0.714284	0.019395	0.103364	0.030929
mBNU3	0.238709	0.208160	0.525362	0.327059	1	0.026983	0.928853	0.005500	0.030341	0.008322
iMDca	0.257874	0.208160	0.525362	0.327059	1	0.043679	0.889651	0.008292	0.045674	0.012704
TPrGf	0.364800	0.909158	0.525362	0.760564	2	0.091087	0.090952	0.383672	0.247013	0.187277
hmKbd	0.695739	0.743499	0.525362	0.856470	2	0.009724	0.005908	0.952859	0.012336	0.019173
iKr4k	0.743364	0.848906	0.525362	0.933131	2	0.019636	0.012825	0.902205	0.024893	0.040442
hmlCi	0.988311	0.981938	0.525362	0.915207	2	0.072768	0.044665	0.636545	0.079280	0.166742
hmMVt	0.381271	0.848906	0.525362	0.987621	2	0.094984	0.092233	0.490270	0.177513	0.145000
iM9qi	0.424854	0.508885	0.525362	0.327059	3	0.105410	0.089865	0.030031	0.695897	0.078797
WmBmY	0.443330	0.654548	0.525362	0.327059	3	0.071706	0.059271	0.042702	0.676938	0.149383
lNx6Q	0.342199	0.743499	0.525362	0.327059	3	0.061543	0.071127	0.051701	0.685940	0.129690
mAlob	0.115182	0.743499	0.525362	0.327059	3	0.083065	0.161221	0.069250	0.574846	0.111618
xkE5t	0.519585	0.508885	0.525362	0.685082	3	0.198205	0.116230	0.240518	0.277672	0.167375
hmbnN	0.603643	0.743499	0.525362	0.327059	4	0.059992	0.033660	0.055943	0.144465	0.705940
epUCO	0.800508	0.654548	0.525362	0.327059	4	0.061251	0.020782	0.043458	0.051695	0.822813
iNKWY	0.716629	0.743499	0.525362	0.327059	4	0.009521	0.004357	0.009598	0.013592	0.962931
iKUNc	0.569316	0.930213	0.525362	0.327059	4	0.074375	0.054542	0.118702	0.194318	0.558064
215NUN	0.870093	0.508885	0.525362	0.327059	4	0.279837	0.061246	0.098547	0.114228	0.446142

4.2.2. Random Forest (RF)

After segmenting the customers based on the calculated recency (R), frequency (F), importance (I), and duration (D) metrics, the subsequent step involves developing a predictive model to evaluate the accuracy of the clustering process and predict the cluster membership for new customers. For this purpose, the Random Forest (RF) algorithm was selected due to its ability to handle complex, non-linear relationships and its robustness in classification tasks.

To assess the effectiveness of the model, a confusion matrix is generated, as shown in Figure 10. This matrix provides a detailed comparison of the predicted cluster labels against the actual labels, presenting the number of true positives, true negatives, false positives, and false negatives for each cluster. This evaluation ensures the reliability of the model and its ability to accurately predict cluster membership.

The results demonstrate the high accuracy of the Random Forest model, which achieves almost 99% accuracy in classifying customers in the clusters defined by C-means. The confusion matrix reveals that most of the predictions match the original cluster labels, with minimal misclassification errors. This highlights the effectiveness of combining C-means for initial segmentation and Random Forest to refine the classification. Well-defined clusters, based on characteristics such as recency, frequency, importance, and duration, allow the model to distinguish groups of customers with similar behavioral patterns. The synergy between the two methods ensures robust classification and reliable predictions, enabling tailor-made strategies for each cluster. This approach demonstrates its practical applicability by ensuring accurate decision making in customer care and retention strategies, optimizing resource allocation, and improving customer engagement in a B2B environment.

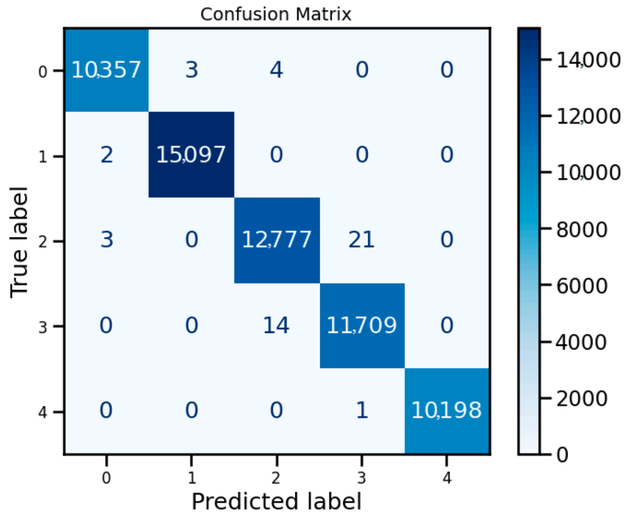

Figure 10. Confusion matrix.

4.3. Application: Explainable Artificial Intelligence

4.3.1. SHAP Global Values in Model Interpretation

SHAP is used to provide a detailed view of the contributions of each feature—recency, frequency, importance, and duration—to the predictions made by the Random Forest model and to particularize for each cluster. Decisions from the Random Forest model can be decomposed into the impact of individual features to each cluster, which helps provide both global and local interpretability.

This interpretability ensures transparency and confidence in the model's predictions, making it easier to align results with business strategies, Figures 11–15.

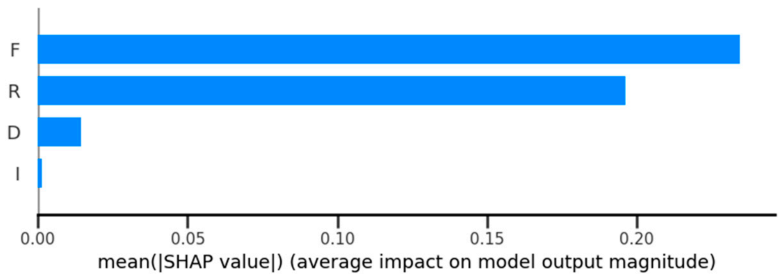

Figure 11. Feature importance for Cluster 0.

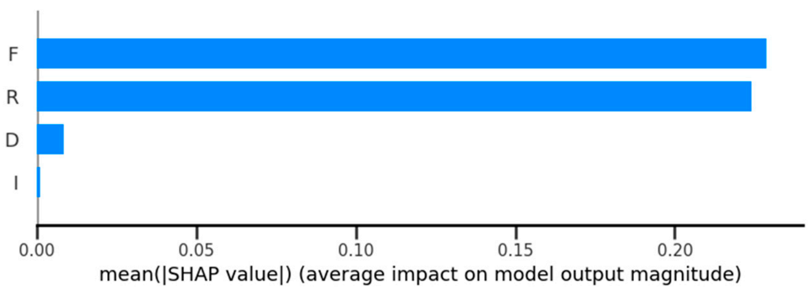

Figure 12. Feature importance for Cluster 1.

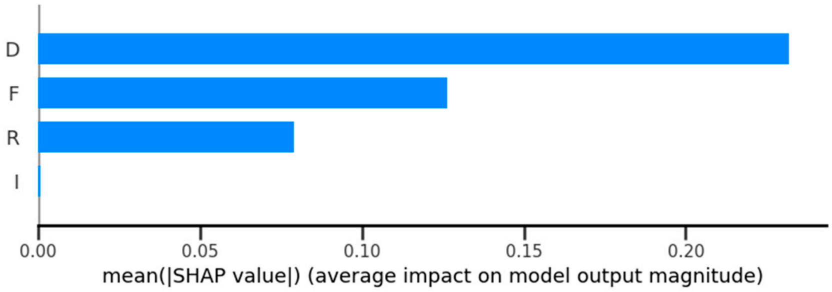

Figure 13. Feature importance for Cluster 2.

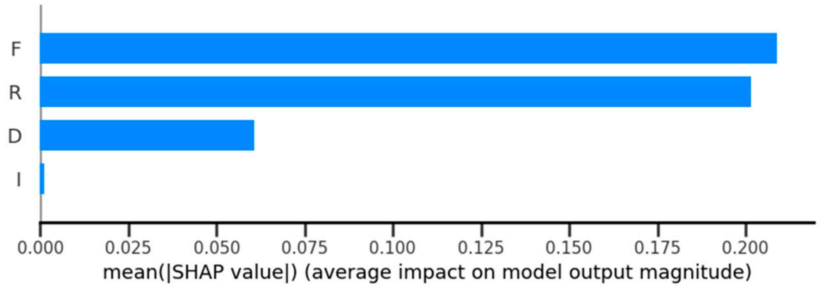

Figure 14. Feature importance for Cluster 3.

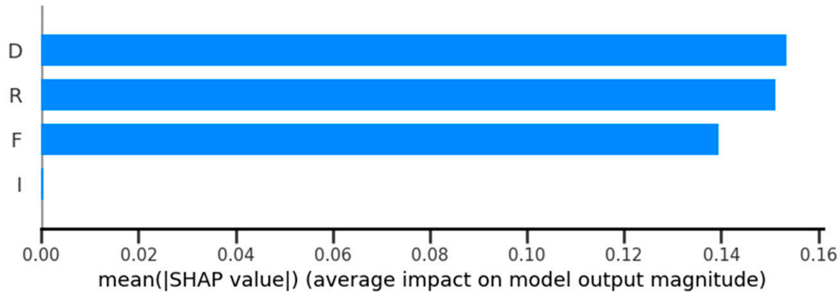

Figure 15. Feature importance for Cluster 4.

In Cluster 0, customers exhibit minimal engagement, with the SHAP analysis indicating a strong dependency on recency and frequency as the most impactful features. These clients tend to interact sporadically and with limited duration. The importance of recency highlights the time since their last interaction, while frequency underscores their rare engagement patterns. To address these characteristics, targeted incentives and strategies aimed at increasing interaction frequency and reducing the time between engagements could help foster stronger client connections and long-term loyalty.

In Cluster 1, customers demonstrate recent but brief and infrequent interactions, as evidenced by the SHAP analysis, which highlights recency and frequency as the dominant features. The high recency values indicate that these clients have interacted recently, while their low Frequency suggests occasional engagement. This cluster likely includes new or low-commitment customers. To strengthen their connection, tailored strategies aimed at increasing interaction frequency and fostering a more consistent relationship could be implemented, addressing their potential for increased engagement.

In Cluster 2, high-demand clients demonstrate infrequent yet resource-intensive interactions when active. The SHAP analysis highlights duration (D) as the most significant factor, followed by frequency (F) and recency (R), indicating that these clients require extended support during their active periods. This emphasizes the need for proactive management strategies, such as pre-scheduling regular check-ins or offering advanced support plans to ensure client satisfaction and optimize resource allocation.

In Cluster 3, the group comprises active clients who engage moderately frequently and maintain consistent, yet short, interactions. The SHAP analysis highlights balanced contributions from recency and frequency as significant factors in their cluster classification. This balance indicates that these clients are receiving adequate support and are likely satisfied with the current engagement strategies. It emphasizes the importance of maintaining steady interaction levels to preserve their satisfaction and long-term engagement.

In Cluster 4, the clients exhibit intensive engagement during active periods but have extended gaps between interactions. The SHAP analysis highlights high frequency when engaged and significant recency since their last interaction as defining features. These patterns suggest the need for targeted reactivation strategies to encourage consistent engagement and reduce the intervals between interactions. Maintaining regular contact could enhance their overall relationship and long-term commitment to the service.

4.3.2. LIME Local Analysis for Individual Predictions

LIME provides explanations by focusing on localized accuracy. For a given data point, it generates a set of similar, slightly modified instances and builds a simplified, interpretable surrogate model, such as linear regression, to approximate the complex model's behavior in the vicinity of that point. This approach is especially valuable for understanding the key factors influencing individual predictions, particularly when working with "black box" models like Random Forest, Figures 16–20.

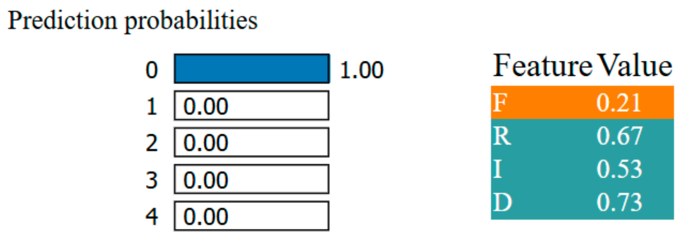

Figure 16. Local cluster prediction (Cluster = 0).

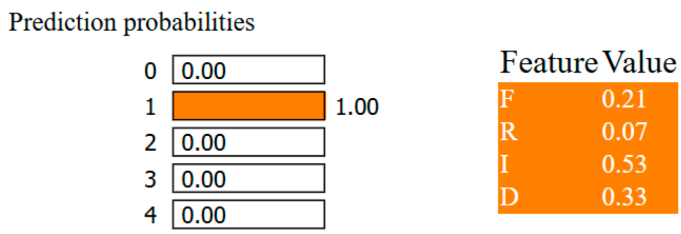

Figure 17. Local cluster prediction (Cluster = 1).

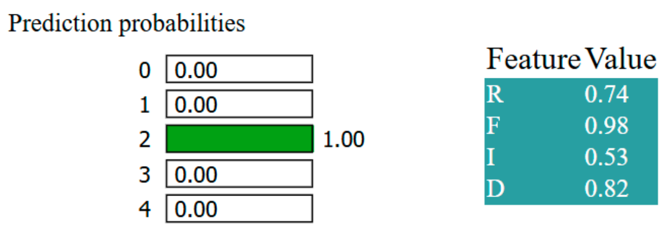

Figure 18. Local cluster prediction (Cluster = 2).

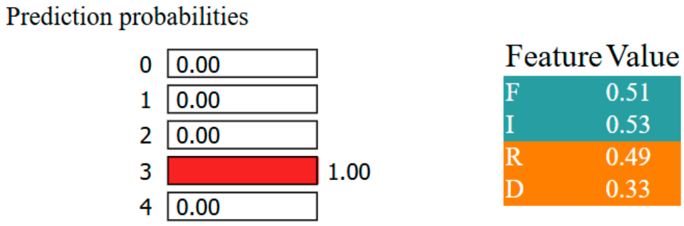

Figure 19. Local cluster prediction (Cluster = 3).

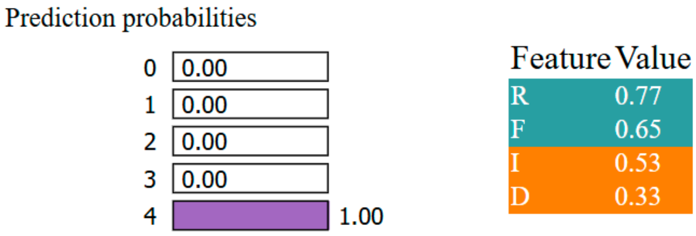

Figure 20. Local cluster prediction (Cluster = 4).

This result is consistent with the structure of the clusters, as the customer characteristics (low frequency and high recency) match those of Cluster 0. LIME confirms that the model bases its decision mainly on low frequency, which makes sense for membership to this cluster.

The customer has a low frequency and a low recency, which fits the profile of Cluster 1, which groups customers who have interacted recently, but infrequently. LIME confirms that the model relies mainly on the low frequency and recent interaction of the customer to assign it to this cluster, validating the consistency of the classification.

The customer has a high frequency and high duration of interactions, along with moderate recency, which matches the profile of the customers in this cluster. LIME confirms that the model relies primarily on high frequency and moderate recency to assign this customer to Cluster 2, which validates the consistency of the classification process and the accuracy of the segmentation.

Cluster 3 groups customers of moderate frequency and recency and of short and medium-sized interactions. The high classification certainty and the key factors highlighted by LIME confirm that the Random Forest model is considering the main characteristics of Cluster 3 to make this assignment, showing that the customer is representative of this group.

Cluster 4 groups customers of high recency (interactions occurred a long time ago), moderate frequency, and a low duration of interactions. The high classification certainty, supported by the insights from LIME, confirms that the Random Forest model effectively utilizes these distinctive characteristics of Cluster 4 to assign customers accurately.

4.4. Weighting Actions Using AHP

The Analytic Hierarchy Process (AHP) was employed to prioritize and weigh seven key criteria for each cluster: Recency of Interaction (RI), Frequency of Contact (FC), Customer Support Quality (CS), Customer Importance (CI), Interaction Duration (DI), Effective Resolution (ER), and Reactivation Incentives (IR). Using pairwise comparisons, the relative importance of each criterion was calculated, producing normalized weights for each cluster (Table 4).

Table 4. Weights per criterion for each cluster.

Cluster	RI	FC	CS	CI	DI	ER	IR
Cluster 0	0.446	0.244	0.106	0.075	0.129	0.000	0.000
Cluster 1	0.086	0.106	0.429	0.195	0.184	0.000	0.000
Cluster 2	0.000	0.183	0.105	0.188	0.432	0.093	0.000
Cluster 3	0.097	0.244	0.379	0.131	0.149	0.000	0.000
Cluster 4	0.429	0.106	0.086	0.184	0.000	0.000	0.195

1. Cluster 0 represents low-engagement clients, where the relevant criteria include Recency of Interaction (RI) at 0.446, Frequency of Contact (FC) at 0.244, and Interaction Duration (DI) at 0.075. For these clients, reactivation campaigns should be introduced to target those with low recent interactions, while the contact frequency can be increased through proactive engagement strategies. Additionally, support processes should be optimized to reduce interaction durations, thereby improving efficiency.
2. Cluster 1 includes high-value clients, with relevant criteria being Recency of Interaction (RI) at 0.086, Frequency of Contact (FC) at 0.106, Importance of the Client (CI) at 0.429, and Interaction Duration (DI) at 0.195. Actions for this cluster involve prioritizing resources for high-importance clients to ensure their needs are promptly addressed, optimizing workflows to reduce interaction durations without compromising service quality, and encouraging regular engagement through periodic communication.
3. Cluster 2 is characterized by high-demand clients, with key criteria such as Frequency of Contact (FC) at 0.183, Interaction Duration (DI) at 0.188, and Effective Resolution (ER) at 0.093. For these clients, specialized resources should be dedicated to managing frequent and long-duration interactions, focusing on effective issue resolutions to enhance satisfaction, and developing proactive follow-ups for consistent support.
4. Cluster 3 includes active and stable clients, where relevant criteria are Recency of Interaction (RI) at 0.097, Frequency of Contact (FC) at 0.244, Client Support Quality (CS) at 0.379, and Interaction Duration (DI) at 0.131. The recommended actions involve maintaining consistent engagement to retain these recently active clients, delivering high-quality support tailored to their needs, and streamlining support processes to ensure short and efficient interaction times.
5. Cluster 4 focuses on reactivation priority clients, with key criteria being Recency of Interaction (RI) at 0.429, Frequency of Contact (FC) at 0.106, and Reactivation Incentives (IR) at 0.195. Actions for this cluster include designing and implementing reactivation campaigns for clients with long gaps since their last interaction, enhancing contact frequency through targeted outreach efforts, and leveraging reactivation incentives to retain and re-engage these clients effectively.

5. Discussion

The findings of this study align with and extend the existing research on customer segmentation and support management in B2B environments. By integrating advanced techniques such as Fuzzy C-means, Random Forest, SHAP, LIME, and the AHP, this methodology provides a comprehensive framework to address the challenges of customer interaction variability, predictive accuracy, and transparency in decision making, while incorporating human–machine interaction into business decision-making processes. Unlike traditional B2B approaches, such as K-means clustering or rule-based systems, which often lack flexibility and interpretability, the proposed methodology offers robust and transparent decision-making capabilities. This integration enables flexible customer segmentation, explainable insights into model predictions, and the objective prioritization of actions based on weighted criteria. Although the framework may require greater computational resources and domain expertise, its ability to produce clear, interpretable, and reliable results positions it as a robust alternative to conventional methods, offering significant advantages in improving strategic decision-making processes in dynamic B2B environments.

1. The interpretation of results in context.

The segmentation process, using Fuzzy C-means, revealed clusters of customers with distinct interaction patterns and support needs. This reinforces findings from previous studies, which suggest that fuzzy clustering approaches are particularly effective in capturing the overlapping and evolving behaviors often observed in customer datasets. In our study, the fuzzy membership allowed for a nuanced understanding of customer profiles, supporting adaptive strategies for engagement and retention.

Random Forest was used after determining the cluster membership of each customer based on their interactions, using the parameters of recency, frequency, importance, and duration. Its purpose was to evaluate the accuracy of the unsupervised classification performed by Fuzzy C-means. This approach allowed for an in-depth understanding of how well the clustering algorithm segmented customers, providing validation and ensuring that the identified clusters were meaningful and robust for further analyses and decision making.

The integration of SHAP and LIME enhanced the interpretability of the predictive model, addressing a gap in many machine learning applications. Previous research has highlighted the "black box" nature of AI models as a barrier to trust and useability. Our findings show that explainable AI techniques can provide actionable insights by elucidating the importance of features like recency, frequency, and duration in customer behavior. This transparency fosters confidence among decision-makers and aligns with broader calls for ethical and accountable AI in business applications.

The use of the AHP to prioritize actions within each customer cluster offers a structured and objective approach to decision making. Previous studies have demonstrated the AHP's effectiveness in multi-criteria evaluations across diverse domains, and our findings further validate its utility in the context of customer support. By weighing criteria specific to each cluster, the methodology ensures that support strategies are tailored to customer needs, maximizing their efficiency and impact. Additionally, the AHP provides a clear and transparent decision-making framework for each cluster, incorporating XAI interpretability and fostering human interaction in the decision-making process. This integration ensures that decisions are not only data-driven but also comprehensible and actionable for human stakeholders.

2. Broad implications.

The implications of this study extend beyond customer support management. The methodology provides a scalable framework for decision making in other B2B contexts, such as marketing strategies, supply chain management, and employee resource allocation. By combining segmentation, prediction, explainability, and prioritization, businesses can adopt a more proactive, data-driven, and transparent approach to managing complex interactions.

Additionally, the results highlight the potential of integrating machine learning with explainability and multi-criteria decision making to bridge the gap between technical accuracy and actionable insights. This is especially relevant in industries where stakeholder trust and interpretability are paramount.

3. Future directions.
   While the methodology demonstrated promising results, future research could explore several avenues:
   - Real-time applications: incorporating real-time data processing to address dynamic changes in customer behavior.

- External data integration: enriching the model with external factors like market trends or customer satisfaction metrics to provide a more comprehensive analysis.
- Alternative models: experimenting with different clustering, prediction, and decision-making techniques to improve performance and adaptability.
- Scalability: developing methods to handle larger datasets efficiently without compromising accuracy or interpretability.
- Cross-domain applications: adapting the methodology to other domains beyond customer support to evaluate its generalizability and broader business impact.

4. Limitations.
   - Computational complexity: although techniques such as Fuzzy C-means, Random Forest, and XAI (SHAP and LIME) are widely used and effective, they can be computationally intensive for extremely large data sets, which may require additional resources.
   - Adaptation to a specific domain: although the methodology was successfully applied in a B2B technology company, adapting it to other industries or business models may require adjustments to account for unique data characteristics and interaction patterns.
   - Dependence on human decision making: the AHP integration relies on the subjective weighting of criteria, which can introduce a bias if not carefully validated by industry experts.

6. Conclusions

This study presents a robust and explainable methodology for customer service management in a B2B environment, combining advanced machine learning techniques, explainability frameworks, and decision-making tools. The results validate the working hypotheses and contribute to the growing body of research on explainable and actionable AI in business contexts. By integrating disciplines such as algorithm interpretability and the AHP, the methodology ensures that final business decisions are a fusion of predictive models and human judgment. By addressing the challenges of segmentation, prediction, and prioritization with a transparent, customer-centric approach, this framework enhances business outcomes and fosters long-term customer relationships. Future research will focus on extending these capabilities to other applications, refining their adaptability, and addressing the evolving dynamics of business environments.

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