



A Machine Learning-Based Approach to Improving Customer Experience and Service Personalization: Customer Segmentation and Decision Rule Extraction

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Received: 2026-04-01

Revised: 2026-08-24

Accepted: 2026-08-31

Initial Publish: 2026-09-30

Final Publish: 2027-01-01

Abstract

This study aimed to develop a machine learning-based framework for improving customer experience and service personalization through multidimensional customer segmentation and extraction of interpretable decision rules. This applied, quantitative, cross-sectional study was conducted among 1,248 customers in Tehran, Iran. Demographic, transactional, behavioral, and customer-experience data were integrated into a unified analytical dataset. Customer behavior was assessed using recency, frequency, monetary value, service-use breadth, digital interaction, promotional responsiveness, complaint behavior, and customer-service contact indicators, while customer experience, perceived personalization, satisfaction, loyalty intention, and recommendation intention were measured using structured Likert-scale items. After preprocessing, standardization, and data-quality assessment, K-means clustering was applied to identify homogeneous customer segments. Candidate cluster solutions were evaluated using the silhouette coefficient, Calinski-Harabasz index, Davies-Bouldin index, and within-cluster sum of squares. Decision Tree, Random Forest, and Gradient Boosting algorithms were subsequently used to predict cluster membership, and interpretable rules were extracted from the optimized Decision Tree. The four-cluster solution demonstrated the strongest internal validity, with a silhouette coefficient of 0.561, Calinski-Harabasz index of 668.45, and Davies-Bouldin index of 0.714. Significant differences were observed among the four clusters across all principal transactional, behavioral, and customer-experience variables (all $p < 0.001$). Random Forest achieved the highest predictive accuracy (0.928), followed by Gradient Boosting (0.919) and Decision Tree (0.887). Macro F1-scores were 0.925, 0.915, and 0.882, respectively. Purchase recency, monetary value, purchase frequency, customer experience, perceived personalization, digital interaction, promotional responsiveness, and complaint behavior emerged as the most influential predictors of segment membership. Integrating unsupervised clustering with supervised machine learning and interpretable decision-rule extraction provides an effective framework for identifying heterogeneous customer groups and supporting targeted, data-driven personalization strategies.

Keywords: Machine Learning, Customer Segmentation, Customer Experience, Service Personalization, K-Means Clustering, Decision Tree, Predictive Analytics, Customer Relationship Management

How to cite this article:

Maleki, M., Sanaei, M., Banihashem, S. Y., & Heydari, S. (2027). A Machine Learning-Based Approach to Improving Customer Experience and Service Personalization: Customer Segmentation and Decision Rule Extraction. Management Strategies and Engineering Sciences, 9(1), 1-19.

1. Introduction

The rapid expansion of digital technologies, artificial intelligence, and data-intensive business models has fundamentally transformed the way organizations understand, interact with, and create value for customers. Contemporary firms increasingly operate in environments

where large volumes of transactional, behavioral, demographic, and interaction data are continuously generated through websites, mobile applications, customer relationship management systems, electronic payments, social media, loyalty programs, and digital service platforms. These data have created new opportunities for



organizations to move beyond broad market classifications and develop more precise representations of customer needs, preferences, behaviors, and value patterns. In this context, machine learning has emerged as an important analytical approach for converting large and complex customer datasets into actionable knowledge that can support customer segmentation, targeting, personalization, retention, and strategic decision-making. Compared with conventional segmentation approaches that frequently depend on predefined demographic categories or managerial assumptions, machine learning methods can identify latent structures and behavioral patterns directly from multidimensional customer data and thereby provide more adaptive and empirically grounded customer classifications [1-4].

Customer segmentation is a central component of customer relationship management because customers differ substantially in purchasing behavior, profitability, engagement, service expectations, price sensitivity, loyalty, digital interaction, and likelihood of responding to marketing activities. Treating all customers as a homogeneous market can therefore reduce the relevance of communication, increase marketing costs, and limit the organization's ability to allocate resources toward customers with different needs and value profiles. Machine learning-based segmentation addresses this problem by organizing customers into internally similar and externally distinct groups on the basis of multiple observable characteristics. Clustering algorithms are particularly useful in this regard because they do not require predefined segment labels and can detect meaningful structures within customer data. Recent evidence has demonstrated the applicability of machine learning clustering to customer segmentation across retail, banking, e-commerce, and other service contexts, with the resulting segments often providing a stronger basis for differentiated marketing and service strategies than traditional classification systems [2, 5-7].

Among the most established approaches to behavioral customer segmentation is the Recency-Frequency-Monetary framework. RFM analysis summarizes customer behavior according to the time elapsed since the most recent transaction, the frequency with which transactions occur, and the total monetary value generated by the customer. These three indicators provide a parsimonious representation of customer engagement and economic contribution and have been widely incorporated into data-driven segmentation models. Customers with recent, frequent, and high-value transactions may represent valuable

and loyal segments, whereas customers with prolonged inactivity, low transaction frequency, and limited monetary contribution may require reactivation or retention strategies. Research has shown that RFM-based segmentation can provide meaningful information for customer classification and repurchase behavior, while the integration of RFM variables with machine learning techniques can further improve the detection of customer heterogeneity [7, 8]. Weighted and modified RFM approaches have also been combined with K-means clustering to improve the quality of e-commerce customer segmentation by accounting for differences in the relative importance of behavioral indicators [9].

Although RFM indicators are valuable, contemporary customer behavior is increasingly multidimensional and cannot be adequately represented by purchasing variables alone. Digital interactions, promotional responsiveness, complaint behavior, service-channel use, product-category breadth, satisfaction, perceived personalization, and loyalty intentions may all contribute to the formation of meaningful customer groups. For example, two customers with similar transaction frequency and monetary value may differ considerably in digital engagement, responsiveness to recommendations, or service dissatisfaction. Consequently, more recent customer analytics research has moved toward integrated segmentation frameworks combining transactional information with demographic, firmographic, relational, behavioral, and digital variables. In banking, the integration of electronic transaction data and demographic information has demonstrated the importance of combining behavioral and customer-profile characteristics when constructing actionable customer groups [6]. Similarly, B2B segmentation research has extended conventional customer profiling through the integration of firmographic information, RFM indicators, and graph-based representations, illustrating the value of combining multiple data structures to represent complex customer relationships [10]. Social media analytics further expands this perspective by enabling organizations to incorporate digital engagement patterns and online customer signals into target-segmentation processes [11].

The selection of an appropriate clustering algorithm is another important methodological consideration. K-means remains one of the most commonly applied approaches because of its computational efficiency, interpretability, and suitability for relatively large customer datasets. It assigns observations to clusters by minimizing within-cluster variance and maximizing similarity among members of the

same group. Studies using K-means have demonstrated its practical utility for identifying distinguishable customer segments that can be translated into differentiated marketing strategies [2, 3]. Nevertheless, segmentation quality can vary depending on cluster structure, initialization, scale, and the assumptions of the algorithm. Comparative evaluation using measures such as the silhouette coefficient, Calinski-Harabasz index, and Davies-Bouldin index is therefore important for selecting an empirically defensible number of clusters and assessing the quality of alternative solutions. Comparative investigations of clustering algorithms emphasize that no single segmentation configuration should be accepted solely on the basis of visual inspection or managerial preference and that internal validation metrics should be used to assess compactness and separation objectively [12]. Alternative density-based methods such as improved DBSCAN algorithms have also been proposed to address customer data characterized by irregular cluster shapes and varying density, highlighting the continuing development of segmentation methodologies [5].

A particularly important implication of customer segmentation concerns service personalization. Personalization refers to the adaptation of services, recommendations, offers, communications, and interactions according to the characteristics, preferences, and behavioral history of individual customers or customer segments. Artificial intelligence and machine learning have substantially expanded the capacity of firms to deliver personalization at scale by identifying patterns that would be difficult to detect through manual analysis. In e-commerce, predictive analytics can be used to anticipate customer interests and tailor service offerings, thereby increasing the relevance and timeliness of customer interactions [13]. AI-enhanced personalization has similarly been linked to improvements in customer experience by enabling organizations to provide more context-sensitive, relevant, and responsive services [14]. From a marketing perspective, AI-driven personalization can support the design of differentiated campaigns, individualized recommendations, adaptive promotional messages, and customized customer journeys rather than uniform communications directed toward heterogeneous populations [15].

The relationship between personalization and customer loyalty is particularly important because personalized interactions may influence customers' perceptions that an organization understands their preferences and responds to their needs. When personalization is relevant and appropriately implemented, it can enhance perceived value,

satisfaction, engagement, and relational continuity. Meta-analytic evidence in e-commerce indicates that AI-driven personalization can contribute meaningfully to customer loyalty, suggesting that personalization should be viewed not only as a short-term promotional mechanism but also as a relationship-building strategy [16]. However, personalization effectiveness depends on the quality of the underlying customer representation. If customers are inaccurately categorized or if recommendations are generated from incomplete behavioral information, personalized offers may be irrelevant and may even reduce customer trust. Therefore, high-quality personalization requires analytical procedures capable of distinguishing customers according to meaningful behavioral, experiential, and relational characteristics rather than relying exclusively on broad demographic groups.

Recommendation systems represent one of the most visible applications of machine learning-based personalization. By analyzing previous behavior, preferences, purchase history, and interactions, recommendation algorithms can identify items, services, or content that are likely to be relevant to individual users. Such systems can increase the efficiency of customer decision-making while simultaneously helping organizations improve engagement and conversion. Recent work has emphasized the role of machine learning algorithms in generating personalized product recommendations and content based on customer behavior, preferences, and purchasing history [17]. Similar principles have been applied in hospitality and tourism, where deep learning and big data have been used to develop personalized restaurant recommendation models supporting customer decision-making [18]. These developments illustrate a broader shift from static customer classification toward intelligent systems in which segmentation, prediction, and recommendation interact to support increasingly individualized service provision.

Digital banking provides another important example of the growing role of AI-driven personalization. Financial institutions generate extensive records of transactions, digital activity, product usage, and service interactions, creating an environment in which customer behavior analytics can support customized financial communication and engagement. AI-powered personalization in digital banking has been examined as a mechanism for understanding behavioral patterns, improving engagement, and delivering services that are more closely aligned with customer needs [19]. Customer segmentation in electronic banking has likewise demonstrated the utility of combining

transaction histories with demographic information to identify customer groups that differ in service use and potential value [6]. These findings are relevant beyond banking because many service industries now generate similarly rich digital traces that can support machine learning-based personalization.

Personalized promotions represent another operational domain in which segmentation can create direct business value. Rather than distributing identical coupons or incentives to all customers, organizations can use segmentation models to match promotions with customer characteristics and behavioral likelihoods. Two-dimensional segmentation approaches for digital coupon issuance have demonstrated how customer classifications can be connected to differentiated promotional strategies [20]. Such approaches are particularly relevant in environments where repeated generic promotions may create unnecessary costs or reduce customer responsiveness. By identifying customers who are highly promotion-responsive, organizations can concentrate incentives where behavioral effects are more probable, while customers who are already highly loyal may instead receive recognition-based or relationship-focused benefits. In contrast, customers displaying low engagement or dissatisfaction may require service-recovery interventions before additional promotional activity is likely to be effective.

Customer experience is therefore closely interconnected with segmentation and personalization. Customer experience encompasses the customer's cognitive, affective, and behavioral responses across interactions with an organization and is shaped by service quality, accessibility, relevance, responsiveness, convenience, problem resolution, and perceived understanding of individual needs. AI-enhanced personalization can improve experience when algorithms reduce information overload, increase service relevance, and facilitate smoother customer journeys [14]. AI-driven personalized marketing can similarly improve perceived relevance and engagement by aligning content and communication with customer interests [15]. However, personalization should not be interpreted as a purely promotional process. Complaint handling, service recovery, retention management, and communication frequency can also be personalized according to customer segment characteristics. Customers with frequent complaints and declining engagement may benefit more from proactive problem resolution than from additional product recommendations, whereas highly engaged customers may

respond positively to cross-selling, loyalty rewards, and preferential services.

Churn prediction provides an important illustration of the need to connect segmentation with predictive decision-making. Customer churn is rarely determined by a single factor and often reflects combinations of declining activity, dissatisfaction, competitive alternatives, unresolved problems, and changing service needs. Integrated frameworks combining churn prediction and customer segmentation have shown that segmentation can improve the interpretation and practical application of customer retention analytics [21]. Data mining approaches have also been used to construct prediction models for customer segmentation and churn classification in e-commerce environments, demonstrating how unsupervised and supervised methods can complement one another [22]. Rather than treating segmentation as the final analytical outcome, these approaches position customer segments as an intermediate layer that can inform subsequent classification, prediction, and intervention.

This integration of unsupervised and supervised learning is especially important from a managerial perspective. Clustering can reveal meaningful customer structures, but cluster membership alone may be difficult to operationalize if the organization cannot explain why a particular customer belongs to a specific group. Many advanced machine learning models achieve strong predictive accuracy but offer limited interpretability, creating challenges for managers who require transparent rules for customer targeting and service allocation. Decision-tree methods provide an important solution because they transform multivariate patterns into hierarchical threshold-based rules. For example, a decision rule may indicate that customers with recent purchases, high transaction frequency, and high monetary value are likely to belong to a high-value segment, whereas customers with prolonged inactivity, low experience scores, and unresolved complaints are likely to belong to an at-risk group. Such rules are readily interpretable and can be incorporated into customer relationship management systems without requiring users to understand complex mathematical models.

The extraction of decision rules also addresses an important gap between analytical segmentation and actionable personalization. Studies have increasingly demonstrated the effectiveness of machine learning for identifying customer groups, but the practical value of segmentation depends on whether resulting classifications can guide concrete managerial decisions. A segmentation

framework developed to improve marketing strategies using machine learning highlights the importance of linking computational clustering with strategically meaningful customer profiles [1]. Similarly, data mining techniques for customer segmentation can enhance targeted marketing when the patterns identified are translated into usable targeting criteria [4]. The ability to generate interpretable rules from customer clusters can therefore strengthen the transition from descriptive analytics to prescriptive customer management by specifying which combinations of characteristics should trigger particular service strategies.

Another methodological issue concerns balancing predictive performance and interpretability. Ensemble algorithms such as Random Forest and Gradient Boosting frequently outperform single decision trees because they aggregate multiple weak or moderate learners and capture complex nonlinear interactions. However, their internal decision structures are less transparent. For customer relationship management, where operational decisions may need to be explained to marketing managers, service teams, or organizational decision-makers, a slightly less accurate but highly interpretable model can sometimes provide greater practical utility. A useful framework is therefore to employ ensemble models as predictive benchmarks while using an optimized decision tree to extract human-readable rules. This approach allows researchers to determine whether interpretability results in a substantial loss of predictive accuracy and simultaneously provides feature-importance information that can be used to identify the most influential customer characteristics.

Despite the growing literature on AI-enabled customer segmentation and personalization, several limitations remain in existing research. Many studies focus primarily on transaction-based clustering, while others concentrate on recommendation systems, churn prediction, social media analytics, or personalization as separate analytical tasks. Fewer studies integrate customer segmentation, customer-experience indicators, predictive classification, and decision-rule extraction within a single framework. In addition, customer value is often represented predominantly by RFM variables without sufficient integration of complaint history, digital engagement, perceived personalization, satisfaction, and loyalty-related attitudes. Yet these variables may be essential for distinguishing customers who have similar economic profiles but substantially different relational or experiential conditions. A customer who temporarily reduces purchasing activity but remains highly satisfied may require a different intervention

from a customer with similarly reduced activity combined with repeated unresolved complaints. Accordingly, multidimensional customer analytics may produce more strategically useful segmentation than purely transactional approaches.

The increasing use of customer data also reinforces the importance of using models that are sufficiently transparent for responsible organizational decision-making. As AI-based personalization becomes more deeply embedded in customer-facing systems, organizations must be able to understand the criteria underlying customer classification and differentiated treatment. Interpretable decision rules can reduce reliance on opaque algorithmic outputs and facilitate managerial evaluation of whether a segmentation strategy is coherent, commercially meaningful, and consistent with customer experience objectives. At the same time, the combination of machine learning and customer analytics can help organizations allocate resources more efficiently by distinguishing between customers requiring retention, cross-selling, service recovery, promotional engagement, or loyalty recognition. Consequently, the value of machine learning lies not merely in achieving accurate classification but in producing knowledge that can be translated into customer-specific actions.

Taken together, previous research demonstrates that customer segmentation, RFM analysis, machine learning clustering, predictive analytics, AI-driven personalization, recommendation systems, and churn classification each contribute important components to contemporary customer management [8, 9, 21, 22]. Recent developments further indicate that customer segmentation can be strengthened through improved clustering algorithms, multidimensional behavioral data, digital interaction indicators, and systematic validation of cluster quality [5, 10-12]. At the same time, advances in predictive analytics, recommendation systems, and AI-driven personalization demonstrate that customer data can increasingly support individualized and context-sensitive service experiences [13, 14, 17, 19]. Connecting these analytical streams through an interpretable machine learning framework can provide organizations with both a robust representation of customer heterogeneity and explicit rules for differentiated service delivery.

Accordingly, the aim of this study was to develop a machine learning-based framework for improving customer experience and service personalization by identifying meaningful customer segments from integrated transactional, behavioral, demographic, and experience-related data and extracting interpretable decision rules for

segment classification and differentiated customer-management strategies.

2. Methodology

This study employed an applied, quantitative, cross-sectional research design with a data-driven machine learning approach to investigate customer segmentation and extract interpretable decision rules for improving customer experience and personalizing services. The study population consisted of customers who had used the products or services of selected service-oriented businesses operating in Tehran, Iran, during 2025. The research framework was designed to integrate behavioral, transactional, demographic, and experience-related customer information so that relatively homogeneous customer groups could be identified and subsequently translated into actionable decision rules for customer relationship management and personalized service delivery. Because machine learning techniques generally require a sufficiently large number of observations to identify stable patterns and reduce sensitivity to random variation, the study included **1,248 customers**. Participants were selected from customers with an active service record during the study period and with sufficient information available for the variables included in the analytical model. Records containing substantial missing information, duplicated customer identifiers, inconsistent transactional data, or insufficient interaction history were excluded before the final analytical dataset was constructed. Customers were drawn from different geographical districts of Tehran in order to achieve greater heterogeneity in demographic characteristics, purchasing patterns, levels of engagement, and service-use behaviors. The unit of analysis was the individual customer, and each observation represented an integrated customer profile developed by combining demographic characteristics with purchasing and interaction indicators and customer-experience measures. Participation in the survey component of the study was voluntary, and respondents were informed about the research purpose and the confidential treatment of their information. Personal identifiers were removed before analysis, and each customer was assigned an anonymous numerical code. Customer records were analyzed only in aggregated form, and no personally identifiable information was incorporated into the machine learning models. The study was conducted in accordance with the principles of confidentiality, voluntary participation, and responsible use of customer data.

Data were collected using an integrated customer information framework consisting of a researcher-developed customer profile form, transactional and behavioral indicators, and a structured customer experience and service personalization questionnaire. The customer profile form was used to obtain basic demographic characteristics, including age, gender, educational level, employment status, and general socioeconomic indicators, as well as information concerning the duration and frequency of the customer's relationship with the service provider. Transactional data were extracted from available customer relationship management and service records after anonymization. These variables included purchase frequency, recency of the most recent purchase or service transaction, total monetary value of transactions, average transaction value, number of services or product categories used, frequency of customer-service contacts, number of complaints, number of successful complaint resolutions, use of promotional offers, and response to previous marketing or service recommendations. The Recency-Frequency-Monetary framework was incorporated into the measurement architecture because these dimensions provide a concise representation of customer activity and value. Recency was operationalized as the number of days between the customer's most recent recorded transaction and the reference date of data extraction, frequency represented the number of recorded transactions within the observation period, and monetary value represented the cumulative financial value of customer transactions during the same period. Additional behavioral indicators included digital channel utilization, frequency of application or website interaction when available, service renewal behavior, customer inactivity periods, and cross-service usage. These variables were included to provide a multidimensional representation of customer behavior beyond conventional transaction-based segmentation.

Customer experience was assessed through a structured questionnaire developed on the basis of commonly used dimensions of customer experience, service quality, perceived value, satisfaction, loyalty intention, and perceived personalization. The questionnaire examined customers' perceptions of service accessibility, responsiveness, reliability, ease of interaction, perceived usefulness of recommendations, relevance of service offers, satisfaction with previous interactions, perceived understanding of individual needs, willingness to continue using the service, and willingness to recommend the service provider to others. Items were rated on a five-point Likert

scale ranging from 1, representing strongly disagree or very low, to 5, representing strongly agree or very high. Higher scores indicated a more favorable customer experience and stronger perceptions of service personalization. The initial item pool was reviewed by specialists in marketing management, customer relationship management, data analytics, and information systems to evaluate content relevance, clarity, and correspondence with the conceptual dimensions of the study. Minor modifications were made to improve item wording and eliminate conceptual redundancy before the final administration. Internal consistency was subsequently evaluated using Cronbach's alpha and composite reliability, with values of 0.70 or greater regarded as acceptable. Construct validity was assessed through examination of inter-item relationships and the factor structure of the questionnaire before the customer-experience variables were incorporated into the machine learning dataset. The final analytical database was therefore constructed by merging standardized survey responses with anonymized transactional and behavioral records through unique study codes. Prior to modeling, variables were inspected for impossible values, extreme observations, missingness, duplicated records, and inconsistencies between data sources. Missing values occurring in a small proportion of observations were imputed using appropriate numerical or categorical procedures, whereas records with extensive missing information were excluded. Continuous variables with markedly different measurement scales were standardized to prevent variables with large numerical ranges from disproportionately influencing distance-based machine learning algorithms. Categorical variables required for predictive modeling were transformed through appropriate numerical encoding procedures.

Data analysis was performed through a multistage machine learning procedure involving data preprocessing, exploratory analysis, customer segmentation, cluster validation, customer-profile interpretation, supervised classification, and extraction of decision rules. Initial descriptive analyses were conducted to examine the distributions, central tendency, dispersion, missingness, and potential outliers of the demographic, behavioral, transactional, and customer-experience variables. Correlation analysis was used to identify highly redundant quantitative predictors, while variables showing insufficient variability or substantial data-quality problems were removed before model development. Continuous variables used for distance-based segmentation were normalized using standard scaling so that each variable contributed

proportionately to the calculation of similarity between customers. Where necessary, highly skewed transactional variables were transformed to reduce the effect of extreme values. The resulting processed dataset was then used for unsupervised customer segmentation.

Customer segmentation was primarily performed using the K-means clustering algorithm because of its computational efficiency, interpretability, and suitability for identifying groups of customers with similar multivariate behavioral profiles in relatively large datasets. To reduce dependence on arbitrary initialization, the algorithm was executed with multiple random centroid initializations, and the solution with the lowest within-cluster sum of squares was retained. Several candidate solutions with different numbers of clusters were estimated rather than specifying the number of customer segments in advance. The optimal number of clusters was determined by simultaneously examining the elbow criterion, average silhouette coefficient, Calinski-Harabasz index, and Davies-Bouldin index. A preferable segmentation solution was defined as one demonstrating comparatively high between-cluster separation, low within-cluster heterogeneity, a higher silhouette and Calinski-Harabasz score, and a lower Davies-Bouldin index while also producing clusters that were sufficiently large and managerially interpretable. Hierarchical agglomerative clustering was additionally used as a robustness procedure to investigate whether the general grouping structure was consistent across alternative clustering approaches. The final clusters were profiled by comparing demographic characteristics, RFM indicators, interaction patterns, customer-experience scores, loyalty indicators, complaint behavior, and responsiveness to personalized services. Cluster labels were assigned only after statistical profiles had been examined so that segment names reflected empirical behavioral characteristics rather than predetermined marketing categories.

After completion of the unsupervised segmentation stage, cluster membership was treated as the target variable in a supervised learning stage designed to identify the combinations of observable customer characteristics that most efficiently predicted segment assignment. Decision tree classification was selected as the principal rule-extraction technique because it produces transparent hierarchical decision structures that can be directly converted into operational customer-management rules. The dataset was randomly divided into training and testing subsets using a stratified procedure to preserve the relative proportion of customers belonging to each identified

segment, with 80% of observations allocated to the training set and 20% to the testing set. Tree complexity was controlled through restrictions on maximum tree depth, minimum observations required for internal nodes and terminal leaves, and cost-complexity pruning in order to reduce overfitting. Hyperparameters were optimized using cross-validation within the training dataset, and the final model was subsequently evaluated on the independent testing sample. Classification performance was assessed using overall accuracy, precision, recall, F1-score, and the confusion matrix. Because cluster sizes could differ, macro-averaged performance indices were considered alongside overall accuracy to prevent large customer segments from disproportionately determining model evaluation.

To assess whether more complex machine learning methods could improve predictive discrimination, the performance of the interpretable decision tree was compared with ensemble classifiers, particularly Random Forest and Gradient Boosting models. These algorithms were used primarily as benchmark models rather than as the final rule-generation mechanism. Model comparison made it possible to determine whether substantial predictive performance was sacrificed in exchange for the greater interpretability of the decision tree. Variable importance measures derived from the ensemble models were also examined to identify which behavioral and experience variables contributed most strongly to differentiation among customer segments. The consistency between tree-based decision rules and feature-importance rankings was considered evidence that the extracted rules represented meaningful patterns in the customer database rather than unstable sample-specific relationships.

The final decision rules were extracted from the terminal paths of the optimized decision tree. Each rule consisted of a sequence of threshold-based conditions relating variables such as purchase recency, purchase frequency, monetary value, customer-experience score, interaction frequency, promotional responsiveness, complaint history, and service usage to membership in a particular customer segment. Rules with very small customer coverage were disregarded in favor of rules that demonstrated adequate support and classification precision. The extracted rules were interpreted in terms of their potential application to personalized service strategies. For example, customers with high transaction frequency, high monetary value, and favorable customer-experience scores could be distinguished from customers characterized by declining interaction, long purchase recency, repeated complaints, or low response to existing

service recommendations. This analytical structure enabled customer segments to be transformed from descriptive clusters into operational decision criteria that could support differentiated communication, recommendation, retention, service-recovery, and loyalty strategies. All statistical and machine learning analyses were conducted using Python and its relevant data analysis and machine learning libraries. Statistical tests were interpreted at a significance level of 0.05 where inferential procedures were applicable, while the selection and evaluation of machine learning models were primarily based on predictive performance, internal validation metrics, generalizability to unseen observations, and practical interpretability.

3. Findings and Results

The final analytical sample consisted of 1,248 customers from Tehran whose demographic, transactional, behavioral, and customer-experience information satisfied the predefined data-quality criteria. Of the participants, 645 customers (51.7%) were women and 603 (48.3%) were men. The mean age of the customers was 37.84 years ($SD = 9.62$), with an age range of 18 to 67 years. Regarding age distribution, 238 participants (19.1%) were aged 18–29 years, 447 (35.8%) were aged 30–39 years, 354 (28.4%) were aged 40–49 years, and 209 (16.7%) were 50 years of age or older. In terms of educational attainment, 197 customers (15.8%) had a high-school diploma or lower level of education, 142 (11.4%) held an associate degree, 548 (43.9%) held a bachelor's degree, 291 (23.3%) held a master's degree, and 70 (5.6%) held a doctoral or equivalent professional degree. With respect to occupational status, 486 participants (38.9%) were employed in private-sector organizations, 274 (22.0%) were employed in government or public-sector organizations, 205 (16.4%) were self-employed or business owners, 101 (8.1%) were university students, 73 (5.8%) were university professors or academic personnel, 57 (4.6%) were homemakers, and 52 (4.2%) reported other occupational statuses. The average duration of the customers' relationship with the service provider was 3.71 years ($SD = 2.18$), indicating that the sample included both relatively recent customers and individuals with an established history of interactions with the organization. Overall, the demographic composition demonstrated sufficient diversity in terms of age, gender, education, occupation, and relationship duration to support the identification of heterogeneous customer segments.

Table 1. Descriptive Statistics for the Principal Customer Behavioral, Transactional, and Experience Variables

Variable	Mean	SD	Minimum	Maximum
Purchase recency, days	47.63	38.14	1.00	219.00
Purchase frequency during observation period	11.84	7.16	1.00	39.00
Total monetary value, million IRR	46.28	31.74	2.40	187.60
Average transaction value, million IRR	4.38	2.17	0.70	14.90
Number of service/product categories used	3.27	1.41	1.00	8.00
Customer-service contact frequency	4.74	3.26	0.00	18.00
Number of complaints	1.38	1.57	0.00	9.00
Complaint resolution rate, %	74.62	25.48	0.00	100.00
Promotional response rate, %	39.74	23.61	0.00	100.00
Monthly digital interaction frequency	13.82	8.43	0.00	46.00
Customer experience score	3.68	0.71	1.43	5.00
Perceived service personalization score	3.54	0.78	1.20	5.00
Customer satisfaction score	3.73	0.74	1.40	5.00
Loyalty intention score	3.61	0.81	1.00	5.00
Recommendation intention score	3.58	0.86	1.00	5.00

As presented in Table 1, considerable variability was observed across the principal transactional, behavioral, and attitudinal variables, providing an appropriate empirical basis for customer segmentation. The mean purchase recency was 47.63 days, although the relatively large standard deviation of 38.14 days and the observed range of 1 to 219 days indicated substantial differences in the time elapsed since customers' most recent transactions. Customers completed an average of 11.84 transactions during the observation period, with individual transaction frequencies ranging from 1 to 39. The average total monetary value was 46.28 million IRR, with a standard deviation of 31.74 million IRR, suggesting pronounced heterogeneity in customer economic value. A similar pattern was evident for average transaction value and the number of service categories used. Customers used an average of 3.27 service or product categories, indicating the presence of both narrowly engaged customers and customers with substantially broader cross-service relationships. The mean number of customer-service contacts was 4.74, whereas the

mean number of complaints was 1.38. The average complaint resolution rate was 74.62%, suggesting that most reported problems were resolved, although the broad standard deviation demonstrated considerable variation in service-recovery outcomes across customers. Promotional responsiveness also differed markedly, with a mean response rate of 39.74%. Customers recorded an average of 13.82 digital interactions per month, but the distribution ranged from customers with no recorded digital activity to highly digitally engaged customers with 46 monthly interactions. Customer experience, perceived personalization, satisfaction, loyalty intention, and recommendation intention were generally above the midpoint of the five-point response scale, with mean values ranging from 3.54 to 3.73. Nevertheless, the dispersion and wide observed ranges of these indicators demonstrated meaningful differences in customers' perceptions and behavioral relationships with the service provider, supporting their inclusion in the subsequent clustering analysis.

Table 2. Comparison of Candidate Customer Segmentation Solutions

Number of Clusters	Silhouette Coefficient	Calinski-Harabasz Index	Davies-Bouldin Index	Within-Cluster Sum of Squares
2	0.412	486.37	1.184	9,864.21
3	0.497	574.82	0.927	7,418.66
4	0.561	668.45	0.714	5,893.27
5	0.492	602.76	0.846	5,147.39
6	0.448	551.29	0.963	4,632.84

Table 2 presents the internal validation indices used to determine the optimal number of customer segments. Candidate K-means solutions containing two through six

clusters were compared. The four-cluster solution produced the highest silhouette coefficient, with a value of 0.561, indicating a comparatively favorable balance between

within-cluster cohesion and between-cluster separation. The same solution also produced the highest Calinski-Harabasz index, 668.45, which further supported the presence of a well-separated four-group structure. In addition, the four-cluster solution generated the lowest Davies-Bouldin index, 0.714, indicating less overlap between clusters than was observed in the alternative candidate solutions. Although the within-cluster sum of squares continued to decrease as the number of clusters increased, which is expected mathematically when additional clusters are introduced, the reduction after the four-cluster solution was substantially smaller relative to the improvements observed between two,

three, and four clusters. This pattern corresponded with the elbow criterion and suggested diminishing returns from introducing a fifth or sixth cluster. The five- and six-cluster solutions also produced lower silhouette and Calinski-Harabasz values and higher Davies-Bouldin indices, indicating that further partitioning reduced the clarity of the customer structure. Accordingly, the four-cluster solution was retained as the final segmentation model. Examination using hierarchical agglomerative clustering yielded a broadly comparable four-group structure, providing additional support for the stability of the selected segmentation.

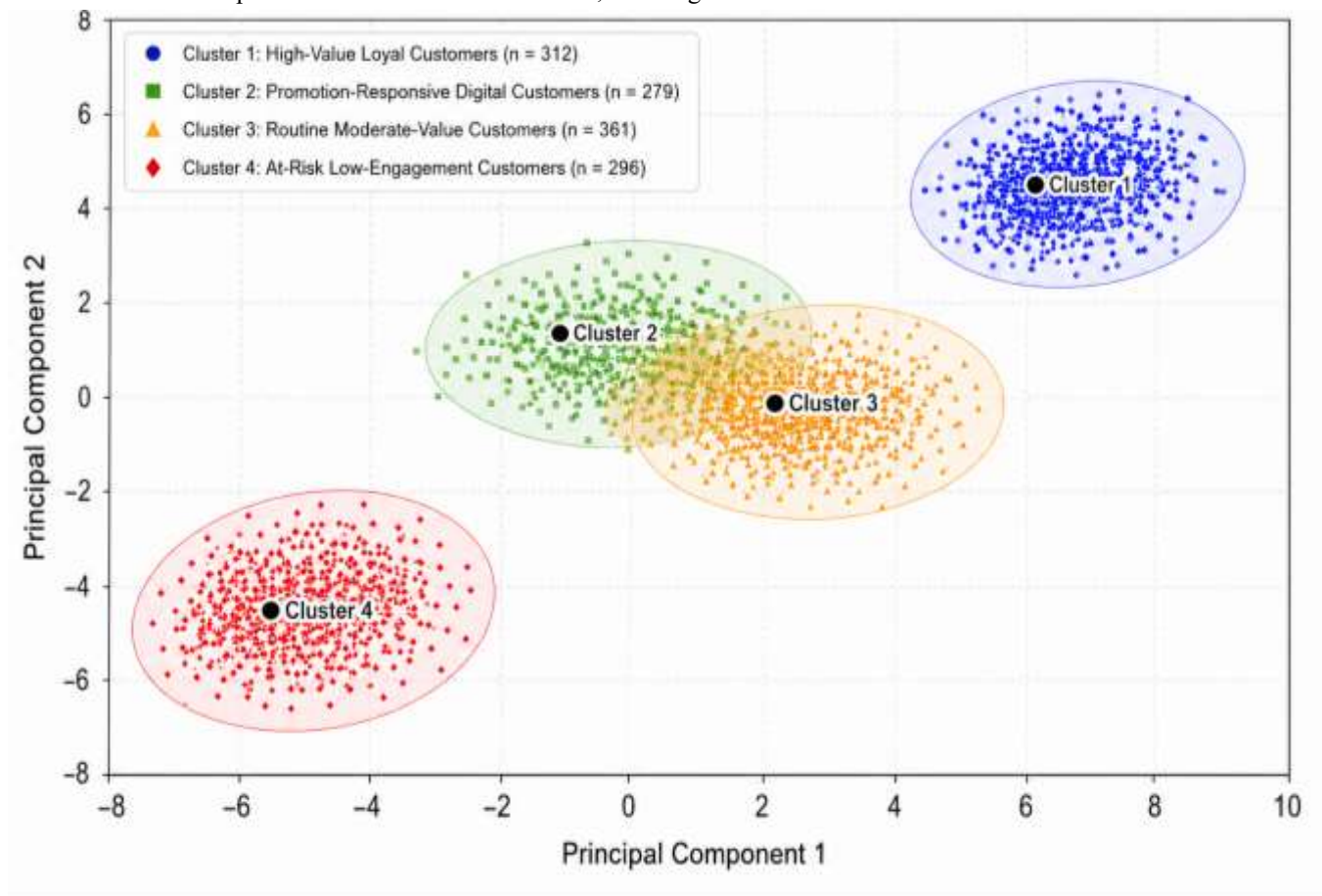


Figure 1. Two-Dimensional Visualization of the Four Customer Segments Based on Principal Component Projection

The two-dimensional projection of the standardized customer data indicated that the four identified customer segments occupied distinguishable regions of the reduced feature space. Although limited overlap was evident at the boundaries of some groups, the central concentrations of the four clusters were clearly differentiated, which was consistent with the silhouette and Davies-Bouldin results. The largest degree of separation was observed between

customers characterized by high economic value and strong experience indicators and customers characterized by prolonged recency, limited transactional activity, low satisfaction, and weak personalization perceptions. Two intermediate clusters occupied partially adjacent regions but remained distinguishable on the basis of engagement intensity, digital interaction, promotional responsiveness, complaint behavior, and monetary contribution. The visual

pattern therefore supported the conclusion that the customer database did not represent a single homogeneous population but instead contained several behaviorally and attitudinally distinct customer groups. The projection also suggested that

segmentation was driven by combinations of variables rather than by a single dominant factor, which supported the use of a multivariate machine learning approach.

Table 3. Behavioral, Transactional, and Experience Profiles of the Four Identified Customer Segments

Variable	Cluster 1: High-Value Loyal Customers (n = 312)	Cluster 2: Promotion-Responsive Digital Customers (n = 279)	Cluster 3: Routine Moderate-Value Customers (n = 361)	Cluster 4: At-Risk Low-Engagement Customers (n = 296)	F	p
Purchase recency, days	18.42	32.76	48.93	91.64	318.47	<0.001
Purchase frequency	20.18	14.63	9.37	4.28	526.83	<0.001
Total monetary value, million IRR	88.74	49.82	35.61	14.27	612.36	<0.001
Average transaction value, million IRR	6.73	4.21	3.98	2.54	187.59	<0.001
Service/product categories used	5.18	3.82	2.74	1.62	394.62	<0.001
Customer-service contacts	3.81	4.16	4.39	6.72	56.81	<0.001
Number of complaints	0.72	0.96	1.21	2.71	142.64	<0.001
Complaint resolution rate, %	91.86	82.74	73.36	49.82	163.48	<0.001
Promotional response rate, %	48.27	68.43	31.62	14.95	309.74	<0.001
Monthly digital interaction frequency	18.76	25.38	9.72	3.96	496.51	<0.001
Customer experience score	4.43	3.92	3.54	2.71	474.28	<0.001
Perceived personalization score	4.31	4.08	3.29	2.47	511.72	<0.001
Customer satisfaction score	4.48	3.94	3.59	2.78	486.35	<0.001
Loyalty intention score	4.52	3.78	3.46	2.54	498.67	<0.001
Recommendation intention score	4.47	3.86	3.38	2.48	476.92	<0.001

The cluster profiles shown in Table 3 demonstrated substantial and statistically significant differences across all principal behavioral, transactional, and customer-experience characteristics. Cluster 1 contained 312 customers, representing 25.0% of the total sample, and was labeled High-Value Loyal Customers. Members of this segment had the shortest average purchase recency of 18.42 days, the highest purchase frequency of 20.18 transactions, and by far the highest monetary value, averaging 88.74 million IRR. These customers also used the greatest number of service categories and reported the highest levels of customer experience, satisfaction, perceived personalization, loyalty intention, and recommendation intention. Their complaint frequency was comparatively low, while their complaint resolution rate was the highest among all segments. Consequently, Cluster 1 represented the organization's most economically valuable and relationally committed customer group. Cluster 2 contained 279 customers, or 22.4% of the sample, and was labeled Promotion-Responsive Digital

Customers. These customers displayed moderately high transaction frequency and monetary value but were most strongly distinguished by digital interaction and promotional responsiveness. Their average monthly digital interaction frequency was 25.38, the highest of all segments, and their promotional response rate reached 68.43%. Their experience and personalization scores were also favorable, suggesting that this group was particularly receptive to targeted digital recommendations, personalized campaigns, and data-driven service offers. Cluster 3 was the largest group, consisting of 361 customers, or 28.9% of the sample, and was labeled Routine Moderate-Value Customers. These customers showed intermediate values for most transactional and experiential variables. Their purchase frequency, monetary value, digital engagement, and service breadth were lower than those observed for Clusters 1 and 2 but substantially higher than those of Cluster 4. Their customer-experience and satisfaction scores remained above the scale midpoint, although perceived personalization and recommendation

intention were comparatively moderate. This group appeared to maintain a stable but less intensive relationship with the service provider and therefore represented a potentially important segment for cross-selling and engagement-development strategies. Cluster 4 consisted of 296 customers, or 23.7% of the sample, and was labeled At-Risk Low-Engagement Customers. These customers had the longest purchase recency, averaging 91.64 days, the lowest transaction frequency, the lowest monetary value, and the narrowest use of service categories. They also had the highest customer-service contact and complaint frequencies, combined with the lowest complaint resolution rate. Their customer experience, satisfaction, perceived personalization, loyalty intention, and recommendation intention scores were substantially below those of all other groups. Differences among the four clusters were statistically significant for every examined variable at $p < 0.001$. The magnitude and consistency of these differences indicated that the selected clustering procedure generated segments with distinct managerial and behavioral profiles

rather than merely statistically differentiated but operationally similar groups.

The segment distribution showed that approximately one quarter of the total customer base belonged to the High-Value Loyal group, whereas almost another quarter belonged to the At-Risk Low-Engagement group. This distribution is particularly relevant from a customer-management perspective because it demonstrates that the organization simultaneously contained a substantial base of highly valuable customers requiring retention and relationship-strengthening strategies and a comparably large group requiring service recovery, reactivation, or churn-prevention interventions. The Promotion-Responsive Digital segment represented customers for whom personalization could be delivered primarily through digital channels, while the Routine Moderate-Value group offered opportunities for relationship intensification through cross-service recommendations, loyalty incentives, and personalized communication. Thus, the segmentation results provided a direct bridge between descriptive customer analytics and differentiated service strategies.

Table 4. Predictive Performance of Machine Learning Models for Customer Segment Classification

Model	Accuracy	Macro Precision	Macro Recall	Macro F1-Score	Cross-Validated Accuracy
Decision Tree	0.887	0.884	0.881	0.882	0.873
Random Forest	0.928	0.926	0.924	0.925	0.916
Gradient Boosting	0.919	0.917	0.914	0.915	0.908

As shown in Table 4, all three supervised machine learning algorithms were capable of predicting customer segment membership with high levels of accuracy. The single Decision Tree achieved an independent testing accuracy of 0.887, with macro precision, recall, and F1-score values of 0.884, 0.881, and 0.882, respectively. Its cross-validated accuracy was 0.873, indicating that predictive performance remained relatively stable across validation folds and was not dependent on a single training-testing partition. The Random Forest model achieved the highest predictive performance, with an accuracy of 0.928 and a macro F1-score of 0.925. The Gradient Boosting classifier produced a similarly strong accuracy of 0.919 and a macro F1-score of 0.915. The difference between the single Decision Tree and the two ensemble methods indicated that combining multiple trees produced an incremental improvement in predictive discrimination. However, the approximately 4-percentage-point improvement obtained by the Random Forest compared with the Decision Tree was accompanied by a substantial reduction in direct

interpretability. Because the main objective of the present study was not only accurate segment prediction but also extraction of transparent and actionable customer-management rules, the optimized Decision Tree was retained as the principal rule-extraction model, while Random Forest and Gradient Boosting were treated as benchmark models. The relatively similar values of accuracy, precision, recall, and F1-score further indicated that model performance was not artificially inflated by preferential classification of the largest customer segment. Examination of the confusion matrix showed that the High-Value Loyal and At-Risk Low-Engagement customers were classified with the greatest accuracy, whereas most classification errors occurred between Promotion-Responsive Digital Customers and Routine Moderate-Value Customers. This pattern was consistent with the cluster visualization, because these two intermediate segments showed greater proximity in some transactional characteristics than the two more behaviorally extreme segments.

Feature-importance analysis based on the Random Forest and Gradient Boosting models showed that purchase recency, total monetary value, purchase frequency, customer experience, perceived service personalization, monthly digital interaction frequency, promotional responsiveness, and complaint behavior were the most influential variables in differentiating customer segments. Purchase recency emerged as the strongest behavioral indicator, demonstrating that the time elapsed since the customer's most recent transaction provided substantial information about ongoing engagement. Monetary value and transaction frequency were also highly influential, confirming the importance of conventional customer-value indicators. However, the predictive importance of customer experience and perceived personalization demonstrated that transaction records alone were insufficient for comprehensive customer segmentation. Customers with superficially similar purchasing patterns could belong to different segments depending on their satisfaction, digital engagement, response to personalized offers, and service-recovery experiences. This finding supported the integrated analytical framework adopted in the present study, in which behavioral data were combined with attitudinal and experience-related measures.

The optimized Decision Tree generated a series of interpretable threshold-based rules that could be used to assign customers to the four identified segments without rerunning the complete clustering procedure for every operational decision. The strongest upper-level split in the tree was associated with purchase recency. Customers whose most recent transaction occurred within approximately 31 days were primarily differentiated on the basis of monetary value, transaction frequency, customer-experience score, and digital engagement. Among these recently active customers, those with total monetary value above approximately 67 million IRR, purchase frequency above 15 transactions, and customer-experience scores greater than approximately 4.05 had a very high probability of being classified as High-Value Loyal Customers. Customers with recent transactions but lower monetary values were more frequently classified as Promotion-Responsive Digital Customers when monthly digital interaction exceeded approximately 18 interactions and promotional response exceeded approximately 52%. This pattern indicated that intensive digital engagement and responsiveness to marketing recommendations distinguished the digitally responsive segment even when its direct economic contribution was lower than that of the high-value segment.

A second set of decision paths distinguished Routine Moderate-Value Customers from At-Risk Low-Engagement Customers. Customers with purchase recency between approximately 31 and 72 days, moderate purchase frequency, moderate monetary value, customer-experience scores above approximately 3.20, and relatively low complaint frequency were predominantly classified as Routine Moderate-Value Customers. In contrast, customers with recency greater than approximately 72 days were increasingly likely to belong to the At-Risk Low-Engagement segment, particularly when transaction frequency was fewer than approximately six transactions, monetary value was below approximately 24 million IRR, or customer-experience scores were below approximately 3.00. The probability of At-Risk classification increased further when complaint frequency exceeded two complaints or complaint resolution was below approximately 60%. These rules showed that disengagement was not determined only by infrequent purchasing. Instead, prolonged inactivity combined with unresolved service problems, weak perceived personalization, and low customer-experience scores provided a substantially stronger indication of customer risk.

Additional decision rules revealed that perceived personalization played an important role in distinguishing behaviorally similar customers. Customers with moderate purchase frequency and monetary value but perceived personalization scores above approximately 3.80 were more likely to belong to the Promotion-Responsive Digital segment when their digital interaction was also high. Conversely, customers with comparable economic behavior but personalization scores below approximately 3.40 were more frequently classified as Routine Moderate-Value Customers. Similarly, customers with declining purchase activity did not invariably belong to the At-Risk segment when their experience and satisfaction evaluations remained positive. Customers whose purchase recency exceeded the overall sample average but who retained customer-experience scores above approximately 3.70 and complaint resolution rates above approximately 80% were frequently classified as Routine Moderate-Value rather than At-Risk customers. This result suggested that behavioral inactivity and negative customer experience should not be treated as interchangeable constructs and that combining both dimensions can produce more precise customer-management decisions.

From an operational perspective, the extracted rules made it possible to associate each segment with a distinct

personalization strategy. High-Value Loyal Customers could be prioritized for retention-oriented personalization, exclusive service benefits, loyalty recognition, proactive service, and recommendations based on their broader cross-category usage. Because these customers already demonstrated high satisfaction and loyalty, personalization for this segment should focus less on short-term promotional stimulation and more on relationship continuity, convenience, recognition, and premium service experiences. Promotion-Responsive Digital Customers, by contrast, represented the most suitable target group for digitally delivered personalized offers, recommendation systems, time-sensitive promotions, application-based engagement, and dynamic campaigns adapted to prior response patterns. Their exceptionally high promotional responsiveness and digital interaction suggested a substantial probability of positive behavioral response when personalization was delivered through the appropriate channel.

Routine Moderate-Value Customers required a different strategy. Their stable but moderate level of activity suggested that indiscriminate promotional intensity would be less appropriate than targeted efforts to broaden service usage and strengthen perceived value. Personalized cross-selling, service-bundle recommendations, educational communication regarding underused services, and loyalty incentives linked to increased engagement appeared particularly relevant to this segment. Finally, the At-Risk Low-Engagement segment required a service-recovery and reactivation strategy rather than conventional sales-oriented personalization. The combination of extended purchase recency, low transaction frequency, low satisfaction, elevated complaint frequency, and poor complaint-resolution experience indicated that further promotional communication without first addressing service problems could be ineffective. Personalized recovery messages, proactive complaint follow-up, targeted retention offers, identification of unresolved service barriers, and simplified re-engagement pathways therefore represented more appropriate interventions for this group.

Overall, the findings demonstrated that the integration of unsupervised and supervised machine learning provided both analytical differentiation and operational interpretability. The unsupervised K-means procedure identified four substantively different customer groups, while supervised tree-based modeling showed that segment membership could subsequently be predicted with a high degree of accuracy using observable transactional, behavioral, and experience variables. The superior

performance of Random Forest and Gradient Boosting confirmed that the segmentation structure contained strong predictive signals, while the Decision Tree translated those signals into a limited set of comprehensible rules suitable for customer relationship management. Most importantly, the results demonstrated that high-quality personalization could not be based solely on conventional economic value indicators. Purchase behavior, digital engagement, promotional responsiveness, complaint history, customer experience, satisfaction, perceived personalization, and loyalty-related attitudes jointly contributed to the differentiation of customer groups. Consequently, the findings provide empirical support for a machine learning-based customer management framework in which customer segmentation and interpretable decision rules are used together to support differentiated, data-driven, and customer-specific service strategies.

4. Discussion and Conclusion

The present study developed and evaluated a machine learning-based framework for improving customer experience and service personalization through customer segmentation and decision-rule extraction. The findings demonstrated that the customer base was not homogeneous and could be meaningfully divided into four distinct groups with clearly different transactional, behavioral, and experiential characteristics. The four-cluster solution showed the strongest overall internal validity among the candidate segmentation structures, with the highest silhouette and Calinski-Harabasz values and the lowest Davies-Bouldin index. The resulting clusters were identified as High-Value Loyal Customers, Promotion-Responsive Digital Customers, Routine Moderate-Value Customers, and At-Risk Low-Engagement Customers. These segments differed significantly in recency, purchase frequency, monetary value, service breadth, digital interaction, complaint behavior, promotional responsiveness, customer experience, perceived personalization, satisfaction, loyalty intention, and recommendation intention. The supervised learning stage further showed that segment membership could be predicted with high accuracy, particularly through Random Forest and Gradient Boosting models, while the Decision Tree retained strong predictive performance and produced interpretable operational rules. Overall, these findings indicate that integrating transactional, behavioral, and experience-related information can generate customer

segments that are both analytically robust and managerially actionable.

The identification of four clearly differentiated customer segments is consistent with the broader literature showing that machine learning can reveal hidden patterns of customer heterogeneity that are difficult to detect through conventional segmentation methods. The strong clustering performance obtained in the present study supports the application of unsupervised learning for classifying customers according to multidimensional similarities rather than relying exclusively on predefined demographic groups. This result is aligned with studies demonstrating the usefulness of K-means and related clustering approaches for creating actionable customer groups in retail, banking, e-commerce, and digital-service environments [1-4]. The present findings also support the argument that segmentation quality should be assessed through multiple internal validation criteria rather than through a single clustering statistic or arbitrary managerial preference. The superiority of the four-cluster solution across several evaluation measures is compatible with comparative clustering research emphasizing the importance of simultaneously considering cohesion, separation, and model interpretability when selecting an optimal segmentation solution [12].

The High-Value Loyal Customers segment was characterized by very recent purchasing activity, the highest purchase frequency, the highest total monetary value, the broadest use of services, favorable complaint resolution, and the strongest customer experience and loyalty indicators. This pattern confirms the continued importance of the RFM framework for identifying valuable customer groups. Recency, frequency, and monetary value provided strong differentiation among the clusters, particularly between the high-value and at-risk segments. The findings are consistent with research demonstrating that RFM variables are effective for classifying customers according to repurchase behavior and economic contribution [8]. They also align with studies combining RFM analysis with machine learning, where high-value customers are typically characterized by recent, frequent, and economically substantial interactions [7, 9]. The current results extend this perspective by showing that high-value status was not defined solely by transactional intensity, because customers in this segment also reported the highest satisfaction, perceived personalization, loyalty intention, and recommendation intention. Thus, high economic value appears to coexist with a favorable relational experience,

supporting a multidimensional conceptualization of customer value.

The Promotion-Responsive Digital Customers segment produced another important finding. These customers were not the highest in monetary contribution, yet they demonstrated the strongest digital interaction and the highest responsiveness to promotional activities. This indicates that customer value should not be evaluated only through current expenditure, because responsiveness, digital engagement, and potential future conversion may represent strategically important dimensions. The result is compatible with research emphasizing the role of digital behavioral data in customer segmentation and personalization. Social media and digital analytics have increasingly been used to identify targetable customer groups based on online activity and behavioral signals [11]. Similarly, AI-powered personalization in digital banking has shown that customer behavior analytics and digital engagement patterns can provide a basis for customized communication and service delivery [19]. The current findings also correspond with personalized coupon and promotion models showing that different customer segments respond differently to promotional mechanisms and therefore require differentiated incentive strategies [20]. In this sense, the Promotion-Responsive Digital segment represents customers whose future value may be increased through targeted digital communication, personalized offers, and adaptive recommendation systems.

The Routine Moderate-Value Customers segment was the largest group and displayed intermediate scores across most variables. These customers demonstrated stable but less intensive purchasing behavior, moderate service use, relatively favorable experience scores, and lower digital and promotional responsiveness than the second cluster. This result is important because many customer analytics systems focus heavily on either highly profitable customers or customers at immediate risk of churn, while moderate-value customers may constitute the largest proportion of the customer base. The present findings suggest that this group should not be treated as strategically neutral. Rather, it may represent an important development segment that can be moved toward greater engagement through cross-selling, personalized recommendations, loyalty programs, and service expansion. This interpretation is consistent with the broader machine learning segmentation literature, which emphasizes that segmentation should support differentiated marketing strategies for multiple levels of customer value rather than only identifying the most profitable customers [1,

4]. The result is also compatible with research showing that segmentation based on electronic transaction and demographic information can distinguish customers with moderate and potentially expandable relationships from both high-value and low-value groups [6].

The At-Risk Low-Engagement Customers segment was distinguished by long purchase recency, low transaction frequency, low monetary contribution, narrow service use, frequent customer-service contacts, more complaints, poorer complaint resolution, and the weakest experience and loyalty indicators. This pattern is strongly aligned with churn and retention research showing that customer attrition is typically associated with declining behavioral activity and unfavorable service experiences. Integrated churn prediction and segmentation models have demonstrated that combining customer classification with predictive analytics can improve the identification of customers who are likely to disengage [21]. Similarly, data mining approaches in e-commerce have shown that customer segmentation and churn classification can complement one another by distinguishing at-risk customers from behaviorally stable groups [22]. The present results reinforce this conclusion by showing that prolonged inactivity alone did not fully define the at-risk segment. Instead, the combination of low purchasing activity, weak perceived personalization, low satisfaction, and unresolved complaints provided a more complete profile of disengagement. This supports the view that churn risk is multidimensional and that service-recovery variables should be incorporated into customer segmentation models.

The finding that customer experience and perceived personalization contributed substantially to cluster differentiation is also theoretically and practically important. Traditional segmentation models often prioritize economic and transactional measures, but the present results showed that customers with similar purchasing profiles could differ according to their subjective experiences and perceptions of personalization. This finding supports studies arguing that AI-enhanced personalization can improve customer experience by increasing the relevance, convenience, and responsiveness of service interactions [14]. It also aligns with evidence suggesting that personalized marketing can strengthen engagement when recommendations and communications are adapted to individual needs and behavior [15]. The positive relationship between perceived personalization and high-value or digitally engaged customer segments further corresponds with the literature linking AI-driven personalization to customer loyalty [16].

These findings suggest that personalization should not be regarded merely as a marketing technique, but as a component of the overall customer experience that may influence continued engagement and relational quality.

The results regarding predictive performance also deserve attention. Random Forest achieved the highest classification accuracy, followed closely by Gradient Boosting, whereas the single Decision Tree produced slightly lower but still strong performance. This pattern is consistent with the general characteristics of ensemble learning, where multiple decision structures typically provide greater predictive stability than a single tree. However, the present study intentionally retained the Decision Tree as the principal rule-extraction model because of its transparency. This trade-off between predictive performance and interpretability is particularly relevant for customer relationship management. Black-box models may provide marginal gains in predictive accuracy, but operational decision-making often requires understandable criteria that can be translated into marketing or service rules. The current findings therefore support a hybrid analytical approach in which complex models are used as performance benchmarks while interpretable models are used for implementation. This is consistent with the broader objective of machine learning-based customer segmentation, which is not only to classify customers accurately but also to improve managerial decision-making and marketing strategy [1].

The extracted decision rules provided clear evidence that combinations of variables were more informative than any single customer indicator. High-Value Loyal Customers were most likely to be identified when low recency, high purchase frequency, high monetary value, and favorable customer experience occurred together. Promotion-Responsive Digital Customers were differentiated by strong digital activity and high promotional responsiveness, even when their economic value was lower than that of the high-value segment. Routine Moderate-Value Customers were characterized by intermediate transactional indicators and relatively stable experience levels, while At-Risk Customers were identified through long recency, low frequency, low monetary value, low experience scores, and unfavorable complaint characteristics. This multivariate decision structure is consistent with studies showing that machine learning-based segmentation becomes more useful when customer characteristics are examined jointly rather than independently [3, 7]. It also corresponds with B2B segmentation research integrating multiple forms of

customer information, including firmographic, RFM, and network-related data, to generate more informative customer categories [10].

The importance of perceived personalization in the decision rules further reinforces the role of recommendation and personalization systems in contemporary customer management. Customers with strong personalization perceptions and high digital engagement were more likely to belong to the promotion-responsive segment, while lower personalization perceptions were associated with routine or at-risk customers. This result is consistent with research on machine learning-based recommendation systems, which emphasizes the use of behavioral history, preferences, and purchasing patterns to deliver individualized products or content [17]. Similar findings have been reported in hospitality and tourism, where deep learning and big data have been used to develop personalized recommendation systems that support customer decision-making [18]. The present findings therefore indicate that personalization can function both as an outcome of machine learning and as an input variable that helps explain customer segmentation.

The observed importance of digital engagement, promotional responsiveness, and customer experience also supports the use of predictive analytics for personalized service design. Predictive analytics has been shown to improve the personalization of e-commerce services by identifying likely customer preferences and tailoring service offerings accordingly [13]. In the current study, customers with strong digital interaction and promotional response formed a distinct cluster, suggesting that predictive service systems can be more effective when they are segment-specific. Rather than recommending the same products, messages, or incentives to all customers, firms can use cluster characteristics to determine the type, timing, and channel of personalization. This interpretation is also aligned with evidence showing that AI-driven personalization can enhance customer engagement when service interactions are adapted to behavioral and contextual information [14, 19].

The present results also demonstrate the value of combining clustering and classification within a single customer analytics framework. Clustering provided an exploratory mechanism for identifying latent customer groups, while supervised learning transformed these clusters into a predictive system that could classify new customers and generate interpretable rules. This combination is consistent with integrated analytical approaches that merge segmentation and churn prediction for operational decision-making [21]. It is also aligned with research using data

mining to connect customer segmentation and classification processes in e-commerce environments [22]. The advantage of such a framework is that segmentation is not limited to retrospective description. Once clusters are established and decision rules are extracted, new customers can be assigned to segments in real time or near real time, allowing personalized actions to be activated without repeatedly conducting the full clustering procedure.

Finally, the present findings support the broader argument that machine learning can enhance customer experience when analytical outputs are connected directly to differentiated service strategies. The identified segments were not merely statistical categories; each represented a different managerial problem and opportunity. High-Value Loyal Customers require retention and recognition, Promotion-Responsive Digital Customers require targeted digital personalization, Routine Moderate-Value Customers require relationship expansion, and At-Risk Low-Engagement Customers require service recovery and reactivation. This strategic interpretation is consistent with the literature showing that machine learning-based segmentation can improve marketing effectiveness by aligning strategies with distinct customer profiles [1, 2]. It is also supported by research on AI-enhanced personalization, which emphasizes that the value of artificial intelligence depends on its ability to improve relevance, engagement, and loyalty rather than merely automate decision-making [15, 16]. Therefore, the main contribution of the present study lies in demonstrating that customer segmentation, predictive classification, and decision-rule extraction can be integrated into a coherent framework for improving both managerial interpretability and personalized customer experience.

Several limitations should be considered when interpreting the findings of this study. First, the study used a cross-sectional design, which means that customer behavior, experience, and segment membership were assessed within a defined observation period rather than tracked dynamically over time. Customer characteristics may change as purchasing habits, economic circumstances, service quality, and competitive conditions change, and therefore the identified clusters should not be interpreted as permanently stable categories. Second, the study was conducted among customers in Tehran, which may limit the generalizability of the findings to other geographical, cultural, or market contexts. Third, although the dataset integrated transactional, behavioral, demographic, and experience-related variables, other potentially important factors such as customer lifetime value, price sensitivity, channel-specific

satisfaction, psychological characteristics, brand trust, and competitor usage were not included. Fourth, some customer-experience variables were based on self-report measures and may therefore have been affected by response bias or temporary perceptions. Finally, although the decision-tree rules were highly interpretable, the model showed slightly lower predictive accuracy than the ensemble models, indicating an unavoidable trade-off between transparency and predictive optimization.

Future research should examine customer segmentation longitudinally to determine how customers move between segments over time and which behavioral or experiential changes most strongly predict transitions from loyal to at-risk states or from moderate-value to high-value relationships. Replication across different cities, industries, and service contexts would also be useful for determining the stability and generalizability of the four-segment structure. Future studies could incorporate additional variables such as customer lifetime value, channel preferences, price sensitivity, brand trust, service recovery satisfaction, and competitive switching behavior. Dynamic clustering and online learning approaches may also be applied to update segment membership continuously as new customer data become available. In addition, future research could compare interpretable machine learning techniques with advanced explainable artificial intelligence approaches in order to determine whether predictive performance can be improved without substantially reducing transparency. Experimental designs may further test whether segment-specific interventions actually increase satisfaction, retention, spending, or loyalty relative to standard undifferentiated marketing strategies.

Organizations should integrate customer segmentation into their customer relationship management systems so that service strategies can be adapted according to the specific behavioral and experiential profile of each segment. High-Value Loyal Customers should receive retention-focused benefits, proactive support, recognition, and premium service opportunities, while Promotion-Responsive Digital Customers should be prioritized for personalized digital offers, app-based communication, and adaptive recommendation campaigns. Routine Moderate-Value Customers should be targeted with cross-selling, service-bundle recommendations, educational communication, and incentives designed to deepen engagement. At-Risk Low-Engagement Customers should be approached primarily through service recovery, complaint resolution, personalized reactivation messages, and retention-oriented interventions

rather than generic promotional communication. Organizations should also regularly update customer classifications because segment membership can change over time, and managers should monitor not only transaction indicators but also customer experience, digital engagement, and complaint behavior when making personalization decisions.

Authors' Contributions

Authors equally contributed to this article.

Acknowledgments

Authors thank all participants who participate in this study.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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