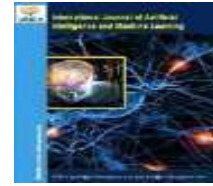




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AI-Powered Personalized Financial Services Using Machine Learning and Behavioral Analytics

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Abstract

Artificial intelligence and machine learning are increasingly being integrated into financial services to improve customer understanding and support more personalized service strategies. Behavioral analytics provides additional information by capturing patterns in financial and transactional activity that may not be evident from demographic characteristics alone. This study aimed to examine demographic, financial, and transactional characteristics and identify distinct client-level behavioral patterns using machine-learning-based customer segmentation. A structured financial transaction dataset was analyzed using descriptive statistical methods and client-level behavioral aggregation. Relevant demographic, financial, and transactional variables were examined, while transaction frequency, spending, average transaction value, credit score, and yearly income were incorporated into a K-means clustering framework. Numerical features were standardized before clustering, and cluster quality was assessed using the silhouette coefficient. The analysis demonstrated substantial heterogeneity in customer demographic, financial, and transactional characteristics. K-means clustering identified distinct behavioral segments with differing patterns of transaction activity, spending, credit characteristics, and income. The resulting segmentation provided an interpretable representation of customer-level behavioral differences and demonstrated the usefulness of combining financial and transactional variables within a machine-learning framework. Machine-learning-based behavioral segmentation can provide a structured analytical foundation for understanding heterogeneous customer profiles and developing differentiated approaches to personalized financial services. However, the identified segments should be interpreted as analytical patterns rather than direct financial recommendations. Further validation using real-world longitudinal customer data and outcome-based evaluation is necessary before applying such segmentation approaches in operational financial-service environments.

Keywords: Artificial intelligence, machine learning, behavioral analytics, customer segmentation, personalized financial services.

1. Introduction

Artificial intelligence (AI) has increasingly influenced the delivery of financial services by enabling institutions to process large volumes of customer, transactional, and behavioral information. Machine learning, predictive analytics, neural networks, and automated decision-support techniques can identify patterns that may not be readily apparent through conventional analytical approaches. Within banking and financial services, these capabilities have been associated with fraud detection, risk assessment, customer engagement, payment processing, and financial decision-making (Ibrahim *et al.*, 2025). The increasing adoption of digital banking has also created opportunities to tailor financial services according to customer characteristics and observed behavioral patterns. AI-powered personalization can therefore support more individualized interactions, particularly when financial institutions integrate customer information with transaction and behavioral analytics (Ashrafuzzaman *et al.*, 2025).

Personalization is particularly relevant because customers differ in their financial circumstances, transaction habits, income levels, credit profiles, and patterns of service utilization. AI can process these characteristics simultaneously and generate analytical representations of customer behavior (Devan *et al.*, 2023). Research on consumer digital banking has highlighted the potential of AI to support smart personalization while also addressing other customer-facing functions such as fraud detection (Kotla, 2023). Similarly, AI-powered financial strategy and predictive analytics can assist organizations in using historical information to improve business decision-making (Ahirrao *et al.*, 2025). These developments provide an important foundation for investigating how machine-learning techniques can be applied to customer financial data to identify behavioral patterns relevant to personalized services.

Machine learning provides computational approaches for extracting meaningful patterns from structured financial information. Predictive models can estimate potential outcomes, while unsupervised algorithms can

organize observations according to similarities without requiring predefined categories (Kannan, 2022). Within financial services, these capabilities have been applied to customer analysis, risk management, fraud detection, payment systems, and financial forecasting (Pamisetty, 2023). Behavioral analytics extends these applications by transforming observed customer activities into measurable indicators, including transaction frequency, spending levels, payment behavior, and financial characteristics (Fonkem, 2025). Combining these indicators with machine-learning techniques can provide a more detailed representation of customer behavior than isolated demographic variables.

Research has demonstrated the relevance of AI-based behavioral analysis for understanding customer activity across financial domains. Rajasekaran and Selvam (2025) examined AI-powered behavior analysis in financial services, while Rani *et al.* (2025) highlighted predictive approaches for forecasting consumer financial behavior. Related work in insurance has also demonstrated how machine learning can be used to model customer behavior, policy utilization, and risk-related characteristics (Dunka, 2023). In payment environments, neural-network-based approaches have been investigated for extracting real-time consumer insights and supporting personalized payment systems (Malempati, 2022). Collectively, these studies indicate that behavioral information can serve as an important analytical component in AI-supported financial decision-making.

Customer segmentation involves organizing customers into groups according to shared characteristics or behavioral patterns. In financial services, segmentation can help reveal differences in customer activity that may otherwise remain hidden when the entire population is treated as homogeneous. Machine-learning-based segmentation is particularly useful since algorithms can identify groups according to relationships among multiple variables. K-means clustering is one commonly used unsupervised learning approach for partitioning observations into groups based on similarity. When applied to financial customer data, clustering can incorporate transaction frequency, spending behavior, income, credit characteristics, and other measurable attributes.

The relevance of segmentation to personalization is reflected in research examining AI-driven customer engagement and financial services. Kaluarachchi and Sedera (2024) discussed personalized solutions within banking customer engagement, while Kagalwala *et al.* (2025) described the broader role of AI and machine learning in digital banking and payment systems. AI-powered personal finance applications have similarly been investigated as tools for supporting individualized financial management and customer-oriented services (Saini *et al.*, 2025). Furthermore, AI-based financial advisory systems can use machine-learning and natural-language technologies to support real-time customer interaction and personalized recommendations (Mitta, 2022). These developments demonstrate the potential value of customer segmentation as an analytical foundation for personalization.

Despite its potential, AI-driven personalization presents several methodological and operational challenges. Financial datasets can contain complex behavioral patterns, and customer activity may change over time. Models must therefore be constructed carefully to ensure that identified patterns are meaningful and reproducible. Fraud detection research, for example, demonstrates the importance of processing financial information rapidly while maintaining reliable analytical performance (Marripudugala, 2024). Similarly, behavioral biometric approaches illustrate how increasingly detailed behavioral information can be incorporated into financial cybersecurity systems (Salami *et al.*, 2025). These applications demonstrate the need to consider both the analytical value of behavioral data and the responsible handling of information used by AI systems.

Another challenge concerns the interpretation of machine-learning outputs. A customer cluster represents statistical similarity within the selected variables and does not necessarily represent an individual's complete financial needs or preferences. Therefore, machine-learning-generated segments should be interpreted within the characteristics included in the analytical model. AI-powered personalization research has emphasized customer behavior and engagement, but translating analytical patterns into appropriate financial services requires careful consideration of context and model limitations. Consequently, transparent segmentation and clear reporting of the variables used are important when developing analytical foundations for personalized financial services.

Existing research demonstrates extensive interest in applying AI and machine learning to financial services, including predictive analytics, behavioral analysis, personalization, fraud detection, financial advisory systems, and digital banking (Anjum *et al.*, 2025). However, much of the existing work focuses on individual applications such as risk prediction, fraud prevention, advisory systems, or customer engagement. Comparatively less attention is given to integrating demographic, financial, and transaction-level characteristics into a unified client-level behavioral segmentation framework that can provide an interpretable foundation for personalized financial services. In addition, studies frequently employ different datasets, variables, analytical approaches, and objectives, making direct interpretation across applications difficult.

Recent work on predictive consumer behavior emphasizes the ability of AI to identify behavioral patterns from customer information (Alam *et al.*, 2025), while research on AI-powered financial strategy emphasizes predictive analytics for broader organizational decision-making. These approaches establish the relevance of AI but leave scope for further examination of customer-level heterogeneity using combined financial and transactional characteristics. The study addresses this analytical gap by applying machine-learning-based segmentation to client-level financial and behavioral information, thereby examining whether distinct customer patterns can be identified systematically.

The study had two objectives: first, to characterize the demographic, financial, and transactional profiles represented in the dataset by examining variables such as age, gender, yearly income, credit score, transaction amount, transaction method, and transaction frequency; and second, to apply K-means clustering at the client level to identify distinct behavioral segments using transaction frequency, total spending, average transaction value, credit score, and yearly income. Together, these objectives were intended to establish an analytical basis for understanding heterogeneous customer behavior and supporting the development of data-driven personalized financial-service strategies.

2. Materials and Methods

2.1 Study Design

This study used a quantitative, data-driven design to examine customer financial characteristics, transaction behavior, and machine-learning-based behavioral segmentation. The analytical framework combined descriptive analysis with unsupervised machine learning to identify groups of clients exhibiting different financial and transactional patterns. The investigation included three analytical components: demographic and financial profiling, transaction and behavioral characterization, and client-level segmentation using K-means clustering. The approach was designed to provide an empirical basis for understanding heterogeneous customer behavior relevant to personalized financial services. No primary survey, interview, or experimental intervention was conducted. All analyses were performed using the available dataset and predefined computational procedures throughout.

2.2 Data Source

The analysis used the *India Customer Financial Profiles & Transactions* dataset, comprising 20,000 synthetic transaction-level records with demographic, financial, credit, and transactional variables. The dataset includes information on client characteristics, age, gender, yearly income, credit score, transaction amount, transaction method, merchant information, and transaction identifiers. Transaction records covered the period from 2023 through 2025. The dataset is synthetic; the findings represent analytical patterns within the dataset and should not be interpreted as estimates of actual banking customers. The dataset was retained in its original structure before preprocessing, while relevant variables were selected and transformed according to the analytical objectives of the study.

2.3 Study Population

The dataset comprised 20,000 transaction records representing 4,941 unique clients. Transaction-level records were used for descriptive summaries of demographic, financial, and payment characteristics, whereas the client was the unit for behavioral segmentation. Transactions associated with the same client were therefore aggregated before applying the clustering procedure to avoid treating repeated observations as independent clients. Client-level measures included transaction frequency, cumulative transaction spending, and average transaction amount. Demographic and financial attributes, including credit score and yearly income, were incorporated to characterize differences between client groups. This two-level analytical structure allowed transaction behavior and client segmentation to be examined consistently across the study population.

2.4 Data Preparation

Data preparation involved reviewing the dataset structure, checking completeness, identifying client identifiers, and organizing transaction records carefully. Transaction frequency was calculated as the number of records associated with each client. Total spending was obtained by summing transaction amounts for each client, while average transaction value was calculated from client transactions. Credit score and yearly income were retained as financial characteristics. Categorical descriptive variables were summarized separately for distribution analyses. For clustering, numerical behavioral variables were prepared at the client level and standardized before model fitting so that variables measured on different numerical scales would contribute comparably to distance calculations. These procedures established the analytical dataset used for subsequent modeling.

2.5 K-Means Customer Segmentation

K-means clustering was applied to the client-level analytical dataset to identify distinct behavioral segments. The clustering procedure partitioned clients into four groups by minimizing within-cluster variation based on standardized numerical features. The variables included transaction frequency, total spending, average transaction amount, credit score, and yearly income, thereby combining behavioral and financial characteristics. Cluster membership was summarized using client counts, percentages, and mean values for the principal analytical variables. The silhouette coefficient was calculated to assess the separation and cohesion of the resulting clusters. The resulting segments were interpreted descriptively and were not considered inherently superior or inferior customer groups within the financial-service context.

2.6 Statistical Analysis

Descriptive statistics were used to summarize categorical distributions and transaction characteristics, with frequencies and percentages reported for relevant variables. Client-level clustering results were presented using cluster size, proportion of clients, and mean financial and behavioral measures. Figures were generated from the values reported in the tables to maintain consistency between textual and graphical results. K-means clustering was implemented using a standardized feature matrix, with four clusters specified for segmentation. The silhouette coefficient was reported as a clustering diagnostic to assess cluster separation and cohesion. All calculations were derived from the stated dataset, and source information was retained under the relevant tables to support transparency and reproducibility. Statistical outputs were interpreted descriptively.

3. Results

3.1 Customer Profile and Financial Position

The dataset comprised 20,000 transaction records representing 4,941 unique clients. The age distribution was relatively balanced across the defined groups, with customers aged 19–29 years accounting for 21.83%, followed by those aged 60–70 years (20.29%), 50–59 years (19.57%), 30–39 years (19.32%), and 40–49 years (19.00%), as shown in Table 1. Male records represented 49.28% of observations, while female records accounted for 47.40%. Regarding credit status, the largest proportion had good credit scores (34.10%), followed by fair scores (29.80%). Customers with yearly incomes of 600,001–1,000,000 represented the largest income category (38.90%), indicating substantial variation in financial characteristics across the dataset.

Table 1. Distribution of Records According to Demographic and Financial Characteristics

Characteristic	Category	n	%
Age (years)	19–29	4,365	21.83
	30–39	3,864	19.32
	40–49	3,800	19.00
	50–59	3,913	19.57
	60–70	4,058	20.29
Gender	Male	9,855	49.28
	Female	9,479	47.40
	Other	666	3.33
Credit score	Poor (≤ 579)	978	4.89
	Fair (580–669)	5,960	29.80
	Good (670–739)	6,819	34.10
	Very good (740–799)	3,943	19.72
	Excellent (800–900)	2,300	11.50
Yearly income	$\leq 300,000$	1,702	8.51
	300,001–600,000	6,627	33.14
	600,001–1,000,000	7,780	38.90
	$> 1,000,000$	3,891	19.46

Source: Authors' calculations based on the India Customer Financial Profiles & Transactions Dataset (Bedmutha, 2025).

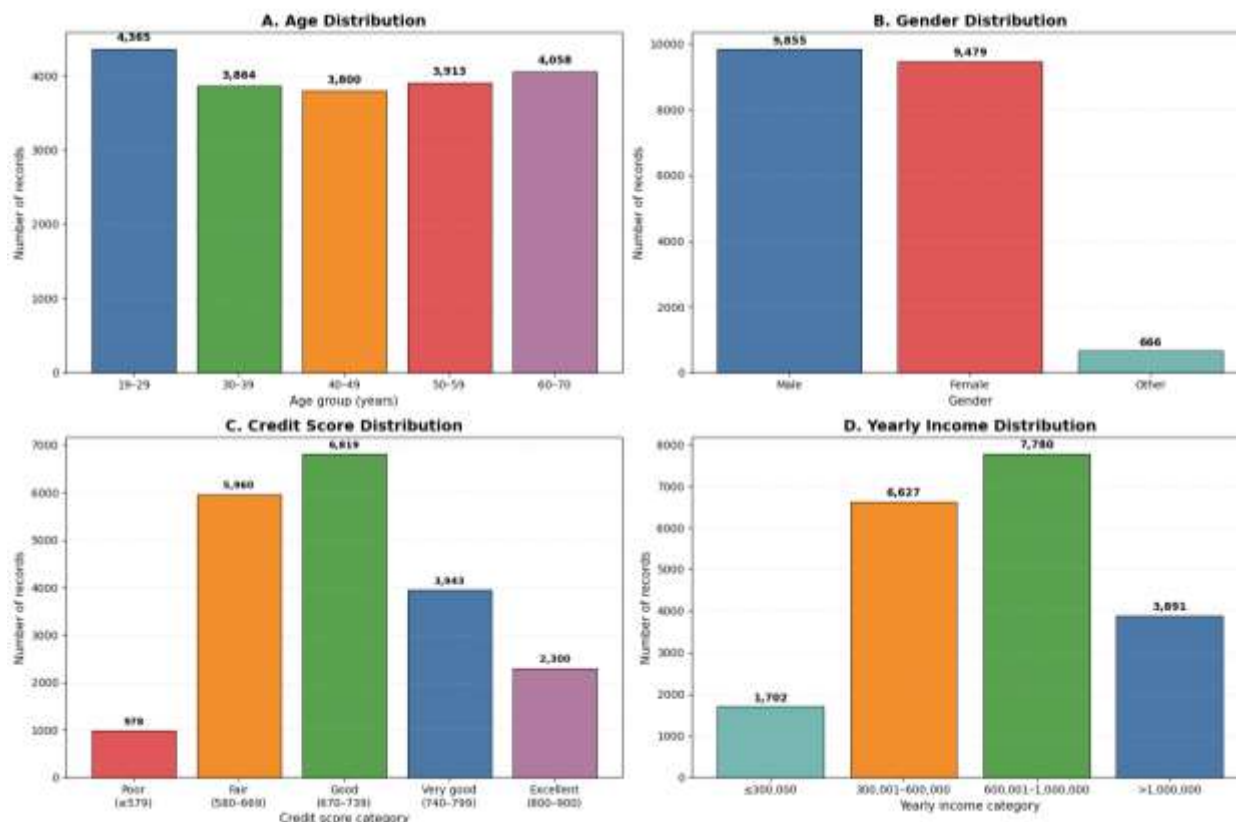


Figure 1. Distribution of Records According to Demographic and Financial Characteristics

The distribution of records across demographic and financial characteristics. The age distribution was relatively balanced, with the 19–29-year group representing the largest category at 4,365 records, followed by the 60–70-year group with 4,058 records, as shown in Figure 1. Male records were slightly more frequent than female records, while other gender records constituted a smaller proportion. Credit scores were concentrated in the good and fair categories, with 6,819 and 5,960 records, respectively. Regarding yearly income, the 600,001–1,000,000 category had the highest representation, comprising 7,780 records. The figure demonstrates substantial variation across financial characteristics within the dataset.

3.2 Spending and Transaction Behavior

Transaction behavior showed variation in both transaction value and customer activity. Transactions valued between 2,501 and 5,000 constituted the largest category, representing 36.02% of all records, followed closely by transactions between 1,001 and 2,500 (35.49%), as shown in Table 2. Chip-based transactions accounted for 69.64% of observations, whereas non-chip transactions represented 30.37%. At the client level, customers with two to three transactions formed the largest group (36.13%), followed by those with four to five transactions (20.22%) and six to ten transactions (20.12%). Clients with a single transaction represented 18.94%, while 4.60% had more than ten transactions.

Table 2. Distribution of Transactional and Behavioral Characteristics

Behavioral characteristic	Category	n	%
Transaction amount	≤1,000	2,480	12.40
	1,001-2,500	7,097	35.49
	2,501-5,000	7,204	36.02
	5,001-10,000	3,013	15.07
	>10,000	206	1.03
Transaction method	Chip	13,927	69.64
	Non-chip	6,073	30.37
Transactions per client	1 transaction	936	18.94

	2–3 transactions	1,785	36.13
	4–5 transactions	999	20.22
	6–10 transactions	994	20.12
	>10 transactions	227	4.60

Source: Authors' calculations based on the India Customer Financial Profiles & Transactions Dataset (Bedmutha, 2025).

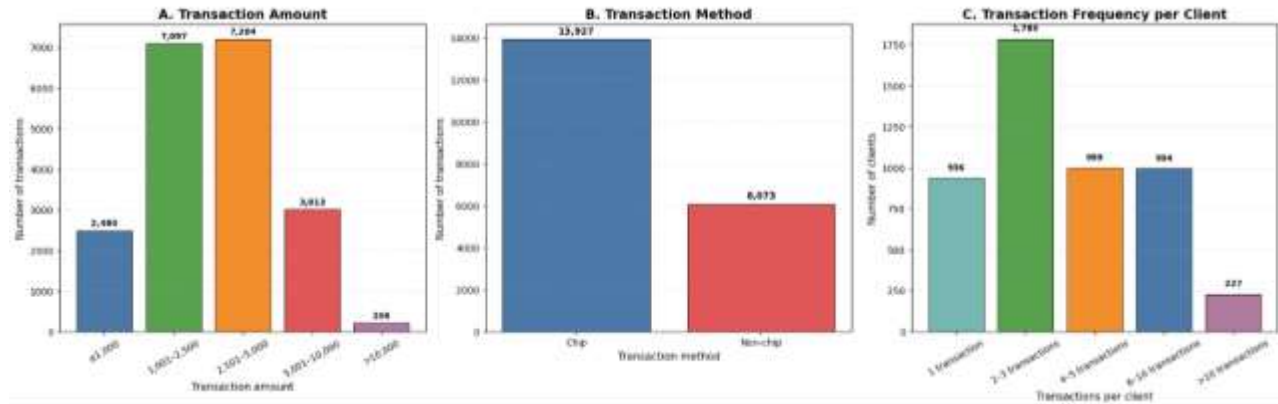


Figure 2. Distribution of Transactional and Client-Level Behavioral Characteristics

The transaction-level and client-level behavioral characteristics in the dataset. Transaction amounts were concentrated between 1,001 and 5,000, with 7,097 transactions in the 1,001–2,500 category and 7,204 in the 2,501–5,000 category, as shown in Figure 2. Chip-based payments accounted for 13,927 transactions, substantially exceeding non-chip transactions (6,073). At the client level, 2–3 transactions represented the largest frequency group, comprising 1,785 clients. Single-transaction clients numbered 936, while 227 clients recorded more than ten transactions. The distribution indicates varied spending intensity and transaction frequency, providing behavioral information that can support machine-learning-based customer segmentation and personalized financial service analysis across different client groups.

3.3 Machine-Learning Customer Segmentation

The K-means analysis identified four customer clusters with different behavioral and financial profiles. Cluster 1 contained the largest proportion of clients (43.98%) and showed 2.59 transactions per client with average total spending of 5,981.20, as shown in Table 3. Cluster 2 represented 21.84% of clients and demonstrated the highest transaction frequency (8.46) and total spending (27,210.12). Cluster 3 comprised 13.92% of clients and had the lowest mean credit score (674.86), while its mean yearly income was 743,277.07. Cluster 4 represented 20.26% of clients and recorded the highest average transaction value (4,565.58). These differences provide a basis for behavioral customer profiling.

Table 3. Machine-Learning-Based Customer Behavioral Segmentation Using K-Means

Customer cluster	Clients, n (%)	Transactions per client	Total spending per client	Average transaction value	Credit score	Yearly income
Cluster 1	2,173 (43.98)	2.59	5,981.20	2,788.62	710.98	609,101.00
Cluster 2	1,079 (21.84)	8.46	27,210.12	3,202.64	711.66	701,771.68
Cluster 3	688 (13.92)	4.07	11,816.48	3,136.87	674.86	743,277.07
Cluster 4	1,001 (20.26)	2.44	11,147.98	4,565.58	690.37	613,993.38
Total	4,941 (100.00)	4.05	12,476.37	3,074.17	701.92	642,193.88

Source: Authors' calculations based on the India Customer Financial Profiles & Transactions Dataset (Bedmutha, 2025).

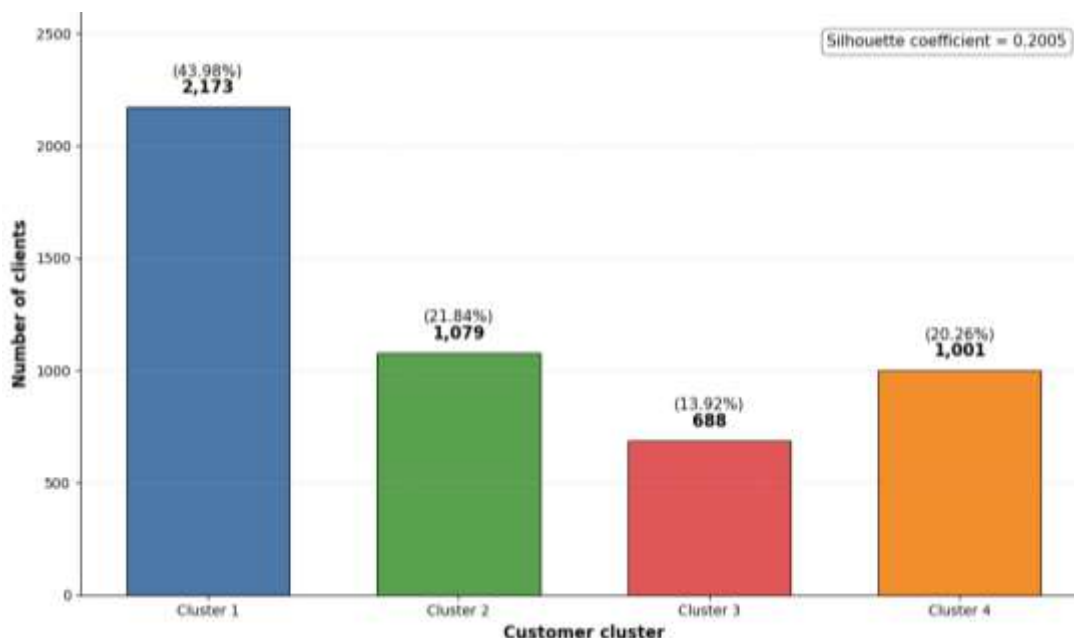


Figure 3. Client Behavioral Segmentation Using K-Means Clustering

The client-level segmentation was generated using K-means clustering. Cluster 1 contained the largest group, with 2,173 clients (43.98%), followed by Cluster 2 with 1,079 clients (21.84%). Cluster 4 comprised 1,001 clients (20.26%), whereas Cluster 3 represented 688 clients (13.92%), as shown in Figure 3. The cluster sizes indicate that behavioral patterns were not evenly distributed across the client population. The silhouette coefficient was 0.2005, providing a quantitative measure of the separation and cohesion of the resulting clusters. These segments summarize differences in client transaction behavior and financial characteristics and provide an analytical basis for examining differentiated patterns relevant to personalized financial services.

4. Discussion

The demographic and financial distribution indicates substantial variation across the records examined in this study. Age groups were relatively balanced, while the credit-score distribution showed greater representation within the fair and good categories. Yearly income was concentrated particularly within the 600,001–1,000,000 range. These patterns indicate that financial characteristics cannot be adequately represented by a single customer profile. AI-based financial services can incorporate multiple characteristics simultaneously to create more differentiated customer representations. Saxena and Muneeb (2024) emphasized that combining artificial intelligence with customer data analytics can facilitate hyper-personalized financial experiences. Similarly, Singh et al. (2025) described AI-powered analytical approaches as useful for extracting financial insights from complex datasets. The findings provide a descriptive foundation for such analytical applications. The transaction results demonstrated meaningful variation in spending levels, payment methods, and transaction frequency. Most transactions were concentrated within the intermediate transaction-value categories, while chip-based transactions represented the majority of payment records. At the client level, the distribution of transaction frequency showed that customers differed considerably in the number of transactions associated with their profiles. Such behavioral differences are important because transaction activity can provide information beyond static demographic characteristics. AI-based personalization can use behavioral signals to distinguish customers with different patterns of financial activity and engagement. Data-driven personalization can improve the understanding of individual customer characteristics, while Turki (2025) highlighted the importance of behavioral information within AI-powered personalization frameworks. Therefore, transaction behavior provides a useful analytical dimension for customer-oriented financial services.

The K-means analysis identified four client-level behavioral clusters with different distributions of transaction frequency, spending, average transaction value, credit score, and yearly income. Cluster 1 represented the largest segment, whereas Cluster 3 contained the smallest number of clients. The differences in transaction frequency and spending across clusters demonstrate that clients within the dataset were not behaviorally homogeneous. This finding supports the use of unsupervised machine learning for identifying customer groups from multidimensional financial characteristics. The application of predictive analytics and AI in personalized

financial decision-making includes wealth management and risk assessment. Yaramolu (2025) similarly described intelligent automation as a mechanism for incorporating customer and portfolio information into financial management. In the analysis, clustering provides an interpretable analytical mechanism for distinguishing behavioral profiles before considering individualized financial-service strategies.

The identified clusters have potential implications for personalized financial-service design because different behavioral profiles may require different forms of engagement. Clients with higher transaction frequencies and greater cumulative spending could represent a distinct behavioral pattern from clients with fewer transactions or different spending levels. The differences in credit scores and income may provide additional contextual information when interpreting transaction behavior. AI-based personalization can potentially combine these dimensions to support differentiated communication, financial education, product information, or service recommendations. However, cluster membership should not be interpreted as a direct recommendation or as evidence that a particular financial product is appropriate for an individual. Wah (2025) emphasized the potential of AI-enabled predictive analytics for personalized financial planning, while Yaramolu (2025) discussed intelligent approaches to individualized portfolio-management processes. The findings therefore provide an analytical foundation rather than a completed recommendation system.

A major methodological consideration is the distinction between transaction-level analysis and client-level analysis. Multiple transactions can belong to the same client; aggregation was necessary before behavioral clustering to prevent repeated transactions from being treated as independent customers. The use of standardized client-level numerical characteristics also enabled variables with different measurement scales to contribute more comparably to the clustering procedure. The silhouette coefficient of 0.2005 provides a quantitative indication of the separation and cohesion of the four-cluster solution, although it does not establish that the resulting segments represent definitive real-world customer categories. Singh *et al.* (2025) emphasized the value of AI-powered analytical insights for financial decision-making, while highlighting the importance of data analytics in developing personalized financial experiences. These considerations reinforce the need for transparent and reproducible analytical procedures.

Several limitations should be considered when interpreting these findings. First, the dataset consists of synthetic records; therefore, the observed patterns should not be generalized directly to actual banking customers or the wider financial population. Second, the analysis uses a limited set of demographic, financial, and transaction variables, and additional behavioral information could produce different segmentation structures. Third, K-means clustering requires the number of clusters to be specified and is sensitive to the characteristics and scaling of the selected variables. Finally, the analysis identifies behavioral segments but does not independently evaluate whether personalized recommendations based on these segments improve customer outcomes. Future studies could validate the segmentation framework using real-world banking data, longitudinal customer histories, additional behavioral variables, and alternative clustering algorithms. Research could also evaluate recommendation accuracy, fairness, explainability, and customer outcomes before deployment in operational financial-service systems.

5. Conclusion

This study examined the potential of machine-learning-based behavioral analysis for understanding differences within customer financial profiles and transaction activities. The findings demonstrated noticeable variation in demographic characteristics, yearly income, credit scores, transaction amounts, payment methods, and transaction frequencies across the analyzed records. These differences indicate that customers cannot be adequately represented through a single financial or demographic profile. Client-level K-means clustering further identified four behavioral segments characterized by different combinations of transaction frequency, total spending, average transaction value, credit score, and yearly income. The resulting segments provide an interpretable analytical structure for examining customer heterogeneity and can serve as a foundation for developing more differentiated financial-service strategies. The analysis also demonstrates the usefulness of combining behavioral and financial variables within an artificial-intelligence-oriented framework rather than relying on individual characteristics alone. Nevertheless, the findings should be interpreted within the boundaries of the dataset; the analyzed records are synthetic and therefore do not directly represent the behavior of real banking customers. In addition, customer segmentation alone does not establish that a particular financial product or recommendation would be appropriate for a specific customer. Future research should therefore validate the identified patterns using real-world longitudinal datasets and assess recommendation accuracy, explainability, fairness, and customer outcomes. Such validation would strengthen the practical application of machine-learning-driven personalization in financial services.

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