Journal of Information Systems Engineering and Management
2026, 11(1s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Machine Learning-Driven Behavioural Insights into Customer Expectations for Personalized Banking Services

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ARTICLE INFO

Received: 24 Dec 2024

Revised: 12 Feb 2025

Accepted: 26 Feb 2025

ABSTRACT

Introduction: This study aims to explore the domain of behavioural finance using machine learning algorithms to derive conclusions about the customers in order to improve as well as personalize the services rendered. By employing machine learning and statistical analysis on banking data, the study provides actionable insights into how financial institutions can tailor their services to match distinct customer segments

Objectives: To separate the population data into 3 different segments and to test Hypothesis to ascertain the influence and expectations of personalization on customers, testing it based on the frequency of transactions, their age groups, and the average balance amount.

Methods: The study is carried out by utilizing a secondary data. An exploratory data analysis (EDA) is done to understand the demographic and transactional patterns found among the customers. K-means clustering algorithm is deployed to segment customers into distinctive behavioural profiles based on age, credit usage, frequency of transaction and account tenure. Random forest algorithm was used to predict customer preferences with regard to banking services.

Results: The findings throw light on the significance of demographic and transactional profiling in enabling precise personalization of banking experiences.

Conclusions: The study has outlined the distinguishable behavioural patterns that highlights expectations of personalized services. It is observed that transaction behaviour, credit usage and account longevity indicate to digital preferences. The segmentation suggests that personalization should differ from customer to customer based on their banking activities and the age group they belong to. These findings will be of use in behavioural finance literature as it is contextualizing the customer behaviour in a digital banking environment.

Keywords: Personalization, Machine Learning, BehaviourL Finance, Customer Segmentation, customer satisfaction.

INTRODUCTION

In the past decade with impact and fast growth of technology and Artificial Intelligence in particular Banking landscape has undergone a meticulous transformation. In particular post pandemic period has seem an increased adaptation of digital baking. This also means customers expect personalized banking experience which is also available at any time anywhere in the finger tips. Customer centric services are being researched upon and are built every minute of the day. This is posing a highly challenging situation on financial institution to meet the growing needs and to sustain their customers. Retention and engagement rates have come to great importance. Behavioural finance which is combing psychological insights with financial decision making provides a valuable framework for understanding customer behaviour, specifically on how they make decisions during uncertain situations.

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Though Behavioural finance is gaining huge momentum there is still a significant gap in contextual studies which explores the preferences and expectations of banking customers. The varying demography and evolving digital landscape necessitate the study of customer behaviour. This study aims to bridge this gap by employing machine learning based data analysis to understand and emphasis the customer's preferences for personalized baking products. The main methods employed in the paper include the Exploratory Data Analysis, Customer Segmentation and predictive modelling. The Exploratory Data Analysis enables understanding the dataset's structure, trends and potential relationship between variables, this is necessary to comprehend which model or hypothesis testing shall be employed. Segmenting the customers gives insights on spending behaviour and what type of preferences they have when it comes to financial products. This also throws light in the financial literacy of the segmented section of people. The Customer preference prediction model trains random forest classifier on transaction behaviour and demographics. It shows the importance of understanding features with variables that influence customer preferences. The statistical test of ANOVA and Pearson's Correlation test have also been employed, which shall be discussed in depth in the following sections.

LITERATURE REVIEW

This section highlights the evolving landscape of finance, which is largely influenced by the behavioural factors of consumers as well as technological advancements. A significant body of research has emerged in behavioural finance demonstrating that investor decisions are not always rational.[1] The integration of Artificial Intelligence (AI) is transforming financial services. Emerging concepts such as robo-advisors, which provide personalized solutions and are poised to replace traditional wealth management, are gaining traction [8]. AI lending platforms are also proving beneficial, offering banks a competitive edge by leveraging customer data more effectively [5]. According to a bibliometric review published in The Journal of Behavioural and Experimental Finance, empirical and quantitative studies predominantly utilize behavioural and prospect theories. Important research areas include personal traits, psychological factors, investor sentiment, asset market experiments, overconfidence, disposition effects, external variables (such as COVID-19), socially conscious investing, and herding behaviour [3]. The dynamic nature of this field is further underscored by a study charting the evolution of keywords in behavioural finance from 2000 to 2020, revealing two distinct research streams within the discipline [4]. Further illuminating this field, Berlinger et al. (2025)[6] examined the behavioural gender gap in financial literacy among university students, revealing disparities in attitude, knowledge, and behaviour that tend to collapse as levels of financial education increase, particularly with specialized talent management programs. In contrast, some research suggests that the adaptation of financial technology has a pronounced impact on consumer behaviour, where higher digital engagement leads to increased expectations for personalized banking experiences. Additionally, findings also highlight that consumers are increasingly likely to choose banks that offer enhanced personalized services, indicating a significant shift in customer preferences toward tailored financial solutions. They also stress the importance of understanding emotional and cognitive biases that can shape these preferences in a digital context. Lastly, the Indian commercial banking industry has exhibited robust growth in 2023–2024, bolstered by the ongoing demand for personal loans and a broad-based credit expansion across the services sector. The Reserve Bank of India (2024) [32] reported sustained profitability for six consecutive years, highlighting the importance of adapting to customer preferences in a rapidly changing financial landscape. This section highlights the evolving landscape of finance, that is being influenced largely by behavioural factors of the consumers as well as the technological. A considerable body of research has delved into customer behaviour and their involvement in business using various machine learning algorithms such as Decision Tree (DT), Random Forest (RF), Logistic Regression (LR), and Support Vector Machine (SVM) [17]. Understanding consumption patterns, including those related to financial products, necessitates behavioural segmentation; such approaches have been applied in case studies like electricity consumption pattern analysis [18]. Clustering techniques, particularly the K-means algorithm, have been widely adopted in behavioural analysis due to their simplicity, efficiency, and scalability [30]. Identifying significant customer segments aids in developing structured marketing strategies by aligning suitable products with targeted groups [19]. Exploratory factor analysis has also been instrumental in distinguishing underlying factors in data, thereby enabling the delivery of personalized services that benefit both businesses and customers [20]. Cross-selling optimization and customer segmentation, using transaction and shopping pattern data along with collaborative filtering models, have shown improved recommendation accuracy [21], [22]. Additionally, studies have explored customers' willingness to integrate Artificial

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Intelligence (AI) into banking services [23], emphasizing the importance of digital financial education to increase awareness about online financial tools [24]. The role of chatbots in enhancing customer convenience has been highlighted [25], along with broader discussions on how digitalization transforms the banking sector [26] and accommodates institutional variety [27]. Other research suggests the need for product diversification based on customer loyalty [28], and examines cognitive factors influencing the adoption of Fintech in digital banking [29]. Furthermore, aspects of customer retention in multichannel settings [9], satisfaction in banking services [10], and the determinants of retention [11] have been extensively studied. A two-dimensional framework has been proposed for analysing customer behaviour [12], while other contributions include conceptual models for entrepreneurial financial firms [13], evaluations of financial literacy and digital finance usage [14], the impact of customer voice on managerial decision-making [15], and the customer's perspective on sustainable finance and technology [16].

RESEARCH METHODOLOGY

The study adopts a quantitative-data driven approach to analyse the customer expectations using secondary data. The BankChurners dataset which is available on Kaggle is employed in the process, it reflects realistic banking customer's behaviour. Python is used as the primary analytical tool, along with its libraries such as pandas, seaborn, matplotlib and scikit-learn. These have been used for data manipulation and visualization. The analysis includes EDA, customer segmentation using K-means clustering and predictive modelling using Random Forest Classifiers.

The methodology's major aim is to identify and group distinct customer segments and to predict their preferences.

3.1. Data Description and Preprocessing:

The dataset comprises of variables such as age, credit limit, total transaction count and account tenure. These depict both demographic and behavioural traits of the customers. The data pre-processing involves removing null values and eliminating redundancy. Outliers were managed using the z-score filtering. To obtain consistency in clustering and modelling, the features had to be standardized using z-score normalization. An additional binary synthetic target variable (Prefers Digital Banking) was introduced to understand and comprehend customer's likelihood of engaging in personalized digital services

3.2. Exploratory Data Analysis (EDA):

The EDA results reveal key demographic trends, a balanced age distribution, there is concentration of customers on moderate credit limits and variability in transaction frequency. Correlation analysis showed strong relationship between transaction count and credit limit, account tenure. This suggests that these are critical indicators of customer engagement.

Diagrammatic representation using visuals were made for easier understanding of the results. Histograms, boxplots, and heatmaps are included. These reveal facts like: younger customers tended to have higher transaction volumes; this shows that youngsters are inclined to digital engagement whereas older customers demonstrate low frequency of usage but are quite consistent. These observations form a foundation for choosing features for segmentation and modelling.

3.3. Customer Segmentation:

Customer segmentation is deployed to identify the behavioural segmentation, K-Means clustering algorithm is applied on features including age, credit limit, total transaction credit etc. The number clusters identified is three.

The clusters separated are as listed:

- Segment 0: Younger and digitally active customers who have high transaction volume.
- Segment 1: Middle aged customers who have moderate credit, engagement levels
- Segment 2: Older, low but stable engagement customers

The segments give useful insights about tailoring differential products to each profile of customers.

3.4. Predictive Modelling:

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Random Forest Classifier is trained to predict the variable Prefers_Digital_Banking. The training vs test set of data is divided into 70:30 ratio. The model achieved an accuracy, precision and recall score of 85%.

The confusion matrix shows low false negative which points to high sensitivity in identifying digital preferred customers. The important features identified include the total transaction and credit limit as most influential. This aligns with behavioural finance theories about effort and perceived control over finances.

ANOVA (Analysis of Variance) has been implemented to personalization expectations of the segments. The results show that there are significant differences between age groups and their preferences.

In this paper, the following Hypothesis are tested:

H1: Customers who have high frequency of transaction are more likely to be receptive to personalized recommendations of banking products and services.

H2: There is a significant difference in personalization expectations across different age groups.

H3: Customers with higher average account balance have a greater expectation for personalized investment product.

The methods listed above and their results shall ascertain the acceptance or rejection of the said Hypothesis.

Before hypothesis testing, the data has been analysed for understanding its demography through multiple data interpretations. The following graphs explain the same.

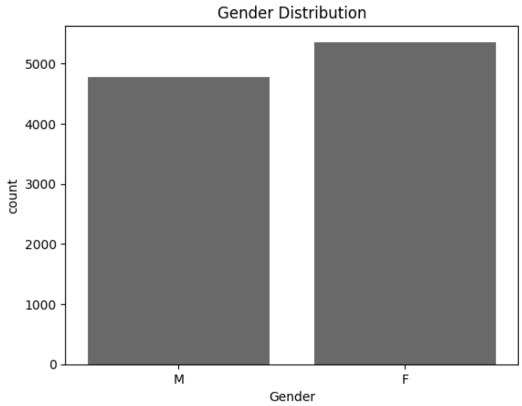

Figure 1: Gender vs Count Distribution Graph

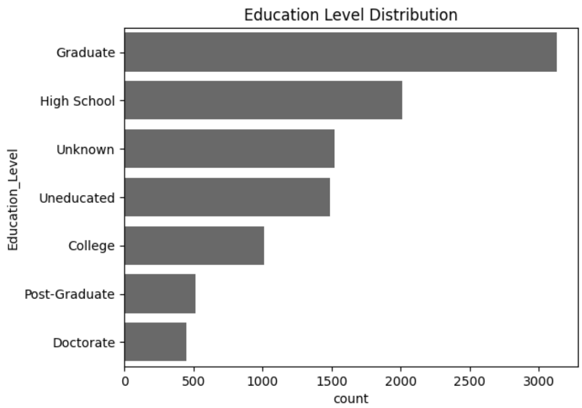

Figure 2: Education level distribution graph

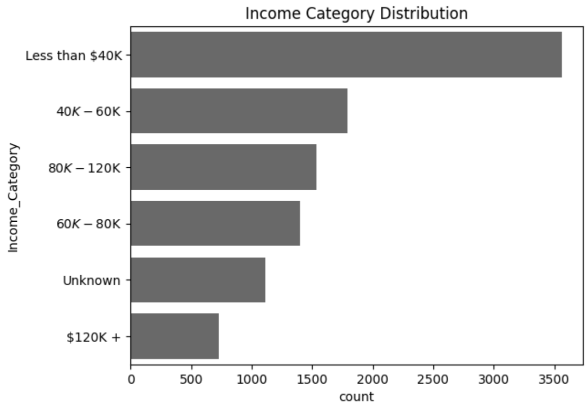

Figure 3: Income Category Distribution Graph

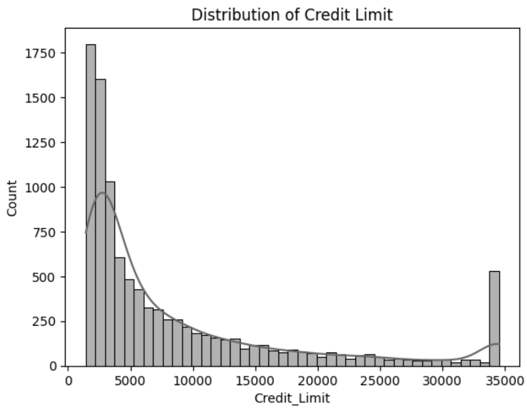

Figure 4: Distribution of Credit Limit Graph

The graphs represent the Gender, Education levels, Income category and Credit Limit pictorially for a short and easy understanding of the data to be analysed.

CONCLUSION AND DISCUSSIONS

The study has outlined the distinguishable behavioural patterns that highlights expectations of personalized services. It is observed that transaction behaviour, credit usage and account longevity indicate to digital preferences. The segmentation suggests that personalization should differ from customer to customer based on their banking activities and the age group they belong to. These findings will be of use in behavioural finance literature as it is contextualizing the customer behaviour in a digital banking environment. This work is evidence to support the incorporation of behavioural finance concepts combining it with Machine Learning to ascertain the customer needs and provide the best services accordingly. Banks should deploy such segmentation and modelling strategies to design customer centric products for each specific behavioural profile.

Banks should encourage data infrastructure development and digital literacy that can enhance the process to support personalization at scale. This study serves as evidence supporting the need for personalized banking services and customer centric products, further analysis will enable in creation of newer and better products and alteration of existing banking products to suit every individual customer's need.

REFERENCES

[1] Guzavicius, A. & Vilkė, R. & Barkauskas, V. (2014) "Behavioural finance: corporate social responsibility approach", Procedia - Social and Behavioral Sciences, Vol. 156, pp518-523. https://doi.org/10.1016/j.sbspro.2014.11.232

[2] Journal of Behavioral and Experimental Finance (2021) "Erratum regarding missing Declaration of Competing Interest statements in previously published articles", Journal of Behavioral and Experimental Finance, Vol. 30, art. 100430. https://doi.org/10.1016/j.adoms.2025.100590
[3] Kumar, S. & Rao, S. & Goyal, K. & Goyal, N. (2022) "Journal of Behavioral and Experimental Finance: A bibliometric overview", Journal of Behavioral and Experimental Finance, Vol. 34, art. 100652. https://doi.org/10.1016/j.jbef.2022.100652
[4] Corzo, T. & Hernán, R. & Pedrosa, G. (2024) "Behavioral finance in a hundred keywords", Heliyon, Vol. 10, art. e35979. https://doi.org/10.1016/j.heliyon.2024.e35979
[5] Königstorfer, F. & Thalmann, S. (2020) "Applications of Artificial Intelligence in commercial banks - A research agenda for behavioral finance", Journal of Behavioral and Experimental Finance, art. 100352. https://doi.org/10.1016/j.jbef.2020.100352
[6] Berlinger, E. & Dömötör, B. & Megyeri, K. & Walter, G. (2025) "Financial literacy of finance students: a behavioral gender gap", International Journal of Educational Management, Vol. 39, No. 8, pp116-133. https://doi.org/10.1108/IJEM-04-2024-0221
[7] Chauhan, G.S. & Huseynov, F. (2018) "Corporate financing and target behavior: New tests and evidence", Journal of Corporate Finance, Vol. 48, pp840-856. https://doi.org/10.1016/j.jcorpfin.2016.10.013
[8] Shanmuganathan, M. (2020) "Behavioural finance in an era of artificial intelligence: Longitudinal case study of robo-advisors in investment decisions", Journal of Behavioral and Experimental Finance, Vol. 27, art. 100297. https://doi.org/10.1016/j.jbef.2020.100297
[9] Chang, C.W. & Zhang, J.Z. (2016) "The Effects of Channel Experiences and Direct Marketing on Customer Retention in Multichannel Settings", Journal of Interactive Marketing, Vol. 36, pp77-90. https://doi.org/10.1016/j.intmar.2016.05.002
[10] Ozataca, N. & Saner, T. & Sen, Z.S. (2016) "Customer Satisfaction in the Banking Sector: The Case of North Cyprus", Procedia Economics and Finance, Vol. 39, pp870-878. https://doi.org/10.1016/S2212-5671(16)30229-1
[11] Zhengmeng, C. & Malik, M. & Hussain, M. & Hussain, S. (2024) "Exploring customer retention dynamics: A comparative investigation of factors affecting customer retention in the banking sector using mediation-moderation approach", Heliyon, Vol. 10, art. e36919. https://doi.org/10.1016/j.heliyon.2024.e36919
[12] Hosseini, M. & Abdolvand, N. & Harandi, S.R. (2022) "Two-dimensional analysis of customer behavior in traditional and electronic banking", Digital Business, Vol. 2, art. 100030. https://doi.org/10.1016/j.digbus.2022.100030
[13] Alvi, F.H. & Ulrich, K. (2023) "Innovation finance ecosystems for entrepreneurial firms: A conceptual model and research propositions", Journal of Business Research, Vol. 156, art. 113450. https://doi.org/10.1016/j.jbusres.2023.113450
[14] Yang, J. & Wu, Y. & Huang, B. (2023) "Digital finance and financial literacy: Evidence from Chinese households", Journal of Banking and Finance, Vol. 156, art. 107005. https://doi.org/10.1016/j.jbankfin.2023.107005
[15] Saxena, D. & Brady, M. & Lamest, M. & Fellenz, M. (2022) "Bridging the marketing-finance divide: use of customer voice in managerial decision-making", Quality Management Journal, Vol. 25, No. 3, pp361-382. https://doi.org/10.1080/10686967.2022.2043039
[16] Palos-Sanchez, P.R. & Chang-Tam, R.J. & Folgado-Fernández, J.A. (2025) "The role of Neobanks and FinTech in sustainable finance and technology. The customer/user perspective for entrepreneurs", Sustainable Technology and Entrepreneurship, Vol. 4, art. 100109. https://doi.org/10.1016/j.sus-tech-entre.2025.100109
[17] GhorbanTanhaei, H., Boozary, P., Sheykhan, S., Rabiee, M., Rahmani, F., & Hosseini, I. (2024). Predictive analytics in customer behavior: Anticipating trends and preferences. Results in Control and Optimization, 17, 100462. https://doi.org/10.1016/j.rico.2024.100462
[18] Kaur, R., & Gabrijelčič, D. (2022). Behavior segmentation of electricity consumption patterns: A cluster analytical approach. Knowledge-Based Systems, 251, 109236. https://doi.org/10.1016/j.knosys.2022.109236
[19] Ashraf, A., Rayed, C. A., Awad, N. A., & Sabry, H. M. (2025). A framework for customer segmentation to improve marketing strategies using machine learning. Procedia Computer Science, 260, 616–625. https://doi.org/10.1016/j.procs.2025.616625

[20] Mele, E., Dubosson, M., & Schegg, R. (2025). Are all luxury guests the same? A benefit segmentation of 5-star hotel customers. Journal of Hospitality and Tourism Insights, 8(11), 39–54. https://doi.org/10.1108/JHTI-10-2024-0201
[21] Lee, M., Cho, J., Kim, Y., & Kim, H.-J. (2025). Extracting offline retail shopping patterns: A restricted Boltzmann machines approach to customer segmentation and cross-selling. Expert Systems with Applications, 294, 128797. https://doi.org/10.1016/j.eswa.2025.128797
[22] Ullah, S., Liew, C. Y., & Nobanee, H. (2025). Digital transactions and financial development: The moderating role of global integration across income levels. International Review of Economics and Finance, 98, 103861. https://doi.org/10.1016/j.iref.2025.103861
[23] Ikhsan, R. B., Fernando, Y., Prabowo, H., Yuniarty, & Gui, A., & Kuncoro, E. A. (2025). An empirical study on the use of artificial intelligence in the banking sector of Indonesia by extending the TAM model and the moderating effect of perceived trust. Digital Business, 5, 100103. https://doi.org/10.1016/j.digbus.2025.100103
[24] Wang, K.-H. (2025). Beyond digital finance: The impact of internet banking adoption on subjective life satisfaction. Finance Research Open, 1, 100012. https://doi.org/10.1016/j.frl.2025.100012
[25] Petersson, A. H., Pawar, S., & Fagerstrøm, A. (2023). Investigating the factors of customer experiences using real-life text-based banking chatbot: A qualitative study in Norway. Procedia Computer Science, 219, 697–704. https://doi.org/10.1016/j.procs.2023.14
[26] Łasak, P., & Wycíslak, S. (2024). The dichotomy of inclusiveness and vulnerability as a consequence of banking platform development. Research in International Business and Finance, 72, 102536. https://doi.org/10.1016/j.ribaf.2024.102536
[27] Errico, L., Rondinella, S., & Trivieri, F. (2024). Diversity in banking and new firm formation. Insights from the Italian local credit markets. International Review of Economics and Finance, 91, 1095–1109. https://doi.org/10.1016/j.iref.2024.1095
[28] Kim, L., Jindabot, T., & Yeo, S. F. (2024). Understanding customer loyalty in banking industry: A systematic review and meta-analysis. Heliyon, 10, e36619.
[29] Tariq, M., Maryam, S. Z., & Shaheen, W. A. (2024). Cognitive factors and actual usage of Fintech innovation: Exploring the UTAUT framework for digital banking. Heliyon, 10, e35582. https://doi.org/10.1016/j.heliyon.2024.e36619
[30] Y. Chen, P. Tan, M. Li, H. Yin, and R. Tang, (2024) "K-means clustering method based on nearest-neighbor density matrix for customer electricity behavior analysis," International Journal of Electrical Power and Energy Systems, Vol. 161, Art. no. 110165. https://doi.org/10.1016/j.ijepes.2024.110165
[31] A. Abdurrahman, (2025) "Examining the impact of digital transformation on digital product innovation performance in banking industry through the integration of resource-based view and dynamic capabilities," Journal of Strategy & Innovation, Vol. 36, Art. no. 200540. https://doi.org/10.1016/j.jsinno.2025.200540
[32] Reserve Bank of India. (2024). Annual report 2023–2024: Reserve Bank of India - Trend and Progress of Banking in India