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Clustering Indonesian Neobanking Users Through Extended UTAUT 3 for Retention Campaign Strategy

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Abstract

Research Originality: This study develops a behavior-anchored segmentation framework for Indonesian neobank users by extending the Unified Theory of Acceptance and Use of Technology (UTAUT-3) with trust and marketplace application usage, providing deeper insights into user behavior.

Research Objectives: The research aims to identify distinct neobank user segments and key behavioral drivers to support targeted strategies in digital financial services.

Research Methods: An extended UTAUT-3 model incorporating trust and marketplace usage was validated through Structural Equation Modeling (SEM). Balanced Iterative Reducing and Clustering using Hierarchies (BIRCH) clustering was applied to data from 386 active users, with segment validity confirmed using Elbow, Gap, and Silhouette methods.

Empirical Results: The results revealed that trust, habit, and marketplace usage emerged as primary drivers of engagement and user recommendations. This study identifies four user segments: transitioning explorers, urban occasionalists, rural digital enthusiasts, and cost-conscious digital natives.

Implications: Urban Occasionalists and Rural Digital Enthusiasts show strong potential for long-term growth. Targeted engagement and personalized retention strategies for these segments can enhance customer lifetime value and strengthen user advocacy.

Keywords:
clustering; loyalty; neobank; retention; user segmentation

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INTRODUCTION

Indonesia's digital landscape has experienced significant growth in recent years, with the number of internet users reaching over 202 million as of 2021 (Sari et al., 2023). This expansion has been particularly transformative in the financial industry, which is undergoing rapid change driven by digitalization and shifting consumer expectations. The development of neobanks, branchless, mobile-first financial service providers, has redefined banking in the country. Despite the rise in digital access, the penetration of neobank users remains low, accounting for only 6.93% of digital banking users. This condition highlights a significant gap between the potential for adoption and actual sustained engagement. While neobanks are especially appealing to younger consumers due to their positive digital experiences (Hopkinson & Klarova, 2019), understanding what drives continued use and advocacy remains a significant challenge. Despite the substantial user base of neobanks, these users may also exhibit lower engagement frequency compared to traditional banking customers. This infrequent usage can contribute to a higher churn rate, where users discontinue their engagement with the neobank application. This churn is predominantly attributed to users drawn by promotional incentives who utilize the neobank application for specific, limited transactions, thereby restricting user retention and long-term engagement.

To explain user behavior in adopting digital services, previous research largely relied on theoretical frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003), its extensions UTAUT-2 (Venkatesh et al., 2012) and UTAUT-3 to explain behavior intention in digital service adoption (Bhatnagr & Rajesh, 2024; Farooq et al., 2017; Pinto et al., 2022). While these models are valuable for predicting behavior intention, they often fall short in translating those insights into practical strategies for user retention. Furthermore, critical constructs such as trust and cross-platform behavior, including marketplace usage, are frequently overlooked. These factors are increasingly relevant in Indonesia's integrated digital ecosystem, where users frequently engage with multiple platforms and services.

To address these gaps, this research extends the UTAUT-3 model by incorporating two additional constructs that are highly relevant to the Indonesian digital context: trust and marketplace usage. Trust plays a critical role in shaping user confidence in digital finance and reducing perceived risk (Kim & Koo, 2016; Rouibah et al., 2016), while marketplace usage reflects users' engagement across interconnected digital platforms (Chong et al., 2018). The extended model was tested using Structural Equation Modeling (SEM) to validate its constructs. The validated behavior indicators were then used in Balanced Iterative Reducing and Clustering using Hierarchies (BIRCH), a clustering method well-suited to large-scale behavior data.

The BIRCH clustering method is effective for identifying interpretable user profiles based on complex behavior patterns. In their seminal work, Zhang et al. (1997) demonstrate the effectiveness of BIRCH through experimental evaluations on various datasets, showing its scalability and competitive clustering quality compared to other clustering algorithms, such as DBSCAN and CLARANS. They also highlight the

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advantages of BIRCH in terms of its ability to handle noise and outliers, its computational efficiency, and its suitability for data mining tasks in large databases. John et al. (2023) did research about people's awareness of online purchases and developed a customer segmentation model to improve decision-making processes in the retail market industry using several state-of-the-art (SOTA) clustering algorithms, namely, K-means clustering, the Gaussian mixture model (GMM), density-based spatial clustering of applications with noise (DBSCAN), agglomerative clustering, and BIRCH clustering. The research using BIRCH clustering analysis got a 0.64 silhouette score.

The novelty of this research lies in combining an extended UTAUT-3 framework with trust and marketplace behavior and applying a hybrid SEM–BIRCH approach to generate behavior-based user segments. This method not only predicts behavioral intention but also translates theoretical constructs into practical tools for retention and implementation. The objectives of this research are to extend UTAUT-3 with trust and marketplace usage to reflect user behavior in the Indonesian context better, to validate the extended model using SEM, to segment neobank users based on behavioral data using BIRCH clustering, and to propose targeted retention strategies for each identified segment. The contributions of this research are threefold. Theoretically, it enhances the explanatory power of UTAUT-3 by including trust and cross-platform behavior. Methodologically, it introduces a novel combination of SEM and BIRCH for behavior-based segmentation. Practically, it provides actionable insights for neobank providers to design segment-specific retention campaigns, especially for high-potential segments such as Urban Occasionalists and Rural Digital Enthusiasts. This research bridges the gap between behavioral theory and practical strategy, supporting long-term user engagement in the rapidly evolving digital banking sector in Indonesia.

METHODS

A quantitative method was employed to develop a segmentation framework that supports retention campaign strategies for Indonesian neobank users. The theoretical foundation was based on UTAUT-3, which was extended with two context-specific variables: trust and marketplace application usage. These additions reflect the role of users' confidence and digital ecosystem interaction in shaping neobank adoption behavior. Data were gathered through an online survey targeting active neobank users in three provinces: DKI Jakarta, West Java, and East Java, selected based on mobile internet penetration and digital financial activity. A total of 386 qualified respondents were selected using purposive sampling, with the sample size determined based on the Lemeshow formula, assuming a 95% confidence level ($Z = 1.96$). Each respondent had used neobank applications for a minimum of five times per month in the last three months. Respondents were users of applications such as Jago Bank, BNC, Sea Bank, Aladin Bank, or Allo Bank.

In this research, the Likert scale was used to measure the variables of Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit, Trust, Perceived Risk, Financial Risk, Personal Information Risk, Behavioral Intention, Use Behavior, and Behavioral Intention to Recommend.

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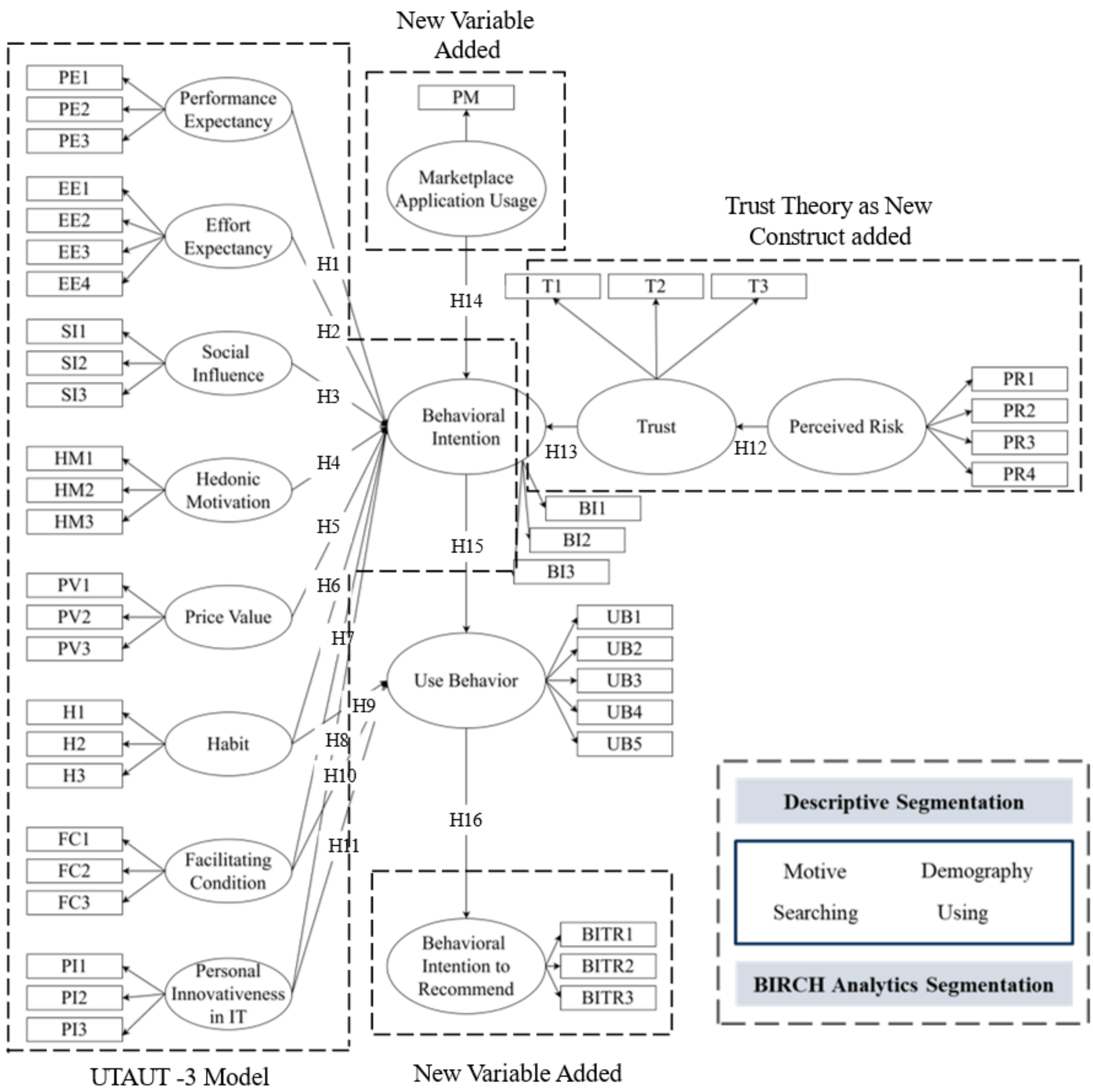
Meanwhile, the variable of using the marketplace application behavior is assessed using an ordinal scale. This research also incorporates sociodemographic and behavioral aspects related to marketplace and neobank application usage to inform user segmentation. The variables used in the sociodemographic and behavior aspects are explained in Table 1.

The conceptual framework, presented in Figure 1, illustrates how the operational variables and indicators of each construct interact within the research model, providing a structured overview of the hypothesized relationships examined in this research.

Figure 1. Conceptual Framework



The purpose of hypothesis testing is to determine if any independent variables have a significant influence on behavior intention and behavior intention to recommend Neobanking services. This testing also confirmed the indirect relationships between independent and dependent variables, mediated by intervening variables indicators (Hair et al., 2013). In addition, SEM verifies the significance of its latent variables.

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After conducting Structural Equation Modeling (SEM) analysis, the next step involves performing Clustering and Segmentation. This process aims to categorize the subjects or data into distinct groups based on similarities in their characteristics or responses. User segmentation allows neobanking institutions to focus their efforts on developing centered marketing strategies for specific user segments with high potential for neobanking adoption. The final segments represent distinct behaviour-based neobank user groups, enabling the development of targeted retention campaign strategies.

Table 1. Operational of Sociodemographic and Behavior

Variables	Variables Definition	Data Type
Age (Wang et al., 2020)	Respondent's age	Interval
Gender (Wang et al., 2020)	Respondent's gender	Nominal
Income per Month (Rahi et al., 2019)	Respondent's monthly income	Interval
Education (Rahi et al., 2019)	Respondent's last education	Ordinal
Residence	Respondent's living place	Nominal
Neobanking Experience	Frequency of using neobank application	Ordinal
Webrooming Experience	Frequency of using marketplaces and digital payment application	Ordinal

RESULTS AND DISCUSSION

Structural Model and Key Behavior Drivers Behavior constructs derived from the extended UTAUT-3 model were first validated using Structural Equation Modeling (SEM). The analysis confirmed the significant influence of performance expectancy, habit, trust, and marketplace usage on behavior intention, use behavior, and recommendation intent. Specifically: Trust and habit emerged as the strongest behavior drivers, Marketplace usage positively influenced intention to use and recommend, use behavior strongly predicted recommendation. These findings reinforce the relevance of integrating trust and marketplace-related behavior into technology acceptance frameworks, particularly for digital financial services in emerging markets like Indonesia (see Table 2 and Figure 2).

Table 2. Result of Hypothesis Test

Hypothesis	Coeff	T-Values	P-Values	Conclusion
H_1 (Performance Expectancy → Behavior Intention)	0,151	2,986	0,003	Accepted
H_2 (Effort Expectancy → Behavior Intention)	0,083	1,502	0,134	Rejected
H_3 (Social Influence → Behavior Intention)	0,138	2,385	0,017	Accepted
H_4 (Hedonic Motivation → Behavior Intention)	0,117	2,342	0,020	Accepted
H_5 (Price Value → Behavior Intention)	0,096	1,699	0,090	Rejected
H_6 (Habit → Behavior Intention)	0,155	2,528	0,012	Accepted
H_7 (Facilitating Condition → Behavior Intention)	0,062	1,160	0,247	Rejected

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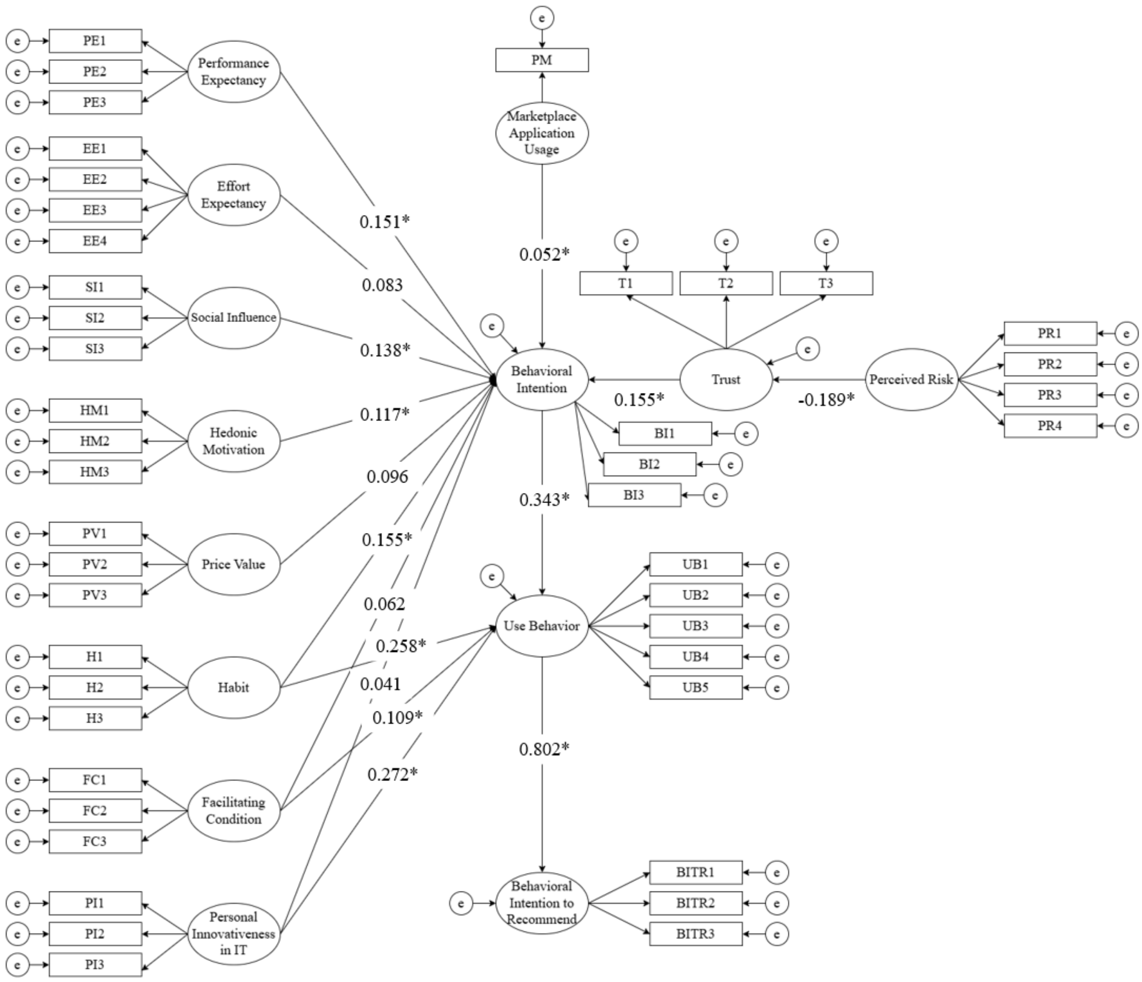
Hypothesis	Coeff	T-Values	P-Values	Conclusion
H_8 (Personal Innovativeness in IT → Behavior Intention)	0,041	0,791	0,429	Rejected
H_9 (Marketplace Usage → Behavior Intention)	0,052	2,621	0,009	Accepted
H_{10} (Trust → Behavior Intention)	0,155	2,985	0,003	Accepted
H_{11} (Perceived Risk → Trust)	-0,189	2,276	0,023	Accepted
H_{12} (Habit → Use Behavior)	0,258	5,422	0,000	Accepted
H_{13} (Facilitating Condition → Use Behavior	0,109	2,424	0,016	Accepted
H_{14} (Personal Innovativeness in IT → Use Behavior)	0,272	5,104	0,000	Accepted
H_{15} (Behavior Intention → Use Behavior	0,343	5,885	0,000	Accepted
H_{16} (Use Behavior → Behavior Intention to Recommend)	0,802	25,049	0,000	Accepted

Figure 2. Result of SEM Model



The UTAUT-3 model demonstrated strong predictive power, explaining significant proportions of the variation in usage intention, neobanking usage, and intention to recommend. Key factors driving intention and adoption include performance expectancy,

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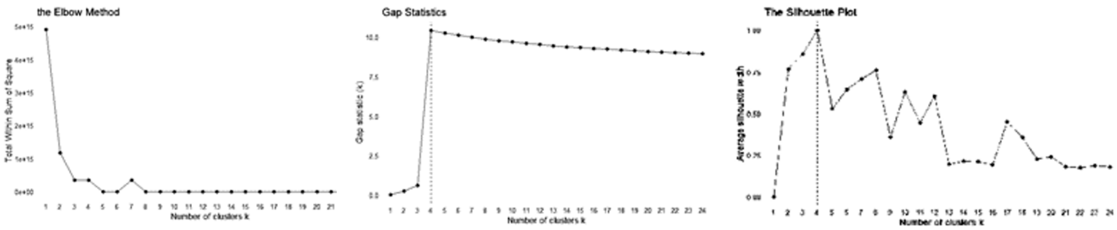
social influence, hedonic motivation, habit, and the integration of neobanking with marketplaces and trust.

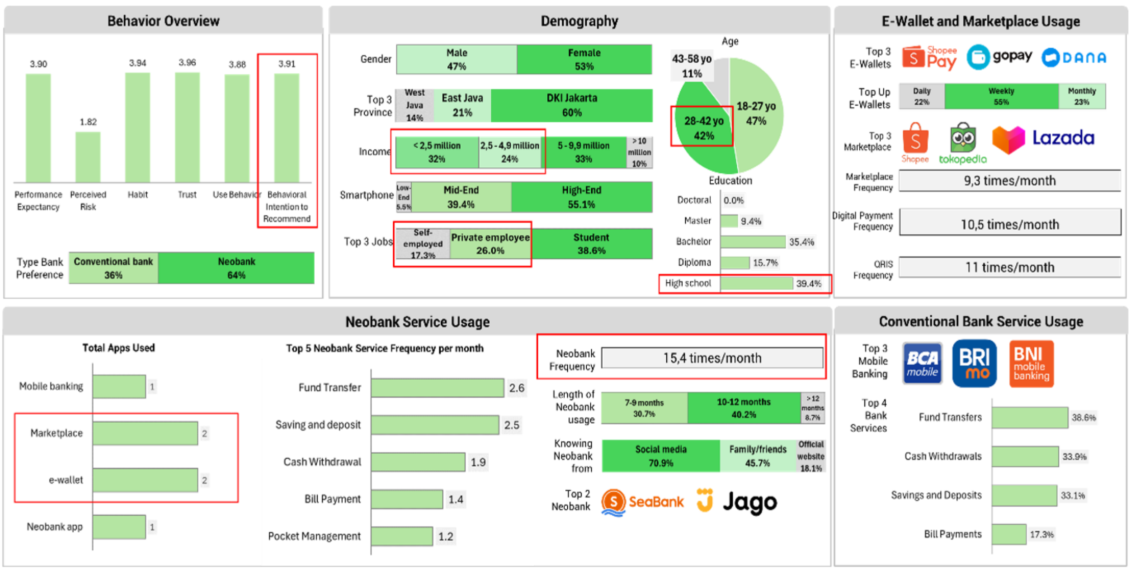
Figure 3. Determination of Optimal Segment Using Analytics Approach (a) Elbow Method (b) Gap Statistics (c) Silhouette Plot



(a) (b) (c)

Segmentation Using BIRCH Clustering. After validation, behavior scores were used as input for clustering via the Balanced Iterative Reducing and Clustering using Hierarchies (BIRCH) method. The number of clusters was determined through the Elbow Method, Gap Statistic, and Silhouette Plot, with four clusters selected based on interpretability and completeness of segmentation. Each cluster reflects distinct patterns of trust, marketplace usage, usage frequency, and intention to recommend, enabling tailored retention strategies.

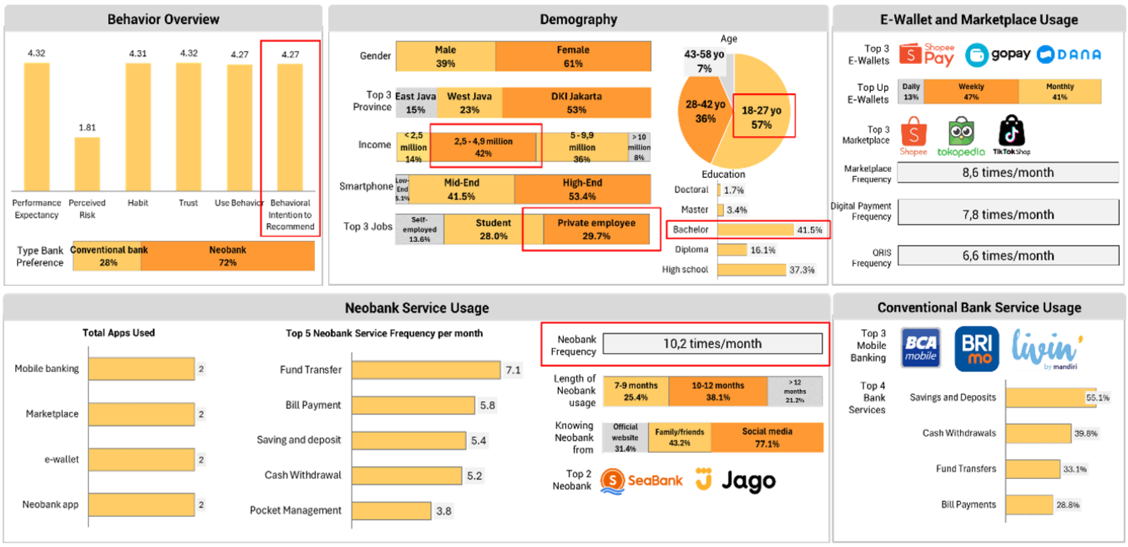
Figure 4. Profile of Transitioning Explorer User Segment



Four Segments are identified from the results of determining the optimal number of clusters as shown as follow. First, transitioning explorer (32.9%) Users are in the early phase of adoption (see Figure 4). The transitioning explorer engages with neobanking about 15 times/month, mainly through digital payments and QRIS. However, this group has the lowest trust and intention to recommend. Most are urban-based, mid-income private, or self-employed individuals exploring platforms through social media promotions. The switching behavior suggests uncertainty about neobank value. Retention strategies should focus on onboarding support, trust-building messaging, and feature transparency.

Second, urban occasionalist (30.6%) Users use neobanking around 10 times/month with equal marketplace usage. The urban occasionalists are private employees with steady income (IDR 2.5–5 million), largely from Jakarta (see Figure 5). The engagement is casual, often motivated by convenience rather than necessity. Although familiar with the technology, the dependence remains low and these individuals represent reactivation potential through gamified engagement, social referral programs, and showing time-saving features.

Figure 5. Profile of Urban Occasionalist User Segment



Third, rural digital enthusiast (28.5%) A highly engaged segment, using neobanking 16 times/month and marketplaces 12 times/month. Users exhibit high trust, high usage, and the highest intention to recommend (see Figure 6). The rural digital enthusiasts are based in suburban/rural areas and view neobank as integral to financial activity. Users are ideal targets for loyalty programs, premium upgrades, and community-led advocacy initiatives.

Fourth, cost-conscious digital native (8.0%) Young, digitally active users with limited income, engaging in up to 21 neobank transactions/month. Despite high trust, users have low perceived value, and usage is significantly driven by promotions and QRIS payments (see Figure 7). The cost-conscious digital natives are loyal but sensitive to cost. Providers should focus on value clarity, bundled offers, and student-oriented savings features to enhance long-term retention.

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Figure 6. Profile of Rural Digital Enthusiast User Segment

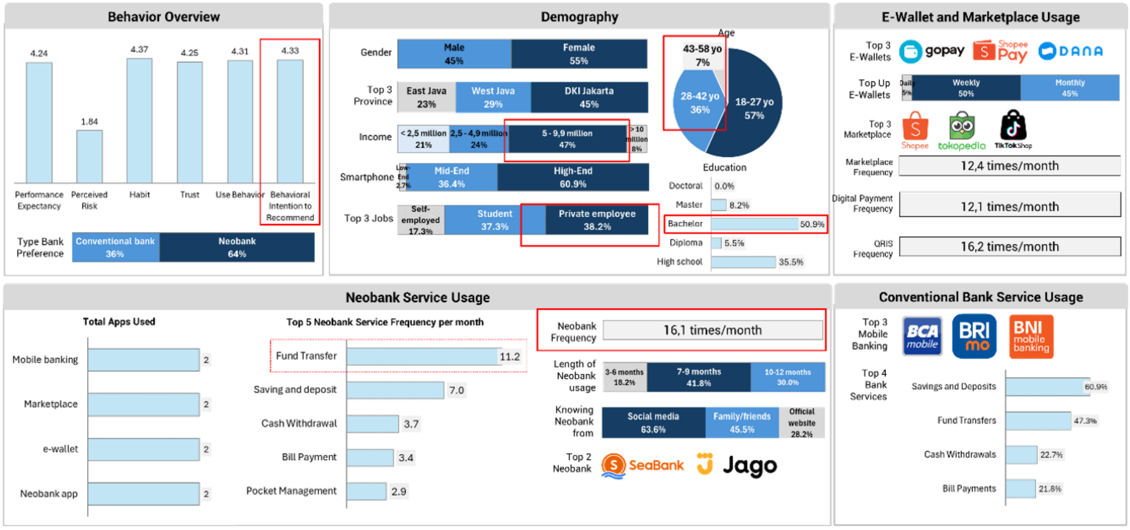
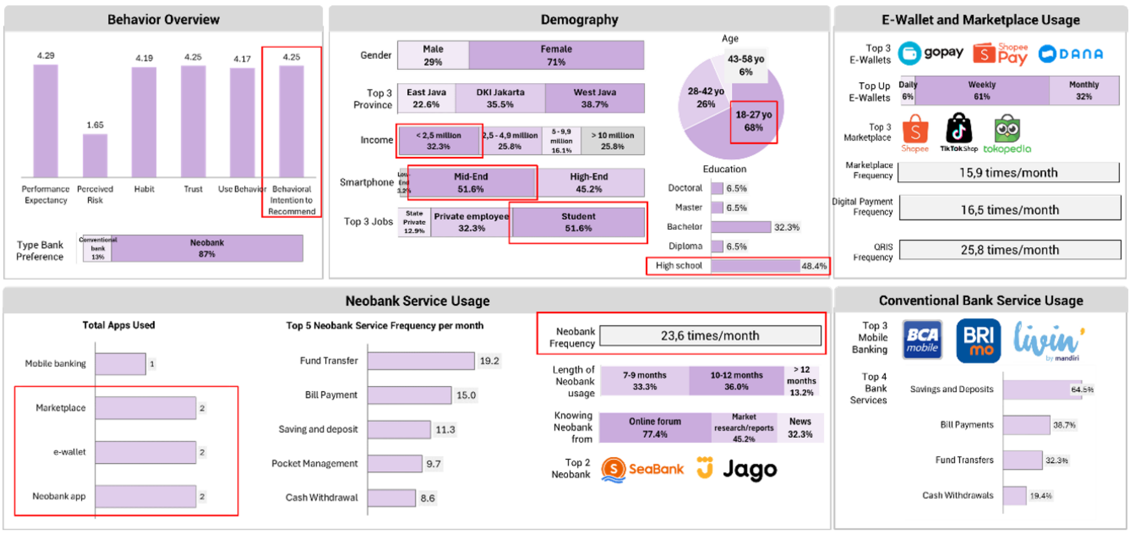


Figure 7. Profile of Cost-Conscious Digital Native User Segment



The results of this research revealed four distinct clusters of Indonesian neobank users, based on behavior constructs from an extended UTAUT-3 model: Transitioning Explorers, Urban Occasionalists, Rural Digital Enthusiasts, and Cost-Conscious Digital Natives. These clusters were formed based on an extended UTAUT-3 model, which included additional constructs, namely trust and marketplace usage. Unlike traditional segmentation based on demographics or transaction volume, this approach used validated behavioral indicators to capture how users actually engage with neobank services. These results contributed to the growing literature on digital banking behavior by offering a segmentation perspective rooted in trust, usage patterns, and engagement within the digital ecosystem.

Table 3. Segment Summary Characteristics

Segment Name	Population Size	Segment Profile
Transitioning Explorer User	32,9%	Using the neobanking application 15x/month and the marketplace 9x/month. Located in the urban area of DKI Jakarta, this individual is a mixed private and self-employed individual with an income of 2.5-5 million IDR/month. They are aware of the neobanking application through social media and have the lowest intention of recommending it.
Urban Occasionalist User	30,6%	Utilizing neobanking application 10x/month and 9x/month the marketplace application is utilized. A private employee who resides in the urban area of DKI Jakarta. They are aware of the neobanking application through social media, family, and friends, and monthly income ranges from 2.5 -5 million IDR.
Rural Digital Enthusiast User	28,5%	Utilizing the neobanking application on average of 16x/month, as well as 12x months for the marketplace. Resides in a rural area in the west and east of Java, employee of a private company. Aware of the neobanking application through social media with monthly income ranges from 5-10 million IDR
Cost-Conscious Digital Native User	8%	Using the neobanking applications 23 x/month and the marketplace 16x/month. Student from a rural area in West Java, with an income less than 2.5 million IDR/Month. Aware of the neobanking application through an online forum.

The confirmation of trust, habit, and marketplace usage as key drivers of behavior is consistent with previous research (Kim & Koo, 2016; Rouibah et al., 2016). The role of habit and convenience aligns with the work of Farooq et al. (2017) and Gunasinghe et al. (2020), who found these factors to be critical in driving behavioral intention in UTAUT-2 and UTAUT-3 models. However, this research goes further by linking these constructs not only to intention but also to actual usage, recommendation behavior, and behavior-based clustering, thus providing deeper insight into user lifecycle management.

Compared to prior UTAUT-based research, such as Venkatesh et al. (2003) and Alalwan (2020), which focuses on behavioral intention in the initial stages of technology adoption. This present research advances the discussion by connecting behavior predictors to actual usage, recommendation intention, and behavior-based segmentation for retention strategy design. In comparison, Bhatnagr and Rajesh (2024) introduced trust and perceived risk into their neobank adoption models, which were limited to the early stages of use. This research builds upon and extends these frameworks by applying a hybrid approach of SEM and BIRCH clustering, enabling the translation of behavioral constructs into strategic segmentation. In contrast to studies conducted in mature digital economies where social influence or facilitating conditions tend to dominate, this study shows that trust and habitual behavior are more influential in Indonesia's multi-platform, mobile-first ecosystem.

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Each segment identified in this study presents unique strategic considerations. Rural digital enthusiasts demonstrated a high frequency of use and strong trust in neobanks, despite being located outside major urban centers and typically having moderate income levels. This result challenges prior assumptions, such as those suggested by Rahi et al. (2019), that higher income and education are correlated with deeper engagement. This research identified that Rural Digital Enthusiasts with moderate income but high trust and usage frequency were among the most loyal and engaged. Urban Occasionalists exhibit moderate engagement and trust, suggesting potential for increased loyalty through consistent communication and user-centered feature enhancements. The Transitioning Explorer segment confirms previous results about promotional behavior (Hopkinson & Klarova, 2019). However, this concept contradicts the view that digital-native users inherently build loyalty. This group exhibited low trust and minimal intention to recommend, showing that digital fluency does not guarantee engagement.

Methodologically, this research complements the work of John et al. (2023) and Pradana & Ha (2021) by implementing BIRCH clustering in a novel behavioral context. While many previous studies used demographic or psychographic clustering, this study used constructs validated through SEM, offering more robust, theory-grounded profiles that are also practical for business applications. This approach enhances the interpretability and utility of user segments, allowing service providers to develop more targeted and effective engagement strategies. Beyond user retention, this segmentation model offers value for product development, user experience (UX) design, and cross-platform service integration.

The results confirm that trust, habit, and marketplace usage are key differentiators across clusters. Behavior segmentation using BIRCH provides deeper insights than traditional demographics, enabling neobank providers to align retention strategies with actual user behavior. Urban Occasionalists and Rural Digital Enthusiasts should be prioritized for growth-focused campaigns, given their latent or demonstrated loyalty to the brand. Transitioning Explorers represent high churn risk and need focused onboarding and trust-building content. Cost-conscious digital natives offer frequent engagement but require careful communication of value and educational content. By aligning retention efforts with validated behavioral patterns, this segmentation framework provides an actionable path to sustain engagement, reduce churn, and foster long-term loyalty in Indonesia's growing digital banking market.

CONCLUSION

This research developed a behavior-anchored segmentation framework for Indonesian neobank users by extending the UTAUT-3 model with two contextually relevant constructs such as trust and marketplace application usage. These extensions were empirically validated through SEM and subsequently used in the BIRCH clustering algorithm to classify users into four distinct segments, such as Transitioning

Explorers, Urban Occasionalists, Rural Digital Enthusiasts, and Cost-Conscious Digital Natives. The results revealed the central role of trust, habit, and marketplace usage in influencing behavioral intention, actual usage, and recommendation behavior in the neobanking context. These variables also served to meaningfully differentiate users' clusters, providing critical insights for designing segment-specific retention campaign strategies.

From a managerial perspective, the research provides actionable recommendations. Urban Occasionalists and Rural Digital Enthusiasts exhibited high potential for sustained engagement and advocacy, while Transitioning Explorers posed a greater churn risk due to low trust and inconsistent usage patterns. The segmentation results suggested that neobank providers should adopt differentiated engagement methods based on behavior profiles. For Urban Occasionalists, strategies should focus on product familiarization, lifestyle-oriented personalization, and reactivation incentives. Rural Digital Enthusiasts, who showed high trust and frequent usage, represented an ideal target for loyalty programs, bundled services, and community-based referrals. However, Transitioning Explorers required structured onboarding, trust-building communication, and reinforced value delivery. Cost-conscious digital natives were highly sensitive to costs and would benefit from value-based messaging and student-centric offerings to strengthen retention.

The findings highlight the importance of strengthening digital trust ecosystems through effective regulation and infrastructure development. Regulatory bodies should enforce data privacy and security standards to ensure that users, especially those in rural or economically vulnerable groups, can trust the digital financial platforms they use. Promoting interoperability among platforms also helps reduce friction in multi-app digital ecosystems, thereby fostering a more inclusive financial environment. Targeted financial literacy programs, particularly for younger and cost-sensitive populations, can enhance users' understanding of digital financial tools and reduce the risk of disengagement caused by misinformation or unmet expectations. Policymakers can collaborate with neobanks and educational institutions to integrate digital banking education into broader digital literacy initiatives.

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