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The Impact of a Loyalty Program on Credit Card Portfolio Performance: A Cluster-Based Analysis of Redeemers and Non-Redeemers in Q Rewards, Q-Bank Qatar

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ABSTRACT

Qatar is one of the wealthiest nations globally, with a relatively small population of approximately 3 million. It has attracted nearly 20 active banks, resulting in a highly saturated and intensely competitive market. In Qatar's market, Q-Bank positions the Q-Rewards loyalty program as a core strategic differentiator and has made significant investments to boost customer engagement and profitability. However, with rising reward liabilities, it is critical to assess whether the program contributes meaningfully to revenue generation. This research studies the effectiveness of Q-Bank (pseudonym), Qatar's loyalty program, "Q-Rewards," and its impact on credit card portfolio performance—based on the correlation between loyalty program engagement and profitability—through behavior-based customer segmentation. The research draws on credit card transaction data from Q-Bank customers between 2023 and 2024, using K-means clustering analysis in Tableau software. The research identifies five distinct behavioral and profitability clusters, each with unique characteristics in terms of loyalty engagement, spending categories, income, age, tenure, nationality, digital usage, and contribution to overall portfolio profitability. It reveals that redeemers—customers who utilize their loyalty points—tend to be significantly more engaged and profitable than non-redeemers, generating approximately 1.2 to 2.4 times higher profitability across all clusters. This finding demonstrates that redemption behavior correlates positively with profitability. This research also offers a practical framework for Q-Bank to optimize its loyalty program by implementing personalized engagement strategies, enabling the bank to better manage reward liabilities and strengthen its competitive positioning in Qatar's dynamic banking environment.

KEYWORDS Loyalty Program, Cluster Analysis, Customer Segmentation, Customer Personas, Redeemers, Profitability, Qatar Banking.

INTRODUCTION

The Qatari banking sector is one of the most developed and dynamic banking ecosystems in the Gulf Cooperation Council (GCC) region (Al-Jaidi & Omar, 2019; Hassan & Rahman, 2021). The banking sector is stable, well-capitalized, highly liquid and operating within a highly regulated environment overseen by the Qatar Central Bank (QCB) (Al-Ahmad, 2020; Yousaf et al., 2019) and comprises a mix of local conventional and Islamic banks, along with international banks operating as branches (Abdelrahman, 2022). Experiencing this competitive pressure, banks in Qatar are turning to loyalty programs as a core strategic differentiator (Al-Mahmood & Al-Qudah, 2021; El-Bassiouny, 2021).

Loyalty programs are proving to be a pivotal strategic tool to retain high-value customers, build engagement across multiple channels, and create lasting emotional connections with the brand (Chaudhuri & Holbrook, 2018; Kumar & Shah, 2020). These programs, which were once centered on simple points-based rewards, are evolving into comprehensive customer

engagement platforms, rewarding customers from card usage and salary transfers to bill payments and digital interactions (Lemon & Verhoef, 2019; Sweeney & Soutar, 2021).

The same condition happens with “Q-Bank” (pseudonym) in Qatar with their pan-bank loyalty program “Q-Rewards” (pseudonym) that it was launched in 2013. Q-Bank itself was established in 1964 and became the largest financial institution in the Middle East and Africa (MEA) region as of 2024.

Previously, the bank has only 2 (two) co-branded credit cards to be offered to their customers: (1.) Qatar Airways co-branded credit cards, with Avios as the card reward, and (2.) Ooredoo Co-branded credit cards, with Nojoom points as the card reward. In result, the bank needed to compensate to their co-branded partners for all the rewards given to the customers based on their credit cards transaction, either the rewards given have been redeemed or not (Sun et al., 2023; Zhao et al., 2022).

As part of the bank strategy, the bank has launched a new pan-bank loyalty program, “Q-Rewards”, where their customers can earn Q-Rewards in every step of the way: from the first-time customers open a salary account, to maintaining their average balance, providing a good referral, and using Q-Rewards credit cards or debit card. Since then, the program has been accepted well by the customers, shown by the higher growth of redemption rate and customer engagement rate for period between 2016 and 2024:

The program is also able to increase the Q-Rewards credit cards’ portfolio where more than 90 percent of the reward given is through credit card spending. The figure below indicates that the Q-Rewards credit card portfolio is growing, and its share compared to other credit card products is also increasing.

The more customers spend using Q-Rewards credit cards, the more customers earn Q-Rewards points. Thus, the growth of Q-Rewards credit cards usage is impacting to the growth of Q-Rewards points liabilities, as part of the bank’s commitment to their customers. Loyalty programs also offer a powerful source of customer data and behavioral insights, enabling banks to adopt data-driven strategies for customer segmentation and personalization offers. This is particularly critical in a saturated market, where a well-designed loyalty program can become a key differentiator.

Richard Fairbank, Founder of Capital One (2018) said that “Credit cards aren't banking - they're information". In 2023, there were approximately 665 billion global purchase card transactions, and this figure is projected to grow to 891 billion by 2027 (Statista, 2025; Nilson Report, 2025). This surge presents a significant opportunity for banks to monetize big data and reshape their engagement strategies by delivering relevant benefits and value propositions to the right customer segments (Chaffey & Ellis-Chadwick, 2019; Smith & Rios, 2020). However, despite this potential, many banks continue to rely on mass marketing and high-cost campaigns, overlooking the strategic advantage of personalized, data-driven customer segmentation (Arora et al., 2019; Kumar et al., 2020). Unlocking the full value of loyalty data could be the key to long-term competitive advantage in the evolving banking landscape (Verhoef et al., 2021; Lemon & Verhoef, 2022).

In this context, it is essential for Q-Bank to recognize that its Q-Rewards loyalty program has effectively rewarded and retained its most profitable customers, where their rewarding system is based on income-based customer segmentation. The bank’s transaction data can

provide a valuable foundation for uncovering spending patterns, customer behavior, and profitability profiles through advanced customer segmentation and analytics.

Q-Bank can clearly identify which group of customers are driving value and which one that needs more strategic attention to convert unprofitable customers into profitable ones. Q-Bank can also ensure that the rewards given are strategically aligned with these groups of customers. This approach not only validates the impact of the loyalty program but also enables the bank to fine-tune its reward structures to manage their loyalty cost effectively. By connecting data-driven insights with targeted reward mechanisms, Q-Bank can maximize both customer satisfaction and long-term portfolio profitability.

This research aims to analyze the correlation between Q-Bank's existing customer segmentation in the Q-Rewards loyalty program and the profitability of credit cardholders. Analyze the profitability between customers who redeem Q-Rewards (Redeemers) and those who do not (Non-redeemers). And to identify new customer clusters and develop data-driven personas based on behavioral and profitability segmentation, in order to guide Q-Bank's strategic targeting for personalized loyalty program offers.

METHOD

This study evaluated the effectiveness of Q-Bank's loyalty program by analyzing the profitability of customers engaged in the program using a quantitative approach. Data were collected from Q-Bank's internal database covering the period from January 2023 to December 2024, including customer profiles, transaction behavior, product ownership, digital channel engagement, and profitability metrics. The data underwent cleaning and preprocessing before analysis using the K-Means Clustering algorithm in Tableau software to segment customers based on loyalty behavior and profitability.

The clustering model was validated using statistical metrics such as p-value, F-value, WCSS, BCSS, R-Squared, and the Calinski-Harabasz Score. The final output included in-depth cluster analysis and the development of customer personas, which served as strategic tools for delivering personalized offers and optimizing the loyalty program to enhance the bank's credit card portfolio.

RESULT AND DISCUSSION

Data Analysis: The Validation of New Clustering Model

Table 1. Analysis of Variance (ANOVA) for the selected variables

Variable	F-value	p-value	Interpretation
Tenure (Average)	19,100	0	🔵 Very High: Strongly separates long tenured compared to new customers
Customer Global ID (Count)	18,900	0	🔵 Very High: Ensures distinct customer-level clusters
Credit Card Purchase in USD (Average)	523.9	0	🔵 High: Captures spending differences
Total Profit in USD (Average)	452.7	0	🔵 High: Distinguishes customer value
Loyalty Points Earned (Average)	384.7	0	🟢 Medium–High: Reflects engagement level

Credit Card Transactions (Average)	375.6	0	Medium–High: Differentiates activity volume
Credit Card International Spend (Average)	334.8	0	Medium: Indicates travel spending
Loyalty Points Redeemed (Average)	325.0	0	Medium: Shows reward usage patterns
Debit Card International Spend (Average)	256.1	0	Medium: Adds insight on debit card behavior

All selected variables returned statistically significant in distinguishing clusters, with all p-values are 0.000, indicating statistically significant at 99.9% confidence level and high F-values, indicating these variables contribute strongly to cluster separation. The F-value for key behavioral variables, such as Tenure (F = 19,100), Total Profit (F = 452.7), Credit Card Purchase (F = 523.9), Loyalty Points Earned (F = 384.7), and Points Redeemed (F = 325.0) were all statistically significant and demonstrate that the clusters are not only distinct but also highly influenced by loyalty behavior, spending patterns, and profitability indicators.

This confirms the segmentation is based not only on static income value but also on engagement and behavioral diversity, which is essential for targeted loyalty program and reward design. Furthermore, the model yielded was also being evaluated using standard clustering quality metrics as explained in Chapter III, with the following statistical diagnostics result:

Table 2. The summary diagnostics for clustering model review

Metric Diagnostics	Score	Interpretation
Total Sum of Squares (TSS)	14,581	Total variation in customer data
Within-Cluster Sum of Squares (WCSS)	877.22	Low within-cluster variation (good compactness)
Between-Cluster Sum of Squares (BCSS)	13,704	Variation explained by clustering (very high)
R-Squared (R^2)	94.0%	Very strong cluster separation
Calinski-Harabasz Score (CH)	312,306	Excellent clustering quality

The K-Means clustering model applied in this research achieved R-Square of 94%, calculated as the ratio of Between-Group Sum of Squares (BSS = 13,704) to Total Sum of Squares (TSS = 14,581), indicating that 94% of the variation in customer behavior is well-explained by the differences between the five identified clusters, while only 6% remains as unexplained variance within the clusters.

This high R-Squared value, supported by a low Within-Cluster Sum of Squares (WCSS = 877.22) and a very high Calinski-Harabasz Score (~312,306, >100,000), indicating a strong structure of the segmentation and giving a validation that the clustering model is not only statistically robust, but also practically relevant. The five clusters show meaningful differences in key business behaviors such as profit, tenure, loyalty redemption, and spending, making them highly useful for loyalty strategy development, targeting customers, and rewards campaign design.

The optimum total cluster for the new segmentation model is validated using The Elbow Method. The Elbow method is made through simulation for the total clusters from 1 to 10 as the x-axis and compared it with the value of WCSS given by the Tableu as the y-axis, to create The Elbow graphic as shown as Figure 1 below.

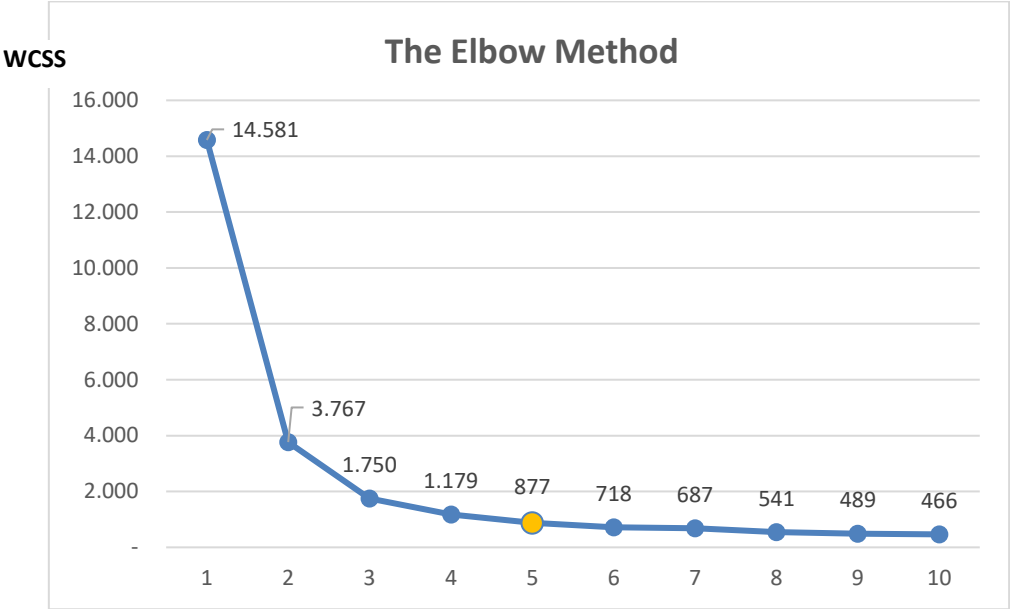


Figure 1. Elbow Method for the New Clusters Segmentation

Based on this Elbow Method graphic, WCSS drops sharply from 1 to 3 clusters, then it is gradually decreasing from clusters 4 to 5, becoming stable from cluster 6 onwards. This pattern indicates that the rate of improvement slows after the 5th (the fifth) cluster, forming an "elbow" shape as shown on the above graphic. Therefore, the Elbow Method suggests that the five clusters is the optimal total clusters, as it balances segmentation accuracy with simplicity, avoiding unnecessary complexity from adding more clusters.

Data Analysis: The New Clusters Segmentation

The model has generated 5 (five) distinct clusters, were identified based on parameters such as points earned, points redeemed, transaction volume, international and domestic card usage, profit in USD, and tenure.

Table 3. The New Cluster Composition & Separation

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Total Customers	17,642	11,027	15,502	17,852	18,538
Avg. Total Profit (USD)	550.4	320.9	247.2	249.7	195.1
Normalized	0.009057	0.005192	0.00398	0.00309	0.0027
Avg. Loyalty Points Redeemed (pts)	105,070	69,259	54,093	48,297	37,424
Normalized	0.014674	0.002943	0.002319	0.00178	0.001334
Avg. Total CC Purchases (USD)	24,421	17,683	13,993	12,238	9,938
Normalized	0.007614	0.005663	0.004226	0.003758	0.002533
Avg. Loyalty Points Earned (pts)	108,000	72,000	57,000	49,000	41,000
Normalized	0.005914	0.003878	0.003112	0.00256	0.002056
Avg. Tenure (Years)	20	14	10	7	3
Normalized	0.015189	0.009589	0.006429	0.002953	0.001052
Avg. CC International Usage (USD)	2,354	1,798	1,346	1,046	826
Normalized	0.003671	0.002566	0.001161	0.0014	0.001032
Avg. Total CC Transactions	69	72	67	61	53

Normalized	0.037052	0.038614	0.030091	0.026881	0.02502
Avg. DC International Usage (USD)	922	786	650	601	498
Normalized	0.004926	0.002842	0.002229	0.001835	0.001471

The table shows that Cluster 1 is the most valuable and engaged customer segment, where it has the highest values across nearly all variables: profitability, points redeemed, credit card purchases, tenure, and international card usage. This cluster is likely composed of long-standing, high-income customers who are deeply involved with the bank's loyalty program. Their high engagement in both earning and redeeming points suggests that they have perceived strong values in the rewards offered, and their heavy usage on international indicating them as global traveler and financially active lifestyle.

Meanwhile. Cluster 5 shows the lowest levels across key metrics, indicating that they likely haven't yet developed loyalty or higher transactional value. Clusters 2, 3, and 4 form in between. Cluster 2 shows promising engagement and moderate profitability, positioning it as a potential growth target for upselling or loyalty conversion. Cluster 3 and Cluster 4 appear mid-range in spending but lower in tenure and loyalty activity, suggesting for improvement through targeted campaigns and reward activation. Overall, the segmentation confirms a strong behavioral separation, offering valuable direction for tiered loyalty strategies, resource prioritization, and retention planning.

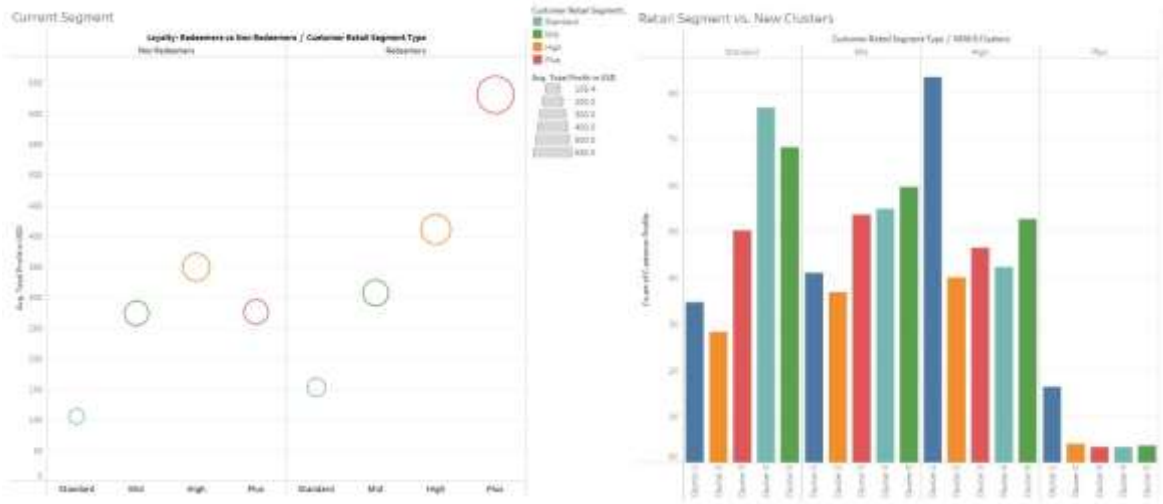


Figure 2. Average Profitability Based on The Current Segmentation

Across all the current retail segments (Standard, Mid, High, Plus), Redeemers consistently generate higher average profit than Non-Redeemers. While the current segmentation based on customers income expects for customers from "Plus" segment to be the most profitable, however this figure shows some overlapping, revealing that some "Mid" or "High"-tier customers can outperform even "Plus"-tier profiles if they actively engage in rewards. This figure also reveals that the traditional segmentation based on income or status (the current retail segmentation) does not accurately reflect behavioral value or profitability. Customers from the same current retail segmentation behave very differently. Therefore, a static income segmentation alone is not sufficient to predict engagement, redemption, or revenue contribution.

The first research question:

What is the relationship between Q-Bank's current customer segmentation in the Q-Rewards program and the actual profitability of its credit cardholders. This finding advises that a static segmentation based on income (salary) or status relationship tier, like the current Q-Bank's customer segmentation does not fully reflect their profitability and behavioral value. This also confirms that loyalty redemption is correlated with higher profitability, challenging the assumption that redemption equals cost. This insight supports moving toward behavior-based segmentation over status or income/salary segmentation base, for more accurate customer targeting and loyalty optimization.

Table 4. Comparison Between the Current Segmentation with The New Clusters Model

Traditional Segment	Limitation	New Cluster Model	Advantage
Based on salary /relationship only	Misses' behavioral loyalty & usage patterns	Uses profit, tenure, points, CC/DC usage	Captures actual value
Redeemers not always targeted	Redeemers shown to be more profitable	Redeemer clusters prioritized	Enables ROI-focused loyalty strategy
Tier status ≠ behavior	e.g., Plus Non-Redeemers underperform	High-profit, high-loyalty cluster detected	Enables precise targeting

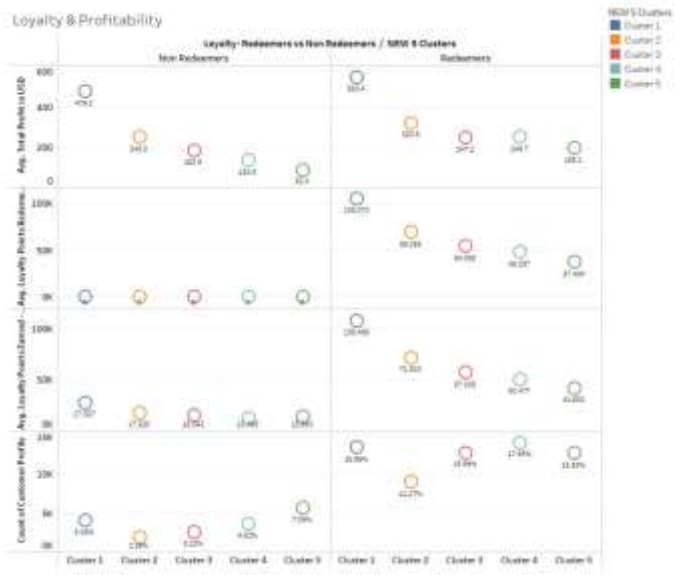


Figure 3. Average Profitability Based on The New Clusters Model

This figure reveals that Redeemers in all clusters outperform Non-Redeemers by +14.9% to +137% in profitability regardless of their salary or customers status, reinforcing the value of having an active loyalty strategy. Cluster 1 Redeemers have the highest average profit (USD 550.4) and also the highest loyalty points redeemed (105,070 points), representative of 16.88% of total customers.

This confirms that redemption behavior is strongly associated with profitability, especially within this top-tier cluster. Non-Redeemers from the same cluster are still highly profitable (USD 479.2), but Redeemers's profit has surpassed them by over USD 100 in

average, suggesting the loyalty program is not a cost burden but a profitability driver for this group. Even in Cluster 3 and Cluster 4, where the profit difference is narrower, Redeemers still show higher engagement through points earned and redeemed.

Table 5. The Profitability Comparison between Redeemers and Non-Redeemers for The New Clusters Segmentation

Cluster	Average Profit (USD)		Δ Profitability (Redeemer - Non-Redeemer)	Interpretation
	Non-Redeemers	Redeemers		
Cluster 1	479.2	550.4	71.2 +14.9% increase	Highly engaged Redeemers drive the most profit.
Cluster 2	249.3	320.9	71.6 +29% Increase	Redeemers spend more, possibly due to active engagement.
Cluster 3	182.9	247.2	64.3 +35% Increase	Redeemers still more profitable overall, but gap is smaller.
Cluster 4	133.5	249.7	116.2 +87% Increase	Big uplift among Redeemers in this young cluster.
Cluster 5	82.4	195.1	112.7 +137% Increase	Newer customers: Redeemers show strong potential.

Referring to the above table, Redeemers outperform Non-Redeemers between USD 64.3 and USD 116.2 on average or around 1.2 to 2.4x higher than Non-Redeemers across all clusters, proving that redemption behavior correlates positively with profitability.

The second research question:

How does the profitability of credit cardholders differ between those who redeem Q-Rewards (Redeemers) and those who do not (Non-Redeemers). Referring the above data insights, the customers who redeem are more involved with the brand and therefore drive higher revenue and profitability. Therefore, “Points Redemption” is a predictor of high-value customer behavior, not just a result of income or tier status. This is consistent with the research done by Meyer-Waarden (2008) and Filipović (2020) that total Redeemers has higher total spending during the year, in comparison with Non-Redeemers, and research done by Li et al. (2024) that customers engage more with the company when they periodically redeem points, and customers with higher purchase depth and redemption recency are more likely to redeem points.

Figure 4. Profile The New Cluster Based on Average Tenure, Average Age and Average Income

Referring to the finding as showing on Figure 4.3, Cluster 1 stands out compared to other clusters, with the highest average customer's income of ~QAR 39,173, having the longest tenure (~20 years), and also the oldest age profile (average ~50 years old). These profiles indicate that this cluster is a highly loyal and stable customer base, likely contributing significantly to overall profitability. Their long-term relationship with the bank suggests strong brand trust and satisfaction, making them as our priority candidates for targeted portfolio campaigns promoting premium service, and tailored loyalty enhancements.

Conservatively, Clusters 4 and Cluster 5 comprise relatively younger customers with lower customer's income levels (between average QAR 21,540 and QAR 25,258) with shortest tenure (between 2.56 and 6.58 years). Despite their lower profitability, these segments present potential growth if the bank able to nurture it effectively through engagement, education, and incentive-driven loyalty programs. Clusters 2 and Cluster 3 are in transitional category with moderate income, tenure, and age, indicating potential upward movement.

The nationalities of the clusters could also influence their persona. This research has grouped the clusters based on Qatari and Expat indicators and also grouping them based on the top 20 nationalities and other ethnicities group in Qatar, with the result as shown at Figure 4.4. below.

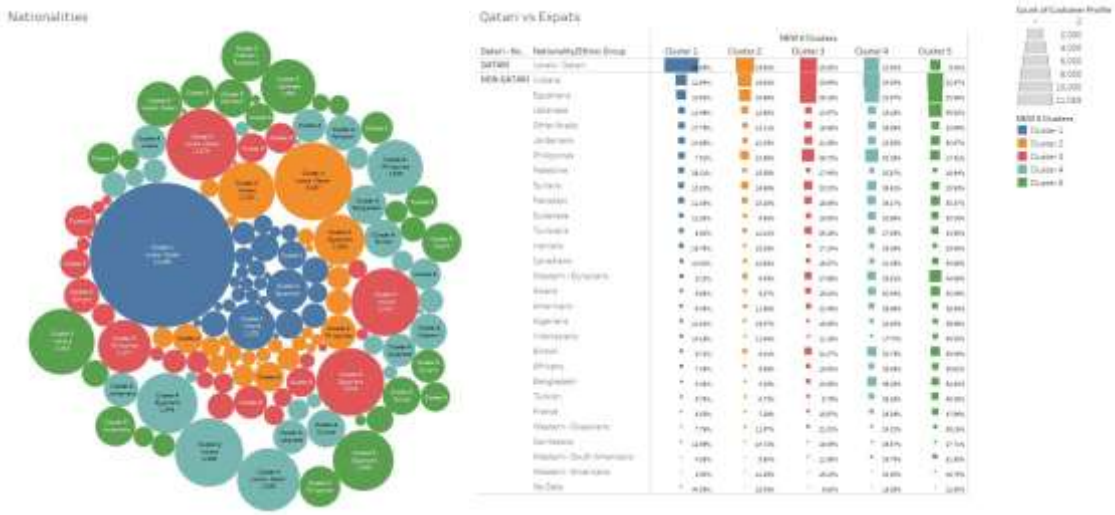


Figure 5. Profile The New Cluster based on Nationalities

The figure gives district patterns on their nationalities and ethnicities across the five customer clusters. Cluster 1 is predominantly composed of Qatari nationals (55%), representing the largest segment of local high-income, long-tenured individuals with mature financial profiles. Cluster 2 and Cluster 3 show a mix of both Qatari and non-Qatari profiles, with notable representation from Egyptians, Indians, Lebanese and Filipinos, indicating segments with mid-level income, moderate tenure, and diverse spending behaviors.

These clusters are likely composed of actively working expatriates who have integrated into the local economy with stable engagement levels. In contrast, Clusters 4 and 5 are largely dominated by non-Qatari expatriates, particularly from South Asia (e.g., Indians, Pakistanis, and Bangladeshis), as well as Westerners (e.g., Americans, British, and Western Europeans) and African origins.

These clusters exhibit relatively shorter tenure and younger average age. The high share of Western expatriates is in Cluster 5, also implies a digitally savvy, upwardly mobile group with strong potential for future profitability. This finding is highlighting the importance of tailoring loyalty strategies not just by retail segment or income, but also by cultural background, language, and tenure to increase their engagement, especially in the market with typical like Qatar that having expats with more than 160 nationalities.

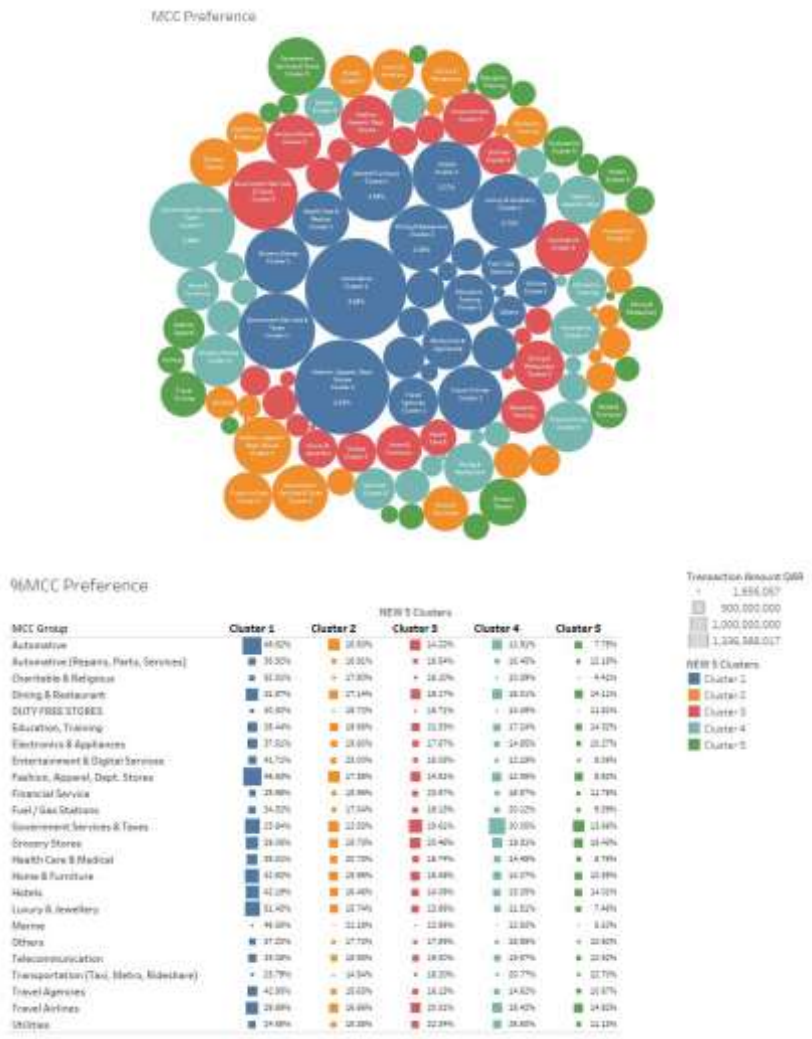


Figure 6. Profile The New Cluster based on their purchases on MCC

This clustering analysis reveals distinct purchases patterns based on their MCC (merchant category code) preferences, across the five new clusters. Cluster 1 has majority of their spending in lifestyle-related categories, with a strong emphasis on MCC automotive: Very high % in Automotive (49.62%), Charitable & Religious (52.51%), Luxury & Jewellery (51.43%), Marine (48.35%) and also high in Fashion, Home & Furniture, and Hotels (46.63%). Cluster 2 focuses heavily on leisure and social activities, Entertainment (23%), Health Care (20.73%), Fashion (17.38%), Hotels (16.46%) and also high in Automative, Luxury & Jewellery, Marine and Dining & Restaurants, with lower in essential categories like Groceries and Utilities.

Cluster 3 exhibits a balanced spending distribution across various MCC categories with slightly higher percentage in Dining, Groceries, Travel Airlines, and Utilities. In contrast, Cluster 4 concentrates its spending on essential and recurring needs such as Government Services & Taxes (30.05%), and also high in Groceries, Utilities, but low in spending like Luxury and Hotels. Cluster 5 demonstrates low percentages across most categories, with slightly relative higher for spending in Transportation (22.70%), Travel Airlines (14.82%) and Hotels (14.01%).

Figure 7. Profile The New Cluster based on their Digital Banking engagement and Language preference

This above figure shows the distribution of customers across five clusters based on their digital banking engagement and also their language preference (Arabic "AR" or English "GB"). Cluster 1 has the highest share of Arabic-speaking customers, with higher digital banking users and a slightly portion of non-digital banking users. Cluster 2 shows low engagement and limited digital adoption in overall. Cluster 3 is digitally engaged with higher share of English-speaking customers. Cluster 4 shows a mix of engagement levels, with a moderate share of English digital users. Cluster 5 has the highest English-speaking digital user base, yet still retains a significant non-digital segment.

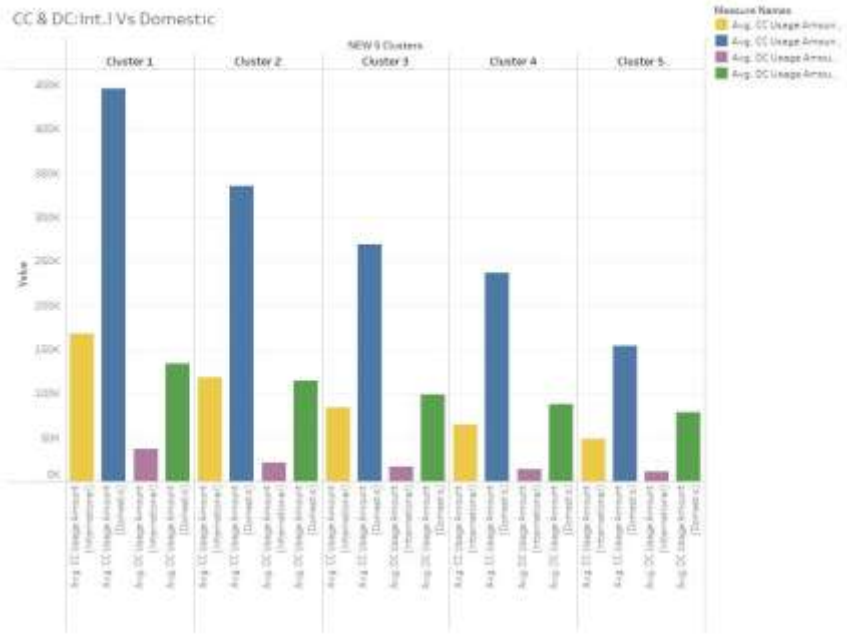


Figure 8. Profile The New Cluster based on their International and Domestic Spending

This figure shows the usage comparison of credit and debit cards across international and domestic transactions for each cluster. Cluster 1 shows the highest usage overall, heavy users of both credit and debit cards, especially abroad. Cluster 2 also records strong usage, frequent travelers with high credit card use, but slightly lower than Cluster 1. Cluster 3 has moderate usage in all categories, slightly lower in international usage than Clusters 1 and Cluster 2.

Cluster 4 demonstrates relatively low credit card usage share, with a higher domestic debit card usage, suggesting a more conservative, cash-based spending pattern. Cluster 5 has the lowest credit card usage share compared to debit card and relies more on domestic debit card transactions. This Cluster 5 appears to be the least engaged in card-based spending, particularly internationally.

The behavioral segmentation as explained above has revealed the five distinct new clusters segmentation where each cluster represents a unique profile of their financial behavior, profitability, loyalty engagement, and demographic background. The comparison between each cluster can be seen in Table 4.6.

Tabel 6. The Characteristic Comparison between The New Clusters Segmentation

Cluster	Key Behaviour Personalities	Cluster Name
Cluster 1	▪ Predominantly Qatari locals, older (average ~50 years old), with high income and long tenure (~20 years) ▪ The most profitable and loyal segment, with the highest loyalty points earned and redeemed. ▪ Very high international credit card usage, indicating global travel and luxury purchasing ▪ Heavy spenders on Automotive, Luxury & Jewellery, Charitable, Marine, Fashion, Home & Furniture, and Hotels. ▪ High digital engagement, with majority Arabic preference users	**"The Prestige Redeemers"**
Cluster 2	▪ Mid-income Qatari, Arab expats, primarily Egyptians, Lebanese, Syrians, Jordanians, and Indians. Middle-aged (average ~44 years old), and family-oriented with long tenure (~14 years) ▪ Moderate profitability with decent redemption ▪ Strong credit card usage, but slightly lower than Cluster 1 ▪ Focus on leisure and social activities: Entertainment, Health Care, Fashion, Hotels and also high in Automative, Luxury, Marine and Dining, with lower in essential categories like Groceries and Utilities ▪ Centered around lifestyle categories: Dining & Restaurants, Fashion, Entertainment, and Hotels. Lower in essential like Groceries and Utilities ▪ Moderate digital engagement, slightly more English preference users.	**“The Gulf Settler”**
Cluster 3	▪ Mid to low income (average ~42 years old), mostly Indian, Egyptian, Filipino, and Syrian expats, with tenure ~10 years. ▪ Moderate to low profitability and redemption ▪ Primarily domestic spending with lower credit card usage. Often seeking discounts and price-sensitive offers. ▪ Exhibit a balanced spending across various MCC categories with slightly higher percentage in Dining, Groceries, Travel Airlines, and Utilities. ▪ Digitally engaged with higher share of English-speaking customers	**“The Value Chaser”**
Cluster 4	▪ Lower income, relatively younger (average ~40 years old), and newer customers (tenure ~6.6 years). Majority are non-Qatari and diverse expat mix (British, Indians, Egyptians, Pakistani, Bangladeshi, Filipino and African origins) ▪ Moderate profitable group (higher than Cluster 3), with higher redemption rate efficiency (95.68%) ▪ Relatively low credit card usage with higher domestic debit card usage shared, suggesting more conservative, cash-based spending ▪ Necessity-focused, with high spending in government services, groceries, utilities, but low in like Luxury and Hotels	**"The Strategic Redeemer"**

	▪ Mix of engagement levels, with a moderate share of English digital users	
Cluster 5	▪ Frequent travelers, mid-income expat, younger (average ~39 years old) and newer customers (tenure ~2.6 years). Highly diversified expat base, mostly Western expats ▪ Mid to low profitability with lower redemption rate (89.54%) ▪ Focus on mobility, travel convenience, education, and digital services, balancing between essentials with lifestyle perks. ▪ Tech-savvy, with English preferred digital users	**"The Global Voyager"**

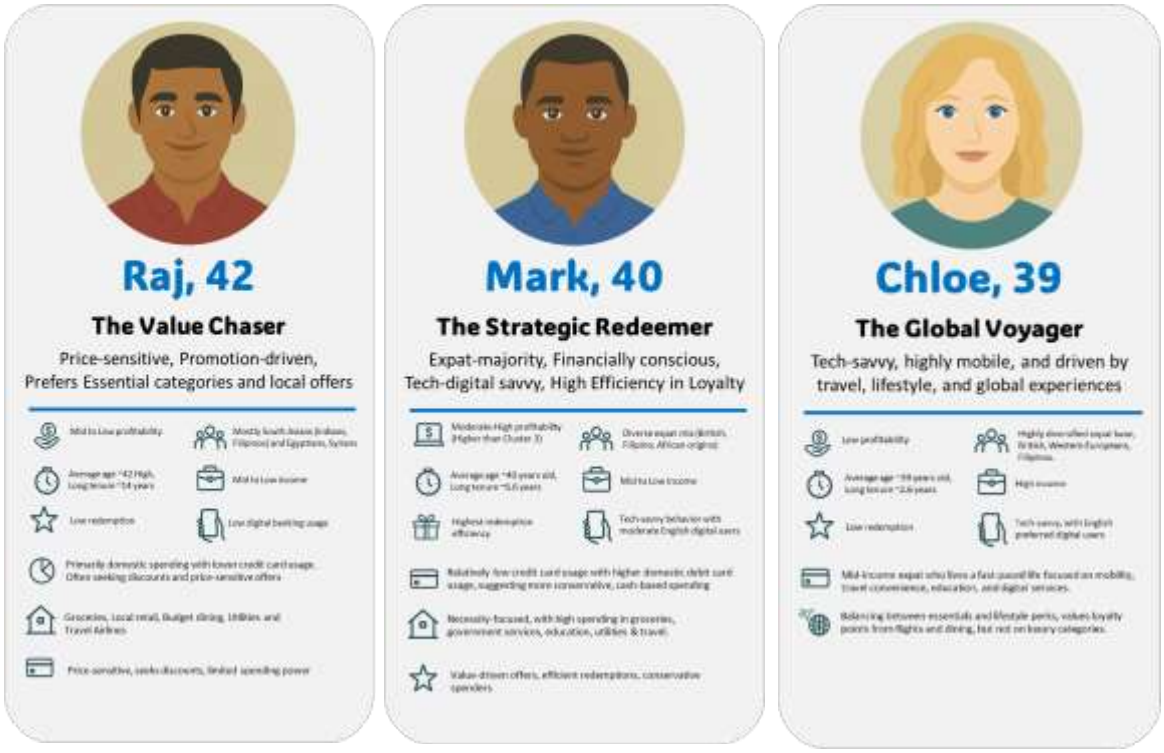
The third research question:

What new customer clusters and personas can be identified through behavioral and profitability-based segmentation analysis? and how can these insights guide Q-Bank's strategic targeting for personalized loyalty program offers?

The resulting segmentation model by utilizing Tableau as the visualization and analytics platform, have produced five distinct clusters where each cluster demonstrating unique characteristics in terms of loyalty engagement, spending categories, digital usage, and contribution to the overall portfolio profitability as explained on Table 4.6. To translate these quantitative findings into actionable strategy, five refined Customer Personas were developed based on the five new clusters segmentation. These personas humanize the clusters, empowering targeted loyalty programs to make it more to personalized offers, with engagement strategy is aligned with each segment's lifestyle, financial profile, and loyalty behavior. Please find the Customer Personas based on this research result, as shown on Figure 4.9.

Cluster 1.

Cluster 2.



Cluster 3. **Cluster 4.** **Cluster 5.**

Figure 9. Customer Personas for Q-Rewards Customers

These images display five well-defined customer personas derived from segmentation analysis based on Q-Rewards credit cardholders data, providing a valuable humanizing framework for targeted loyalty program strategies.

1) Cluster 1: Prestige Redeemers, characterized by individuals like Jassim, 50 years old, represents affluent, long-tenure Qatari locals who exhibit the highest profitability and loyalty engagement. Their spending behavior is centered on luxury, automotive, charitable giving, and international travel, with notably high international credit card usage. They also show strong digital engagement, particularly in Arabic. These customers are ideal for exclusive, high-value loyalty campaigns, including automative, elite privileges, luxury retail experiences, and premium service bundles that reflect their elite lifestyle and global footprint.
2) Cluster 2: The Gulf Settler, represented by Zayed, 44 years old, includes mid to high income Arab expats, primarily Egyptians, Syrians, Lebanese, Jordanians, and some Indians. They demonstrate moderate profitability and solid redemption behavior, with an average tenure of ~14 years. Their spending is focused on family-oriented categories such as dining, entertainment, fashion, and groceries, with a balanced mix of domestic and international purchases. While digital engagement is moderate, there is an increasing preference for English interfaces. Loyalty strategies for this segment should highlight family-centric offers like group dining, family hotel deals, and bundled retail promotions that match their lifestyle and income level.
3) Cluster 3: The Value Chaser, characterised by a person like Raj, 42 years old representing as a cost-conscious segment primarily made up of Indian, Egyptian, Filipino, and Syrian

expats. Raj is more price-sensitive and focused on essentials, displaying lower profitability and redemption, despite having long tenure of ~14 years. Their financial behavior is conservative, with a focus on basic needs and savings, spending mainly on groceries, utilities, and budget airlines. With limited credit card usage and low digital engagement, they are unlikely to be attracted by aspirational rewards. Loyalty programs aimed at this group should offer highly practical, tangible benefits, such as discounts on essential goods, basic service bundles, or redemption on credit card payment.

4) Cluster 4: The Strategic Redeemer, characterised by a person like Mark, 40 years old, representing as a segment of diverse nationalities and financially-savvy expats, who are relatively new to the bank (~6.6 years tenure) but demonstrate moderate to high profitability and having the highest loyalty redemption efficiency (the comparison between points earned and points redeemed), driven by calculated usage and strategic redemption behavior. This group tends to be digitally savvy, with strong English preference, and spends on necessities such as education, government services, and groceries. Loyalty programs aimed at this group should be using value-optimized loyalty schemes, such as point multipliers on utility bills, digital (voucher) redemptions, or education-related partnerships, focusing on practical benefit over luxury.
5) Cluster 5: The Global Voyager, characterised by a person like Chloe, 39 years old, representing as a younger, affluent expatriate segment, largely from Western countries. They are new to the bank (with average ~2.6 years tenure) and exhibit the lowest profitability across all segments. This segment shows frequent spending on transportation, airlines, hotels, and dining, reflecting an active, on-the-go lifestyle rather than high-end consumption.

   They are digitally engage with mobile banking and online transactions, favoring English-language. Their engagement with the loyalty program is low, both in terms of points earned and redeemed. Loyalty programs targeting this group should not focus on luxury rewards, but rather on practical, convenience-oriented travel benefits, such as: Airport lounge access, transportation and ride-hailing discounts, dining and hotel vouchers, and flexible digital redemptions integrated with mobile apps, digital wallets or global travel apps.

These personas suggest the strategic need to differentiate loyalty program designs: premium tiers and luxury partnerships for affluent groups like Jassim and Zayed, essentials category rewards and promo-heavy campaigns for cost conscious expats group like Raj, digital and efficiency-oriented rewards for the pragmatic redeemers like Mark and travel rewards for Chloe. By aligning reward types with user behaviors, Q-Bank can improve customer engagement, loyalty redemption, and ultimately cardholder long-term portfolio profitability.

CONCLUSION

This research on Q-Bank Qatar's Q-Rewards Loyalty Program demonstrates that customer engagement via redemption significantly boosts profitability, with Redeemers outperforming Non-Redeemers across all clusters by profit uplifts of 14.9% to 137%; behavioral segmentation via Tableau and K-Means clustering provides superior predictive power for customer value compared to static income tiers, identifying five distinct personas for targeted strategies that cut costs and enhance returns—particularly in lower-tier segments, challenging assumptions about high-income responsiveness. The findings position loyalty

programs as strategic assets driving engagement and spending, recommending a hybrid approach of income-based simplicity with behavioral clustering and real-time dashboards for personalized offers. For future research, extend the analysis to multi-year trends across GCC banks to validate generalizability and uncover region-wide strategic insights.

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