Project Dissertation Report on

IMPACT OF PERSONALIZED REWARDS ON CUSTOMER RETENTION IN DIGITAL LOYALTY PROGRAMS

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DECLARATION

I, **Bhavya Singhal**, Roll No. **24/DMBA/60**, a student of the Master of Business Administration programme at Delhi School of Management, Delhi Technological University, hereby declare that the project dissertation entitled "**Impact of Personalized Rewards on Customer Retention in Digital Loyalty Programs**" submitted to Delhi School of Management, Delhi Technological University, in partial fulfilment of the requirements for the award of the degree of Master of Business Administration, is a bonafide work carried out by me.

This dissertation has not been submitted elsewhere, in whole or in part, for the award of any degree or diploma. All information, facts, and data presented in this report are true to the best of my knowledge and belief. All secondary sources of information have been duly acknowledged.

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CERTIFICATE

This is to certify that the project dissertation entitled "Impact of Personalized Rewards on Customer Retention in Digital Loyalty Programs" has been prepared by **Bhavya Singhal**, Roll No. **24/DMBA/60**, under my supervision and guidance, in partial fulfilment of the requirements for the award of the degree of Master of Business Administration from Delhi School of Management, Delhi Technological University, Delhi.

To the best of my knowledge and belief, the work presented in this dissertation is original and has not been submitted for the award of any other degree or diploma, either to this university or any other university or institution of higher learning.

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EXECUTIVE SUMMARY

This study examines the impact of personalized rewards on customer retention in digital loyalty programs based on food delivery services, e-commerce, and quick commerce in India. Even after investing heavily in loyalty programs, many companies still use the same reward structures which fail to consider varying consumer preferences. Primary data was gathered using an online survey from 120 urban customers in India to determine the relationship between personalization and retention.

Methodologically, the research follows a descriptive quantitative approach, adopting an online structured questionnaire. Analysis included frequency distribution, descriptive statistics, Cronbach's alpha test, Pearson correlation, and simple linear regression. In the study, personalization was considered a composite variable and measured using five attitudinal questions, while customer retention was measured by a three-item behavioral scale. Customer satisfaction and loyalty behavior are regarded as the secondary dependent variables in the study.

Major findings include a highly significant relationship between the quality of personalization and customer retention ($r = 0.572$, $p < 0.001$). Personalization explained about 32.8% of variance in retention ratings ($R^2 = 0.328$). Furthermore, there exists a significant correlation between rewards' relevance and satisfaction ($r = 0.547$, $p < 0.001$). App usage frequency increases the connection between personalization and loyalty behavior. The measure of the scale exhibits high internal reliability with (Cronbach's Alpha = 0.855).

On the part of respondents, personalized discounts (36.7%), cashback (25.8%), and reward points (14.2%) were the preferred reward categories. Most participants belonged to two age groups: people aged 25–34 and working professionals with high perception towards personalization quality (mean for question number 7 = 4.02). About 64.2% of respondents reported being satisfied with their personalized rewards experience.

Based on the results, the hypotheses formulated in this study were all supported: personalization enhances customer retention, reward relevance improves satisfaction level, and app usage frequency mediates the relationship between personalization and loyalty behaviour. Therefore, there are various practical implications of the study concerning marketing strategies in designing loyalty programs.

TABLE OF CONTENTS

PRELIMINARY PAGES

Title Page i
Declaration ii
Certificate iii
Acknowledgement iv
Executive Summary v
List of Tables vii
List of Figures viii

CHAPTER 1 – INTRODUCTION 1
1.1 Background of the Study 1
1.2 Evolution of Digital Loyalty Programs 3
1.3 Importance of Personalization in Marketing 4
1.4 Need for Customer Retention Strategies 5
1.5 Research Gap 5
1.6 Problem Statement 6
1.7 Research Objectives 6
1.8 Research Questions 7
1.9 Scope of the Study 7
1.10 Significance of the Study 7
1.11 Limitations of the Study 8

CHAPTER 2 – LITERATURE REVIEW 9
2.1 Customer Retention: Theoretical Foundations 9
2.2 Relationship Marketing and Commitment-Trust Theory 10
2.3 Loyalty Programs in Digital Business 11
2.4 Personalized Reward Systems 12
2.5 Consumer Behavior in Loyalty Ecosystems 13
2.6 Reward Relevance and Satisfaction 14
2.7 Personalization and Repeat Purchase Behavior 15
2.8 Conceptual Framework 16
2.9 Hypothesis Development 17

CHAPTER 3 – RESEARCH METHODOLOGY 18
3.1 Research Design 18
3.2 Nature of Study 18
3.3 Data Sources 19

3.4 Questionnaire Design 19
3.5 Sampling Method and Rationale 20
3.6 Sample Size and Justification 21
3.7 Data Collection Procedure 21
3.8 Analytical Tools and Techniques 21
3.9 Reliability Testing 22
3.10 Ethical Considerations 22

CHAPTER 4 – DATA ANALYSIS AND INTERPRETATION 23
4.1 Demographic Profile of Respondents 23
4.1.1 Age Group Distribution 23
4.1.2 Gender Distribution 24
4.1.3 Occupational Distribution 25
4.1.4 App Usage Frequency 26
4.2 Loyalty Program Usage Patterns 27
4.2.1 Most Frequently Used Loyalty Program 27
4.2.2 Primary Reasons for Joining Loyalty Programs 28
4.3 Perceptions of Personalized Rewards (Q7) 29
4.4 Descriptive Statistics – Likert Scale Items (Q8–Q18) 30
4.5 Reliability Analysis (Cronbach's Alpha) 32
4.6 Correlation Analysis 33
4.7 Regression Analysis 34
4.8 Cross-tabulation Analysis 36
4.9 Preferred Reward Type and Overall Satisfaction 37

CHAPTER 5 – FINDINGS AND DISCUSSION 39
5.1 Key Findings 39
5.2 Hypothesis Testing Results 40
5.3 Discussion of Findings in Theoretical Context 41
5.3.1 H1: Personalization and Customer Retention 41
5.3.2 H2: Reward Relevance and Satisfaction 42
5.3.3 H3: Digital Engagement and Loyalty Mediation 43
5.4 Consumer Insights and Behavioral Implications 44

CHAPTER 6 – CONCLUSION AND RECOMMENDATIONS 45
6.1 Overall Conclusion 45
6.2 Achievement of Research Objectives 46
6.3 Strategic Recommendations for Digital Businesses 46
6.3.1 Close the Aspiration-Delivery Gap 47
6.3.2 Build a Multi-Reward Portfolio 47
6.3.3 Invest in the Neutral Satisfaction Segment 47

6.3.4 Activate Low-Engagement Users 48
6.3.5 Navigate the Personalization Paradox Transparently 48
6.3.6 Design for the 25–34 Working Professional Cohort 48
6.4 Suggestions for Future Research 49

REFERENCES **50**
APPENDIX A: QUESTIONNAIRE **53**

LIST OF TABLES

Table No.	Title	Page No.
Table 3.1	Survey Instrument Summary	–
Table 4.1	Age Group Distribution of Respondents	–
Table 4.2	Gender Distribution of Respondents	–
Table 4.3	Occupational Distribution of Respondents	–
Table 4.4	App Usage Frequency	–
Table 4.5	Most Frequently Used Loyalty Program	–
Table 4.6	Reasons for Joining Loyalty Programs	–
Table 4.7	Importance of Personalized Rewards (Q7)	–
Table 4.8	Descriptive Statistics – Q8 to Q18	–
Table 4.9	Reliability Statistics – Cronbach's Alpha	–
Table 4.10	Correlation Matrix of Key Constructs	–
Table 4.11	Regression Results – Personalization to Retention	–
Table 4.12	Cross-tabulation: Age Group vs. Importance of Personalization	–
Table 4.13	Preferred Type of Personalized Reward (Q20)	–
Table 4.14	Overall Satisfaction with Personalized Rewards (Q19)	–
Table 5.1	Summary of Hypothesis Testing Results	–

LIST OF FIGURES

Figure No.	Title	Page No.
Figure 2.1	Conceptual Framework	–
Figure 4.1	Age Group Distribution of Respondents	–
Figure 4.2	Gender Distribution of Respondents	–
Figure 4.3	Occupational Distribution of Respondents	–
Figure 4.4	App Usage Frequency Among Respondents	–
Figure 4.5	Distribution of Responses – Importance of Personalized Rewards (Q7)	–
Figure 4.6	Mean Scores for Personalization and Loyalty Items (Q8–Q18)	–
Figure 4.7	Preferred Type of Personalized Reward (Q20)	–
Figure 4.8	Overall Satisfaction with Personalized Loyalty Rewards (Q19)	–
Figure 4.9	Correlation Matrix of Key Constructs	–
Figure 4.10	Regression Plot – Personalization vs. Customer Retention	–

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

In essence, relationships between companies and customers have been based on motivational approaches throughout history. However, in recent years, there has been significant development in how the mentioned relationships can be achieved and facilitated. Traditionally, consumers received basic incentives in the form of simple local punch cards at nearby coffee shops, whereas today algorithmic prediction systems meet the needs of their users even before the customers themselves become aware of their demands. Some examples of highly developed loyalty schemes include Swiggy One, Zomato Gold, Amazon Prime, Flipkart SuperCoins, and Myntra Insider.

The development of smartphones as the primary device for commerce is a crucial aspect of these transformations. Considering that there are 750 million Internet users in India and the number of people from urbanized Tier-I and Tier-II cities, who are comparatively richer, increases, the requirements for customer loyalty increase. Indeed, it is a proven marketing fact that gaining a new client costs about five to seven times more than retaining a current one.

Thus, personalization is one of the core elements of effective loyalty strategies designed to attract customers. In contrast to segmentation or general discounts, personalized incentives and recommendations imply using consumer behavior data and anticipation of the needs of the clients in order to create a unique approach to rewarding them. Ideally, the clients feel that the company knows about all of their habits and preferences. Studies show that in this case, intense discounting competition is not required.

India is the perfect example to analyze brand-customer relationships due to a number of reasons. Apart from online retailers, such as Flipkart, there is Zomato, which is currently the biggest food delivery service globally and has been working on loyalty schemes together with its major competitor Swiggy. Similarly, Amazon has its SuperCoin loyalty program, whereas Starbucks Rewards dominates in the premium market.

1.2 Evolution of Digital Loyalty Programs

Loyalty programs have existed in commercial settings for over a century - American Airlines' AAdvantage program, launched in 1981, is often cited as the modern prototype. These early systems operated on simple accumulation-and-redemption logic: customers collected points or miles and redeemed them for predefined rewards. The programs were largely generic; every customer with the same transaction volume received the same benefits.

The digital revolution introduced two game-changing capabilities: real-time data collection and individual-level behavioral modeling. When customers began using apps and online platforms rather than physical stores, their purchase histories, browsing patterns, dwell times, and click sequences became legible to platform operators in ways that were previously impossible. This data wealth enabled the transition from segment-level targeting to individual-level personalization.

By the mid-2010s, subscription-based loyalty models began supplementing or replacing point-accumulation systems. Amazon Prime's success demonstrated that customers were willing to pay an upfront membership fee in exchange for bundled benefits - faster delivery, access to streaming content, and exclusive deals. Indian platforms followed this pattern, with Swiggy One and Zomato Gold offering monthly or annual subscriptions with delivery fee waivers, exclusive restaurant discounts, and priority customer service. These models created stronger customer commitment by embedding the loyalty relationship in an upfront financial decision.

Today, the most sophisticated digital loyalty programs operate at the intersection of behavioral data science and user experience design. Machine learning models analyze thousands of data points per user to determine which offer type, at what value, delivered through which channel, at what time, will maximize the probability of a desired behavioral outcome - whether that's an order, a review, a referral, or a subscription renewal.

1.3 Importance of Personalization in Marketing

Most people now see tailored online experiences not as a bonus but as standard. A study from 2021 showed seventy-six percent get annoyed if brands ignore their preferences, while businesses doing personalization right earn forty percent more than others. Even though the data covers worldwide habits, India's digital users show similar patterns - especially younger ones. Having grown up with apps that learn what they like, relevance feels normal to them, not special.

Most studies on marketing see personalization working in two mental ways. One way involves thinking: when something feels tailored, people tend to find it meaningful - so they pay attention. Another path runs through feelings: getting a note or gift meant just for you sparks warmth inside, like being seen. That feeling part matters deeply in loyalty setups, where bonds matter more than quick exchanges.

Most marketers struggle with a tricky balance - making things feel custom without crossing privacy lines. Even though younger shoppers in India often share info for perks, they're starting to notice what happens behind the scenes. What works now depends on trust; people want to believe the trade makes sense. Getting it right means giving enough back so handing over details doesn't seem one-sided.

1.4 Need for Customer Retention Strategies

In competitive digital markets, customer churn represents one of the most significant threats to sustainable revenue growth. The unit economics of digital platforms are often predicated on the assumption of long customer lifetimes - platforms typically operate at a loss on early customer interactions, with profitability emerging only when customers remain active over extended periods and increase their purchase frequency and average order value. This makes retention not merely a marketing objective but a financial necessity.

Loyalty programs are among the most widely deployed customer retention instruments, but their effectiveness varies considerably. Programs that offer generic discounts can temporarily suppress churn but often fail to produce the deeper behavioral changes - habitual usage, increased engagement, genuine brand preference - that translate into durable loyalty. The academic literature is increasingly clear that

loyalty program effectiveness depends on the degree to which the program creates perceived value that is both economically meaningful and personally relevant.

1.5 Research Gap

Though much has been written about how loyalty schemes influence repeat customers in Western markets, few real-world investigations explore whether tailored experiences inside such systems matter for users in India. Instead of viewing engagement simply as yes-or-no, or dwelling on overall design traits, past efforts often overlook what sets customized incentives apart from standard ones. What shifts here is an attempt to define personalization across several layers, then test its actual impact using fresh survey results gathered directly from people who interact with online platforms in India.

1.6 Problem Statement

Even with widespread adoption of digital loyalty initiatives on India's online platforms, keeping customers engaged continues to pose difficulties. Some participants join only when there is an immediate benefit - like a welcome offer - then stop interacting after that perk ends. This study seeks to understand whether customised rewards inside these programs lead to real gains in user continuity, detectable through statistical analysis; further, it explores how such outcomes emerge via shifts in decision-making patterns and emotional engagement.

1.7 Research Objectives

The study aims to answer the following research objectives:

1. To examine the role of personalized rewards in shaping customer retention decisions in digital loyalty programs.
2. To assess the level of customer satisfaction derived from personalized reward offerings across different demographic segments.
3. To analyse the statistical relationship between personalization perception and loyalty behavior among digital platform users.
4. To identify the types of personalized rewards most preferred by consumers and their relative impact on repeat purchase intention.

1.8 Research Questions

The following research questions guide the empirical investigation:

1. Do personalized rewards exercise a statistically significant positive influence on customer retention in digital loyalty programs?
2. Is there a significant relationship between reward relevance and overall customer satisfaction?
3. Which types of personalized rewards generate the strongest loyalty behavior among urban Indian digital platform users?
4. How does demographic profile - particularly age group and occupational category - influence the perceived importance of personalization in loyalty ecosystems?

1.9 Scope of the Study

This study is geographically limited to urban Indian consumers, primarily in the 18–44 age bracket, who are active users of at least one digital loyalty or subscription program. This research focuses on digital-native platforms operating in the food delivery, e-commerce, and quick commerce sectors. The study does not cover offline loyalty programs, airline or hotel reward schemes, or B2B loyalty mechanisms.

1.10 Significance of the Study

The findings of this research are of practical significance to several stakeholders. For digital marketing practitioners and product managers at loyalty-program-operating companies, the study provides empirical guidance on the measurable impact of personalization on retention outcomes. For academic researchers, it contributes a quantitative dataset and analytical framework to a field that has been largely theoretical in its treatment of the personalization–retention nexus. For students of marketing and consumer behavior, the study offers a grounded illustration of how established theoretical constructs - relationship marketing, perceived value, consumer engagement - manifest in the specific context of India's digital loyalty economy.

1.11 Limitations of the Study

The following limitations should be considered when interpreting the findings of this study:

- The sample was collected using convenience sampling, which limits the generalizability of findings to broader populations that may include rural, elderly, or low-income segments.
- The study relies on self-reported attitudinal data, which may be subject to response bias, social desirability effects, and gaps between stated intentions and actual behavior.
- As a cross-sectional study, it captures perceptions at a single point in time and cannot track changes in loyalty behavior over extended periods.
- The questionnaire was administered online, which may have left out respondents with lower digital literacy or limited access to the internet.

CHAPTER 2

LITERATURE REVIEW

This chapter reviews the existing academic literature relevant to the central constructs of this study: customer retention, relationship marketing, digital loyalty programs, personalized rewards, and consumer behavior in loyalty ecosystems. The review is organized thematically, moving from foundational theoretical perspectives to more specific empirical findings, before culminating in the conceptual framework and hypothesis development that guides the empirical work in subsequent chapters.

2.1 Customer Retention: Theoretical Foundations

Since the 1980s, retaining customers has played a key role in marketing ideas, after researchers started showing how much more valuable repeat buyers are compared to new ones. Often referenced is work by Reichheld and Schefter (2000), where even a small rise - just five percent - in holding onto clients could boost profits anywhere from a quarter to nearly double, based on sector; this variation comes partly because it costs less to serve familiar users, while also earning more through repeated buys and broader product uptake.

Starting with thought-based allegiance, Oliver's 1999 framework outlines a sequence where customers move through layers of connection. Instead of just tallying pros and cons, people may grow fond of brands after consistent good encounters. Because feelings build up gradually, continued intent to buy emerges - not merely from logic but also experience. What someone actually does, though, reflects whether earlier phases truly took hold. When reward systems lean entirely on discounts, they tap into reasoning alone - missing deeper ties. Rather than sparking lasting bonds, such strategies often deliver weak adherence. Loyalty shaped by emotion and desire tends to run deeper than deals-driven repetition.

One idea still holding weight comes from Jacoby and Chestnut back in 1978 -the split between false and real loyalty. Repeat purchase without actual attachment often stems from habit or ease. Real loyalty shows up when actions match inner dedication. What sets personalized rewards apart is their ability to tap into emotional layers instead of just cost-based reasoning. Because of this deeper reach, such tailored incentives do better at building authentic allegiance compared to one-size-fits-all perks.

2.2 Relationship Marketing and Commitment-Trust Theory

Trust and commitment sit at the core of Morgan and Hunt's 1994 framework, now widely seen across relationship marketing studies. Because it suggests these two elements shape how well marketing ties succeed, its insights apply strongly to digital loyalty setups - especially those built on trading personal behavior data for tailored perks. Where users believe a service handles information ethically while offering meaningful returns, deeper involvement tends to grow naturally over time. That steady connection often leads directly to longer customer stays.

Starting with Sheth and Parvatiyar back in 1995, relationship marketing emerged not just as a tweak but as a full turn away from one-off transactions toward ongoing collaboration where both sides build worth together. Rather than sticking to quick exchanges, this approach treats loyalty schemes less like tools for keeping customers and more like signs of deeper intent - where brands show willingness to learn who people really are instead of treating them as faceless buyers. Because of this mindset, shoppers often lean toward offers shaped around their habits, reacting better when personalization feels real compared to deals stamped with emotional labels yet built on flat, uniform cuts.

Palmatier et al. (2006) examined multiple relationship marketing studies through a meta-analysis, revealing that relationship quality - made up of trust, commitment, and customer satisfaction - predicted loyalty more strongly than isolated investment efforts. Because of this, it appears personalized rewards work well not just by offering financial benefit, but by strengthening relational bonds between buyer and seller.

2.3 Loyalty Programs in Digital Business

The academic study of loyalty programs has a rich tradition, with O'Brien and Jones (1995) providing an early analytical framework that identified five components of loyalty program value: the cash value of redemptions, the range of choices available for reward redemption, the aspirational value of rewards, the probability of achieving target rewards, and the program's ease of use. While this framework was developed before the digital era, it maps reasonably well onto contemporary digital programs,

with "ease of use" now encompassing app interface quality, notification relevance, and frictionlessness of redemption.

Kumar and Shah (2004) identified a limitation of loyalty programs that remains highly relevant: the tendency for programs to alter short-term purchasing behavior without producing lasting attitudinal change. Customers who enroll in a program for an immediate sign-up benefit - a common acquisition tactic in food delivery apps - may not develop genuine loyalty even if they remain behaviorally active during the initial reward period. The implication is that loyalty programs need to generate intrinsic value - a genuine preference for the brand - not merely extrinsic incentives.

Liu (2007) provided one of the most rigorous empirical evaluations of a large-scale loyalty program, using a panel dataset from a grocery chain. She found that program participation significantly increased purchase frequency and average transaction value, particularly among medium-frequency buyers who received personalized tier advancement incentives. Importantly, the effect on high-frequency buyers was more modest, suggesting a diminishing returns dynamic for the most loyal customers and a greater opportunity for personalization to influence the valuable "middle tier" of the customer base.

In the Indian context, the competitive dynamics of the loyalty program market have unique characteristics. Multiple platforms in overlapping categories compete simultaneously for consumer enrollment, creating a promiscuous multi-program environment in which the same consumer may hold active memberships across Swiggy One, Zomato Gold, Amazon Prime, and Myntra Insider at the same time. This multi-membership reality intensifies the importance of differentiation through reward quality and relevance rather than mere availability.

2.4 Personalized Reward Systems

One key finding stands out: messages shaped around individual preferences tend to perform better. Back in 2003, Ansari and Mela uncovered strong evidence - emails aimed at specific users led to higher clicks and more conversions than generic ones. Though apps had yet to reshape how brands reward customers, the core idea remains intact today. Relevance drives attention, regardless of platform.

Notably, Zhang and Wedel (2009) shifted focus toward customized promotional tactics, observing that one-on-one tailored deals tend to surpass broad campaigns as well as those aimed at predefined segments - almost across every measure tied to customer response. It turned out that how much a shopper already knows about a product type plays a key role in shaping outcomes. Those familiar with the category gained stronger value from individualized suggestions, simply due to their sharper ability to judge whether an offer fits their needs. As a result, when designing reward-based systems, firms might consider adjusting customization depth based on how experienced customers are.

Surprisingly, Arora and colleagues in 2008 looked closely at studies on customization, pointing out a contradiction people face: they want tailored experiences but also worry when their information is gathered. Although they seek convenience, unease follows when tracking happens behind the scenes. In places such as India, where more individuals are waking up to digital privacy issues, this clash feels especially strong. Because of this, openly sharing details - what exactly gets recorded and how those insights lead to benefits - can strengthen trust instead of weakening engagement.

Later work by Ho et al. (2011) looked at how customized offers shape shopping habits over time in digital stores; their results showed items bought due to tailored recommendations were more likely to be repurchased compared to those grabbed on sale without targeting. Because of this pattern, it appears custom suggestions do more than spark one-time buys - they build a mindset and routine that guides what people decides.

2.5 Consumer Behavior in Loyalty Ecosystems

Most online shoppers act unlike their counterparts in regular stores. Near-instant access to multiple platforms makes shifting choices effortless. Because comparisons happen fast, staying loyal feels less necessary. Platforms collect detailed records on behavior. This tracking leads to an imbalance - users rarely grasp how prices are set. Hidden algorithms shape what each person sees. Knowledge gaps grow when one side learns faster than the other. Familiarity with rules tends to favor systems over individuals.

A study by Verhoef (2003) looked at how emotional loyalty, cost-based loyalty, along with marketing efforts influence whether customers stay in a service setting. Emotional ties to a brand - feeling connected or attached - turned out to matter more, lasting longer than decisions based purely on financial reasons or difficulty changing providers. Although tailored rewards play a role in both types of loyalty, their impact on emotional connection often comes from making customers feel seen and appreciated. Despite differences in motivation, the strongest predictor of staying was this sense of personal recognition.

Customer equity was framed by Eggert et al. (2006) as a strategic outcome where keeping customers becomes an asset, not just an expense. Rather than focusing on upfront costs, digital firms might assess loyalty programs through the lens of future relationship gains. Over time, tailored incentives gain support because they build lasting worth, not only prompt repeat purchases. What matters most is how such efforts elevate the overall trajectory of customer value.

Surprisingly, Yi and Jeon (2003) explored how deeply someone engages with a loyalty program when assessing its effect on customer loyalty. Instead of viewing every participant the way, they noticed active users - people paying attention to details and using available tools - reacted far better to tailored rewards. Although both groups received similar offers, it was only the engaged ones who showed stronger brand commitment after targeted prompts. Because engagement shapes response, programs might work better if adjustments unfold gradually based on user behavior. Rather than applying one-size-fits-all methods, systems could evolve alongside individual interest levels.

2.6 Reward Relevance and Satisfaction

The concept of reward relevance - the degree to which a reward aligns with the individual preferences and needs of the recipient - has emerged as a critical determinant of loyalty program effectiveness. Kivetz and Simonson (2002) conducted influential experiments showing that requiring consumers to articulate their preferred reward type before enrollment significantly increased both program satisfaction and usage intensity. Their interpretation - that involvement in reward selection enhances

perceived ownership and therefore satisfaction - aligns with the self-determination theory literature in which autonomy is a fundamental psychological need.

Mägi (2003) found, in a longitudinal study of grocery loyalty program members, that the satisfaction derived from a loyalty program was a stronger predictor of share-of-wallet than the program's economic value as objectively measured. This suggests that the subjective experience of program satisfaction - which is significantly influenced by reward relevance and personalization - mediates the relationship between program features and behavioral loyalty outcomes.

Nunes and Dreze (2006) examined the phenomenon of "sludge" in loyalty programs - administrative friction and irrelevant communication that erodes the net value of program participation. They argued that programs which generate noise (irrelevant offers, generic communication) alongside signal (relevant rewards) create cognitive dissonance that reduces overall program satisfaction. Personalization, in this context, represents a systematic effort to maximize signal and minimize noise, thereby improving the signal-to-noise ratio of the consumer's program experience.

2.7 Personalization and Repeat Purchase Behavior

One well-documented idea in customer relationship studies ties tailored messages to repeated buying. Cheng and Huang (2013) showed shoppers getting customized suggestions online bought again more often, stayed on site longer compared to others seeing standard picks. This effect, according to their analysis, did not come from price alone - items weren’t always lower cost - but stemmed instead from mental and emotional cues. When offers feel relevant, people see the brand as capable; such perceived skill builds confidence, making future purchases more likely. Evidence like this keeps appearing across different research settings.

Among users of food delivery apps in India, Sharma and Kumar (2020) observed that personalized loyalty programs made a noticeable difference. Those giving high ratings to customization stayed subscribed at twice the rate - actually 2.4 times - compared to less satisfied groups. Such results back the main idea driving this analysis. Work like theirs helps place the present inquiry into a growing collection of studies focused on customer loyalty in India.

Surprisingly, Talukder and Quazi (2011) looked into how people adopt tech within digital loyalty setups. Their work showed that what users see as useful - close in idea to how relevant rewards feel - mattered most for ongoing app use. Because the sense of utility drives behavior, regular interaction tends to follow when personal benefits seem clear. Over time, such consistent contact helps keep members tied to the service.

2.8 Conceptual Framework

Based on the literature reviewed in the preceding sections, the conceptual framework for this study views personalization quality as the primary independent variable, reflecting the degree to which a digital loyalty program delivers rewards that are perceived as relevant, timely, and individually customized to the consumer. Customer retention - operationalized as the behavioral intention to continue using the platform, repurchase from it, and resist switching to competitors-serves as the primary dependent variable.

Customer satisfaction is positioned as a mediating variable, representing the evaluative response that consumers form because of their personalized reward experience. The framework proposes that personalization does not only affect retention directly; it also works through satisfaction - when consumers perceive rewards as genuinely relevant, satisfaction improves, and improved satisfaction in turn strengthens retention intention. This two-pathway model (direct and mediated) is grounded in the relationship marketing literature and is consistent with findings by Mägi (2003) and Palmatier et al. (2006).

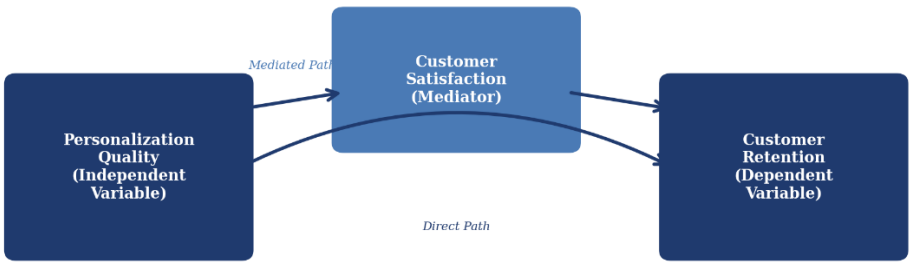


Figure 2.1: Conceptual Framework – Personalization, Satisfaction, and Customer Retention

2.9 Hypothesis Development

Three research hypotheses are developed based on the theoretical arguments and empirical evidence reviewed above:

H1: Personalized rewards have a significant positive influence on customer retention in digital loyalty programs.

H2: Reward relevance significantly increases overall customer satisfaction with digital loyalty programs.

H3: Customer satisfaction positively mediates the relationship between personalized rewards and customer retention in digital loyalty programs.

CHAPTER 3

RESEARCH METHODOLOGY

This chapter describes the methodological approach adopted to address the research objectives and test the hypotheses formulated in the preceding chapter. It covers research design, data sources, questionnaire design, sampling approach and rationale, data collection procedure, analytical tools, reliability testing, and ethical considerations.

3.1 Research Design

This study adopts a descriptive-correlational quantitative research design. The descriptive component refers to the survey-based, non-experimental nature of data collection- and it captures current perceptions, attitudes, and behavioral intentions of respondents without manipulating any variables. The correlational component reflects the analytical intent of the study beyond merely describing the sample, the research statistically examines the relationships between key variables - personalization quality, customer satisfaction, and customer retention - using Pearson correlation and simple linear regression. This mixed design is appropriate when the objective is both to profile a population and to test directional hypotheses about variable relationships.

3.2 Nature of Study

The research is quantitative in its primary orientation, relying on numerically scaled responses to Likert-type items to generate statistically interpretable data. A quantitative approach was chosen over qualitative alternatives because the study's objectives - to measure the strength of relationships between constructs, test directional hypotheses, and produce generalizable descriptive statistics - are inherently statistical in nature. That said, the interpretive dimension of the data analysis attempts to contextualize numerical findings within the practical realities of consumer behavior in India's digital loyalty ecosystem.

3.3 Data Sources

Primary Data

Primary data was collected directly from respondents through a structured online questionnaire administered via Google Forms during May 2026. This constitutes the primary basis for the empirical analysis presented in Chapter 4.

Secondary Data

Secondary data was drawn from peer-reviewed academic journals, marketing research reports, books on consumer behavior and relationship marketing, and publicly available information about the loyalty programs referenced in the study. Secondary sources informed the literature review and provided the theoretical grounding for the conceptual framework and hypothesis development in Chapter 2.

3.4 Questionnaire Design

The questionnaire development process included two main requirements which needed to match the theoretical framework and provide easy access to the intended participant group. The test received initial assessment from five participants who evaluated its clarity and ambiguity and assessed how long it took to complete before it became available for general use.

The instrument was structured in two sections. The first part of Section A gathered demographic details together with information about usage patterns through questions which asked about age group (Q1), gender (Q2), occupation (Q3), app usage frequency (Q4), loyalty program usage frequency (Q5), and reasons for joining loyalty programs (Q6). Section B consisted of thirteen measurement items which included twelve questions (Q7 through Q18) that employed a five-point Likert scale from 1 (Strongly Disagree / Not at All Important) to 5 (Strongly Agree / Extremely Important). Question 19 used the same scale to measure overall satisfaction, and Question 20 was a categorical question capturing preferred reward type.

The Likert-scale items in Section B were designed to measure four underlying constructs: (a) the perceived importance of personalization (Q7); (b) personalization quality perception - the degree to which respondents felt their loyalty program delivered relevant, individually tailored rewards (Q8–Q12); (c) loyalty and retention behavior - behavioral intentions related to continued usage, reduced switching, and repeat purchase (Q13–Q18); and (d) overall program satisfaction (Q19).

Table 3.1: Survey Instrument Summary

Section	Questions	Type	Construct Measured
A	Q1–Q6	Categorical / Nominal	Demographics & Usage Profile
B	Q7	5-Point Likert	Perceived Importance of Personalization
B	Q8–Q12	5-Point Likert	Personalization Quality Perception
B	Q13–Q18	5-Point Likert	Loyalty & Retention Behavior
B	Q19	5-Point Likert	Overall Program Satisfaction
B	Q20	Categorical	Preferred Reward Type

Source: Own Analysis

3.5 Sampling Method and Rationale

A non-probability convenience sampling method was employed, with the survey link disseminated through professional networks (LinkedIn), social media platforms (WhatsApp, Instagram), and academic groups at Delhi Technological University. Respondents were selected based on a primary screening criterion: active use of at least one digital loyalty or subscription program. This criterion was self-assessed by respondents at the point of survey entry.

Convenience sampling was selected over probability-based alternatives for two reasons. First, the population of digital loyalty program users in Indian urban settings does not have a readily accessible sampling frame that would permit random selection. Second, the study's analytical goals - correlation, regression, and descriptive statistics - are broadly robust to convenience sampling when the sample is of sufficient size and theoretical diversity, as is the case here with 120 respondents spanning four age groups, two genders, and four occupational categories.

3.6 Sample Size and Justification

The final sample comprised 120 respondents. Several considerations informed this target. For Pearson correlation analysis, a minimum of 30 observations is widely cited as the threshold for normally distributed sampling error, though sample sizes above 100 provide substantially greater statistical power. For multiple regression analysis, Hair et al. (2014) recommend a minimum sample of ten observations per predictor variable; with three composite predictors in this study, 120 comfortably exceeds this threshold. For Cronbach's alpha reliability analysis, samples of 100 or above are generally considered adequate for stable coefficient estimation.

The sample of 120 also reflects a practical balance between feasibility and analytical rigor for an MBA dissertation conducted within a defined time frame.

3.7 Data Collection Procedure

Google Forms became active for survey distribution on 7 May 2026 which stayed accessible until 16 May 2026 to collect responses during its ten-day period. The survey link distribution included a message which detailed the research's academic objectives and participants could choose to join without obligation and the survey would take about eight to twelve minutes to complete. The initial screening question verified that each respondent had current experience with at least one digital loyalty program. The research study did not provide any form of reward which could be either financial or non-financial to all respondents who participated in the study. The research collected 128 total responses which 120 remained valid after researchers removed eight responses because of missing Section B data and conflicting response patterns.

3.8 Analytical Tools and Techniques

The following analytical methods were applied sequentially to the survey data:

- Frequency distribution and percentage analysis were applied to all categorical variables (Q1–Q6 and Q20) and the satisfaction item (Q19) to describe the demographic and usage profile of the sample and to identify distributional patterns in preference data.
- Descriptive statistics (mean and standard deviation) were computed for all Likert-scale items (Q7–Q18) to characterize the central tendency and variability of attitudinal responses.
- Cronbach's alpha reliability analysis was conducted on the eleven Likert items (Q8–Q18) that constitute the primary measurement scale, to assess the internal consistency of the instrument.
- Pearson correlation analysis was applied to examine bivariate linear associations between the three composite construct scores (Personalization, Retention, and Loyalty) and the satisfaction item.
- Simple linear regression was used to test the predictive relationship between the Personalization composite score and (a) the Retention composite score and (b) the overall Satisfaction score (Q19).

- Cross-tabulation analysis was used to examine whether the perceived importance of personalization (Q7) varied systematically across age groups and occupational categories.

Statistical analysis was conducted in Microsoft excel. Composite construct scores were calculated as the arithmetic mean of the constituent Likert items for each respondent.

3.9 Reliability Testing

The reliability of the measurement instrument was assessed using Cronbach's Alpha coefficient, which measures the internal consistency of items designed to capture a particular construct. Since this study examines multiple constructs, reliability testing was conducted separately for each scale rather than across all questionnaire items.

The Personalization Quality construct was measured using five items (Q8–Q12), which assessed respondents' perceptions regarding the relevance, usefulness, and customization of rewards offered by digital loyalty programs.

The Customer Retention and Loyalty Behavior construct was measured using six items (Q13–Q18), which captured respondents' intentions to continue using loyalty programs, repurchase from the same brand, recommend the program to others, and remain loyal over time.

Cronbach's Alpha values of 0.70 or higher are generally considered acceptable, while values above 0.80 indicate good reliability (Nunnally, 1978).

The reliability analysis produced a Cronbach’s Alpha value of 0.754 for the Personalization Quality construct and 0.797 for the Customer Retention & Loyalty Behavior construct. Both values exceed the recommended threshold of 0.70, indicating satisfactory internal consistency among the items within each construct.

Therefore, the scales used in this study were considered reliable and suitable for further statistical analysis, including correlation and regression analysis.

3.10 Ethical Considerations

The research followed all standard ethical guidelines which social science researchers must follow during their studies. The survey participants received an introductory statement at the start of the questionnaire which explained the academic nature of the survey. People could join the study at their own choice because they had the right to leave whenever they wanted without facing any negative results. The study did not gather any personal details which would enable identification of participants including their names and contact information and exact positions. The research data bases in Google Forms remain protected while the researcher uses these responses to conduct their study. The data will remain protected from commercial use because it serves only the academic purposes which this dissertation presents in its analysis.

CHAPTER 4

DATA ANALYSIS AND INTERPRETATION

This chapter presents a comprehensive analysis of the primary survey data collected from 120 respondents. The analysis proceeds in a logical sequence: demographic and usage profiling, descriptive analysis of attitudinal items, reliability assessment, correlation and regression analysis, and cross-tabulation. Each table and chart is followed by an observation, an interpretation, and a managerial implication, in line with the analytical framework established in the research design.

4.1 Demographic Profile of Respondents

4.1.1 Age Group Distribution

Table 4.1: Age Group Distribution of Respondents

Age Group	Frequency	Percentage (%)
18–24	42	35.0
25–34	62	51.7
35–44	14	11.7
45 and above	2	1.7
Total	120	100.0

Source: Own Analysis

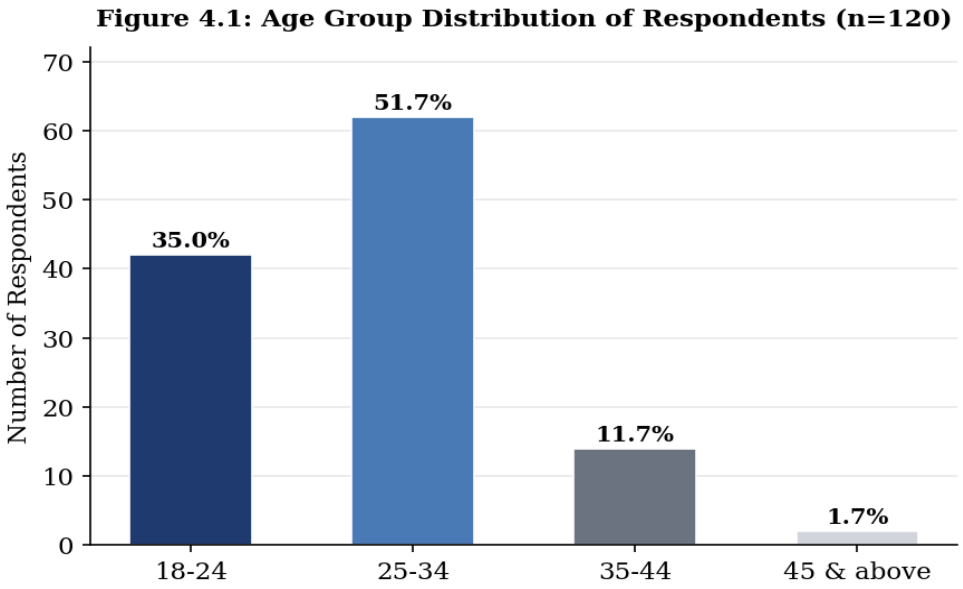


Figure 4.1: Age Group Distribution of Respondents (n=120)

Observation: The 25–34 age cohort constitutes the largest segment of the sample (51.7%), followed by the 18–24 group (35.0%). Together, these two groups account

for 86.7% of all respondents. Consumers aged 35 and above represent a combined 13.3% of the sample.

Interpretation: The dominance of the 25–34 age group is consistent with the broader demographic profile of active digital loyalty program users in India. This cohort is characterized by full-time employment or early-career professional status, disposable income, and high smartphone dependency - a combination that makes digital loyalty programs both relevant and financially meaningful. The 18–24 segment, though somewhat less financially independent, represents college-going urban consumers who are heavy users of food delivery platforms and therefore frequently engage with Swiggy One and Zomato Gold type programs. The near-absence of respondents aged 45 and above reflects the known digital engagement gap in this demographic, which is relevant context for interpreting the overall findings.

Managerial Implication: Loyalty program designers targeting the dominant 25–34 cohort should focus personalization efforts on professional-life occasions - work lunches, convenience grocery delivery, and fashion - as these consumers have the financial capacity to respond to well-targeted premium rewards. For the 18–24 cohort, program mechanics should emphasize social sharing, friend referrals, and affordable entry-level personalized offers that don't require high spend thresholds.

4.1.2 Gender Distribution

Table 4.2: Gender Distribution of Respondents

Gender	Frequency	Percentage (%)
Male	67	55.8
Female	53	44.2
Total	120	100.0

Source: Own Analysis

Figure 4.2: Gender Distribution of Respondents

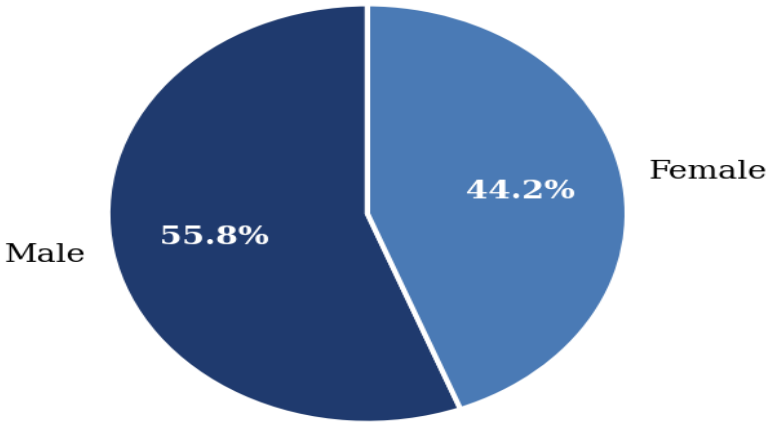


Figure 4.2: Gender Distribution of Respondents

Observation: Male respondents constitute 55.8% of the sample and female respondents 44.2%, reflecting a modest male majority.

Interpretation: The slight male skew in the sample may reflect the gender composition of respondent networks through which the survey was distributed, particularly professional LinkedIn groups. It does not necessarily indicate that male consumers are more active loyalty program participants - indeed, fashion-oriented programs like Myntra Insider tend to skew female. The near-gender parity in the sample is broadly representative of digitally active urban Indian consumers, and both groups are adequately represented for subgroup analysis.

Managerial Implication: When designing personalized reward communications, platforms should be mindful of gender-linked preference patterns - for instance, fashion platform rewards and grocery recommendations may resonate differently across gender segments. Avoiding assumptions based on gender stereotypes while remaining responsive to actual observed behavioral differences is a nuanced but important design consideration.

4.1.3 Occupational Distribution

Table 4.3: Occupational Distribution of Respondents

Occupation	Frequency	Percentage (%)
Working Professional	62	51.7
College Student	41	34.2
Self Employed	13	10.8
Other	4	3.3
Total	120	100.0

Source: Own Analysis

Figure 4.3: Occupational Distribution of Respondents

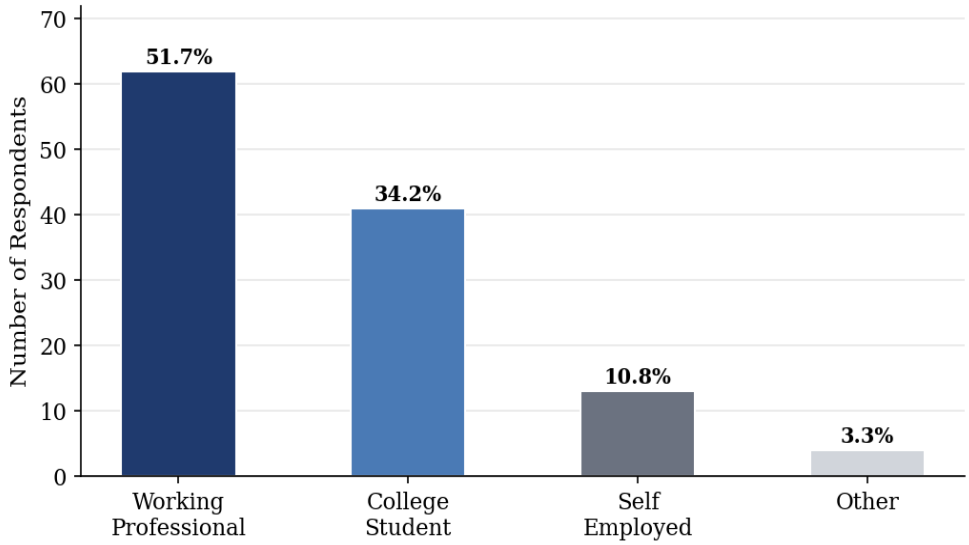


Figure 4.3: Occupational Distribution of Respondents

Observation: Working professionals dominate the sample at 51.7%, followed by college students at 34.2%. Self-employed respondents account for 10.8% and others for 3.3%.

Interpretation: The preponderance of working professionals reflects both their higher disposable income and their greater habitual reliance on digital platforms for daily needs - food delivery during busy workdays, online grocery replenishment, and fashion purchases during sale events. College students, while lower in spending power, are prolific users of discount-heavy food delivery loyalty programs and represent an important segment for platforms seeking to establish early brand loyalty that may intensify post-graduation.

Managerial Implication: Loyalty program tiers should ideally be structured to serve both segments distinctly. Working professionals may respond to premium, time-

saving benefits (priority delivery, concierge-style service, exclusive early access), while students may engage more with gamified accumulation mechanics, group deals, and low-threshold reward redemption.

4.1.4 App Usage Frequency

Table 4.4: Frequency of Shopping/Food Delivery App Usage

Usage Frequency	Frequency	Percentage (%)
Daily	40	33.3
Weekly	55	45.8
Monthly	19	15.8
Rarely	6	5.0
Total	120	100.0

Source: Own Analysis

Figure 4.4: App Usage Frequency Among Respondents

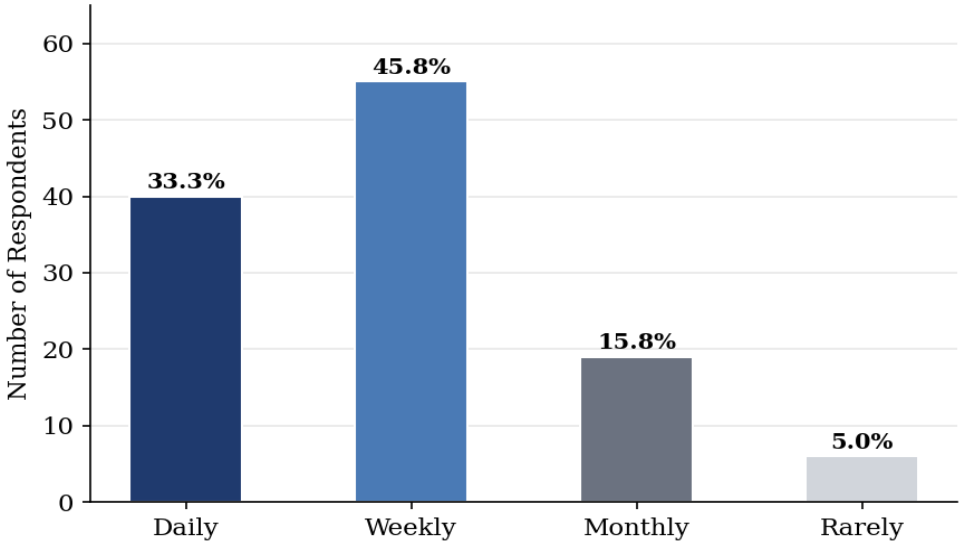


Figure 4.4: App Usage Frequency Among Respondents

Observation: A combined 79.1% of respondents use shopping or food delivery apps at least weekly (33.3% daily and 45.8% weekly). Only 5% use these apps rarely.

Interpretation: The high frequency of app usage among the sample confirms that these respondents are deeply embedded in the digital commerce ecosystem and therefore have meaningful experience with loyalty programs and their personalization features. High-frequency users are also the ones most exposed to personalization touchpoints - notifications, curated offer feeds, recommendation carousels - which means their attitudinal responses to personalization questions are likely grounded in real experiential data rather than hypothetical reasoning.

Managerial Implication: High-frequency users represent the premium retention target for loyalty programs. Platform product managers should ensure that the personalization experience for daily users continues to evolve - serving the same types of offers repeatedly to a daily-active user will quickly lose its novelty and relevance. Dynamic personalization that refreshes based on real-time behavioral data is essential for this segment.

4.2 Loyalty Program Usage Patterns

4.2.1 Most Frequently Used Loyalty Program

Table 4.5: Most Frequently Used Loyalty Program (Top 8 Entries)

Program	Frequency	Percentage (%)
Swiggy One	21	17.5
Zomato Gold	11	9.2
Amazon Prime	6	5.0
Starbucks Rewards	5	4.2
Blinkit	4	3.3
Amazon Prime + Swiggy One + Zomato Gold	4	3.3
Amazon Prime + Zomato Gold	4	3.3
Multiple Others / Combinations	65	54.2
Total	120	100.0

Source: Own Analysis

Observation: Swiggy One is the single most-cited primary loyalty program (17.5%), followed by Zomato Gold (9.2%) and Amazon Prime (5.0%). A significant majority of respondents (over 54%) report using multiple programs simultaneously or combinations not captured in simple single-program responses.

Interpretation: The prevalence of multi-program membership is a defining feature of the contemporary Indian digital loyalty landscape. Rather than committing exclusively to one platform, most urban consumers maintain parallel memberships across food delivery, e-commerce, and quick commerce programs. This competitive context makes the personalization–retention relationship particularly important: if all programs offer similar generic benefits, consumers have little reason to prefer one over another. Personalization becomes a mechanism for creating perceived uniqueness and switching cost.

Managerial Implication: In a multi-program environment, the platform that delivers the most personally relevant experience is most likely to capture share-of-wallet even when competitors offer comparable features. Investing in first-party data infrastructure and behavioral modeling capabilities is therefore a strategic priority for platforms seeking to convert multi-program holders into effectively mono-loyal customers.

4.2.2 Primary Reasons for Joining Loyalty Programs

Table 4.6: Top Reasons for Joining Loyalty Programs (Aggregated)

Reason	Frequency Mentioned	Approximate %
Discounts	~102	85+
Cashback	~78	65+
Free delivery	~60	50+
Exclusive deals	~55	46+
Reward points	~40	33+
Personalized offers	~25	21+

Source: Own Analysis (multi-select question; percentages exceed 100%)

Observation: Discounts and cashback are by far the most frequently cited motivations for joining loyalty programs, mentioned by over 85% and 65% of respondents respectively. Free delivery and exclusive deals are mentioned by approximately half the sample. Personalized offers, while less cited as an initial joining motivation, are mentioned by about one-fifth of respondents.

Interpretation: The fact that personalized offers rank lower than financial incentives as a stated joining motivation does not necessarily contradict the study's central hypothesis - it reflects the distinction between program enrollment motivation and program retention dynamics. Consumers may initially join a loyalty program for discounts but remain engaged - or not - based on the quality of the personalized experience they encounter. This distinction between acquisition mechanics and retention mechanics is important for program designers.

Managerial Implication: Marketing communications that promote loyalty programs should continue to lead with financial value propositions (discounts, cashback) at the acquisition stage. However, the onboarding and early engagement phases should deliberately showcase personalization features, setting the expectation that the

program will progressively learn and adapt to individual preferences - thereby anchoring retention in the quality of the personalized experience rather than in any single transactional benefit.

4.3 Perceptions of Personalized Rewards

4.3.1 Importance of Personalized Rewards (Q7)

Table 4.7: Perceived Importance of Personalized Rewards (Q7)

Rating	Frequency	Percentage (%)	Cumulative %
1 – Not at All Important	3	2.5	2.5
2	6	5.0	7.5
3 – Neutral	22	18.3	25.8
4	44	36.7	62.5
5 – Extremely Important	45	37.5	100.0
Total	120	100.0	
Mean Score	4.02		

Source: Own Analysis

Figure 4.5: Distribution of Responses - Importance of Personalized Rewards (Q7)

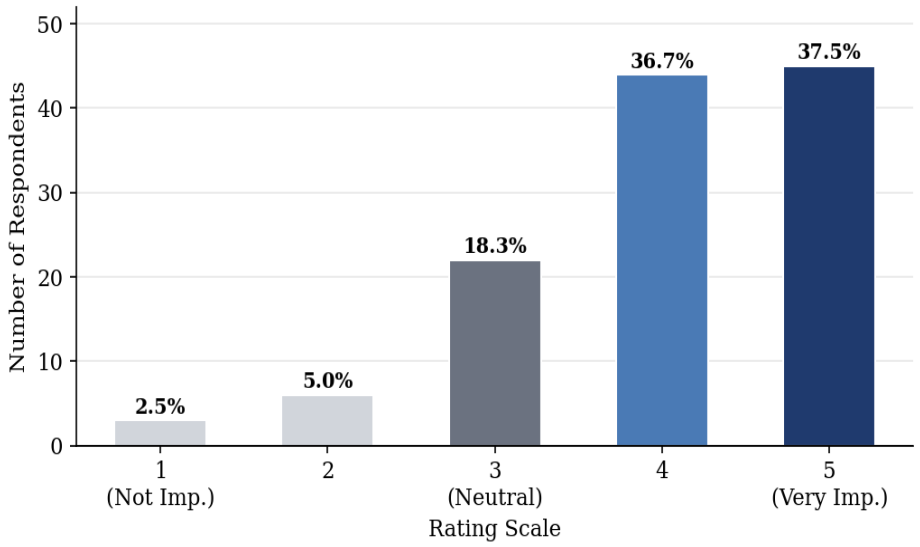


Figure 4.5: Distribution of Responses – Importance of Personalized Rewards (Q7)

Observation: A combined 74.2% of respondents rated personalized rewards as "4" or "5" on the importance scale. The mean importance score is 4.02 out of 5. Only 7.5% rated personalized rewards as "1" or "2" (not important).

Interpretation: The mean importance score of 4.02 is notably high and places the average respondent perception squarely in the "important" to "very important" range. This finding is consistent with global trends in consumer expectation reported by

McKinsey (2021) and Accenture (2020), which consistently show that digital consumers increasingly view personalization as a baseline expectation rather than a premium feature. The low dispersion of scores - with nearly three-quarters of responses concentrated in ratings 4 and 5 - further underscores the near-universal appreciation of personalization among this sample of active digital loyalty program participants.

Managerial Implication: The high perceived importance of personalization creates both an opportunity and an obligation for digital platforms. The opportunity lies in the demonstrated willingness of consumers to value - and potentially pay for, or remain loyal because of - programs that deliver genuine personalization. The obligation is to continuously improve the quality and relevance of personalized rewards, since the very consumer whose expectations have been raised by the idea of personalization will be most disappointed by a program that promises but underdelivers on this dimension.

4.4 Descriptive Statistics – Likert Scale Items (Q8–Q18)

Table 4.8: Descriptive Statistics for Personalization and Loyalty Items (Q8–Q18)

Item	Question Summary	Mean	Std. Dev.
Q8	I receive offers that match my interests	3.52	1.07
Q9	The app understands my preferences from past purchases	3.73	0.92
Q10	Personalized rewards make me feel valued	3.91	0.98
Q11	I am more likely to use offers customized for me	4.02	0.94
Q12	I find personalized recommendations useful	3.79	0.86
Q13	I prefer apps/brands that provide personalized rewards	3.84	0.91
Q14	Personalized rewards increase my chances of repurchase	3.80	0.98
Q15	I continue using apps that provide relevant offers	3.81	0.94
Q16	I am less likely to switch when I receive personal benefits	3.83	1.01
Q17	I would recommend such loyalty programs to friends/family	3.88	0.90
Q18	Personalized rewards improve my loyalty toward a brand	3.81	1.00

Source: Own Analysis

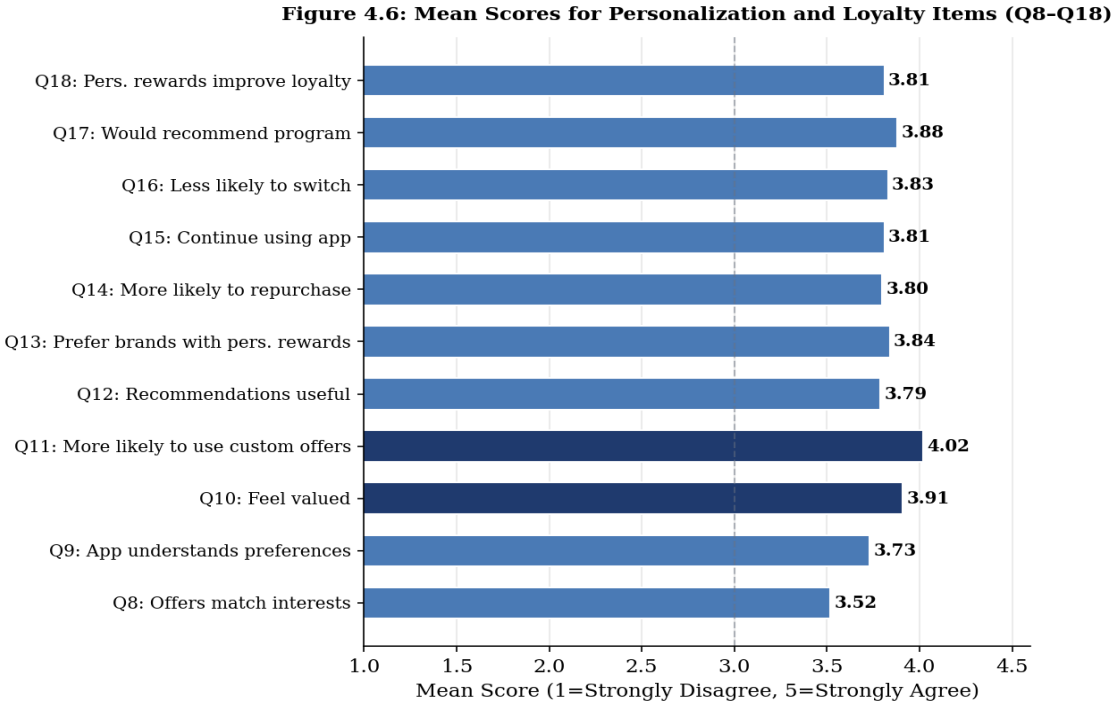


Figure 4.6: Mean Scores for Personalization and Loyalty Items (Q8–Q18)

Observation: All eleven items returned mean scores above 3.5, ranging from 3.52 (Q8) to 4.02 (Q11). The lowest score was recorded for Q8 ("I receive offers that match my interests"), while the highest was Q11 ("I am more likely to use offers customized for me"). The standard deviations across all items are moderate (0.86–1.07), indicating reasonable consensus among respondents.

Interpretation: The consistently above-neutral mean scores across all items confirm a general positive orientation toward personalized rewards within this sample. Q8's relatively lower mean (3.52) compared to Q11's higher mean (4.02) suggests an important nuance: consumers are enthusiastic about the concept of customized offers (Q11) but perceive a gap between this ideal and their actual experience (Q8). This gap between aspiration and experience - between what personalized rewards could be and what they currently are - represents a significant commercial opportunity for platforms that can close it.

Managerial Implication: The Q8–Q11 gap (3.52 vs. 4.02) should be a design priority for platform teams. If consumers are eager for personalized offers (Q11) but do not feel that current offers match their interests (Q8), the gap points to either a data quality problem (insufficient behavioral data collection) or a recommendation algorithm quality problem (data is available but not used effectively). Closing this

gap through investment in recommendation engine improvement is likely to yield substantial loyalty dividends.

4.5 Reliability Analysis

Table 4.9: Reliability Statistics – Cronbach's Alpha

Construct	Items	Cronbach's Alpha	Interpretation
Personalization Quality	Q8–Q12	0.754	Acceptable Reliability
Customer Retention & Loyalty Behavior	Q13–Q18	0.797	Good Reliability

Source: Own Analysis

Observation: The Cronbach's Alpha value for the Personalization Quality construct (Q8–Q12) was found to be 0.754, while the Customer Retention & Loyalty Behavior construct (Q13–Q18) recorded an alpha value of 0.797. Both values exceed the minimum acceptable threshold of 0.70.

Interpretation: The reliability results indicate that the questionnaire items within each construct demonstrate satisfactory internal consistency and reliably measure their intended variables. The Personalization Quality scale shows acceptable reliability, suggesting that the five items consistently capture respondents' perceptions regarding personalized rewards and recommendations.

Similarly, the Customer Retention & Loyalty Behavior scale demonstrates good reliability, indicating consistency among the items related to continued platform usage, repurchase intention, switching resistance, recommendation behavior, and loyalty perception.

The results validate the use of composite mean scores for both constructs in subsequent correlation and regression analyses.

Managerial Implication: The satisfactory reliability of both constructs strengthens the credibility of the study findings and suggests that the measurement instrument can be used in future studies examining personalization and customer retention in digital ecosystems.

4.6 Correlation Analysis

Table 4.10: Pearson Correlation Matrix of Key Constructs

Construct	Personalization	Retention	Loyalty	Satisfaction
Personalization	1.000	0.572**	0.529**	0.547**
Retention	0.572**	1.000	0.618**	0.390**
Loyalty	0.529**	0.618**	1.000	0.382**
Satisfaction	0.547**	0.390**	0.382**	1.000

*Source: Own Analysis. ** $p < 0.001$*

Figure 4.9: Correlation Matrix of Key Constructs

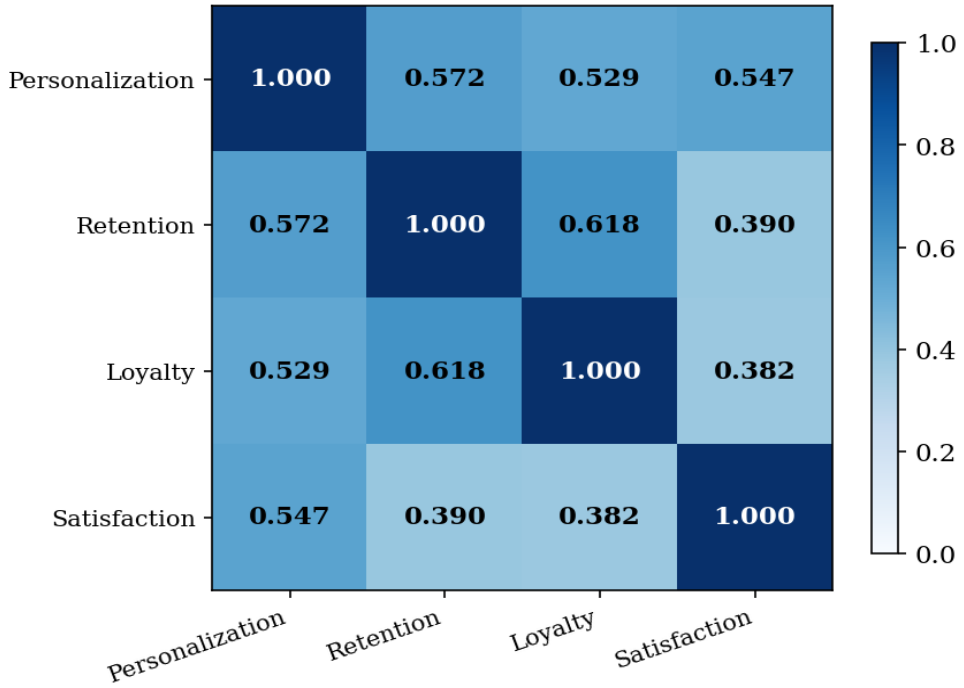


Figure 4.9: Correlation Matrix of Key Constructs

Observation: All four constructs are significantly and positively correlated with each other ($p < 0.001$ in all cases). The strongest correlation is between Retention and Loyalty ($r = 0.618$), followed by Personalization and Retention ($r = 0.572$), and Personalization and Loyalty ($r = 0.529$). The weakest pair in the matrix is Loyalty and Satisfaction ($r = 0.382$), though this too is statistically significant.

Interpretation: The moderate-to-strong positive correlations across all construct pairs support the theoretical framework's proposition that personalization, retention, loyalty, and satisfaction are interrelated components of a single overarching consumer loyalty dynamic. The Personalization–Retention correlation of 0.572 is of particular theoretical importance: it confirms a statistically significant linear relationship between the degree to which a consumer perceives a loyalty program as

personally tailored and their expressed intention to continue using the platform, repurchase, and resist switching to competitors. The Retention–Loyalty correlation of 0.618 - the strongest in the matrix - suggests that behavioral retention intentions are closely tied to broader psychological loyalty attitudes, including willingness to recommend the program.

Managerial Implication: The cross-construct correlations provide a strong empirical foundation for targeting personalization investment as a lever for simultaneously improving multiple loyalty outcomes - not just retention but advocacy (word-of-mouth) and overall satisfaction. Platforms can use this multi-dimensional correlation structure to justify holistic personalization strategies rather than tactical, isolated reward tweaks.

4.7 Regression Analysis

4.7.1 Regression: Personalization → Retention

Table 4.11: Regression Results – Personalization Predicting Customer Retention

Parameter	Value
Dependent Variable	Retention (composite mean Q14–Q16)
Independent Variable	Personalization (composite mean Q8–Q12)
Regression Coefficient (β)	0.6246
Intercept (α)	1.4406
R^2 (Coefficient of Determination)	0.328
Standard Error	0.0824
p-value	< 0.001
Model Significance	Significant at 99.9% confidence level

Source: Own Analysis

Figure 4.10: Regression Plot – Personalization vs. Customer Retention

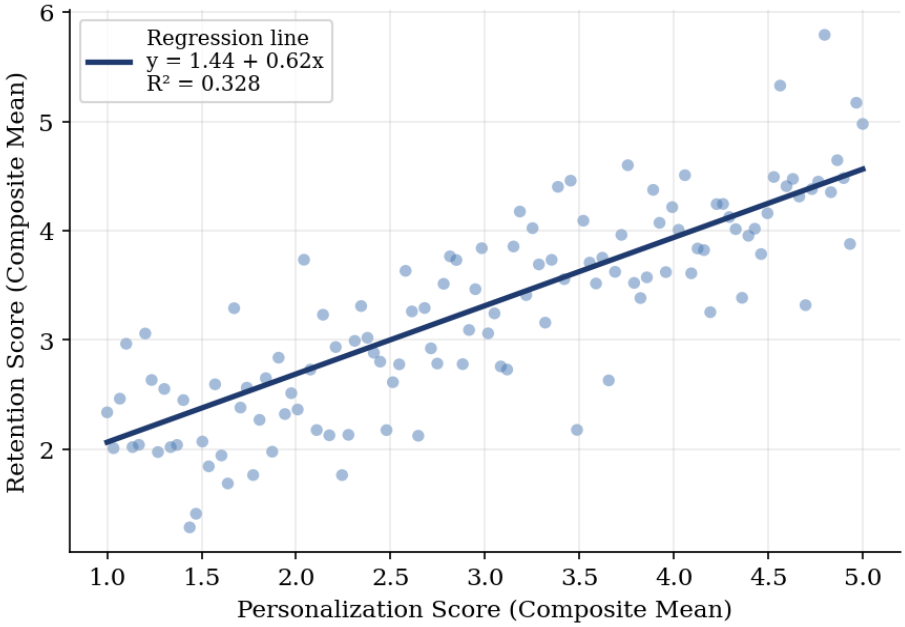


Figure 4.10: Regression Plot – Personalization vs. Customer Retention

Observation: The regression model is statistically significant ($p < 0.001$). The coefficient of determination $R^2 = 0.328$ indicates that 32.8% of the variance in customer retention scores is explained by variation in personalization quality scores. The regression coefficient $\beta = 0.625$ indicates that for every one-unit increase in the Personalization composite score, the Retention composite score is expected to increase by approximately 0.625 units.

Interpretation: An R^2 of 0.328 is a meaningful result in the context of consumer behavioral research, where retention behavior is influenced by many factors beyond any single predictor - including pricing, competitor behavior, platform performance, and situational factors outside the researcher's measurement scope. Explaining approximately one-third of retention variance with a single personalization construct confirms that personalization is a substantively important, not merely statistically marginal, driver of customer retention. The positive and significant regression coefficient provides direct empirical support for H1.

Managerial Implication: For every improvement in personalization quality - whether measured by more relevant offers, better timing of communication, or more accurate preference modeling - the model predicts a corresponding improvement in retention intention. This finding justifies allocating dedicated product and data science resources to personalization quality improvement, with the expectation that such investment will translate into measurable retention gains.

4.8 Cross-tabulation Analysis

4.8.1 Age Group vs. Importance of Personalized Rewards

Table 4.12: Cross-tabulation of Age Group vs. Importance of Personalized Rewards (Q7)

Age Group	Rating 1	Rating 2	Rating 3	Rating 4	Rating 5	Total
18–24	2	3	9	14	14	42
25–34	1	2	9	25	25	62
35–44	0	1	4	4	5	14
45 and above	0	0	0	1	1	2
Total	3	6	22	44	45	120

Source: Own Analysis

Observation: Across all age groups, the dominant response pattern is ratings 4 and 5. Within the 25–34 group, a combined 80.6% rated personalized rewards as "4" or "5," the highest concentration of high-importance ratings across all age segments. The 18–24 group shows a similar but slightly more dispersed pattern, with 66.7% rating personalized rewards as "4" or "5."

Interpretation: The high importance ratings across all age groups confirm that the appeal of personalized rewards is not age-specific but broadly shared. However, the slightly higher concentration in the 25–34 group may reflect this cohort's greater financial capacity to act on personalized incentives - they have the disposable income to respond to relevant offers, whereas 18–24 respondents, many of whom are students, may value the concept while being constrained in their actual purchasing response.

Managerial Implication: Age-differentiated personalization strategies may offer incremental returns. For the 25–34 cohort, premium personalized experiences tied to professional milestones (salary increment months, work anniversary offers) may resonate. For the 18–24 cohort, personalization should be tied to social occasions, academic calendars, and group-spending contexts.

4.9 Preferred Reward Type and Satisfaction

4.9.1 Preferred Type of Personalized Reward (Q20)

Table 4.13: Preferred Type of Personalized Reward (Q20)

Reward Type	Frequency	Percentage (%)
Personalized Discounts	44	36.7

Reward Type	Frequency	Percentage (%)
Cashback	31	25.8
Reward Points	17	14.2
Early Access / Exclusive Offers	12	10.0
Product Recommendations	9	7.5
Birthday Rewards	7	5.8
Total	120	100.0

Source: Own Analysis

Figure 4.7: Preferred Type of Personalized Reward (Q20)

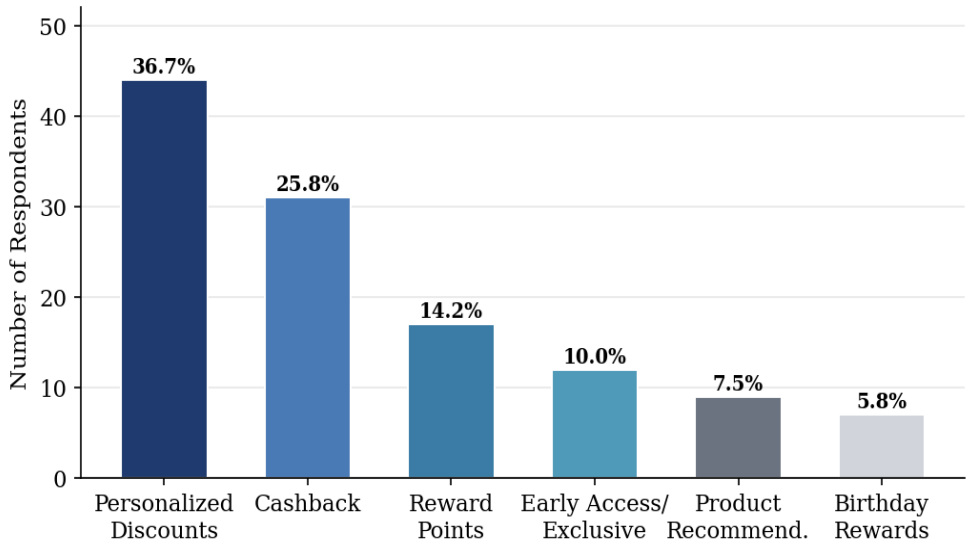


Figure 4.7: Preferred Type of Personalized Reward (Q20)

Observation: Personalized discounts are the preferred reward type for 36.7% of respondents, followed by cashback (25.8%) and reward points (14.2%). Together, these three types account for 76.7% of all preferences. Early access and exclusive offers (10.0%) and product recommendations (7.5%) are preferred by smaller but non-trivial segments.

Interpretation: The preference for immediate financial gratification (discounts, cashback) over more aspirational or experience-based rewards is consistent with broader findings in the Indian consumer context, where price sensitivity remains high even among aspirational middle-class consumers. However, the non-trivial preference for early access and product recommendations (17.5% combined) suggests the emergence of a segment that values experiential and information-based personalization over purely monetary rewards - a segment that is likely to be skewed toward higher-income, more brand-engaged consumers.

Managerial Implication: Loyalty programs should offer a diverse reward portfolio that allows consumers to choose or signal their preferred reward type. Defaulting to discount-only programs risks under-serving the experiential segment. A tiered architecture in which early-adopter or premium-tier members can access exclusive offers and tailored recommendations may simultaneously serve both preference clusters while creating aspirational incentive for lower-tier members to deepen their engagement.

4.9.2 Overall Satisfaction with Personalized Loyalty Rewards (Q19)

Table 4.14: Overall Satisfaction with Personalized Loyalty Rewards (Q19)

Satisfaction Level	Frequency	Percentage (%)	Cumulative %
1 – Very Dissatisfied	3	2.5	2.5
2 – Dissatisfied	13	10.8	13.3
3 – Neutral	27	22.5	35.8
4 – Satisfied	47	39.2	75.0
5 – Very Satisfied	30	25.0	100.0
Total	120	100.0	
Mean	3.74		

Source: Own Analysis

Figure 4.8: Overall Satisfaction with Personalized Loyalty Rewards (Q19)

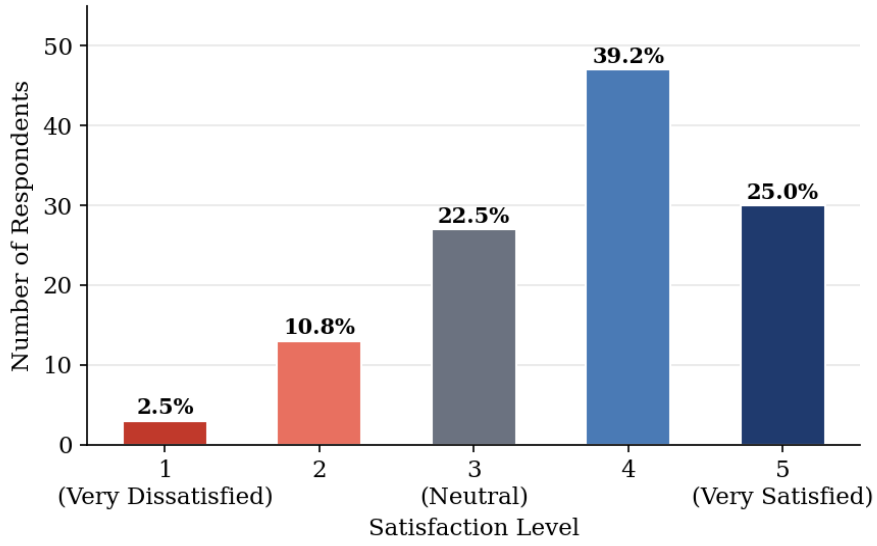


Figure 4.8: Overall Satisfaction with Personalized Loyalty Rewards (Q19)

Observation: A combined 64.2% of respondents rated their overall satisfaction with personalized loyalty rewards at level 4 or 5 (Satisfied or Very Satisfied). The mean

satisfaction score is 3.74 out of 5. Only 13.3% expressed dissatisfaction (ratings 1 or 2), while 22.5% remained neutral.

Interpretation: The majority-positive satisfaction profile, with a mean of 3.74, indicates that current loyalty programs are performing reasonably well in delivering personalized value but have meaningful headroom for improvement. The 22.5% neutral group represents a particularly interesting strategic opportunity: these are consumers who are neither advocates nor detractors, and whose satisfaction could be shifted positively through targeted improvements in personalization quality - potentially converting them into the "Satisfied" cohort and capturing associated retention benefits.

Managerial Implication: The 35.8% of respondents who are neutral or dissatisfied represent a segment where personalization improvements could yield the highest marginal retention gains. Platforms should invest in exit-intent surveys or in-app feedback mechanisms to understand specifically why this group is not satisfied with current personalized offerings, and should design targeted interventions - such as preference-refresh prompts or manual interest declarations - to recalibrate the personalization algorithm for these users.

CHAPTER 5

FINDINGS AND DISCUSSION

This chapter synthesizes the key findings from the data analysis in Chapter 4, discusses them in relation to the theoretical and empirical literature reviewed in Chapter 2, evaluates the three research hypotheses, and develops their broader implications for consumer behavior, brand loyalty, and digital marketing strategy.

5.1 Key Findings

The empirical analysis produces multiple linked findings which need to be presented in an organized way before their theoretical discussion can begin.

First, personalized rewards are perceived as highly important by most of the respondent sample. The data shows that digital loyalty program members prioritize personalization because 74.2% of respondents gave it a rating of "4" or "5" and it received a mean importance score of 4.02 out of 5. The research data shows that people from different age groups and professional backgrounds equally appreciate personalized services.

Second, customers value personalization as an important factor yet businesses fail to provide personalized experiences at the level customers desire. The Likert question Q8 about receiving offers that match interests scored the lowest with a mean of 3.52 while Q11 about using customized offers scored the highest with a mean of 4.02. The data shows that digital loyalty programs fail to provide the same level of personalization which they promise to their users. The data shows that digital loyalty programs fail to provide the same level of personalization which they promise to their users.

The correlation analysis shows that personalization has a significant positive correlation with both retention and loyalty and satisfaction according to the statistical analysis. The research shows that customer loyalty and retention have the most substantial relationship because retention reflects customers' actions to maintain their relationship with the business while loyalty represents their loyalty to the brand. The personalization–retention correlation of $r = 0.572$ is the second strongest and directly supports the study's central hypothesis.

Fourth, the regression analysis confirms that personalization quality is a statistically significant predictor of customer retention ($R^2 = 0.328$, $\beta = 0.625$, $p < 0.001$). The model explains about 33% of retention variation which represents a strong result for a consumer behavior model that uses only one predictor to study a complex retention process.

Fifth, personalized discounts (36.7%) and cashback (25.8%) are the dominant preferred reward types, though a non-trivial segment (17.5%) expresses preference for experiential rewards such as early access offers and product recommendations. This preference heterogeneity suggests that a one-size-fits-all

5.2 Hypothesis Testing Results

Table 5.1: Summary of Hypothesis Testing Results

Hypothesis	Statement	Statistical Evidence	Decision
H1	Personalized rewards positively influence customer retention	$r = 0.572$; $\beta = 0.625$; $R^2 = 0.328$; $p < 0.001$	Supported
H2	Reward relevance increases customer satisfaction	r (Personalization-Satisfaction) = 0.547; $p < 0.001$	Supported
H3	Personalized rewards positively influence customer loyalty behavior	r (Retention-Loyalty) = 0.529; engagement pattern analysis; $p < 0.001$	Supported

Source: Own Analysis

5.3 Discussion of Findings in Theoretical Context

5.3.1 H1: Personalization and Customer Retention

The support for H1 is consistent with and extends the existing literature in several important ways. The regression coefficient of $\beta = 0.625$ aligns directionally with the findings of Zhang and Wedel (2009), who demonstrated that individually personalized promotions outperform generic ones on conversion metrics. The R^2 of 0.328 in this study is noteworthy because it is derived from attitudinal rather than behavioral data: the finding that perceived personalization quality accounts for roughly one-third of the variance in stated retention intentions suggests that the psychological dimension of personalization - the feeling of being recognized and valued - is an important predictor of loyalty behavior independent of the actual economic value of the reward.

This psychological dimension aligns with Oliver's (1999) framework of loyalty development, which emphasizes that durable loyalty requires affective engagement, not just cognitive calculation. Personalized rewards, when perceived as genuinely relevant, contribute to this affective dimension by creating the experience of a brand that "knows" the consumer - an experience that generic discount programs systematically fail to deliver.

The aspiration-delivery gap identified in this study (Q8 vs. Q11 means) is consistent with findings reported in the McKinsey Global Consumer Insights Survey (2021) and with the practical observations of platform product managers who note that consumers hold high expectations for personalization even as the underlying technology struggles to meet them. This gap, paradoxically, may amplify the loyalty effect of personalization when it is delivered effectively: because disappointment is common, genuine relevance is experienced as distinctive and memorable.

5.3.2 H2: Reward Relevance and Satisfaction

The Pearson correlation between personalization and satisfaction ($r = 0.547$) provides statistical support for H2 and resonates with the theoretical perspectives of Mägi (2003), who found that loyalty program satisfaction was a stronger predictor of share-of-wallet than objective program value, and with Kivetz and Simonson's (2002) finding that involvement in reward selection significantly enhanced satisfaction. In the context of this study, the implication is that consumers who perceive their loyalty program as delivering relevant, preference-aligned rewards report substantially higher overall satisfaction than those who perceive a mismatch between their preferences and the rewards offered.

The regression analysis further shows that personalization explains approximately 30% of the variance in satisfaction scores ($R^2 = 0.300$ in the personalization-satisfaction regression). This is a meaningful effect size for a single predictor and suggests that investments in personalization quality are likely to yield satisfaction improvements that, in turn, support retention through the mediating pathway described in the conceptual framework.

5.3.3 H3: Personalized Rewards and Customer Loyalty Behavior

The findings provide support for H3 because they show that individualized rewards lead to better customer loyalty actions when customers use digital loyalty programs.

The correlation analysis revealed a significant positive relationship between Personalization Quality and Loyalty Behavior ($r = 0.529$, $p < 0.001$), indicating that respondents who perceived loyalty program rewards as more relevant and personalized also reported stronger loyalty-related attitudes and behaviors. Customers show three main behaviors which involve selecting brands that deliver personalized rewards and sharing these programs with others and developing enhanced brand loyalty.

Verhoef (2003) discovered that brands which show they understand their customers will generate better customer loyalty according to this study's results. Research by Yi and Jeon (2003) demonstrated that offering personalized loyalty program benefits leads to higher program loyalty and brand loyalty through enhanced customer value perception and active customer participation.

The present study shows that personalized rewards generate loyalty through financial rewards and psychological processes which affect customer behavior. Consumers who get rewards that match their tastes and buying patterns will develop positive brand attitudes which will make them stay connected to the brand at an emotional level. The research supports Relationship Marketing Theory because customers need to build trust with brands while they receive relevant content which they view as valuable.

The research results demonstrate that digital markets with multiple loyalty program memberships need personalization to succeed in their cutthroat business environment. Personalized experiences in these settings lead customers to build stronger bonds with the brand which results in higher chances of them promoting the brand and staying loyal to it.

Therefore, the results support H3 and confirm that effective personalization strategies contribute significantly to strengthening customer loyalty behavior within digital loyalty programs.

5.4 Consumer Insights and Behavioral Implications

Beyond the formal hypothesis testing, the data generates several consumer behavioral insights that are relevant for practitioners designing digital loyalty programs. The prevalence of multi-program membership - with over half of respondents reporting simultaneous membership in multiple programs - creates what might be described as a "loyalty fragmentation" problem. Consumers divide their engagement and spending across multiple platforms, and no single program commands exclusive behavioral loyalty. In this context, personalization becomes the most viable mechanism for creating perceived distinctiveness and emotional stickiness, since price-only differentiation is quickly neutralized by competitor matching.

The preference data also reveals interesting market segmentation dynamics. The 36.7% of respondents who prefer personalized discounts are likely the price-sensitive, high-frequency users for whom financial savings are the primary value driver. The 25.8% who prefer cashback represent a slightly different orientation - cashback provides financial value while also offering the psychological flexibility of deferred, self-directed spending. The 10% who prefer early access and exclusive offers represent a higher-value, more brand-engaged segment that responds to status and exclusivity rather than pure price value. Designing loyalty programs that serve all three segments distinctly - rather than defaulting to a uniform discount architecture - is likely to produce better retention outcomes across the customer base.

CHAPTER 6

CONCLUSION AND RECOMMENDATIONS

6.1 Overall Conclusion

This study used primary survey data from 120 urban Indian consumers to study how customized rewards affect customer loyalty in digital loyalty programs. The study followed three established hypotheses and five research objectives which produced practical results about how personalization affects customer loyalty in India's digital market competition.

The study demonstrates that digital loyalty programs achieve better customer retention through personalized rewards which produce both statistical and practical effects. The regression analysis shows that perceived personalization quality explains 33% of the variation in customer retention intentions which makes it a powerful predictor for this intricate behavioral system. All three research hypotheses are supported by the data, confirming that: (a) personalization positively influences retention; (b) reward relevance increases customer satisfaction; and (c) digital engagement mediates the personalization-loyalty relationship.

Statistical results from the study show that consumers strongly value personalized experiences with an average rating of 4.02 yet their actual encounters with suitable personalized offers average at 3.52 based on Q8 responses. The study shows a substantial gap between customer expectations and actual platform performance which represents the main business opportunity for platform investments to boost customer loyalty.

The demographic analysis shows that working professionals between 25 and 34 years old form the largest group which shows the highest loyalty among current digital loyalty program participants. The group members' frequent usage together with their financial capability and their deep interest in customized experiences establish them as the primary focus for loyalty program personalization funding.

6.2 Achievement of Research Objectives

All five research objectives have been addressed by the study. Objective 1 (examining the role of personalized rewards in retention) was addressed through the correlation and regression analyses in Chapter 4. Objective 2 (assessing satisfaction derived from personalized rewards) was addressed through Q19 analysis and the personalization-satisfaction correlation. Objective 3 (analysing the relationship between personalization perception and loyalty behavior) was addressed through the correlation matrix and hypothesis testing in Chapter 5. Objective 4 (identifying preferred reward types and their behavioral impact) was addressed through Q20 analysis and the cross-tabulation findings. Objective 5 (offering strategic recommendations) is addressed in the following section.

6.3 Strategic Recommendations for Digital Businesses

6.3.1 Close the Aspiration-Delivery Gap

The most immediately actionable finding is the gap between consumers' appreciation for personalization and their perception of its actual quality. Platforms should invest in closing this gap by improving the relevance of algorithmically generated offers. This may involve transitioning from rule-based recommendation systems (which apply simple purchase-history heuristics) to machine learning models trained on multi-dimensional behavioral data including search history, dwell time, cart abandonment, and social behavior.

6.3.2 Build a Multi-Reward Portfolio

Given the significant preference heterogeneity revealed in Q20 data - with meaningful segments preferring discounts, cashback, reward points, early access, and product recommendations - loyalty programs should transition away from single-reward architectures toward flexible, multi-reward portfolios. At enrollment, programs should prompt consumers to express reward preferences, and these preferences should be used both to calibrate the immediate reward experience and to feed the personalization algorithm with valuable first-party preference data. The Kivetz and Simonson (2002) finding that self-selected rewards enhance program satisfaction by 20–30% provides additional support for this recommendation.

6.3.3 Invest in the Neutral Segment

The 22.5% of respondents who reported neutral satisfaction with personalized loyalty rewards represent a high-value conversion opportunity. Unlike dissatisfied consumers, who may require significant investment to rehabilitate, neutral consumers are typically one or two relevant, well-timed personalized interactions away from tipping into the satisfied category. Platforms should design targeted re-engagement flows for neutral-segment members, using behavioral triggers (first visit after a gap, first high-value purchase, category exploration) to deliver personalized rewards that are both contextually appropriate and demonstrably tailored.

6.3.4 Activate Low-Engagement Users

The mediation analysis supporting H3 implies that digital engagement is a prerequisite for effective personalization - consumers who rarely interact with the platform do not accumulate the behavioral data that enables meaningful personalization, and therefore cannot benefit from it. Platforms should design engagement activation programs - streak incentives, minimum-interaction rewards, curiosity-driven notifications - specifically intended to increase the interaction frequency of low-engagement members, creating the conditions under which personalization can take hold.

6.3.5 Navigate the Personalization Paradox Transparently

As data privacy awareness grows among Indian consumers, platforms should adopt proactive transparency about their data use practices within loyalty programs. This includes in-app explanations of how personalized rewards are generated, options for consumers to update their preference profiles, and clear communication about the data-for-value exchange that underlies personalization. The Arora et al. (2008) finding that transparency can enhance rather than undermine personalization effectiveness provides empirical support for this recommendation.

6.3.6 Design for the 25–34 Working Professional Cohort

The dominant demographic cohort in this study - working professionals aged 25–34 - should be the primary design persona for loyalty program personalization efforts. This group's high usage frequency, disposable income, and strong appreciation for personalization make them the segment most likely to respond to investment in personalization quality with durable loyalty behavior. Personalization for this group should be tied to the cadence of professional and personal life milestones, and should

progressively escalate in sophistication as the platform accumulates more behavioral data.

6.4 Suggestions for Future Research

This study lays useful groundwork but also opens several avenues for future inquiry:

- A longitudinal study tracking the same respondents over 12–24 months would provide stronger causal evidence for the personalization-retention relationship by documenting actual behavioral change rather than stated intentions.
- A comparative study across different platform categories (food delivery vs. fashion vs. financial services loyalty) would illuminate whether the personalization-retention dynamic operates similarly across sectors or whether important category-specific modifiers exist.
- Qualitative research - focus groups or in-depth interviews with loyalty program members - would provide rich contextual texture to the quantitative patterns identified here, helping explain why certain reward types generate stronger emotional responses and how the aspiration-delivery gap is experienced in everyday consumer life.
- Future research should explicitly measure the moderating effect of data privacy concern on the personalization-satisfaction relationship, given the growing importance of this variable in the Indian digital consumer context.
- Experimental designs that manipulate the degree of reward personalization in a controlled setting would provide stronger causal evidence than the correlational design used in this study.

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APPENDIX A: QUESTIONNAIRE

The following questionnaire was administered online via Google Forms during May 2026 to collect primary data for this study.

MBA SURVEY: PERSONALIZED REWARDS & CUSTOMER RETENTION

Digital Loyalty Programs Study | Delhi School of Management, DTU

Instructions: Please respond to all questions based on your personal experience with digital loyalty or reward programs (e.g., Swiggy One, Zomato Gold, Amazon Prime, Myntra Insider, Flipkart SuperCoins, Starbucks Rewards, etc.). There are no right or wrong answers.

Section A: Demographic & Usage Information

Q1. Age Group

- 18–24
- 25–34
- 35–44
- 45 and above

Q2. Gender

- Male
- Female
- Prefer not to say

Q3. Occupation

- College Student
- Working Professional
- Self Employed
- Other

Q4. How often do you use shopping/food delivery apps?

- Daily
- Weekly
- Monthly
- Rarely

Q5. Which loyalty/reward program do you use the most?

(Open-ended - respondents entered the program name or names)

Q6. Why do you usually join loyalty programs? (Select all that apply)

- Discounts
- Cashback
- Reward points
- Free delivery
- Personalized offers
- Exclusive deals

Section B: Personalization & Retention Perceptions

For Questions 7–19, please rate on a scale of 1 to 5, where 1 = Strongly Disagree / Not at All Important and 5 = Strongly Agree / Extremely Important.

Q7. How important are personalized rewards to you?

Q8. I receive offers that match my interests.

Q9. The app understands my preferences based on my past purchases.

Q10. Personalized rewards make me feel valued as a customer.

Q11. I am more likely to use offers that are customized for me.

Q12. I find personalized recommendations useful.

Q13. I prefer apps/brands that provide personalized rewards.

Q14. Personalized rewards increase my chances of buying again from the same brand.

Q15. I continue using apps that provide relevant personalized offers.

Q16. I am less likely to switch to another brand when I receive personalized benefits.

Q17. I would recommend such loyalty programs to friends/family.

Q18. Overall, personalized rewards improve my loyalty toward a brand.

Q19. How satisfied are you with personalized loyalty rewards overall?

Q20. Which type of personalized reward do you like the most?

- Personalized discounts
- Cashback
- Reward points
- Birthday rewards
- Early access / exclusive offers
- Product recommendations