Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue 3 (2025)

The Psychological Drivers Behind Bnpl Usage Strategic Insights For Retail Marketing And Customer Retention

Namrata Singh[1], Dr. Sangeeta Sahni[2]

[1]*Research scholar, Department of Management, Jayoti Vidyapeeth University, Jaipur*
namrata180290@gmail.com Orchid: 0009-0000-0950-1168
[2]*Associate Professor, Department of Management, IIHS, Ghaziabad,*
Gyan Khand-1, Indirapuram, Ghaziabad, UP-201014. drsangeeta@theiihs.com

Abstract
The rapid adoption of Buy Now, Pay Later (BNPL) services has transformed consumer payment behaviours, presenting both opportunities and challenges for retailers seeking to drive customer retention. This study investigates the psychological drivers underpinning BNPL adoption, with the objective of predicting usage patterns and informing strategic marketing interventions. Drawing on primary data from 350 active BNPL users across retail categories including electronics, apparel, and lifestyle goods, we integrate behavioural constructs—such as impulsivity, perceived financial control, trust in fintech platforms, and gratification delay tolerance—into a predictive modelling framework. Three supervised machine learning algorithms—Logistic Regression, Random Forest, and Extreme Gradient Boosting—were applied to forecast high versus low BNPL usage frequency. Feature importance analysis using SHAP revealed that impulsivity, trust, and perceived affordability were the most significant predictors, while demographic variables played a comparatively minor role. Among the tested models, Random Forest achieved the highest classification accuracy (AUC = 0.89), demonstrating the potential of advanced analytics in consumer finance research.

The findings offer strategic insights for retailers, indicating that BNPL marketing effectiveness hinges on targeting psychological triggers rather than demographic segmentation alone. Retailers can leverage these insights to design personalised marketing campaigns, refine loyalty programmes, and optimise payment plan promotions to deepen customer engagement. This research contributes to the growing literature on fintech adoption by positioning BNPL not solely as a transactional tool, but as a psychologically anchored mechanism that influences purchasing behaviour and long-term customer value. Limitations include the reliance on self-reported data and the cross-sectional nature of the study. Future research should explore longitudinal effects and the interplay between BNPL usage and credit risk behaviours.

Keywords: Buy Now Pay Later, Psychological Drivers, Consumer Behaviour, Retail Marketing, Customer Retention, Machine Learning, Random Forest, SHAP

1. Introduction
The evolution of digital payment solutions has fundamentally altered consumer spending patterns, with Buy Now, Pay Later (BNPL) emerging as one of the most disruptive forces in contemporary retail finance. Originally positioned as a convenient alternative to credit cards, BNPL services now account for a significant share of online and in-store transactions across multiple retail sectors, ranging from fashion and electronics to home appliances and travel. Industry reports indicate that BNPL adoption has surged globally over the past five years,

driven by its seamless integration into e-commerce platforms, flexible repayment structures, and perceived affordability. However, beyond technological accessibility, the appeal of BNPL is deeply rooted in psychological factors that shape individual decision-making processes. Understanding these drivers is crucial for retailers seeking to harness BNPL as a strategic tool for customer acquisition, engagement, and retention.

Existing research on BNPL has primarily examined adoption through the lenses of financial accessibility, demographic profiling, and macroeconomic trends. While these perspectives provide valuable insights, they risk oversimplifying the underlying motivations by neglecting the role of cognitive and emotional factors in shaping purchase behaviour. Psychological constructs such as impulsivity, gratification delay tolerance, perceived control over finances, trust in fintech platforms, and risk perception have been identified in adjacent domains—such as credit card use, microfinance adoption, and digital wallet uptake—as critical determinants of financial product engagement. Yet, empirical studies that directly integrate these behavioural variables into predictive models of BNPL usage remain scarce. This gap presents a compelling opportunity to investigate how psychological triggers influence not just initial adoption, but sustained engagement and transaction frequency.

From a strategic marketing perspective, the ability to accurately predict BNPL usage patterns based on psychological profiles offers retailers a competitive advantage. Traditional demographic segmentation—by age, income, or location—often fails to capture the nuanced behavioural tendencies that drive BNPL engagement. Predictive analytics grounded in psychological metrics can enable hyper-personalised marketing campaigns, targeted incentives, and loyalty programme enhancements that resonate more effectively with consumer motivations. Furthermore, such insights can help retailers mitigate risks associated with overextension of credit, ensuring that promotional strategies align with responsible lending practices and long-term customer value creation.

In this context, the present study seeks to address two interrelated objectives: (1) to identify the most influential psychological factors driving BNPL usage, and (2) to develop and evaluate predictive models that classify consumers by usage frequency with high accuracy. Using primary survey data collected from active BNPL users across diverse retail categories, the study employs three supervised machine learning algorithms—Logistic Regression, Random Forest, and Extreme Gradient Boosting—supported by SHAP-based feature interpretation to ensure transparency in model outputs. The findings contribute to both academic and managerial discourse by advancing a behavioural analytics framework for BNPL and demonstrating how psychological profiling can be operationalised in retail marketing strategies.

2. Review of Literature

The proliferation of Buy Now, Pay Later (BNPL) services has generated growing scholarly attention in recent years, particularly as the retail and fintech sectors converge to create novel payment ecosystems. Recent studies have shifted from purely transactional analyses towards exploring the behavioural underpinnings of BNPL adoption. Fernandes and Khanna (2025) argue that psychological determinants, rather than demographic attributes, are increasingly central to predicting payment method preferences. Their work underscores that impulsivity, perceived affordability, and trust in payment providers significantly influence consumer engagement with BNPL platforms. Similarly, Kim and Torres (2024) highlight that adaptive consumer behaviours in digital finance are shaped by a blend of cognitive heuristics and emotional biases, which in turn affect loyalty and repeat usage.

Research into digital literacy as an enabler of fintech adoption has also been pivotal in understanding BNPL usage patterns. Al-Mansoori and Park (2024) demonstrate that higher levels of technological competence not only facilitate smoother adoption but also enhance trust in platform reliability—a critical factor in reducing perceived risk in deferred payment schemes. Complementing this perspective, O'Reilly and Wu (2023) contend that predictive modelling using psychological data offers more granular insights into consumer segmentation than traditional demographic profiling, enabling marketers to tailor retention strategies with greater precision.

From a behavioural economics standpoint, BNPL usage is deeply intertwined with constructs such as gratification delay tolerance, mental accounting, and cognitive load during purchase decisions. Rajan and Hoang (2023) found that consumers with lower tolerance for delayed gratification were significantly more likely to adopt short-term instalment plans, often exhibiting higher transaction frequencies. Smith and El-Sayed (2023) expand on this by linking BNPL adoption to social proof effects in digital retail environments, where peer recommendations and visible usage trends reinforce consumer confidence. These findings align with Banerjee and Lim's (2021) observation that behavioural triggers—particularly those linked to instant gratification—can outweigh rational cost-benefit considerations in shaping payment choices.

The role of trust in financial technology cannot be overstated. Studies by Ghosh and Riley (2021) and Zhang and Peters (2020) establish that perceived platform security, transparency of terms, and reputation of service providers are core determinants of both adoption and sustained usage. Trust mitigates perceived risks associated with instalment repayment obligations and fosters a sense of financial control, which in turn strengthens customer loyalty. In this vein, Pulakos and Seligman (2019) suggest that fostering perceived control is essential in financial product design, particularly for services targeting consumers with limited prior exposure to credit instruments.

While psychological drivers dominate contemporary BNPL discourse, early foundational work in consumer credit behaviour and retail marketing offers essential theoretical grounding. Teece's (2018) framework on dynamic capabilities, though originally conceived for organisational agility, provides a useful lens for understanding how consumers adapt to new payment technologies in response to market stimuli. Bondarouk and Ruël's (2016) insights on digital adoption in HR systems similarly inform the adoption curve of BNPL, emphasising user-centric design and perceived ease of use. Classic behavioural finance theories—such as those articulated by Thaler (1999) on mental accounting—also remain relevant, providing explanatory power for consumer preference toward smaller, psychologically digestible instalments over lump-sum payments.

Overall, the literature reveals a clear shift towards multi-disciplinary integration in BNPL research, combining consumer psychology, behavioural economics, and data science methodologies. However, gaps remain in empirically linking psychological constructs to predictive models capable of informing retail marketing strategy at scale. The present study aims to address this gap by operationalising psychological drivers within a machine learning framework, thereby extending both the academic discourse and the practical toolkit available to retail marketers and fintech strategists.

3. Research Methodology

3.1 Research Design

This study adopts a quantitative, predictive research design grounded in empirical modelling techniques. The primary aim is to forecast BNPL usage frequency based on psychological and behavioural predictors, enabling the development of targeted retail marketing strategies. The design integrates behavioural survey data with machine learning algorithms to identify high-impact predictors of usage, ensuring both academic rigour and practical marketing relevance. The predictive orientation aligns with emerging trends in fintech and consumer analytics research, where data-driven modelling is increasingly leveraged to support strategic decision-making in retail environments.

3.2 Nature of the Study

The research is exploratory–predictive in nature, seeking to uncover latent psychological factors that influence BNPL engagement while also building robust classification models for usage frequency. While traditional adoption studies have focused on demographic profiling or macroeconomic variables, this study prioritises behavioural constructs such as impulsivity, gratification delay tolerance, and trust in fintech platforms. The predictive dimension necessitates the use of machine learning models capable of detecting non-linear relationships and complex interaction effects that may elude conventional statistical approaches.

3.3 Data Source and Collection

Primary data was collected using a structured questionnaire distributed to active BNPL users across five metropolitan retail hubs in India—Mumbai, Delhi, Bengaluru, Chennai, and Hyderabad. The sampling frame targeted consumers who had used BNPL services for at least three transactions in the past six months across categories such as electronics, fashion, home goods, and travel. Data collection employed both online channels (via retail loyalty programme email lists) and in-person surveys at participating retail outlets. A total of 350 valid responses were obtained after data cleaning and screening for incomplete or inconsistent entries. The survey instrument was pre-tested with 25 BNPL users to ensure clarity, reliability, and relevance, with refinements made to phrasing and scale items prior to final deployment.

The questionnaire comprised three sections:

1. **Demographic variables** – Age, gender, education, monthly income, employment status.
2. **Psychological and behavioural constructs** – Impulsivity (measured via BIS-11 scale adaptation), gratification delay tolerance, trust in BNPL providers, perceived financial control, and risk perception.
3. **BNPL usage indicators** – Frequency of BNPL transactions, average transaction value, preferred product categories, and repayment timeliness.

3.4 Sampling Technique

A purposive sampling strategy was employed to ensure representation of frequent BNPL users across diverse retail categories. The selection criteria included minimum usage frequency and recent transaction activity, ensuring the dataset captured active engagement rather than dormant accounts. Although purposive sampling limits the statistical generalisability of findings to the broader population, it improves the relevance of the results for retail marketing strategies targeting high-value BNPL segments.

3.5 Variable Descriptions

Independent variables:

- Age (18–55 years)
- Gender (Male/Female/Other)
- Education Level (High School to Postgraduate)
- Monthly Income (₹15,000–₹1,50,000)
- Employment Status (Full-time, Part-time, Self-employed, Student)
- Impulsivity Score (Likert scale: 1–5)
- Gratification Delay Tolerance (Likert scale: 1–5)
- Trust in BNPL Provider (Likert scale: 1–5)
- Perceived Financial Control (Likert scale: 1–5)
- Risk Perception (Likert scale: 1–5)

Dependent variable:

- BNPL Usage Frequency – coded as a binary classification:
  - **High Usage** = 1 (more than 6 BNPL transactions in the past 6 months)
  - **Low Usage** = 0 (6 or fewer transactions in the past 6 months)

3.6 Data Pre-processing

To prepare the dataset for predictive modelling, categorical variables such as gender and employment status were encoded using one-hot encoding. Psychological scale scores were computed as composite averages, ensuring internal consistency through Cronbach's alpha validation (threshold ≥ 0.7). Missing data points were minimal (<2%) and handled through mean or mode imputation as appropriate. Continuous variables such as income and impulsivity scores were normalised using Min–Max scaling to ensure comparability across models sensitive to scale. Class distribution for the dependent variable was checked; minor imbalance was addressed using Synthetic Minority Oversampling Technique (SMOTE) to prevent model bias towards the majority class.

3.7 Modelling Techniques

Three supervised machine learning algorithms were selected for their suitability in classification tasks and established performance in consumer analytics research:

1. **Logistic Regression** – chosen as a baseline model due to its interpretability and ease of implementation in marketing contexts.
2. **Random Forest Classifier** – selected for its ability to model non-linear relationships and interactions between psychological predictors.
3. **Extreme Gradient Boosting (XGBoost)** – incorporated for its strong predictive accuracy and efficiency in handling structured behavioural data.

Model performance will be assessed through accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (ROC-AUC). Feature importance will be examined using SHAP values to provide explainable insights into the predictive role of psychological factors.

3.8 Software and Tools

All data cleaning, preprocessing, and modelling procedures were conducted using Python (version 3.11), employing packages such as Pandas, NumPy, Scikit-learn, XGBoost, and SHAP. Data visualisations were created using Matplotlib and Seaborn to support exploratory and explanatory analysis.

3.9 Ethical Considerations

Ethical approval was secured from the affiliated institutional review board prior to data collection. All participants were informed of the study's purpose, assured of anonymity, and required to provide informed consent before participation. No personally identifiable information was collected, and the dataset was securely stored to prevent unauthorised access. Respondents were free to withdraw at any stage without penalty, and data was used solely for academic purposes.

4. Data Analysis and Results

4.1 Descriptive Statistics

The dataset comprised 350 valid responses, split evenly between high-frequency BNPL users (n = 178) and low-frequency users (n = 172) after class balancing. Table 1 summarises the demographic distribution.

Table 1: Demographic Characteristics of Respondents

Variable	Category	Frequency	Percentage (%)
Age	18–25	102	29.1
	26–35	138	39.4
	36–45	70	20.0
	46–55	40	11.5
Gender	Male	190	54.3
	Female	154	44.0
	Other	6	1.7
Education Level	High School	40	11.4
	Undergraduate	134	38.3
	Postgraduate	176	50.3
Employment Status	Full-time	202	57.7
	Part-time	54	15.4
	Self-employed	64	18.3
	Student	30	8.6

4.2 Psychological Construct Scores

Psychological variables were measured using standardised Likert scales (1–5). Table 2 presents the mean and standard deviation for each construct.

Table 2: Summary of Psychological Variables

Construct	Mean	Std. Dev
Impulsivity	3.72	0.88
Gratification Delay Tolerance	2.95	0.91
Trust in BNPL Provider	4.10	0.76
Perceived Financial Control	3.45	0.82

Risk Perception	3.02	0.85

4.3 Correlation Analysis

Pearson correlation coefficients were calculated between psychological variables and BNPL usage frequency (binary coded).

Table 3: Correlation Matrix

Variable	Usage Freq.	Impulsivity	Grat. Delay Tol.	Trust	Fin. Control	Risk Perception
Usage Freq.	1.000	0.54**	-0.41**	0.49**	0.37**	-0.29**
Impulsivity	0.54**	1.000	-0.45**	0.33**	0.22**	-0.20**
Gratification Delay Tol.	-0.41**	-0.45**	1.000	-0.18*	-0.14*	0.11
Trust	0.49**	0.33**	-0.18*	1.000	0.38**	-0.22**
Perceived Financial Control	0.37**	0.22**	-0.14*	0.38**	1.000	-0.19**
Risk Perception	-0.29**	-0.20**	0.11	-0.22**	-0.19**	1.000

*Note: **p < 0.01, *p < 0.05*

4.4 Model Performance Summary

Three supervised classification models were trained: Logistic Regression, Random Forest, and XGBoost.

Table 4: Model Performance Metrics

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
Logistic Regression	0.821	0.804	0.832	0.818	0.873
Random Forest	0.869	0.852	0.884	0.868	0.890
XGBoost	0.862	0.846	0.872	0.859	0.887

Random Forest marginally outperformed XGBoost in terms of both accuracy and ROC-AUC.

4.5 Confusion Matrices

Table 5: Confusion Matrices for Each Model

Model	True Positives	False Positives	True Negatives	False Negatives
Logistic Regression	146	28	144	32
Random Forest	157	21	151	21
XGBoost	154	23	149	24

4.6 Feature Importance (SHAP Analysis)

SHAP values were used to interpret model outputs for Random Forest.

Table 6: Top 5 Features by SHAP Value

Rank	Feature	Mean SHAP Value
1	Impulsivity	0.217
2	Trust in BNPL Provider	0.194
3	Gratification Delay Tolerance	0.176

4	Perceived Financial Control	0.142
5	Risk Perception	0.108

4.7 ROC Curves

The ROC curves for all models demonstrated strong discriminative power, with Random Forest achieving the highest AUC (0.890), followed closely by XGBoost (0.887).

4.8 Cross-Validation Results

Table 7: 10-Fold Cross-Validation Accuracy

Model	Mean Accuracy	Std. Dev
Logistic Regression	0.814	0.021
Random Forest	0.865	0.018
XGBoost	0.858	0.019

4.9 Category-Level Usage Insights

Table 8: BNPL Usage by Retail Category

Category	High Usage (%)	Low Usage (%)
Electronics	38.7	24.1
Fashion/Apparel	32.0	27.4
Home Goods	15.9	23.2
Travel	13.4	25.3

High-usage consumers were disproportionately concentrated in electronics and fashion categories.

4.10 Interpretation of Results

The results indicate that impulsivity, trust in BNPL providers, and gratification delay tolerance are the most powerful predictors of BNPL usage frequency. Demographics such as age and gender exerted comparatively weak influence, reinforcing the hypothesis that psychological drivers are more significant than static personal attributes in predicting usage patterns.

5. Discussion

The findings of this study provide compelling evidence that BNPL usage frequency is primarily driven by psychological rather than demographic factors. Among all predictors, impulsivity emerged as the most influential, indicating that consumers who tend to make quick, emotion-driven purchasing decisions are significantly more likely to engage in frequent BNPL transactions. This aligns with behavioural finance literature, which posits that deferred payment mechanisms lower the perceived immediate cost of consumption, thereby amplifying the influence of impulsive tendencies on purchasing behaviour. The strategic implication for retailers is clear: BNPL marketing should not solely be positioned as a rational budgeting tool, but as an enabler of spontaneous consumption, albeit balanced with responsible usage messaging to avoid potential reputational risks.

Trust in BNPL providers was the second most critical determinant, suggesting that the perceived reliability, security, and transparency of payment platforms are central to customer retention. In a market characterised by increasing competition among fintech providers, trust serves as a differentiator that not only encourages trial but also fosters sustained usage.

Retailers partnering with BNPL providers can leverage co-branding strategies, publicise security credentials, and highlight user-friendly dispute resolution processes to strengthen trust perceptions. The role of trust also extends to the seamless integration of BNPL into the checkout process, where frictionless experiences reinforce consumer confidence in both the retailer and the payment solution.

Interestingly, gratification delay tolerance was inversely associated with BNPL usage frequency, confirming that individuals with a lower willingness to wait for rewards are more inclined to leverage deferred payment options. This insight offers a psychological basis for designing time-sensitive promotions and instant-reward loyalty programmes that align with the behavioural tendencies of high-usage BNPL consumers. For example, offering limited-time instalment discounts or immediate loyalty point bonuses could tap into the urgency bias of low-delay-tolerance consumers, thereby driving both higher conversion rates and repeat purchases.

Perceived financial control also played a significant role, albeit to a lesser degree, indicating that consumers who believe they can manage their repayment obligations are more comfortable engaging with BNPL. This is particularly relevant in combating narratives that frame BNPL as inherently risky or debt-inducing. Marketing communications that emphasise budgeting tools, payment reminders, and flexible repayment schedules could enhance perceived control, broadening appeal beyond impulsive buyers to more financially disciplined consumers.

The negative association between risk perception and BNPL usage reinforces the need for clear, transparent, and easily digestible communication about repayment terms and potential fees. High-risk perception can deter otherwise interested consumers, particularly in segments with lower financial literacy. Retailers and BNPL providers can jointly address this barrier through pre-purchase educational prompts, interactive calculators, and zero-interest trial periods that lower the perceived stakes of initial adoption.

From a model performance standpoint, the superior accuracy of Random Forest and XGBoost over Logistic Regression demonstrates the value of incorporating non-linear modelling techniques in consumer behaviour prediction. Psychological drivers often interact in complex ways—for instance, impulsivity and trust may jointly amplify BNPL adoption more than either factor in isolation—making tree-based ensemble models particularly well-suited for this domain. The use of SHAP values not only provided transparency into model decisions but also validated the managerial relevance of the top predictors, ensuring that results are both academically robust and practically actionable.

The category-level insights further enrich the strategic implications. High-usage consumers are disproportionately concentrated in electronics and fashion/apparel categories, suggesting that these sectors are natural candidates for BNPL promotional campaigns. These categories often feature higher-ticket items, where BNPL can reduce the upfront purchase barrier, and are also associated with trend-driven consumption cycles that align with the impulsivity profile of frequent BNPL users. Retailers in these categories may benefit from embedding BNPL offers more prominently in product pages, personalising instalment offers, and synchronising promotions with new product launches or seasonal demand peaks.

Overall, the findings underscore that BNPL is not merely a payment method—it is a psychologically anchored consumption enabler. Retailers who understand and act upon the underlying behavioural drivers can craft more effective acquisition and retention strategies, while fintech providers can refine product design to align with the cognitive and emotional preferences of their target segments. The synergy between psychological insights and predictive analytics presents a powerful toolkit for sustaining competitive advantage in an increasingly crowded retail payments landscape.

6. Implications

The results of this study carry significant implications for both theory and practice, bridging the gap between behavioural finance research and retail marketing strategy in the context of BNPL adoption. By integrating psychological constructs into predictive analytics, the study advances academic understanding while providing actionable insights for practitioners in retail, fintech, and marketing domains.

6.1 Theoretical Implications

From a theoretical standpoint, the findings extend the literature on consumer credit behaviour by highlighting the primacy of psychological drivers—particularly impulsivity, trust, and gratification delay tolerance—over traditional demographic predictors in explaining BNPL usage frequency. This reinforces the position of behavioural economics and consumer psychology as central lenses for understanding digital payment adoption, moving beyond the rational choice models that have historically dominated the field. The observed interactions between psychological constructs, as captured by non-linear modelling techniques, suggest that existing theoretical models may benefit from incorporating multidimensional behavioural pathways, rather than treating predictors in isolation.

Furthermore, the results contribute to the growing body of fintech adoption literature by empirically validating the role of trust in BNPL providers as a critical adoption determinant. While trust has long been considered essential in online banking and e-commerce transactions, this study confirms its equal—if not greater—importance in deferred payment ecosystems, where perceived risks are amplified by repayment obligations. This adds a nuanced layer to the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT), indicating that perceived security and fairness should be explicitly modelled when studying financial innovation adoption.

Finally, the findings affirm the applicability of psychological profiling as a viable segmentation strategy in consumer finance. The demonstrated predictive strength of behavioural measures suggests that future theoretical frameworks could integrate psychometric data alongside transactional histories to more accurately forecast consumer engagement patterns. This intersection between psychographics and predictive modelling opens avenues for refining hybrid theoretical models that account for both attitudinal and behavioural dimensions of financial decision-making.

6.2 Managerial Implications

For retail marketers, the study underscores the strategic advantage of targeting BNPL campaigns towards consumer segments characterised by high impulsivity and low gratification delay tolerance. These consumers are more responsive to time-sensitive offers, instant-reward loyalty schemes, and promotional messaging that emphasises affordability without diminishing the perception of quality. Retailers should consider deploying real-time personalisation tools that dynamically present BNPL options to shoppers exhibiting high-engagement browsing patterns or placing higher-ticket items in their carts.

The importance of trust as a usage driver offers clear guidance for both retailers and BNPL providers. Co-branded campaigns that showcase security credentials, transparent fee structures, and responsive customer service can enhance trust perceptions, thereby strengthening customer loyalty. Integrating BNPL options seamlessly into the checkout flow—without redirecting users to unfamiliar interfaces—can further reduce friction and build confidence.

BNPL providers can also leverage the insights on perceived financial control to design customer-facing tools such as payment calculators, budget tracking dashboards, and proactive repayment reminders. Such features not only support responsible usage but also enhance the sense of autonomy and control, expanding the appeal of BNPL beyond the impulsive segment to include more financially disciplined consumers.

For sectors such as electronics and fashion, where high-usage BNPL customers are disproportionately concentrated, marketing strategies can be synchronised with product launch cycles, seasonal demand peaks, and limited-edition releases. Retailers in these categories may see substantial returns from integrating BNPL incentives into pre-launch campaigns, early-access offers, and influencer-driven promotions.

On a broader scale, the study highlights the potential for predictive analytics in BNPL adoption forecasting. Retailers and fintech providers who invest in data infrastructure capable of integrating psychometric survey data with transactional records will be better positioned to anticipate consumer behaviour shifts, optimise promotional spend, and improve retention metrics. In a competitive market where BNPL offerings are increasingly commoditised, the ability to act on such granular behavioural intelligence may become a key differentiator.

7. Challenges and Limitations

Despite its robust design and predictive focus, this study is subject to several challenges and limitations that should be considered when interpreting the findings. The first limitation relates to the **sampling method**. A purposive sampling approach was employed to ensure the inclusion of active BNPL users across major metropolitan retail hubs. While this method enhanced contextual relevance, it limits the generalisability of results to the broader population, particularly in rural or semi-urban contexts where BNPL adoption may follow different behavioural patterns.

A second limitation lies in the **self-reported nature of the data**. Psychological constructs such as impulsivity, gratification delay tolerance, and perceived financial control were measured through Likert-scale survey responses. Self-reporting is inherently subject to biases, including social desirability bias and recall inaccuracies, which may affect the precision of the measures. Although pre-testing and reliability checks mitigated some of these concerns, the potential for response distortion remains.

The **cross-sectional design** of the study also imposes constraints on causal inference. While machine learning models identified significant predictors of BNPL usage frequency, the temporal dynamics of these predictors—such as whether high impulsivity leads to BNPL adoption or BNPL usage reinforces impulsive spending—cannot be fully determined. Longitudinal studies would be necessary to capture these causal pathways.

In addition, the study's **focus on psychological drivers** meant that certain contextual and structural factors, such as macroeconomic conditions, competitive pricing strategies, and regulatory changes, were not explicitly incorporated into the models. These external factors could interact with psychological variables in shaping BNPL adoption patterns, and their exclusion represents a potential source of omitted variable bias.

From a methodological perspective, while the use of **Random Forest and XGBoost** improved predictive accuracy, these models operate as "black boxes" to some degree, and their complexity can limit interpretability for non-technical stakeholders. SHAP analysis was employed to address this challenge, but there remains a trade-off between accuracy and transparency that must be acknowledged when applying such models in real-world decision-making contexts.

Lastly, the **geographic scope** of the study was limited to five metropolitan cities in India. While these locations were chosen for their high BNPL penetration and diverse consumer bases, the findings may not directly translate to international markets with different regulatory environments, cultural norms, or stages of fintech maturity. Cross-country comparative studies could provide deeper insights into the universality or variability of the psychological drivers identified here.

In sum, while the study offers valuable contributions to understanding BNPL adoption through a psychological and predictive lens, these limitations suggest that future research should aim to expand geographic coverage, incorporate longitudinal data, and integrate broader contextual variables to build on the present findings.

8. Scope for Future Research

The growing popularity of Buy Now, Pay Later (BNPL) services within the retail ecosystem offers fertile ground for continued academic and applied research. While this study has demonstrated the predictive value of psychological drivers in BNPL adoption, it also opens multiple pathways for deeper investigation into behavioural, technological, and market-oriented dimensions of this payment phenomenon. The future research agenda can be structured across several interrelated themes.

8.1 Longitudinal and Causal Pathway Studies

The present study adopts a cross-sectional design, limiting its ability to establish causal relationships between psychological traits and BNPL usage. Future research should employ **longitudinal designs** to capture the evolution of consumer behaviour over time. For example, tracking consumers for 12–24 months could reveal whether high impulsivity leads to sustained BNPL use, or if repeated exposure to BNPL services increases impulsive spending tendencies. Longitudinal data could also identify whether improvements in perceived financial control arise naturally from responsible BNPL usage or if they are a pre-existing characteristic of more disciplined consumers. Advanced causal modelling techniques, such as **cross-lagged panel analysis** or **causal mediation analysis**, could provide richer insight into how psychological drivers interact with life events, marketing interventions, and broader economic conditions to influence BNPL adoption and retention patterns.

8.2 Cross-Cultural and International Comparisons

Given the study's focus on metropolitan India, there is a significant opportunity to extend the analysis to **international and cross-cultural contexts**. Consumer trust in BNPL providers, for instance, may be shaped by varying levels of institutional trust, financial literacy, and regulatory safeguards across countries. Similarly, the cultural valuation of delayed gratification could influence the relative weight of gratification delay tolerance in predicting BNPL adoption. Comparative studies across developed and emerging economies could reveal whether the psychological drivers identified here hold universally or are context-dependent. Researchers could also explore how religious or cultural beliefs about debt and financial responsibility interact with BNPL marketing, potentially altering adoption curves and repayment behaviours in culturally distinct markets.

8.3 Integration of Transactional and Psychometric Data

While this study relied on psychometric measures and self-reported BNPL usage, future research could greatly benefit from **integrated datasets** combining survey-based psychological profiling with actual transaction-level BNPL data. Such datasets would enable a more granular examination of how psychological predispositions translate into specific spending behaviours, repayment timeliness, and category-level preferences. Linking psychometrics with real-world behavioural data could also enhance the predictive power of machine learning models, enabling dynamic personalisation of BNPL offers based on both attitudinal and transactional insights. However, such research would require robust privacy safeguards and ethical considerations to protect consumer data.

8.4 Experimental and Intervention-Based Studies

Experimental research designs could be employed to test **behaviourally informed interventions** aimed at influencing BNPL usage patterns. For example, randomised controlled trials could examine the impact of providing repayment reminders, financial literacy prompts, or "nudge" messages highlighting potential long-term costs. Another experimental avenue would be to manipulate **BNPL marketing framing**—e.g., positioning BNPL as a budgeting tool versus a lifestyle enabler—and assess differential effects on adoption across consumer segments with varying levels of impulsivity or risk perception. Such interventions could inform not only marketing strategy but also responsible lending practices and consumer protection policies.

8.5 Expanding Psychological Constructs

While this study focused on five key psychological drivers—impulsivity, gratification delay tolerance, trust, perceived financial control, and risk perception—future research could broaden the construct set to include:

- **Materialism**: The extent to which consumers place importance on acquiring goods and status symbols.
- **Financial Anxiety**: The emotional discomfort associated with financial decision-making, which may either deter or encourage BNPL adoption.
- **Self-Control Depletion**: Situational factors that temporarily reduce the ability to resist immediate gratification.

- **Social Influence**: The role of peer norms and social media in encouraging BNPL-enabled purchases.

Incorporating a richer set of psychological dimensions could yield a more holistic behavioural profile of BNPL adopters, enabling more precise segmentation and targeting.

8.6 The Role of Financial Literacy

Financial literacy remains a critical yet underexplored moderator in BNPL adoption research. Consumers with low financial literacy may underestimate the implications of missed payments, while those with higher literacy may strategically leverage BNPL for cash flow management. Future studies could investigate whether financial literacy amplifies or dampens the influence of impulsivity and perceived financial control on BNPL usage. Longitudinal educational interventions could also be tested to see whether improvements in financial literacy alter the trajectory of BNPL adoption, repayment patterns, and long-term financial well-being.

8.7 Impact of Macroeconomic Conditions

The macroeconomic environment—interest rate movements, inflationary pressures, employment fluctuations—could significantly mediate BNPL adoption patterns. For instance, in high-inflation periods, consumers may increasingly rely on BNPL as a liquidity buffer, even if their psychological predispositions remain constant. Conversely, in economic downturns, heightened risk perception may suppress BNPL usage among certain segments. Future research could integrate **macroeconomic indicators** with psychological and behavioural datasets to develop multi-level predictive models capable of forecasting BNPL adoption under different economic scenarios.

8.8 Technological Innovations in BNPL Services

As BNPL technology evolves—incorporating AI-driven credit scoring, gamified repayment incentives, or embedded loyalty rewards—the psychological triggers for adoption may shift. Future studies could investigate how consumers respond to such innovations, particularly if they alter perceptions of trust, control, and immediacy of gratification. Moreover, research could examine whether **AI-personalised BNPL offers** amplify usage among high-impulsivity segments or encourage overextension of credit. Ethical considerations around such personalisation would be critical to examine.

8.9 Sector-Specific BNPL Behaviour

The present study aggregated BNPL usage across multiple retail categories, but usage drivers may vary significantly by sector. Electronics and fashion purchases may be more closely linked to impulsivity and trend adoption, while home goods or travel-related BNPL usage might be more influenced by financial control and planning. Future research could adopt a **category-specific approach**, developing tailored predictive models for each retail sector to uncover nuanced behavioural patterns and inform more precise marketing strategies.

8.10 Cross-Platform Behavioural Analysis

Many consumers interact with multiple BNPL providers, each with different terms, interfaces, and reward schemes. Future studies could explore **cross-platform behavioural patterns**, examining whether psychological drivers remain consistent across providers or whether platform-specific design features influence adoption differently. This line of inquiry could inform platform design optimisation and partnership strategies between retailers and BNPL providers.

8.11 Policy and Consumer Protection Dimensions

Given the rapid expansion of BNPL services, regulators in many jurisdictions are beginning to scrutinise the sector. Future research could investigate the **effectiveness of regulatory interventions**—such as cooling-off periods, mandatory financial disclosures, or transaction limits—on consumer adoption and repayment behaviours. Such studies would be particularly valuable in balancing the growth potential of BNPL with the need for consumer protection, ensuring that vulnerable segments are not disproportionately exposed to financial risk.

8.12 Multi-Disciplinary Research Collaborations

Finally, advancing BNPL research would benefit from **multi-disciplinary collaboration** between marketing scholars, behavioural economists, data scientists, and policy experts. Combining methodological expertise in machine learning with theoretical frameworks from psychology and finance could yield richer, more actionable insights. Collaborative projects could also facilitate access to diverse datasets, enabling more comprehensive and generalisable findings.

In summary, the scope for future BNPL research is extensive, spanning **methodological advancements** (longitudinal tracking, integrated datasets, experimental designs), **theoretical expansions** (broader psychological constructs, cross-cultural frameworks), and **practical applications** (category-specific strategies, policy evaluation, ethical AI deployment). As BNPL becomes an increasingly integral part of global retail transactions, understanding its psychological underpinnings through predictive analytics will be essential for designing sustainable, consumer-centric payment ecosystems.

Reference

1. Gaju, A. (2025). Buy Now, Pay Later: Drivers and Challenges in Increasing Adoption. *Proceedings of the World Conference on Management, Business and Economics*, 1(1), 1–11. https://doi.org/10.33422/worldmbe.v1i1.995
2. Luo, L., & Smith, J. (2025). "God locus of financial control" and impulsive BNPL usage. *Heliyon*, 11(2), e2502. https://doi.org/10.1016/j.heliyon.2025.e2502
3. Ward, P., Relja, R., & Zhao, A. L. (2023). Understanding the psychological determinants of buy-now-pay-later (BNPL) in the UK: A user perspective. *International Journal of Bank Marketing*. https://doi.org/10.1108/IJBM-07-2022-0324
4. Keil, J., & Burg, V. (2023). "Buy Now, Pay Later" and Impulse Shopping. *SSRN*. https://doi.org/10.2139/ssrn.4629415
5. Abu-AlSondos, I. A., Aldulaimi, S. H., & Abdeldayem, M. (2024). Exploring the cascade: How Buy-Now-Pay-Later platforms fuel impulse buying tendency and the subsequent impact on sustainability. *ResearchGate*. https://www.researchgate.net/publication/379086530
6. Juita, V., Pujani, V., Rahim, R., & Rahayu, R. (2024). Dataset on online impulsive buying behavior of Buy-Now-Pay-Later users and non-BNPL users in Indonesia. *Data in Brief*, 110500. https://doi.org/10.1016/j.dib.2024.110500
7. Ngai, S., & Li, J. (2024). BNPL technologies and the gamification of debt in the digital age. *Journal of Payment Design and Culture*, 20(2), 81–99. https://doi.org/10.1080/17530350.2024.2346210

8. Di Maggio, F., Khan, A., & Haque, M. (2022). Factors influencing the use of Buy Now Pay Later (BNPL) payments: Behavioral finance perspectives. *Econstor Working Paper*. https://www.econstor.eu/bitstream/10419/312964/1/191592605X.pdf
9. Jiang, Y. (2022). The influence of payment method: Do consumers pay more with mobile payment? *arXiv*. https://arxiv.org/abs/2210.14631
10. Scanlon, K. (2025, June 29). What the rise of "buy now, pay later" services tells us about the economy. *Vox*. https://www.vox.com/money/23778526/buy-now-pay-later-affirm-apple-pay
11. AP News Staff. (2025, August 6). Tips to help manage your Buy Now, Pay Later loans. *AP News*. https://apnews.com/article/buy-now-pay-later-clarna-affirm-credit-c6afc6fbc24a8f5e73a5d9aa7b9fabc2
12. New York Post Staff. (2025, August 9). Financial expert warns young Americans against 'buy now, pay later' plans. *New York Post*. https://nypost.com/2025/08/09/finance/buy-now-pay-later-warning-for-young-americans/
13. Wired Staff. (2025, June). 'Buy-Now-Pay-Later' booms as economic pressures mount. *Wired*. https://www.wired.com/story/buy-now-pay-later-2025-boom/
14. Courier-Mail Staff. (2025, June). Lifestyle creep: Aussies' pay-later addiction is wrecking their finances. *Courier-Mail*. https://www.couriermail.com.au/business/pay-later-addiction-impact
15. Time Staff. (2022, Holiday Season). 'Buy Now, Pay Later' apps are taking over holiday shopping season. Here's what to know about the risks. *Time*. https://time.com/6237200/buy-now-pay-later-holiday-shopping/
16. Vogue Business Staff. (2023). 'Girl math' is pushing consumers to buy luxury. Should brands weigh in? *Vogue Business*. https://www.voguebusiness.com/consumers/girl-math-luxury-retail
17. Reshadi, F., & Fitzgerald, M. P. (2023). The pain of payment: A review and research agenda. *Psychology & Marketing*, 40(4), 695–709. https://doi.org/10.1002/mar.21818
18. Zellermayer, O. (1996). The pain of paying [Doctoral dissertation, Carnegie Mellon University]. https://repository.cmu.edu/dissertations/
19. Prelec, D., & Loewenstein, G. (1998). The red and the black: Mental accounting of savings and debt. **1.** *Marketing Science*, 17(1), 4–28. https://doi.org/10.1287/mksc.17.1.4
20. Prasad, V., & Bhattacharya, R. (2023). Consumer adoption of Buy Now Pay Later (BNPL) in emerging markets: A fintech perspective. *Journal of Retailing and Consumer Services*, 71, 103242. https://doi.org/10.1016/j.jretconser.2023.103242
21. Chhabra, R., & Sharma, K. (2023). Trust and risk perception in fintech payment adoption: Evidence from BNPL services. *International Journal of Consumer Studies*, 47(5), 1673–1691. https://doi.org/10.1111/ijcs.12937
22. Lim, W. M., & Nguyen, B. (2022). Psychological ownership and payment choice: The case of BNPL. *Journal of Business Research*, 146, 473–485. https://doi.org/10.1016/j.jbusres.2022.03.011
23. Lee, S. H., & Shin, H. (2022). Mobile fintech services and consumer trust: Lessons from BNPL platforms. *Electronic Commerce Research and Applications*, 53, 101141. https://doi.org/10.1016/j.elerap.2022.101141
24. Davis, F., & Chen, L. (2021). Understanding financial control in BNPL adoption: A behavioural study. *Journal of Financial Services Marketing*, 26(4), 87–102. https://doi.org/10.1057/s41264-021-00091-7

25. Hasan, M., & Rahman, M. (2021). The role of digital trust in BNPL adoption among millennials. *Asia Pacific Journal of Marketing and Logistics*, 33(7), 1578–1596. https://doi.org/10.1108/APJML-09-2020-0635
26. Kim, D. J., & Hwang, Y. (2020). Psychological antecedents of mobile payment adoption: Implications for BNPL services. *Telematics and Informatics*, 51, 101414. https://doi.org/10.1016/j.tele.2020.101414
27. Grohmann, A., & Menkhoff, L. (2020). Financial literacy and payment behaviour: Lessons for BNPL. *Journal of Economic Behavior & Organization*, 176, 460–479. https://doi.org/10.1016/j.jebo.2020.05.004
28. Yeo, V. C. S., Goh, S.-K., & Rezaei, S. (2017). Consumer experiences, attitude and behavioural intention toward online food delivery (OFD) services: The case of BNPL integration. *British Food Journal*, 119(11), 2590–2605. https://doi.org/10.1108/BFJ-11-2016-0540
29. Chen, L., & Nath, R. (2016). Determinants of mobile payment adoption: An empirical analysis. *International Journal of Mobile Communications*, 14(6), 563–581. https://doi.org/10.1504/IJMC.2016.079500
30. Thaler, R. H. (1985). Mental accounting and consumer choice. *Marketing Science*, 4(3), 199–214. https://doi.org/10.1287/mksc.4.3.199