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Logistic Regression Model for Predicting Buy Now Pay Later Default Risk Among Generation Z Users

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Abstract

The rapid expansion of Buy Now Pay Later (BNPL) services has reshaped consumption patterns among Generation Z, a demographic characterized by high digital adoption but comparatively limited financial experience. This study develops a binary logistic regression model to predict BNPL default risk among Generation Z users, incorporating financial literacy, financial self-control, impulsive buying tendency, income level, digital transaction frequency, and peer influence as predictors. Using an illustrative dataset structured to mirror a survey of 300 Generation Z BNPL users (aged 17–27). The model was evaluated using odds ratios, the Hosmer Lemeshow goodness-of-fit test, Nagelkerke R^2, classification accuracy, and the ROC AUC. In the illustrative run, financial literacy and financial self-control were associated with lower odds of default, while impulsive buying tendency, transaction frequency, and peer influence were associated with higher odds of default, consistent with the hypothesized directions; income level was not statistically significant. The model demonstrated adequate discriminative ability (illustrative AUC = 0.72) and good calibration (Hosmer-Lemeshow $p > 0.05$). These findings, once confirmed with primary survey data, are expected to offer practical implications for credit risk management, responsible lending policy, and product design in fintech lending platforms.

Keywords: buy now pay later; logistic regression; default risk; generation Z; fintech; credit risk management; machine learning.

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INTRODUCTION

The digitalization of consumer finance has accelerated the growth of **Buy-Now-Pay-Later (BNPL)** services, which have emerged as one of the fastest-growing fintech lending products in emerging markets, particularly across Southeast Asia. BNPL enables consumers to purchase goods or services immediately while deferring payment through scheduled instalments, typically without requiring a credit card or an extensive formal credit history. This accessibility has made BNPL particularly attractive to **Generation Z**, generally defined as individuals born between 1997 and 2012, who have grown up alongside smartphones, e-commerce, and app-based financial services.

Recent evidence suggests that Generation Z represents one of the fastest-growing user segments of BNPL platforms while simultaneously exhibiting a relatively high risk of repayment difficulties and loan default compared with other age cohorts (Chrisayu &

Anggraeni, 2023). At the global level, BNPL adoption continues to expand rapidly, prompting increasing regulatory concern regarding consumer over-indebtedness, repayment capacity, and responsible lending practices (Berg et al., 2024). Although BNPL provides convenience and greater access to short-term credit, its ease of use may also encourage excessive consumption and the accumulation of multiple repayment obligations, particularly among younger and financially inexperienced consumers.

Generation Z presents a particularly important context for examining BNPL default risk. While this cohort generally demonstrates high levels of digital fluency, its members may possess comparatively limited financial literacy, inconsistent income, and weaker financial self-control, especially among students and early-career workers. Such characteristics may increase vulnerability to excessive borrowing and repayment failure (Nga & Yeoh, 2025; Sari & Tasman, 2025). Behavioral tendencies, including impulsive buying and peer-driven consumption, may further intensify this risk because BNPL reduces the immediate perceived financial burden of consumption.

For fintech lending providers, accurately identifying users who are likely to default is critical for sustainable credit-risk management, customer screening, pricing, portfolio monitoring, and responsible lending. In this context, **binary logistic regression** provides an appropriate analytical approach because BNPL default represents a dichotomous outcome, typically classified as default or non-default. Logistic regression remains widely used in credit-risk research because it combines predictive capability with strong interpretability. Previous studies in peer-to-peer and digital lending contexts have demonstrated that logistic regression can perform competitively relative to more complex machine-learning techniques while offering clearer explanations of the contribution of individual predictors (Serrano-Cinca et al., 2015; Coulibaly, 2019). Unlike many “black-box” algorithms, logistic regression generates coefficients that can be transformed into odds ratios, enabling researchers, managers, and regulators to assess how changes in particular financial or behavioral characteristics are associated with changes in default probability.

Despite increasing scholarly attention to BNPL adoption and consumer behavior, empirical evidence explaining **default risk specifically among Generation Z users remains comparatively limited**. Existing studies have largely focused on adoption intention, purchasing behavior, or general digital-credit usage, while fewer studies have integrated financial capability, behavioral tendencies, socioeconomic characteristics, and digital usage patterns within a predictive default-risk framework. Addressing this gap is important because the determinants of BNPL adoption may differ substantially from the factors that ultimately predict repayment failure.

Accordingly, this study aims to: (1) identify the key financial and behavioral determinants associated with BNPL default risk among Generation Z users; (2) develop a binary logistic regression model to estimate the probability of BNPL default based on these determinants; and (3) evaluate the model's classification performance and derive managerial implications for fintech credit-risk management. By focusing specifically on Generation Z, the study contributes to the emerging literature on digital consumer credit while offering practical insights for fintech providers, policymakers, and consumer-protection authorities seeking to promote more responsible BNPL use.

Buy-Now-Pay-Later and Default Risk

BNPL is a form of short-term instalment credit commonly offered at the point of sale, allowing consumers to divide purchases into several scheduled payments. Compared with traditional credit cards and personal loans, BNPL services frequently involve simplified application procedures, rapid approval, and relatively limited conventional credit assessment. While these characteristics increase financial accessibility, they may also expose providers to higher credit risk when users accumulate obligations beyond their repayment capacity (Berg et al., 2024).

Research on peer-to-peer lending, digital microcredit, and other forms of technology-enabled lending suggests that default risk is shaped by a combination of financial, socioeconomic, demographic, and behavioral factors (Serrano-Cinca et al., 2015; Xu et al., 2021). However, empirical evidence focusing specifically on BNPL default behavior among Generation Z remains relatively scarce (Fauziah & Ramadhan, 2023). Therefore, examining both financial capacity and behavioral characteristics may provide a more comprehensive understanding of repayment risk within this increasingly important consumer segment.

Financial Literacy and Default Risk

Financial literacy refers to an individual's ability to understand and apply fundamental financial concepts, including budgeting, borrowing, interest, risk, and financial planning. Individuals with higher financial literacy are generally better able to evaluate repayment obligations, manage cash flows, and understand the long-term implications of using credit.

In the BNPL context, financially less-literate consumers may underestimate the cumulative burden created by multiple instalment commitments across different transactions or platforms. This may increase the likelihood of repayment difficulties and eventual default (Mat, 2025; Sari & Tasman, 2025). Conversely, financially literate users are expected to make more informed borrowing decisions and maintain better control over their repayment commitments.

H1: Financial literacy is negatively associated with the probability of BNPL default among Generation Z users.

Financial Self-Control and Default Risk

Financial self-control reflects an individual's ability to regulate consumption impulses, postpone immediate gratification, and prioritize longer-term financial obligations. Strong financial self-control may help consumers resist unnecessary purchases and maintain spending within their available financial resources.

Previous research suggests that lower self-control is associated with excessive spending, impulsive consumption, and greater repayment difficulties. In the context of BNPL, limited self-control may encourage consumers to make repeated purchases because the immediate financial cost appears relatively small when payments are divided into instalments. Such behavior can result in the accumulation of repayment obligations that exceed consumers' financial capacity (Nga & Yeoh, 2025).

H2: Financial self-control is negatively associated with the probability of BNPL default among Generation Z users.

Impulsive Buying Tendency and Default Risk

Impulsive buying tendency refers to an individual's propensity to make spontaneous and unplanned purchasing decisions driven by emotional, situational, or promotional stimuli rather than deliberate financial evaluation. BNPL services may reinforce such behavior by separating the consumption decision from the immediate full payment of the purchase price.

Consumers with stronger impulsive buying tendencies may therefore undertake multiple purchases without fully considering their cumulative repayment obligations. Evidence among Generation Z consumers indicates that BNPL usage may be closely associated with impulsive and consumption-oriented behavior, potentially increasing financial stress and repayment problems (Podin et al., 2025; Nga & Yeoh, 2025).

H3: Impulsive buying tendency is positively associated with the probability of BNPL default among Generation Z users.

Income Level and Default Risk

Income level represents an important indicator of a consumer's financial capacity to meet credit obligations. Individuals with higher and more stable income are generally better positioned to allocate sufficient resources toward scheduled repayments, whereas individuals with limited or irregular income may experience greater difficulty meeting instalment obligations.

This issue is particularly relevant among Generation Z because a substantial proportion of this cohort consists of students, part-time workers, and individuals in the early stages of their careers. Lower or unstable income may constrain repayment capacity and increase exposure to financial distress. Prior evidence also indicates that BNPL repayment problems tend to be more pronounced among consumers with weaker creditworthiness and limited financial resources (Berg et al., 2024).

H4: Income level is negatively associated with the probability of BNPL default among Generation Z users.

Digital Transaction Frequency and Default Risk

Digital transaction frequency reflects the extent to which consumers regularly use BNPL and other digital financial services. High transaction frequency may represent familiarity with digital finance; however, it may also indicate greater reliance on technology-enabled consumption and deferred-payment mechanisms.

When high transaction frequency involves repeated BNPL use across purchases or platforms, consumers may accumulate multiple concurrent repayment commitments. Such patterns may increase repayment burden and raise the probability of missed payments, particularly when financial resources are limited (Fauziah & Ramadhan, 2023).

H5: Digital transaction frequency is positively associated with the probability of BNPL default among Generation Z users.

Peer Influence and Default Risk

Peer influence refers to the extent to which individuals' consumption decisions are shaped by friends, social networks, social-media trends, and perceived social norms. Generation Z consumers are particularly exposed to digitally mediated social interactions in which products, lifestyles, and consumption experiences are continuously shared and compared.

Strong peer influence may encourage individuals to purchase goods or services to maintain social conformity or desired lifestyles, even when such purchases exceed their current financial capacity. When facilitated through BNPL, socially driven consumption may lead to excessive borrowing and increased repayment pressure (Mat, 2025).

H6: Peer influence is positively associated with the probability of BNPL default among Generation Z users.

Conceptual Framework

Based on the theoretical arguments and hypotheses developed above, this study conceptualizes **BNPL default status** as the dependent variable, coded as **1 = default** and **0 = non-default**. The probability of default is predicted by six primary explanatory variables: **financial literacy, financial self-control, impulsive buying tendency, income level, digital transaction frequency, and peer influence**.

Financial literacy, financial self-control, and income level are expected to reduce the probability of default, whereas impulsive buying tendency, digital transaction frequency, and peer influence are expected to increase default probability. In addition, **age, gender, education level, and employment status** are incorporated as control variables to account for demographic and socioeconomic differences that may influence repayment behavior.

The proposed model is subsequently estimated using binary logistic regression to determine the magnitude and direction of each predictor's association with the probability of BNPL default and to evaluate the model's ability to correctly classify default and non-default users.

METHODOLOGY

Research Design and Population

This study employs a quantitative, cross-sectional survey design. The target population comprises Generation Z individuals (aged 17–27) who have used at least one BNPL service (e.g., Shopee PayLater, Kredivo, Akulaku, OVO PayLater, or equivalent platforms) within the past 12 months. A purposive/convenience sampling technique was used, supplemented by screening questions to confirm eligibility.

Sample Size

Following common guidelines for binary logistic regression (a minimum of ten events per predictor variable), and with six primary predictors, a sample of 300 respondents was targeted in this document, the 300 observations primary data.

Table 1Measurement of Variables

Variable	Type	Operational Definition / Indicators	Measurement Scale
BNPL Default Status	Dependent (Y)	Self-reported history of late payment/default (>=30 days) in the last 12 months	Binary (1 = default, 0 = non-default)
Financial Literacy	Independent (X1)	Knowledge of interest, budgeting, and credit cost concepts	Composite score, 5-point Likert
Financial Self-Control	Independent (X2)	Ability to delay gratification and control spending impulses	Composite score, 5-point Likert
Impulsive Buying Tendency	Independent (X3)	Frequency of unplanned purchases via BNPL	Composite score, 5-point Likert
Income Level	Independent (X4)	Monthly income/allowance category	Ordinal (1-4)
Digital Transaction Frequency	Independent (X5)	Number of BNPL/digital payment transactions per month	Ordinal (1-4)
Peer Influence	Independent (X6)	Degree to which social circle/media shapes spending decisions	Composite score, 5-point Likert

Model Specification

logit(p) = ln[p / (1 − p)] = β0 + β1(Financial Literacy) + β2(Financial Self-Control) + β3(Impulsive Buying) + β4(Income Level) + β5(Transaction Frequency) + β6(Peer Influence) + ε

Estimation and Evaluation Procedure

Data screening: multicollinearity check (Variance Inflation Factor / VIF). Model estimation: maximum likelihood estimation (MLE) via Python statsmodels (equivalent to SPSS/R glm binomial). Overall model fit: −2 Log Likelihood, Hosmer-Lemeshow goodness-of-fit test, Nagelkerke R^2. Coefficient significance: Wald test at $\alpha = 0.05$, reported with odds ratios and 95% confidence intervals. Classification performance: confusion matrix (accuracy, sensitivity, specificity, precision, F1-score). Discrimination ability: ROC curve and Area Under the Curve (AUC).

RESULT AND DISCUSSION

Table 2 summarizes the demographic, income, platform, and usage-frequency profile of the 300 simulated Generation Z BNPL users, together with the observed default rate within each subgroup. Overall, 75 of 300 respondents (25.0%) were classified as having defaulted (≥30 days late payment) in the past 12 months.

Table 2 Respondent Profile (N=300)

Characteristic	n	%
Gender: Female	169	56.3

Characteristic	n	%
Gender: Male	131	43.7
Age 17-20	100	33.3
Age 21-24	125	41.7
Age 25-27	75	25.0
Occupation: Student	167	55.7
Occupation: Employed	101	33.7
Occupation: Unemployed/Other	32	10.7
Platform: ShopeePayLater	117	39.0
Platform: Kredivo	63	21.0
Platform: Akulaku	36	12.0
Platform: OVO PayLater	34	11.3
Platform: Indodana	21	7.0
Platform: Other	29	9.7
Default status: Non-default (Y=0)	225	75.0
Default status: Default (Y=1)	75	25.0

Multicollinearity Test

Variance Inflation Factor (VIF) values for all predictors ranged from 1.01 to 1.03, well below the common threshold of 10, indicating no multicollinearity concern among the independent variables.

Table 3 Binary Logistic Regression Results

Variable	B	S.E.	Wald (z)	Sig.	Exp(B)	95% CI for Exp(B)
Constant	-2.492	1.151	-2.164	0.030	0.083	0.009 - 0.790
Financial Literacy	-0.361	0.171	-2.116	0.034	0.697	0.499 - 0.974
Self-Control	-0.371	0.161	-2.302	0.021	0.690	0.503 - 0.946
Impulsive Buying	0.568	0.168	3.394	0.001	1.765	1.271 - 2.451
Income Level	-0.199	0.156	-1.272	0.204	0.820	0.603 - 1.114
Transaction Frequency	0.444	0.145	3.064	0.002	1.558	1.173 - 2.069
Peer Influence	0.385	0.160	2.402	0.016	1.470	1.074 - 2.013

Table 4 Model Fit and Classification Performance

Metric	Illustrative Value (Simulated Data)
-2 Log Likelihood (null model)	337.40
-2 Log Likelihood (final model)	297.72
Cox & Snell R^2	0.124
Nagelkerke R^2	0.183
Hosmer-Lemeshow $\chi^2(8)$	9.52, $p = 0.300$
Overall Classification Accuracy	78.0%
Sensitivity (Recall for Default)	21.3%
Specificity	96.9%
Precision	69.6%
F1-Score	0.327
AUC (ROC)	0.723

The Hosmer-Lemeshow test was not statistically significant ($p = 0.300$), indicating adequate calibration between predicted and observed default probabilities. The AUC of 0.723 indicates acceptable discriminative ability. Sensitivity was notably lower than specificity, suggesting that at the default 0.5 classification threshold the illustrative model was conservative in flagging actual defaulters; a lower threshold (e.g., 0.3) or class-weighting could be explored to improve recall in an actual study, particularly given the practical cost asymmetry between missing a true defaulter and over flagging a non defaulter.

Financial literacy (H1) and financial self-control (H2) were negatively associated with default, consistent with the view that greater financial knowledge and self-regulation reduce the likelihood of repayment failure. This aligns with prior findings that financially literate Gen Z consumers still exhibit paradoxical impulsive tendencies unless self-control is also present (Nga & Yeoh, 2025). Impulsive buying tendency (H3) showed the strongest positive association with default among the behavioral variables, echoing evidence that BNPL availability itself increases the likelihood of unplanned purchases (Podin et al., 2025) and that impulsivity is a central mechanism linking BNPL usage to financial strain (Fauziah & Ramadhan, 2023).

Digital transaction frequency (H5) and peer influence (H6) were also positively associated with default, consistent with the notion that overreliance on multiple concurrent instalment obligations and social-comparison-driven consumption elevate repayment risk among digitally native, socially connected Generation Z consumers (Mat, 2025). Income level (H4) was not statistically significant in the illustrative run, which if replicated in real data would suggest that behavioral and psychological factors may matter more than raw income in explaining BNPL default among Gen Z, a pattern that would itself be a notable contribution given that most conventional credit-scoring models emphasize income and credit history (Coulibaly, 2019; Serrano-Cinca et al., 2015).

CONCLUSION

Subject to empirical confirmation using primary data, this study highlights the potential importance of behavioral and financial-capability factors in explaining BNPL default risk among Generation Z users. Rather than relying solely on income-based indicators, the proposed framework suggests that financial literacy, financial self-control, impulsive buying tendency, digital transaction frequency, and peer influence may provide additional insight into users' repayment risk. These factors may therefore complement conventional financial indicators in developing more comprehensive and interpretable credit-risk assessment models for BNPL services.

Managerial Implications

The findings provide several practical implications for fintech and BNPL providers. First, lenders may consider incorporating appropriate proxies for financial literacy, financial self-control, and behavioral tendencies into credit assessment processes, particularly for younger applicants with limited formal credit histories. Such indicators could complement traditional measures of repayment capacity and improve early-stage risk identification.

Second, fintech providers may adopt dynamic credit-limit policies in which new Generation Z users begin with relatively conservative limits that are gradually increased based on verified repayment behavior and transaction history. This approach may help balance financial inclusion with prudent credit-risk management.

Third, behavioral interventions embedded within BNPL applications may help reduce repayment risk. Features such as spending alerts, repayment reminders, personalized spending limits, outstanding-obligation summaries, and financial education content may encourage more responsible borrowing and reduce impulsive consumption.

Finally, where the predictive model demonstrates an imbalance between sensitivity and specificity, providers may adjust the classification threshold according to the relative costs of false positives and false negatives. In practice, greater emphasis may be placed on detecting potential defaulters when the financial cost of failing to identify high-risk users exceeds the cost of incorrectly classifying low-risk users as high risk.

Limitations and Future Research

This study is subject to several limitations. First, the use of cross-sectional and self-reported data may introduce social desirability, common-method, and recall biases. Future research should therefore validate self-reported financial and behavioral measures against actual transaction histories, repayment records, and platform-level behavioral data.

Second, findings derived from a single country or a limited number of BNPL platforms may restrict generalizability. Future studies could conduct cross-platform and cross-country comparisons to examine whether the determinants of BNPL default remain consistent across different regulatory, cultural, and market environments.

Third, although binary logistic regression offers strong interpretability, its predictive performance may be constrained when relationships are nonlinear or involve complex interactions. Future research could therefore benchmark logistic regression against machine-learning approaches such as random forest, gradient boosting, and XGBoost. Such comparisons would provide greater insight into the trade-off between model interpretability and predictive accuracy in BNPL credit-risk assessment.

Finally, longitudinal research is encouraged to examine how changes in users' financial literacy, spending behavior, repayment history, and digital transaction patterns influence default risk over time. Integrating behavioral, financial, and transaction-level data may ultimately support the development of more robust and responsible fintech credit-scoring systems.

References

Berg, T., Burg, V., Keil, J., & Puri, M. (2024). The economics of "Buy Now, Pay Later": A merchant's perspective (NBER Working Paper No. 33152). National Bureau of Economic Research. https://www.nber.org/papers/w33152

Chrisayu, N., & Anggraeni, R. (2023). Buy Now Pay Later services on Generation Z: Exploratory data analysis using machine learning. Journal of Theoretical and Applied Information Technology, 101(11), 4194-4205.

Coulibaly, A. (2019). Credit risk estimation in the age of peer to peer lending [Master's thesis, St. Cloud State University]. The Repository at St. Cloud State.

Fauziah, N., & Ramadhan, F. (2023). The impact of Buy Now, Pay Later services on the impulsive buying behavior of Generation Z in Shah Alam, Malaysia. International Journal of Research and Innovation in Social Science, 9.

Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). Applied logistic regression (3rd ed.). John Wiley & Sons.

Mat, A. (2025). Buy Now, Pay Later: Understanding BNPL trends among Generation Z. Journal of Business and Management, 2025, 161-170.

Nga, J. K. H., & Yeoh, K. K. (2025). The Buy Now Pay Later paradox: Financially literate yet impulsive? Understanding the intricacies of risky indebtedness, impulse buying and perceived risk in Buy-Now-Pay-Later adoption. Asia Pacific Journal of Marketing and Logistics. https://doi.org/10.1108/APJML-08-2023-0759

Podin, N., Yusoff, N. T. I., Jie, N. R., Halim, S. N. A., Amran, N. F. A., & Fakhruddin, F. M. (2025). Exploring the impacts of Buy Now, Pay Later (BNPL) payment method among millennials and Generation Z in Malaysia. [Conference/Journal details to be verified].

Saputra, U. W. E., Dananjaya, I. B. G., Nurfakhrurozi, R., & Basmantra, I. N. (2024). The determinant of fintech adoption among Gen Z in Indonesia. Atlantis Press.

Sari, S. N., & Tasman, A. (2025). Financial technology adoption, financial literacy, and financial behavior among Generation Z: The mediation role of financial attitude. Indonesian Journal of Development Studies. Universitas Pendidikan Indonesia.

Serrano-Cinca, C., Gutiérrez-Nieto, B., & López-Palacios, L. (2015). Determinants of default in P2P lending. PLOS ONE, 10(10), e0139427. https://doi.org/10.1371/journal.pone.0139427

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1), 157-178.

Xu, B., Su, Z., & Celler, J. (2021). Evaluating default risk and loan performance in UK peer-to-peer lending: Evidence from Funding Circle. Journal of Advanced Computational Intelligence and Intelligent Informatics, 25(5), 530-538.