Machine Learning-Based Prediction of Credit Default Risk and Profiling of High-Risk Users in Buy Now, Pay Later (BNPL) Services

Xinru Lu

School of Shanghai University of Finance and Economics, Shanghai, China

2023110620@stu.sufe.edu.cn

Abstract. This study looks at BNPL credit risk using Kaggle data. We use several machine learning models, along with clustering and association rules, to predict defaults, group users, and find risk patterns. Logistic regression works best among the models. Monthly income predicts default better than debt ratios; this shows the cash-flow limits caused by BNPL's zero down payment, small orders, and weak credit records. Clustering splits users into three groups, with low-income and high-debt users showing the highest risk. Association rules find high-default trait pairs like “low income + young” and “high debt + young”. These results offer useful guidance for BNPL platforms in risk checks, user grouping, and different risk controls.

Keywords: BNPL, credit risk, default prediction, machine learning, user profiling, association rules.

1. Introduction

1.1. Research Background and Significance

1.1.1. Research Background

Driven by the integration of the digital economy and consumer finance, the Buy Now Pay Later (BNPL) model has grown rapidly for its low-threshold access and flexible instalment options. While lowering consumption barriers and stimulating consumer demand, BNPL also brings notable credit-risk concerns. Limited credit records, heterogeneous user credit qualifications and inadequate risk-identification capacity of platforms make user default risk in BNPL more complex than that in conventional credit businesses.

This study uses a public BNPL dataset from Kaggle. The overall sample default rate reaches 39.05 %, signalling substantial credit risk among users. Characterised by zero-down-payment arrangements, frequent small-value transactions and insufficient credit reporting coverage, BNPL involves intertwined user behaviours across income, liability, consumption and repayment. Conventional credit-scoring techniques alone cannot capture risk comprehensively. Furthermore, many platforms still have defects in user segmentation, differentiated credit granting and risk early-warning mechanisms. Accordingly, how to identify default risk, profile high-risk customer groups and extract valid risk rules from multi-dimensional user data constitutes a key practical challenge for BNPL risk control.

1.1.2. Research Significance

Theoretically, this paper establishes an integrated analytical framework incorporating default prediction, user clustering and association-rule mining tailored to BNPL business contexts. User default behaviours are analysed from risk drivers, prediction models, user profiling and risk-rule perspectives. Special attention is paid to the distinct effects of income and debt indicators under zero-down-payment, small-ticket repeated transactions and weak-credit-reference conditions. It adds empirical evidence for consumer-finance credit-risk research within this specific scenario.

Practically, this work identifies critical determinants of BNPL user default. Prediction models, user segmentation and association rules jointly characterise customer groups of varied risk levels, furnishing empirical support for platforms to conduct risk assessment, differentiated credit allocation, risk warning and tiered user management.

1.2. Research Status

1.2.1. Research on BNPL Credit Risk

Existing research explores BNPL user characteristics, financial constraints and consumer-protection issues. Di Maggio et al. examine BNPL users and their spending patterns [1]. Hayashi and Routh investigate financial constraints among BNPL users [2]. Liang discusses the risks of consumer over-indebtedness and related rights protection under BNPL arrangements [3], while Jose and Kelly focus on financial vulnerability among pay-later users [4]. Related studies of conventional and online credit provide comparative perspectives. Zhang and Liu investigate credit-card default-risk identification and scoring [5]. Ma et al. examine borrower-performance incentives in online lending[6], and Zhang and Gao investigate cultural differences and credit risk in internet finance [7]. The characteristics of these credit products differ from those of BNPL, so their findings require further examination in the BNPL context.

Research on digital consumer finance has also considered the reconstruction of consumer-credit evaluation frameworks [8] and the development of credit-risk evaluation systems [9]. Studies of digital footprints further explore their role in default prediction [10]. Taken together, prior research highlights the relevance of user characteristics, repayment capacity and financial liabilities. However, the relative predictive contributions of income and debt variables under BNPL-specific operating conditions warrant further investigation.

1.2.2. Machine-learning Applications in Credit Risk Control

Growing financial data availability has encouraged the application of machine-learning methods in credit risk assessment. Ayari et al. systematically review machine-learning approaches to financial credit scoring [11]. Sun et al. develop high-risk micro-loan user profiles using logistic regression [12]. Dai and Liu investigate consumer-finance credit evaluation with GBDT and XGBoost [13], while Ghoujdam et al. compares logistic regression with advanced machine-learning techniques for credit-risk assessment [14]. BNPL-focused research has compared ensemble-learning models for loan-default prediction [15] and machine-learning methods with conventional credit-risk models [16]. Mahmud et al. examine AI-driven BNPL credit-risk assessment using alternative data and predictive analytics [17], and Mishra et al. discuss relevant regulatory and ethical challenges [18].

For related credit-risk evaluation tasks, Yuan et al. examines P2P online-lending platforms [19]. Tanantong and Loetwiphut consider association-rule mining for credit-risk analysis in peer-to-peer lending [20]. These studies suggest that segmentation and association rules can complement prediction models, although their application to BNPL requires attention to the specific data and business setting.

In general, abundant prediction approaches have been developed for credit risk management. A large share of prior work concentrates on separate models or independent analytical tasks. Only a small number of papers integrate risk prediction, customer clustering and association rule mining in a systematic way. This creates research gaps for multi-technique combined analysis tailored specifically to BNPL services.

1.2.3. Comprehensive Literature Review

Three key shortcomings can be summed up from past scholarly works. To start with, when discussing risk mechanisms, most existing studies explain income and debt influencing factors based on conventional credit theories. Most studies overlook BNPL traits (zero down payment, small orders, limited credit) and rely on single methods, offering weak support for user segmentation or risk control. We fill this gap by combining machine learning, clustering, and association rules on public data to profile high-risk users and identify risk factors.

1.3. Research Methods

1.3.1. Research Questions

This study raises three BNPL default questions, one is which user features affect default risk most, two is what user risk groups exist and how they differ in income, debt and spending, three is which feature sets signal default and how we can use them for user checks.

1.3.2. Analytical Pipeline

This study completes four steps, clean data to remove wrong and repeated records, build features and adjust data values, test models to select the best for default prediction, split users into groups and explain group features, use Apriori rules to find default-linked feature sets, these results help spot high-risk users and run layered risk control.

2. Data Analysis

2.1. Data Description

2.1.1. Data Source and Overview

We use the Kaggle BNPL dataset, covering transactions from 2023 to 2024 across six countries. After cleaning, 10,345 valid samples remain, with a default rate of 39%. Key variables include age, employment, monthly income, spending, product type, instalment period, app frequency, region, and debt-to-income ratio. These support default prediction, user clustering, and association rule mining; detailed definitions are in Table 1.

Table 1. Description of Data Fields

field	field description
user_id	Unique user identifier
age	User age
employment_type	Type of employment
monthly_income	User's monthly income
purchase_amount	Single-transaction purchase amount
product_category	Category of consumed products
bnpl_installments	Number of BNPL instalment periods
app_usage_frequency	APP usage frequency
location	User's geographic region
debt_to_income_ratio	Debt-to-income ratio
debt_burden	Derived score of debt pressure
default_flag	Default flag (0 = non-default, 1 = default)

2.2. Data Preparation and Analysis

2.2.1. Data Preparation

We removed invalid negative values (income, debt-to-income, spending) and duplicate records, then created debt_burden by combining debt-to-income and spending to reflect overall financial pressure. Preprocessing yielded 10,345 valid samples.

2.2.2. Monthly Income Distribution

Figure 1 shows a right-skewed distribution (median about 24,000). Most users earn between 10,000 and 56,000; high-income outliers are few, indicating clear income inequality.

2.2.3. Debt-to-Income Ratio Distribution

Figure 2 also follows a right-skewed pattern: most users have low ratios, while a few with high ratios face greater repayment pressure. This variable thus serves as a key indicator for default prediction and user segmentation.

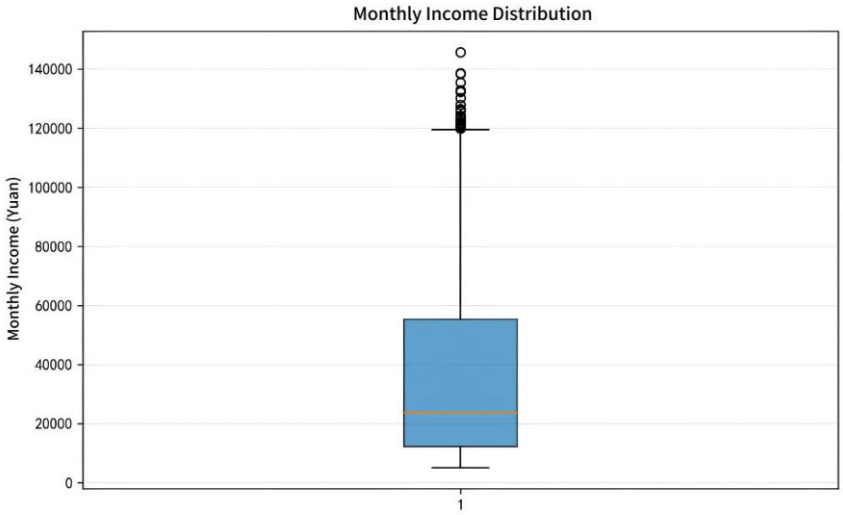


Figure 1. Box Plot of Monthly Income Distribution

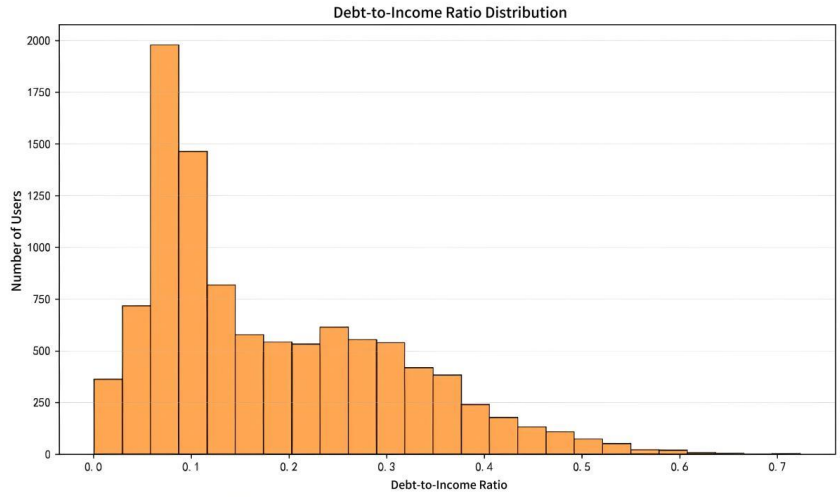


Figure 2. Histogram of Debt-to-Income Ratio Distribution

2.3. Data Partition and Standardization

This study divides the dataset into an 8:2 training set and test set through stratified sampling based on default labels to ensure stable and comparable model results, which can obtain 8276 training samples and 2069 test samples; all numeric features get standardized before model training, and PCA dimensionality reduction is adopted for clustering tasks to retain 95.3% of total variance and simplify ten original features into seven optimized features, and the processed data can serve as valid input for subsequent model training and user clustering.

3. Default Risk Prediction and Key Factor Mining

3.1. Model Construction and Training

3.1.1. Model Selection

This study employs logistic regression as the baseline model for BNPL default prediction, alongside random forest, XGBoost and LightGBM; random forest identifies key risk features, and the two gradient boosting models assess ensemble learning performance for credit risk evaluation.

3.1.2. Imbalance Handling and Evaluation Metrics

Class imbalance is tackled by tuning relevant hyperparameters in the training phase. We set class_weight="balanced" and adjust scale_pos_weight to assign greater weights to default cases. We

evaluate model performance through AUC, recall, precision and F1-score. Particular attention falls on two metrics: AUC, which reflects the overall discriminative power, and recall, representing the model's ability to pick out users who will default.

3.2. Model Performance Comparison and Analysis

Table 2 lists all prediction outcomes generated by these four models on the test dataset.

Table 2. Performance Comparison of Four Models

Model	AUC	Recall	Precision	F1
Logistic Regression	0.6455	0.7327	0.4747	0.5762
XGBoost	0.6296	0.6597	0.4663	0.5464
LightGBM	0.6277	0.6621	0.4685	0.5487
Random Forest	0.6178	0.3032	0.4537	0.3635

The outcomes show logistic regression attains an AUC value of 0.6455 and recall equal to 0.7327. It surpasses the remaining three models and delivers a decent F1-score as well. Taking overall discrimination capability, default detection effectiveness and model interpretability into consideration, we pick logistic regression as the baseline model to carry out later risk factor exploration and credit scoring work.

Broadly speaking, every model only attains medium AUC scores. This situation mostly stems from restrictions within the dataset. The collected samples primarily contain static historical data and miss dynamic indicators, for instance income fluctuations, cross-platform multiple loans and long-term time-series consumption logs. Absence of such data makes it hard to fully reflect users' actual debt conditions and cash flow situations, thereby limiting model capacity to spot hidden default risks.

3.3. Mining of Key Risk Factors

3.3.1. Ranking of Key Risk Factors

We leverage the logistic regression model to measure how strongly each feature influences prediction outputs. Table 3 displays the sorted list of major risk factors.

Table 3. Ranking of Key Risk Factors

Feature Name	Importance Weight
monthly_income	1.0592
debt_to_income_ratio	0.3877
purchase_amount	0.1917
debt_burden	0.1368
employment_type	0.0770
age	0.0511
bnpl_installments	0.0412
product_category	0.0178
app_usage_frequency	0.0029
location	0.0009

Our results confirm monthly income is the most dominant predictor of BNPL default, followed by the debt-to-income ratio that reflects repayment pressure. Purchase amount and debt burden also play important roles, whereas age, employment type and instalment period have limited predictive power. Overall, user credit risk is primarily driven by individual repayment capacity and debt stress.

3.3.2. Differentiated Mechanism of Risk Factors

Traditional credit assessment heavily relies on debt indicators for credit card and large consumer loan evaluation. However, this study finds monthly income outperforms debt-related metrics in predicting BNPL defaults. Such divergence stems from three unique BNPL features: zero down payment, recurrent small instalments and limited credit data coverage.

Zero-down-payment transactions let users accumulate multiple debts quickly with no upfront cost. Platforms can only observe in-platform liabilities, missing cross-platform debt, which underestimates financial pressure and weakens risk discrimination based solely on debt indicators.

Small frequent BNPL payments drain user cash flow and create long-term repayment pressure; stable income thus supports sustainable repayment, and income fluctuations can easily lead to overdue payments. Most BNPL users lack sufficient credit records, so monthly income acts as a more reliable repayment indicator; users with weak financial reserves are more sensitive to income changes and strengthen income's predictive effect. Debt indicators still work effectively, income reflects internal repayment ability while debt reflects external constraints, and both factors can jointly support comprehensive risk evaluation.

3.4. Model Optimization and Risk Scorecard

3.4.1. Classification Threshold Tuning

We pick 0.4 as the cutoff: it raises recall from 73.27% (at 0.5) to 85.77% while AUC stays 0.6455, improving default detection with slight precision loss, and avoids the false-positive jump seen below 0.3.

3.4.2. Risk Scorecard Construction

We built a 0–1000 scorecard from logistic-regression default probability P(default). Higher scores indicate lower credit risk. Formula:

$$\text{credit}_{\text{risk}_{\text{score}}} = \big(1 - \text{P(default)}\big) \times 1000$$

Based on business needs, risk levels are: ≥700 low, 400–699 moderate, and <400 high. See Table 4 for examples.

Table 4. Examples of Risk Scorecard

user_id	credit_risk_score	final_risk_level	default_prob
1	713	Low Risk	0.2866
2	339	High Risk	0.6608
3	501	Medium Risk	0.4991
4	328	High Risk	0.6716
5	494	Medium Risk	0.5062

4. User Clustering and Construction of High-Risk User Profiles

4.1. Preprocessing for Clustering

4.1.1. Feature Selection

Ten features are selected for clustering analysis, namely age, employment type, monthly income, purchase amount, product category, BNPL instalment terms, APP usage frequency, geographic region, debt-to-income ratio and debt burden. User heterogeneity is characterised from demographic attributes, income-debt status and consumption behaviour dimensions.

4.1.2. Standardization and PCA Dimension Reduction

Clustering-oriented features are standardized to eliminate dimensional discrepancies among variables. PCA is subsequently implemented for dimension reduction. Under the condition of retaining 95 % cumulative variance information, the original 10-dimensional features are reduced to 7 dimensions, with a cumulative explained variance ratio of 0.953.

4.2. Determination of Optimal Cluster Number

The elbow method, silhouette coefficient and Calinski-Harasz (CH) index are jointly applied to select the optimal number of clusters. Within the range of $K = 2$ to $K = 7$, the within-cluster

sum-of-squares error, silhouette coefficient and CH index are calculated. The evaluation outputs are summarised in Table 5.

Table 5. Evaluation Results for Optimal Cluster Number

K	Inertia	Silhouette	CH Score
2	78609.30	0.2260	3268.41
3	67207.65	0.2369	2788.52
4	62823.89	0.1615	2229.07
5	60310.55	0.1292	1849.03
6	57969.07	0.1200	1622.34
7	56073.46	0.1194	1455.77

The results show that the silhouette coefficient reaches its peak value of 0.2369 at K=3, with a distinct elbow inflection point and a relatively high CH index. Synthesising the three indicators, 3 is selected as the optimal cluster number, as illustrated in Figure 3.

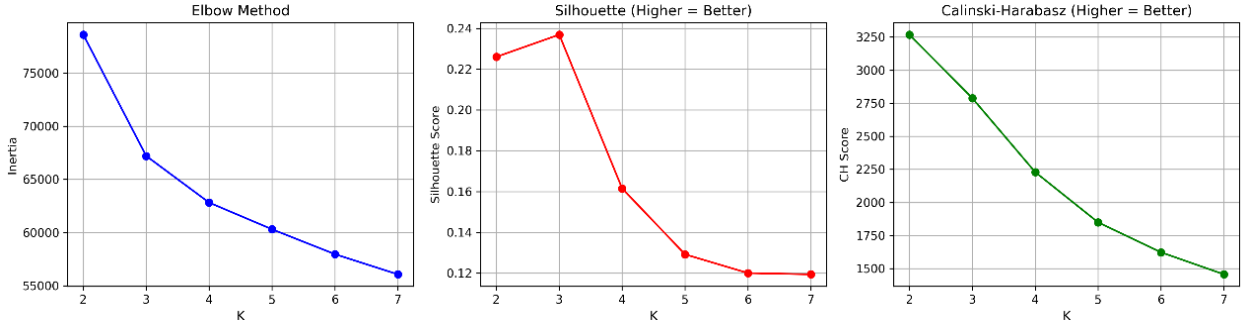


Figure 3. Determination of Optimal K-value Based on Elbow Method, Silhouette Coefficient and CH Index

4.3. Comparison and Selection of Clustering Algorithms

Three clustering algorithms including K-Means, hierarchical clustering and GMM are compared. Silhouette coefficient, CH index and SSE are adopted to evaluate clustering performance. Comparative results are presented in Table 6.

Table 6. Performance Comparison of Clustering Algorithms

Method	Silhouette Coefficient	CH Index	SSE	Characteristics
K-Means	0.1396	2183.64	69313.13	Fast clustering speed; moderate boundary clarity
Hierarchical Clustering	0.2304	2785.84	64067.26	Strong inter-cluster separation; good stability
GMM	0.1140	1856.73	72537.36	Soft partitioning; relatively weak cluster cohesion and separation

The results demonstrate that hierarchical clustering outperforms the other two algorithms in terms of silhouette coefficient and CH index, accompanied by a relatively low SSE. It achieves satisfactory overall clustering performance and is therefore selected as the final clustering algorithm.

When PCA-reduced data are projected onto a two-dimensional plane, observable separation can be found among the three user groups. The clustering outputs are visualised in Figure 4.

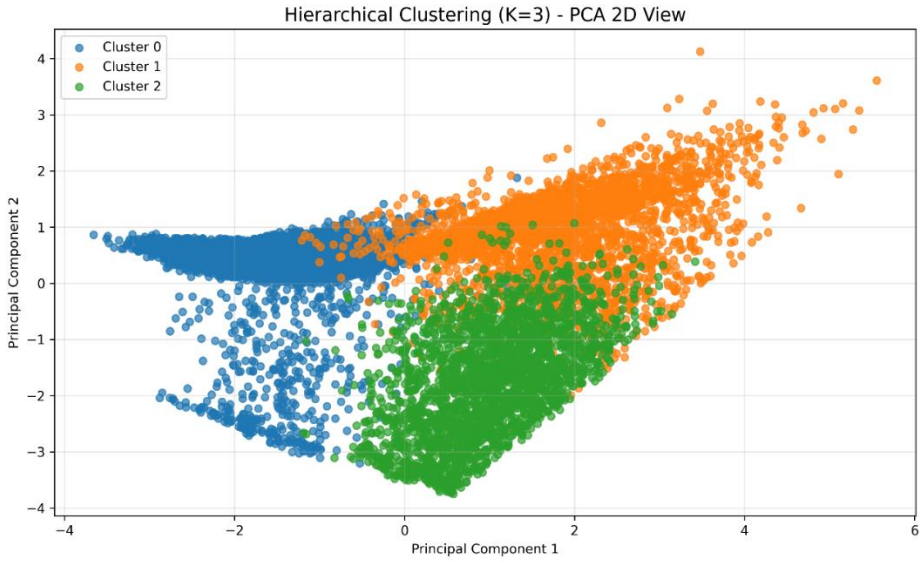


Figure 4. 2D Scatter Plot of Hierarchical Clustering (K=3)

4.4. Hierarchical Clustering Results and User Profile Construction

Based on hierarchical clustering outputs, three user groups are profiled from dimensions including income level, debt characteristics, consumption behaviours and instalment habits, and corresponding risk portraits are established.

4.4.1. Core Findings

Clustering results suggest that BNPL users can be divided into three groups with distinct risk profiles. Cluster 0, robust high-quality users, accounts for approximately 47.42 % and constitutes the major low-risk group of the platform.Cluster 1 represents high-risk indebted users, making up 29.04% of samples and serving as the top priority for risk management.Cluster 2 (23.54%) shows moderate risk and growth potential. Income/debt differences across groups confirm their role in BNPL risk. Low silhouette coefficient suggests feature overlap (see Chapter 6).

4.4.2. User Profile Construction

Hierarchical clustering yields three groups:

Cluster 0 (47.42%): high income, low debt (ratio 0.091), strong repayment, low default. Moderate spending, cautious instalments, steady app – core low-risk, high-value.

Cluster 1 (29.04%): low income, heavy debt (ratio 0.321), weak repayment, highest default. Impulsive, zero-down small purchases with multi-category instalments; rising debt – primary risk target.

Cluster 2 (23.54%): younger, lower income, moderate ratio (0.191). Low spending, regular instalments, frequent app – medium risk, basic potential.

4.5. Stratified Risk Control and Operational Suggestions

Based on income, debt, and spending differences, apply differentiated controls:

Stable high-quality: moderately raise credit limits, offer flexible instalments to retain and engage.

High-risk indebted: tighten limits/terms, monitor debt-to-income and overdue. If debt rises or early delinquency appears, adjust limits or warn to stop accumulation.

Ordinary potential: dynamically track debt and repayment, adjust credit by real-time risk, guide to lower-risk state.

In general, applying user segmentation results to credit granting, monitoring and risk early-warning links improves the pertinence of platform risk identification. It restrains default probability among high-risk users while satisfying normal credit demands of high-quality and potential users.

5. Mining of Default-Related Association Rules

5.1. Feature Discretization and Transaction-Oriented Dataset Construction

To satisfy requirements for association-rule mining, continuous variables are discretized. Age is split into four categories: young, young-and-middle-aged, middle-aged and elderly. Monthly income is divided into low-income, middle-income and high-income groups. Debt-to-income ratio is categorised as low-debt, medium-debt and high-debt. Default status falls into two classes: default and non-default.

Each user record is transformed into transaction-format data composed of discretized features. A total of 10345 transaction records are generated, such as “elderly, high-income, low-debt, non-default”, for subsequent Apriori association-rule mining.

5.2. Results of Association-rule Mining

With minimum support set to 0.05 and minimum confidence set to 0.3, the Apriori algorithm is utilised to generate association rules. Taking default and non-default as exclusive consequents, core high-risk and low-risk rules are filtered, as presented in Table 7.

Table 7. High-risk Default-related Association Rules

Category	Antecedent	Consequent	Support	Confidence	Lift
Low-risk	Middle-aged, low-debt, high-income	Non-default	0.0717	0.8638	1.4173
Low-risk	Low-debt, high-income, elderly	Non-default	0.0690	0.8592	1.4098
Low-risk	Low-debt, high-income	Non-default	0.2300	0.8353	1.3706
Low-risk	Middle-aged, high-income	Non-default	0.0782	0.8306	1.3628
Low-risk	High-income, elderly	Non-default	0.0746	0.8292	1.3605
High-risk	High-debt, medium-income	Default	0.0518	0.4949	1.2673
High-risk	Low-income, young	Default	0.0594	0.4924	1.2608
High-risk	High-debt, young	Default	0.0514	0.4917	1.2590
High-risk	High-debt	Default	0.1624	0.4872	1.2476
High-risk	Medium-debt, young	Default	0.0562	0.4866	1.2460

The results reveal that “high-debt + medium-income”, “young + low-income” and “high-debt + young” constitute core association patterns for BNPL user default. Confidence near 50% and lift >1.2 indicate above-average default risk. Low-risk profiles follow "high income + low debt"; with middle/older age, non-default confidence exceeds 85% (lift 1.42). Risk factors: high debt, youth, low income; protective: high income, low debt. Three-feature rules fail significance tests due to sample limits.

5.3. Association Rules

Rules "low income + young" and "high debt + young" strongly signal default (fragile-income new users, young debt-burdened). The single "high debt" rule, with high support/coverage, is a baseline for screening.

Notably, the “high debt + medium income” rule yields higher confidence than “high debt + young”. This demonstrates that even users with certain income capacity may suffer substantially squeezed repayment capacity under excessive debt. Accordingly, risk assessment for such users should not rely merely on income level; debt-to-income ratio ought to be integrated for comprehensive evaluation.

Low-risk rules are dominated by the combined pattern of “high-income + low-debt”. Middle-aged and elderly users under such combination demonstrate more stable credit behaviours. Therefore, association rules can supplement single-indicator judgement via multi-feature combinations and support platforms in user risk identification and differentiated management.

5.4. Visualisation of High-Risk Rules

The top-5 high-risk rules are selected for visualisation. Confidence and lift show consistent trends, verifying satisfactory rule effectiveness. The visualisation of high-risk association rules is illustrated in Figure 5.

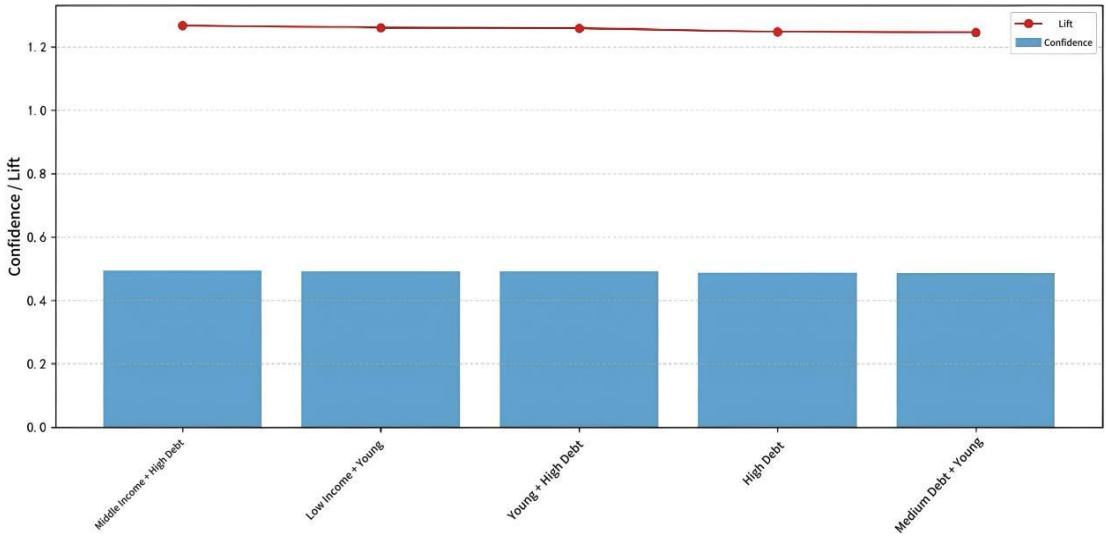


Figure 5. Visualisation of Top-5 High-risk Association Rules

6. Conclusions and Future Work

6.1. Research Conclusions and Contributions

Targeting credit default risk among BNPL users, this paper carries out empirical research combining machine learning, cluster analysis and association-rule mining. The results suggest that monthly income exerts greater influence on user default risk than debt-oriented indicators such as debt-to-income ratio. Users are further divided into three cohorts: robust high-quality users, high-risk indebted users and ordinary potential users, among whom low-income and high-debt users display the most prominent risk features. Association-rule analysis further identifies strongly indicative feature combinations including "low-income + young" and "high-debt + young".

The main contribution of this study lies in analysing the differentiated effects of income and debt indicators under BNPL's business characteristics including zero-down payment, small-sized multiple instalments and limited credit-reference coverage. Furthermore, default prediction, user segmentation and rule mining are integrated within a unified analytical framework. The research extends from standalone risk prediction to user profiling and combined-feature identification, providing a relatively complete analytical paradigm for BNPL credit-risk studies.

6.2. Research Limitations and Future Outlook

Several limitations remain in this research. First, the dataset is static data from a single platform. Dynamic information such as cross-platform indebtedness, income volatility and long-term consumption behaviours is absent, which constrains model capability to reflect real-world cash-flow and debt status. Second, the optimal silhouette coefficient of hierarchical clustering is only 0.2369, implying feature overlap across user groups. This can be partly attributed to continuous distribution of income, debt and consumption variables, limited dimensionality of static features, as well as the inherent deficiency of clustering algorithms in capturing dynamic behavioural shifts. Third, fixed thresholds for minimum support and confidence are applied in association-rule mining, leaving room for adaptability improvement across diverse business scenarios.

Future research may integrate multi-platform datasets and user time-series behavioural records to supplement features such as cross-platform debt, income variation and dynamic consumption. Clustering algorithms more suitable for complex user structures can be introduced, together with

dynamic rule thresholds tailored for various practical scenarios. On this basis, default prediction, user segmentation and association-rule mining can be further combined to enhance the effectiveness of BNPL credit-risk identification and stratified management.

References

[1] Di Maggio M, Williams E, Katz J. Buy Now, Pay Later Credit: User Characteristics and Effects on Spending Patterns[R]. NBER Working Paper No. 30508, 2022. DOI: 10.3386/w30508.

[2] Hayashi F, Routh A. Financial Constraints Among Buy Now, Pay Later Users[J]. Economic Review, 2025, 110(4): 1-18. DOI: 10.18651/ER/v110n4HayashiRouth.

[3] Liang H C. The Construction of Legal Mechanism for Consumer Over-Indebtedness Risk and Rights Protection under "Buy Now, Pay Later" Model[J]. E-Commerce Letters, 2025, 14(10): 397-404. DOI: 10.12677/ecl.2025.14103158.

[4] Jose A, Kelly J. Who Clicks "Pay Later"? Financial Vulnerability and Buy Now Pay Later Usage[R]. Central Bank of Ireland Staff Insights, No. 7/SI/25, 2025.

[5] Zhang J, Liu Y. Credit-card consumer-credit default-risk identification and credit-scoring model[J]. Theory and Practice of Finance, 2023(7): 89-97.

[6] Ma Y C, Hong H Q, Lin L Q. Reverse incentives for borrower performance in online lending: Empirical evidence from Renrendai platform[J]. Journal of Finance and Economics, 2020, 46(5): 66-80.

[7] Zhang Y W, Gao W H. Self-construals, Cultural Difference and Credit Risk: Evidence from Internet Finance[J]. Journal of Finance and Economics, 2020, 46(1): 34-48. DOI: 10.16538/j.cnki.jfe.2020.01.003.

[8] Li Y, Liu L. Reconstructing consumer-credit evaluation framework in digital era[J]. Journal of Financial Research, 2021(11): 1-18.

[9] Li J J, Wang S Z. Research on user credit risk-evaluation system under consumer-finance scenarios[J]. Theory and Practice of Finance, 2022(5): 45-51.

[10] Hu J, Li Q, Zeng Y, Tian X, Liu S. Digital footprints and default prediction: Evidence from consumer credit[J]. Journal of Management Sciences in China, 2025, 28(2): 115-139.

[11] Ayari H, Guetari R, Kraïem N. Machine learning powered financial credit scoring: A systematic literature review[J]. Artificial Intelligence Review, 2026, 59: Article 13. DOI: 10.1007/s10462-025-11416-2.

[12] Sun L, Wang X Y, Ma R X. Bad-user profiling for micro-loan based on Logistic model[J]. Statistics and Applications, 2023, 12(6): 1696-1706.

[13] Dai W S, Liu Z X. Research on big-data credit assessment in consumer finance: Based on GBDT and XTBoost[R]. IMI Working Papers No. 1925, International Monetary Institute, Renmin University of China, 2019.

[14] Ghoujdam M E K, Chaabita R, Elkhalfi O, et al. Consumer credit risk analysis through artificial intelligence: A comparative study between the classical approach of logistic regression and advanced machine learning techniques[J]. Cogent Economics & Finance, 2024, 12(1): 2414926. DOI: 10.1080/23322039.2024.2414926.

[15] Khalili P, Kargari M, Rastegar M A, et al. Predicting BNPL Loan Defaults: A Comparison of Ensemble Learning Models Combined with Balancing Techniques and an Analysis of the Impact of Digital Literacy[J]. Engineering Reports, 2026, 8(2): e70601. DOI: 10.1002/eng2.70601.

[16] Taş C. Comparison of Machine Learning and Standard Credit Risk Models' Performances in Credit Risk Scoring of Buy Now Pay Later Customers[D]. Ankara: Middle East Technical University, 2023.

[17] Mahmud M R, Hoque M R, Ahammad T, et al. Advanced AI-Driven Credit Risk Assessment for Buy Now, Pay Later (BNPL) and E-Commerce Financing: Leveraging Machine Learning, Alternative Data, and Predictive Analytics for Enhanced Financial Scoring[J]. Journal of Business and Management Studies, 2024, 6(2): 180-189. DOI: 10.32996/jbms.2024.6.2.19.

[18] Mishra A, Mou S N, Ara J, et al. Regulatory and Ethical Challenges in AI-Driven and Machine Learning Credit Risk Assessment for Buy Now, Pay Later (BNPL) in U.S. E-Commerce: Compliance, Fair Lending, and Algorithmic Bias[J]. Journal of Business and Management Studies, 2025, 7(2): 42-51. DOI: 10.32996/jbms.2025.7.2.3.

[19] Yuan Y, Yang Y, Wang H Q. Research on Credit Risk Assessment of P2P Lending Platform[J]. Management Science and Engineering, 2020, 9(3): 157-164. DOI: 10.12677/mse.2020.93021.

[20] Tanantong T, Loetwiphut P. Association rule mining framework for financial credit-risk analysis in peer-to-peer lending platforms[J]. Science, Engineering and Health Studies, 2023, 17: 23020006. DOI: 10.69598/sehs.17.23020006.