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Extension of Traditional Credit Scoring Models Based on FICO Scores: The Impact of Loan Purpose on Default Predictive Performance

Junjie Guan[1,*]

[1] School of Management, Harbin Institute of Technology, Harbin, Heilongjiang, 150001, China
*Corresponding author: 2024112206@stu.hit.edu.cn

Abstract:
P2P online lending is a vital component of the fintech sector, and its rapid growth has heightened demands for predicting default risks. Traditional credit scoring models primarily rely on structured metrics such as FICO scores and debt-to-income ratios (DTI), yet they often overlook the predictive value of soft information like loan purpose. Using Lending Club's 2016 loan data as a case study, this research constructs comparative models and employs machine learning methods including decision trees, random forests, logistic regression, and XGBoost to empirically examine the impact of loan purpose on default prediction accuracy. Results reveal a significant correlation between loan purpose and default risk, demonstrating its positive role in enhancing model accuracy. Particularly under recall-prioritized risk control strategies, the logistic regression and XGBoost models exhibit superior performance in default identification coverage. This study not only enriches the theoretical dimensions of credit risk modeling but also provides empirical evidence and practical pathways for P2P platforms and credit institutions to optimize their risk control systems.

Keywords: FICO Score; Loan Purpose; Default Prediction; Machine Learning; Credit Risk Model

1. Introduction

As a key product of the fintech revolution, P2P online lending has experienced rapid growth worldwide. Lending Club, the world‘s largest P2P lending platform, has become an industry benchmark since its founding in 2006. Its new loan volume for the full year of 2015 reached $8.36 billion, far surpassing other platforms in the industry. However, the rapid growth of P2P lending has also brought challenges in risk management. Accurately assessing borrower default risk has become a critical issue for the sustainable development of platforms [1].

Traditional credit risk assessment primarily relies on

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hard data metrics such as FICO scores, debt-to-income ratios (DTI), and credit history. Lending Club itself employs a comprehensive credit scoring system that categorizes borrowers into seven grades (A-G) with 35 sub-levels, each corresponding to different loan interest rates. However, growing research in recent years indicates that beyond traditional financial metrics, borrowers' behavioral characteristics and loan purposes may significantly influence default risk [2, 3]. Although platforms like Lending Club collect loan purpose information, in-depth mining and analysis of such data remain relatively limited, failing to be fully leveraged in risk pricing and risk management [4, 5].

Against this backdrop, this study poses the core research question: Does the purpose of borrowing influence default risk in P2P lending? And can information about borrowing purposes enhance the predictive performance of traditional risk assessment models? Specifically, this research focuses on two aspects: First, whether significant differences in default risk exist across different borrowing purposes; second, whether incorporating borrowing purpose information into traditional risk factors—such as FICO scores and debt-to-income ratios—can significantly improve the accuracy of default predictions.

This study holds significant theoretical value and practical implications. Theoretically, it enriches the application of behavioral finance and information economics within the P2P lending domain, revealing the predictive value of loan purpose as "soft information" in risk forecasting. Practically, the findings provide decision support for multiple stakeholders. For credit institutions, it enables optimization of risk pricing models, enhances the efficiency of credit resource allocation, and achieves more precise risk control. For regulators, it aids in identifying potential default groups and strengthening control over systemic risks [1]. For borrowers, it helps address adverse selection and credit discrimination stemming from information asymmetry [2]. In summary, this research holds significant importance for promoting high-quality development within the P2P lending industry and the broader credit market.

2. Literature Review

Previous studies have shown that in the field of credit risk assessment, traditional credit scoring models have long relied on structured financial metrics such as FICO scores and debt-to-income ratios (DTI). FICO scores provide financial institutions with critical risk assessment criteria by quantifying borrowers' credit histories, repayment behaviors, and debt levels. However, such metrics exhibit significant limitations: First, FICO scores primarily reflect historical credit behavior, lacking dynamic responsiveness to current economic conditions and borrowers' future income potential. Second, while DTI measures short-term repayment capacity, it overlooks how loan purpose may influence long-term repayment willingness and ability. Third, such static metrics struggle to capture risks arising from sudden economic shocks or shifts in individual behavior [6]. Research indicates that models relying solely on traditional metrics exhibit unstable performance across economic cycles, with predictive efficacy significantly declining during financial crises [7].

To address the limitations of traditional models, recent research has increasingly incorporated non-traditional factors to enhance predictive performance. On one hand, behavioral data such as consumption habits and online activities can extract latent risk signals through machine learning methods [8]. On the other hand, macroeconomic variables (e.g., unemployment rates, economic cycles) have been demonstrated to exhibit significant correlations with default rates [1]. Furthermore, borrowers' demographic characteristics (e.g., education, occupation) have been incorporated into models to enhance discriminative power [7]. By providing more comprehensive borrower profiles, these factors have improved model generalization and robustness to some extent.

Among numerous non-traditional factors, the purpose of borrowing has gradually gained attention as a key variable reflecting borrowers' motivations and capital allocation patterns. A limited number of studies have indicated correlations between borrowing purposes and default probabilities. For instance, education loans exhibit lower default rates due to their potential long-term returns, whereas consumer loans carry higher risks owing to the absence of asset backing [3]. However, existing research exhibits notable limitations: most literature offers only qualitative discussions on the relationship between purpose and risk, lacking systematic quantitative analysis across different purpose categories. Furthermore, loan purpose is often treated as a supplementary variable rather than a core predictor in models, and its standalone and combined predictive efficacy remains insufficiently validated [4, 5]. Therefore, it is necessary to empirically test the practical value of loan purpose in enhancing default prediction accuracy by constructing comparative models.

In summary, existing research provides diverse variable options and methodological support for credit risk assessment. However, a research gap remains in the systematic modeling of loan purposes, necessitating further empirical analysis to explore its underlying mechanisms and predictive efficacy.

3. Research Design and Methodology

3.1 Research Data

3.1.1 Data Sources

This study utilizes publicly available loan data from Lending Club, a globally renowned peer-to-peer lending platform. The dataset originates from the complete quarterly loan data released by Kaggle for 2016. The selection of this data was primarily based on the following considerations: First, 2016 represented a period of relative economic stability in the United States, with sufficient temporal distance from the 2008 financial crisis to accurately reflect lending behavior characteristics under normal economic conditions. Second, as an industry-leading platform, Lending Club provides high-quality data with a comprehensive variable system, offering a reliable foundation for research [1]. Third, the four-quarter data span a complete annual cycle, effectively mitigating the impact of seasonal factors on model stability.

3.1.2 Key Variables

(1) Target variables: purpose, loan_status

(2) Feature Selection for Traditional Models (Table 1 to Table 2)

Table 1. Feature selection of traditional model

Listed	Explanation
loan_amnt	Loan amount
term	Loan term (36/60 months)
int_rate	Interest rate
installment	Monthly repayment amount
grade	Lending Club grade
sub_grade	Subgrade
emp_length	Employment length
home_ownership	Home ownership
annual_inc	Annual income
verification_status	vertification status
dti	Debt-to-income ratio
delinq_2yrs	Number of delinquencies within the past two years
fico_range_low	FICO range low
fico_range_high	FICO range high
open_acc	Number of credit accounts currently opened
pub_rec	Number of public records
revol_bal	Revolving credit balance
revol_util	Revolving credit utilization rate
total_acc	Total number of credit accounts
initial_list_status	Initial list status
application_type	Application type

(3) Characteristics related to the purpose of the loan

Table 2. Features associated with the purpose of the loan

Listed	Explanation
purpose	Purpose of loan
title	Loan title (more detailed description of loan purpose)

3.2 Research Methods

To systematically evaluate the contribution of the non-traditional feature of loan purpose to credit risk prediction, this paper employs a comparative modeling approach [3]. First, during the feature analysis phase, exploratory analysis is conducted using visualization methods to examine the distribution patterns of loan purposes, the statistical characteristics of default status, and the correlation between the two. This aims to identify risk distribution pat-

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terns and potential regularities across different loan purposes, providing theoretical foundations and data support for subsequent modeling. Regarding model construction, two predictive models were designed for comparative study: the baseline model utilizes only traditional structured features such as FICO scores, debt-to-income ratios, and credit history length; the extended model incorporates the critical non-traditional variable of loan purpose alongside traditional features. For model algorithm selection, four mainstream machine learning methods—decision trees, random forests, logistic regression, and XGBoost—were comprehensively employed to fully evaluate the adaptability of different algorithm architectures to feature combinations [8, 9]. Regarding the model evaluation framework, accuracy and recall were adopted as core performance metrics, supplemented by precision and F1 score for multidimensional comprehensive assessment [4, 7]. It is particularly noteworthy that, given the paramount importance of comprehensive risk coverage in financial risk control, this study explicitly adopts a recall-priority modeling strategy. This approach focuses on maximizing the identification of potential defaulting customers, prioritizing the reduction of false negative risks. Even if this entails a potential increase in false positive costs, it aligns with the decision logic of financial institutions in practical risk control operations, where risk prevention takes precedence over profit pursuit [10].

Through the aforementioned comparative experimental design, this paper aims to validate the supplementary value of loan purpose as a soft information feature to traditional credit scoring models from the perspective of predictive performance. It provides methodological references and empirical support for refining intelligent risk control models based on multidimensional features.

4. Empirical Analysis

4.1 Feature Visualization Analysis

4.1.1 Distribution of Loan Purposes

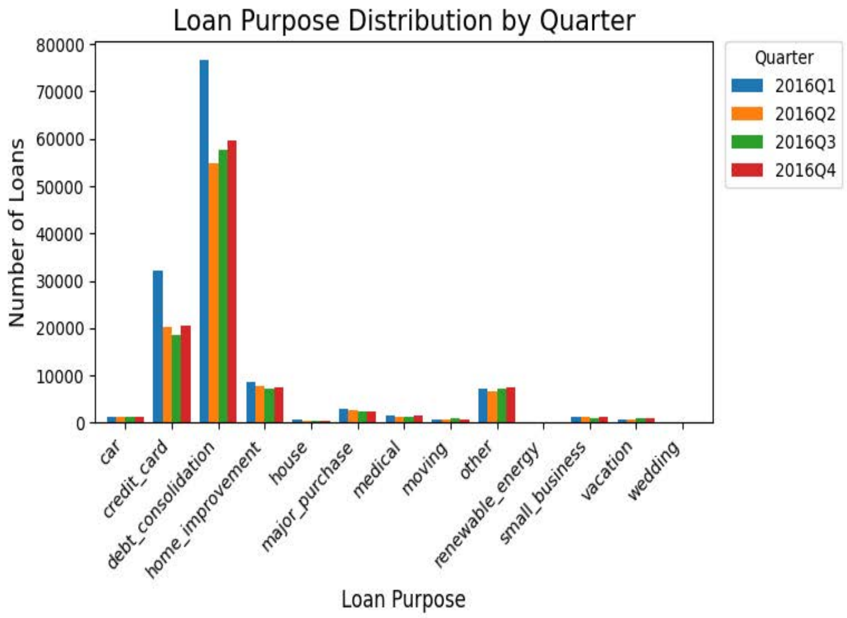

Fig. 1 Bar chart depicting loan purpose across four different quarters of 2016 (Picture credit: Original)

As shown in Figure 1, debt consolidation consistently dominates, with loan volumes significantly higher than other categories. It remained relatively stable across all quarters of 2016, reflecting sustained consumer demand for credit consolidation. Credit card and home improvement loans also maintained high levels, indicating that consumer finance and housing-related expenditures remain key drivers of borrowing [3]. Notably, small business loans, though modest in scale, exhibit a gradual upward trend, potentially suggesting unmet financing needs among micro and small enterprises. Furthermore, specific-purpose loans such as medical and wedding loans remain low in volume, indicating limited credit penetration in these scenarios. Overall, the distribution of loan purposes reflects that consumer credit behavior remains centered on debt optimization and large-ticket consumption, while also exhibiting certain scenario-specific characteristics [1].

4.1.2 Distribution of Default Conditions

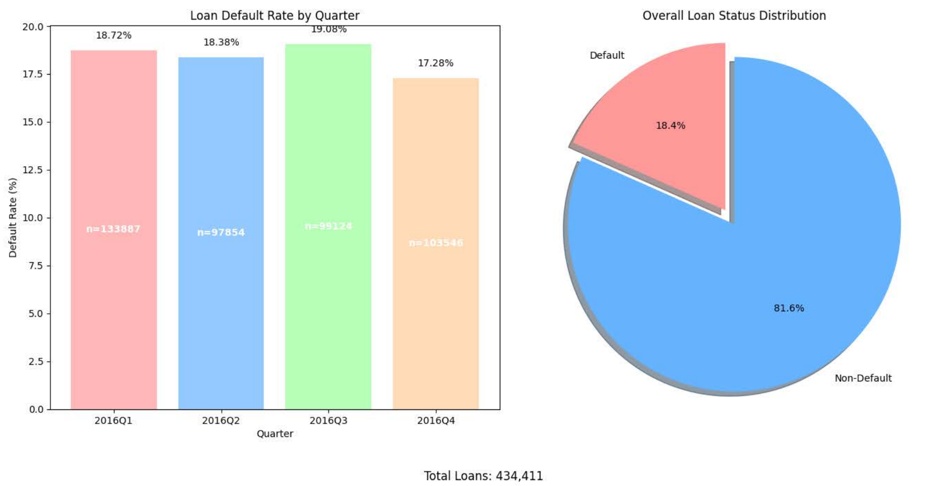

Fig. 2 The loan default rated and their distribution across the four quarters of 2016 (Picture credit: Original)

Figure 2 illustrates the loan default rates and their distribution across the four quarters of 2016. The left chart shows that the default rate in the first quarter of 2016 was 18.72%, involving 133,887 loans; the default rate slightly decreased to 18.38% in the second quarter, with the number of loans decreasing to 97,854; The third quarter saw an increase to 19.08% with 95,124 loans; the fourth quarter experienced a significant decline to 17.28% with 103,546 loans. Overall, quarterly default rates fluctuated minimally throughout 2016, though the third quarter recorded the highest rate, potentially linked to economic conditions or changes in lending policies during that period. The chart on the right illustrates the distribution of overall loan statuses, with defaulted loans accounting for 18.4% and non-defaulted loans representing a substantial 81.6%. This indicates that despite a certain proportion of defaults, the majority of loans are being repaid on schedule, demonstrating the overall stability of the loan portfolio [6].

4.1.3 Analysis of the Correlation Between Loan Purpose and Default Status

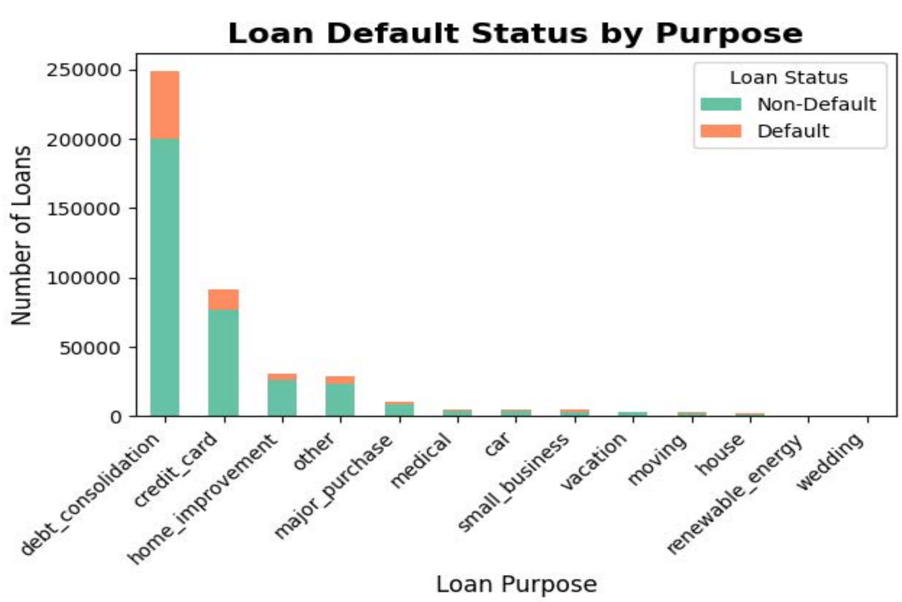

Fig. 3 Stacked bar chart depicting the correlation between loan purpose and default status (Picture credit: Original)

Figure 3 clearly reveals a significant correlation between loan purpose and default risk by comparing the distri-

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bution of default statuses across different loan purposes. Specifically, "Debt Consolidation" loans exhibit a higher proportion of defaults, suggesting this purpose may carry stronger credit risk. In contrast, loans for other purposes show relatively lower default rates, reflecting systematic differentiation in repayment capacity and default propensity stemming from variations in fund usage [10]. This finding indicates that loan purpose serves as a crucial indicator for assessing default risk, potentially reflecting differences in cash flow characteristics, cyclical attributes, and borrowers' repayment willingness across various uses [3]. Consequently, credit risk assessment models should prioritize incorporating loan purpose as a predictive factor within default forecasting frameworks to enhance risk differentiation and model accuracy.

4.2 Comparison of Model Results

4.2.1 Traditional Model Modeling

Table 3. The performance of the four traditional machine learning models

	Decision Tree	Random Forest	Logistic Regression	XGBoost
Accuracy	0.6294	0.6390	0.6245	0.7813
Recall	0.7377	0.6606	0.6672	0.7234
Precision	0.6055	0.6333	0.3016	0.6887
F1 Score	0.6248	0.6388	0.5694	0.7740

In Table 3, comparing the performance of benchmark machine learning models built from traditional features reveals significant differences among several commonly used algorithms in default prediction tasks, highlighting the critical impact of feature structure and model selection on predictive efficacy. The XGBoost model demonstrated comprehensive superiority across all four-evaluation metrics, achieving an accuracy of 0.7813 and an F1 score of 0.7740. This significantly outperformed decision trees, random forests, and logistic regression models, highlighting the advantages of ensemble learning algorithms in handling high-dimensional structured data and nonlinear relationships [8]. Although the accuracy (0.6390) and F1 score (0.6388) of the Random Forest model outperformed the single decision tree and logistic regression models, its recall rate (0.6606) was relatively low. This suggests that the model may exhibit a conservative tendency in identifying actual default cases [9].

The logistic regression model demonstrated the weakest overall performance, achieving an accuracy rate of 0.6245. Particularly noteworthy is its extremely low precision rate (0.3016), indicating significant noise in positive class classification and a high false positive rate [5]. This outcome aligns with expectations, as logistic regression—being a linear model—has limited capacity to capture complex interactions and nonlinear relationships among variables, particularly when confronted with high-dimensional, multicollinear traditional financial features. Although the decision tree achieved the highest recall (0.7377), indicating strong coverage of default samples, its precision (0.6055) and F1 score (0.6248) were both low, reflecting issues of overfitting or insufficient generalization capability [4].

Overall, the benchmark model results indicate that relying solely on traditional structured variables such as FICO scores, debt-to-income ratios, and credit history—even when employing high-performance machine learning algorithms like XGBoost—leaves room for improvement in predictive capability. This also supports the rationale for this study from a model evaluation perspective: incorporating non-traditional features with high discriminative power, such as "loan purpose," is necessary to further enhance the model's distinguishing ability and robustness.

4.2.2 Incorporate loan purpose feature modeling

Table 4. The performance of four models with the addition of loan purpose feature to the benchmark model

	Decision Tree	Random Forest	Logistic Regression	XGBoost
Accuracy	0.8956	0.9357	0.8314	0.8047
Recall	0.5678	0.3420	0.7635	0.7789
Precision	0.7123	0.7185	0.2143	0.1986
F1 Score	0.6321	0.4637	0.3342	0.3168

As shown by the Table 4, incorporating loan purpose features into the baseline model (built using traditional features) has altered the outcomes across different models. We will now conduct a detailed analysis of the changes in predictive performance for each model.

4.2.3 Comparison of Model Results

(1) Decision Tree (Table 5)

Table 5. Performance comparison of Model 1 and Model 2 in decision tree

	Model 1	Model 2	Change
Accuracy	0.6294	0.8956	+0.2662
Recall	0.7377	0.5678	-0.1699
Precision	0.6055	0.7123	+0.1068
F1 Score	0.6248	0.6321	+0.0073

The comparison results show that after incorporating the loan purpose feature, Model 2 demonstrates significant differences across multiple evaluation metrics compared to Model 1, which only uses traditional features like FICO scores. This highlights the crucial role of this soft information variable in credit risk assessment. First, the accuracy rate increased substantially from 0.6294 in Model 1 to 0.8956 in Model 2, representing a gain of 0.2662. This indicates that incorporating loan purpose significantly enhances the model‘s overall discrimination accuracy, enabling more reliable differentiation between defaulting and non-defaulting customers.

In contrast, the recall of Model 2 (0.5678) declined by 0.1699 relative to Model 1 (0.7377). This suggests that although the new model exhibits stronger overall discriminative ability, its effectiveness in capturing actual default cases has weakened, thereby heightening the risk of misclassification. One possible explanation is that the inclusion of loan purpose data may have led the model to adopt a more conservative prediction strategy, or that the interaction between categorical feature encoding and the model architecture diminished its sensitivity to the minority class (i.e., default instances) [10]. Meanwhile, precision improved from 0.6055 to 0.7123, reflecting a higher proportion of true defaults among the predicted positives, fewer false positives, and greater predictive reliability [4]. However, the F1 score rose only slightly by 0.0073, indicating that the balance between precision and recall has not yet been optimized, and the model's overall performance still has room for further enhancement.

Overall, the introduction of loan purpose significantly improved the model‘s overall classification accuracy and decision certainty, but it also carries the risk of reduced recall rates, necessitating further refinement of the model.

(2) Random Forest (Table 6)

Table 6. Performance comparison of Model 1 and Model 2 in random forest

	Model 1	Model 2	Change
Accuracy	0.6390	0.9357	+0.2967
Recall	0.6606	0.3420	-0.3186
Precision	0.6333	0.7185	+0.0852
F1 Score	0.6388	0.4637	-0.1751

Based on the model performance comparison results, the accuracy rate increased significantly from 0.6390 in Model 1 to 0.9357 in Model 2, representing an increase of 0.2967. This indicates that incorporating loan purpose data substantially improved the model‘s overall classification accuracy, enabling more reliable differentiation between defaulting and non-defaulting customers.

However, in terms of recall, Model 2 (0.3420) shows a significant decline compared to Model 1 (0.6606), with a decrease of 0.3186. This indicates that the new model exhibits a markedly reduced coverage in identifying actual defaulting individuals, meaning an increased risk of misclassification [4]. This shift suggests that incorporating loan purpose data may have made the model more conservative, or that complex interactions between category features and the tree model structure reduced sensitivity toward minority class samples (default cases) [10]. In risk control practice, a decline in recall implies heightened risk of "missing defaults," warranting critical attention [1]. On the other hand, precision improved from 0.6333 to 0.7185, indicating a higher proportion of actual defaults among samples classified as positive cases, with fewer false positives. The F1 score decreased by 0.1751, suggesting that the model‘s overall performance at the current threshold still has room for optimization.

In summary, a model with high accuracy does not necessarily equate to an effective risk control model. If the model optimization direction runs counter to the business

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objective (risk identification), its practical application value is zero regardless of how high its accuracy may be [4]. We believe that in financial risk control, risk prevention and mitigation are driven by profit pursuit. Therefore, we have adopted a recall-first strategy to build the next two models.

(3) Logistic Regression (Table 7)

Table 7. Performance comparison of Model 1 and Model 2 in logistic regression

	Model 1	Model 2	Change
Accuracy	0.6245	0.8314	+0.2068
Recall	0.6672	0.7635	+0.0963
Precision	0.3016	0.2143	-0.0873
F1 Score	0.5694	0.3342	-0.2352

Under a recall-priority modeling strategy, incorporating loan purpose features increased accuracy from 0.6245 to 0.8314—a gain of 0.2068. This indicates that adding loan purpose data significantly improved the model‘s overall prediction accuracy, enabling more effective differentiation between defaulting and non-defaulting customers.

More crucially, in terms of the recall metric, Model 2 achieved 0.7635, an improvement of 0.0963 over Model 1‘s 0.6672. This demonstrates a significant increase in the model‘s coverage rate for identifying actual defaulting individuals, thereby reducing the risk of missed judgments. This improvement aligns with the conservative risk management principle in risk control practice of “better to over-report than under-report,” reflecting the model‘s greater tendency to identify potential defaults and facilitating early risk intervention [10]. Notably, precision decreased from 0.3016 to 0.2143, and the F1 score also declined. This indicates that while pursuing high recall, the model incurred the cost of increased misclassification—more non-defaulting customers were incorrectly flagged as defaulters. This may elevate manual review costs but also reflects the trade-off between sensitivity and specificity in default identification [9].

Overall, Model 2 demonstrates superior coverage of defaulting customers and higher overall classification accuracy when prioritizing high recall, making it more suitable for financial risk control scenarios.

(4) XGBoost (Table 8)

Table 8. Performance comparison of Model 1 and Model 2 in XGBoost

	Model 1	Model 2	Change
Accuracy	0.7813	0.8047	+0.0234
Recall	0.7234	0.7789	+0.0555
Precision	0.6887	0.1986	-0.4901
F1 Score	0.7740	0.3168	-0.4572

Under this model, the accuracy rate improved from 0.7813 to 0.8047. Although the increase was only 0.0234, it indicates that the model‘s overall discriminative capability has been further optimized. More importantly, recall significantly improved from 0.7234 to 0.7789, an increase of 0.0555. This change highlights Model 2‘s superior performance in identifying genuine defaulting customers, effectively reducing the risk of missed judgments.

This performance pattern aligns closely with the intended recall-first strategy, where a certain degree of precision is sacrificed in exchange for broader coverage in detecting defaulting customers. From a risk management standpoint, this compromise carries substantial practical significance. In the P2P lending context, the potential losses from failing to identify defaulters generally outweigh the costs associated with misclassifying non-defaulters. Consequently, prioritizing recall is often more meaningful in practice than maximizing precision [6].

Overall, incorporating loan purpose information allows the model to preserve high accuracy while markedly improving its capacity to identify potential defaulters, making it particularly applicable in financial settings that demand stringent risk control.

5. Conclusion

This study examines the impact of loan purpose on default prediction using 2016 Lending Club data. By comparing a baseline model (traditional features only) with an extended model (adding loan purpose), key findings emerge: loan purpose significantly correlates with default risk; its inclusion boosts accuracy in most models, especially decision trees and random forests. However, recall rates vary—tree-based models show decreased recall, while logistic regression and XGBoost achieve higher recall under recall-priority strategies, aligning with practical risk control that prioritizes reducing false negatives.

In summary, this study demonstrates significant theoretical and practical value. Theoretically, it integrates behavioral finance insights into credit risk assessment, validating „loan purpose“ as an effective non-traditional predictor and enriching credit scoring theory. Practically, it offers actionable pathways for P2P platforms and traditional lenders to enhance risk assessment, improve loan pricing accuracy, allocate capital more efficiently, and reduce default rates. Additionally, it helps mitigate information asymmetry, increases financing efficiency for borrowers, and supports healthier development of credit markets.

However, this study still has several limitations. First, the data source is limited to Lending Club‘s 2016 annual data, failing to cover a longer time span and different economic cycles, which may affect the model‘s generalization ability. Second, the loan purpose was introduced as a categorical variable without conducting in-depth natural language processing analysis on its textual descriptions (such as the title field), potentially overlooking more granular semantic information.

Given these limitations, future research could be expanded in the following directions: First, incorporate NLP techniques to conduct sentiment analysis and topic modeling on textual descriptions of loan purposes, thereby extracting deeper risk signals. Second, conduct comparative studies across cycles and markets to validate the predictive efficacy of loan purposes under varying conditions.

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