Case Study:
Loan Repayment Analysis

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Agenda

Identifying the Challenge

Users’ Purchasing Habits

Users’ Repayment Behavior

User Loan Eligibility

Loan Repayment Model and Analysis

Next Steps and Considerations

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Identifying the Challenge

29%

of high-risk loans,
resulting in

R$ 5.5m

of accumulated loan debt,
causing lenders to incur financial loss and increased administrative burdens.

58%

of customers with high-risk repayment behavior,
causing damage to their credit score and additional fees and interest.

Based on 3,046 users who generated 6,588 loans

Key Concept: High-Risk Loans and Candidates

Loans Resulting in Repayment

... are assessed based on their **default rate**. **High-risk loans are considered those with a default rate that is an outlier compared to the category they belong to**.

The categories are defined based on the principal amount.
Outliers = Q3 + 1.5 x IQR

Loans Resulting in Debt

... are considered **high-risk loans**.

A user's risk is defined by linking their **purchasing and loan repayment behavior** with the **characteristics and quality of the loan**.

1. **2.** 3. 4. 5. 6.

Users’ Purchasing Habits

Identifying our users' purchasing habits

Based on RFM modeling

8%
Champions

Extremely active with *moderate to high* monetary value.

Prefer to use *both* credit and debit cards.

Opt for installment plans that span an *avg. of 3 installments*.

Low transaction rejection rate (avg. 10%).

3%
Big Spenders

Active customers with *high* monetary value.

Slight preference for online purchases.

Opt *frequently* for installment plans, typically spanning an *avg. of 6 installments*.

High transaction rejection rate (avg. 30%).

35%
Promising

Active customers with *low to moderate* monetary value.

Opt *periodically* for installment plans, typically spanning an *avg. of 3 installments*.

6%
Recent

Customers who entered our base *recently* with *low to moderate* monetary value.

Opt *frequently* for installment plans, typically spanning an *avg. of 5 installments*.

Moderate transaction rejection rate (avg. 21%).

48%
Inactive

Customers with *extremely low* activity.

Opt *frequently* for installment plans, typically spanning an *avg. of 5 installments*.

Moderate transaction rejection rate (avg. 20%).

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Users’ Repayment Behavior

Identifying our users’ loan portfolio

Champions

Mainly large loans (90%).

Mostly loans with small interest and large interest rates (58% and 38% respectively).

Prefer to breakdown the repayment into **multiple small** ones **(39 of R$265 each on average).**

Big Spenders

Exclusive preference for large loans (97%).

Mostly loans with small interest and large interest rates (70% and 27% respectively).

Prefer to breakdown the repayment into **fewer larger** ones **(14 of R$835 each on average).**

Promising

Mainly large loans (89%).

A good mixture of loans with different interest rates (72% small, 7% medium and 21% large).

Prefer to breakdown the repayment into **multiple small** ones **(40 of R$257 each on average**).

Recent

Mainly large loans (79%).

A good mixture of loans with different interest rates (55% small, 12% medium and 33% large).

Prefer to breakdown the repayment into **fewer larger** ones **(14 of R$663 each on average).**

Prefer manual repayments over an automated plan.

Inactive

Mainly large loans (89%).

Tend to avoid loans of medium to large interest rates (only 2%).

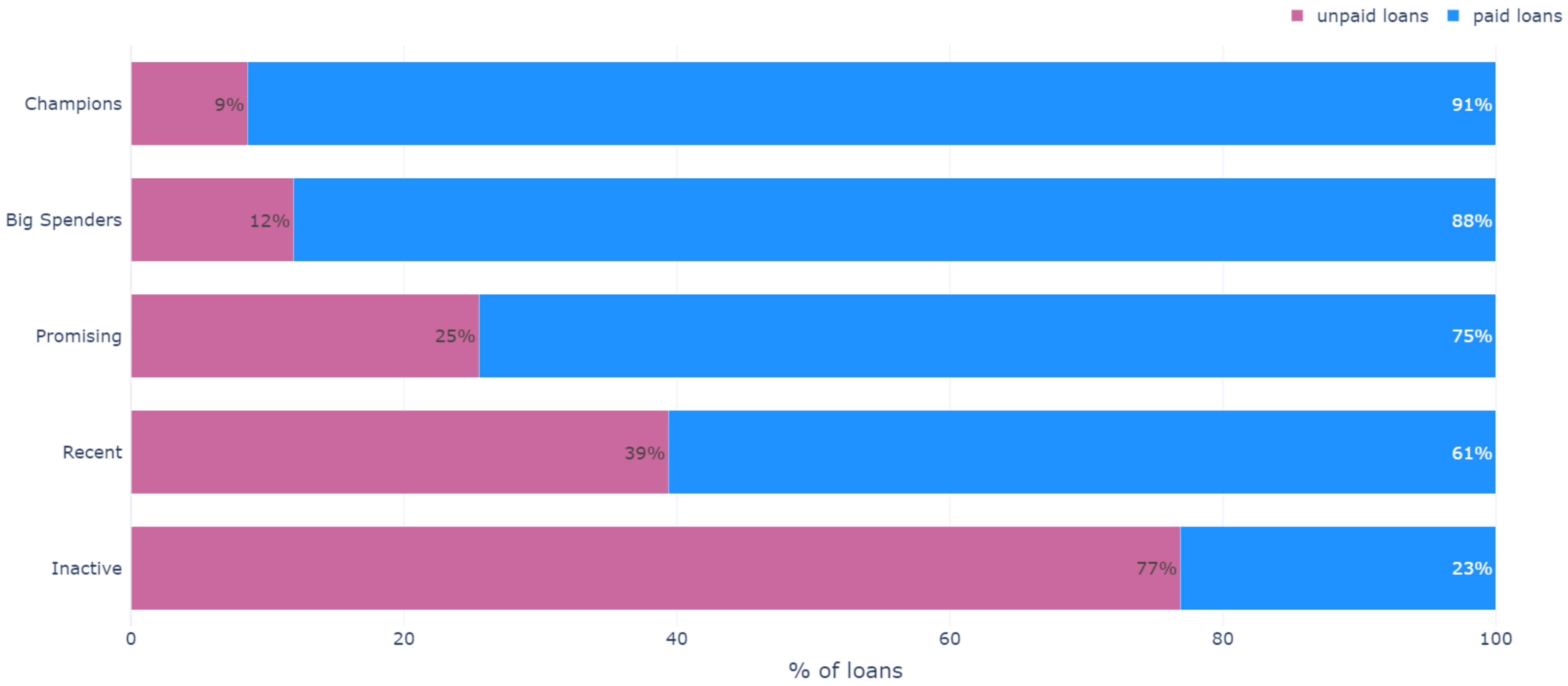
Prefer to breakdown the repayment into **fewer larger** ones **(21 of R$464 each on average)**.

Prefer manual repayments over an automated plan.

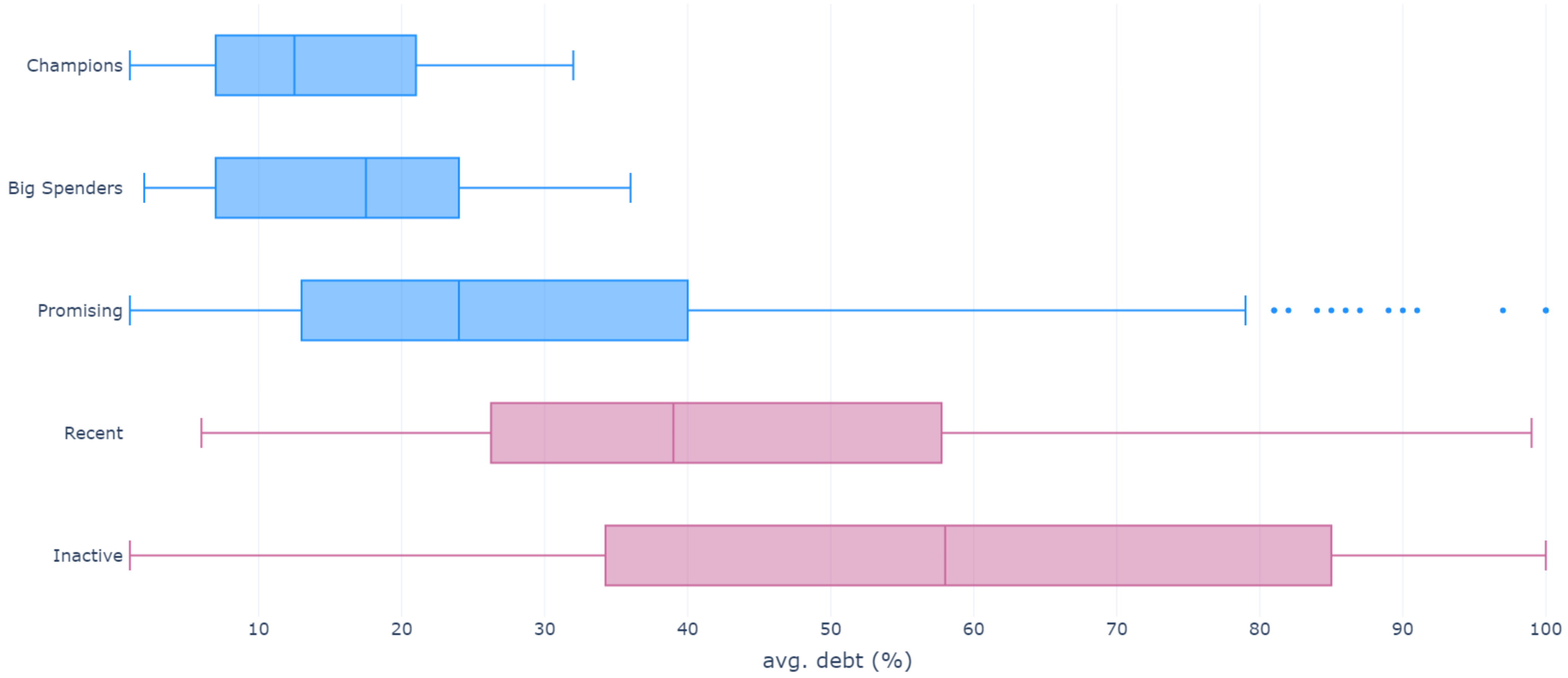
Amount: small: *less than R$ 3k,* ***medium:*** *R$ 3k – 5k,* ***large:*** *more than R$ 5k*

Interest Rate: small: *less than 40%,* ***medium:*** *40% - 100% ,* ***large:*** *greater than 100%*

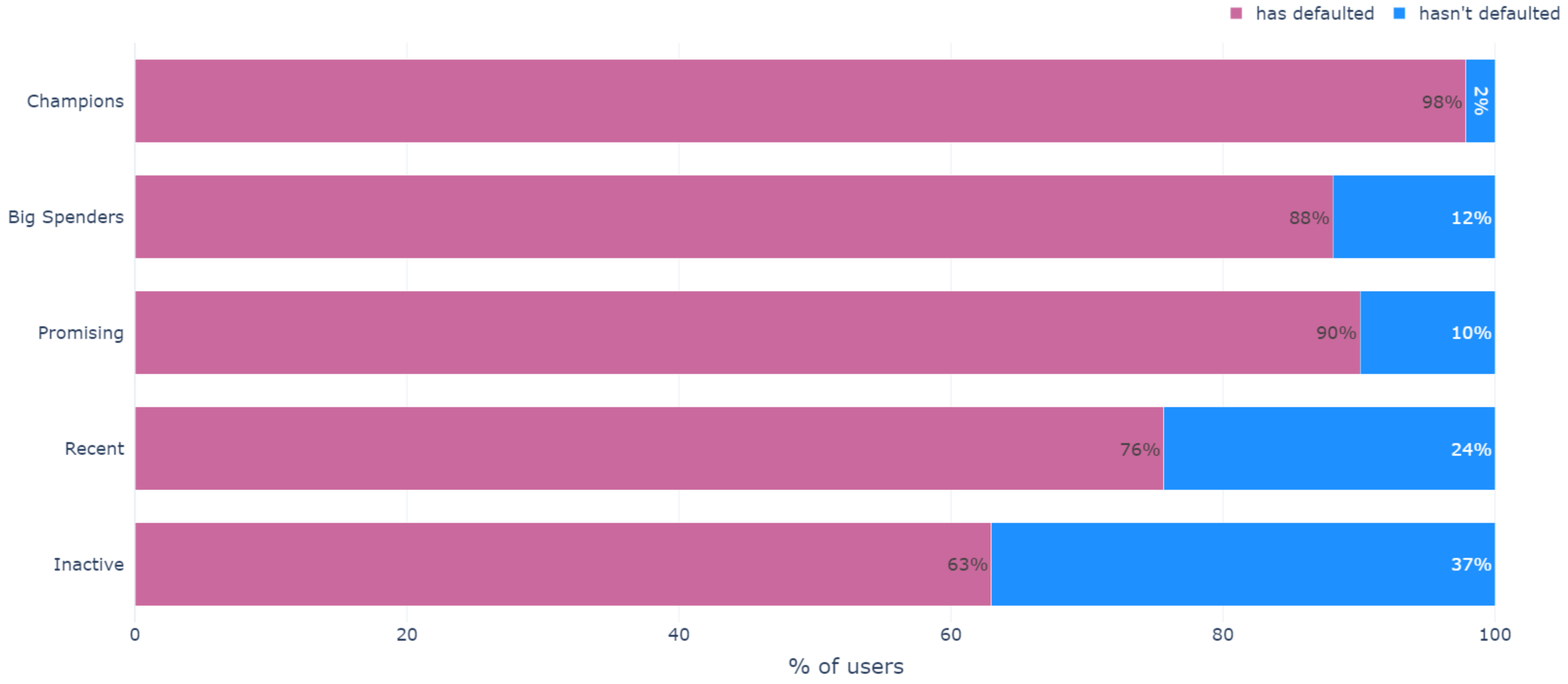
Recent and Inactive users are more prone incurring loan debt ...



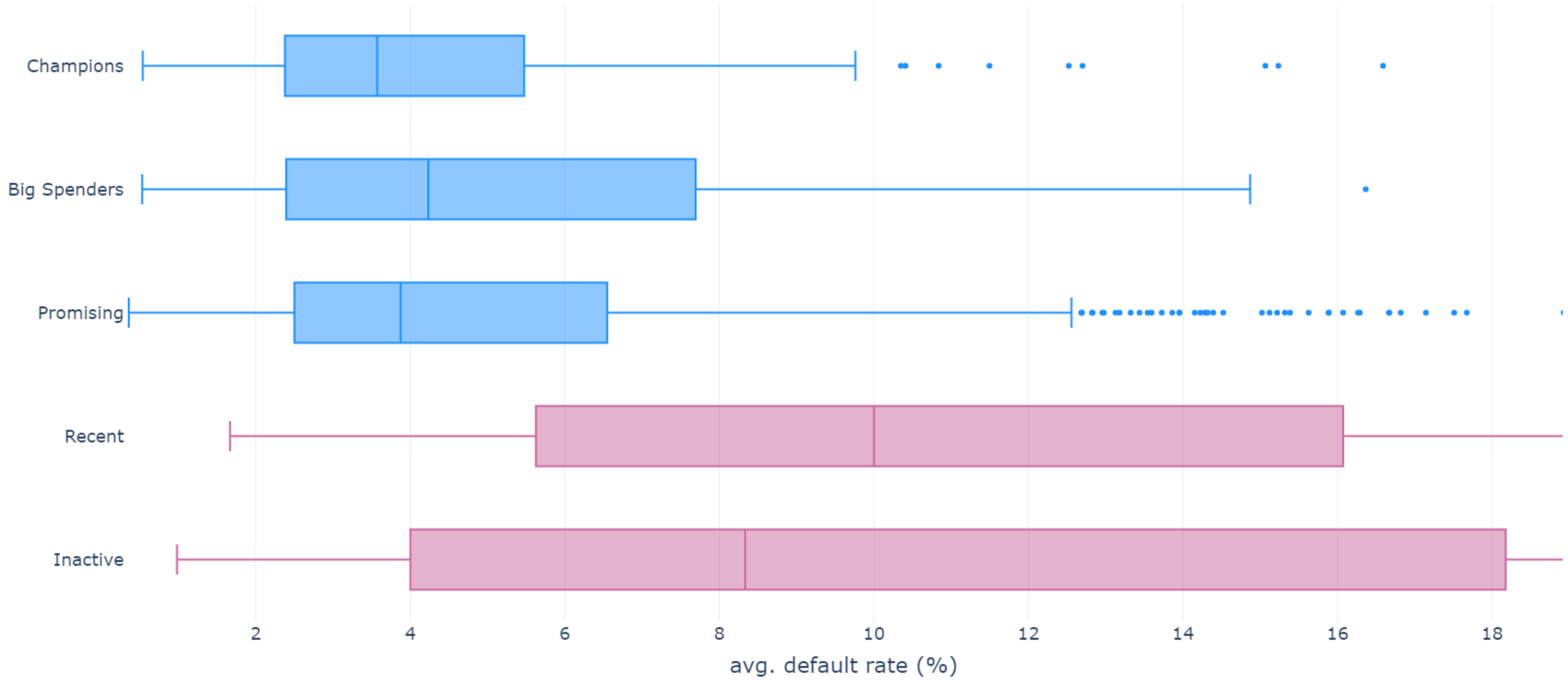
… and can potentially owe more than 50% of the loan amount



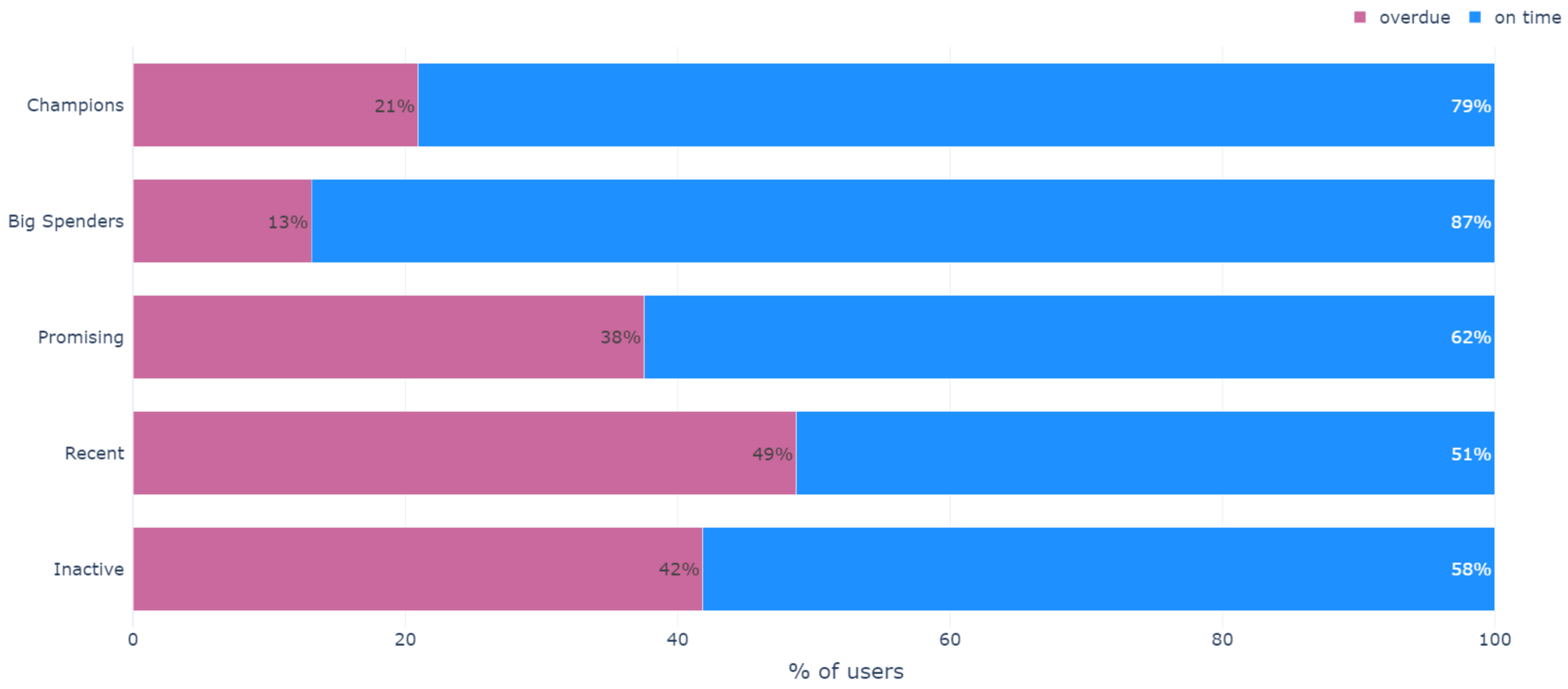
Frequent users exhibit a higher tendency towards defaulting ...



… however, infrequent users show greater repayment uncertainty



Users with low to moderate spending habits are likely to fall behind the due date



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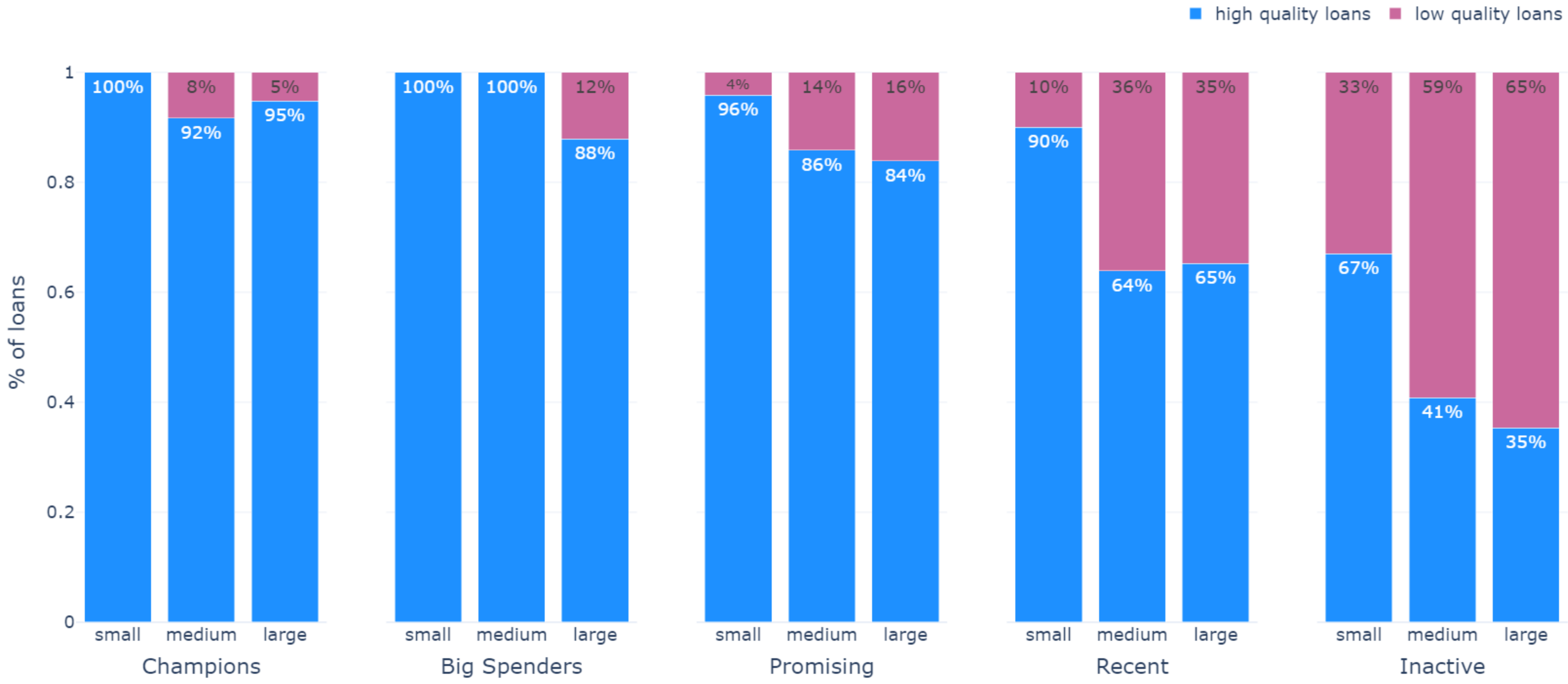
User Loan Eligibility

Infrequent users present a high-risk repayment behavior

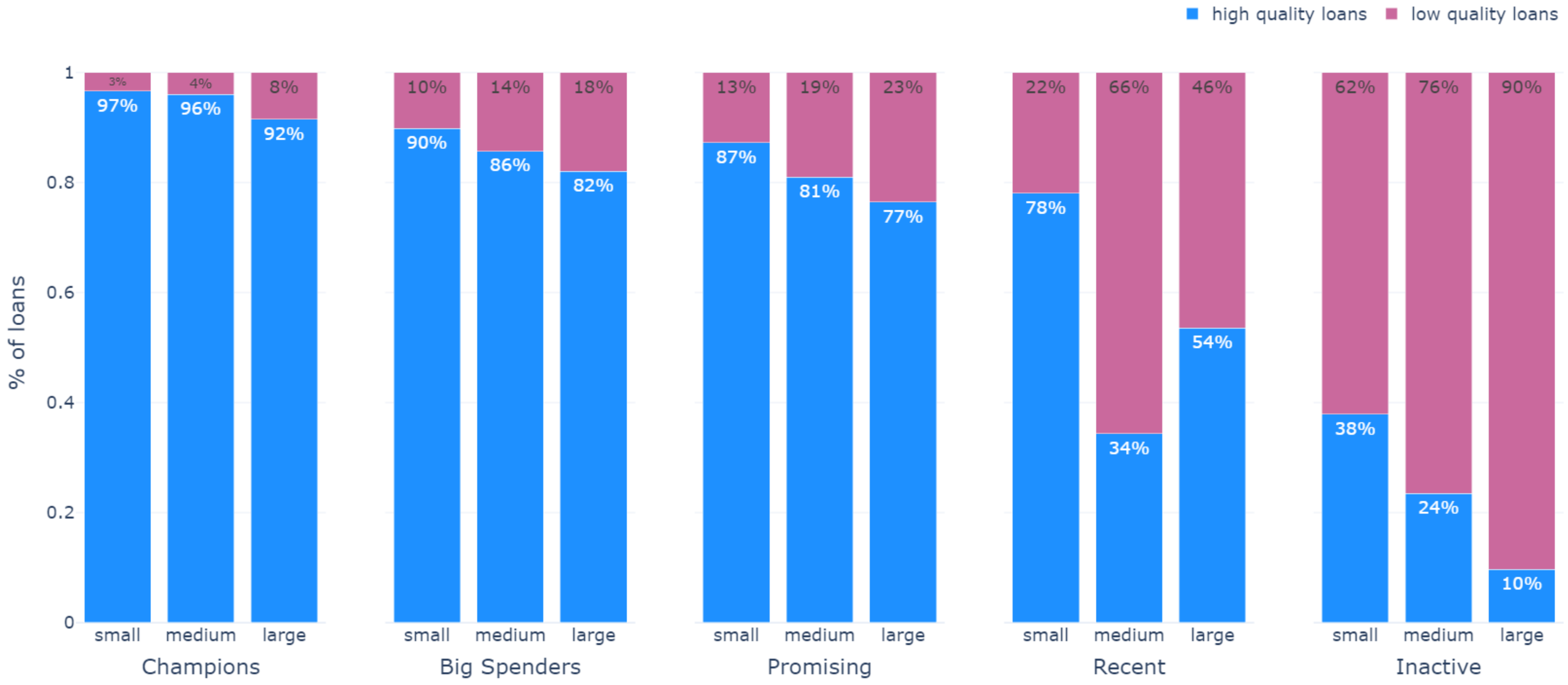
Champions	Big Spenders	Promising	Recent	Inactive
5%	12%	15%	32%	63%
high-risk loans	high-risk loans	high-risk loans	high-risk loans	high-risk loans

Risk increases with the loan amount, with *Recent* and *Inactive* users exhibiting a high-risk repayment behavior



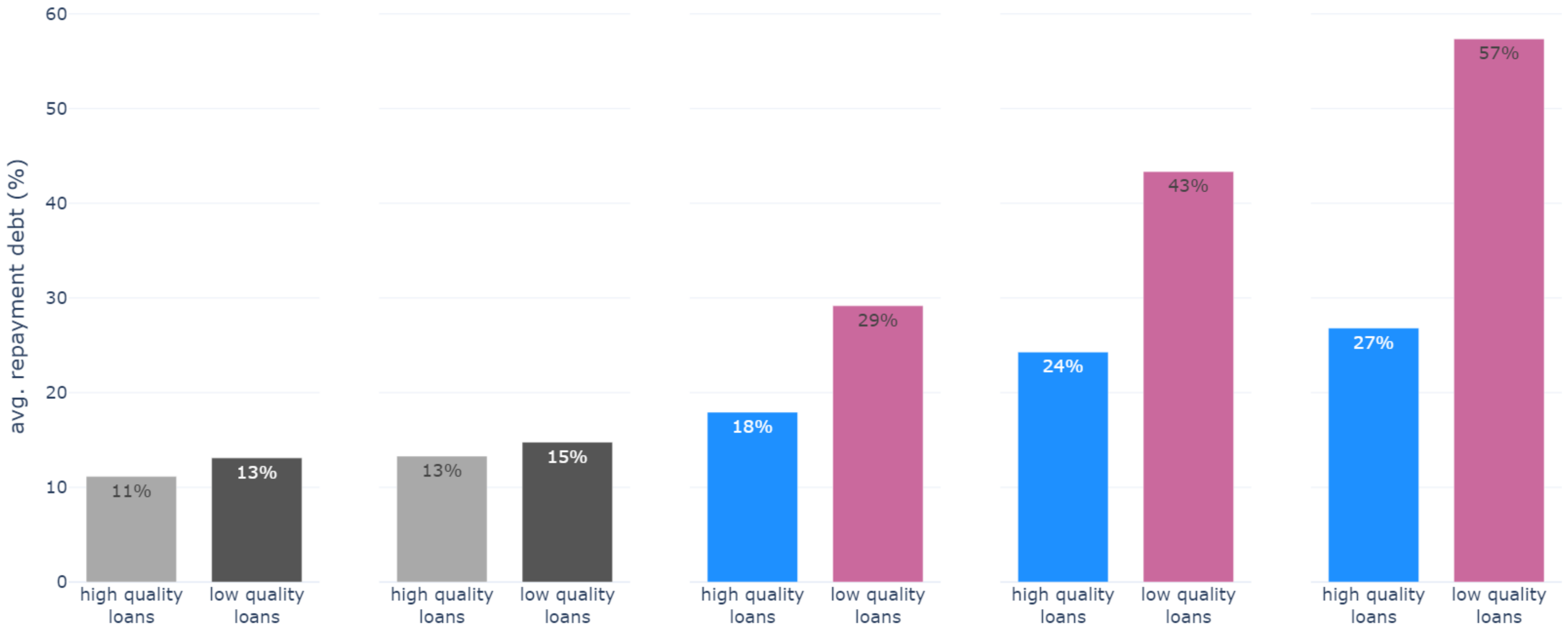
small: *less than R$ 3k,* ***medium:*** *R$ 3k – 5k,* ***large:*** *more than R$ 5k*

Similar risk can be observed in relation to the loan interest rates

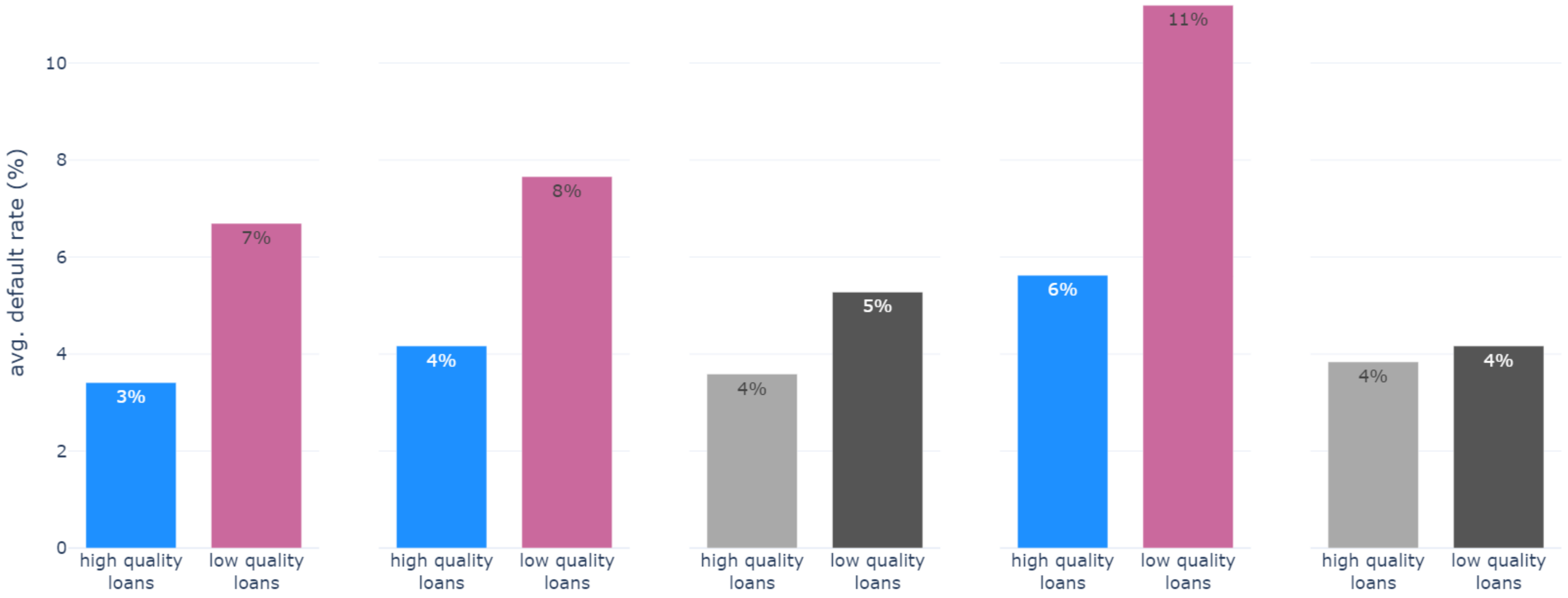


small: *less than 40%,* ***medium:*** *40% - 100% ,* ***large:*** *greater than 100%*

Users with a significant repayment debt, particularly *Recent* and *Inactive* users, exhibit poor repayment behavior

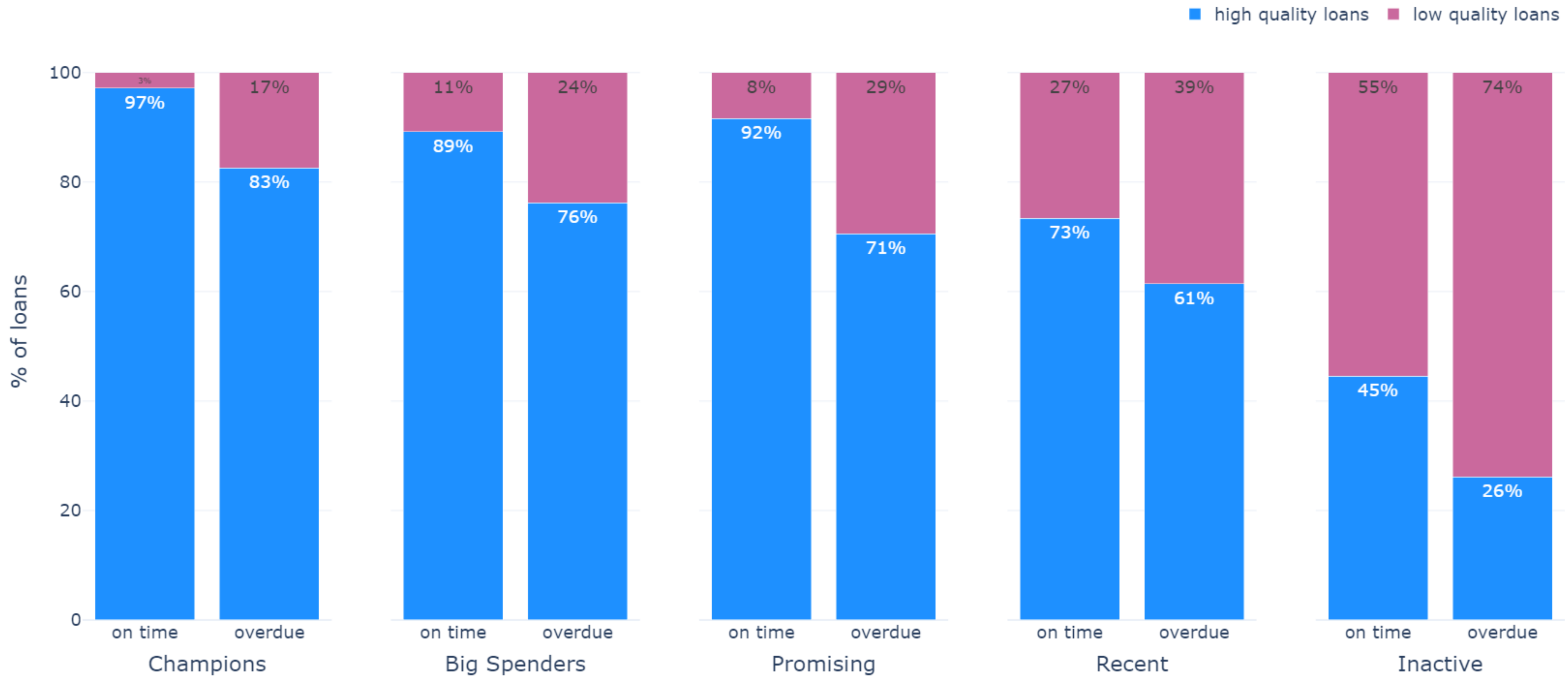


Higher default rates within the user segments are indicators of high-risk repayment behavior

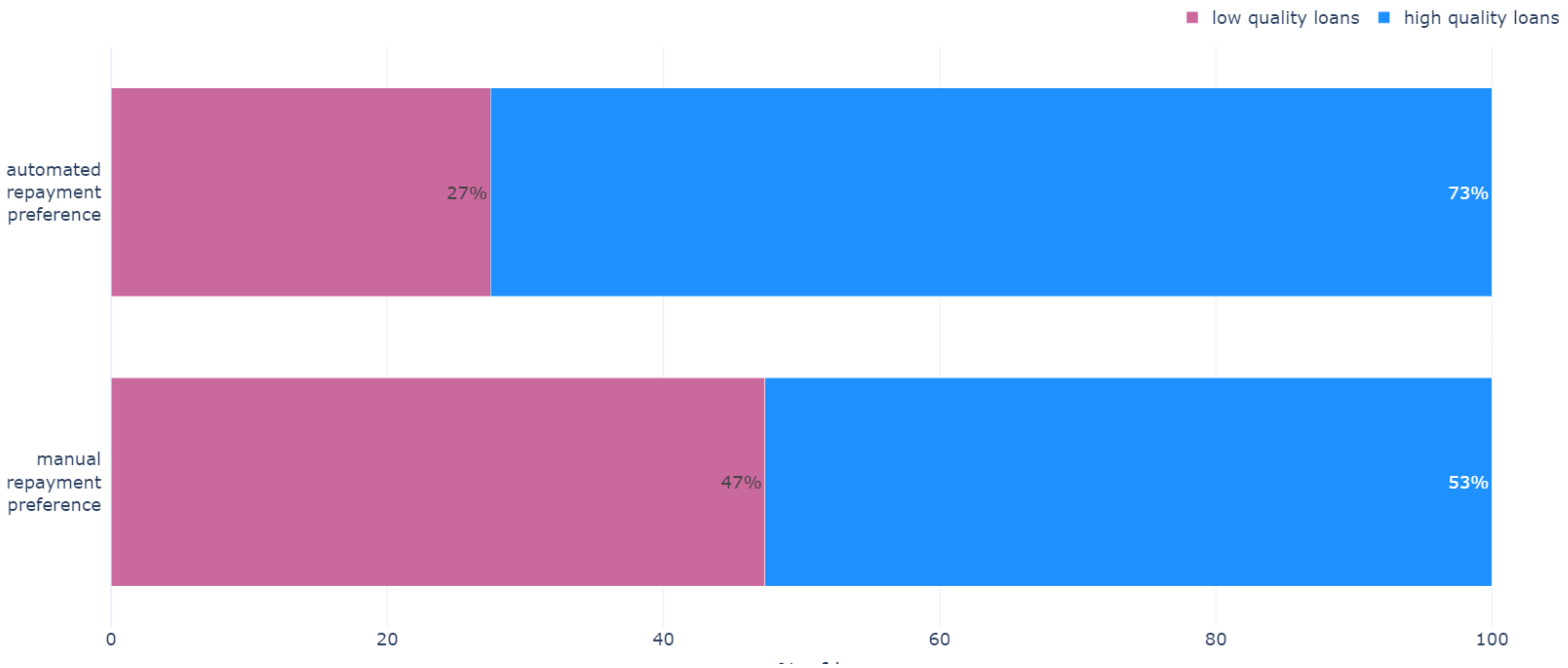


Users who exceed the repayment due dates are typically associated with riskier repayment behaviors

Recent and Inactive users have shown a higher propensity to miss their due dates



Users who don’t prefer automated repayment schedules are more likely to exhibit riskier repayment behavior



1. 2. 3. 4. **5.** 6.

Loan Repayment Model and Analysis

The model identifies 71% of the high-risk loan candidates, however, with low confidence levels

Results on the test set

	Precision	Recall	F1 score
low-risk candidate	88%	83%	85%
high-risk candidate	62%	71%	66%
overall	80%	80%	80%

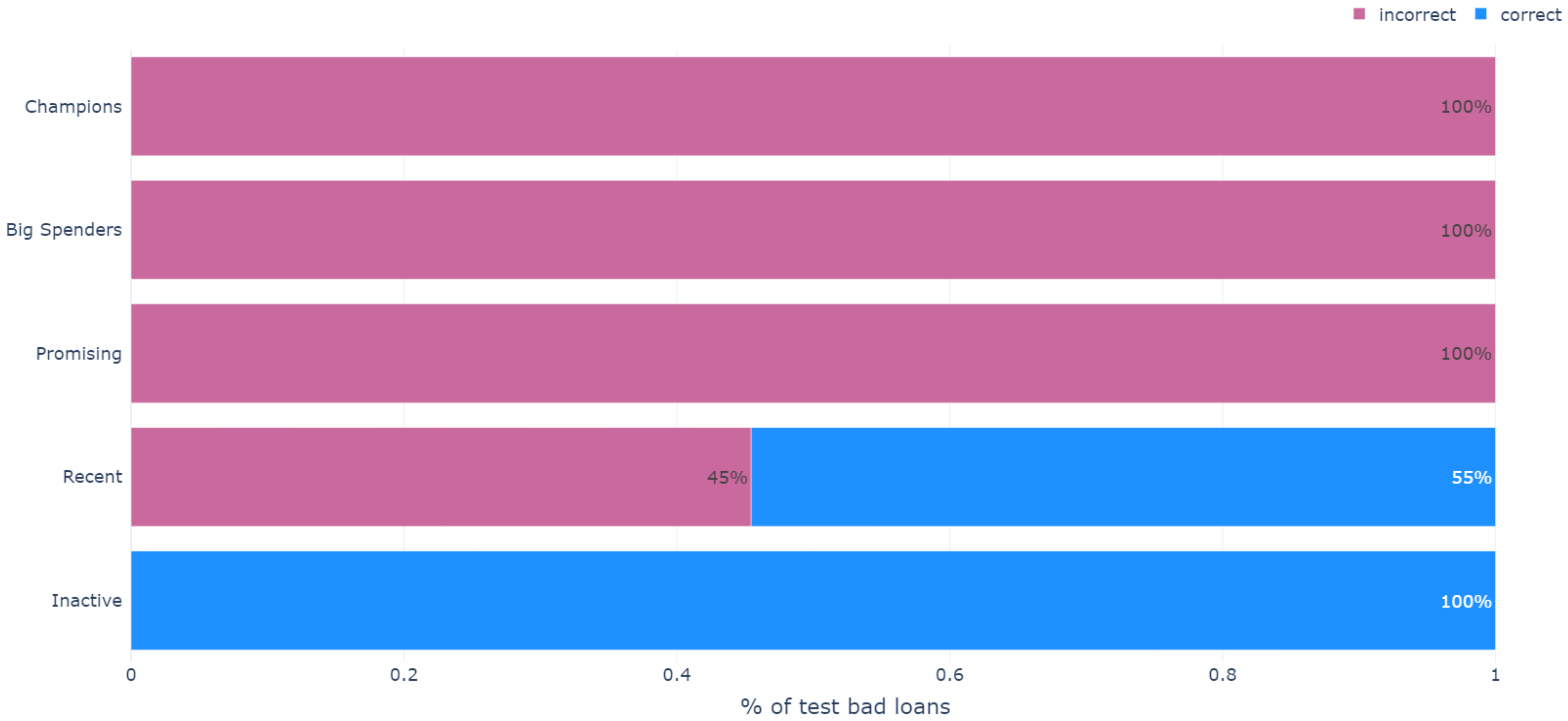
weighted avg. scores for Random Forest

Top predictive factors include

- **purchasing behavior** (RFM segments, transaction rejection rate, installment preference, preference of purchasing online)
- **repayment behavior** (preference of manual repayments, avg. repayment amount, users' portfolio of amount and interest rate sizes)
- **loan characteristics**

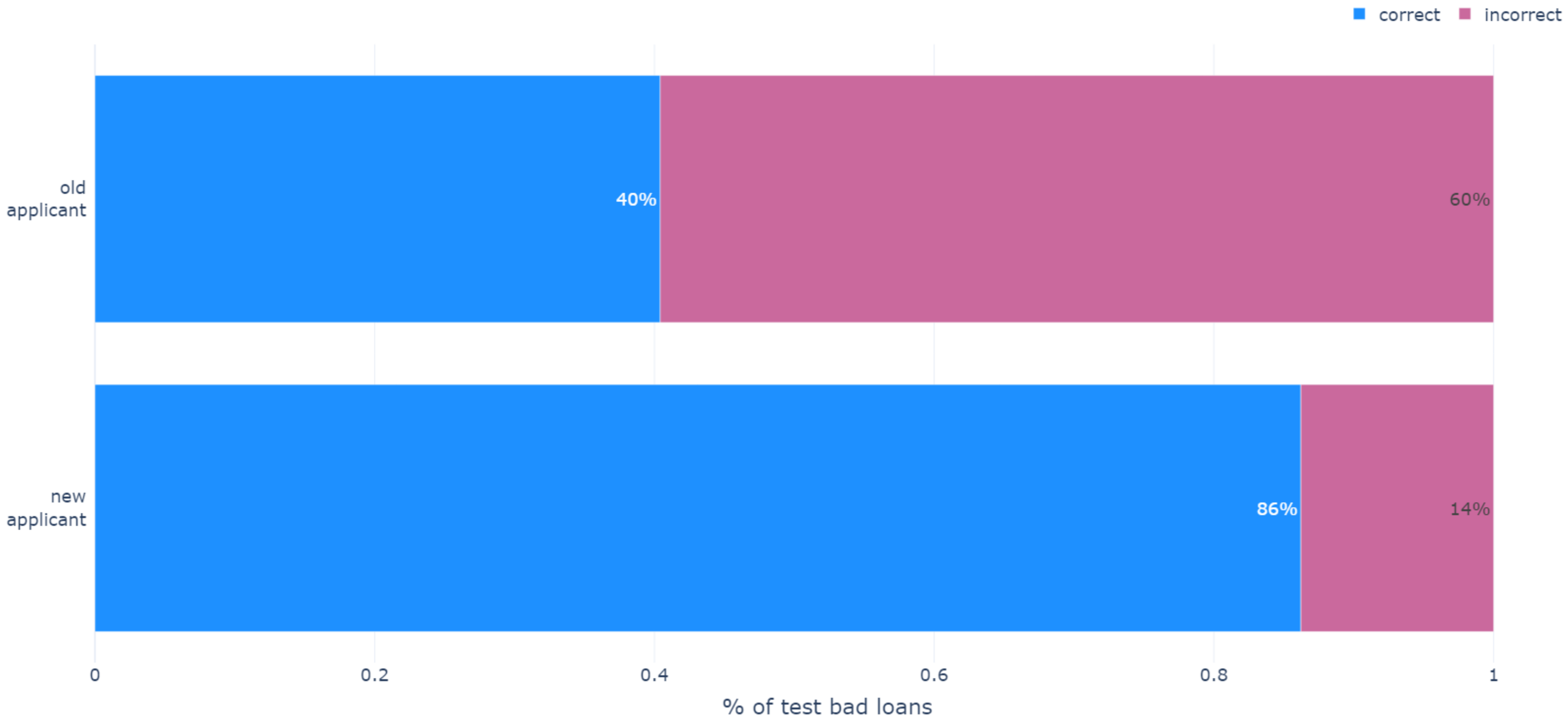
Challenge in predicting when “healthy” users incur high-risk loans

High-risk candidates in the test set



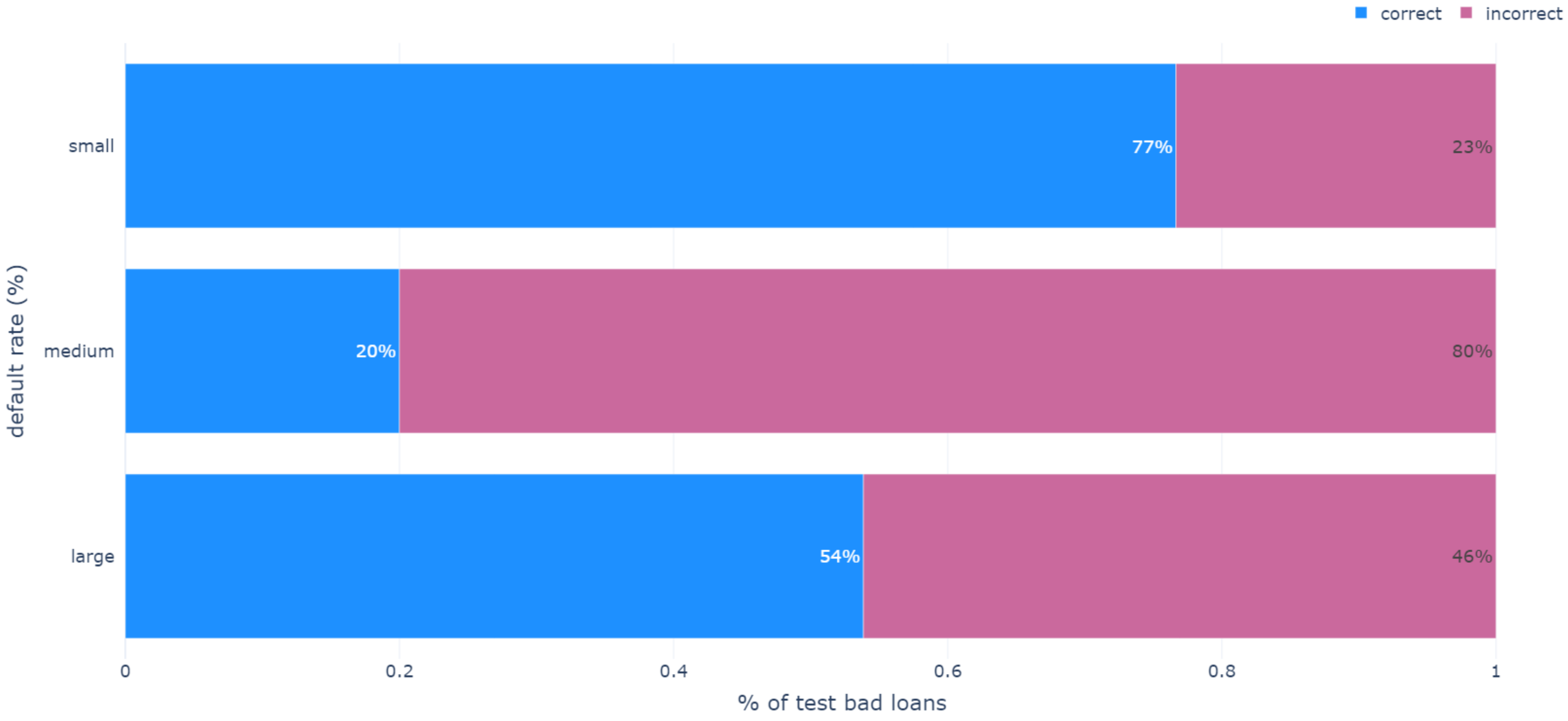
Although the model is accurate when assessing new applicants, its performance declines for old applicants

High-risk candidates in the test set



Difficulty to capture bad loan candidates with medium to large default rates

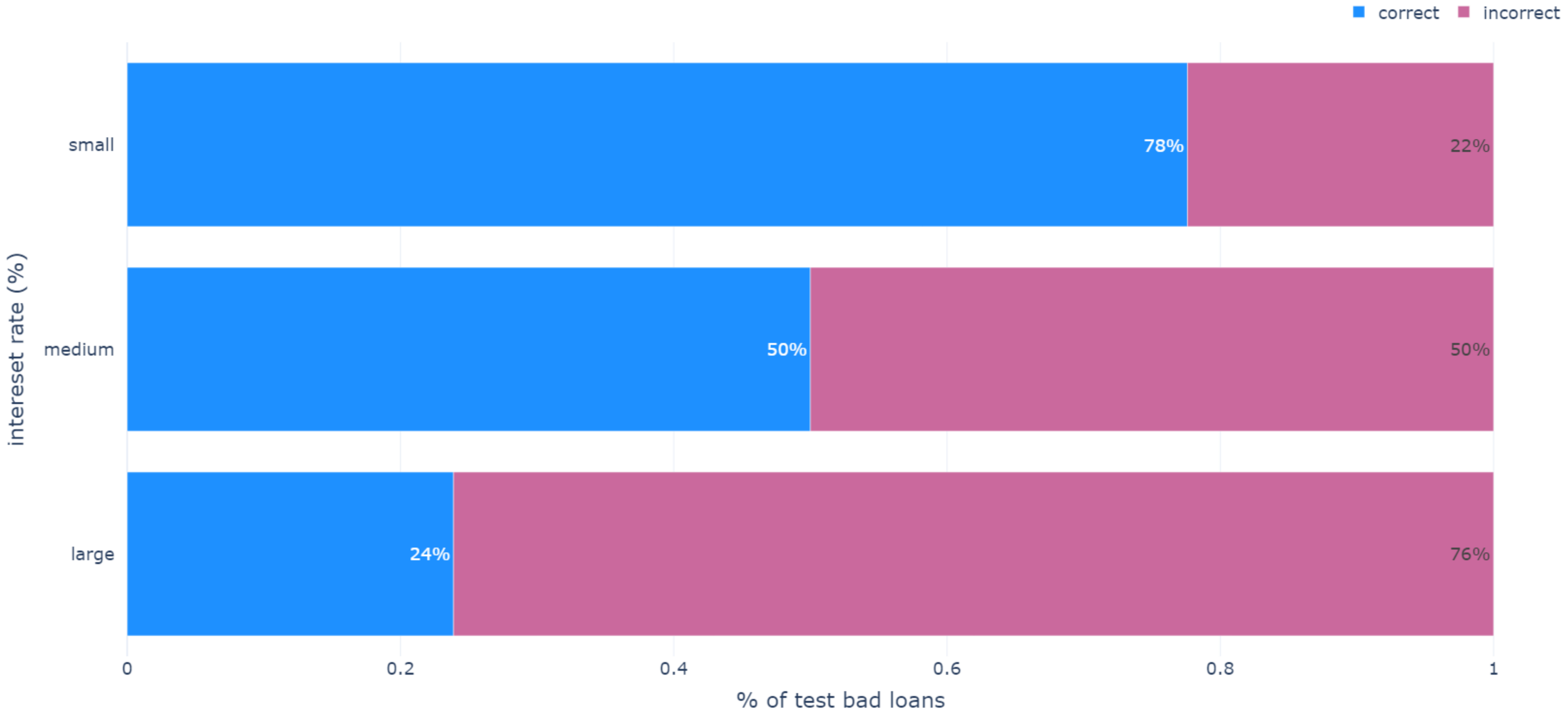
High-risk candidates in the test set



small: *less than 5%,* ***medium:*** *5% - 10% ,* ***large:*** *greater than 10%*

The model cannot capture bad repayment patterns mainly for loans with medium to large interest rates

High-risk candidates in the test set



***small:** less than 40%, **medium:** 40% - 100% , **large:** greater than 100%*

1. 2. 3. 4. 5. **6.**

Next Steps and Considerations

Next Steps and Considerations

- **Expand the set of features** to include user demographics (e.g., state, age, occupation, etc.) and other various loan characteristics (e.g., loan purpose, etc.).

- Transition from RFM customer analysis to a more refined **clustering** method to model customer purchasing behavioral patterns.

- **User embeddings** to capture complex and nuanced information about the users' behaviors, attributes, and interactions.

- **Signal features** about the user, e.g., when the user is taking loans, changes in lending amounts, etc.. Withing the context of Lending, *different signals* have *different strengths* and can quantify when the user is **switching context**.

Thank You!

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QnA Session