

# BANK LOAN APPROVAL & RISK ANALYSIS DASHBOARD WITH POWER BI

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## PROJECT OVERVIEW:

- This project analyzes synthetic bank loan application data to uncover insights on loan approvals, customer risk, and financial patterns. Built in Power BI, it demonstrates how banks can make informed decisions in loan processing and risk evaluation.

## PROBLEM STATEMENT

- Banks process a high volume of loan applications from individuals with varying income levels, credit scores, and financial behavior. Without proper evaluation, there's a risk of approving high-risk applicants or rejecting creditworthy ones. This project explores how data analysis can support smarter approval decisions, reduce defaults, and improve lending outcomes.

## PROJECT GOAL

- To analyze loan applications and borrower profiles to identify key approval patterns, assess loan risks, and help banks optimize decision-making.

## DASHBOARD PACKAGE

- A 3-page interactive Power BI report containing:
  1. **Loan Approval Overview:** Key metrics and approval trends by income, credit score, and age
  2. **Risk & Financial Behavior:** Borrower risk analysis based on credit score, defaults, and employment
  3. **Customer Segments & Repayment:** Insights into repayment behavior across loan amounts and demographics

## LINKS

- Dataset: <https://www.kaggle.com/datasets/lorenzozoppelletto/financial-risk-for-loan-approval>
- GitHub: <https://github.com/marktheanalyst103/-loan-risk-powerbi-dashboard>

## KEY QUESTIONS

### LOAN APPROVAL OVERVIEW

- *How many loan applications were submitted in total?*
- *What is the average approval rate across all applications?*
- *What are the average financial traits of the applicants?*
- *How does annual income impact loan approval rate?*
- *What credit score ranges are most common among approved applicants?*
- *Which age groups have higher or lower approval rates?*
- *How have application and approval trends changed over the years?*

### RISK AND FINANCIAL BEHAVIOR

- *Which employment statuses have the highest number of previous loan defaults?*
- *What is the approval rate across different loan purposes when segmented by employment status?*
- *What's the average risk score, default count, and debt-to-income ratio for each loan purpose?*
- *How does credit score affect loan approvals and denials?*

### CUSTOMER SEGMENTS AND REPAYMENT

- *What are the average loan terms across the applicant pool?*
- *How does credit score influence the interest rate offered?*
- *Which employment status group contributes the most to total monthly loan payments?*
- *How do education level and marital status affect approval rates?*
- *Which loan amount categories carry the highest monthly payment obligations?*

## DATA UNDERSTANDING:

### ◆ Dataset Description

- Total Records: 20k
- Columns:
  - Application Date, Age, Annual Income, Credit Score, Employment Status, etc

ApplicationDate	Age	AnnualIncome	CreditScore	EmploymentStatus	EducationLevel	Experience	LoanAmount	LoanDuration	MaritalStatus	NumberOfDependents	HomeOwnershipStatus	MonthlyPayment
Tuesday, July 17, 2018	41	29020	583	Employed	High School	16	16570	60	Married	2	Mortgage	125
Monday, December 31, 2018	48	15248	515	Employed	High School	27	19403	36	Married	0	Mortgage	100
Sunday, February 24, 2019	40	81906	456	Employed	High School	18	76598	36	Married	0	Mortgage	100
Friday, November 8, 2019	26	15000	580	Employed	High School	5	10046	72	Married	2	Mortgage	125
Monday, February 3, 2020	38	30741	516	Employed	High School	15	13478	96	Married	0	Mortgage	100
Wednesday, April 8, 2020	34	45732	532	Employed	High School	13	19673	36	Married	3	Mortgage	125
Tuesday, July 26, 2022	33	26410	589	Employed	High School	11	12913	24	Married	1	Mortgage	75
Saturday, October 8, 2022	37	33640	552	Employed	High School	13	36165	36	Married	1	Mortgage	75
Wednesday, March 15, 2023	36	34995	557	Employed	High School	14	12923	48	Married	2	Mortgage	125
Saturday, August 17, 2024	52	70016	574	Employed	High School	30	20323	120	Married	2	Mortgage	125
Tuesday, March 25, 2025	61	36162	582	Employed	High School	40	47710	60	Married	1	Mortgage	75
Wednesday, May 21, 2025	24	15000	542	Employed	High School	3	35509	24	Married	3	Mortgage	125
Sunday, May 17, 2026	25	43148	438	Employed	High School	3	14211	72	Married	1	Mortgage	75
Saturday, June 20, 2026	38	23059	601	Employed	High School	13	18211	48	Married	3	Mortgage	125
Sunday, September 19, 2027	26	35302	548	Employed	High School	3	28857	36	Married	3	Mortgage	125
Saturday, November 20, 2027	40	33137	572	Employed	High School	18	13007	24	Married	1	Mortgage	75
Monday, July 10, 2028	23	37239	480	Employed	High School	4	34803	60	Married	1	Mortgage	75
Tuesday, December 12, 2028	59	36976	573	Employed	High School	36	20908	36	Married	1	Mortgage	75
Wednesday, January 24, 2029	49	49505	574	Employed	High School	25	25809	108	Married	2	Mortgage	125
Friday, May 11, 2029	33	20151	580	Employed	High School	9	23135	12	Married	1	Mortgage	75
Thursday, August 2, 2029	56	22915	619	Employed	High School	32	19122	60	Married	0	Mortgage	100
Thursday, November 1, 2029	54	52319	521	Employed	High School	30	11636	48	Married	3	Mortgage	125
Saturday, November 2, 2030	22	20112	564	Employed	High School	4	15945	36	Married	0	Mortgage	100
Monday, November 4, 2030	39	59025	488	Employed	High School	17	28662	36	Married	0	Mortgage	100
Wednesday, April 2, 2031	32	33327	547	Employed	High School	6	30303	108	Married	1	Mortgage	75
Monday, June 2, 2031	35	20115	530	Employed	High School	11	11427	60	Married	4	Mortgage	125
Thursday, August 7, 2031	28	16600	497	Employed	High School	7	16472	72	Married	0	Mortgage	100

### ◆ Data Cleaning

- Cleaned the **LoanPurpose** column by handling null and inconsistent entries, assigning missing values to "Others" for clarity and consistency.

LoanPurpose	Age	AnnualIncome	CreditScore	EmploymentStatus	EducationLevel	Experience	LoanAmount	LoanDuration	MaritalStatus	NumberOfDependents	HomeOwnershipStatus	MonthlyPayment
Other	41	29020	583	Employed	High School	16	16570	60	Married	2	Mortgage	125
Other	48	15248	515	Employed	High School	27	19403	36	Married	0	Mortgage	100
Other	40	81906	456	Employed	High School	18	76598	36	Married	0	Mortgage	100
Other	26	15000	580	Employed	High School	5	10046	72	Married	2	Mortgage	125
Other	38	30741	516	Employed	High School	15	13478	96	Married	0	Mortgage	100
Other	34	45732	532	Employed	High School	13	19673	36	Married	3	Mortgage	125
Other	33	26410	589	Employed	High School	11	12913	24	Married	1	Mortgage	75
Other	37	33640	552	Employed	High School	13	36165	36	Married	1	Mortgage	75
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Other	52	70016	574	Employed	High School	30	20323	120	Married	2	Mortgage	125
Other	61	36162	582	Employed	High School	40	47710	60	Married	1	Mortgage	75
Other	24	15000	542	Employed	High School	3	35509	24	Married	3	Mortgage	125
Other	25	43148	438	Employed	High School	3	14211	72	Married	1	Mortgage	75
Other	38	23059	601	Employed	High School	13	18211	48	Married	3	Mortgage	125
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Other	59	36976	573	Employed	High School	36	20908	36	Married	1	Mortgage	75
Other	49	49505	574	Employed	High School	25	25809	108	Married	2	Mortgage	125
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Other	35	20115	530	Employed	High School	11	11427	60	Married	4	Mortgage	125
Other	28	16600	497	Employed	High School	7	16472	72	Married	0	Mortgage	100

## ◆ Data Exploration

- Created custom columns for binned and ranged data, and added calculated fields to support analysis and visualization.

The screenshot shows a data analysis tool interface. At the top, there's a menu bar with 'File', 'Home', 'Help', 'Table tools', and 'Column tools'. Below the menu, there's a 'Name' field set to 'AgeGroup2' and a 'Data type' dropdown set to 'Text'. To the right, there are options for 'Format' (Text), 'Summarization' (Don't summarize), and 'Data category' (Uncategorized). Further right are icons for 'Sort by column', 'Data groups', 'Manage relationships', and 'New column calculations'. The main area is divided into 'Structure' and 'Properties' tabs. The 'Structure' tab is active, showing a list of columns: RiskScore, CreditScore (bins), CreditScoreTier, CreditScoreTier2, Income Group, IncomeGroup2, AgeGroup, AgeGroup2, LoanStatusLabel, YearGroup, CreditScore (bins2), BankruptcyHistoryStatus, and LoanAmount. The 'AgeGroup2' column is highlighted. A red box highlights the formula for 'AgeGroup2' in the 'Structure' tab:

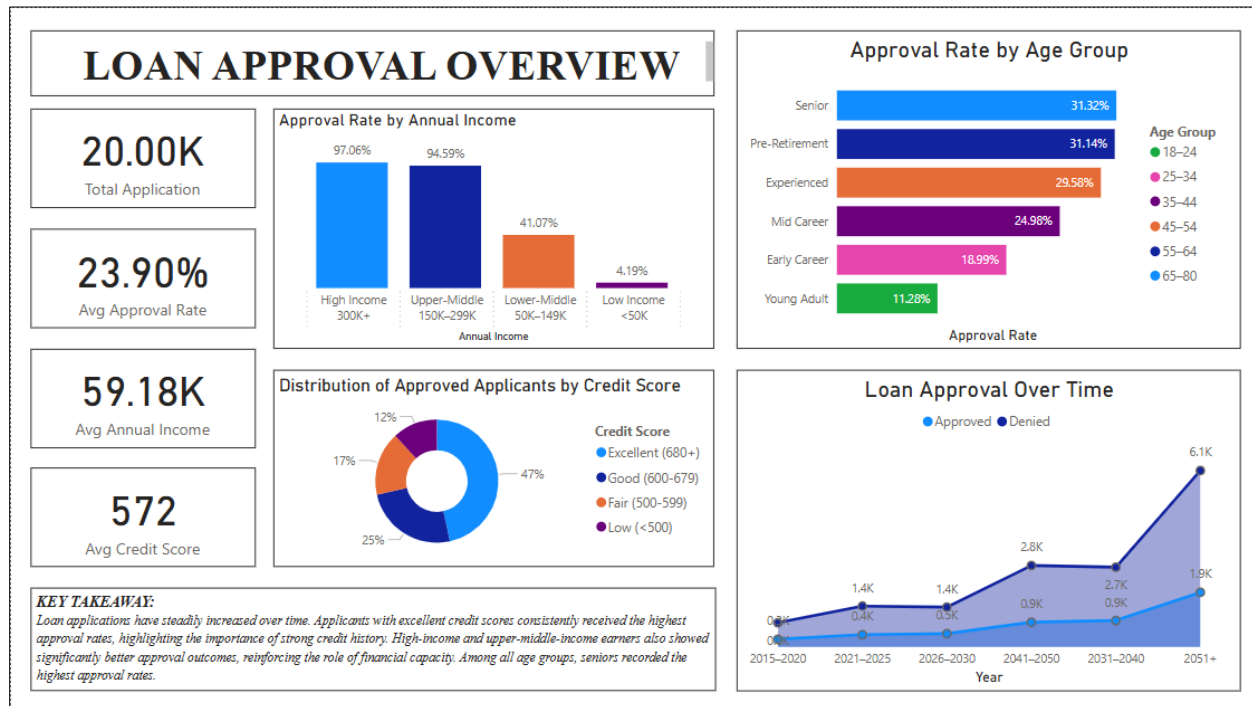
```
1 AgeGroup2 =  
2 SWITCH(TRUE(),  
3   Loan[Age] >= 18 && Loan[Age] <= 24, "Young Adult",  
4   Loan[Age] >= 25 && Loan[Age] <= 34, "Early Career",  
5   Loan[Age] >= 35 && Loan[Age] <= 44, "Mid Career",  
6   Loan[Age] >= 45 && Loan[Age] <= 54, "Experienced",  
7   Loan[Age] >= 55 && Loan[Age] <= 64, "Pre-Retirement",  
8   Loan[Age] >= 65 && Loan[Age] <= 80, "Senior",  
9   "Other"  
10 )
```

Below the formula, a table of data is shown. The table has 12 columns: RiskScore, CreditScore (bins), CreditScoreTier, CreditScoreTier2, Income Group, IncomeGroup2, AgeGroup, AgeGroup2, LoanStatusLabel, YearGroup, CreditScore (bins2), BankruptcyHistoryStatus, and LoanAmount. The table contains 20 rows of data. A red box highlights the 'AgeGroup2' column in the table, showing values like 'Mid Career', 'Experienced', 'Pre-Retirement', 'Young Adult', 'Early Career', and 'Senior'.

RiskScore	CreditScore (bins)	CreditScoreTier	CreditScoreTier2	Income Group	IncomeGroup2	AgeGroup	AgeGroup2	LoanStatusLabel	YearGroup	CreditScore (bins2)	BankruptcyHistoryStatus	LoanAmount
53	500	Fair (500-599)	500-599	Low Income	<50K	35-44	Mid Career	Denied	2015-2020	575	No	<25k
57	500	Fair (500-599)	500-599	Low Income	<50K	45-54	Experienced	Denied	2015-2020	500	No	<25k
54	400	Low (<500)	<500	Lower-Middle	50K-149K	35-44	Mid Career	Denied	2015-2020	450	No	75k-124k
59	500	Fair (500-599)	500-599	Low Income	<50K	25-34	Early Career	Denied	2015-2020	575	No	<25k
55	500	Fair (500-599)	500-599	Low Income	<50K	35-44	Mid Career	Denied	2015-2020	500	No	<25k
57	500	Fair (500-599)	500-599	Low Income	<50K	25-34	Early Career	Denied	2015-2020	525	No	<25k
52	500	Fair (500-599)	500-599	Low Income	<50K	25-34	Early Career	Denied	2021-2025	575	No	<25k
52	500	Fair (500-599)	500-599	Low Income	<50K	35-44	Mid Career	Denied	2021-2025	550	No	25k-74k
56	500	Fair (500-599)	500-599	Low Income	<50K	35-44	Mid Career	Denied	2021-2025	550	No	<25k
59	500	Fair (500-599)	500-599	Lower-Middle	50K-149K	45-54	Experienced	Denied	2021-2025	550	No	<25k
52	500	Fair (500-599)	500-599	Low Income	<50K	55-64	Pre-Retirement	Denied	2021-2025	575	No	25k-74k
54	500	Fair (500-599)	500-599	Low Income	<50K	18-24	Young Adult	Denied	2021-2025	525	No	25k-74k
59	400	Low (<500)	<500	Low Income	<50K	25-34	Early Career	Denied	2026-2030	425	No	<25k
54	600	Good (600-679)	600-679	Low Income	<50K	35-44	Mid Career	Denied	2026-2030	600	No	<25k
56	500	Fair (500-599)	500-599	Low Income	<50K	25-34	Early Career	Denied	2026-2030	525	No	25k-74k
52	500	Fair (500-599)	500-599	Low Income	<50K	35-44	Mid Career	Denied	2026-2030	550	No	<25k
58	400	Low (<500)	<500	Low Income	<50K	18-24	Young Adult	Denied	2026-2030	475	No	25k-74k
56	500	Fair (500-599)	500-599	Low Income	<50K	55-64	Pre-Retirement	Denied	2026-2030	550	No	<25k
50	500	Fair (500-599)	500-599	Low Income	<50K	45-54	Experienced	Denied	2026-2030	550	No	25k-74k
59	500	Fair (500-599)	500-599	Low Income	<50K	25-34	Early Career	Denied	2026-2030	575	No	<25k

## DATA INSIGHTS AND INTERPRETATION

### LOAN APPROVAL OVERVIEW



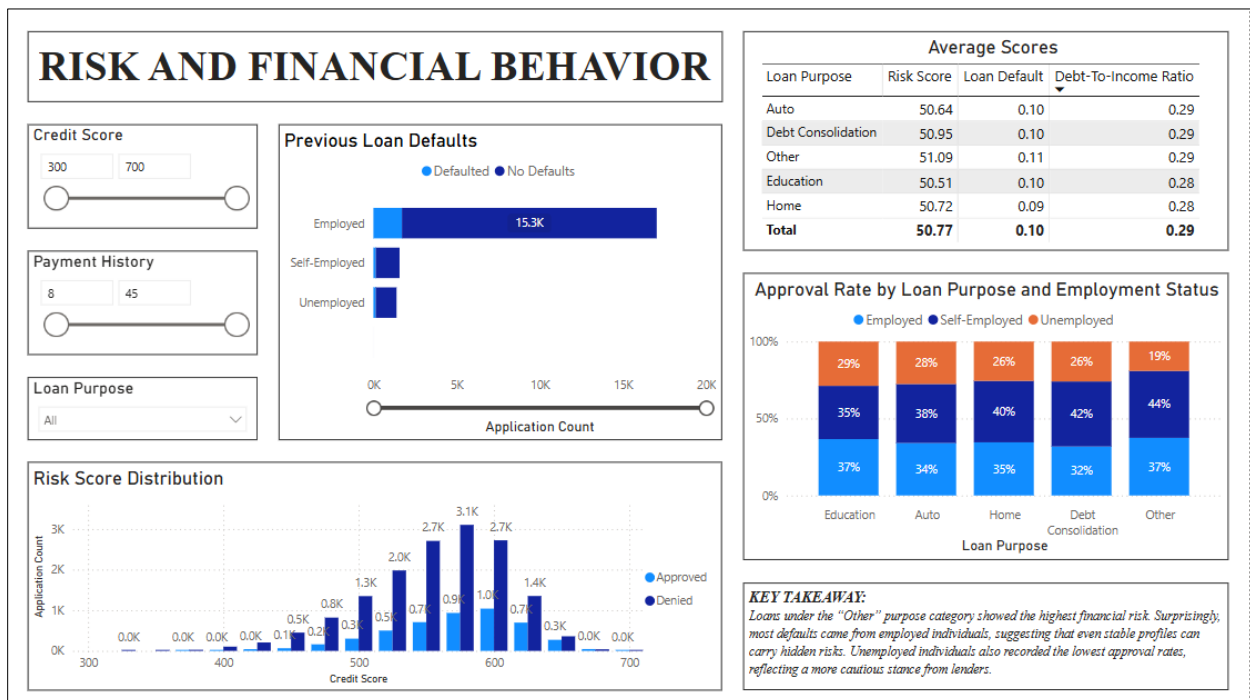
- This page provides a high-level summary of loan applicant trends, financial characteristics, and approval performance across time and demographic groups.

#### Key Questions Answered:

- How many loan applications were submitted in total?
  - 20k
- What is the average approval rate across all applications?
  - 23.90%
- What are the average financial traits of the applicants?
  - On average, applicants earn \$59.18K annually and have a credit score of 572, placing them within the lower-middle income and fair credit score tiers.
- How does annual income impact loan approval rate?
  - Loan approval is nearly guaranteed for applicants earning over \$150K, especially those in the high-income bracket (\$300K+), indicating a strong correlation between income and approval.
- What credit score ranges are most common among approved applicants?
  - Applicants with excellent credit scores (680+) accounted for the highest proportion of approved applications at 47%, followed by those with good (600-679), fair (500-599), and low (<500) credit scores.

- Which age groups have higher or lower approval rates?
  - *Approval rates were highest among applicants in the senior (31.32%) and pre-retirement (31.14%) age groups, suggesting greater lender confidence in older borrowers. In contrast, younger applicants in the early career (18.99%) and young adult (11.28%) categories experienced significantly lower approval outcomes.*
- How have application and approval trends changed over the years?
  - *The synthetic dataset shows a rising trend in loan applications over time, with the highest volume recorded in 2051+, totaling approximately 6.1K applications.*

## RISK AND FINANCIAL BEHAVIOR

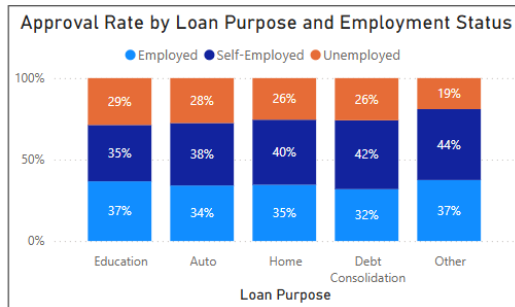


- This page explores the financial behavior and risk profiles of applicants through metrics like credit scores, loan default history, and debt-to-income ratio.

### Key Questions Answered:

- Which employment statuses have the highest number of previous loan defaults?
  - *Despite being considered financially stable, employed applicants had the highest volume of loan defaults, reaching 15.3K, highlighting that employment alone does not guarantee repayment reliability.*

- What is the approval rate across different loan purposes when segmented by employment status?



○ These results show that self-employed applicants generally receive higher approval rates across most loan purposes, while unemployed applicants consistently experience the lowest approval rates, particularly under the “Other” category.

- What’s the average risk score, default count, and debt-to-income ratio for each loan purpose?

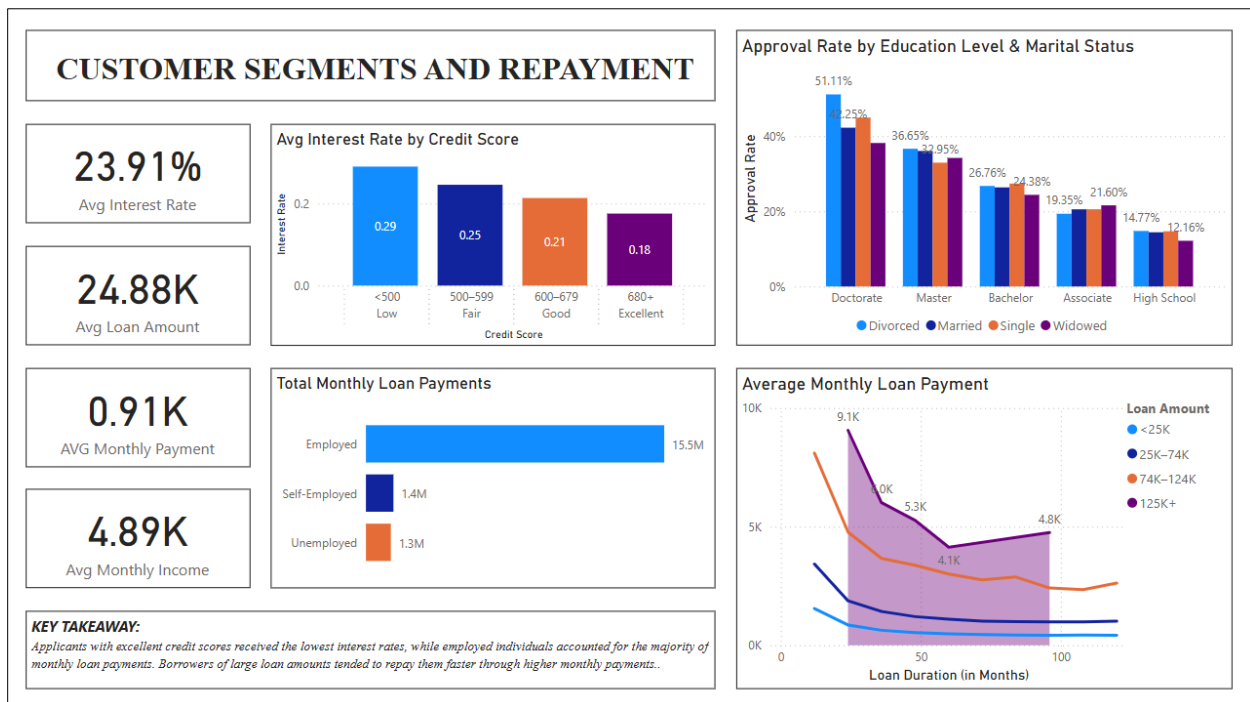
Average Scores			
Loan Purpose	Risk Score	Loan Default	Debt-To-Income Ratio
Auto	50.64	0.10	0.29
Debt Consolidation	50.95	0.10	0.29
Other	51.09	0.11	0.29
Education	50.51	0.10	0.28
Home	50.72	0.09	0.28
<b>Total</b>	<b>50.77</b>	<b>0.10</b>	<b>0.29</b>

• Across all loan purposes, the average risk score, default count, and debt-to-income ratio remain remarkably consistent. This consistency suggests that loan purpose alone may not be a strong differentiator in financial risk, and that deeper insights may depend more on other factors such as employment status or credit score.

- How does credit score affect loan approvals and denials?
  - The Risk Score Distribution shows a strong positive relationship between credit score and loan approval. High credit score ranges have visibly higher approval counts, while low scores correspond to increased denials.



## CUSTOMER SEGMENTS AND REPAYMENT



- This page profiles customer segments based on financial obligations and demographic characteristics, helping uncover patterns in repayment behavior and approval trends.



### Key Questions Answered:

- What are the average loan terms across the applicant pool?
  - 23.91%**  
Avg Interest Rate
  - 0.91K**  
AVG Monthly Payment
  - 24.88K**  
Avg Loan Amount
  - 4.89K**  
Avg Monthly Income
  - These values indicate that most applicants are managing moderately sized loans relative to their income. Monthly payments account for less than 20 percent of their earnings, which suggests a generally sustainable debt burden.*
- How does credit score influence the interest rate offered?
  - Higher credit scores are associated with lower interest rates. Applicants in the excellent credit tier (680+) receive an average rate of 18 percent, which is the lowest offered in the dataset. This highlights how strong creditworthiness directly improves loan affordability.*



- Which employment status group contributes the most to total monthly loan payments?
  - *Employed applicants contribute the highest total in monthly loan payments, amounting to 15.5 million. This reflects their larger presence and borrowing capacity within the applicant pool.*
  
- How do education level and marital status affect approval rates?
  - *Applicants with higher education levels tend to have higher approval rates. Doctorate holders lead in approval success, followed by those with master's, bachelor's, associate, and high school degrees. Marital status, however, appears to have little impact, as no clear trend is observed.*
  
- Which loan amount categories carry the highest monthly payment obligations?
  - *Loan amounts above \$125K carry the highest monthly payment obligations, peaking at \$9.1K. These large loans are also typically repaid over shorter periods, resulting in higher monthly costs.*



## KEY INSIGHTS

- Loan applications have steadily increased over time. Applicants with excellent credit scores consistently received the highest approval rates, highlighting the importance of strong credit history. High-income and upper-middle-income earners also showed significantly better approval outcomes, reinforcing the role of financial capacity. Among all age groups, seniors recorded the highest approval rates.
- Loans under the “Other” purpose category showed the highest financial risk. Surprisingly, most defaults came from employed individuals, suggesting that even stable profiles can carry hidden risks. Unemployed individuals also recorded the lowest approval rates, reflecting a more cautious stance from lenders.
- Applicants with excellent credit scores received the lowest interest rates, while employed individuals accounted for the majority of monthly loan payments. Borrowers of large loan amounts tended to repay them faster through higher monthly payments.



## RECOMMENDATIONS

- Prioritize applicants with excellent credit scores and strong income levels, as they consistently show higher approval rates and repayment reliability
- Implement stricter criteria or additional review steps for loans under the “Other” purpose category, which carry higher financial risk
- Conduct deeper risk profiling for employed applicants, since many defaults were recorded from this group despite their stable employment status
- Consider offering lower interest rates as incentives for applicants with excellent credit to encourage responsible borrowing
- Explore flexible repayment structures for high-value loans, since borrowers with larger amounts tend to repay faster through higher monthly payments



## REFLECTION & NEXT STEPS

- This project improved my skills in using Power BI to uncover insights on credit risk, income, and loan approvals. It deepened my understanding of borrower behavior and data-driven decision-making. Next, I plan to enhance the dashboard with real-time updates and explore basic predictive risk modeling.