POWER BI PROJECT

📊 How I Built a Power BI Report to Monitor Customer Credit Risk in Real Time For A Utility Company

This article is Part 3 of a 3-Part Series on Customer Credit Rating Modelling and Monitoring. *In Part 1, we engineered our utility billing dataset with diverse behavioral profiles. In Part 2, we trained a machine learning model to classify risk based on that behavior. Now, we bring those predictions to life in Power BI—creating an interactive dashboard that helps business users track trends, investigate accounts, and take action with confidence.*

By Jase Tran.

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1. Introduction

Motivation: Making Risk Predictions Actionable

While working as a Data Analyst at **Manitoba Hydro**, I saw firsthand how late-stage delinquency could erode revenue and disrupt operations. Early detection of at-risk accounts dramatically improved our ability to intervene and recover debt. But the real challenge wasn't just building predictive models—it was helping business teams understand and act on those predictions.

That insight led me to create a full-cycle credit risk monitoring solution. This three-part project series walks through that journey:

- ✅ **Part 1: Data Engineering** – Created a realistic utility billing dataset modeling customer behavior over time
- ✅ **Part 2: Machine Learning Classification** – Trained a model to assign behavioral risk classes (A, B, C) based on delinquency history
- 🔄 **Part 3: Power BI Report** – Built an interactive report to monitor risk, explain predictions, and support operational decision-making

What This Article Covers

In this final chapter, we turn machine learning predictions into real-time decision tools with Power BI. You'll see how the full risk pipeline—from data engineering to classification—comes together in an interactive dashboard designed for action. Here's what's inside:

- **Section 2: Dataset Summary**
  Recaps the simulated billing data and model predictions from earlier parts—highlighting key features like delinquency scores and risk classifications that drive our report.

- **Section 3: Report Walkthrough**
  Guides you through the three Power BI pages—Portfolio Overview, Account Explorer, and In-Depth Analysis—showing how each serves a unique operational need, from executive monitoring to account-level investigation.

- **Section 4: Case Studies**
  Presents six real example accounts (Classes A–C) to illustrate how different behaviors manifest in predictions—and how teams can respond based on model insights.

- **Section 5: Reflections and Takeaways**
  Summarizes what the report achieves, why it works in practice, and how it connects business teams to risk signals they can understand and act on.

By the end, you'll see how explainable analytics can transform raw data and predictive models into a live dashboard that powers informed credit and collections decisions.

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2. Dataset Summary: Foundation for Monitoring

Our solution starts with two core data layers developed earlier in this series: a behavioral billing dataset and a predictive model trained on account history. Together, they give us the tools to monitor delinquency risk at both the operational and strategic level.

Account & Billing Data

From Part 1 – Data Engineering Project

In Part 1, we built a synthetic dataset simulating over 14,000 utility accounts across six years of billing activity. This forms the foundation for all monitoring. Each account is tracked monthly in the **Balance Snapshots** table, capturing how their financial behavior evolves over time. Key elements include:

- **Delinquency Status** – Flags whether an account is active, suspended (temporarily frozen), or closed (written off due to non-payment)
- **Balance & Penalty** – Tracks financial pressure from missed or delayed payments
- **Delinquency Score** – A cumulative index that increases with payment issues and resets when accounts get back on track

Central to our delinquency monitoring system is the **delinquency score**, which acts as a behavioral thermometer and reflects accumulated debt pressure. Each missed or partial payment adds between **0.5 to 2.0** penalty points. As the delinquency score builds up:

- At **5.0**, the account is **suspended**—meaning no new activity until payment is made
- At **10.0**, it is **closed** and written off as uncollectible

This score-based system reflects how many real-world utilities handle delinquency escalation, and it creates clear behavioral signals we can use to detect and respond to risk.

Risk Prediction Data

From Part 2 – Machine Learning Project

In Part 2, we used this behavioral data to train a machine learning model that predicts credit risk based on account patterns. Every three months, the model classifies each account snapshot with:

- **Risk Class** – A (Low), B (Medium), or C (High)
- **Confidence Score** – Indicates how certain the model is in its prediction

- **SHAP-Based Explanations** – Lists top behavioral features influencing that decision

From our model training, we also uncovered clear patterns in how these risk groups behave:

- **Class A (Low Risk)** – Consistent payers, rarely miss, almost never face suspension or closure
- **Class B (Medium Risk)** – Mixed behavior; some recover, others deteriorate
- **Class C (High Risk)** – Repeatedly delinquent; account for **97% of all closures** and represent the most serious financial risk

These classifications help credit and collections teams focus their attention where it matters most.

Why This Data Matters for Monitoring

Together, these data layers give us exactly what we need for real-time credit risk monitoring:

- **Billing data** tells the story of what's already happened—missed payments, penalties, suspensions, and closures
- **Risk predictions** help us see what might happen next—and explain why

Power BI serves as the ideal platform to operationalize these insights, providing an interactive platform that supports daily operations, strategic review, and model transparency. In the next section, we'll walk through how these insights are brought to life across the report's three core pages.

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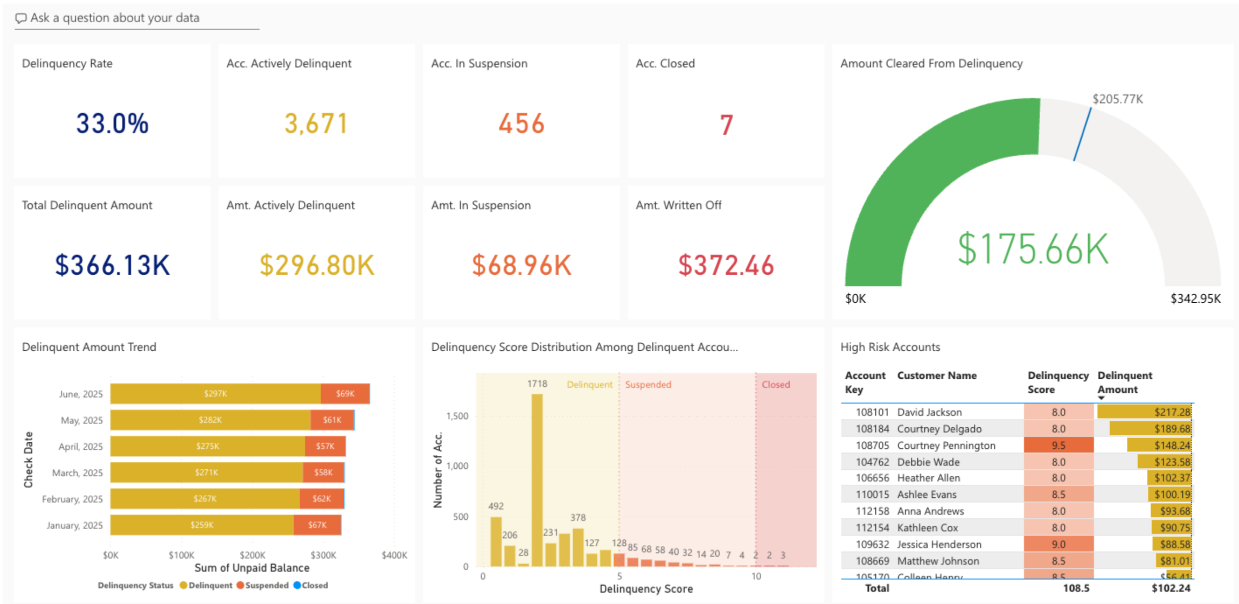
3. Report Walkthrough: From Portfolio Insights to Individual Accounts

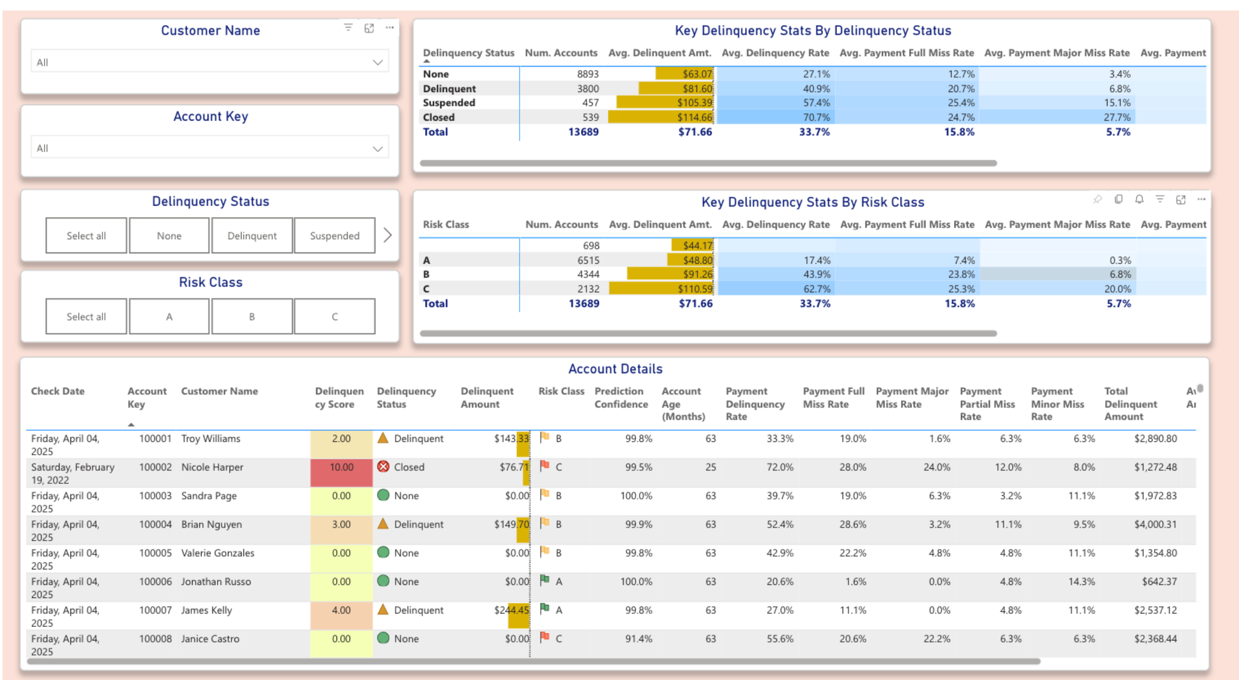
In this final stage of the project, we bring the risk classification outputs into a practical tool that supports real-time decision-making. We designed a powerful Power BI Report to help different users—from executives to analysts—monitor risk, investigate accounts, and take action based on predictions.

The report is divided into three interactive pages, each serving a specific use case:

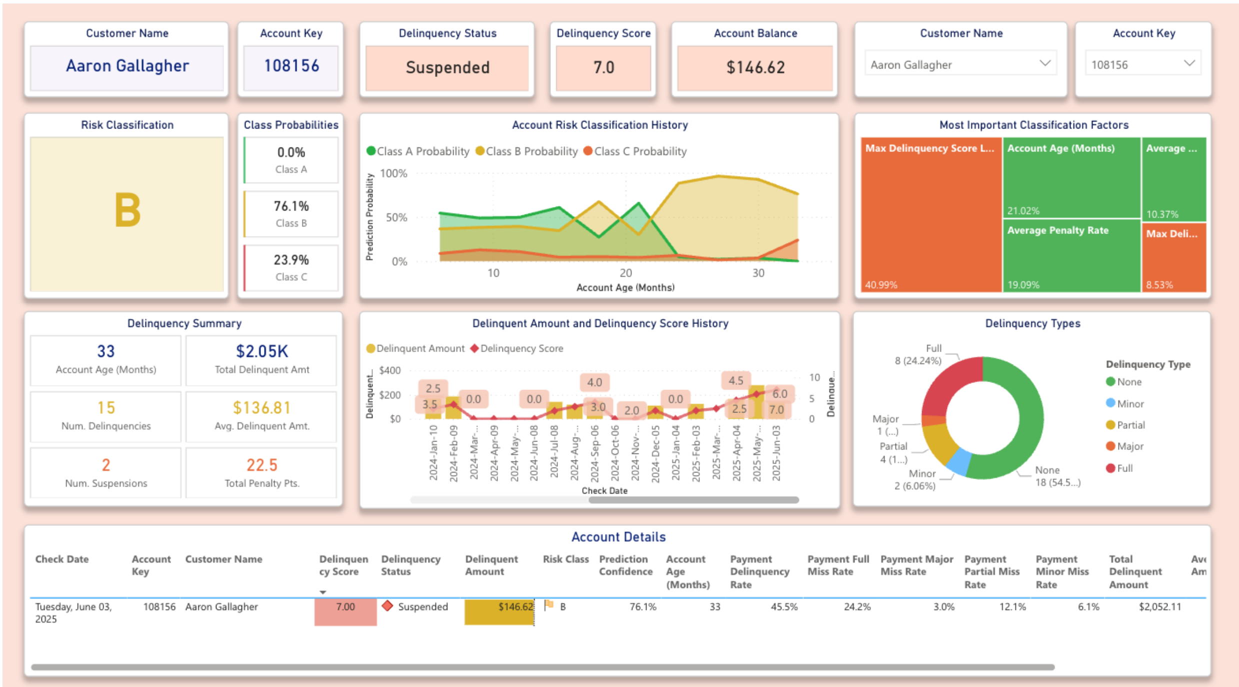
- **Page 1: Portfolio Overview Dashboard** provides a high-level view of delinquency trends, financial exposure, and recovery metrics. This dashboard is where leadership teams can assess overall risk and portfolio performance.



- **Page 2: Account Explorer** allows operational teams to search, segment, and evaluate specific accounts. Filters and summary tables help users find high-risk cases and compare behavior across groups.

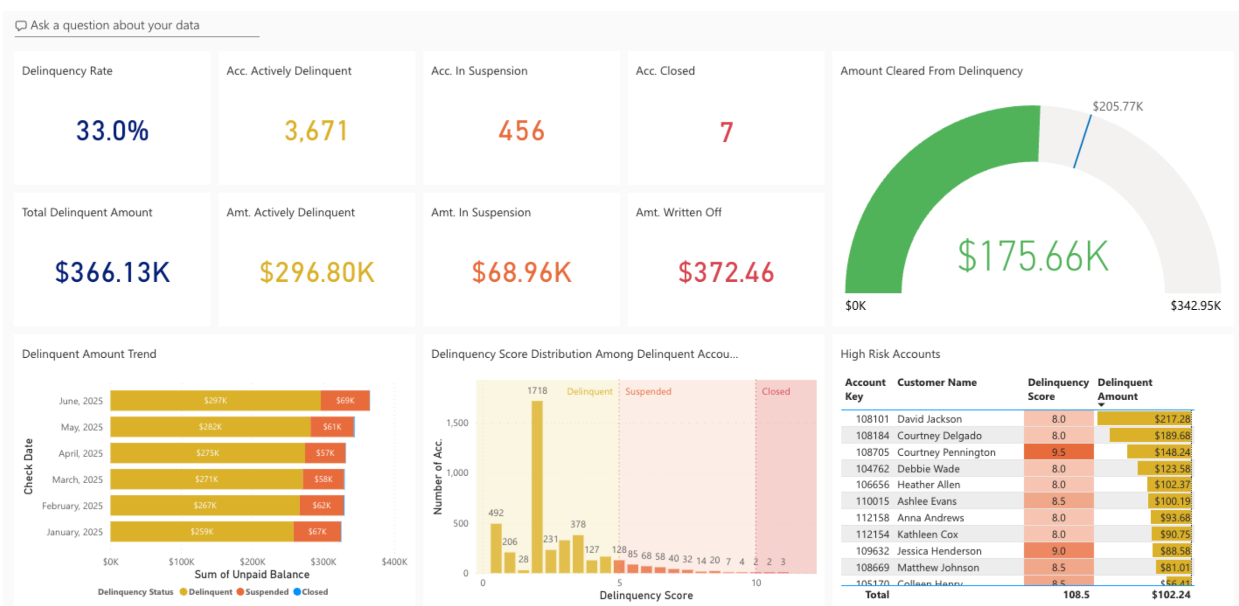


- **Page 3: In-Depth Analysis** is for detailed investigation. It shows how a prediction changed over time, what caused the risk score to increase or decrease, and which behaviors were most influential.



Page 1: Portfolio Overview Dashboard – Monitoring Risk at Scale

The **Portfolio Overview** dashboard gives a top-level summary of risk across the account base. This is where executives and finance leaders can track overall delinquency, monitor recovery progress, and spot emerging issues.



What it helps answer:

- How much of our portfolio is currently delinquent?
- Is risk getting better or worse over time?
- Where is risk most concentrated, and which accounts or are most exposed?

Behind the Scenes:

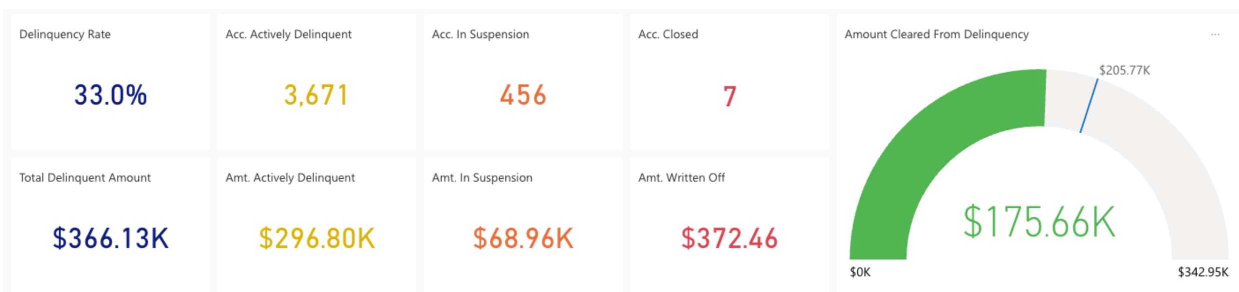
- These metrics are built with DAX logic using the final snapshot for each account. The filters update everything in real time, which supports dynamic exploration.

Key Components

1. Risk Exposure KPIs
A set of summary cards shows the latest metrics:

- **Delinquency Rate** – Percentage of active accounts with missed or partial payments
- **Delinquent Amount** – Total unpaid balance across those accounts
- **Suspended / Closed Accounts** – Counts of accounts in advanced delinquency stages
- **Recovery Amount vs. Target** – Measures how much delinquent debt has been recovered, compared to a target benchmark (set at 60%)

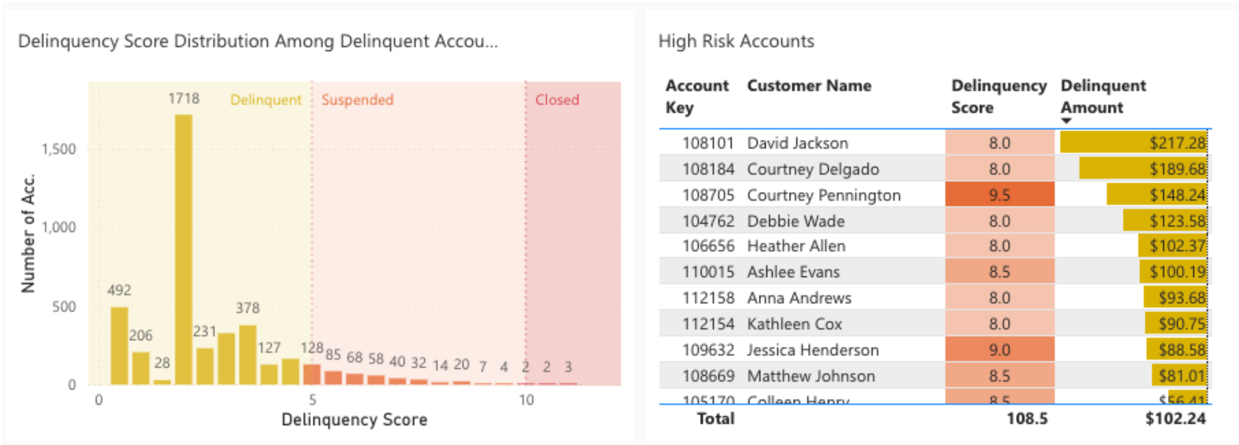
This section helps leadership track performance against goals and understand the scale of current risk.



2. Risk Distribution and Top Accounts
The next section gives more detail:

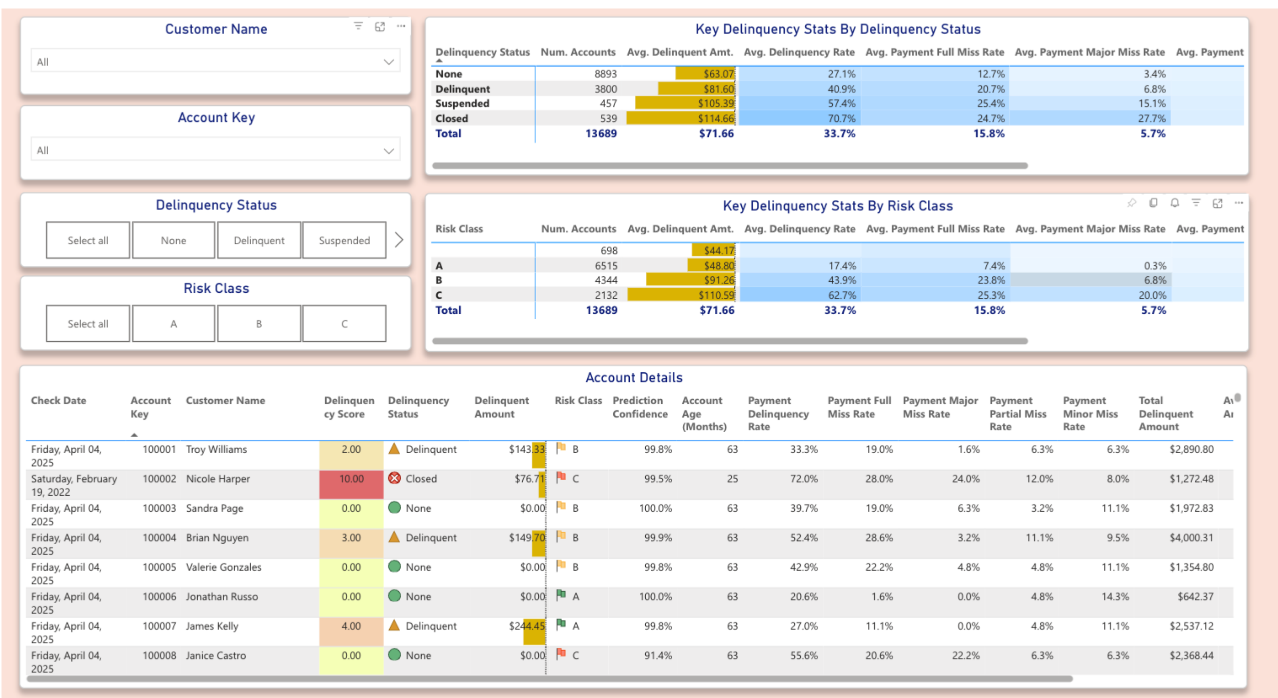
- A **delinquency score histogram** shows how accounts are distributed across risk bands.
- A **top accounts table** lists the highest-risk accounts based on their score and outstanding balance.

These views help collection and operations teams identify which accounts require immediate review or escalation.



Page 2: Account Explorer – Identifying At-Risk Accounts

The **Account Explorer** page is where analysts and operations teams go when they want to act. This is the main workspace for reviewing specific customers, comparing groups, and building intervention strategies.



What it helps answer:

- Which accounts are currently showing risky behavior?
- What does their payment history look like?
- How do different groups compare (e.g., Class C vs. Suspended)?

Behind the Scenes:

- This view uses the final snapshot from each account, with DAX and conditional formatting to flag red flags like high delinquency scores or persistent missed payments.

Key Components

1. Interactive Filter Panel

At the top of the page, users can filter by:

- Customer name or account ID
- Account status (delinquent, suspended, closed)
- Predicted risk class (A, B, or C)

These filters drive the entire page, making it quick to locate and compare specific segments.

2. Account Details Table

This is the core of the page. Each row represents one account and includes:

- Risk class and confidence
- Delinquency type and frequency
- Current status and outstanding balance

This is where teams can scan for issues, flag high-risk accounts, and prepare for outreach.

< Back to report | ACCOUNT DETAILS

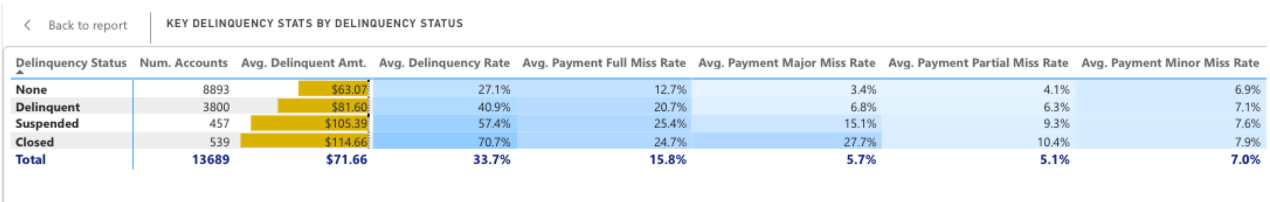
Check Date	Account Key	Customer Name	Delinquency Score	Delinquency Status	Delinquent Amount	Risk Class	Prediction Confidence	Account Age (Months)	Payment Delinquency Rate	Payment Full Miss Rate	Payment Major Miss Rate	Payment Partial Miss Rate	Payment Minor Miss Rate	Total Delinquent Amount	Average Amoun
Friday, April 04, 2025	100001	Troy Williams	2.00	Delinquent	$143.33	B	99.8%	63	33.3%	19.0%	1.6%	6.3%	6.3%	$2,890.80	
Saturday, February 19, 2022	100002	Nicole Harper	10.00	Closed	$76.71	C	99.5%	25	72.0%	28.0%	24.0%	12.0%	8.0%	$1,272.48	
Friday, April 04, 2025	100003	Sandra Page	0.00	None	$0.00	B	100.0%	63	39.7%	19.0%	6.3%	3.2%	11.1%	$1,972.83	
Friday, April 04, 2025	100004	Brian Nguyen	3.00	Delinquent	$149.70	B	99.9%	63	52.4%	28.6%	3.2%	11.1%	9.5%	$4,000.31	
Friday, April 04, 2025	100005	Valerie Gonzales	0.00	None	$0.00	B	99.8%	63	42.9%	22.2%	4.8%	4.8%	11.1%	$1,354.80	
Friday, April 04, 2025	100006	Jonathan Russo	0.00	None	$0.00	A	100.0%	63	20.6%	1.6%	0.0%	4.8%	14.3%	$642.37	
Friday, April 04, 2025	100007	James Kelly	4.00	Delinquent	$244.45	A	99.8%	63	27.0%	11.1%	0.0%	4.8%	11.1%	$2,537.12	
Friday, April 04, 2025	100008	Janice Castro	0.00	None	$0.00	C	91.4%	63	55.6%	20.6%	22.2%	6.3%	6.3%	$2,368.44	
Friday, April 04, 2025	100009	Julia Rodriguez	0.00	None	$0.00	A	100.0%	63	7.9%	1.6%	0.0%	1.6%	4.8%	$125.00	
Friday, April 04, 2025	100010	Wendy Baldwin	2.00	Delinquent	$104.40	B	100.0%	63	44.4%	25.4%	0.0%	11.1%	7.9%	$3,183.58	
Friday, April 04, 2025	100011	Nathaniel Phillips	1.00	Delinquent	$10.60	A	100.0%	63	19.0%	1.6%	0.0%	4.8%	12.7%	$196.74	
Friday, April 04, 2025	100012	Daniel Nolan	0.00	None	$0.00	A	100.0%	63	7.9%	3.2%	0.0%	1.6%	3.2%	$223.38	
Friday, April 04, 2025	100013	Edwin Garcia	0.00	None	$0.00	B	99.3%	63	47.6%	25.4%	7.9%	4.8%	9.5%	$4,167.57	
Friday, April 04, 2025	100014	Mr. Dylan Hudson	0.00	None	$0.00	A	100.0%	63	19.0%	9.5%	0.0%	1.6%	7.9%	$742.89	
Friday, April 04, 2025	100015	Sarah Fitzpatrick	0.00	None	$0.00	A	78.7%	63	28.6%	19.0%	0.0%	7.9%	1.6%	$778.65	
Friday, April 04, 2025	100016	David Small	0.00	None	$0.00	B	99.9%	63	41.3%	25.4%	4.8%	7.9%	3.2%	$2,308.96	
Friday, April 04, 2025	100017	Sharon Hall	1.50	Delinquent	$15.58	A	100.0%	63	11.1%	0.0%	0.0%	6.3%	4.8%	$88.98	
Friday, April 04, 2025	100018	Mrs. Brianna Bishop	2.00	Delinquent	$125.49	A	79.9%	63	28.6%	17.5%	1.6%	4.8%	4.8%	$2,185.85	
Wednesday, February 24, 2021	100019	Chelsea Hester	10.00	Closed	$43.37	C	98.6%	13	76.9%	30.8%	23.1%	15.4%	7.7%	$506.02	
Friday, April 04, 2025	100020	Allison Brooks	0.00	None	$0.00	B	82.6%	63	33.3%	14.3%	1.6%	7.9%	9.5%	$778.83	

3. Segment Summary Tables

Two summary tables sit at the top. They show behavioral averages across risk classes and account statuses:

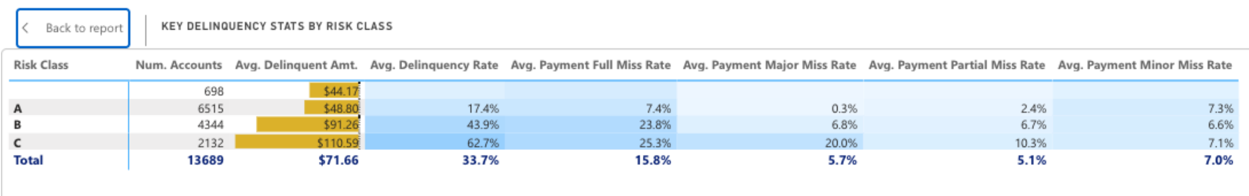
- Delinquency rates
- Payment types (full, partial, missed)
- Balance levels

This helps teams see how the filtered group behaves and compare patterns across segments.



Back to report | KEY DELINQUENCY STATS BY DELINQUENCY STATUS

Delinquency Status	Num. Accounts	Avg. Delinquent Amt.	Avg. Delinquency Rate	Avg. Payment Full Miss Rate	Avg. Payment Major Miss Rate	Avg. Payment Partial Miss Rate	Avg. Payment Minor Miss Rate
None	8893	$63.07	27.1%	12.7%	3.4%	4.1%	6.9%
Delinquent	3800	$81.60	40.9%	20.7%	6.8%	6.3%	7.1%
Suspended	457	$105.39	57.4%	25.4%	15.1%	9.3%	7.6%
Closed	539	$114.66	70.7%	24.7%	27.7%	10.4%	7.9%
Total	**13689**	**$71.66**	**33.7%**	**15.8%**	**5.7%**	**5.1%**	**7.0%**

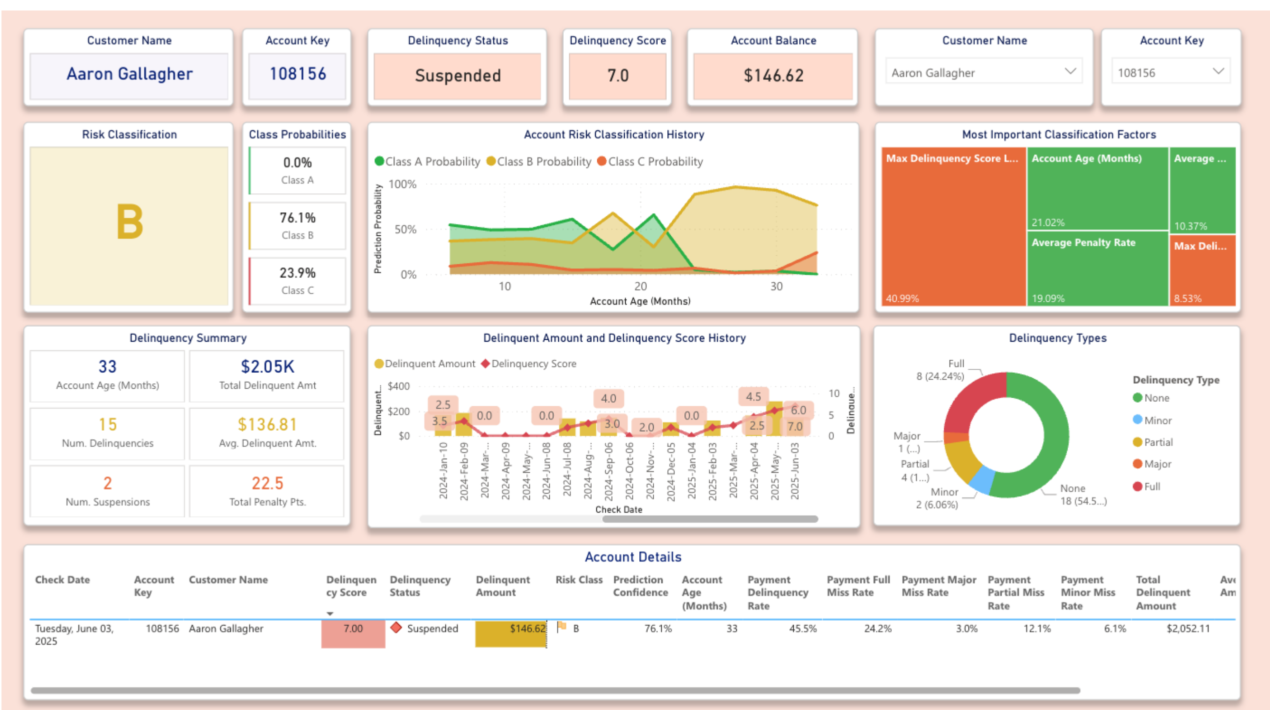


Back to report | KEY DELINQUENCY STATS BY RISK CLASS

Risk Class	Num. Accounts	Avg. Delinquent Amt.	Avg. Delinquency Rate	Avg. Payment Full Miss Rate	Avg. Payment Major Miss Rate	Avg. Payment Partial Miss Rate	Avg. Payment Minor Miss Rate
	698	$44.17					
A	6515	$48.80	17.4%	7.4%	0.3%	2.4%	7.3%
B	4344	$91.26	43.9%	23.8%	6.8%	6.7%	6.6%
C	2132	$110.59	62.7%	25.3%	20.0%	10.3%	7.1%
Total	**13689**	**$71.66**	**33.7%**	**15.8%**	**5.7%**	**5.1%**	**7.0%**

Page 3: In-Depth Analysis – Explaining Model Behavior

The **In-Depth Analysis** page is built for deeper dives. Analysts, model validators, and risk teams can use it to understand how the model reached its predictions and what behaviors were most important.



What it helps answer:

- How did the risk prediction change over time?
- Why did the model label this account as high, medium, or low risk?
- What were the main features driving the score?
- Was the model confident in its prediction?

Behind the Scenes:

- Confidence scores are calculated from the model's highest probability.
- SHAP values are preprocessed for each time point and merged into the dataset.

Key Components

1. Risk Overview Panel

This shows the latest classification:

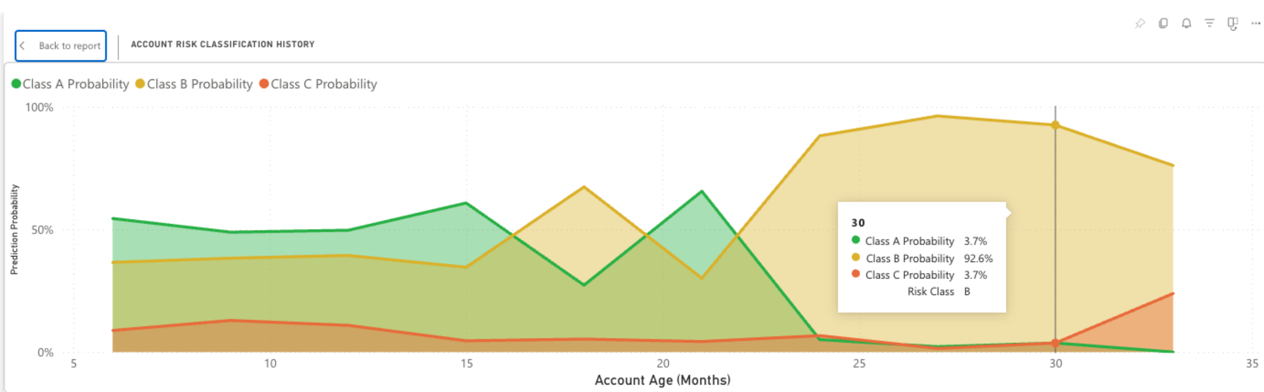
- Risk class and confidence
- Delinquency score, current balance, and account status

It gives a quick summary before diving into the timeline.

2. Risk Trajectory Chart

A line graph shows how the prediction probabilities for A, B, and C changed across the account lifecycle. It visualizes:

- Shifts from low to high risk
- Whether the account is recovering or worsening

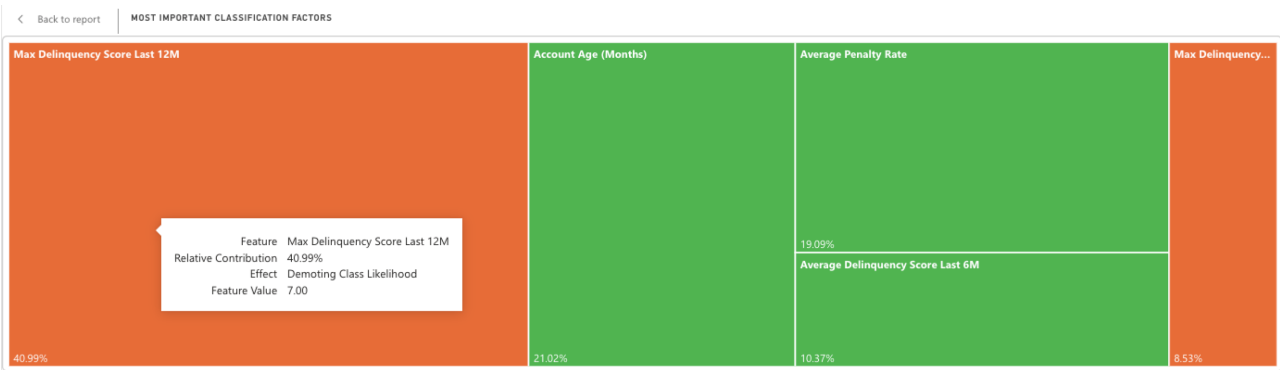


Account Age (Months)	Class A Probability	Class B Probability	Class C Probability	Risk Class
6	54.5%	36.6%	8.8%	A
9	48.9%	38.3%	12.9%	A
12	49.7%	39.4%	10.9%	A
15	60.8%	34.6%	4.6%	A
18	27.3%	67.4%	5.3%	B
21	65.6%	30.1%	4.3%	A
24	5.1%	88.2%	6.7%	B
27	2.2%	96.3%	1.5%	B
30	3.7%	92.6%	3.7%	B
33	0.0%	76.1%	23.9%	B

3. SHAP Feature Treemap

This chart shows the top 5 behaviors that influenced the latest prediction:

- Each block's size shows its impact
- Colors show whether the feature increased or decreased class likelihood.

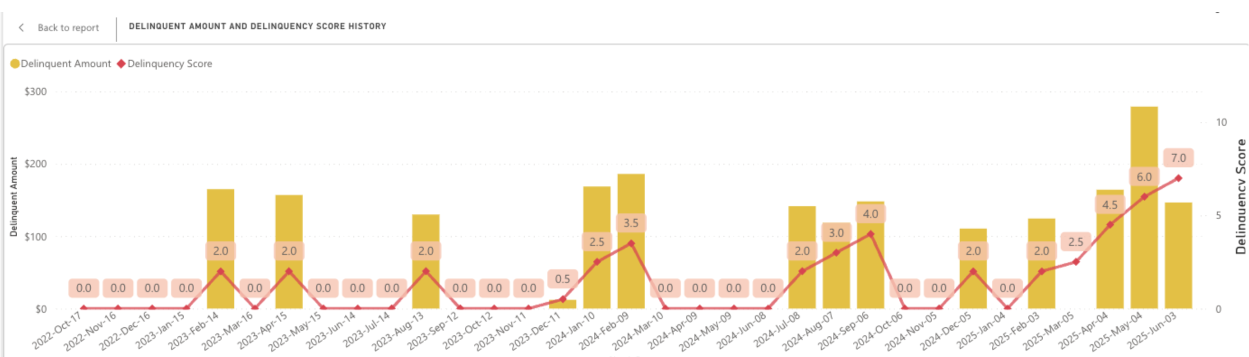


Feature	Relative Contribution	Effect	Feature Value
Max Delinquency Score Last 12M	40.99%	Demoting Class Likelihood	7.00
Account Age (Months)	21.02%	Promoting Class Likelihood	33.00
Average Penalty Rate	19.09%	Promoting Class Likelihood	0.68
Average Delinquency Score Last 6M	10.37%	Promoting Class Likelihood	3.67
Max Delinquency Score	8.53%	Demoting Class Likelihood	7.00

4. Delinquency Timeline

A bar and line chart that shows:

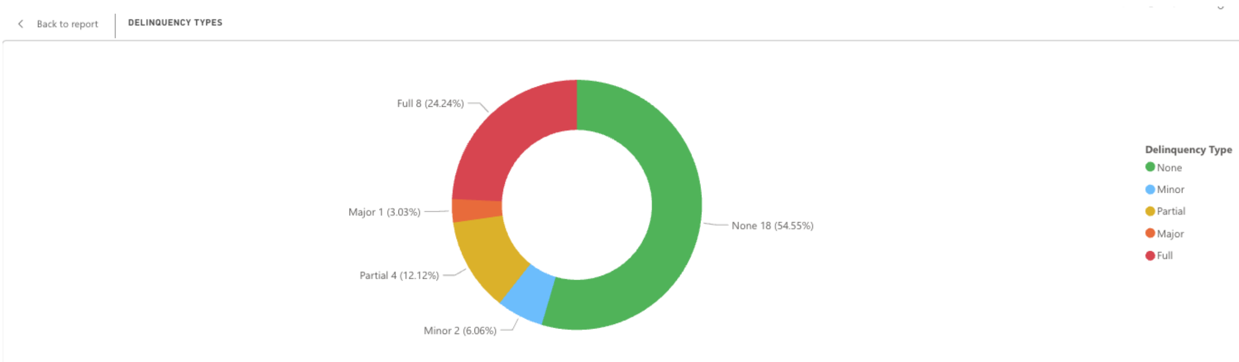
- Monthly delinquency scores
- Missed payments and penalty patterns
- How long the customer stayed in each delinquency state



Check Date	Delinquent Amount	Delinquency Score	Description	% Missed
2024-May-09	$0	0.00	Paid In Full	0.0%
2024-Jun-08	$0	0.00	Paid In Full	0.0%
2024-Jul-08	$141.56	2.00	Missed Full Payment	100.0%
2024-Aug-07	$118.53	3.00	Missed Partial Payment	45.6%
2024-Sep-06	$148.12	4.00	Missed Partial Payment	55.5%
2024-Oct-06	$0	0.00	Paid In Full	0.0%
2024-Nov-05	$0	0.00	Paid In Full	0.0%
2024-Dec-05	$110.57	2.00	Missed Full Payment	100.0%
2025-Jan-04	$0	0.00	Paid In Full	0.0%
2025-Feb-03	$124.45	2.00	Missed Full Payment	100.0%
2025-Mar-05	$0	2.50	Missed Minor Payment	0.0%
2025-Apr-04	$164.27	4.50	Missed Full Payment	100.0%
2025-May-04	$279.18	6.00	Missed Major Payment	89.6%
2025-Jun-03	$146.62	7.00	Missed Partial Payment	34.4%

5. Delinquency Type Breakdown

A donut chart summarizes the mix of full, major, and partial misses. This shows the account's overall payment behavior.



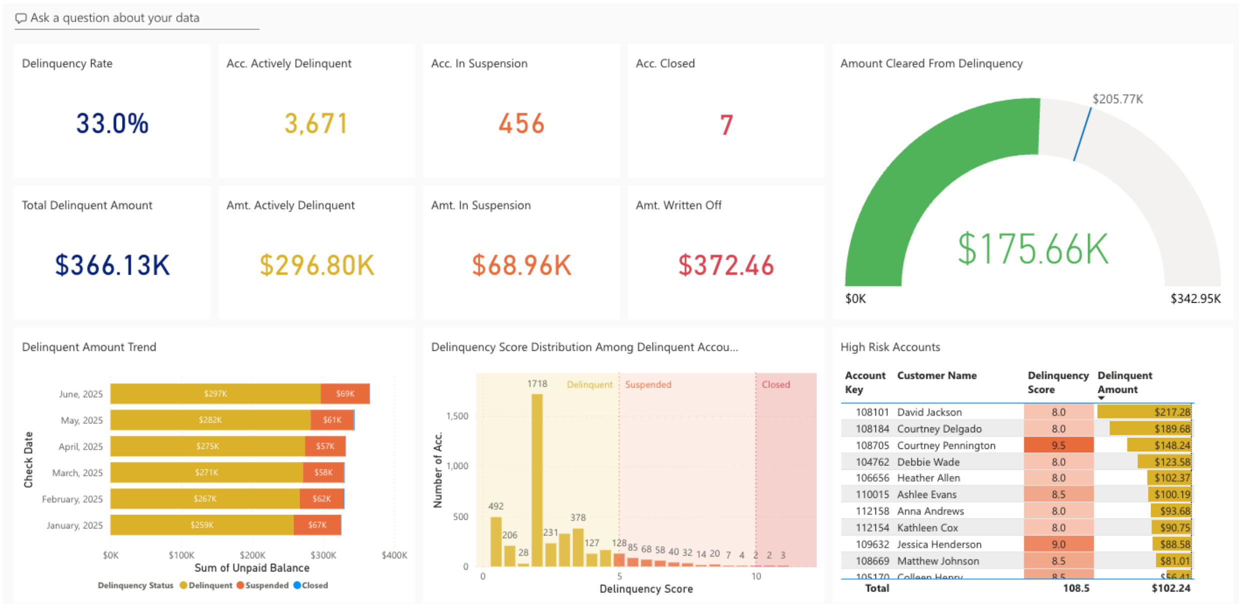
Delinquency Type	Count of Snapshot Key
None	18
Minor	2
Partial	4
Major	1
Full	8

Example Workflow – How a Risk Analyst Uses the Report

To show how everything works together, let's walk through a real example from the report.

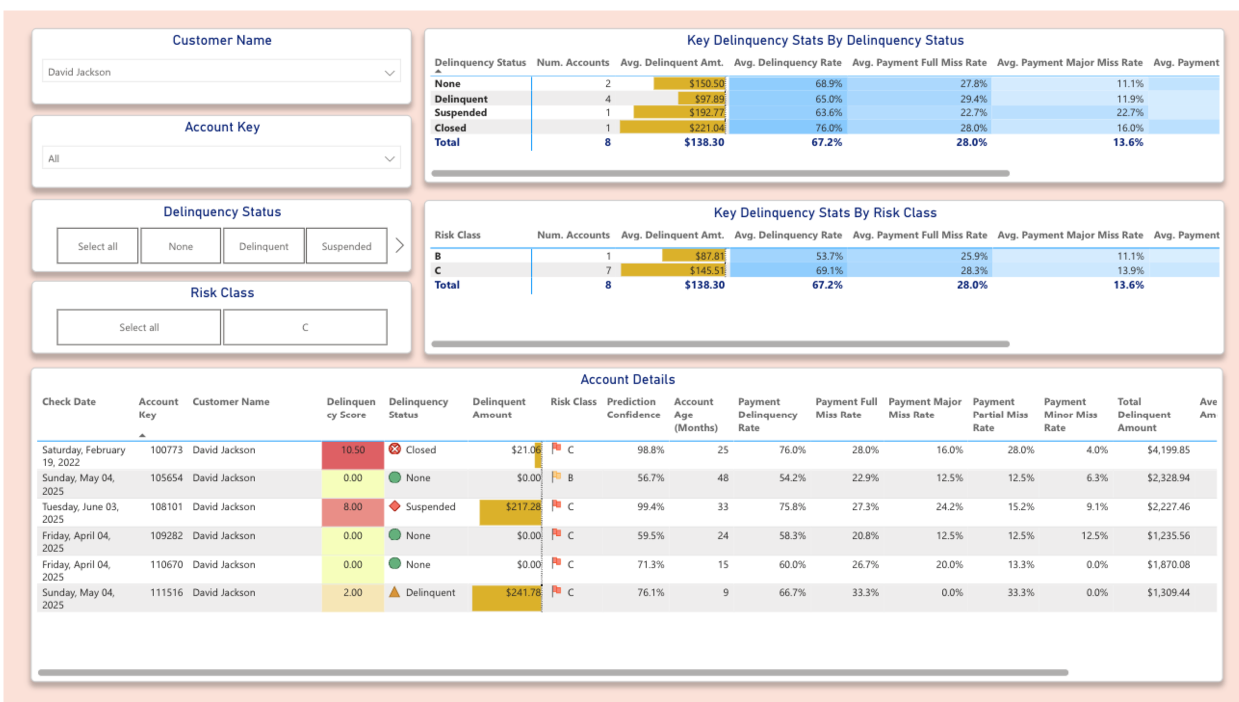
Step 1: Start at the Portfolio Overview

The analyst sees that the delinquency rate is rising, with more accounts trending toward suspension. A customer named **David Jackson** stands out in the Top Accounts list due to his high delinquency score and large unpaid balance.



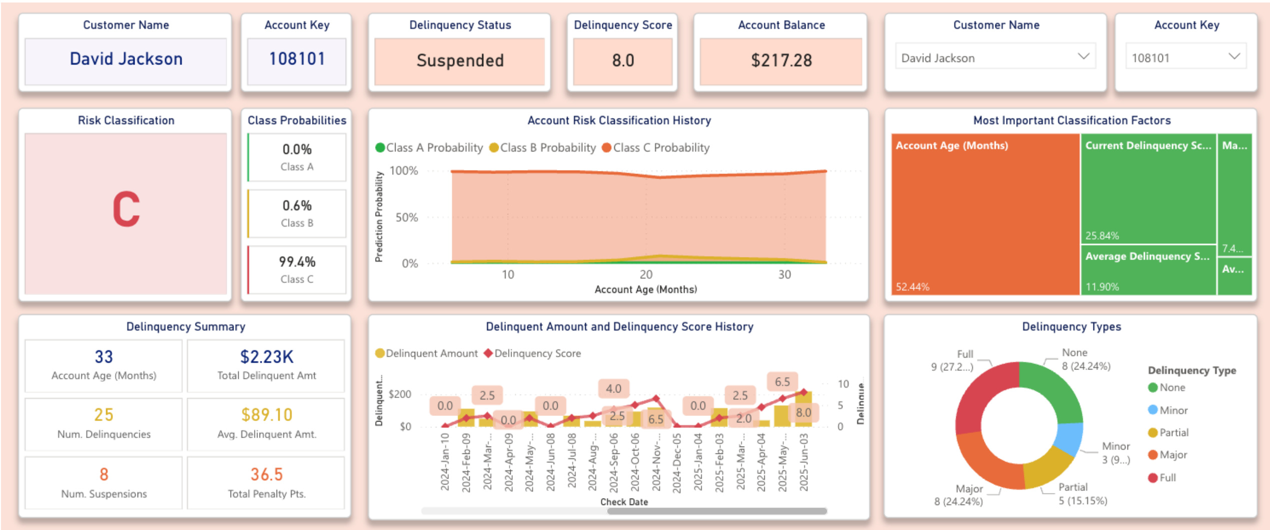
Step 2: Zero in with Account Explorer

The analyst filters for David Jackson. His account shows repeated missed payments and a high Class C risk label. The summary tables confirm that Class C accounts like his have the worst payment performance.



Step 3: Investigate with In-Depth Analysis

The trajectory chart shows that his risk score has been steadily rising. SHAP values show that missed payments and high penalties are the main drivers. His delinquency timeline and composition confirm a long history of instability.



Check Date	Account Key	Customer Name	Delinquency Score	Delinquency Status	Delinquent Amount	Risk Class	Prediction Confidence	Account Age (Months)	Payment Delinquency Rate	Payment Full Miss Rate	Payment Major Miss Rate	Payment Partial Miss Rate	Payment Minor Miss Rate	Total Delinquent Amount	Ave Am
Tuesday, June 03, 2025	108101	David Jackson	8.00	Suspended	$217.28	C	99.4%	33	75.8%	27.3%	24.2%	15.2%	9.1%	$2,227.46	

Step 4: Take Action

The analyst flags this account for collections, shares the SHAP and risk trend in a summary report, and includes visuals in the weekly risk meeting.

This example shows how the report helps analysts connect the dots—from portfolio-level risk signals down to individual decision-making.

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4. Case Studies – Understanding Risk Behavior Through Real Examples

To make the risk classifications and report insights more tangible, let's walk through six representative customer profiles. These examples show how different behaviors manifest across the A–B–C risk spectrum—and how the model interprets those patterns.

Each case tells a story about payment consistency, risk trajectory, and intervention urgency.

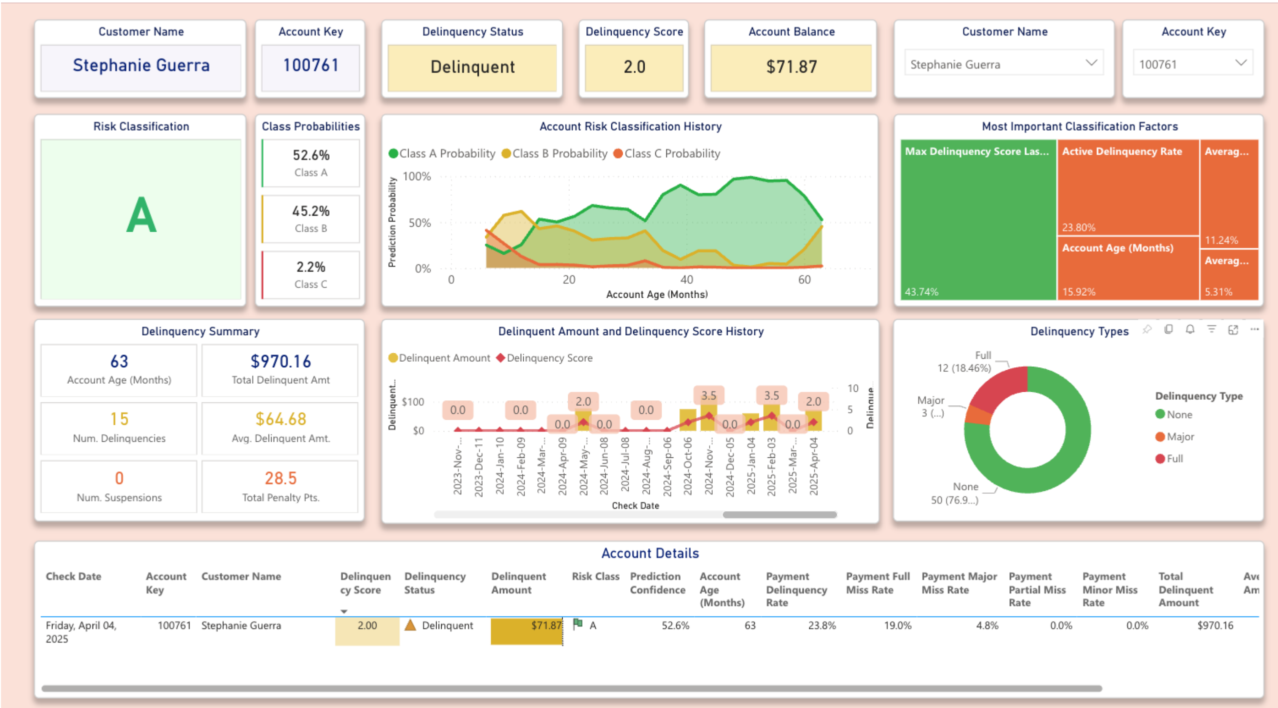
🟩 Class A Account: Sharon Hall – Consistent and Reliable

Snapshot: 63 months, 7 delinquencies, 0 suspensions, 5.5 penalty points

Sharon represents the kind of customer every utility wants. Her payment history is stable, with only a few minor delays across five years. The model consistently places her in Class A with high confidence.

Interpretation: Reliable customer with minimal risk. No action required.

⚠️ Class A– Account: Stephanie Guerra – Early Signs of Deviation



Snapshot: 63 months, 15 delinquencies, 0 suspensions, 28.5 penalty points

Stephanie still falls within Class A, but she's edging closer to risk. Her missed and partial payments have increased over time, and her penalty score is nearing concern thresholds.

Interpretation: This is a watchlist case. Continued issues may push her into Class B.

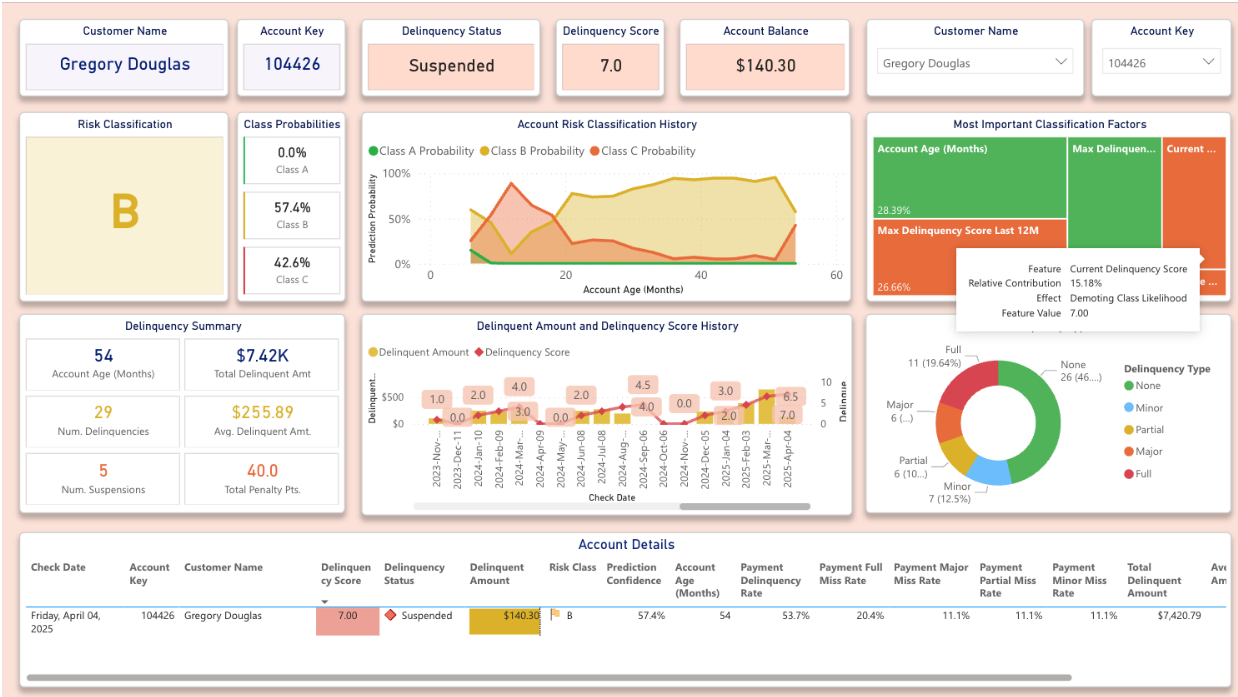
🟨 Class B Account: Brett Bailey – Inconsistent but Manageable

Snapshot: 63 months, 22 delinquencies, 1 suspension, 33.5 penalty points

Brett's behavior is uneven. He frequently misses or delays payments but manages to catch up enough to avoid more serious enforcement. His account was suspended once but recovered.

Interpretation: Medium-risk profile. Needs monitoring, but not urgent.

🟧 Class B– Account: Gregory Douglas – Trending in the Wrong Direction

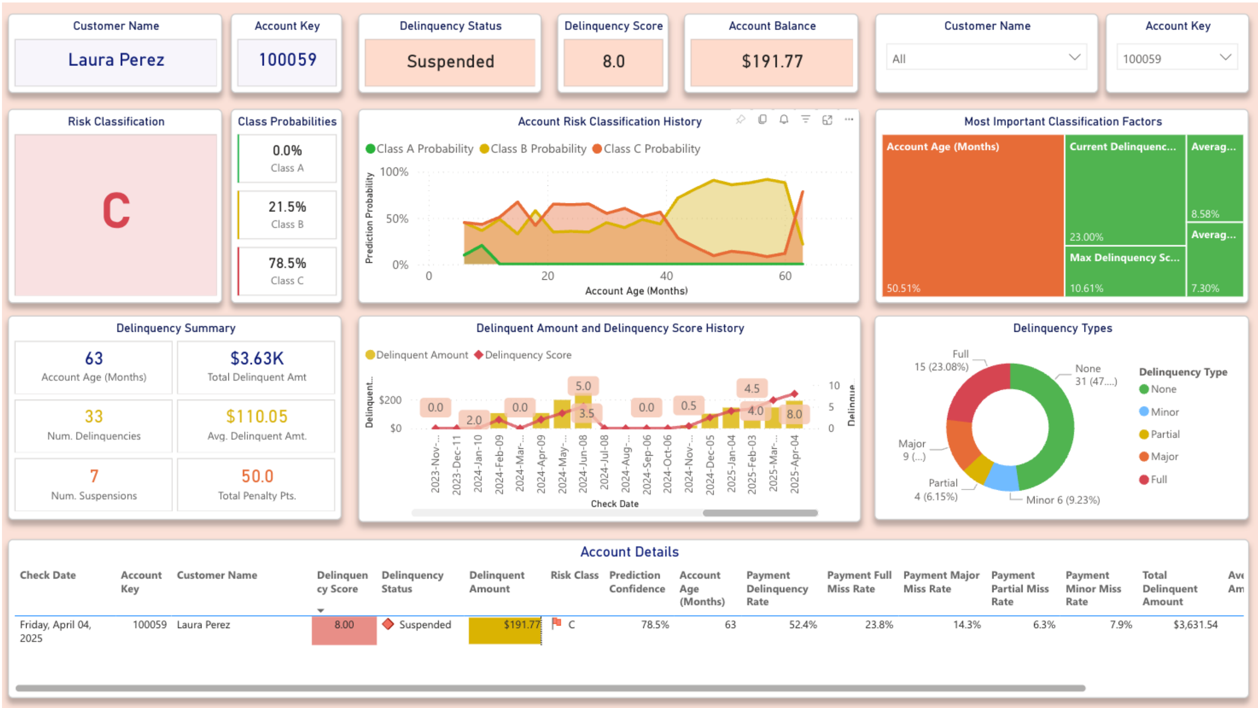


Snapshot: 54 months, 29 delinquencies, 5 suspensions, 40 penalty points
Current Delinquency Score: 7.0

Gregory's history shows volatility. After early risk signals and multiple suspensions, he briefly improved—but recent behavior suggests he's slipping again.

Interpretation: Borderline case moving toward high risk. Worth flagging for review.

🟥 Class C Account: Laura Perez – Chronic Delinquency



Snapshot: 63 months, 33 delinquencies, 7 suspensions, 50 penalty points
Current Delinquency Score: 8.0

Laura's account has struggled for years. Despite occasional payments, her pattern is consistently poor. Her score remains high, and the model sees little sign of improvement.

Interpretation: Classic high-risk account. Should be prioritized for collection or escalation.

🚨 Class C– Account: Ashley Klein – Critical and Likely to Close

Snapshot: 63 months, 41 delinquencies, 13 suspensions, 62 penalty points

Ashley's profile is the most concerning. She's had repeated severe delinquencies, and nearly half of her payments are either missed entirely or significantly short. Her score is well past the closure threshold.

Interpretation: Very high risk. Closure is likely without immediate intervention.

These six cases illustrate how the model doesn't just predict risk—it captures the full behavioral story behind each account. This context is what makes the report useful in practice, helping teams decide where to act and how to respond.

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5. Key Takeaways and Reflections

Project Assessment – What the Report Achieves

Through building a real-time, behavior-driven credit risk report in Power BI, we were able to deliver a tool that transforms predictive model outputs into practical, everyday decisions. The report brings together key data elements—delinquency behavior, model predictions, and explainability—into a single interactive workspace.

Each section of the report is designed for a different level of operational need:

- The **Portfolio Overview** supports executive-level monitoring of exposure and recovery progress.
- The **Account Explorer** helps operational teams triage and prioritize accounts.
- The **In-Depth Analysis** gives analysts the tools to validate predictions and trace behavioral trends.

Together, these views make machine learning predictions not only visible—but usable and actionable.

Purpose and Real-World Impact

This report helps bridge the gap between data science and frontline operations. Instead of keeping model results siloed in notebooks or reports, it presents them in a format that business users can trust and act on.

It enables:

- **Early intervention** on accounts trending toward delinquency
- **Continuous monitoring** of credit exposure across account segments
- **Model transparency** with confidence scores and driver explanations that build user trust

It can be used by credit, collections, and risk teams to make better, faster decisions—helping turn raw data into real financial outcomes.

What I Learned

Building and deploying this report brought several key insights:

- **Interpretability is key**: Business users are far more likely to adopt and trust a model when they can clearly see the reasoning behind each prediction.
- **Confidence scores matter**: Showing how sure the model is helps users make better judgments in uncertain cases.
- **Behavioral risk evolves**: Point-in-time risk scores only tell part of the story. Tracking trends and transitions provides a more accurate view of customer reliability.

Skills and Integration

This project also brought together a variety of technical and analytical skills:

- Integrated machine learning outputs into a live Power BI environment
- Designed DAX logic to compute lifecycle-aware KPIs and filtering mechanisms
- Built an intuitive, role-specific UX that balances detail with clarity
- Applied SHAP explainability techniques to enhance model transparency
- Visualized complex account behaviors and risk trajectories in ways that are easy to interpret

Together, these elements created a solution that is not only technically sound but also practically valuable for real-world credit risk management.

Linked Project In The Series

This article marks the final part of a three-part series focused on modeling and managing customer credit risk in a utility context. Each step in the journey builds on the last, resulting in a full-cycle solution that blends data engineering, predictive modeling, and operational reporting:

1. **Part 1 – Data Engineering**
   We built a realistic synthetic dataset that models utility billing behavior over time—including usage, payments, penalties, suspensions, and closures. This created a flexible foundation for both analytics and modeling.

2. **Part 2 – Risk Classification Model**
   We engineered behavioral features from each account's lifecycle and trained a supervised machine learning model to classify risk levels (A/B/C) with transparency and accuracy. The model output included prediction probabilities and SHAP explanations to support trust and interpretability.
3. **Part 3 – Monitoring Report & Dashboard (This Article)**
   We brought the model insights to life through a Power BI report. This interactive report enables business users to monitor delinquency trends, flag at-risk accounts, and understand the "why" behind each prediction—turning raw output into real-time decisions.

Why This Series Matters

By simulating the data, building a robust model, and surfacing the insights through a clear report, this project demonstrates an end-to-end solution that's adaptable, explainable, and ready for real-world application. It's a practical template for how data analysts and BI professionals can bridge the gap between analytics and business action.

If you're interested in building similar credit risk or lifecycle monitoring solutions—or want to explore how these methods apply in other domains—I invite you to explore the previous parts in the series.