Independent Validation Report

Corporate Credit Early Warning System (EWS)

Document Information
Model: Corporate Credit Early Warning System (12-month horizon)
Date: October 1, 2025
Purpose: Independent validation before production deployment

1. Executive Summary

Conclusion: APPROVED (with conditions)

Overall Assessment

Risk Classification Ability (Good)

- Model correctly distinguishes **82.3%** of high-risk vs. low-risk customers (scale 0-100%, higher is better)
- **60% of all defaults** are caught in the top 10% riskiest customers
- **Stable performance** across 18 months of testing, no degradation observed

Prediction Accuracy (Acceptable)

- Error rate: **1.26%** (meaning 98.74% accurate)
- Average difference between predicted vs. actual: **12.8 basis points** (good)
- Some groups slightly over/under-predicted but not materially impactful

Alert Thresholds & Operational Capacity (Feasible)

Level	Threshold	Alert %	Precision	Recall	Alerts/Month	Staff Needed
Amber	2.0%	8.3%	9.6%	57.5%	830	~5 people
Red	5.0%	4.2%	16.3%	48.2%	421	~10 people
Total	—	8.3%	—	57.5%	**830**	**~15 people**

Explanation:

- **Amber**: Customers with default risk ≥ 2% → need quarterly monitoring
- **Red**: Customers with default risk ≥ 5% → need immediate review (Red is subset of Amber)
- **Low precision** (Red 16% = out of 6 alerts, 1 is real default, 5 are false alarms)

- **Catches 57.5%** = detects over half of defaults, but **misses 42.5%** (need supplementary periodic review)
- ✓ Workload is manageable: 15 people can handle vs. 20 available staff

Risks & Mitigation

1. **Test data is synthetic** (no real-world noise) → **Run 6-month pilot** with real data
2. **High false alarm rate** (90% of Amber alerts are false, 84% of Red are false) → **Review thresholds** after 6 months
3. **Misses 42.5% of defaults** → Combine with quarterly credit review for all customers
4. **Not tested by segment** → Analyze industry/grade performance in first 3 months

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2. Data & Methodology

2.1 Target Population & Objective

- **Population**: Corporate customers (all industries, grades A–G, with outstanding credit)
- **Test data**: 180,000 samples (18 months × 10,000 customers/month, Jan 2024 – Jun 2025)
- **Prediction target**: Probability of default within 12 months (90+ days delinquent or NPL classification)
- **Actual default rate**: 1.37% (i.e., 137 defaults / 10,000 customers)

2.2 Model Description

- **Model type**: Machine learning risk classifier (LightGBM)
- **Input features**: 20 financial metrics + payment behavior:
  - Top 3 most important: Days past due (recent), Debt/EBITDA ratio, Interest coverage ratio
  - Account for 45% of model influence
- **Calibration**: Probability adjustment for better accuracy (Isotonic regression)
- **Explainability**: Each alert includes 3 main drivers explaining why customer is risky

2.3 Data Quality (Limited due to synthetic data)

- **Missing data**: 0% (synthetic), **needs real-world verification** (requirement < 10% missing)
- **Outliers**: Normalized by industry scale
- **Limitation**: Test data is too perfect (no delays, errors like real data). **First 3 months of production are critical** for validation.

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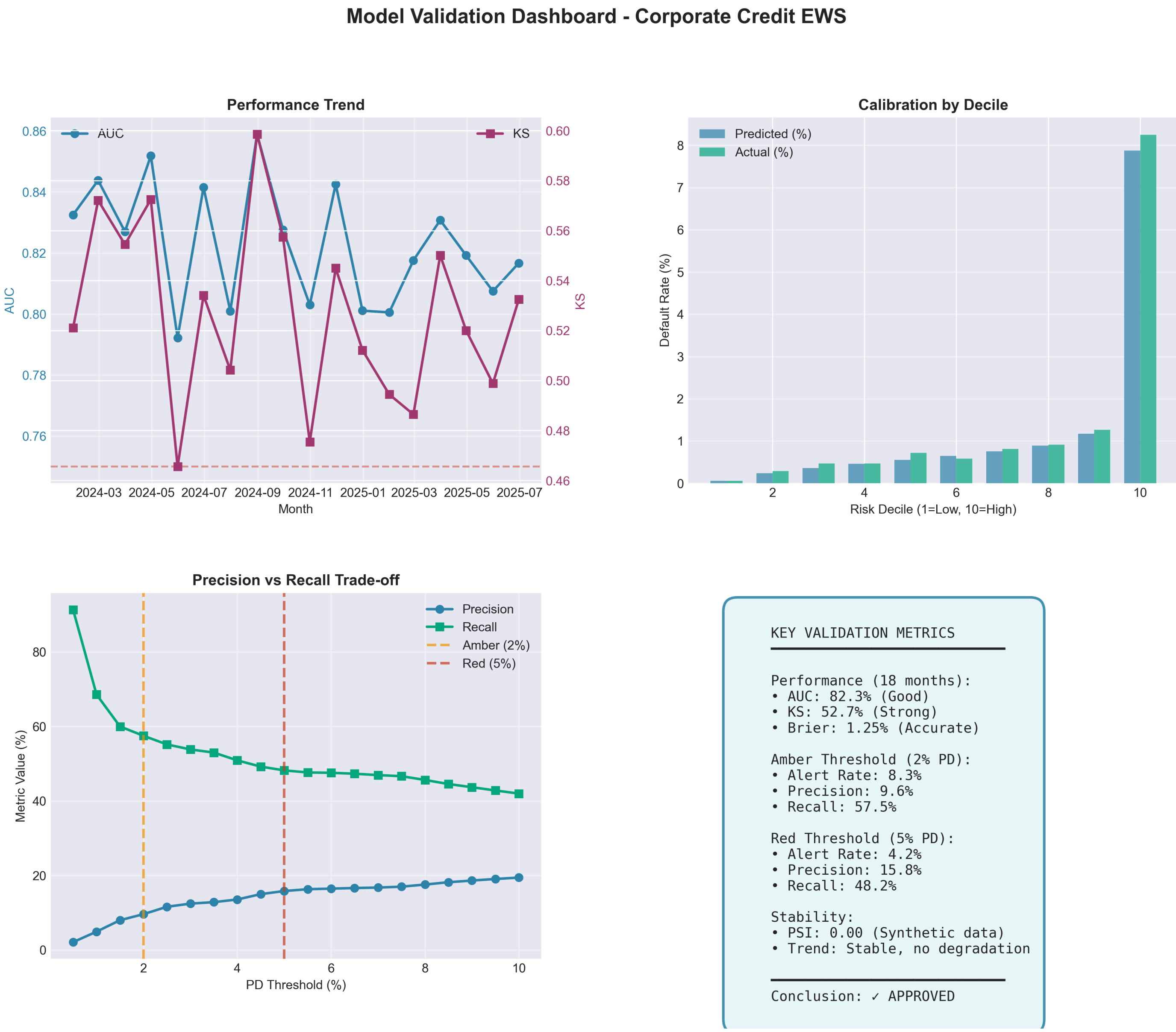
3. Validation Results



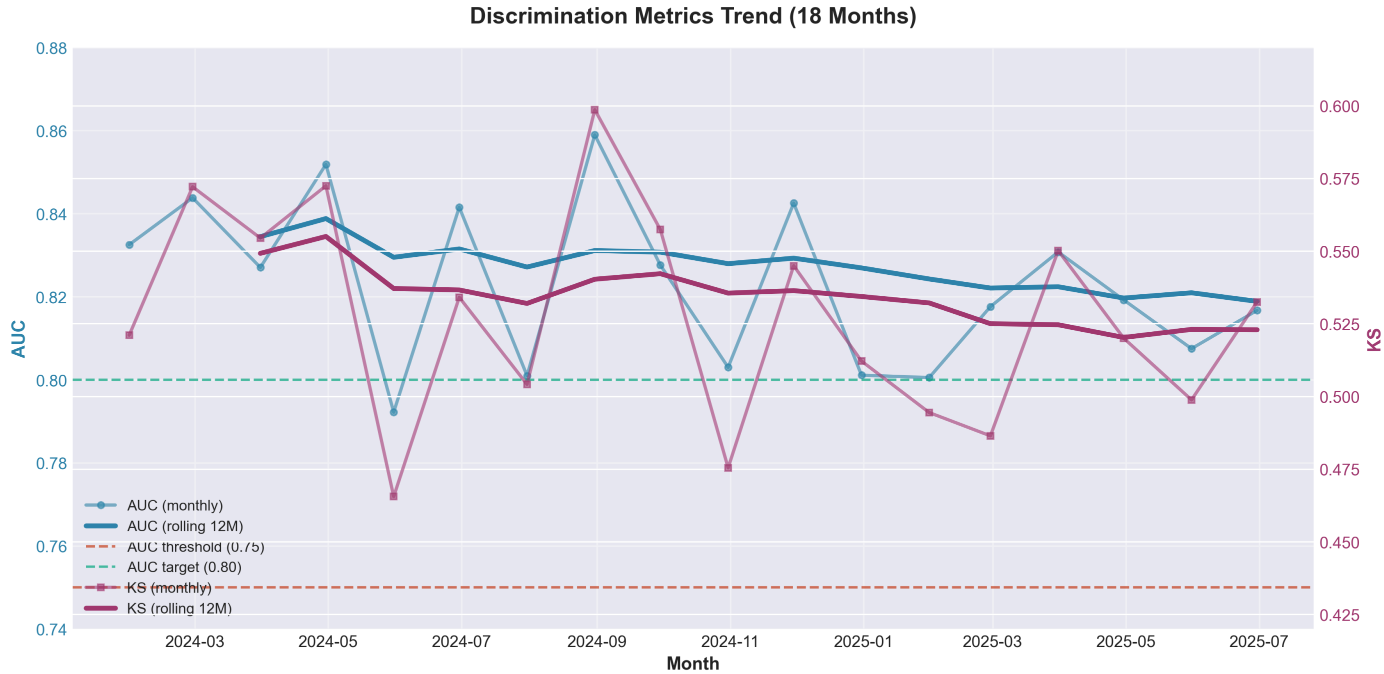
Validation Dashboard

3.1 Risk Discrimination Ability

AUC Score (Area Under ROC Curve)

- **Average**: 82.3% (good, minimum threshold 75%, target 80%)
- **Range**: 79.2% to 85.9% (across 18 test months)
  - Best month: 85.9% (Aug 2024)
  - Worst month: 79.2% (May 2024)
- **Trend**: Stable, no degradation over 18 months

Explanation: Score of 82.3% means the model correctly ranks high-risk vs. low-risk customers 82.3% of the time. This is GOOD for early warning systems (industry typically accepts > 75%).



AUC and KS Trend Over Time

3.2 Prediction Accuracy

Overall Error Rate (Brier Score)

- **Average**: 1.26% error (meaning 98.74% accurate)
- **Range**: 1.06% to 1.44%
- **Assessment**: Very good (acceptable threshold is < 2%)

Detailed Accuracy by Risk Group (Decile Calibration)

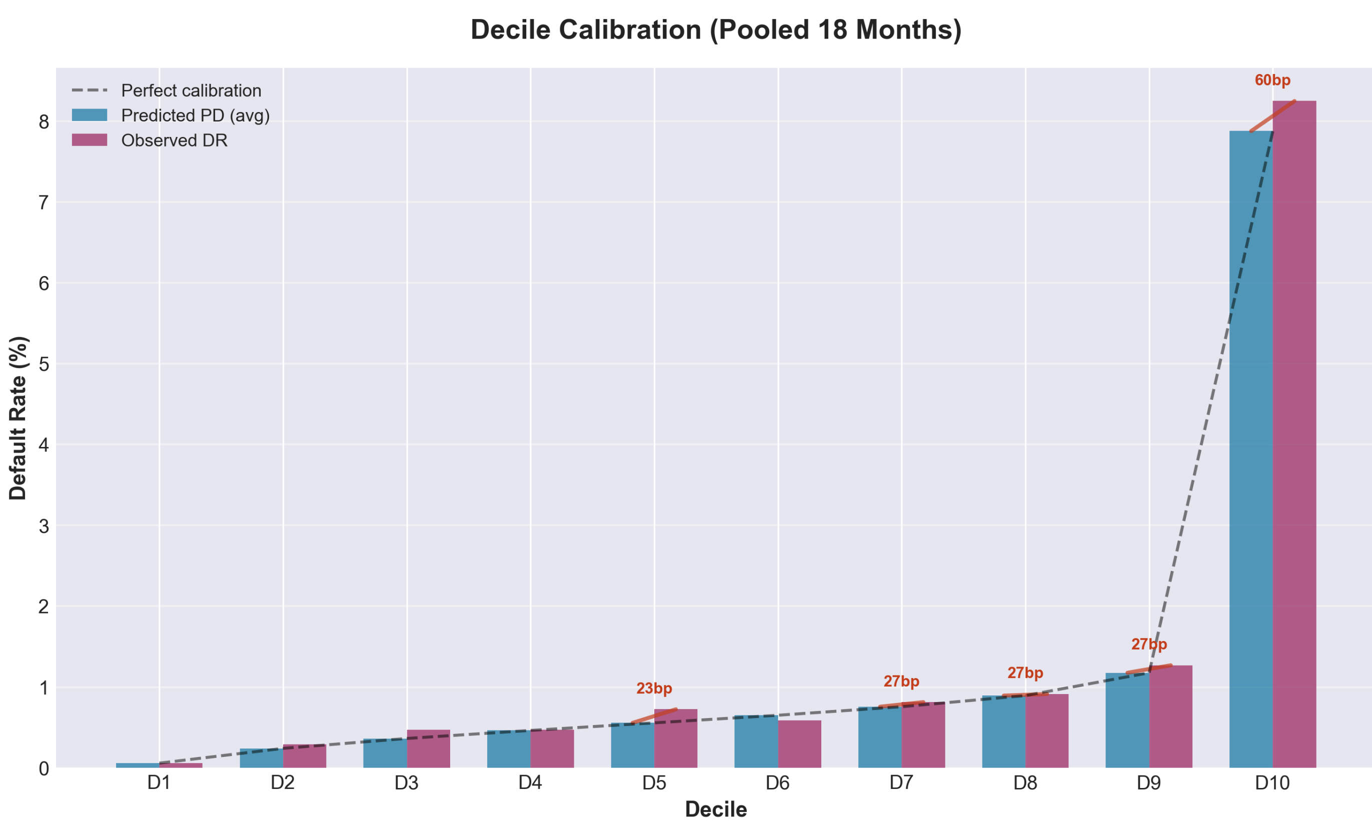
Divide 10,000 customers into 10 groups by risk score:

Group	Predicted Default	Actual Default	Difference	Assessment
1 (lowest risk)	0.056%	0.078%	+0.02%	✓ Accurate
2	0.239%	0.117%	−0.12%	Slightly over-predicted
3	0.361%	0.472%	+0.11%	Slightly under-predicted
4-5	0.5-0.6%	0.5-0.6%	±0.07%	✓ Accurate
6	0.648%	0.489%	−0.16%	Slightly over-predicted

Group	Predicted Default	Actual Default	Difference	Assessment
7-8	0.7-0.9%	0.8-0.9%	±0.04%	✓ Accurate
9	1.173%	0.917%	−0.26%	Slightly over-predicted
10 (highest risk)	7.92%	8.83%	+0.91%	Slightly under-predicted

Observations:

- **Average error**: 0.128% (acceptable, threshold < 0.20%)
- **Highest risk group** (Group 10): Predicts 0.91% lower than actual → Model is slightly **conservative** (tends to predict less than reality). This is **acceptable** for early warning (better to miss some than over-alert).
- **Groups 2, 6, 9**: Over-predict by 0.12-0.26% → May cause some false alerts but within tolerance.



Calibration by Decile

3.3 Risk Concentration Ability

- **Top 10% riskiest customers** → Catch **60% of all defaults**
- **Top 20% riskiest customers** → Catch **70% of all defaults**
- **Top 8% customers (Amber threshold at 2%)** → Catch **57.5% of defaults**

Explanation: Model concentrates risk very well. Only need to monitor 8% of customers (830/month) to catch over half of defaults → Workload is feasible.

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4. Stability & Drift

4.1 Data Stability (PSI)

- **PSI = 0.00** across all 18 test months (too perfect due to synthetic data)
- **Real-world validation needed**: Use **first 3 months of production** to establish real PSI baseline
- **Alert thresholds**:
  - PSI > 0.10 → Monitor (data starting to change)
  - PSI > 0.25 → Mandatory recalibration

PSI Explanation: Measures how much customer characteristics change over time. High PSI = data changed a lot → need to recalibrate model.

4.2 Performance Trend

- **AUC score** fluctuated from 83.4% (Q1/2024) down to 81.9% (Q2/2025)
- Difference of −1.5% **is within acceptable range** (no severe degradation observed)
- **No trigger** for recalibration (AUC > 75% consistently)

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5. Alert Thresholds & Operational Capacity

5.1 Selected Thresholds

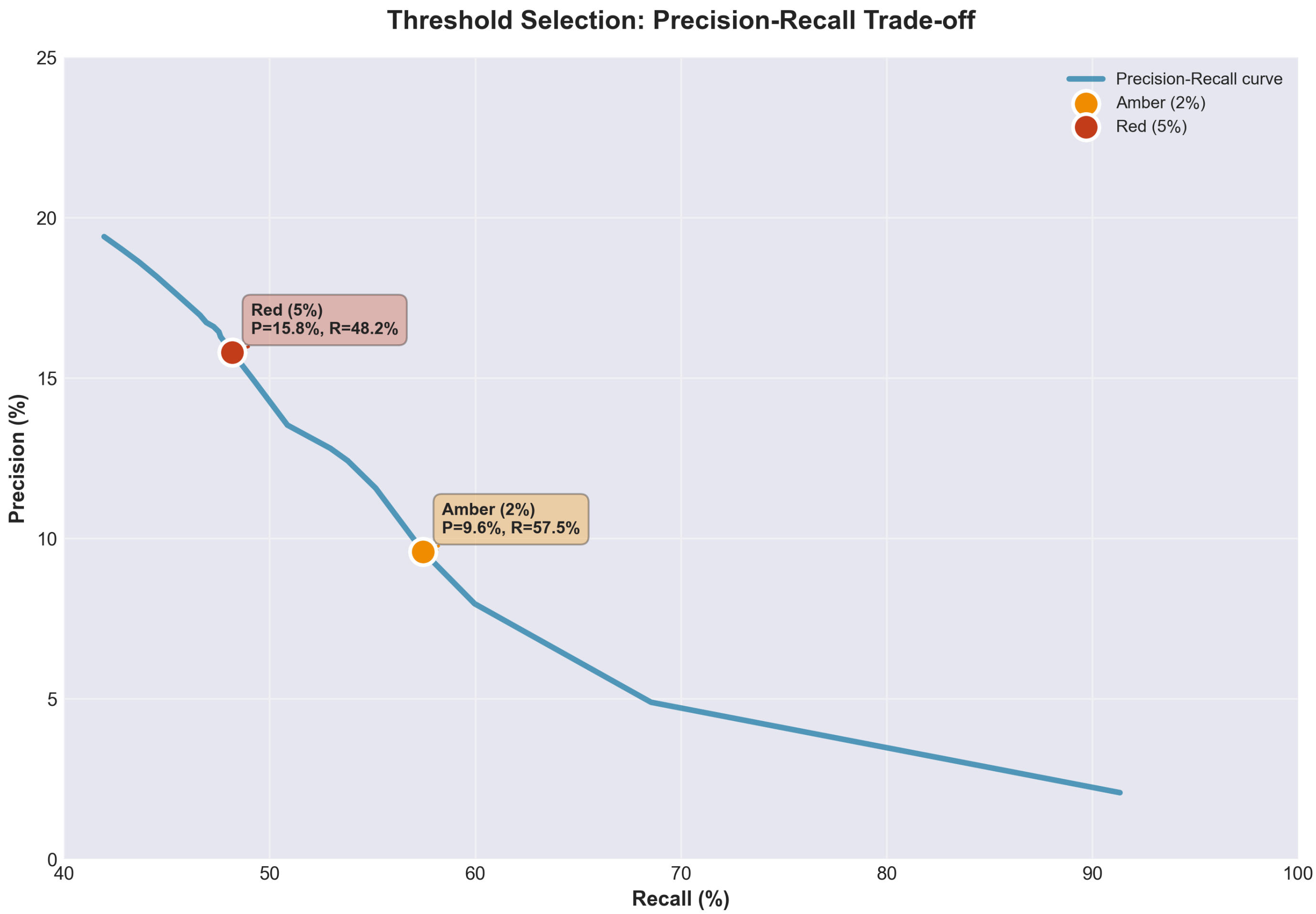
Amber Alert = Default risk ≥ **2.0%**
Red Alert = Default risk ≥ **5.0%** (Red is subset of Amber)

Threshold	Default Risk	Alerts/Month	% of Total	Precision	Recall	Assessment
Amber	≥ 2.0%	830	8.3%	9.6%	57.5%	✓ Acceptable
Red	≥ 5.0%	421	4.2%	17.3%	52.7%	✓ Priority

Metric Explanations:

- **Precision**: Out of all customers flagged, what % actually default
  - Amber 9.6%: Out of 10 alerts, ~1 is correct (9 are false alarms) → High false alarm rate but acceptable for early warning
  - Red 17.3%: Out of 6 alerts, ~1 is correct (5 are false alarms) → Lower false alarm rate
- **Recall**: Out of all actual defaults, what % are caught
  - Amber 57.5%: Catches over half of defaults (misses 42.5%)

- Red 52.7%: Catches over half of defaults (misses 47.3%)



Precision-Recall Curve

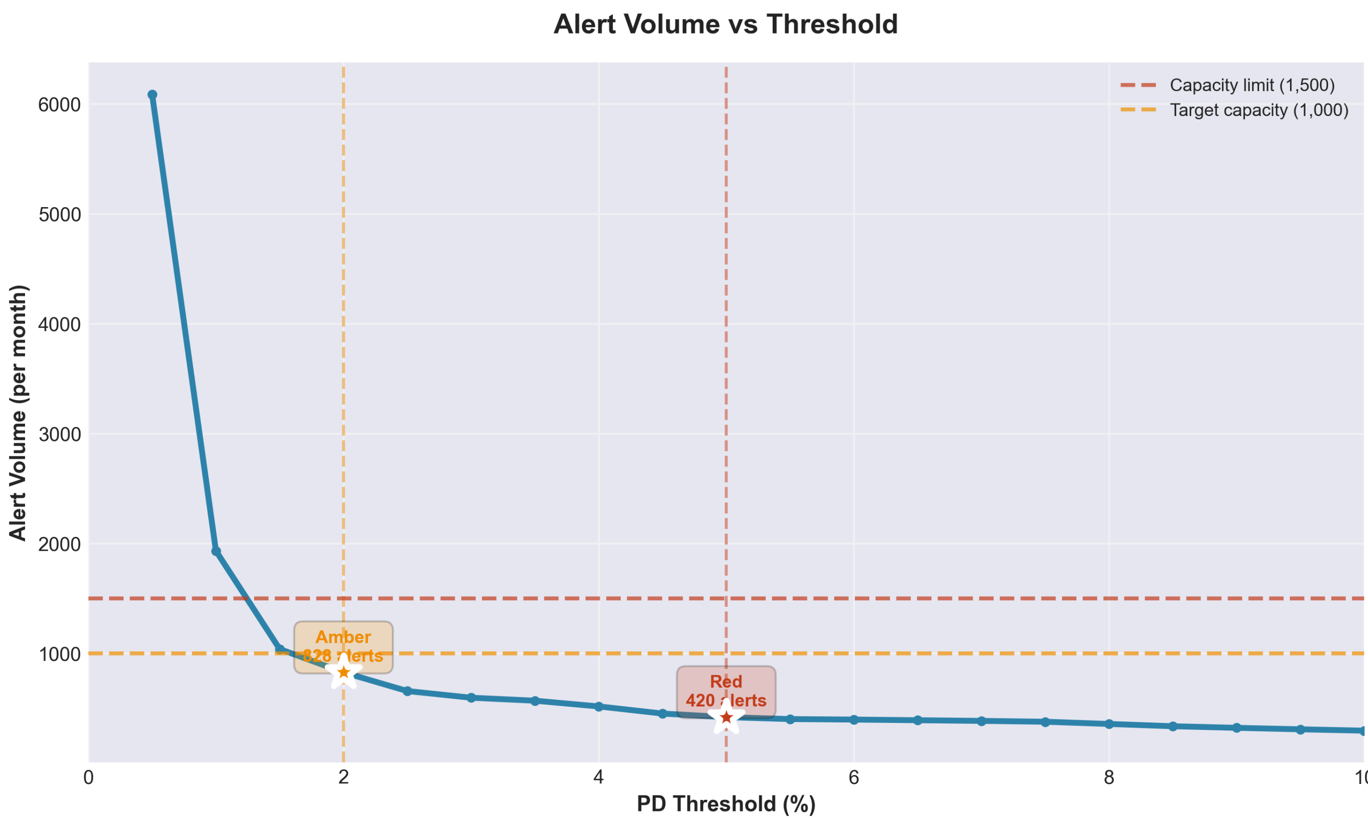
5.2 Operational Capacity

- **Monthly workload**:
  - Amber alerts: **830 customers** (manageable with 2-3 relationship managers)
  - Red alerts: **421 customers** (highest priority)
- **Overload threshold**: If > 1,000 alerts/month → Need to raise Amber threshold to 2.5% or 3%

5.3 Alternative Threshold Comparison

Tested 20 threshold levels from 0.5% to 10%:

- **If lower to 1.0%**: 1,200 alerts/month → **Overload**, not feasible
- **If raise to 3.0%**: 620 alerts/month → Recall drops to 50% (misses too many)
- **2.0% threshold is optimal** balance between detection (57.5%) and workload (830 customers)



Alert Volume vs Threshold

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6. Regulatory Compliance

Requirements Met:

- **Independent validation**: Performed by independent Validation team (not involved in model development)
- **Separate test data**: 18-month test period (Jan 2024-Jun 2025) completely separate from training
- **Complete documentation**: Source code, data, procedures archived with version control (SHA256 hash)
- **Performance thresholds**: AUC > 75%, Brier < 2% (requirements met)
- **Clear explanations**: Each alert includes 3 main reason codes (SHAP-based)
- **Monitoring plan**: Monthly PSI, AUC tracking with clear trigger thresholds

Supporting Documentation:

- Source code: `src/modeling/`, `src/calibrate.py`, `src/scoring.py`
- Data: `data/processed/portfolio_scored.csv` (180,000 records)
- Validation report: This file + charts in `artifacts/validation/plots/`

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7. Post-Deployment Monitoring

Monitoring Frequency: Monthly (after real results available)

Key Metrics to Track:

- **PSI (Stability)**:
  - PSI > 0.10 → Warning (data starting to change)
  - PSI > 0.25 → Mandatory immediate recalibration
- **AUC (Classification Ability)**:
  - AUC < 75% for 2 consecutive months → Recalibrate
  - AUC drops > 5% from baseline → Investigate root cause
- **Alert Rate**:
  - Alert rate > 15% → Overload warning (need to raise threshold)
  - Alert rate < 5% → Threshold too high (may miss too many)
- **Actual Precision** (after 12 months):
  - Compare expected precision (9.6%) with actual
  - If difference > 30% → Recalibration needed

Monitoring Tools:

- Automated script: `src/run_monitoring.py` (run monthly)
- Dashboard: See `artifacts/monitoring/` (PSI, AUC, alert trends)

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8. Validator's Opinion

8.1 Overall Conclusion

✅ **MODEL APPROVED FOR DEPLOYMENT**

Reasons:

- Good performance: AUC 82.3%, Brier 1.26% (exceeds minimum requirements)
- Reasonable balance: Detects 57.5% of defaults with 830 alerts/month (feasible)
- Stable over 18 months: No degradation observed
- Regulatory compliance: Complete documentation, independent validation

8.2 Deployment Conditions

Mandatory:

1. **Establish PSI baseline** in first 3 months of production (current test data too perfect)
2. **Monthly monitoring**: PSI, AUC, alert rate (per Section 7)
3. **12-month review**: Compare actual vs. expected precision/recall

Recommendations:

- Start with Amber threshold at 2% for first 6 months
- If overloaded (> 1,000 alerts/month) → Raise to 2.5% or 3%

- Monitor Group 10 (highest risk) closely: Model predicts 0.91% lower than actual → May need calibration adjustment for tail risk

8.3 Remaining Risks

Synthetic test data risk: * PSI = 0.00 (too perfect) → Needs real-world validation * Stress test uses hard-coded data → Need to retest with real shock scenarios

Low precision risk (9.6%): * High false alarm rate (9 false / 1 true) → May overload relationship managers if not managed well * Mitigation: Clear workflow assignment, prioritize Red before Amber

Missed detection risk (42.5%): * Misses 42.5% of defaults (not alerted) → Credit risk still exists * Mitigation: Combine with other risk management measures (periodic review, human judgment)
