Proactive Collections with Artificial Intelligence

Results from Rivana Artificial Intelligence Engine

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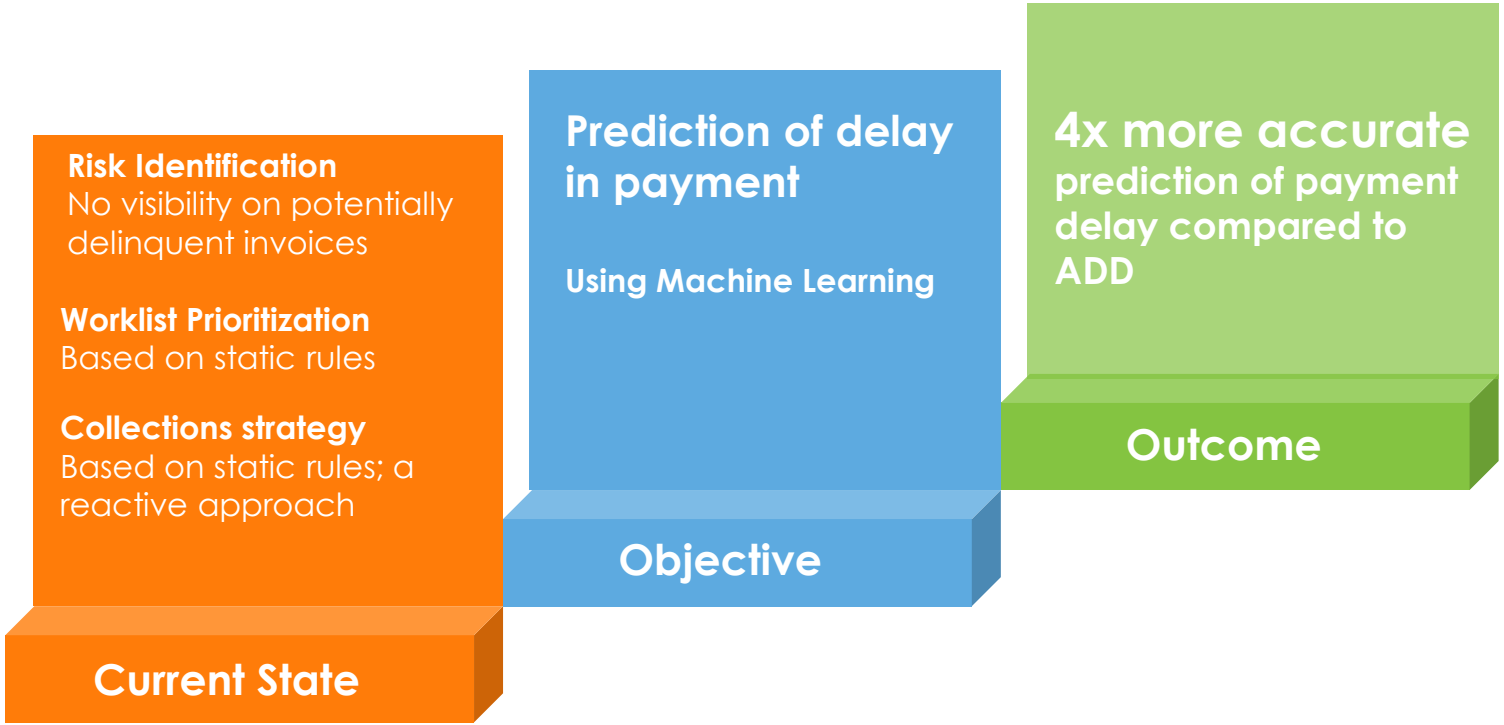
Presentation Brief



Agenda

- **About ShurTech**
- **Labs Project with HighRadius**
  - Key objective: Proactive collections
- **Stage 1: Data Sciences**
  - Creating a data model
- **Stage 2: Live Prediction (Production)**
  - Deploying on the production environment
  - Results from the Labs Project
- **Stage 3: Operationalize**
  - Deploying on a subset of the worklist
- **Summary**

About ShurTape

The Original and The Best

- Manufacturer of the original “Duck” brand duct tape

Global Operations

- 12 world-wide manufacturing and distribution centers
- US, Canada, UK, Germany, Mexico, Peru, United Arab Emirates and China

Industry-leading producer

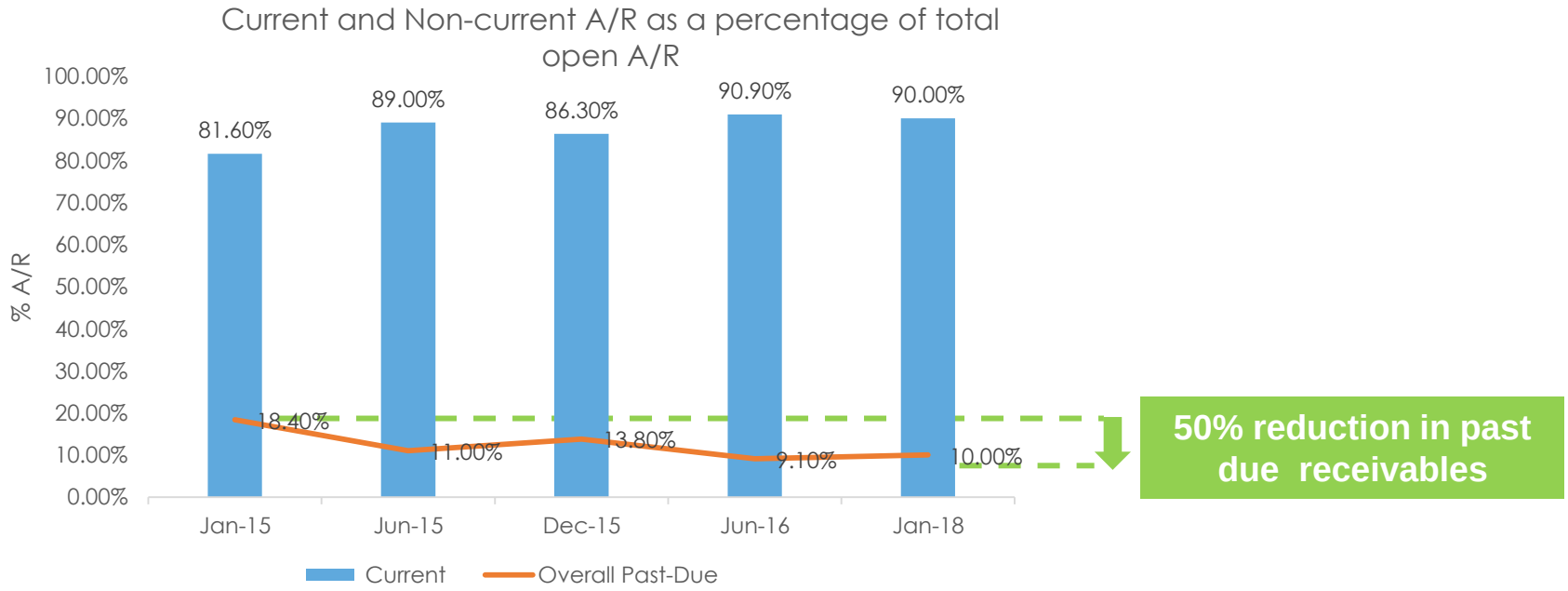
- Pressure-sensitive masking tape
- Duct tape
- Packaging & specialty tape products

Labs Project with HighRadius

Moving to 'Proactive' Collections

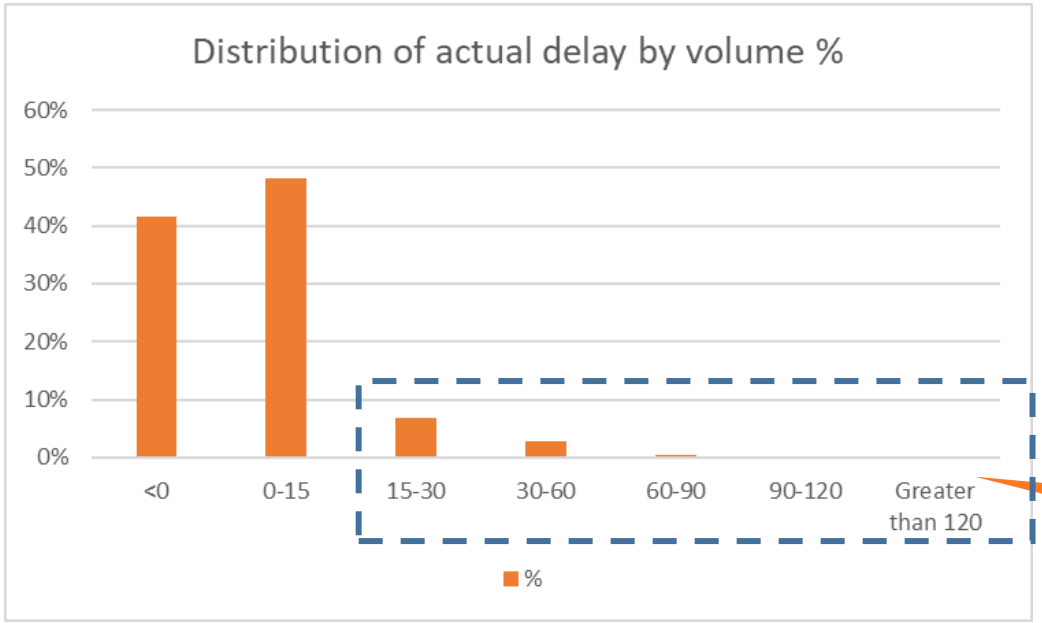
Collections Status Quo at ShurTech

Performance improvements with
HighRadius Collections Cloud + In-house best-practices



Clearly Identified 'Problem' Invoices

90% of invoices paid within 0-15 days of due-date



Buckets	Volume	%
<0	25428	41.57%
0-15	29398	48.06%
15-30	4101	6.70%
30-60	1708	2.79%
60-90	295	0.48%
90-120	110	0.18%
Greater than 120	127	0.21%

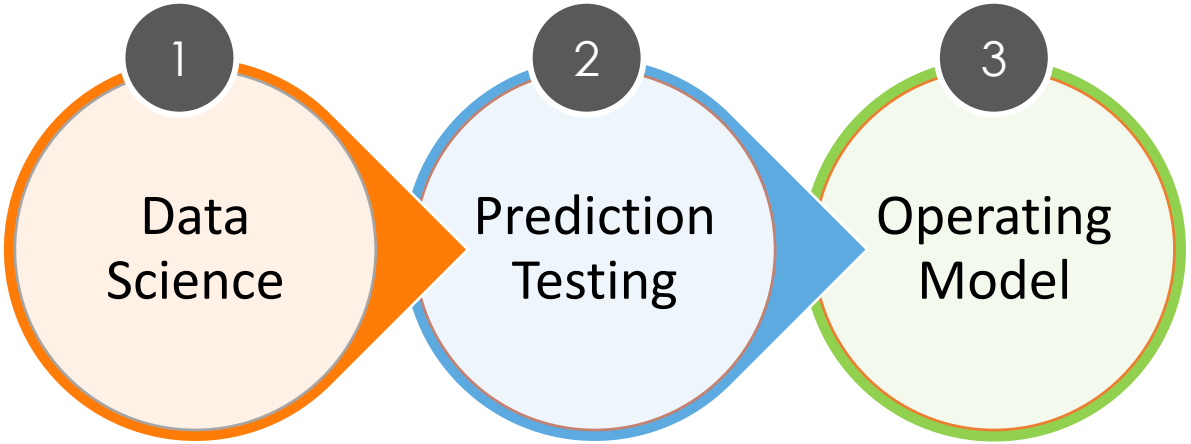
Potentially delinquent invoices

The Plan: Reactive to Proactive Collections

	Reactive (Current State)	**Proactive** (Future State)
Risk identification	No visibility on potentially delinquent invoices	Identify all potentially delinquent invoices
Worklist prioritization	Based on static rules (ADD, partial usage)	Dynamic, driven by AI
Collection strategy	Based on static rules	Best-practices, combined with AI recommendation

Project Overview

Artificial Intelligence in Collections Management



Build a prediction model based on historically available data

Run prediction on live worklist and evaluate results

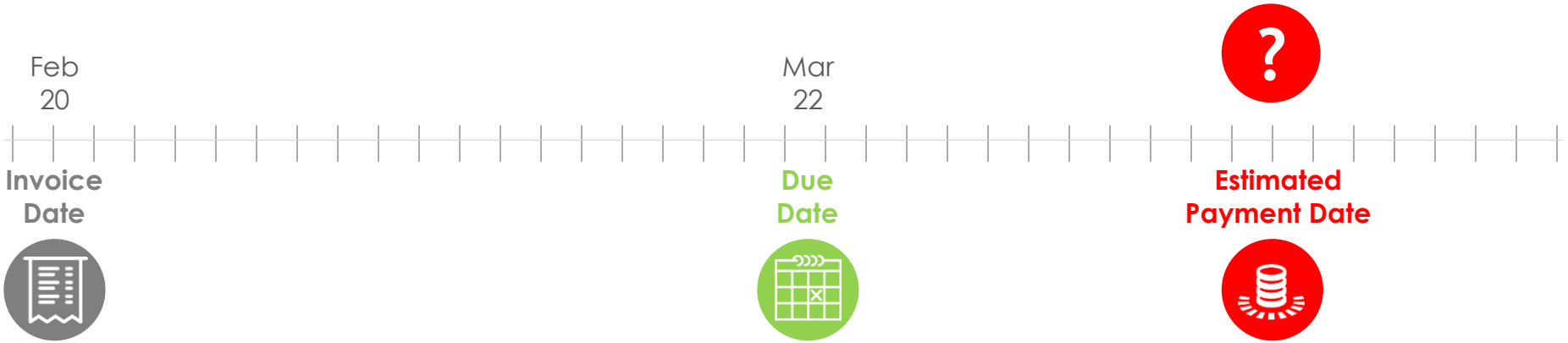
Plan for implementing recommendation engine for a subset of the collection worklist

Stage 1: Data Science

Building a Prediction Model

Problem Statement

Use **Machine Learning** to predict
invoice payment date



Features in Play

ALL FACTORS

INVOICE FACTORS

All invoice related parameters

CUSTOMER FACTORS

All account related parameters

INFLUENCING FACTORS

INVOICE FACTORS

- Past invoice count
- Gap ratio
- Previous payment times
- Due month
- Invoice value
- Total Current Invoice value
- Day of the week due

CUSTOMER FACTORS

- Average number of invoices per payment
- Total open amount
- Gap between payments
- Average delay
- % of payments delayed

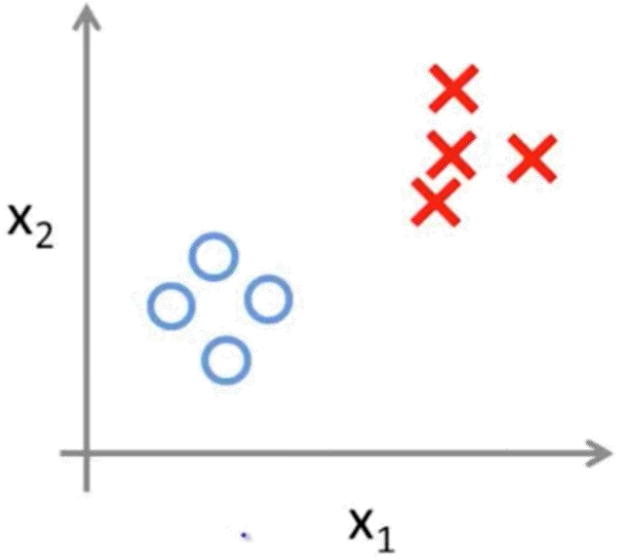
PREDICTION MODELS

Proposed models:

- Binary classification
- Multiclass classification
- Regression predicting delay
- Regression predicting total time

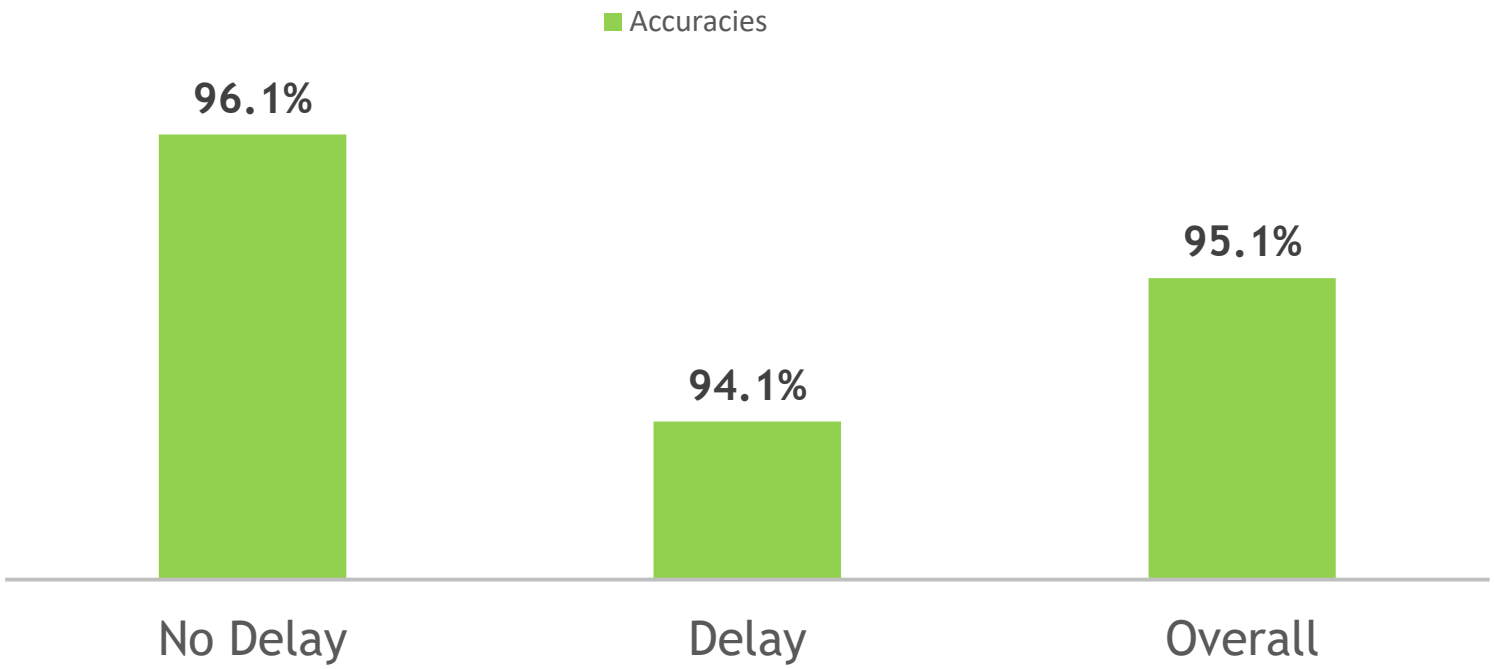
Binary Classification Model

- Classify the elements of a given set into **two groups**
- Based on a classification rule.



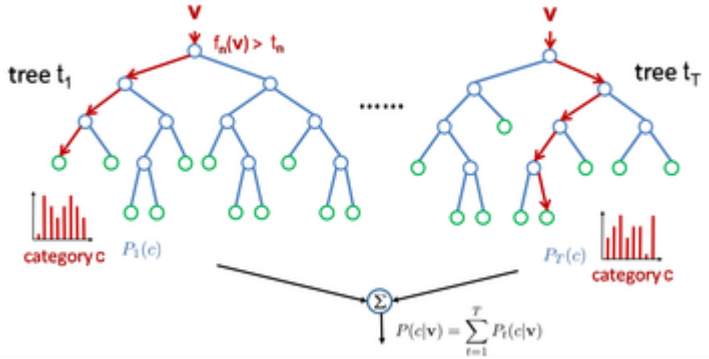
Answers Yes or No to the question:
'Whether payment for a given invoice will be a delayed?'.

Binary Classification: Accuracy



Random Forest Regression Model

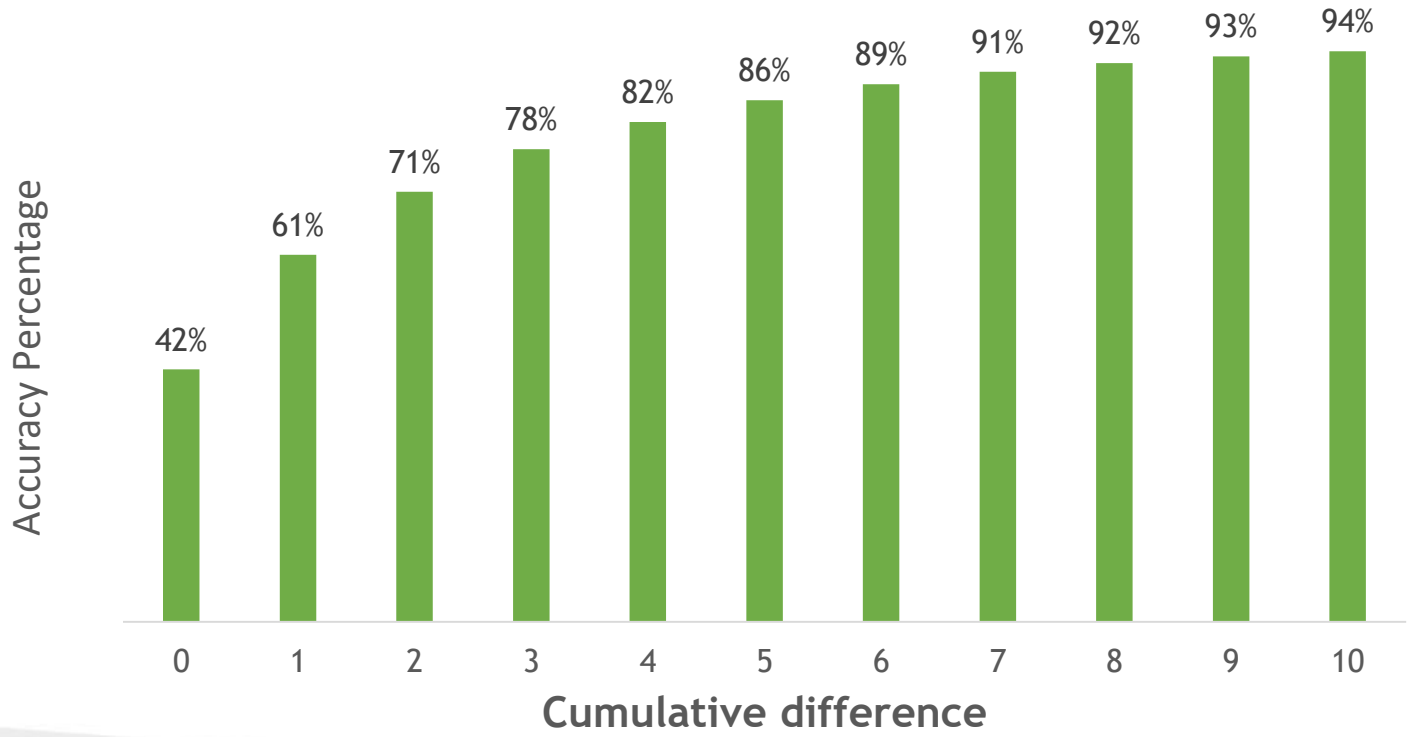
Used to predict a **continuous valued output.**



Predicts an actual payment date based on the features.

Regression

Percentage of Invoices Predicted Correct (cumulative)



Stage 2: Prediction Testing

Evaluating Prediction Performance

Prediction Testing: Defining the Benchmark

Rivana
Machine Learning

v/s

Average
Days Delinquent

Basic, primary predictor used by A/R teams

Rivana (Artificial Intelligence) vs. ADD

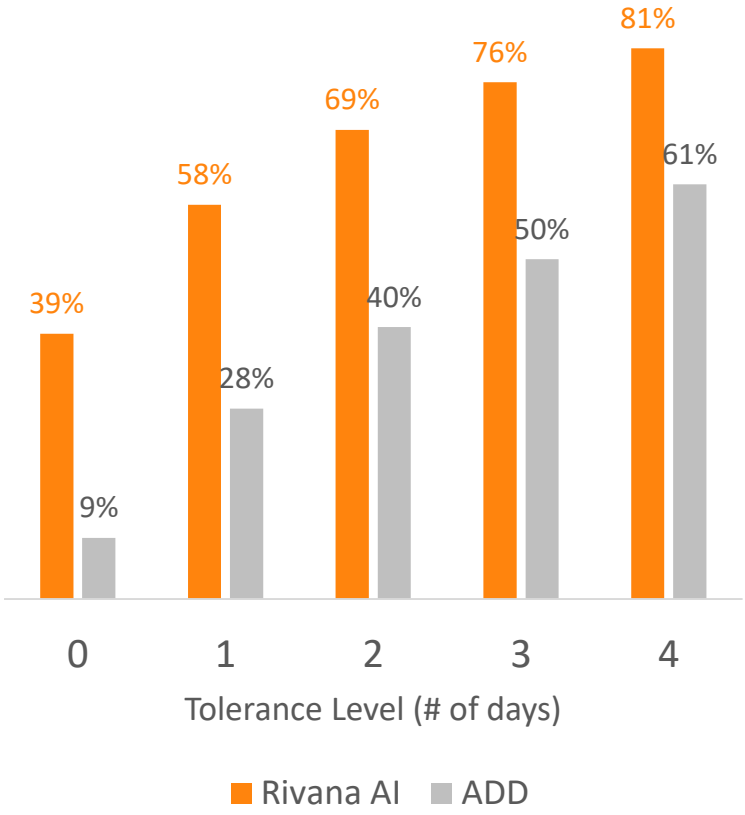
Results Summary

Accuracy

	Rivana	ADD
All Invoices	76%	50%
Delayed Invoices	74%	54%

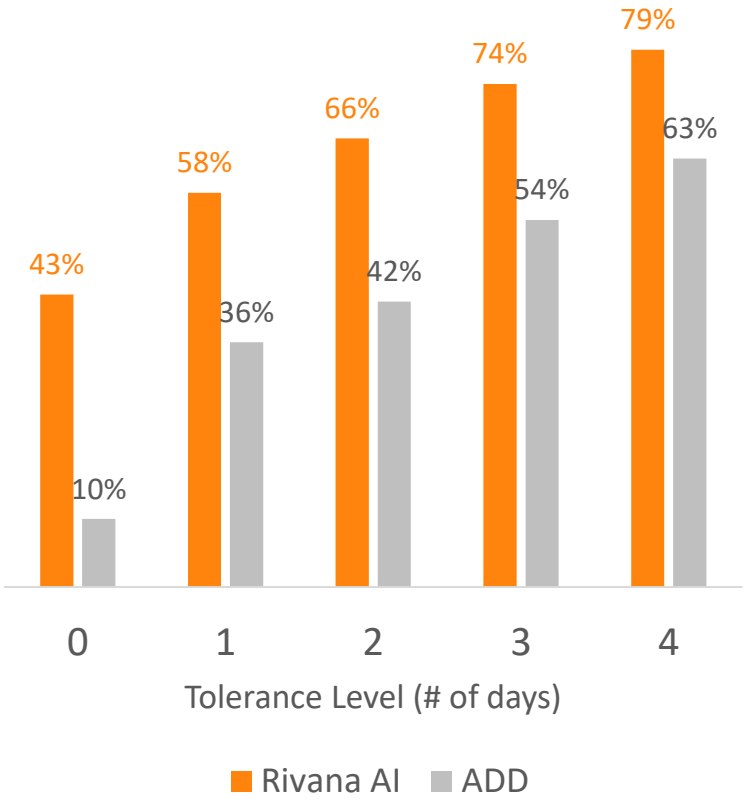
Rivana AI vs ADD – All Data

Tolerance	Rivana	ADD
Zero Days	39%	9%
+/- 3 days	76%	50%



Rivana AI vs ADD – Delayed Invoices

Tolerance	Rivana	ADD
Zero Days	43%	10%
+/- 3 days	74%	54%



Stage 3: Operationalize

Going Live with the Worklist

Simulated Benefits

Invoices	Average Delay (Reactive)	Average Delay (Proactive)	%
All Delayed Invoices	10.7	5.8	45.8%
Invoices delayed by > 15 days	34	20	41.1%

50% faster collection
If the predicted bucket is same or more than actual bucket

25% faster collection
If the predicted bucket is less than actual bucket by 1

10% faster collection
If the predicted bucket is less than actual bucket by more than 1

Operational Approach:
Do not wait for invoices to be past-due
Take proactive actions based on predicted delay

Next Steps for AI in Collections

Deploy on a subset of the collection worklist

Collection Strategies and Rules

Current

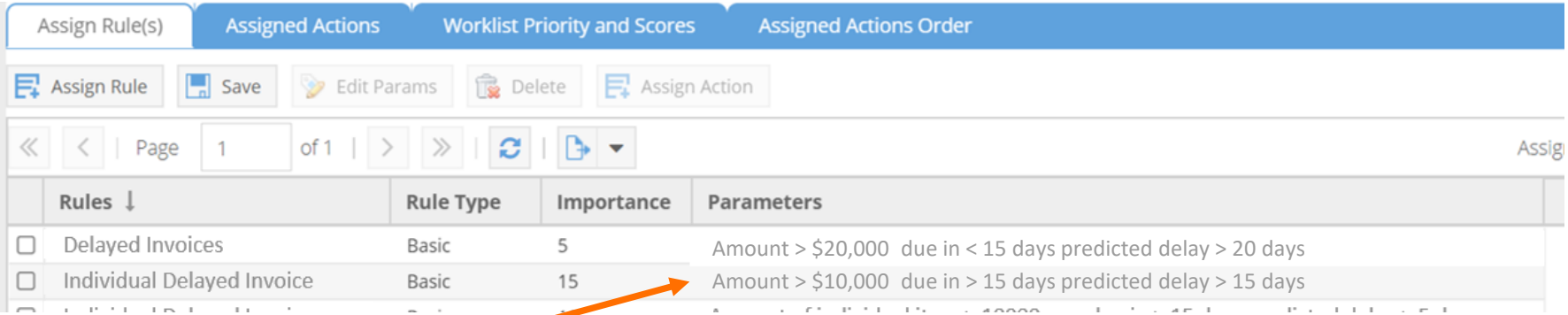
Static data and past-due information (reactive)

With Rivana AI

Proactive strategies
– based on predicted delay

Performance evaluation: Monitor reduction in average delay

Collections Rules Based on Predicted Delay



Collections rules based on

Invoice value
Static parameter from open A/R

Number of days for invoice to be due
Dynamic parameter calculated from open A/R

Predicted delay
Proactive parameter predicted by Rivana AI

Predicted Delay for Order and Credit Management

Predicted Delay could be computed at the time of order creation based on the invoice parameters and customer history.

If Predicted Delay is high:

*Request **upfront payment** for accounts or particular invoices*

*Require **payment commitments** at the time of order creation*

***Updating credit terms** to proactively minimize delay in payment*

Summary

Proactive Collections

Accurate Predictions of Payment Delays

Actions/Strategy Based on Predictions

Proactive Collections

- Focusing on customers with a higher likelihood of delayed payments
- Updating credit terms to proactively minimize delayed payments