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AI-Driven Accounts Receivable Intelligence A Human-in-the-Loop Framework for B2B Payment Risk Prediction, Collection Prioritization, and Decision Support

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DECLARATION

I declare that this research paper is an independent investigation into the application of artificial intelligence to accounts receivable management. Secondary research sources are identified in the references.

This paper does not claim that AVERRA has already solved accounts receivable automation. Instead, it investigates whether an AI-driven, human-supervised approach could improve invoice prioritization, collection workflows, and financial decision support.

No unverified participant data or fabricated research results are presented.

Abstract:

Accounts receivable (AR) is the stage at which a completed B2B transaction is converted into cash. Although businesses increasingly use accounting, ERP, billing, and payment software, overdue-invoice management can still require substantial manual monitoring, prioritization, communication, and follow-up.

This research investigates whether artificial intelligence can move AR from a reactive administrative process toward a proactive decision-support system. The central question is not simply whether reminders can be automated, but whether an intelligent system can determine which invoices require attention, what action is appropriate, when communication should occur, and when a human should intervene.

The study combines secondary research, industry analysis, and a proposed experimental framework comparing manual, rule-based, and AI-assisted invoice prioritization.

Industry evidence suggests a significant automation gap. BillingPlatform's 2025 survey of 104 finance leaders found that 80% considered AR automation important, high priority, or critical, while only 3% reported fully automated AR. The same research found growing interest in AI applications within AR.

The paper proposes a five-layer framework: data, intelligence, prioritization, action, and feedback. AVERRA is positioned as an intelligent orchestration layer that can analyze receivables, estimate risk, prioritize collection tasks, recommend actions, and escalate complex cases to humans.
The central proposition is that the greatest value of AI in AR may not be replacing finance professionals, but allocating their limited attention more intelligently.

Keywords: Accounts Receivable, Artificial Intelligence, B2B Payments, FinTech, Collections, Automation, Machine Learning, Human-in-the-Loop AI, Cash Flow

1. INTRODUCTION

A B2B transaction can be simplified as:
Sale → Invoice → Payment Terms → Due Date → Payment
The transaction may be commercially complete when an invoice is issued, but financially it remains incomplete until payment is received. The resulting accounts receivable represents money earned but not yet converted into cash.
When invoices become overdue, finance teams may need to:

- identify overdue accounts,
- prioritize customers,
- send reminders,
- record responses,
- track payment promises,
- investigate disputes,
- escalate important accounts.

At small scale, these activities may be manageable. As invoice volume grows, however, manually deciding which account deserves attention becomes increasingly difficult.
This leads to the central research question:
How can artificial intelligence improve B2B accounts receivable prioritization and workflow efficiency while preserving human oversight for complex financial decisions?
The research therefore focuses on decision intelligence, rather than automation for its own sake.

2. RESEARCH PROBLEM

Traditional AR systems are generally good at answering factual questions:

- Which invoices are unpaid?
- When are they due?
- How much is outstanding?
- Which customers have overdue balances?

However, finance teams also need decisions:

- Which invoice should be addressed first?
- Which customer is most likely to pay late?
- Which overdue invoice represents the greatest risk?
- Has the customer already promised to pay?
- Is there a genuine dispute?

- Should another automated reminder be sent?
- Does a human need to intervene?

This creates an important distinction:

Information management ≠ decision management

A system can know that an invoice is 20 days overdue without knowing the best action to take.

The research problem is therefore:

How can AI be applied to B2B accounts receivable to improve collection prioritization and workflow efficiency while keeping high-consequence decisions under appropriate human control?

3. RESEARCH QUESTIONS

Primary Question

Can an AI-driven, human-in-the-loop framework improve the prioritization and management of overdue B2B invoices compared with conventional rule-based workflows?

Secondary Questions

1. What are the major inefficiencies in manual AR collection?
2. Which AR activities are most suitable for automation?
3. How can invoice-level payment risk be estimated?
4. How should competing collection tasks be prioritized?
5. Can payment behavior improve prioritization?
6. Can AI produce more context-aware communication than fixed reminder schedules?
7. When should an AI system escalate an account to a human?
8. What risks arise when AI is used in financial communication?
9. Which metrics should be used to evaluate intelligent AR automation?

4. RESEARCH OBJECTIVES

The study aims to:

10. Identify major inefficiencies in manual B2B receivables collection.
11. Examine current adoption of AR automation and AI.
12. Develop a conceptual framework for AI-assisted invoice prioritization.
13. Design a mathematical model for collection priority.
14. Propose an experiment comparing manual, rule-based, and AI-assisted approaches.
15. Define ethical, security, and human-oversight requirements for responsible implementation.

5. INDUSTRY CONTEXT

5.1 Why Receivables Matter

Accounts receivable directly affects working capital and cash flow.

A company can have strong sales while still experiencing financial pressure if customers pay slowly. Effective receivables management therefore affects:

- liquidity,
- working capital,
- financial planning,
- supplier payments,

- borrowing requirements,
- operational flexibility.

The key distinction is:
Revenue is not the same as immediately available cash.

5.2 The Indian B2B Environment

Atradius's 2026 India Payment Practices Barometer reports that around half of B2B sales are conducted on credit. Payment terms commonly extend one to two months, and nearly nine in ten surveyed Indian firms reported overdue invoices.
The research also identifies customer liquidity constraints and operational issues such as approval and banking delays as contributors to late payment.
This matters because an overdue invoice does not always mean a customer is unwilling to pay. Possible causes include:

- internal approval delays,
- cash-flow constraints,
- administrative errors,
- invoice disputes,
- banking problems,
- procurement procedures.

An effective AI system must therefore consider context rather than treating every overdue invoice identically.

6. LITERATURE REVIEW

6.1 From Manual Collection to Intelligent Collection

Traditional collection processes depend heavily on employee judgment. Finance professionals may consider:

- customer history,
- outstanding balance,
- invoice age,
- previous communication,
- payment commitments,
- business relationships.

As the number of accounts increases, evaluating all these variables manually becomes difficult.
Przybyłek et al. (2025) proposed a Smart Debt Collection System using a Design Science Research approach. Their work highlights limitations in conventional systems focused mainly on data gathering, administration, and reporting, and explores intelligent decision-making through a combination of computational methods and process constraints.
This supports a broader shift from recording information toward optimizing decisions.

6.2 AI in Accounts Receivable

Industry research also shows increasing interest in AI.
BillingPlatform's 2025 survey of 104 finance leaders reported:

- 80% considered AR automation important, high priority, or critical.
- 49% were considering AR automation.
- 39% were implementing AR automation.
- 3% reported fully automated AR.
- 67% were evaluating AI applications in AR.
- 14% had deployed AI.

This suggests a gap between:
Interest → Experimentation → Deployment → Full Automation
The opportunity examined in this paper lies within that gap.

7. EXISTING AR TECHNOLOGY

AR technology can be viewed as four broad stages.

Generation 1 — Record Keeping

- invoice creation,
- payment recording,
- customer records,
- accounting.

Generation 2 — Workflow Automation

Example:
If an invoice is overdue → send a reminder.
This is predictable and inexpensive, but usually has limited context.

Generation 3 — Analytics

- dashboards,
- aging reports,
- customer segmentation,
- collection metrics.

Analytics improves visibility but still leaves many decisions to humans.

Generation 4 — Intelligent Decision Systems

Emerging systems can include:

- predictive payment risk,
- dynamic prioritization,
- adaptive communication,
- anomaly detection,
- next-best-action recommendations,
- human escalation.

AVERRA is proposed within this fourth category.

8. RESEARCH GAP

The existing research establishes that AI can support collection activities and that organizations increasingly want AR automation. However, several areas remain important.

8.1 B2B-Specific Prioritization
B2B invoices involve negotiated payment terms, repeated transactions, procurement processes, strategic customers, and disputes. A model designed for general debt collection may not account for these differences.

8.2 Human-AI Boundaries
The key question is not only:
Can AI perform the task?
It is also:
Should AI perform the task independently?

8.3 Context
A numerical score alone may overlook important qualitative information such as disputes, strategic relationships, or confirmed payment promises.

8.4 Communication
Collection is also a business relationship. Increasing pressure may improve short-term collection in some situations while harming long-term relationships in others.

8.5 Evaluation
A useful system should not be judged only by prediction accuracy. It should also be evaluated using:
- collection efficiency,
- human workload,
- resolution time,
- false escalations,
- customer response,
- dispute handling.

9. CONCEPTUAL FRAMEWORK
The proposed framework contains five layers.

Layer 1 — Data
The system receives:
- invoice information,
- due dates,
- payment history,
- communication records,
- disputes,
- payment promises.

Layer 2 — Intelligence
The system analyzes:
- payment probability,
- overdue risk,
- financial exposure,
- customer behavior.

Layer 3 — Prioritization
Accounts are ranked according to urgency, expected value, and risk.

Layer 4 — Action

The system can recommend or execute, within predefined boundaries:

- reminders,
- follow-ups,
- payment confirmation,
- dispute routing,
- human escalation.

Layer 5 — Feedback

Outcomes are recorded and used to improve future recommendations.

The resulting loop is:

Observe → Predict → Act → Measure → Learn

10. RESEARCH METHODOLOGY

This study uses a proposed mixed-method Design Science Research approach.

Quantitative Component

A structured survey can examine:

- invoice volume,
- overdue frequency,
- collection workload,
- automation level,
- willingness to adopt AI.

Qualitative Component

Semi-structured interviews can explore:

- how overdue invoices are handled,
- how prioritization decisions are made,
- where manual work occurs,
- what decisions require human judgment,
- what would create or reduce trust in AI.

Important: No participant history, interview outcome, or response is presented as completed research unless it has actually been collected and verified.

Design Component

The AVERRA framework is developed as the proposed technological artifact.

Experimental Component

A controlled experiment can compare manual, rule-based, and AI-assisted prioritization using clearly labeled synthetic data or properly anonymized data for which permission exists.

11. DATASET DESIGN

A future dataset should contain anonymized observations such as:

Invoice_ID	Anonymous identifier
Industry	Company industry
Company_Size	Employee/revenue category

Monthly_Invoices	Approximate monthly invoice volume
Overdue_Rate	Percentage overdue
Avg_Days_Late	Average payment delay
Manual_Hours	Collection hours
Automation_Level	Current automation
Payment_History	Historical behavior
Human_Approval	Required approval level

No identifying customer information should be included.
For initial testing, synthetic invoice data can contain:

- invoice amount,
- payment terms,
- days overdue,
- historical payment delay,
- previous reminders,
- payment promises,
- dispute status,
- eventual payment outcome.

Synthetic data must be clearly labeled as synthetic.

12. AVERRA FRAMEWORK

AVERRA is proposed as an intelligent AR orchestration layer rather than a replacement for an organization's accounting or ERP system.

ERP / Accounting Software
↓
AVERRA
↓
Intelligence Layer
↓
Collection Actions

12.1 Invoice Intelligence

AVERRA monitors:

- invoice amount,
- customer,
- issue date,
- due date,
- payment status,
- payment history.

12.2 Customer Behavior Model

Potential behavioral features include:

- historical average payment delay,

- payment consistency,
- missed payment promises,
- communication responsiveness.

12.3 Risk Engine

The system estimates:

How likely is this invoice to require intervention?

This is a prediction, not a certainty.

12.4 Priority Engine

The system answers:

Which account should the finance team address first?

This is the central intelligence component.

12.5 Communication Engine

The system determines:

- whether communication is appropriate,
- timing,
- context,
- escalation level.

12.6 Human Escalation

Human review should be triggered for cases such as:

- large strategic accounts,
- legal disputes,
- suspected fraud,
- complex disagreements,
- repeated failed communications.

13. MATHEMATICAL MODEL

A conceptual collection-priority score can be represented as:

$P_i = w_a A_i + w_d D_i + w_r R_i + w_h H_i + w_c C_i$

Where:

- **P_i** = priority score
- **A_i** = normalized invoice amount
- **D_i** = normalized days overdue
- **R_i** = predicted payment risk
- **H_i** = historical payment behavior
- **C_i** = communication/context score

Subject to:

$w_a + w_d + w_r + w_h + w_c = 1$

The weights should be determined through experimentation rather than selected simply because they produce attractive results.

14. EXPERIMENTAL DESIGN

Three approaches can be compared.

Model A — Manual Prioritization
A human decides which invoices to address first.
Model B — Rule-Based Prioritization
Priority is determined using fixed rules, such as:
Higher invoice amount + more days overdue = higher priority.
Model C — AVERRA
Priority incorporates:

- invoice amount,
- invoice age,
- historical payment behavior,
- payment-risk prediction,
- contextual signals.

The objective is to determine whether context-aware prioritization produces better decisions than simple chronological or rule-based ordering.

15. EVALUATION METRICS

The proposed system should be evaluated across several dimensions.
Collection Efficiency
CE = Resolved Overdue Invoices / Total Overdue Invoices
Human Workload
HW = Total Collection Hours
Lower workload is desirable only if collection performance does not deteriorate.
Resolution Time
RT = Date Resolved − Date Overdue
Promise-to-Payment Rate
PP = Promises Resulting in Payment / Total Payment Promises
False Escalation Rate
FER = Unnecessary Human Escalations / Total Escalations
This is important because excessive escalation could simply shift work from humans to AI-generated alerts.

16. EXPECTED DECISION PROCESS

A simplified AVERRA workflow is:
16. Invoice enters the system.
17. Financial and behavioral features are evaluated.
18. Payment-risk estimation is performed.
19. Priority is calculated.
20. A recommended action is generated.
21. Routine, low-risk cases may be automated within predefined limits.
22. High-risk or ambiguous cases are escalated.
23. Outcomes are recorded.
24. Outcomes become future learning data.

This creates a continuous feedback loop:
Observe → Predict → Act → Measure → Learn

17. DISCUSSION

The central purpose of this research is not to determine whether AI can send reminders. Basic workflow automation can already do that.
The more important question is whether AI can improve decision quality.
Consider two simplified situations.
Scenario A
An invoice is several days overdue, but the customer normally pays within a short period, responds to communications, and has a small outstanding balance.
A system that considers context may recommend limited intervention.
Scenario B
An invoice is only a few days overdue but represents a large amount, the customer has a history of delayed payments, and recent communication has stopped.
A context-aware system may prioritize this account immediately.
Chronological ordering would not necessarily distinguish these cases.
This leads to the central argument:
The value of AI in AR may come less from automating communication itself and more from improving the allocation of human attention.

18. THE AUTOMATION PARADOX

Financial automation should not necessarily aim to eliminate human involvement.
An overdue invoice may result from:

- an approval delay,
- a cash-flow problem,
- an invoice error,
- a genuine dispute,
- a procurement delay,
- simple forgetfulness.

These situations can appear identical in a database:
Invoice = Overdue
But they require different responses.
Therefore:
Automation should handle repetition.
AI should support prioritization.
Humans should handle judgment.
AI can:

- monitor,
- classify,
- predict,
- prioritize,

- recommend,
- communicate within predefined boundaries.

Humans should:

- negotiate,
- resolve disputes,
- make high-consequence decisions,
- handle strategic customers,
- override the system when necessary.

19. ETHICAL AND SECURITY CONSIDERATIONS

AI-driven financial systems require strong governance.

Data Privacy

Financial and customer information must be protected.

Explainability

Finance professionals should be able to understand why an invoice was classified as high priority.

Human Oversight

High-consequence decisions should not automatically be delegated to AI.

Communication Safety

AI-generated messages should not make unsupported legal claims, threats, or misleading statements.

Bias

Historical payment data may contain patterns that should not automatically be treated as objective truth.

Security

A production system would require:

- authentication,
- authorization,
- encryption,
- tenant isolation,
- audit logs,
- backups,
- access controls,
- incident response,
- data-retention policies.

20. LIMITATIONS

This research has several limitations.

1. **Primary research:** Conclusions from surveys or interviews cannot be generalized until sufficient real-world data has been collected.
2. **Synthetic data:** Initial experiments may use simulated data rather than real financial records.
3. **Selection bias:** Organizations interested in automation may be more likely to participate in future research.
4. **Generalizability:** A model effective for one industry may not perform equally well in another.

5. **Prediction uncertainty:** A high-risk prediction does not guarantee late payment.
6. **AI errors:** Models may produce incorrect predictions or inappropriate communication.
7. **Long-term effects:** Short-term collection improvements may not capture effects on customer relationships.

21. FUTURE RESEARCH

Future work could investigate:

Predictive Payment Modeling

Whether historical payment behavior can reliably predict future delays.

Next-Best-Action Systems

Whether AI can recommend not only which invoice to prioritize, but what action should follow.

Reinforcement Learning

Whether collection strategies can improve by learning from outcomes.

Industry-Specific Models

Whether different industries require different risk and prioritization models.

Large Language Models

Whether LLMs can safely analyze communication context and assist with personalized financial interactions.

Human-AI Collaboration

Which financial decisions benefit most from AI assistance and which should remain human-controlled.

22. RESEARCH CONTRIBUTION

The main conceptual contribution of this research is separating AR intelligence into three functions:

1. Execution

Automating repetitive actions.

2. Intelligence

Understanding risk and prioritizing attention.

3. Judgment

Determining when human intervention is necessary.

This produces a simple principle:

Automation ≠ Intelligence ≠ Judgment

A system can automate a task without being intelligent. It can also provide intelligent recommendations without having authority to make the final decision.

The research therefore proposes that effective financial AI should deliberately separate these layers.

23. CONCLUSION

Accounts receivable sits at the intersection of sales, finance, customer relationships, and cash flow. Businesses increasingly recognize the value of AR automation, yet complete automation remains uncommon.

The evidence reviewed in this paper suggests that the next stage of AR technology should move beyond simple invoice tracking and fixed reminder workflows.

AVERRA proposes an intelligent approach in which a system:

1. continuously analyzes receivables,
2. estimates payment risk,
3. prioritizes accounts,
4. recommends appropriate actions,
5. automates routine work within defined boundaries,
6. escalates complex situations to humans,
7. learns from outcomes.

The key shift is:
Invoice Tracking → Automation → Intelligence → Decision Support
The most valuable automation may therefore not be the automation of every task. It may be the automation of the decision about which task deserves human attention next.
The framework presented here is designed to be empirically tested through future primary research and controlled experimentation.
Ultimately, AI in accounts receivable should not be measured only by how much human involvement it removes. It should be measured by whether it helps finance professionals spend their limited attention on the situations where that attention creates the greatest value.

24. RESEARCHER'S REFLECTION

This research began with a startup idea: identify a repetitive business problem and build technology that could solve it.
The research changed the question from:
"Can I build something that automates this?"
to:
"Do I actually understand why this problem exists?"
That distinction became one of the most important lessons of the project.
Building software is only one part of creating useful technology. Understanding incentives, workflow, risk, economics, trust, and human behavior is equally important.
The project also changed my view of AI. Rather than seeing AI only as a tool for replacing repetitive work, I became more interested in AI as a mechanism for allocating attention and supporting decisions.
A finance employee cannot manually evaluate every variable across thousands of invoices. A machine can process large amounts of information quickly. But speed alone is not intelligence.
The important question is:
Can the system identify what actually matters?
That question became the foundation of the AVERRA framework.
The broader lesson extends beyond accounts receivable: in many industries, the strongest AI systems may not replace human judgment. They may help humans know where their judgment matters most.

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APPENDIX A — PROPOSED SURVEY

1. What industry does your organization operate in?
2. Approximately how many employees does your organization have?
3. Approximately how many B2B invoices does your organization issue each month?
4. What percentage of invoices typically become overdue?
5. What is the average payment term?
6. How is the collection process currently managed?
7. How many employee hours per week are spent on invoice follow-up?
8. Which collection activities consume the most time?
9. Would your organization consider AI for invoice prioritization?
10. Which AR tasks would you trust AI to perform automatically?
11. Which decisions should require human approval?

APPENDIX B — PROPOSED EXPERIMENT

Experiment 1

Compare chronological/rule-based prioritization with AVERRA prioritization.
Independent variable: Prioritization method.
Dependent variables:

- prioritization accuracy,
- collection efficiency,
- workload,
- resolution time.

Experiment 2

Compare fixed reminder schedules with context-aware communication.
Dependent variables:

- response rate,
- payment rate,
- number of communications,
- human intervention.

Experiment 3

Evaluate human escalation.
Measures:

- percentage of cases escalated,
- percentage of escalations judged necessary,
- false escalation rate,
- human review time.

FINAL RESEARCH MODEL

FINANCIAL DATA
↓
INVOICE INTELLIGENCE
↓
CUSTOMER BEHAVIOR
↓
RISK ESTIMATION
↓
COLLECTION PRIORITIZATION
↓
NEXT-BEST ACTION
↓
AUTOMATED EXECUTION
↓
HUMAN ESCALATION
↓
OUTCOME
↓
FEEDBACK
↓
MODEL IMPROVEMENT

FINAL RESEARCH PROPOSITION

AI-driven accounts receivable systems should be designed not primarily as automated reminder engines, but as human-in-the-loop financial decision systems that continuously transform receivables data into prioritized actions.

This proposition can be tested through primary research and controlled experimentation.

The proposed direction is:

Tracking → Automation → Intelligence → Decision Support

rather than treating automation as the final objective.