

# AI-Driven Optimization of Debt Collection Efficiency in Accounts Receivable: An Action Research Case Study of DK Company

Xu Xiaoli<sup>1,2</sup>, Rafidah Binti Othman<sup>1\*</sup>, Wei Deng<sup>3</sup>

<sup>1</sup>Azman Hashim International Business School, Universiti Teknologi Malaysia, Kuala Lumpur, Malaysia, <sup>2</sup>Guizhou Electronic Commerce Vocational College, Guiyang city, Guizhou province, China, <sup>3</sup>School of Economics and Management, Huizhou University, Guangdong, China

\*Corresponding Author Email: rafidah.othman@utm.my

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## Abstract

This study takes DK Company, a Chinese SME manufacturer, as a case and adopts the action research method to explore the practical application of artificial intelligence (AI) in optimizing the debt collection process in accounts receivable management. DK Company has long struggled with delayed customer payments and a days-sales-outstanding (DSO) ratio well above the industry median. In collaboration with the research team, DK developed and deployed an AI-driven collection system that segments debtors by default risk, predicts payment behavior, and generates personalized, channel-specific dunning strategies. Through continuous interaction between researchers and the company's finance team and multiple rounds of iterations, this system has significantly enhanced the collection efficiency and effectively improved the cash flow situation. The empirical results demonstrate substantial improvements across key operational indicators: DSO decreased by 25.7%, bad debt ratio declined by 41%, and an additional RMB 1.5 million in cash flow was recovered within six months. Beyond quantitative gains, the intervention fostered user acceptance and organizational learning, with cross-departmental collaboration and data-driven decision-making capabilities notably enhanced. This study theoretically expands the application boundaries of artificial intelligence in the field of financial management and provides an operational reference for the accounts receivable management in similar manufacturing settings at the practical level. The main limitation of the research lies in its reliance on a single case. In the future, the universality of the conclusion can be further verified through multi-case comparisons or cross-industry verifications. This study was motivated by the persistent cash flow constraints experienced by small and medium-sized manufacturing enterprises in China. In many cases, reliance on manual debt collection procedures led to operational inefficiencies and intensified financial pressure. The primary contribution of this research lay in the development and empirical examination of a practical AI-driven framework. The findings demonstrated that the proposed framework improved key operational performance

indicators while facilitating organizational adaptation, thereby providing a replicable reference model for enterprises operating in comparable contexts.

**Keywords:** Artificial Intelligence, Accounts Receivable Management, Debt Collection

## Introduction

In an organization's financial operations, accounts receivable (AR) management plays a crucial role in shaping liquidity conditions, cash flow dynamics, and broader financial stability. Although accounts receivable business has been continuously optimized with the trend in recent years, issues such as too many manual operations, long working hours, low invoicing efficiency, and uncontrollable errors have not been adequately addressed. (Zeng, 2022) With the continuous advancement of digital technology, artificial intelligence (AI) offers a feasible approach to alleviate these obstacles through task automation, payment behavior prediction, and precise analytical support.

This research investigates the case of DK Company, a manufacturing company in China specializing in electronic connectors. With an a bad debt ratio exceeding 10%, DK exemplifies the AR challenges facing Chinese manufacturing SMEs. The study aims to improve debt collection processes through AI, addressing the company's ongoing challenges with elevated days sales outstanding (DSO) and labor-intensive recovery efforts. The primary motivation for this research stems from the inefficiencies in the accounts receivable management of small and medium-sized enterprises. Traditional methods are unable to cope with the increasing economic pressure, while AI offers unexploited optimization opportunities that have yet to be fully utilized.

The research is guided by the following questions: (1) In what ways can AI be embedded into existing AR frameworks to enhance debt collection performance? (2) What impact does this integration have on operational efficiency and organizational structure? (3) Which insights can be more widely applied in AR management? This article includes a review of relevant literature, methodological details, implementation phases, empirical results, and future research prospects.

## Literature Review

### *Accounts Receivable Management and Debt Collection Challenges*

The main purpose of accounts receivable management is to timely recover the receivable accounts and effectively avoid the risk of economic loss. (Peng & Tian, 2024) However, due to manual operation, practitioners often grapple with long working hours, uncontrollable errors and low efficiency of invoicing, which elevate operational costs and impede prompt cash inflows. (Yang, 2023) Within manufacturing environments, such as DK Company's operations, these pressures are compounded by supply chain linkages, as the costs will increase through chasing receivables, late payments and default risks in the long run. (Onjewu et al., 2024)

### *Applications of Artificial Intelligence in Financial Operations*

Artificial intelligence has greatly transformed the landscape of financial operations. The integration of big data with advanced technologies like blockchain, artificial intelligence (AI), automation, and machine learning helps create a robust and automated accounting process. (Park et al., 2020) Self-learning AI-based integrated systems can access actual data in real time and, based on this, independently develop solutions, suggestions, forecasts and

trends, which collectively reduce human negligence and accelerate capital recovery. (Najderek, 2020) AI has emerged as a promising tool to enhance system-level performance, particularly in cost reduction, productivity gains, and administrative efficiency. (Lee et al., 2025) Despite these advancements, AI systems need a lot of data to work, which raises privacy and security concerns and makes GDPR compliance difficult. (Patil et al., 2024)

#### *Action Research in AI-Driven Financial Process Improvements*

Action research includes iterative cycles of planning, action, and reflection, whereby participants collect and analyze data, and determine what actions should follow. (Verweij et al., 2023) Therefore, it is particularly suitable for studying how AI reshape financial operations through the ability to process data in real-time and generate predictions while automating sophisticated financial processes. (Joseph Oluwaseyi, 2025) In the field of financial operations, this approach has been employed to jointly create AI solutions with stakeholders, addressing the gaps in traditional implementations by emphasizing context adaptation and iterative optimization. (Petrescu et al., 2024) For instance, research has demonstrated its effectiveness in deploying AI for risk assessment and process automation, where the participation of practitioners ensures consistency with operational realities and promotes sustainable improvements. (Onyeka, 2025) Scholars stress that action research can not only generate actionable insights but also build organizational capabilities, as seen in the case of improving artificial intelligence tools for fraud detection through collaborative feedback loops. (George Thomas, 2025) Despite its advantages, this approach requires careful handling of ethical dilemmas, such as the application of AI requires the processing of enormous amounts of sensitive customer data. Hence, data privacy and security are crucial. (Ridzuan et al., 2024) Overall, this framework promotes an understanding of the role of artificial intelligence in enhancing efficiency and provides a perspective that links theoretical models with tangible process enhancements in accounts receivable and other aspects.

#### *Research Gaps and Contributions*

Although the existing literature on the application of artificial intelligence in the financial sector has increased, there are still three key gaps. Firstly, most studies focus on large institutions or banks, while neglecting small and medium-sized enterprises in the manufacturing sector. These enterprises, due to their resource constraints and close customer relationships, make accounts receivable management more complex. (Roffia et al., 2024) Secondly, previous research on AI applications emphasized technical indicators such as accuracy and speed, while paying limited attention to human factors such as resistance and workflow integration. Thirdly, the application of action research in artificial intelligence collection is still rare, and there is a lack of detailed explanations for the participation of iterative practitioners. By filling these gaps, this study has provided empirical evidence on the application of AI in the accounts receivable management of small and medium-sized enterprises, as well as a structured action research method for the implementation of the technology.

Through three cycles of action research, this study documents the co-evolution of organizational learning, technology, and practices, and investigates AI-driven debt collection in manufacturing SMEs, thereby addressing these gaps. These findings provided theoretical insights for the application of AI in the collection field and practical strategies for similar enterprises to enhance their collection efficiency.

## Research Methodology

### *Research Design: The Action Research Approach*

This study employs an action research design to investigate and implement artificial intelligence enhancements in DK Company's debt collection. Action research is a participatory approach that involves an iterative cycle of planning, action, observation and reflection, allowing researchers and practitioners to collaborate to solve real-world problems while generating theoretical insights.

This method was chosen because it emphasizes practical relevance and adaptability in the organizational environment. It enables stakeholders, such as the finance team, to directly participate and address specific AR challenges through hands-on experiments and feedback, ensuring that the AI system aligns with operational needs rather than relying solely on theoretical models. This approach is especially apt for technology-driven innovations like AI integration, as it facilitates real-time adjustments, reduces implementation risks, and fosters organizational learning.

### *Case Context and Selection: DK Company*

DK Company was established in 2014 and is located in Gui'an New Area, Guizhou Province, China. It is a medium and small-sized high-tech manufacturing enterprise in the electrical connector industry. It has a 4,700-square-meter factory and advanced equipment. Its organizational structure consists of ten departments and 149 employees, focusing on high-precision connectors for aviation, aerospace, electronics and locomotives. It emphasizes specialization, refinement, innovation and intelligent manufacturing.

The selection of cases is purposeful, highlighting DK's representative AR challenges: extended DSO, high bad debt rates, and rising overdue accounts. In an environment of economic uncertainty, these issues provide an ideal backdrop for achieving AI-driven debt collection optimization through action research.

## Data Collection Methods

This study employed a mixed-methods approach to ensure comprehensive data triangulation. Data collection occurred across two phases: pre-implementation (January to June 2025) and post-implementation (July to December 2025).

**Quantitative Data Collection:** Financial indicators were extracted from DK's ERP system and internal financial reports, including: (1) monthly DSO calculations, (2) bad debt ratios, (3) overdue AR amounts by aging category, (4) 30-day collection rates, and (5) monthly cash inflows from AR. Data integrity were verified through cross-referencing with bank statements and audit records.

**Qualitative Data Collection:** A 2-hour focus group discussion was held in January 2026, with participants including 10 department managers, 2 finance department employees, and 5 sales specialists. The group discussion agreement involves five core dimensions:

Table 1

Five core dimensions of the group discussion

Dimension	Sample Questions
System Effectiveness	“What specific changes have you observed in daily collection workflows since AI implementation?”
Prediction Accuracy	“How reliable are the AI-generated risk classifications in identifying problematic accounts?”
Process Efficiency	“Has automated communication reduced your manual workload? Please provide specific examples.”
Cross-departmental Impact	“How has the system affected collaboration between Finance and Sales regarding collection strategies?”
Improvement Suggestions	“What features or adjustments would enhance the system’s utility for your department?”

**Data Analysis Methods**

Quantitative Analysis: Paired t-tests were conducted to assess statistical significance of pre-post differences in key AR indicators. Trend analysis examined monthly variations to identify patterns beyond aggregate changes.

Qualitative Analysis: Thematic analysis followed Braun and Clarke’s (2006) six-phase approach(Walker et al., 2025):

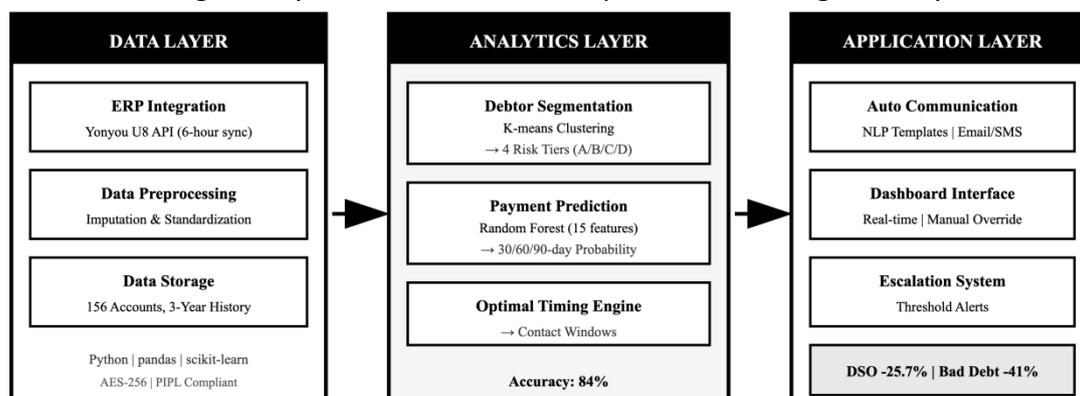
- (1) Familiarization: Repeated reading of transcripts to identify initial patterns.
- (2) Initial Coding: Line-by-line open coding generating 47 initial codes.
- (3) Theme Development: Grouping codes into 12 candidate themes.
- (4) Theme Review: Consolidating to 5 final themes through research team discussion.
- (5) Theme Definition: Establishing clear boundaries and exemplar quotes for each theme.
- (6) Report Production: Integrating themes with quantitative findings.

Triangulation integrated quantitative metrics with qualitative insights to validate findings and ensure participant anonymity through pseudonymization.

**Implementation of the AI-Driven Debt Collection System**

*System Architecture and Core Features*

The artificial intelligence system is built on a cloud-based platform utilizing Python and machine learning libraries including scikit-learn, XGBoost, and pandas for data processing and predictive modeling. The system architecture comprises three integrated layers:



Data Flow: ERP → Data Layer → Analytics Layer → Application Layer → Users

Figure 1. AI-Driven Debt Collection System Architecture

Data Layer: Bidirectional API connection with DK's existing Yonyou U8 ERP system, enabling real-time synchronization of AR records, payment histories, and customer profiles. Data preprocessing modules handle missing value imputation and feature standardization.

Analytics Layer: Three core analytical modules: (1) Debtor Segmentation through K-means clustering based on payment history, credit scores, and transaction volume, classifying customers into four risk tiers (A: Low Risk, B: Medium-Low, C: Medium-High, D: High Risk); (2) Payment Delay Prediction using Random Forest algorithms with 15 input features, outputting probability scores for 30/60/90-day payment delays; (3) Optimal Timing Engine calculating recommended contact windows based on historical response patterns.

Application Layer: (1) Automated communication module generating personalized reminders via email and SMS using NLP templates; (2) Dashboard interface displaying real-time AR status, risk alerts, and collection priorities; (3) Escalation trigger system for accounts exceeding defined thresholds.

### Action Research Implementation

The implementation followed three iterative action research cycles, each comprising planning, action, observation, and reflection phases. Figure 2 illustrates the timeline and key activities of each cycle.

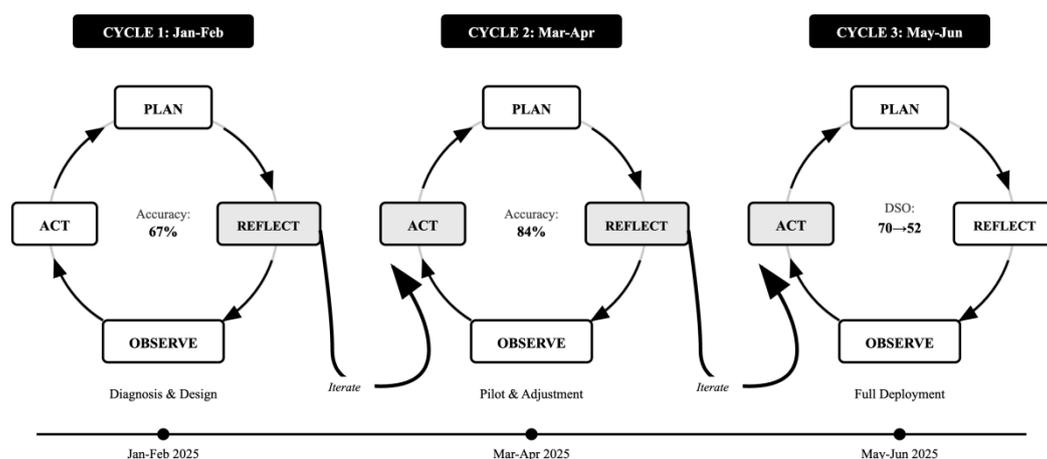


Figure 2. Action Research Cycle

This figure illustrates the three iterative cycles of action research, with the time span from January to June 2025. Each cycle follows the closed-loop process of "Plan , Act , Observe, Reflect". The entire process demonstrates the implementation path of gradually optimizing the AI system through continuous iteration and data-driven feedback.

#### Cycle 1: Problem Diagnosis and System Design

Planning Phase: The research team conducted collaborative workshop with DK's finance department to diagnose existing collection challenges. Using root-cause analysis, participants identified four primary inefficiency driver, including lack of systematic debtor risk visibility, inconsistent follow-up timing leading to missed optimal windows, one-size-fits-all communication strategies regardless of customer profile excessive manual effort in tracking and documentation. Based on these findings, the team prioritized three system requirements:

automated risk classification, payment prediction capability, and personalized communication generation.

Action Phase: System development proceeded with daily meetings between the IT consultant and finance team lead. The initial prototype incorporated payment history from 2022–2024, covering 156 customer accounts, for model training.

Observation: Initial model testing revealed a prediction accuracy of only 67% for 30-day payment delays, below the 75% threshold deemed operationally useful by the finance team.

Reflection: Analysis identified that the model underperformed for aerospace sector clients due to their unique quarterly budget cycles. For instance, aerospace customers almost always pay in March, June, September, and December, which are their fiscal quarters. The model was treating their delayed payments as high-risk when they’re actually predictable.”

*Cycle 2: Pilot Testing and Iterative Adjustment*

Planning Phase: Based on Cycle 1 reflections, the team redesigned the feature engineering approach to incorporate: industry-specific payment cycle indicators, seasonal adjustment factors, and external economic indicators (PMI index). Additionally, 20 high-risk accounts, which were overdue >60 days and value >RMB 200,000 were selected for pilot testing.

Table 2  
20 high-risk accounts for pilot testing

No.	Account ID	Total AR (RMB)	Overdue Amount (RMB)	Overdue Days	Risk Tier (D :High, C:Med-High)	Pre-AI Status	Post-AI Result	Collection Outcome
1	C-0847	458,000	285,000	95	D	No follow-up	Override applied	Full payment
2	C-0523	892,000	520,000	78	D	Quarterly cycle unknown	Timing optimized	Paid at quarter-end
3	C-0612	345,000	210,000	68	C	Generic reminders	Personalized approach	85% recovered
4	C-0891	567,000	380,000	102	D	Escalation delayed	Auto-escalation triggered	Payment plan negotiated
5	C-0234	423,000	245,000	72	C	Manual tracking only	Predictive alert	Full payment within 30 days
6	C-0756	678,000	412,000	88	D	Late intervention	Early warning	70% recovered, 30% restructured
7	C-0345	289,000	178,000	65	C	Inconsistent follow-up	Systematic reminders	Full payment
8	C-0928	534,000	298,000	75	C	No risk visibility	Risk dashboard	Paid at quarter-end
9	C-0167	412,000	267,000	82	D	Missed optimal timing	Optimal window identified	90% recovered

10	C-0489	356,000	198,000	70	C	Manual process only	Automated workflow	Full payment
11	C-0672	623,000	378,000	85	D	No segmentation	Risk tier assigned	80% recovered
12	C-0815	278,000	156,000	62	C	Delayed response	Proactive contact	Full payment within 21 days
13	C-0543	389,000	234,000	78	C	Generic approach	Customer-specific strategy	Full payment
14	C-0921	756,000	445,000	92	D	Cash flow crisis undetected	Early warning triggered	60% recovered before restructuring
15	C-0287	312,000	189,000	67	C	No prediction	Delay predicted accurately	Full payment
16	C-0634	445,000	278,000	80	D	Reactive only	Proactive intervention	85% recovered
17	C-0178	267,000	145,000	63	C	Standard reminder	NLP personalized message	Full payment within 14 days
18	C-0856	589,000	356,000	88	D	Quarterly pattern missed	Pattern recognized	Paid at quarter-end
19	C-0412	378,000	223,000	74	C	Fragmented tracking	Centralized monitoring	Full payment
20	C-0723	298,000	167,000	66	C	Manual process	AI-assisted workflow	Full payment within 25 days

**Action Phase:** The enhanced model was deployed in a controlled pilot environment. Automated reminders were activated for pilot accounts, with finance staff monitoring AI recommendations before taking action. Weekly review meetings documented system performance and user feedback.

**Critical Adjustment:** During Week 2, the system flagged Account “C-0847” as high-risk based on historical patterns. However, the sales representative intervened: “This customer had a one-time delay last year due to factory relocation. They’ve been reliable for five years before that. The aggressive reminder would damage our relationship.” This case prompted the addition of a “relationship context” field and manual override function, enabling staff to input qualitative information not captured in quantitative data.

**Reflection:** The pilot demonstrated that the AI is excellent at pattern recognition, but it cannot understand the story behind the number. Therefore, the pure algorithmic recommendations required human judgment integration.

### *Cycle 3: Full Deployment and Optimization*

**Planning Phase:** Following successful pilot outcomes, the team planned organization-wide rollout with three priorities: comprehensive staff training, integration of manual override capabilities, and establishment of continuous monitoring protocols.

Action Phase: Full deployment occurred on May 1, 2025, covering all 156 active customer accounts. Additionally, the use of digital technologies will increase the quantity and complexity of data requiring highly qualified employees, a one-week training program was conducted.(Leitner-Hanetseder et al., 2021)

Reflection: The full deployment validated the system’s effectiveness while revealing areas for continued optimization.

*Integration with Existing AR Processes*

The AI system was integrated into DK’s existing Yonyou U8 ERP through a phased approach minimizing operational disruption:

Phase 1 (Week 1-2): Finance staff mapped current workflows: invoice issuance, payment tracking, aging analysis.

Phase 2 (Week 3-4): Custom API development enabled bidirectional synchronization: AR records pulled into the AI system every 6 hours for analysis, predictions and alerts pushed back to ERP for staff access.

Phase 3 (Week 5-6): Parallel running period where both manual and AI-assisted processes operated simultaneously, allowing comparison and confidence building.

Phase 4 (Week 7 onwards): Full transition to AI-assisted workflow with manual processes retained only as backup.

*Challenges Encountered and Solutions*

The implementation process encountered several challenges requiring adaptive responses:

Table 3

*Challenges and solutions in implementation*

<b>Challenge Category</b>	<b>Specific Issue</b>	<b>Solution Implemented</b>
Technical	ERP data format incompatibility	Custom data transformation layer
Technical	Initial prediction accuracy below threshold (67%)	Industry-specific feature engineering
Organizational	Staff skepticism toward AI recommendations	Gradual exposure + visible early wins
Organizational	Sales concern about customer relationship damage	“Soft reminder” templates + relationship tags
Data Quality	15% missing values in historical records	Imputation algorithms + external data supplementation
Change Management	Resistance to workflow changes	Kotter's 8-step model + peer champions

## Findings and Evaluation

### Key Operational Performance Metrics

The data from January to June 2025 highlights DK's AR inefficiency: the average DSO is 70 days, indicating an extended collection period. The bad debt ratio is 10.5%, reflecting a high amount of unrecoverable losses. Overdue accounts receivable rose from 2.08 million yuan to 3.44 million yuan, and the default rate was on the rise.

After the implementation of AI, the indicators will be significantly improved from July to December 2025. The DSO was shortened to 52 days, the bad debt rate dropped to 6.2%, and the overdue AR amount decreased to RMB 2.92 million. For DSO,  $t=3.87$ ,  $p < 0.05$ ; for bad debts,  $t=4.12$ ,  $p < 0.01$ ; for the overdue amount,  $t=3.45$ ,  $p < 0.05$ , the paired t-test confirmed the significance, demonstrating the impact of AI on collection efficiency.

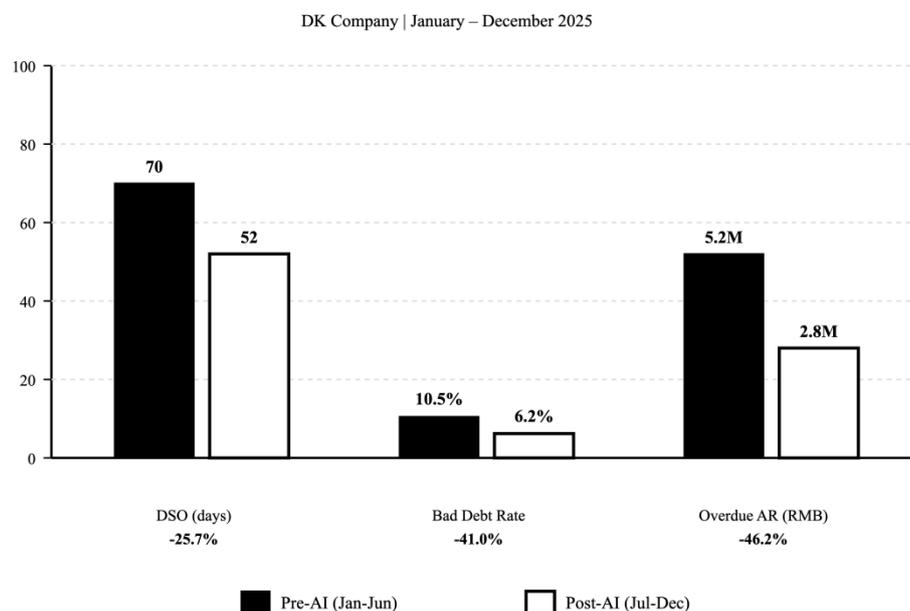


Figure 3. Pre and Post AI Comparison on Operational Performance

### Effects on Collection Efficiency and Cash Flow

The implementation of AI has significantly enhanced the debt collection efficiency of DK Company. Before the application of AI technology, only 72% of invoices could be recovered within 30 days, and it took an average of 40 hours per week to handle the collection reminders. After introducing AI, through automated segmentation and personalized communication, the 30-day recovery rate increased to 88%, the average weekly workload decreased to 25 hours, and the average collection period was shortened from 45 days to 32 days.

These improvement measures have had a positive impact on cash flow, accelerating the inflow of funds and enhancing liquidity. Before the application of AI, the average monthly cash inflow of accounts receivable was RMB 4.38 million. After the application of AI, the average monthly cash inflow increased to RMB 6.80 million, and an additional RMB 1.5 million was recovered within six months.

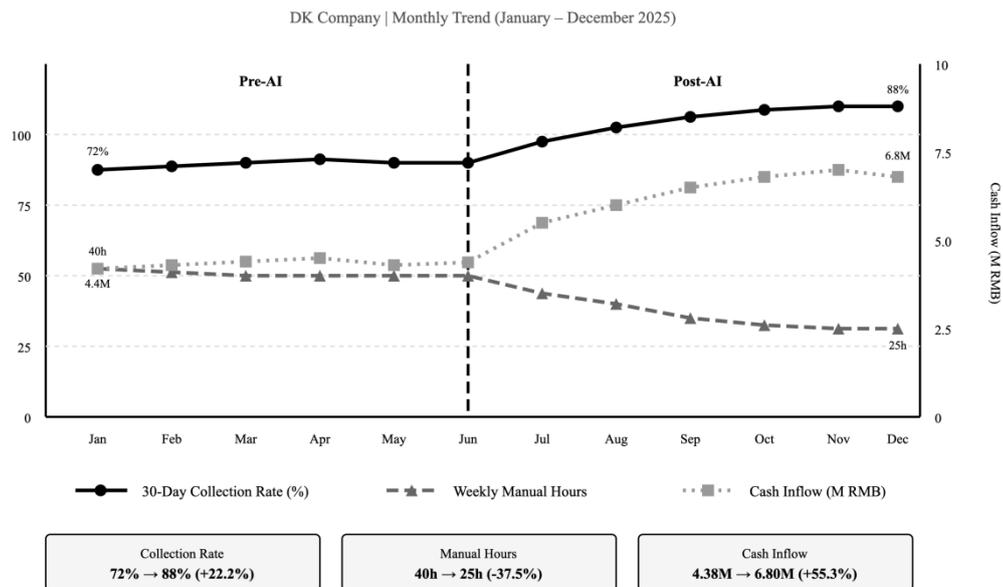


Figure 4. Pre and Post AI Comparison on Collection Efficiency and Cash Flow

### User Perceptions and Organizational Learning Outcomes

The focus group discussion with ten department heads provided rich qualitative insights into user perceptions and organizational impacts. Thematic analysis identified five primary themes, presented with supporting evidence:

#### Theme 1: Enhanced Decision-Making Efficiency

Participants consistently reported that AI-generated risk classifications significantly accelerated their decision-making processes. The finance manager articulated:

*“Before the system, I spent two hours every Monday reviewing the aging report and manually flagging problematic accounts. Now, I open the dashboard and the high-risk accounts are already highlighted. I can make collection calls within 30 minutes instead of waiting until afternoon.”*

#### Theme 2: Workflow Automation Benefits

Automated reminder generation emerged as the most appreciated feature, with the sales representative noting substantial time savings:

*“Previously, I drafted individual reminder emails, sometimes 15-20 per week. Each one took 10-15 minutes to personalize. Now, the system generates appropriate templates based on customer history and risk level. I just review and send. My weekly reminder time dropped from 4 hours to under 1 hour.”*

#### Theme 3: Improved Cross-Departmental Collaboration

The shared dashboard interface facilitated unprecedented visibility across departments. The production manager noted spillover benefits:

*“When I see which customers are flagged as payment risks, I can adjust our production scheduling accordingly. We no longer prioritize orders for customers who historically delay payments.”*

#### Theme 4: Trust Development Through Visible Accuracy

The Sales Representative expressed his views: initial skepticism gradually transformed into confidence as prediction accuracy became evident:

*“To be honest, I did not trust it initially. I thought, how can a computer know my customers better than I do after 10 years? But after the third accurate prediction, I started paying attention. After the tenth, I was convinced.”*

### **Theme 5: Organizational Learning and Capability Development**

The general manager observed broader cultural shifts:

*“The success of this project has changed how we approach other operational challenges. We are now exploring AI applications for inventory optimization and production scheduling. The finance team’s positive experience became a catalyst for digital transformation across the organization.”*

### **Discussion**

#### *Theoretical Contributions to AI in Finance*

This research has made three significant contributions in terms of providing a theoretical understanding of the application of artificial intelligence in financial management. These contributions have enhanced the appeal of the research by integrating AI innovation with the real financial challenges faced by small and medium-sized enterprises.

This study expands the existing risk assessment framework based on artificial intelligence and demonstrates how to adjust machine learning models for the manufacturing sector of small and medium-sized enterprises. Different from the standardized credit scoring methods described in banking literature, (Ala’raj et al., 2021) effective accounts receivable prediction in the manufacturing environment requires feature engineering specific to the characteristics of the industry. This is in line with Rabbani et al (2025) view that the reduction in the cost of artificial intelligence varies greatly depending on the scope of implementation. (Rabbani et al., 2025) Moreover, this study further clarifies the types of contextual adaptation required on this basis.

This study enriches the action research theory in the application of financial technology. Previous literature has emphasized the importance of practitioners’ participation, (Bahoo et al., 2024) but provided limited guidance on how such participation should be structured. This study shows that three iterative cycles, from the diagnostic stage to the pilot testing stage, and to the full deployment stage, provide sufficient iterative opportunities, which are beneficial not only for the improvement of the technology but also for the establishment of trust.

These findings contribute to understanding the organizational learning dynamics during the adoption process of artificial intelligence. The process from initial skepticism to confidence depicts a process of trust development, which is recognized in existing literature but rarely documented in detail. Additionally, the success of the finance department has driven a broader interest in digital transformation, indicating that successful AI implementations can change the organizational culture in ways beyond the direct application domain.

#### *Practical Implications for Accounts Receivable Management*

This research provides practical guidance for the accounts receivable management of small and medium-sized enterprises like DK, demonstrating how AI-driven tools can automatically

segment debtors, predict payment delays, and personalize collections. Managers can adopt a similar integration to the existing ERP system, emphasizing phased pilots and stakeholder training to minimize resistance and ensure scalability. These strategies have increased cash flow, reduced operating costs, and supported active risk management, providing a replicable model for manufacturing enterprises facing similar liquidity challenges.

#### *Study Limitations and Transferability Considerations*

This study, while providing valuable insights into AI-driven debt collection, is constrained by its focus on a single case at DK Company, a mid-sized Chinese manufacturing firm, which limits generalizability to larger organizations or diverse industries where AR dynamics may differ substantially. (Yin, 2018)

Transferability is feasible for similar SMEs in high-tech manufacturing facing cash flow challenges. However, applicability to service sectors or regions with varying regulatory environments requires cautious adaptation, as contextual factors such as data privacy laws influence outcomes. (Excel G Chukwurah, 2024) Future multi-case studies could enhance robustness by testing these approaches across varied contexts.

#### **Conclusion and Directions for Future Research**

This action research case study by DK Company demonstrates the transformative potential of artificial intelligence in debt collection for optimizing accounts receivable management. By integrating predictive analysis, debtor classification and automated communication, the system has shortened the DSO from 70 days to 52 days, reduced the bad debt rate by 41%, and stabilized overdue amounts, thereby enhancing the collection efficiency and recovering an additional cash flow of approximately RMB 1.5 million within six months. These results highlight the role of artificial intelligence in addressing AR challenges for small and medium-sized enterprises, promoting organizational learning through iterative collaboration and practical adaptation.

Future research can assess its universality through cross-industry case comparisons, or explore ethical dimensions, such as data privacy issues in AI-driven finance, which will also enrich this field.

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