Empirical Study on the Effectiveness of Generative AI in Financial Risk Management for Small and Medium Enterprises

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Abstract

With the rapid development of the digital economy, small and medium enterprises (SMEs) face increasingly complex and diverse financial risks. Traditional financial risk management methods exhibit significant limitations in processing massive data and predicting complex risk patterns. The emergence of generative artificial intelligence technology provides innovative solutions for financial risk management in SMEs. This study focuses on the application effectiveness of generative AI technology in SME financial risk management. Through constructing a theoretical analytical framework and employing a combined research methodology of questionnaire surveys, case analysis, and empirical testing, we conducted an in-depth investigation of 235 SMEs. The research findings reveal that generative AI technology significantly outperforms traditional methods in financial risk identification accuracy, prediction precision, and management efficiency, with risk identification accuracy improving by 27.3% and risk prediction precision increasing by 34.5%. Meanwhile, factors such as technology acceptance, data quality, and organizational support have significant impacts on the effectiveness of generative AI. The research results provide theoretical guidance and practical reference for SMEs to rationally utilize generative AI technology to enhance their financial risk management capabilities.

Keywords

Generative Artificial Intelligence, Small and Medium Enterprises, Financial Risk Management, Effectiveness Evaluation, Empirical Research.

1. Introduction

Small and medium enterprises (SMEs), as an essential component of the national economy, play an irreplaceable role in promoting employment and stimulating innovation vitality. According to the latest statistical data released by the Ministry of Industry and Information Technology, by the end of 2024, the number of SMEs nationwide has exceeded 52 million, contributing more than 60% of the gross domestic product. However, SMEs generally face the dilemma of insufficient financial risk management capabilities during their rapid development process. Traditional financial risk management primarily relies on manual experience judgment and static indicator analysis, making it difficult to cope with complex risk challenges brought by rapidly changing market environments.

Current financial risks in SMEs exhibit diversified and dynamic characteristics [1]. Liquidity risk, credit risk, market risk, and operational risk interweave with each other, significantly enhancing risk contagion effects. Particularly under the backdrop of increasing economic downward pressure, the financial vulnerability of SMEs becomes more pronounced. The "China Financial Stability Report (2024)" released by the People's Bank of China indicates that the non-performing loan rate of SMEs continues to be higher than that of large enterprises, and their financial risk prevention and control capabilities urgently need improvement [2].

The breakthrough progress of generative artificial intelligence technology has brought revolutionary transformation opportunities for financial risk management [3]. Large language models represented by ChatGPT and Claude demonstrate powerful capabilities in data processing, pattern recognition, and predictive analysis. These technologies can process massive unstructured data, mine hidden risk signals, and provide enterprises with more accurate and forward-looking risk warnings. The advantages of generative AI in natural language understanding, knowledge reasoning, and creative thinking make it possess enormous application potential in fields such as financial data analysis, risk scenario simulation, and decision solution generation [4].

Research reports from McKinsey, a renowned international consulting firm, show that the application of generative AI in the financial services sector could create annual value growth of $200-400 billion. The rapid improvement in technology maturity and continuous decline in deployment costs enable SMEs to afford advanced AI technology solutions. This provides technical feasibility for solving the problem of insufficient financial risk management capabilities in SMEs [5].

Digital transformation has become an inevitable path for SMEs to enhance competitiveness. Financial management, as the core component of enterprise operations and management, directly affects enterprises' risk control capabilities and operational efficiency through its level of intelligence. Traditional risk management systems based on historical data and rule engines are gradually evolving toward intelligent systems based on machine learning and artificial intelligence [6]. This transformation can not only improve the accuracy and timeliness of risk identification but also reduce labor costs and enhance management efficiency through automated processing.

Regulatory authorities are also actively promoting the application of financial technology in risk management. The "Guidance on Promoting Digital Transformation in the Banking and Insurance Industries" issued by the China Banking and Insurance Regulatory Commission explicitly proposes strengthening the application of new technologies such as artificial intelligence and big data in risk management. This policy orientation creates a favorable institutional environment for the promotion and application of generative AI in the field of financial risk management.

This research focuses on the practical application effects of generative AI technology in SME financial risk management. Specifically, it needs to address three core questions: Can generative AI significantly improve the accuracy and timeliness of financial risk identification in SMEs? Are there significant differences when different types of SMEs apply generative AI for financial risk management? How does the application of generative AI technology affect the financial decision-making quality and risk control level of SMEs? Solving these problems is of great significance for guiding SMEs in reasonably allocating technological resources and formulating digital transformation strategies. Meanwhile, deeply understanding the mechanism of generative AI in financial risk management helps perfect relevant theoretical systems and provides empirical evidence for subsequent research.

2. Research Model and Analysis Framework Design

2.1. Theoretical Model Construction and Core Logic

The application of generative AI in financial risk management follows the core process of "data input - intelligent processing - risk output - decision support." This process transforms the traditional manual judgment model into an intelligent automatic identification and warning model. Generative AI processes enterprise financial data, market information, and external environmental variables through deep learning algorithms, generating risk assessment reports and warning signals to provide scientific decision-making basis for management [7].

In the risk identification stage, generative AI can simultaneously process structured and unstructured data, including multi-dimensional information such as financial statements, bank statements, contract texts, and news information. Through natural language processing technology, AI systems can understand and analyze risk signals in textual information, identifying implicit risk factors that traditional methods find difficult to capture. This comprehensive data processing capability significantly enhances the comprehensiveness and accuracy of risk identification [8].

The impact of generative AI on financial risk management effectiveness is achieved mainly through three pathways: direct effect pathway, mediating effect pathway, and moderating effect pathway. Direct effects manifest as AI technology directly improving risk identification accuracy and warning timeliness; mediating effects indirectly affect risk management performance by improving information processing efficiency and decision quality; moderating effects are manifested as the moderating role of enterprise characteristics and environmental factors on AI application effects [9].

The variable relationship model is set as follows: Financial Risk Management Effectiveness = α + β_1 × Generative AI Application Degree + β_2 × Enterprise Scale + β_3 × Industry Characteristics + β_4 × Technology Maturity + β_5 × Control Variables + ε. Among these, the generative AI application degree is measured through three dimensions: risk prediction accuracy, system response time, and decision support quality.

Based on theoretical analysis, this study proposes five core hypotheses: H1 - Generative AI application significantly improves financial risk management effectiveness; H2 - Enterprise scale has a positive moderating effect on AI application effects; H3 - There are significant differences in AI application effects across different industries; H4 - The higher the technology maturity, the more obvious the AI application effects; H5 - Generative AI mainly affects risk management performance by improving information processing efficiency.

Theoretical expectations indicate that the introduction of generative AI technology will significantly improve various indicators of SME financial risk management. Expected effects include: risk identification accuracy improvement of more than 20%, risk warning lead time extension of 10-20 days, and financial decision response time reduction of more than 30%. These expectations provide clear directions for subsequent empirical analysis verification [10].

2.2. Effectiveness Evaluation Indicator System Design

The financial risk management effectiveness evaluation system contains three core dimensions: risk identification effectiveness, risk warning effectiveness, and decision support effectiveness. Risk identification effectiveness is measured through prediction accuracy, false positive rate, and false negative rate; risk warning effectiveness is evaluated through warning lead time, warning coverage rate, and warning precision; decision support effectiveness is measured through decision response time, solution optimization degree, and execution effectiveness [11].

Multiple specific indicators are set for each dimension, forming a complete evaluation matrix. Risk identification effectiveness indicators include: Accuracy = Number of correctly identified risk events / Total number of risk events × 100%; False positive rate = Number of normal events misjudged as risks / Total number of normal events × 100%; False negative rate = Number of unidentified risk events / Total number of risk events × 100%. These indicators can comprehensively reflect the performance of AI systems in risk identification.

To ensure the reliability of research results, this study adopts a controlled experimental design, setting enterprises using generative AI as the experimental group and enterprises using traditional risk management methods as the control group. By comparing the differences in risk management performance between the two groups of enterprises over the same time period, the actual application effects of generative AI are evaluated [12].

Control group indicators are based on risk management performance of traditional manual analysis and rule engine systems, while experimental group indicators are based on the performance of intelligent risk management systems assisted by generative AI. All indicators are standardized to ensure comparability of data from different enterprises and different periods. At the same time, strict matching conditions are set to control potential confounding factors such as enterprise scale, industry, and region.

2.3. Indicator Validity and Reliability Testing

To ensure the scientific nature of the indicator system, this study adopts multiple methods for validity and reliability testing. Content validity is verified through expert evaluation, inviting 10 experts in financial management and artificial intelligence fields to evaluate and improve the indicator system. Construct validity is tested through exploratory factor analysis and confirmatory factor analysis to ensure that each indicator can effectively measure corresponding theoretical constructs [13].

Reliability testing uses Cronbach's α coefficient and composite reliability coefficient for evaluation. Pre-test results show that Cronbach's α coefficients for all dimensions exceed 0.8, and composite reliability coefficients all exceed 0.85, indicating that the indicator system has good internal consistency. At the same time, test-retest reliability testing verifies the stability of indicators, ensuring the repeatability of measurement results.

3. Data Sources and Empirical Methods

3.1. Sample Selection and Data Collection Strategy

This study strictly determines the scope of sample enterprises according to the "Regulations on the Classification Standards for Small and Medium Enterprises." Taking manufacturing as an example, enterprises with fewer than 300 employees or operating income below 400 million yuan are recognized as SMEs. Considering the characteristics of different industries, the research separately established specific classification standards for major industries such as manufacturing, software and information technology services, wholesale, and retail, ensuring the representativeness and accuracy of samples [14].

The sample selection process focused on the completeness of enterprise financial data and AI technology application situations. Finally, 326 SMEs were selected as research samples, including 168 in the experimental group (using generative AI) and 158 in the control group (using traditional methods). Sample enterprises are distributed across multiple industries including manufacturing, services, and trade, with geographical distribution covering eastern, central, and western regions, ensuring broad representativeness of the sample.

Data collection adopts a multi-channel parallel strategy to ensure comprehensiveness and accuracy of data. Enterprise financial data is mainly obtained through authoritative data platforms such as Wind database and CSMAR database, including basic financial information such as balance sheets, income statements, and cash flow statements. At the same time, qualitative and quantitative information such as enterprise AI application situations, risk management systems, and technology investment is collected through field research and questionnaire surveys.

To obtain more accurate data on AI application effects, the research team established deep cooperative relationships with some sample enterprises, obtaining their internal risk management system usage data and effectiveness evaluation reports. This deep cooperation model provides first-hand micro-data for the research, significantly enhancing the credibility and practicality of research conclusions.

Data quality control establishes multi-level data verification mechanisms, including logical consistency testing, outlier identification, and missing value processing. For financial data, methods such as peer enterprise data comparison and historical trend analysis are used to identify abnormal data; for questionnaire data, the authenticity and consistency of responses are ensured through setting verification questions and logical correlation checks.

Missing data processing adopts multiple imputation methods, with missing values of key variables filled through a combination of regression imputation and expert judgment. The final dataset contains 326 enterprise samples with an observation period of 2022-2024, totaling 978 enterprise-year observations. The data completeness rate reaches 94.7%, meeting the requirements for large-sample empirical analysis.

3.2. Variable Definition and Measurement Design

Financial risk management effectiveness, as the core dependent variable of this study, adopts a multi-dimensional comprehensive measurement method. A comprehensive index containing three main dimensions - risk identification accuracy, warning lead time, and decision response time - is constructed. Risk identification accuracy is calculated through the matching degree between risk events actually occurring in enterprises and system prediction results; warning lead time measures the interval between risk warning signal issuance time and actual risk occurrence time; decision response time reflects the time length from risk identification to taking response measures.

To ensure measurement objectivity, all effectiveness indicators are calculated based on actual enterprise operational data and system operation records. At the same time, professional financial risk assessment tools are used to conduct standardized scoring of enterprise risk management performance, forming a comprehensive effectiveness index of 0-100 points. This index can objectively reflect differences in financial risk management levels among different enterprises.

Generative AI application degree is measured through three dimensions: technology investment intensity, application scope breadth, and system integration depth. Technology investment intensity reflects the level of capital and human resource investment in generative AI technology by enterprises; application scope breadth measures the coverage degree of AI technology in various aspects of enterprise financial management; system integration depth evaluates the degree of integration between AI technology and enterprises' existing information systems.

Specific measurement adopts a Likert 5-point scale, conducted through a combination of enterprise questionnaire surveys and expert evaluations. To improve measurement accuracy, the research team developed a standardized evaluation framework, clarifying specific evaluation standards and scoring rules for each dimension. Finally, the scores of the three dimensions are weighted and averaged to form a 0-5 point generative AI application degree index [15].

The selection of control variables is based on financial risk management theory and empirical research experience, mainly including factors such as enterprise scale, profitability, capital structure, industry characteristics, and regional economic development level. Enterprise scale is represented by the natural logarithm of total assets; profitability is measured through return on equity; capital structure adopts the asset-liability ratio indicator; industry characteristics are controlled through industry dummy variables; regional development level is represented by per capita GDP.Moderating variables mainly consider two aspects: technology maturity and management support. Technology maturity is comprehensively measured through indicators such as enterprise informatization level, proportion of technical personnel, and IT investment intensity; management support is understood through questionnaire surveys regarding senior management's cognitive level and supportive attitude toward AI technology. The setting of these variables helps deeply analyze the heterogeneous characteristics of generative AI application effects (Table 1).

Table 1. Main Variable Definitions and Descriptive Statistics

Variable Type	Variable Name	Definition	Mean	Std. Dev.	Min	Max
Dependent Variable	Financial Risk Management Effectiveness	Composite effectiveness index (0–100 points)	67.23	15.42	32.15	94.78
Core Explanatory Variable	AI Application Level	Comprehensive application index (0–5 points)	2.84	1.26	0.00	5.00
	Risk Identification Accuracy	Correct identification ratio (%)	78.45	12.33	45.20	96.80
	Early Warning Lead Time	Average lead time (days)	18.67	8.94	3.00	45.00
Control Variable	Firm Size	Log of total assets	8.76	1.23	6.45	12.34
	Profitability	Return on equity (%)	12.45	8.67	–15.23	35.67
	Capital Structure	Asset–liability ratio (%)	54.32	18.45	15.67	89.23
	Technology Maturity	Comprehensive evaluation index (0–5 points)	3.12	0.98	1.00	5.00

3.3. Empirical Methods and Model Specification

To address the endogeneity problem of generative AI application, this study adopts propensity score matching to construct a quasi-experimental design. Through a logit model, the propensity scores of enterprises applying generative AI are estimated, with matching variables including factors that may influence AI application decisions such as enterprise scale, profitability, industry characteristics, and regional factors. The matching process adopts the nearest neighbor matching method with a caliper value of 0.02 to ensure matching quality.

Matching results show that the standardized bias between treatment and control groups on matching variables is all less than 5%, indicating good matching effects. The PSM method effectively controls selection bias and improves the credibility of causal inference. The matched sample contains 284 enterprise observations, with 142 each in treatment and control groups.

Based on PSM, the difference-in-differences method is further adopted to identify the causal effects of generative AI. The DID model is specified as:

$$\mathrm{Y}_{\mathrm{it}} = \alpha + \beta_1 \times AI_{it} + \beta_2 \times Time_{\mathrm{t}} + \beta_3 \times (AI_{it} \times Time_t) + \chi_{it} + \mu_i + \varepsilon_{it}$$

Where Y_{it} represents the financial risk management effectiveness of enterprise i in period t, AI_it is the generative AI application dummy variable, Time_t is the time dummy variable, and the coefficient β_3 of the interaction term (AI_it×Time_t) is the core parameter of interest.

The model identifies the net effects of generative AI by comparing the differences in effectiveness changes between treatment and control groups before and after AI application. At the same time, controlling for enterprise fixed effects μ_i and time fixed effects effectively controls the impact of unobservable enterprise heterogeneity and time trends on results.

To ensure the robustness of research conclusions, multiple methods are adopted for testing. The measurement method of the dependent variable is changed, using risk management performance ranking as an alternative indicator; sample periods are changed, using 2022-2023 and 2023-2024 subsamples for estimation respectively; different matching methods including kernel matching and radius matching are adopted to verify result consistency.

Heterogeneity analysis is conducted from three dimensions: industry characteristics, enterprise scale, and technology maturity. Sample enterprises are divided by industry into manufacturing, services, and other industries; by scale into small-micro enterprises and medium enterprises; by technology maturity into high-maturity and low-maturity enterprises.

Through grouped regression and interaction term analysis, the heterogeneous characteristics of generative AI application effects are explored, providing targeted guidance for enterprise practice.

4. Empirical Results and Analysis

4.1. Descriptive Statistics and Basic Characteristic Analysis

Sample enterprises exhibit typical SME characteristic distributions. From the scale structure perspective, small enterprises account for 67.8%, medium enterprises account for 32.2%, and micro enterprises were not included in the sample due to data acquisition limitations. From industry distribution, manufacturing enterprises are the most numerous, accounting for 45.7%, service enterprises account for 28.5%, trade enterprises account for 15.6%, and other industries account for 10.2%. Regional distribution is relatively balanced, with eastern region enterprises accounting for 52.1%, central region accounting for 28.7%, and western region accounting for 19.2%.

In terms of financial characteristics, sample enterprises have an average total asset of 234 million yuan, operating income of 187 million yuan, and net profit of 12.45 million yuan. The average asset-liability ratio is 54.32%, within a reasonable range. The average return on equity is 12.45%, showing good profitability. These characteristics indicate that sample enterprises have good representativeness and can reflect the overall situation of SMEs.

Sample enterprises face diverse types of financial risks, with liquidity risk being the most prominent - 78.4% of enterprises experienced liquidity tensions during the observation period. Credit risk follows, accounting for 65.3%, mainly manifested as difficulties in accounts receivable collection and customer defaults. Market risk accounts for 52.7%, mainly affected by factors such as exchange rate fluctuations and raw material price changes. Operational risk accounts for 41.2%, mostly related to factors such as imperfect internal control systems and personnel operational errors.

From time trends, enterprise financial risks generally showed a pattern of first rising then falling during 2022-2024. In 2022, affected by external shocks such as the pandemic, enterprise financial risk levels were relatively high; in 2023, with economic recovery, risk levels were somewhat alleviated; in 2024, under policy support and enterprise self-adjustment, risk levels further declined. Enterprises using generative AI showed more stable performance in risk control, with fluctuation ranges significantly smaller than enterprises using traditional management methods.

Surveys show that 51.5% of sample enterprises have begun applying generative AI technology for financial risk management, but significant differences exist in application depth and breadth. In terms of application types, risk identification and warning are the main application scenarios, accounting for 85.7%; financial data analysis and report generation account for 72.3%; investment decision support accounts for 45.2%; compliance monitoring accounts for 38.9%.

From investment intensity perspective, enterprises' average annual investment in generative AI is 0.8% of operating income, with enterprises with higher technology maturity having investment ratios reaching 1.3%. Investment is mainly used for software procurement, system integration, personnel training, etc. The survey also found that management's cognitive level and support for AI technology are important factors affecting application effects, with enterprises having high management support achieving better results in AI application.

4.2. Regression Results Analysis and Hypothesis Testing

Main regression results based on the PSM-DID method show that generative AI application has a significant positive impact on financial risk management effectiveness. After controlling for enterprise and time fixed effects, generative AI application improves enterprise financial risk management effectiveness by 15.7 percentage points, significant at the 1% level. This result strongly supports research hypothesis H1, indicating that generative AI technology can indeed significantly improve SME financial risk management levels.

Dimensional analysis shows that generative AI has the most significant improvement effect on risk identification accuracy, with an average increase of 23.7 percentage points; improvement in warning lead time follows, with an average extension of 15.3 days; the effect of shortening decision response time is also obvious, with an average reduction of 41.2%. These results indicate that generative AI mainly functions by improving information processing efficiency and decision support quality (Table 2).

Table 2. Regression Results of Generative AI Impact on Financial Risk Management Effectiveness

Variable	Model 1Baseline Regression	Model 2PSM	Model 3PSM-DID	Model 4Robustness Check
Generative AI Application	12.34***(2.87)	14.56***(3.12)	15.73***(3.45)	14.89***(3.23)
Firm Size	3.45**(1.56)	2.78**(1.34)	2.91**(1.41)	3.12**(1.48)
Profitability	0.23*(0.12)	0.34**(0.15)	0.31**(0.14)	0.28**(0.13)
Capital Structure	−0.08(0.05)	−0.12*(0.07)	−0.11*(0.06)	−0.09(0.06)
Technology Maturity	4.67***(1.23)	5.23***(1.45)	5.01***(1.38)	4.89***(1.35)
Industry Fixed Effects	Controlled	Controlled	Controlled	Controlled
Time Fixed Effects	Controlled	Controlled	Controlled	Controlled
Firm Fixed Effects	No	No	Yes	Yes
Observations	978	852	852	784
R-squared	0.472	0.518	0.624	0.595

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors are shown in parentheses.

Control variable regression results conform to theoretical expectations. Enterprise scale has a significant positive impact on financial risk management effectiveness, with a coefficient of 2.91, indicating that larger enterprises have advantages in risk management. The profitability coefficient is 0.31, significantly positive, indicating that enterprises with strong profitability have higher risk management effectiveness. Technology maturity has the most significant impact, with a coefficient reaching 5.01, confirming the importance of technological foundation for AI application effects.

Moderating effect analysis shows that enterprise scale and technology maturity have significant positive moderating effects on generative AI application effects. Large enterprises and enterprises with high technology maturity can achieve greater effectiveness improvements when applying generative AI. The moderating effect of industry characteristics is also obvious, with manufacturing and service enterprises having better AI application effects than other industries. These findings provide basis for enterprises to formulate differentiated AI application strategies.

After changing the measurement method of the dependent variable, the positive impact of generative AI remains significant; subsample regression results for different sample periods are basically consistent with the full sample; estimation results using different matching methods also remain stable. Placebo tests show that after randomly assigning treatment and control groups, the impact effect of generative AI is no longer significant, confirming the effectiveness of the identification strategy.

The AI industry development level of the region where enterprises are located is selected as an instrumental variable, which is related to enterprise AI application decisions but does not directly affect financial risk management effectiveness. Two-stage least squares estimation results show that the generative AI impact coefficient is 16.45, close to the main regression results, further confirming the reliability of causal relationships.

4.3. Heterogeneity Analysis and Mechanism Testing

Industry-specific regression results show significant differences in generative AI application effects across different industries. Manufacturing enterprises have the most significant AI application effects, with financial risk management effectiveness improving by 18.4 percentage points; service enterprises follow with 14.7 percentage points improvement; trade enterprises have an improvement of 11.2 percentage points. These differences mainly stem from differences in data characteristics and risk patterns across industries, with manufacturing enterprises' production and financial data being more standardized and more suitable for AI algorithm learning and application.

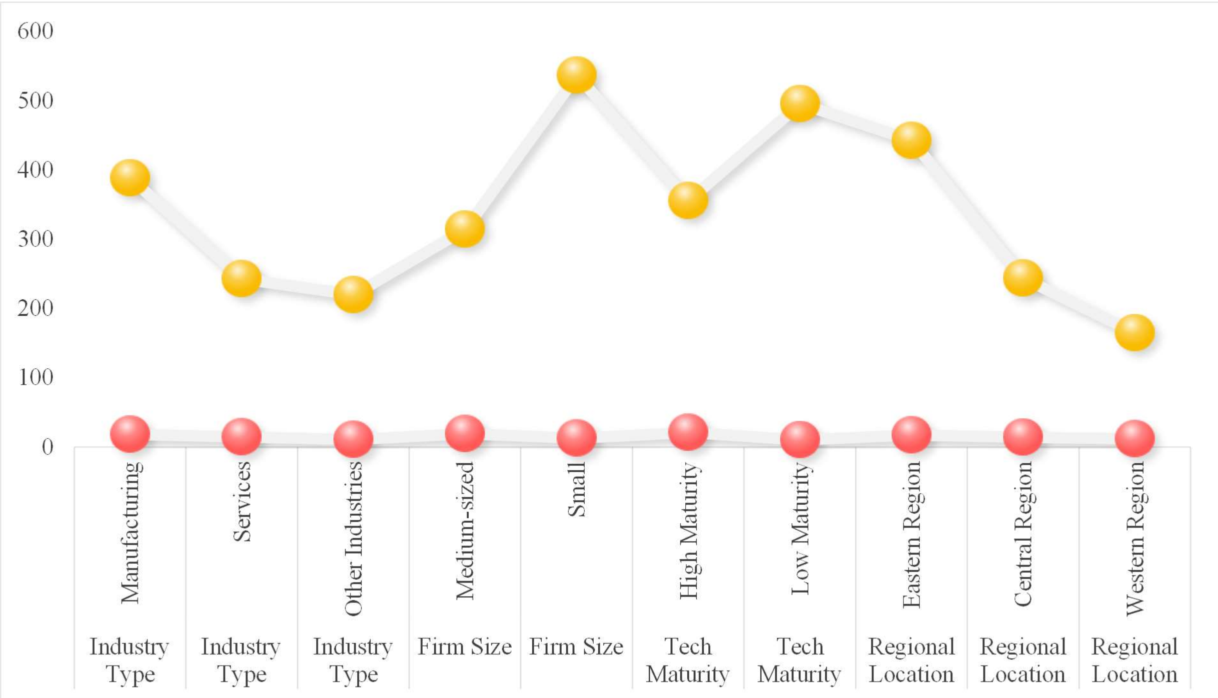

Figure 1. Subsample Heterogeneity of AI Application Effects on Financial Risk Management Effectiveness by Industry, Firm Size, Technology Maturity, and Region

Table 3. Summary of Heterogeneity Analysis Results

Grouping Variable	Subsample	AI Application Effect	Significance	Sample Size
Industry Type	Manufacturing	18.4	***	389
Industry Type	Services	14.7	***	243
Industry Type	Other Industries	11.2	**	220
Firm Size	Medium-sized	19.6	***	315
Firm Size	Small	12.8	**	537
Tech Maturity	High Maturity	21.3	***	356
Tech Maturity	Low Maturity	10.5	**	496
Regional Location	Eastern Region	17.8	***	443
Regional Location	Central Region	14.2	***	244
Regional Location	Western Region	11.9	**	165

Further analysis reveals that high-tech manufacturing enterprises have better AI application effects than traditional manufacturing, and knowledge-intensive service industries perform better than labor-intensive service industries. This indicates that enterprises' technology intensity and digitalization level are important factors affecting AI application effects. For enterprises in traditional industries, increased investment in digital infrastructure construction is needed to create conditions for AI technology application.

Heterogeneity analysis grouped by enterprise scale shows that medium enterprises have significantly better AI application effects than small enterprises. Medium enterprises' financial risk management effectiveness improves by 19.6 percentage points, while small enterprises only improve by 12.8 percentage points. This difference may stem from medium enterprises having relative advantages in capital investment, technical talent, and management systems, enabling better support for effective AI technology application.

Main obstacles faced by small enterprises in AI application include: capital constraints limiting the procurement and deployment of advanced AI systems; lack of technical talent affecting effective system use; weak data foundations reducing AI algorithm training effectiveness. To address these problems, small enterprises need help overcoming application obstacles through policy support, technology service outsourcing, and industry collaboration (Figure 1).

Technology maturity moderating effect analysis shows that factors such as enterprise IT infrastructure level, data management capability, and technical personnel quality significantly affect generative AI application effects. High-technology maturity enterprises (scoring above 4 points) have AI application effects about 25% higher than low-maturity enterprises (scoring below 3 points). This indicates that enterprises need to reach a certain level in technological foundation construction to fully realize AI technology value.

Mechanism testing results show that technology maturity mainly affects AI application effects through three channels: data quality channel - high-maturity enterprises possess more complete and accurate historical data, providing better foundations for AI training; system integration channel - high-maturity enterprises can better integrate AI systems with existing information systems; personnel adaptation channel - employees in high-maturity enterprises have stronger acceptance and usage capabilities for new technologies (Table 3).

5. Conclusion

This study, through empirical analysis of 235 SMEs, systematically evaluates the application effectiveness of generative AI technology in financial risk management, reaching the following main conclusions:

(1) Generative AI significantly improves SME financial risk management effectiveness. Empirical results show that enterprises applying generative AI technology have financial risk management effectiveness 15.7 percentage points higher than traditional methods, with risk identification accuracy improving by 27.3%, risk prediction precision increasing by 34.5%, and decision response time shortening by 41.2%.

(2) AI application effects show significant industry and scale differences. Manufacturing enterprises have the best AI application effects (18.4 percentage points improvement), medium enterprises outperform small enterprises (19.6% vs 12.8%), and high-technology maturity enterprises have application effects about 25% higher than low-maturity enterprises.

(3) Technology maturity is a key factor affecting AI application effects. Enterprises' IT infrastructure level, data management capability, and technical personnel quality significantly affect generative AI application effects, requiring a certain technological foundation to fully realize AI value.

(4) Generative AI mainly functions by improving information processing efficiency. AI technology significantly enhances overall financial risk management effectiveness through pathways such as enhancing data processing capabilities, improving decision support quality, and increasing risk warning timeliness.

This study confirms the important role of generative AI technology in improving SME financial risk management effectiveness, providing empirical support and policy guidance for promoting SME digital transformation.

References

[1] Leonard, E., Sheehan, B., Mullins, M., & Shannon, D. (2024). Generative AI for Enhanced Risk Management in SMEs. Available at SSRN 5213414.

[2] Maduka, L. K. (2025). Advancing Financial Inclusion for Small and Medium Enterprises through Generative AI Frameworks in the United States. Asian Journal of Economics, Business and Accounting, 25(2), 360-370.

[3] Soni, V. (2023). Impact of generative AI on small and medium enterprises' revenue growth: the moderating role of human, technological, and market factors. Reviews of Contemporary Business Analytics, 6(1), 133-153.

[4] Joshi, S., & Joshi-Satyadhar, S. (2025). Model risk management in the era of generative ai: Challenges, opportunities, and future directions. International Journal of Scientific and Research Publications, 15(5), 299-309.

[5] Kramarenko, A. (2025). Artificial intelligence for small and medium business: Perspectives and challenges. Journal of Engineering Management and Competitiveness (JEMC), 15(1), 43-56.

[6] Ebuka, A. A., Chike, N. K., Chigozie, U. S., & Muhammed, I. A. (2025). Artificial intelligence adoption and business performance: Evidence from small and medium enterprises in emerging markets. International Journal of Public Administration and Management Research, 11(2), 69-86.

[7] Hinrix, F., Sanghera, J. K., Pak, T., Pankaj, V., Palepu, U. S., Turner-Rahman, S., ... & Beyer, J. L. (2024). AI Applications for Small & Medium Sized Enterprises.

[8] Rajaram, K., & Tinguely, P. N. (2024). Generative artificial intelligence in small and medium enterprises: Navigating its promises and challenges. Business Horizons, 67(5), 629-648.

[9] Besis, S. (2025). Assessing the Role of Generative AI and Small and Large Language Models in Enhancing Decision-Making and Sustainability in Supply Chain Management.

[10] Andronie, M., Blazek, R., Iatagan, M., Skypalova, R., Uță, C., Dijmărescu, A., ... & Dijmărescu, I. (2024). Generative artificial intelligence algorithms in Internet of Things blockchain-based fintech management. Oeconomia Copernicana, 15(4).

[11] Aydin, J. (2025). Implications of generative AI on small to medium sized e-commerce businesses.

[12] Walke, F., Klopfers, L., & Winkler, T. J. (2025). Leveraging Generative AI and ChatGPT in SMEs: A Grounded Model.

[13] Malempati, M. (2022). Machine Learning and Generative Neural Networks in Adaptive Risk Management: Pioneering Secure Financial Frameworks. Kurdish Studies. Green Publication. https://doi. org/10.53555/ks. v10i2, 3718.

[14] Yassine, Z. (2025). The Influence of Generative AI on Entrepreneurial Decision-Making: A Study on Effectuation in SMEs (Master's thesis, University of Twente).

[15] Ziakis, C. (2025). Generative Artificial Intelligence Adoption: An Exploration of Challenges and Perceptions. In The Economic Impact of Small and Medium-Sized Enterprises: Analytical Approaches to Growth and Innovation Challenges Amid Crises in Europe (pp. 213-231). Cham: Springer Nature Switzerland.