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The Impact of Artificial Intelligence Adoption on Corporate Default Risk: Empirical Evidence Based on Large Language Models

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Abstract

Against the backdrop of rapid advances in digital technologies and growing uncertainty in the business environment, artificial intelligence (AI) offers firms new opportunities to strengthen risk identification, improve managerial decision-making, and mitigate default risk. Using firm-level data from Chinese A-share listed companies over the period 2009–2024, this study empirically examines the relationship between AI adoption and corporate default risk.

The results indicate that AI adoption is associated with a significant reduction in corporate default risk. This finding remains robust to alternative fixed-effects specifications, different levels of standard-error clustering, and the exclusion of observations from periods affected by major external shocks. Heterogeneity analyses further reveal that the negative association is particularly pronounced among firms in non-high-tech industries and those located in eastern and central China.

By examining AI adoption from a corporate risk management perspective, this study extends the literature on the economic consequences of AI adoption and provides firm-level empirical evidence on the role of digital technologies in mitigating financial risk. The findings also offer policy implications for integrating AI into corporate management practices and strengthening firms' risk governance capabilities.

Keywords: artificial intelligence adoption, corporate default risk, large language models, risk management, corporate governance

1. Introduction

In recent years, the global economy has undergone structural shifts in its growth drivers, while financial market volatility and growing uncertainty in the business environment have made the determinants and transmission mechanisms of corporate default risk increasingly complex. As a key dimension of corporate financial risk, default risk not only directly affects a firm's ability to meet its debt obligations and maintain business continuity but also influences the efficiency of financial resource allocation through credit risk premiums, financing costs, and creditor–debtor relationships. Traditional credit risk theory suggests that the probability of default increases as the value of a firm's assets approaches the threshold required to meet its debt obligations. Asset value volatility, capital structure, and financial conditions are therefore fundamental determinants of default risk (Merton, 1974). Bharath and Shumway (2008) further demonstrate the importance of firm-specific financial characteristics and market information in predicting default risk. As business operations become increasingly complex, the sources of default risk extend beyond financial leverage and cash flow volatility to encompass operational efficiency, internal management, information processing capabilities, and the ability to respond to external shocks. Identifying the determinants of corporate default risk and exploring effective approaches to mitigating it have consequently

become important priorities for strengthening firm-level operational stability and improving corporate risk governance.

Meanwhile, the ongoing technological transformation driven by artificial intelligence (AI) is fundamentally reshaping corporate operations and risk management practices. Unlike conventional information technologies, which primarily facilitate information storage, transmission, and process automation, AI enables firms to process complex and nonlinear business information through machine learning, predictive analytics, pattern recognition, and data analysis. These capabilities provide technological support for production planning, resource allocation, and managerial decision-making (Kleinberg et al., 2018; Duan et al., 2019). On the one hand, AI adoption can enhance operational efficiency, improve resource allocation and cost management, and thereby strengthen profitability and firms' capacity to service their debt. On the other hand, AI can assist firms in detecting unusual operational patterns, assessing potential risks, and improving investment decisions, allowing them to respond more promptly to changes in the business environment. Previous studies have documented a close relationship between AI technologies and improvements in firm productivity (Yang, 2022; Czarnitzki et al., 2023), while machine-based prediction has been shown to provide valuable information for complex decision-making (Kleinberg et al., 2018). Nevertheless, AI adoption may also entail substantial initial investment costs, uncertainty surrounding technological implementation, and organizational adjustment pressures, potentially placing additional strain on short-term liquidity and operational stability. Whether AI adoption can effectively reduce corporate default risk therefore remains an open theoretical and empirical question. Against this background, examining the relationship between AI adoption and corporate default risk is important for understanding the implications of emerging technologies for corporate risk governance.

To address this question, this study constructs a firm-level panel dataset of Chinese A-share listed companies on the Shanghai and Shenzhen stock exchanges over the period 2009–2024, integrating information on AI adoption and corporate default risk. AI adoption (Ai) serves as the key explanatory variable, while corporate default risk (Edf) is the dependent variable. A two-way fixed-effects model incorporating firm and year fixed effects is employed, with controls for firm-specific financial characteristics, operating conditions, and corporate governance attributes. The empirical results reveal a significant negative association between AI adoption and corporate default risk. The estimated coefficient on AI adoption remains negative and statistically significant at the 1% level as additional control variables are progressively introduced. This finding is robust to alternative fixed-effects specifications, changes in the clustering of standard errors, and the exclusion of observations from periods affected by major external shocks. Further heterogeneity analyses indicate that the negative association is primarily observed among firms in non-high-tech industries and those located in eastern and central China. By contrast, the estimated coefficients for firms in high-tech industries and western China do not reach conventional levels of statistical significance. These findings suggest that the relationship between AI adoption and corporate default risk may vary according to industry-specific technological characteristics and regional development conditions.

This study makes three potential contributions to the existing literature.

First, from a research perspective, it extends the literature on the determinants of corporate default risk by examining the role of AI adoption. Previous studies have primarily explained corporate default risk through capital structure, profitability, operating cash flows, and capital market information (Shumway, 2001; Campbell et al., 2008; Bharath & Shumway, 2008). Research on AI, by contrast, has largely focused on its microeconomic implications for productivity, technological innovation, and organizational decision-making (Yang, 2022; Czarnitzki et al., 2023). Although recent studies have begun to explore the relationship between AI and corporate debt default risk, the economic role of AI in corporate risk governance warrants further investigation, particularly given its combined capabilities in information processing, intelligent prediction, and decision support. By incorporating AI adoption into the analytical framework of corporate default risk, this study examines the economic implications of emerging technologies from the perspective of corporate financial stability and provides additional firm-level empirical evidence on the role of AI in risk governance.

Second, in terms of methodology, this study employs a large language model (LLM) to measure firm-level AI adoption, offering an alternative approach to identifying AI applications within firms. Existing studies have commonly relied on industrial robot penetration, AI-related patent counts, and the frequency of relevant keywords in corporate annual reports to measure AI adoption. However, each of these approaches has limitations. Industrial robot indicators primarily capture production automation and may not adequately reflect AI applications in business management and strategic decision-making. Patent-based measures focus on technological innovation outputs rather than the actual deployment of AI technologies. Conventional keyword-frequency methods are susceptible to variations in document length, differences in terminology, and conceptual disclosures, making it difficult to accurately identify the specific meaning of AI-related statements. In comparison, LLMs offer advanced natural language understanding and contextual interpretation capabilities, allowing them to identify AI-related activities disclosed by firms while distinguishing general technological references from descriptions of actual

business applications. By using an LLM to identify firm-level AI adoption, this study seeks to reduce the semantic classification errors associated with conventional keyword matching and improve the measurement accuracy and economic interpretability of the key explanatory variable. In doing so, it offers a new measurement approach for research on the microeconomic consequences of AI adoption.

Third, in terms of empirical findings, this study investigates heterogeneity in the relationship between AI adoption and corporate default risk across industry technological characteristics and regional development environments, thereby providing further insight into the conditions under which AI may contribute to corporate risk governance. Existing research suggests that the economic effects of AI depend not only on the technology itself but also on firms' knowledge bases, organizational capabilities, and external technological environments (Helfat & Raubitschek, 2018; Kemp, 2024). The results of this study show that the negative association between AI adoption and corporate default risk is concentrated among firms in non-high-tech industries and those located in eastern and central China, whereas no statistically significant relationship is observed among firms in high-tech industries or western China. These findings suggest that the potential risk governance benefits of AI adoption may depend jointly on firms' technological foundations and regional development conditions. By examining differences across industry types and regional environments, this study provides empirical evidence on the contextual boundaries of AI-related risk governance effects and offers insights for developing differentiated policies to support corporate AI adoption.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 presents the theoretical analysis and develops the research hypothesis. Section 4 describes the research design. Section 5 reports and discusses the empirical results. Section 6 concludes with policy recommendations and directions for future research.

2. Literature Review

The first strand of literature relevant to this study examines the determinants of corporate default risk. Existing research suggests that corporate default risk is shaped not only by a firm's financial condition and debt-servicing capacity but also by the external economic environment, information asymmetry, and operational efficiency. From the perspective of financial fundamentals, asset values, capital structure, and cash flow conditions are among the primary determinants of default risk. A decline in asset values, an increase in debt obligations, or a deterioration in operating cash flows can weaken a firm's ability to meet its financial commitments, thereby increasing its likelihood of default (Merton, 1974; Campbell et al., 2008). With regard to external financing conditions, macroeconomic uncertainty and financial market volatility may exacerbate corporate financial vulnerability by raising financing costs, restricting credit availability, and intensifying operational pressures. These effects can be particularly pronounced among financially constrained firms, where external shocks are more likely to disrupt liquidity and impair debt repayment capacity (Albuquerque, 2024; Wang & Huang, 2025). From an internal operational perspective, technological innovation, resource allocation, and risk management capabilities also play important roles in determining default risk. Technological innovation can enhance operational stability by improving productivity and strengthening competitive advantages. However, substantial research and development expenditures, together with the inherent uncertainty of innovation activities, may place additional pressure on short-term liquidity. The overall implications for risk therefore depend on the relative magnitude of the benefits and costs associated with innovation (Safiullah et al., 2024). As digital technologies become increasingly embedded in corporate operations, recent studies have further suggested that digital transformation may reduce default risk by improving information processing efficiency, alleviating financing constraints, and enhancing resource allocation. Conversely, it may also increase financial vulnerability through substantial technological investment costs, resource misallocation, and greater managerial complexity (Chen et al., 2025; Wu & Lu, 2025). Taken together, the literature indicates that corporate default risk is influenced by financial structure and external conditions, as well as firms' information processing and managerial capabilities. Nevertheless, existing studies have concentrated primarily on conventional financial determinants and digital transformation more broadly, leaving the distinctive contributions of AI to predictive analytics, risk identification, and managerial decision-making relatively underexplored. Examining corporate default risk specifically through the lens of AI adoption may therefore provide additional firm-level evidence on the role of emerging technologies in corporate risk governance.

The second strand of literature focuses on the conceptual foundations, measurement approaches, and microeconomic implications of AI. Conceptually, AI encompasses a range of technologies, including machine learning, natural language processing, and pattern recognition, that enable computer systems to perform functions involving perception, prediction, learning, and decision support. Unlike conventional information technologies, which primarily facilitate data storage, information transmission, and process automation, AI can identify complex relationships within large datasets and generate predictions. It is therefore widely regarded as a general-purpose technology with considerable potential across economic activities. Its economic value extends beyond the

automation of routine tasks to the augmentation of human cognitive capabilities and organizational decision-making (Acemoglu & Restrepo, 2018; Kemp, 2024). In terms of measurement, previous studies have employed indicators such as industrial robot penetration, AI-related patents, demand for AI-skilled workers, and corporate textual disclosures to capture different dimensions of AI development. Industrial robot measures primarily reflect automation in production processes, while patent-based indicators capture technological innovation capabilities. AI-related job postings provide information on firms' demand for specialized technical expertise, whereas AI-related keywords in annual reports can indicate firms' strategic attention to and deployment of these technologies (Acemoglu et al., 2022; Yang, 2022; Czarnitzki et al., 2023). However, these indicators capture different aspects of technological activity, and a firm's capacity to innovate in AI does not necessarily correspond to its actual level of AI adoption. The choice of measurement should therefore reflect the research question and the underlying economic mechanisms, while accounting for potential discrepancies between technological disclosure and actual implementation. Regarding microeconomic effects, AI can improve factor allocation and operational efficiency through production automation, predictive analytics, and data-driven analysis. It can also facilitate technological innovation and organizational improvements by strengthening firms' capabilities in knowledge discovery and information integration (Helfat & Raubitschek, 2018; Czarnitzki et al., 2023). Furthermore, AI can enhance information processing and risk identification in complex business environments, providing technological support for investment decisions, resource allocation, and operational risk management (Kleinberg et al., 2018; Duan et al., 2019). Nevertheless, AI adoption may also involve substantial investment costs, organizational restructuring pressures, and algorithmic decision-making biases. Its economic outcomes consequently depend on the extent to which technological applications align with firms' resource endowments, organizational capabilities, and operating environments. Overall, although the existing literature has established the microeconomic value of AI in improving productivity, fostering technological innovation, and supporting organizational decision-making, whether these benefits translate into stronger debt-servicing capacity and lower corporate default risk remains an empirical question that warrants further investigation, particularly in relation to firms' actual AI adoption and financial risk characteristics.

3. Theoretical Analysis and Research Hypothesis

Corporate default risk refers to the likelihood that a firm will be unable to meet its contractual debt obligations within a specified future period. It is determined not only by the relationship between asset values and outstanding debt but also by operational efficiency, cash flow stability, and risk management capabilities. Previous studies have identified declining profitability, increasing financial leverage, and asset value volatility as important indicators of heightened default risk. Uncertainty in business operations and inefficient resource allocation may further undermine a firm's debt-servicing capacity (Merton, 1974; Campbell et al., 2008; Bharath & Shumway, 2008). As digital technologies become increasingly integrated into corporate operations, AI has evolved from a supplementary information processing tool into a technology embedded in production processes and strategic decision-making. Its implications extend beyond productivity improvements to changes in how firms process operational information, allocate resources, and respond to risks. Through machine learning, predictive analytics, and data analysis, AI enables firms to process complex business information and provides new technological capabilities for improving managerial decisions and strengthening financial stability (Duan et al., 2019; Kemp, 2024). Accordingly, AI adoption may influence corporate default risk through three principal channels: operational efficiency, decision-making quality, and risk responsiveness.

First, AI adoption may strengthen firms' debt-servicing capacity by improving operational efficiency and resource allocation. Corporate default risk is closely associated with insufficient operating income and liquidity constraints, while productivity and resource allocation efficiency are important determinants of profitability and internal capital accumulation. By employing predictive analytics, data analysis, and process optimization, AI can improve firms' ability to anticipate market demand, coordinate production schedules, and monitor resource utilization, thereby reducing inefficient expenditures and operational waste. On the one hand, AI can improve the allocation of labor, capital, and other production factors, enhance coordination across production processes, and reduce unit production costs, ultimately contributing to stronger profitability. Previous research has established a close association between AI adoption and firm productivity, suggesting that its economic value lies not only in automating routine tasks but also in improving production organization and operational efficiency (Acemoglu & Restrepo, 2018; Yang, 2022; Czarnitzki et al., 2023). On the other hand, AI can support more efficient inventory management, capital utilization, and operational planning, reducing working capital requirements and inefficient investment while allowing firms to allocate more resources to higher-return activities. Improvements in operational and resource allocation efficiency may generate more stable operating income and greater internal capital accumulation, thereby reducing dependence on external financing and easing debt repayment pressures. At the same time, stronger profitability and cash flow generation can improve the extent to which asset values cover outstanding debt obligations, reducing the likelihood of financial distress arising from insufficient operating funds. AI adoption may therefore provide an operational foundation for lower corporate default risk by enhancing

efficiency and strengthening firms' capacity to generate economic value.

Second, AI adoption may reduce financial risks arising from investment errors and resource misallocation by improving information processing efficiency and the quality of managerial decision-making. Corporate decisions typically require managers to evaluate substantial amounts of information concerning market demand, expected investment returns, financing costs, and operational risks. When information is fragmented or processing capabilities are limited, managers may struggle to accurately assess the potential value of business projects, resulting in inefficient investment and suboptimal capital allocation. These challenges become particularly pronounced in complex business environments characterized by intensified market competition, where decision-making based primarily on managerial experience and limited information may fail to identify emerging operational risks in a timely manner. By integrating financial data, operational information, and external market signals, AI can strengthen firms' ability to identify relationships within data, detect anomalous patterns, and anticipate changes in business conditions. These capabilities can provide a more comprehensive information base for investment project selection, financial planning, and adjustments to business strategies. Existing research suggests that machine-generated predictions can offer valuable information for complex decisions, although their effectiveness ultimately depends on how well predictive insights are integrated with managerial judgment (Kleinberg et al., 2018; Duan et al., 2019; Csaszar et al., 2024). From the perspective of corporate financial risk, poor managerial decisions may lead to asset losses, excessive capital commitments, and deteriorating cash flows. AI adoption can help firms assess expected investment returns and potential losses more accurately, thereby reducing resource allocation distortions caused by incomplete information. Moreover, AI can improve the timeliness of financial analysis, enabling managers to identify abnormal operating expenditures, liquidity pressures, and emerging financial risks and adjust their decisions accordingly. As investment decisions and capital allocation become more efficient, the adverse effects of inefficient operations on asset values and cash flow stability may diminish, contributing to lower corporate default risk.

Finally, AI adoption may enhance operational stability and reduce the likelihood that business disruptions develop into financial default by strengthening firms' ability to identify and respond to external shocks. Corporate default risk is influenced not only by existing financial conditions but also by external factors such as macroeconomic fluctuations, changes in market demand, and supply chain uncertainty. When external shocks disrupt production, reduce operating revenue, or constrain liquidity, firms may face increasing pressure to meet their debt obligations. The ability to identify emerging risks, adjust business strategies, and maintain operational continuity is therefore essential to mitigating default risk. Through real-time data analysis, predictive analytics, and anomaly detection, AI can improve firms' awareness of changes in their operating environments, allowing managers to recognize potential threats earlier and develop appropriate responses. AI can also facilitate internal information sharing and coordination across business functions, improving the efficiency of resource allocation between departments and enabling firms to adjust production schedules, procurement arrangements, and capital utilization in response to changing external conditions. Previous studies have suggested that digital technologies can strengthen firms' ability to integrate resources and coordinate organizational activities, while the organizational value of AI depends on effective collaboration between technological systems and human managers (Helfat & Raubitschek, 2018; Raisch & Krakowski, 2021). Furthermore, effective corporate risk management requires more than access to relevant risk information; it also depends on managers' ability to translate that information into timely and appropriate business decisions (Crawford et al., 2024). When AI is effectively integrated into corporate risk management processes, it can help firms detect operational anomalies in advance, respond more efficiently to changing circumstances, and mitigate losses arising from external shocks. These improvements may contribute to greater stability in operating cash flows and asset values, thereby reducing the likelihood of corporate debt default.

Based on the preceding theoretical analysis, this study proposes the following research hypothesis:

H1: Ceteris paribus, AI adoption significantly reduces corporate default risk.

4. Research Design

4.1 Model Specification

Following the approach adopted in the existing literature, this study constructs a two-way fixed-effects model to empirically examine the relationship between AI adoption and corporate default risk:

$$\mathrm{Edf}_{it} = \alpha_0 + \alpha_1 Ai_{it} + \sum CV_{it} + \varphi_i + \theta_t + \varepsilon_{it} \quad (1)$$

where the subscripts *i* and *t* denote firms and years, respectively. Edf_{it} represents the default risk of firm *i* in the year *t*, while Ai_{it} denotes the level of AI adoption by firm *i* in the year *t*. The vector of control variables captures a range of firm-specific characteristics that may influence default risk. Firm fixed effects account for time-invariant unobserved heterogeneity across firms, while year fixed effects control for common temporal shocks. The error term captures other unobserved factors affecting corporate default risk.

4.2 Variable Measurement and Description

4.2.1 Corporate Default Risk

The dependent variable in this study is corporate default risk (Edf), which measures the likelihood that a firm will be unable to meet its debt obligations when they fall due. Following Bharath and Shumway (2008) and Safiullah et al. (2024), this study measures corporate default risk using the expected default probability derived from a structural credit risk model. This approach incorporates the market value of equity, outstanding debt obligations, and asset value volatility into a unified analytical framework. By estimating the distance between a firm's asset value and its default threshold, the model captures the firm's underlying exposure to debt repayment risk.

Specifically, the measurement procedure involves three steps. First, the firm's asset value and asset volatility are estimated using information on the market value of equity, debt obligations, and return volatility. Second, the distance to default (DD) is calculated by incorporating the relevant debt default threshold. Finally, the distance to default is converted into a model-implied expected default probability (Edf) using the standard normal distribution. A higher Edf value indicates a greater likelihood that the firm's asset value will fall below the default threshold, implying a higher level of corporate default risk. Compared with individual accounting-based financial indicators, the structural credit risk model provides a more comprehensive assessment of corporate financial risk by jointly considering debt obligations and capital market information.

4.2.2 Corporate AI Adoption

The key explanatory variable is firm-level AI adoption (Ai). Previous studies have primarily measured corporate AI development using indicators such as industrial robot penetration, AI-related patent counts, recruitment information for AI-related positions, and the frequency of AI-related keywords in corporate annual reports (Acemoglu et al., 2022; Yang, 2022; Czarnitzki et al., 2023). However, these approaches capture different dimensions of AI-related economic activity and are subject to several limitations. Industrial robot penetration primarily reflects automation in production processes and may not adequately capture AI applications in business management and strategic decision-making. AI patent counts mainly represent technological research and development capabilities and innovation outputs rather than the actual deployment of AI technologies. Although conventional keyword-frequency measures can reflect firms' attention to AI, they are sensitive to document length, differences in terminology, and conceptual disclosures, making it difficult to determine whether AI-related statements refer to actual technological applications. For instance, firms may frequently discuss AI industry trends or government policies in their annual reports without having implemented AI in their business operations. Consequently, relying solely on the frequency of specific keywords may fail to distinguish between firms' strategic interest in AI and their actual adoption of the technology.

To address these measurement limitations, this study employs the natural language understanding and contextual semantic recognition capabilities of a large language model (LLM) to identify AI-related applications disclosed in corporate annual reports and construct a firm-level AI adoption indicator. Unlike conventional keyword-matching methods, LLMs can interpret the semantic context, technological content, and practical application scenarios of relevant statements, allowing them to determine whether firms have deployed AI technologies in activities such as research and development, product design, manufacturing, business management, marketing, and risk control. For example, disclosures describing the use of machine learning algorithms for product quality inspection or intelligent forecasting systems for production planning are classified as evidence of AI adoption. By contrast, statements that merely discuss industry trends, policy support, or prospective AI strategies without indicating actual implementation are not directly classified as evidence of adoption. This context-sensitive identification approach can help reduce measurement errors arising from ambiguous terminology and non-substantive disclosures, thereby producing an indicator that more closely reflects the AI-related activities firms report having implemented.

The firm-level AI adoption indicator is constructed through the following procedure. First, annual reports are collected for the sample firms, and text relating to actual business operations is extracted from sections covering management discussion and analysis, principal business activities, research and development, and operating performance. The extracted text is cleaned, deduplicated, and segmented into semantically coherent passages to create a firm-year-level textual dataset for classification. Second, a standardized set of semantic identification criteria is developed based on the technological characteristics and application scenarios of AI. The LLM is then used to determine whether each passage describes an AI-related activity that has already been implemented by the firm. The classification criteria consider both the technological nature of the activity and its implementation status. Specifically, a qualifying statement must describe activities involving machine learning, intelligent recognition, natural language processing, knowledge reasoning, or other technologies with identifiable AI characteristics. It must also provide evidence that the technology has been applied in actual business operations rather than merely discussed in the context of government policies, industry developments, or future strategic plans. Third, the classification results are aggregated at the firm-year level to construct the corporate AI adoption indicator.

To assess the accuracy of the LLM-based identification procedure, this study conducts a manual validation exercise

using a randomly selected sample of 1,000 textual passages from corporate annual reports. Researchers manually annotate these passages according to the standardized classification criteria, and the resulting annotations serve as reference labels against which the LLM-generated classifications are evaluated. The model achieves an accuracy of 94.20%, precision of 93.10%, recall of 92.40%, and an F1 score of 92.75%. These results suggest that the LLM can effectively distinguish actual AI applications from general technological descriptions, reducing the semantic classification errors associated with conventional keyword-matching approaches and improving the measurement validity of the firm-level AI adoption indicator.

4.2.3 Control Variables

To mitigate potential estimation bias arising from differences in firm characteristics, this study incorporates a set of control variables covering basic firm attributes, operating conditions, and corporate governance. Specifically, state ownership (Soe) is a dummy variable indicating whether a firm is state-owned. Firm size (Size) controls for differences in resource endowments and the capacity to absorb business risks across firms of different sizes. Firm age (Age) captures differences in operating experience and stages of corporate development. Return on assets (Roa) measures profitability, while operating cash flow (Cashflow) reflects the firm's internal liquidity position. Tobin's Q (Tobinq) captures market valuation and growth opportunities. Board size (Board), CEO duality (Dual), and the proportion of independent directors (Indep) are included to account for differences in corporate governance structures. Together, these variables control for observable factors related to operational fundamentals, financial conditions, and governance arrangements that may influence corporate default risk.

4.3 Data Sources and Sample Selection

This study examines Chinese A-share listed companies on the Shanghai and Shenzhen stock exchanges and constructs a firm-year panel dataset to investigate the relationship between AI adoption and corporate default risk. Firm-level AI adoption data are derived from corporate annual reports, with AI-related technological applications identified through LLM-based semantic analysis and aggregated at the firm-year level. Corporate default risk (Edf) is calculated using firm-level financial information and capital market data. Control variables relating to financial characteristics, operating conditions, and corporate governance are primarily obtained from the China Stock Market & Accounting Research (CSMAR) database. Data from these sources are matched using firms' stock codes and reporting years to construct the panel dataset for empirical analysis.

To improve the reliability and comparability of the sample, the study applies the following screening and data-processing criteria. First, firms operating in the financial and insurance sectors are excluded because their distinctive asset-liability structures, regulatory requirements, and business models may complicate the measurement of corporate default risk. Second, firms designated as ST, *ST, or PT are excluded to minimize the influence of abnormal financial and operating conditions on the estimation results. Third, firm-year observations with missing values for the dependent variable, key explanatory variable, or principal control variables are removed to ensure the completeness of the regression dataset. Fourth, observations containing clearly abnormal or economically implausible values for key financial indicators, such as total assets and operating revenue, are excluded to improve data quality. Fifth, the main continuous variables are winsorized at the 1st and 99th percentiles to limit the influence of extreme observations on regression estimates. After these data-processing procedures, the final sample used in the baseline regressions comprises 37,621 firm-year observations.

4.4 Descriptive Statistics

Table 1 presents the descriptive statistics for the main variables. The dependent variable, Edf, has a mean of 0.0068 and a standard deviation of 0.0594, with values ranging from 0 to 0.5721. This suggests that the overall level of corporate default risk is relatively low, although some variation exists across observations. The AI adoption indicator (Ai) has a mean of 0.3708 and a standard deviation of 0.6938, with a minimum value of 0 and a maximum value of 3.0910, indicating considerable variation in AI adoption across sample firms. The remaining variables also exhibit variation within their respective ranges, without displaying excessively extreme values. Overall, the descriptive statistics indicate sufficient cross-sectional and temporal variation in the principal variables to support the subsequent empirical analysis.

Table 1. Descriptive Statistics of the Main Variables

Variable	Observations	Mean	Std. Dev.	Min.	Max.
Edf	37,621	0.0068	0.0594	0.0000	0.5721
Ai	37,621	0.3708	0.6938	0.0000	3.0910
Soe	37,621	0.3868	0.4870	0.0000	1.0000

Size	37,621	22.4213	1.2665	20.0128	26.1363
Age	37,621	3.0018	0.3096	2.0794	3.6109
Roa	37,621	0.0297	0.0636	-0.2189	0.1932
Cashflow	37,621	0.0451	0.0669	-0.1489	0.2278
Tobinq	37,621	1.9598	1.1659	0.8299	7.2759
Board	37,621	2.1211	0.1972	1.6094	2.6391
Dual	37,621	0.2640	0.4408	0.0000	1.0000
Indep	37,621	0.3772	0.0540	0.3333	0.5714

5. Empirical Results and Analysis

5.1 Baseline Regression Results

Table 2 presents the baseline regression results examining the relationship between AI adoption and corporate default risk. To assess the stability of the estimates, control variables are introduced progressively, with firm and year fixed effects included in all specifications. Specifically, Column (1) controls for basic firm characteristics, including state ownership, firm size, and firm age. Column (2) further incorporates financial and operating variables, namely return on assets, operating cash flow, and Tobin's Q. Column (3) additionally accounts for corporate governance characteristics, including board size, CEO duality, and the proportion of independent directors.

The results show that the estimated coefficients on AI adoption (Ai) are consistently negative and statistically significant at the 1% level across all three specifications. The negative association remains statistically significant as additional control variables are introduced. In Column (3), which includes the full set of controls, the estimated coefficient on Ai is −0.0027, indicating that higher levels of AI adoption are significantly associated with lower corporate default risk. These findings are consistent with the theoretical expectations and provide empirical support for Hypothesis H1.

Table 2. Baseline Regression Results

	(1)	(2)	(3)
Variables	Edf	Edf	Edf
Ai	-0.0025***	-0.0027***	-0.0027***
	(0.0007)	(0.0007)	(0.0007)
Soe	0.0037*	0.0027	0.0026
	(0.0022)	(0.0022)	(0.0022)
Size	0.0119***	0.0139***	0.0139***
	(0.0013)	(0.0014)	(0.0014)
Age	-0.0090	-0.0126	-0.0122
	(0.0097)	(0.0098)	(0.0098)
Roa		-0.0667***	-0.0670***
		(0.0082)	(0.0082)
Cashflow		-0.0137**	-0.0136**
		(0.0065)	(0.0065)
Tobinq		0.0023***	0.0023***
		(0.0004)	(0.0004)
Board			0.0040
			(0.0043)
Dual			0.0014
			(0.0012)

Indep			-0.0042
			(0.0125)
Constant	-0.2339***	-0.2697***	-0.2763***
	(0.0377)	(0.0385)	(0.0410)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	37,621	37,621	37,621
R^2	0.236	0.239	0.240

5.2 Robustness Checks

5.2.1 Alternative Fixed-Effects Specifications

To further account for potential unobserved factors that may influence the estimation results, this study examines the robustness of the baseline findings using alternative fixed-effects specifications. Specifically, Columns (1) and (2) of Table 3 introduce industry and city fixed effects, respectively, in addition to firm and year fixed effects. Column (3) includes firm fixed effects and industry-by-year fixed effects. Column (4) further considers city-by-industry fixed effects, while Column (5) incorporates firm fixed effects and city-by-year fixed effects.

The regression results indicate that the estimated coefficients on Ai remain negative and statistically significant at the 1% level across all specifications. Although the magnitude of the coefficients varies somewhat with the fixed-effects structure, the negative association between AI adoption and corporate default risk remains consistent. These findings suggest that the baseline results are robust to alternative fixed-effects specifications.

Table 3. Robustness Checks Using Alternative Fixed-Effects Specifications

	(1)	(2)	(3)	(4)	(5)
Variables	Edf	Edf	Edf	Edf	Edf
Ai	-0.0027***	-0.0027***	-0.0017***	-0.0027***	-0.0031***
	(0.0007)	(0.0007)	(0.0006)	(0.0007)	(0.0008)
Constant	-0.2762***	-0.2762***	-0.3207***	-0.2762***	-0.2391***
	(0.0410)	(0.0412)	(0.0402)	(0.0417)	(0.0468)
Controls	YES	YES	YES	YES	YES
Firm FE	YES	YES	Yes	Yes	Yes
Year FE	YES	YES		Yes	
Ind FE	YES				
Citycode FE		YES			
IndYear FE			Yes		
CityInd FE				Yes	
CityYear FE					Yes
N	37,621	37,621	37,616	37,621	35,534
R^2	0.240	0.240	0.263	0.240	0.325

5.2.2 Alternative Clustering Levels

To examine whether the estimation results are sensitive to the level at which standard errors are clustered, this study re-estimates the baseline model using alternative clustering structures. This approach accounts for potential correlations in regression disturbances within different geographical and industry groupings. Specifically, Columns (1)–(5) of Table 4 cluster standard errors at the industry, city, industry-year, city-industry, and city-year levels, respectively.

The results show that the estimated coefficient on Ai remains −0.0027 across all five specifications, consistent with the baseline regression. The coefficient is negative and statistically significant at the 10% level in Column

(1), while the remaining four specifications yield negative coefficients significant at the 1% level. Although the estimated standard errors and levels of statistical significance vary across clustering methods, the negative association between AI adoption and corporate default risk remains statistically significant throughout. This indicates that the baseline findings are not driven by a particular clustering specification, providing further support for their robustness.

Table 4. Robustness Checks Using Alternative Clustering Levels

	(1)	(2)	(3)	(4)	(5)
Variables	Edf	Edf	Edf	Edf	Edf
Ai	-0.0027*	-0.0027***	-0.0027***	-0.0027***	-0.0027***
	(0.0014)	(0.0005)	(0.0008)	(0.0007)	(0.0006)
Constant	-0.2762***	-0.2762***	-0.2762***	-0.2762***	-0.2762***
	(0.0622)	(0.0312)	(0.0519)	(0.0433)	(0.0352)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Cluster	Ind	Citycode	IndYear	CityInd	CityYear
N	37,621	37,621	37,621	37,621	37,621
R^2	0.240	0.240	0.240	0.240	0.240

5.2.3 Exclusion of Observations from Special Periods

To account for the potential influence of major external shocks on corporate operations and default risk, this study conducts additional robustness checks by excluding observations from periods affected by exceptional economic events.

First, given that the global financial crisis may have influenced corporate default risk through changes in financing conditions, asset values, and operating cash flows, the model is re-estimated after excluding the relevant crisis-affected years. The results are reported in Column (1) of Table 5. Second, considering the substantial disruptions to business operations and liquidity caused by the COVID-19 pandemic, the study further excludes observations from pandemic-affected years, with the corresponding results presented in Column (2).

The results indicate that the estimated coefficients on Ai remain negative and statistically significant at the 1% level in both specifications. These findings suggest that the negative association between AI adoption and corporate default risk persists after observations from periods affected by major external shocks are removed, further confirming the robustness of the baseline results.

Table 5. Robustness Checks Excluding Special-Period Observations

	(1)	(2)
	Excluding Financial Crisis	Excluding COVID-19 Pandemic
Variables	Edf	Edf
Ai	-0.0023***	-0.0078***
	(0.0006)	(0.0016)
Constant	-0.2032***	-0.3258***
	(0.0402)	(0.0642)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	33,894	19,814
R^2	0.252	0.289

5.3 Heterogeneity Analysis

5.3.1 High-Tech and Non-High-Tech Industries

Firms operating in industries with different levels of technological intensity may differ substantially in their technological capabilities, production processes, and risk management requirements. These differences may give rise to heterogeneous relationships between AI adoption and corporate default risk.

Firms in high-tech industries generally possess stronger research and development capabilities and more extensive technological knowledge, allowing AI applications to complement their existing technological systems. However, these firms often face substantial R&D expenditures, rapid technological change, and uncertainty associated with innovation. Consequently, improvements in operational efficiency resulting from AI adoption may not immediately translate into lower financial risk.

By contrast, firms in non-high-tech industries may rely more heavily on conventional managerial practices and traditional production inputs, leaving greater scope for improvements in information processing, process optimization, and resource allocation. AI can help these firms optimize production schedules, improve operational forecasting, and enhance capital utilization efficiency, thereby reducing operating costs and cash flow volatility and alleviating debt repayment pressures. Accordingly, the potential risk governance benefits associated with AI adoption may be more pronounced among firms in non-high-tech industries.

To examine these differences, the sample is divided into high-tech and non-high-tech firms, and separate regressions are estimated for each group. The results in Columns (1) and (2) of Table 6 show that the estimated coefficient on Ai is −0.0003 for high-tech firms, but it does not reach conventional levels of statistical significance. For non-high-tech firms, the coefficient is −0.0057 and is statistically significant at the 1% level.

These findings indicate that the negative association between AI adoption and corporate default risk is primarily concentrated among non-high-tech firms. One possible explanation is that these firms have greater opportunities to improve conventional operating processes and risk management practices through AI adoption, making the associated reductions in financial risk more apparent.

5.3.2 Regional Heterogeneity: Eastern, Central, and Western China

Differences in economic development, digital infrastructure, and access to financial resources across regions may influence both the effectiveness of AI adoption and its potential contribution to corporate risk governance. Effective AI implementation requires not only firm-level technological investment but also supporting data infrastructure, skilled professionals, and appropriate management systems.

Eastern and central China generally benefit from relatively well-developed digital infrastructure, a larger pool of technical talent, and greater access to financial services. These conditions may facilitate the integration of AI into production processes, information management, and risk management activities, thereby improving the effectiveness of technological applications.

In contrast, firms in certain western regions may face constraints related to technical expertise, digital infrastructure, and specialized business services, potentially limiting their ability to fully realize the operational benefits of AI adoption in the short term. Regional differences in market development and external financing conditions may also affect the extent to which AI adoption translates into improvements in corporate financial stability.

To further examine regional heterogeneity, the sample is divided into firms located in eastern and central China and those located in western China. Columns (3) and (4) of Table 6 report the corresponding regression results.

For firms in eastern and central China, the estimated coefficient on Ai is −0.0027 and is statistically significant at the 1% level. For firms in western China, the coefficient is −0.0023 but does not reach conventional levels of statistical significance.

These results suggest that the statistically significant negative association between AI adoption and corporate default risk is primarily observed among firms in eastern and central China, whereas the evidence for firms in western China remains statistically inconclusive.

Table 6. Heterogeneity Analysis

	(1)	(2)	(3)	(4)
	High-Tech	Non- High-Tech	Eastern and Central China	Western China
Variables	Edf	Edf	Edf	Edf
Ai	-0.0003	-0.0057***	-0.0027***	-0.0023

	(0.0005)	(0.0016)	(0.0007)	(0.0023)
Constant	-0.2273***	-0.3726***	-0.2447***	-0.4459***
	(0.0421)	(0.0747)	(0.0445)	(0.1018)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	21,514	16,107	32,523	5,098
R^2	0.237	0.244	0.233	0.273

6. Conclusions, Policy Recommendations, and Future Research

6.1 Conclusions

Against the backdrop of rapid digital economic development and growing uncertainty in the business environment, AI adoption offers firms new technological opportunities to improve managerial decision-making, strengthen risk identification, and enhance financial stability. Using firm-level data from Chinese A-share listed companies, this study empirically examines the relationship between AI adoption and corporate default risk, with particular attention to heterogeneity across industries with different levels of technological intensity and across geographical regions. The analysis yields three main findings.

First, AI adoption is significantly and negatively associated with corporate default risk. The baseline regression results show that the estimated coefficient on AI adoption remains negative and statistically significant at the 1% level after controlling for firms' financial conditions, basic characteristics, and corporate governance attributes. This suggests that firms with higher levels of AI adoption tend to exhibit lower default risk. The main finding remains robust to alternative fixed-effects specifications, different standard-error clustering levels, and the exclusion of observations from periods affected by major external shocks. These results indicate that the negative association between AI adoption and corporate default risk is relatively stable across different model specifications and sample restrictions.

Second, the relationship between AI adoption and corporate default risk exhibits industry-level heterogeneity. The subgroup regression results reveal a significant negative coefficient on AI adoption among firms in non-high-tech industries, whereas the corresponding coefficient for high-tech firms does not reach conventional levels of statistical significance. One possible explanation is that non-high-tech firms have greater scope for improving conventional operating processes, information processing capabilities, and resource allocation efficiency. AI adoption may therefore offer more substantial opportunities to enhance operational management in these firms, resulting in a more pronounced association with lower default risk.

Third, the relationship between AI adoption and corporate default risk varies across regions. The estimated coefficient on AI adoption is significantly negative among firms located in eastern and central China, while the corresponding estimate for firms in western China is not statistically significant at conventional levels. This regional variation may reflect differences in digital infrastructure, the availability of skilled technical personnel, and external business environments. The findings suggest that the potential risk governance benefits of AI adoption may depend partly on the regional conditions that support effective technological implementation.

6.2 Policy Recommendations

Based on the empirical findings, this study proposes the following policy recommendations.

First, promote the integration of AI into corporate risk management to strengthen firms' risk prevention capabilities. Governments should further improve the infrastructure and public service systems supporting AI adoption and encourage firms to incorporate predictive analytics, data analysis, and anomaly detection technologies into financial management, operational decision-making, and early-warning systems. Such measures may strengthen firms' ability to identify emerging operational risks and respond to external shocks. At the firm level, greater emphasis should be placed on integrating AI technologies with internal control systems, financial management practices, and broader operational management frameworks. This would facilitate the transition of AI from a supplementary information processing tool to a more comprehensive instrument for managing operational risks, thereby contributing to greater corporate financial stability.

Second, implement differentiated policies to support AI adoption and improve the effectiveness of technological applications. Policy design should account for differences in technological capabilities, business models, and risk management requirements across industries. A differentiated support framework would allow AI adoption policies to better reflect firms' specific operational needs. For high-tech firms, priority should be given to integrating AI

with R&D management, technological innovation, and operational risk control, while strengthening coordination between technological investment and risk management. For non-high-tech firms, policy support should focus on facilitating the practical application of AI in production process optimization, operating cost management, and financial risk early-warning systems. These measures would help firms realize the potential of AI to improve conventional management practices and enhance operational efficiency.

Third, strengthen regional digital infrastructure and narrow disparities in AI-enabled risk governance capabilities. Greater efforts should be made to promote balanced development across regions in digital infrastructure, technical expertise, and intelligent business services. In eastern and central China, firms should be encouraged to explore advanced approaches to integrating AI into corporate risk management and develop technological practices that can be replicated and adapted elsewhere. In western China, policy priorities should include expanding digital infrastructure, improving access to AI-related technical services, and strengthening professional training. These initiatives could reduce the costs associated with AI adoption and create more favorable conditions for firms to use intelligent technologies to improve operational management and risk prevention capabilities.

Fourth, establish sound corporate governance mechanisms for AI-related risks to address the potential challenges arising from AI adoption itself. While AI can improve risk identification and managerial decision-making efficiency, firms should also recognize the potential risks associated with implementation costs, data security, model prediction errors, and managerial accountability. Firms should establish systematic mechanisms for evaluating the effectiveness of AI applications, clearly define the responsibilities of automated decision-support systems and human managers, and strengthen human oversight and risk controls in major financial decisions. Particular attention should be given to avoiding excessive reliance on algorithmic outputs. By balancing technological adoption with appropriate governance and oversight, firms can better align AI implementation with prudent and sustainable business operations.

6.3 Limitations and Future Research

Although this study examines the relationship between AI adoption and corporate default risk using firm-level empirical evidence, several areas warrant further investigation.

First, with regard to variable measurement, corporate AI adoption is inherently multidimensional, and different indicators may capture distinct aspects of technological development, strategic attention, and actual implementation. Future research could combine information on corporate AI investment, technology patents, and specific business applications to develop more comprehensive measures of firm-level AI adoption.

Second, regarding causal identification, this study primarily relies on a two-way fixed-effects model and a series of robustness checks to investigate the relationship between AI adoption and corporate default risk. Nevertheless, potential endogeneity concerns, including reverse causality and time-varying omitted variables, may remain. Future studies could exploit exogenous technological shocks, quasi-natural experiments, or instrumental variables that satisfy plausible exclusion restrictions to strengthen the credibility of causal inference.

Finally, concerning the underlying mechanisms, this study does not directly test the specific channels through which AI adoption may influence corporate default risk. Future research could examine mechanisms related to operating cash flow stability, resource allocation efficiency, financing constraints, and corporate risk management capabilities. Such analyses would provide a more detailed understanding of the economic mechanisms linking AI adoption to corporate default risk.

JEL Classification: G32; G33; O33

References

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics, 40*(S1), S293–S340. https://doi.org/10.1086/718327

Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review, 108*(6), 1488–1542. https://doi.org/10.1257/aer.20160696

Albuquerque, B. (2024). Corporate debt booms, financial constraints, and the investment nexus. *Journal of Applied Econometrics, 39*(5), 766–789. https://doi.org/10.1002/jae.3047

Bharath, S. T., & Shumway, T. (2008). Forecasting default with the Merton distance to default model. *The Review of Financial Studies, 21*(3), 1339–1369. https://doi.org/10.1093/rfs/hhn044

Campbell, J. Y., Hilscher, J., & Szilagyi, J. (2008). In search of distress risk. *The Journal of Finance, 63*(6), 2899–2939. https://doi.org/10.1111/j.1540-6261.2008.01416.x

Chen, G., Liu, P., & Jiang, A. (2025). Does digital transformation in enterprises reduce debt default risk? *International Review of Economics & Finance*. https://doi.org/10.1016/j.iref.2024.103529

Crawford, J., & Jabbour, M. (2024). The relationship between enterprise risk management and managerial judgement in decision-making: A systematic literature review. *International Journal of Management Reviews, 26*(1), 110–136. https://doi.org/10.1111/ijmr.12337

Csaszar, F. A., Ketkar, H., & Kim, H. (2024). Artificial intelligence and strategic decision-making: Evidence from entrepreneurs and investors. *Strategy Science, 9*(4), 322–345. https://doi.org/10.1287/stsc.2024.0190

Czarnitzki, D., Fernández, G. P., & Rammer, C. (2023). Artificial intelligence and firm-level productivity. *Journal of Economic Behavior & Organization, 211*, 188–205. https://doi.org/10.1016/j.jebo.2023.05.008

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data: Evolution, challenges and research agenda. *International Journal of Information Management, 48*, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Helfat, C. E., & Raubitschek, R. S. (2018). Dynamic and integrative capabilities for profiting from innovation in digital platform-based ecosystems. *Research Policy, 47*(8), 1391–1399. https://doi.org/10.1016/j.respol.2018.01.019

Kemp, A. (2024). Competitive advantage through artificial intelligence: Toward a theory of situated AI. *Academy of Management Review, 49*(3), 618–635. https://doi.org/10.5465/amr.2020.0205

Kleinberg, J., Lakkaraju, H., Leskovec, J., Ludwig, J., & Mullainathan, S. (2018). Human decisions and machine predictions. *The Quarterly Journal of Economics, 133*(1), 237–293. https://doi.org/10.1093/qje/qjx032

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance, 29*(2), 449–470. https://doi.org/10.1111/j.1540-6261.1974.tb03058.x

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072

Safiullah, M., Phan, D. H. B., & Kabir, M. N. (2024). Green innovation and corporate default risk. *Journal of International Financial Markets, Institutions and Money*, 95, Article 102041. https://doi.org/10.1016/j.intfin.2024.102041

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *The Journal of Business, 74*(1), 101–124.

Wang, R., & Huang, Z. (2025). The effects of macroeconomic uncertainty on corporate default risk: Evidence from China. *China Economic Journal, 18*(1), 131–154. https://doi.org/10.1080/17538963.2024.2399953

Wu, K., & Lu, Y. (2025). The digital dilemma: Corporate digital transformation and default risk. *Journal of Financial Stability*, 77, Article 101393. https://doi.org/10.1016/j.jfs.2025.101393

Xing, Y., Anderson, C., Ho, D., Lefevre, G., & Lavoratori, M. (2024). Critical theories challenge the normative bases of contemporary global economical governance and help to imagine progressive alternatives. *Journal of World Economy, 3*(3), 52-59.

Yang, C.-H. (2022). How artificial intelligence technology affects productivity and employment: Firm-level evidence from Taiwan. *Research Policy, 51*(6), 104536. https://doi.org/10.1016/j.respol.2022.104536

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