

Article

Artificial Intelligence and Corporate Internal Control Quality: Evidence from Chinese Listed Firms

Junming Yang ¹, Jingbo Cai ², Li He ^{3,*}, Jiya Hu ³ and Xiaoyu Ma ⁴

¹ School of Business, University of Chinese Academy of Social Sciences, Beijing 102488, China; 20231131108@ucass.edu.cn

² Lingnan College, Sun Yat-sen University, Guangzhou 510275, China; caijingbo666@163.com

³ Faculty of Applied Economics, University of Chinese Academy of Social Sciences, Beijing 102488, China; skdhujiya@126.com

⁴ International Business School, Beijing Foreign Studies University, Beijing 100089, China; maxiaoyu@bfsu.edu.cn

* Correspondence: heli2022@ucass.edu.cn; Tel.: +86-188-0121-0181

Abstract

Against the backdrop of a new wave of scientific and technological revolution and industrial transformation, artificial intelligence has emerged as a pivotal technology for fostering new quality productive forces and advancing high-quality development, and is profoundly reshaping firms' production organization and governance structures. Using data on Chinese A-share listed companies from 2016 to 2024, this study empirically examines the impact of AI on corporate internal control quality and its underlying mechanisms. The results indicate that AI significantly improves corporate internal control quality, mainly by enhancing firms' human capital and reducing agency costs. Further heterogeneity analysis shows that the positive effect of AI on internal control quality is more pronounced among manufacturing firms, firms with higher levels of digital infrastructure, and firms with greater information transparency. From the perspective of internal corporate governance, this study extends the literature on the economic consequences of AI and provides empirical evidence on how AI, as embedded in a complex socio-technical system, empowers high-quality corporate development through institutional governance mechanisms. The findings also offer useful implications for governments seeking to refine AI-related policies and for firms aiming to promote the coordinated upgrading of intelligent transformation and internal control systems.

Keywords: artificial intelligence; corporate internal control quality; human capital; agency costs



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1. Introduction

With the rapid advancement of a new wave of technological revolution and industrial transformation, artificial intelligence, as a representative technology of the new generation of information technologies, is profoundly reshaping firms' production modes, management practices, and governance structures. At the national strategic level, "AI+" has been clearly identified as a key policy instrument for cultivating new quality productive forces and promoting high-quality development. In July 2017, the State Council issued the "Development Plan for the Next Generation of Artificial Intelligence," which emphasized the need to "take the overall national development context into account, accurately assess global

trends in artificial intelligence, identify key breakthroughs and priority areas, comprehensively strengthen the foundational capabilities for scientific and technological innovation, fully expand the depth and breadth of applications in key fields, and comprehensively enhance the level of intelligence in economic and social development as well as national defense applications.” Under this policy framework, AI has been endowed with a strategic role that goes beyond a purely technical tool, becoming a critical technological foundation for driving transformations in quality, efficiency, and growth momentum.

At the firm level, the application of AI is no longer limited to localized improvements in operational efficiency but increasingly triggers digital restructuring across production factors and business processes. On the one hand, the integration of AI into research and development, production, and supply chain management facilitates the transition from experience-driven operations to data-driven decision-making and from reactive responses to predictive management, thereby improving resource allocation efficiency and organizational resilience (Song et al., 2024). On the other hand, AI encourages firms to undertake systematic adjustments in organizational structures, business processes, and governance mechanisms, promoting the transformation and upgrading of traditional industries while fostering new AI-native business models and emerging forms of economic activity. Through these processes, AI provides sustained momentum for achieving transformations in quality, efficiency, and growth dynamics. Therefore, in the broader context of high-quality development and industrial upgrading, examining how AI affects corporate internal governance systems has both important practical relevance and theoretical value.

Internal control is a process implemented by the board of directors, management, and other employees to provide reasonable assurance regarding the achievement of operational objectives, the reliability of financial reporting, and compliance with applicable laws and regulations (Doyle et al., 2007). High-quality internal control helps mitigate agency conflicts, reduce operational risks, and enhance long-term firm value. Existing studies generally suggest that internal control quality is shaped by multiple factors, including the external institutional environment, corporate governance structures, and the characteristics of managers and employees. However, as business environments become increasingly complex and corporate processes become more digitally integrated, traditional internal control models that rely largely on human judgment and ex post monitoring are facing new challenges. Firms therefore increasingly rely on emerging technologies to enhance the effectiveness and adaptability of internal control systems. Against the backdrop of the widespread adoption of AI, an important question arises: whether and how AI influences corporate internal control quality.

Compared with many other countries, China possesses distinctive advantages in AI adoption, digital infrastructure development, and the implementation of AI technologies across industrial scenarios, providing a rich and representative context for examining the governance implications of AI (H. Jiang & Murmann, 2022). Chinese A-share listed companies constitute a large and diverse sample across industries and have been actively advancing digital transformation and internal control system development (Q. Wu et al., 2025; Xue & Jin, 2025). This setting offers a valuable opportunity to systematically identify the impact of AI on corporate internal control quality and its underlying mechanisms. Based on data from Chinese A-share listed companies from 2016 to 2024, this study examines how AI affects internal control quality and explores the mechanisms through which this effect occurs. The results show that AI significantly improves corporate internal control quality, and that the enhancement of human capital and the reduction in agency costs serve as important channels through which AI exerts this influence. Heterogeneity analysis further indicates that the positive effect of AI is more pronounced among manufacturing firms,

firms with higher levels of information transparency, and firms operating in regions with more developed digital infrastructure.

Although some studies have begun to examine the relationship between AI and internal corporate governance, Monteiro et al. (2023) found that AI adoption intensity significantly improves the quality of internal control systems and further enhances accounting information system quality. However, their analysis is mainly based on survey data, and the authors explicitly note that the sample is based on convenience and non-probability sampling, which limits the external validity of their findings. Therefore, further evidence based on large-scale archival data is still needed to clarify whether AI can systematically improve internal control quality in broader firm settings. Against this background, this study makes three main contributions.

First, it extends the literature on the economic consequences of AI from the perspective of internal corporate governance. Existing studies primarily focus on the economic effects of AI in terms of resource allocation efficiency (Czarnitzki et al., 2023; Babina et al., 2024), operational risk (Liu & Wang, 2025), corporate strategy (Neiroukh et al., 2025; Doshi et al., 2025), and macro-level outcomes such as industrial upgrading and international competitiveness (Kumar et al., 2025). In contrast, relatively little attention has been paid to AI's impact on institutional governance arrangements such as internal control systems. By linking AI with corporate internal control quality, this study deepens the understanding of how AI can promote high-quality development through governance mechanisms. In addition, compared with prior survey-based research, this study conducts empirical tests using a large sample of listed companies, offering broader sample coverage and greater robustness and generalizability.

Second, this study enriches the literature on the determinants of internal control quality. Prior research has examined the influence of macro-level factors such as institutional constraints and market supervision (H. Chen et al., 2019), economic policy environments (B. Zhang et al., 2025), and ownership structures (Ong et al., 2024), as well as micro-level factors such as organizational structures and managerial capabilities (Lisic et al., 2016; Zhou & Liu, 2022). However, technological drivers such as AI have received relatively limited attention, despite their transformative role in the ongoing technological and industrial revolution. By examining the role of AI in shaping internal control quality, this study provides new insights into the technological determinants of corporate governance. Beyond systematically examining the effect of AI on internal control quality, this study further explores the underlying mechanisms, thereby providing a more detailed account of the pathways through which AI affects internal corporate governance.

Third, this study provides micro-level empirical evidence on how AI can enhance corporate governance and internal control systems. By identifying the mechanisms and heterogeneous effects through which AI improves internal control quality, the findings offer useful implications for policymakers seeking to refine “AI+” policies and for firms aiming to promote the coordinated upgrading of technological application and governance capacity. The results may also provide valuable references for other countries seeking to advance the application of AI in corporate governance.

2. Literature Review

2.1. The Impact of Artificial Intelligence on Firms' High-Quality Development

As a strategic technology leading a new round of scientific and technological revolution and industrial transformation, artificial intelligence has exerted profound effects on firms' operations, innovation, governance, and performance. Existing studies have gradually shifted from macro-level analysis to micro-level firm evidence, showing that AI can improve productivity, resource allocation efficiency, and firm value. For example,

Czarnitzki et al. (2023) found that AI adoption significantly enhances firm productivity based on German firm-level survey data, while Babina et al. (2024) showed that corporate AI investment promotes growth in sales, employment, and market valuation. From the perspective of high-quality development, Ahdadou et al. (2025) argued that AI facilitates firms' transition from scale expansion to efficiency improvement and quality optimization by promoting managerial innovation and process reengineering. In addition, AI can strengthen firms' information acquisition, risk identification, and early-warning capabilities, thereby reducing operational risk and enhancing organizational resilience (Liu & Wang, 2025; Han et al., 2025). AI is also increasingly embedded in strategic decision-making processes. By improving decision speed and decision quality, AI capabilities can enhance organizational performance (Neiroukh et al., 2025), reshape the evaluation of strategic alternatives (Doshi et al., 2025), promote new firm entry through improvements in the entrepreneurial ecosystem (Khan et al., 2025), and strengthen firms' export market exploration, export market exploitation, and overseas business performance (Kumar et al., 2025).

Beyond operating performance and strategic behavior, recent studies have begun to emphasize the governance implications of AI. In board and managerial decision-making, AI-based advisory systems can expand decision-makers' information sets and improve the timeliness and accuracy of strategic judgments, although excessive reliance on algorithmic advice may weaken managerial judgment and accountability (Keding & Meissner, 2021). AI also reshapes the roles and capabilities required of boards of directors, making board-level AI expertise and AI oversight mechanisms increasingly important for corporate governance (Agnese et al., 2025). From an organizational governance perspective, effective AI governance requires the coordination of data governance, model governance, and system governance, indicating that AI can generate governance value only when embedded in formal rules, responsibilities, and control procedures (Schneider et al., 2023). In the auditing and disclosure fields, AI has been found to improve audit quality by reducing financial restatements and strengthening auditors' risk assessment capabilities (Fedyk et al., 2022; Law & Shen, 2025; Rahman et al., 2024). It also affects financial reporting judgments and disclosure quality by improving information processing efficiency, reporting accuracy, and transparency (Estep et al., 2024; J. Li, 2026; Naveed et al., 2025). Taken together, the literature suggests that AI promotes firms' high-quality development not only through productivity improvement, risk reduction, and market expansion, but also by optimizing corporate governance mechanisms such as decision support, audit assurance, information disclosure, and internal control.

2.2. Determinants of Corporate Internal Control Quality

From the external environment perspective, institutional constraints and market mechanisms are important exogenous determinants of internal control quality. Prior studies show that capital market discipline can significantly affect internal control quality. Based on China's margin trading and short-selling system, H. Chen et al. (2019) found that firms experience a significant improvement in internal control quality after being included in the short-selling list, with a stronger effect among non-state-owned firms, suggesting that external market monitoring strengthens firms' incentives to improve internal control. Kim and Kim (2017) showed that firms facing more intense product market competition are more likely to disclose material internal control weaknesses, indicating that competitive pressure may also undermine internal control effectiveness. Uncertainty in the macro-policy environment can likewise affect internal control through its influence on corporate governance and the information environment. B. Zhang et al. (2025) argued that economic policy uncertainty increases litigation risk by weakening internal control and corporate transparency and by aggravating fraud risk. In terms of property rights and ownership

structure, [Ong et al. \(2024\)](#) found a significant negative association between ownership concentration and internal control, indicating that ownership arrangements alter internal control quality by affecting the strength of governance constraints. Overall, external market monitoring, the competitive environment, policy uncertainty, and ownership structure all shape governance incentives and risk pressure, thereby exerting important effects on internal control quality.

From the perspective of internal firm characteristics, corporate governance structure, managerial and employee attributes, and technological conditions are important endogenous determinants of internal control quality. Regarding managerial power structure, [Lisic et al. \(2016\)](#) showed that the stronger the CEO's power, the weaker the restraining effect of audit committee independence and financial expertise on internal control weaknesses. From the perspective of managerial ability, [Zhou and Liu \(2022\)](#) found an inverted U-shaped relationship between managerial ability and internal control quality, suggesting that managerial behavioral characteristics play an important role in internal control effectiveness. In addition, managerial culture and values also affect the development of internal control systems. [Abernethy et al. \(2023\)](#) found that more conservative political values within top management teams are significantly associated with more effective internal control systems. Further, [Luo \(2020\)](#) showed that improvements in employee compensation incentives and knowledge capabilities help enhance the control environment and information communication, thereby significantly improving internal control quality. With the development of the digital economy, technological factors have gradually become an important entry point in internal control research. [He \(2025\)](#) found that digital transformation improves internal control quality by increasing information transparency and strengthening risk identification capability.

2.3. Summary and Research Gap

Based on the above literature, existing studies have established a relatively solid foundation from two perspectives: the economic consequences of artificial intelligence and the determinants of corporate internal control quality. However, research on AI has largely focused on economic outputs and performance outcomes, while paying insufficient attention to how AI is embedded in firms' internal governance systems and operates through institutional governance arrangements. Meanwhile, studies on the determinants of internal control quality have mainly examined external institutional environments and internal organizational characteristics. With the development of the digital economy, some studies have begun to explore the effect of digital transformation on internal control quality, suggesting that digital technologies can improve internal control by enhancing information transparency and risk identification capability. Nevertheless, most existing studies focus on general digital transformation or traditional governance factors, and have not fully explained how AI, as a more intelligent, autonomous, and data-driven technology, systematically affects the five components of internal control: the control environment, risk assessment, control activities, information and communication, and monitoring activities.

Although recent research has begun to directly examine the relationship between AI and internal control, [Monteiro et al. \(2023\)](#) found that AI adoption intensity improves internal control system quality and further enhances accounting information system quality. However, their study is mainly based on survey data collected through convenience and non-probability sampling, which limits the external validity of their findings. Therefore, further research is needed to provide large-sample empirical evidence, identify the underlying mechanisms, and examine the boundary conditions of this relationship. Accordingly, using Chinese A-share listed companies as the research sample, this study systematically examines the impact of AI application on corporate internal control quality and further

investigates its mechanisms and heterogeneous effects, thereby revealing the specific pathways and applicable contexts through which AI affects firms' internal governance.

3. Theoretical Foundation and Hypothesis Development

3.1. *The Impact of Artificial Intelligence on the Quality of Internal Control in Enterprises*

Internal control is a systematic governance mechanism established to help firms achieve operational, reporting, and compliance objectives. According to the COSO internal control framework, an effective internal control system consists of five interrelated components: control environment, risk assessment, control activities, information and communication, and monitoring activities (COSO, 2013). The strengths of artificial intelligence in data processing, intelligent analysis, and process automation provide a new technological foundation for optimizing corporate internal control systems.

Specifically, in terms of the control environment, AI promotes data-driven management and standardized business processes, helps clarify internal responsibilities and accountability, reduces managerial opportunism and agency costs, and thereby strengthens the organizational foundation for effective internal control. Prior studies show that AI can improve decision-making efficiency and reduce agency costs by promoting managerial innovation and process standardization (Hu et al., 2025; Neiroukh et al., 2025), providing empirical support for its role in improving the control environment. In terms of risk assessment, AI can efficiently integrate and analyze large volumes of internal and external data, enhancing firms' ability to identify operational, financial, and compliance risks and improving the timeliness and forward-looking nature of risk prevention. Related studies find that AI strengthens firms' information acquisition, risk identification, and early-warning capabilities, thereby reducing operational risk (Neiroukh et al., 2025; J. Zhang et al., 2025). In terms of control activities, intelligent algorithms and automated systems can embed authorization, approval, verification, reconciliation, and exception-handling procedures into business processes, reducing human intervention and operational deviations and improving the stability and consistency of internal control execution (H. Chen et al., 2019). In terms of information and communication, AI improves the timeliness, accuracy, and transparency of information acquisition, processing, and transmission, alleviates internal information asymmetry, and provides high-quality data support for the effective operation of internal control. Evidence from information disclosure research shows that AI adoption improves the readability, accuracy, and transparency of financial reports (J. Li, 2026), which is consistent with the optimization of information and communication in internal control. In terms of monitoring activities, AI enables continuous monitoring, real-time warning, and traceability of business activities and financial processes, promoting the transformation of internal control from traditional ex post supervision to an intelligent control model integrating ex ante risk warning, in-process control, and ex post traceability. Prior studies also show that AI investment improves audit quality, enhances auditors' risk identification capability, and increases the accuracy of internal control opinions (Fedyk et al., 2022; Law & Shen, 2025), indicating that AI can strengthen both internal and external monitoring mechanisms. Overall, AI is expected to improve corporate internal control quality by optimizing the control environment, enhancing risk assessment, strengthening control activities, improving information and communication, and reinforcing continuous monitoring. Based on the above analysis, this study proposes the following hypothesis:

Hypothesis 1. *The application of artificial intelligence has a significant positive effect on the improvement of corporate internal control quality.*

3.2. Hypothesis of the Mechanism of Artificial Intelligence

The effective operation of internal control depends on whether organizational members possess sufficient professional knowledge, technical skills, execution capability, and cognitive understanding. Internal control requirements, such as authorization and approval, risk identification, information reporting, exception handling, and audit support, must ultimately be understood and implemented by employees in daily business processes. Therefore, employees' knowledge structure and capability level constitute an important basis for transforming formal control rules into effective control practices. Prior studies show that managerial ability is significantly associated with internal control effectiveness (Lin & Li, 2024), and enhancing employee knowledge and skills helps improve the control environment and information and communication, thereby enhancing the quality of internal controls (Almaqoushi & Powell, 2021). This suggests that stronger organizational capabilities can improve employees' understanding of control requirements, enhance the consistency of control execution, and provide support of higher quality for risk identification, problem feedback, and audit cooperation.

AI application further strengthens the capability foundation required for internal control operation. As AI becomes embedded in corporate management and business processes, firms' operations become more intensive in data use, more systematic, and more analytically complex, placing higher demands on employees' data literacy, system operation skills, algorithmic understanding, and interdepartmental collaboration. To ensure the effective operation of intelligent systems, firms usually need to introduce data and technical talent, provide position specific retraining, and develop collaboration mechanisms between humans and AI, thereby improving the quality of organizational human capital. In this process, employees can better interpret algorithmic outputs, identify abnormal signals, translate intelligent analytical results into executable control actions, and reduce deviations in control execution, feedback, and correction. Related studies also indicate that AI capability depends not only on technological and data resources but also on human resources and organizational skills (Mikalef & Gupta, 2021), and that corporate AI development can promote the upgrading of human capital structure (Z. Li et al., 2025). Therefore, AI can improve corporate internal control quality by enhancing employees' control knowledge, data processing capability, risk identification capability, and compliance execution capability. Based on this, this study proposes the following hypothesis:

Hypothesis 2. *Artificial intelligence improves corporate internal control quality through the capability enhancement mechanism.*

Internal control is not only an execution system that supports the effective operation of business activities, but also an important governance mechanism that constrains opportunistic behavior and strengthens accountability. Prior studies show that alleviating information asymmetry and reducing agency costs can improve internal control quality and enhance corporate governance effectiveness (Zhao et al., 2023). Similarly, by reducing agency costs and increasing external attention, the suppression of governance failures such as boardroom reciprocity can also improve internal control quality (Huang et al., 2025). Accordingly, constraint mechanisms such as authorization and approval procedures, segregation of duties, process traceability, supervision and inspection, and accountability arrangements can limit excessive managerial discretion, improve the observability of business activities, and strengthen responsibility tracing. These mechanisms reduce the scope for misconduct, opportunistic behavior, and control deviations, thereby promoting the more standardized and effective operation of internal control systems and ultimately improving corporate internal control quality.

Artificial intelligence can further strengthen the constraining function of internal control by improving the frequency, accuracy, and traceability of supervision. By embedding automatic approval, real-time data analysis, anomaly detection, and risk warning systems into business and financial processes, AI enables continuous monitoring of operating activities, timely identification of abnormal transactions and control deviations, and lower dependence on human judgment in supervisory activities. Digital records and algorithmic monitoring also make managerial and employee behavior more observable and verifiable, thereby improving accountability efficiency and restraining opportunistic behavior. Fedyk et al. (2022) find that AI investment by audit firms improves audit quality and reduces the likelihood of financial restatements. Law and Shen (2025) further show that audit firms adopting AI issue more accurate going concern opinions and internal control opinions. Evidence from Chinese listed firms also indicates that AI adoption can reduce agency costs, suggesting that AI has a governance constraint effect (Zhong & Song, 2025). Therefore, AI can improve corporate internal control quality by strengthening continuous monitoring, enhancing behavioral constraints, and improving the enforceability of control systems. Based on this, this study proposes the following hypothesis:

Hypothesis 3. *Artificial intelligence improves corporate internal control quality through a constraint strengthening mechanism.*

The mechanism analysis framework of this research is summarized in Figure 1.

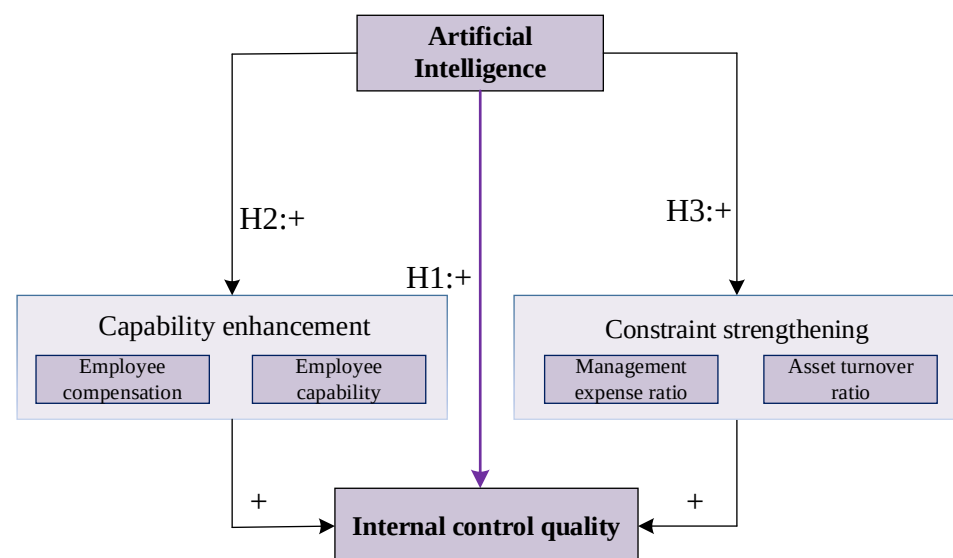


Figure 1. Mechanism analysis framework.

4. Sample Selection and Research Design

4.1. Data Sources

In 2016, artificial intelligence moved from the laboratory into the public spotlight, and China issued the Three-Year Action Plan for the Implementation of “Internet Plus” Artificial Intelligence. Taking this as the starting point, this study selects Chinese A-share listed companies from 2016 to 2024 as the research sample. The data are obtained from the DIB Internal Control and Risk Management Database, the Wind Database, CSMAR and CNRDS. ST and *ST firms, as well as firms with incomplete data, are excluded. All continuous variables are minorized at the upper and lower 1% levels. The final sample consists of 19,191 firm-year observations.

4.2. Variable Definitions

4.2.1. Dependent Variable

The dependent variable in this study is corporate internal control quality (IC). Following X. Wang et al. (2021), this study uses the Internal Control Index disclosed by the DIB database to measure corporate internal control quality and divides the index by 100, denoted as IC; that is, $IC = \text{Internal Control Index} / 100$. A higher value indicates better internal control quality.

4.2.2. Independent Variable

Drawing on the measurement approach proposed by Z. Wang et al. (2024) regarding the level of AI adoption in firms, this study uses the number of AI-related patents held by a firm as a proxy for its level of AI application. Specifically, at the firm-year level, based on patent data of listed companies, this study identifies patent applications whose titles, abstracts, or keywords contain AI-related technical terms, and counts the number of AI-related patent applications filed by firm (i) in year (t). To mitigate the influence of the right-skewed distribution of patent counts, this variable is further transformed by taking the natural logarithm after adding one. AI-related patents reflect firms' knowledge accumulation and technological deployment in AI-related fields, such as algorithmic models, data processing, intelligent recognition, and automated decision-making. Compared with general descriptions of digital transformation, patent data are more technology-specific and can better capture whether firms have embedded AI technologies into R&D, production, management, or business processes. Therefore, a larger number of AI-related patents generally indicates stronger AI technological reserves, broader application deployment, and greater intensity of AI application within the firm (Giczy et al., 2022; Babina et al., 2024; Xue & Jin, 2025).

4.2.3. Mediating Variables

To further examine the mechanisms through which artificial intelligence affects corporate internal control quality, this study constructs mechanism variables from two perspectives: the capability mechanism and the constraint mechanism. The capability mechanism is represented by firms' human capital level. Employee compensation reflects a firm's emphasis on human capital investment and employee incentives and has important implications for productivity and operating performance (Yang & Wang, 2026). Employee educational attainment is an important indicator of human capital quality, and a higher level of employee education helps improve firms' information-processing capability, professional judgment, and investment decision-making efficiency (Jin et al., 2025). Accordingly, this study uses employee compensation and employee capability to measure firms' human capital level. Specifically, employee compensation is measured as cash paid to and on behalf of employees minus executive compensation, divided by the number of employees minus the number of executives, so as to capture compensation incentives at the ordinary employee level. Employee capability is measured as the proportion of employees with a bachelor's degree or above in the total number of employees. If AI application significantly increases employee compensation or employee capability, it indicates that AI may improve internal control quality by strengthening firms' human capital, namely the capability mechanism.

The constraint mechanism is represented by corporate agency costs. Prior studies show that a higher expense ratio reflects greater managerial discretionary spending and resource consumption, whereas higher asset utilization efficiency indicates more efficient resource allocation and weaker agency conflicts (Lee & Tulcanaza-Prieto, 2024; Njoku & Lee, 2025). Accordingly, this study uses the management expense ratio and asset turnover

ratio to measure corporate agency costs. Specifically, the management expense ratio is measured as management expenses divided by operating revenue; a higher value indicates that managers may engage in greater discretionary spending, implying higher agency costs. The asset turnover ratio is measured as operating revenue divided by average total assets; a higher value indicates higher asset-use efficiency and lower agency costs. If AI application significantly reduces the management expense ratio or increases the asset turnover ratio, it indicates that AI may improve corporate internal control quality by reducing agency costs, namely the constraint mechanism.

4.2.4. Control Variables

Following prior studies, this study includes firm size (Size), firm age (Age), return on assets (ROA), leverage (Lev), cash ratio (Cash), board size (Board), proportion of independent directors (Indep), Concentration of Shareholding (TOP-1), Two roles combined (Dual), Audit Quality (Big4) as control variables. The definitions and measurement methods of all variables are reported in Appendix A Table A1.

4.3. Model Specification

To examine the impact of artificial intelligence (AI) on corporate internal control quality, we establish the following benchmark regression model:

$$IC_{i,t} = \alpha_0 + \alpha_1 AI_{i,t} + \sum_k \alpha_k Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

where $IC_{i,t}$ represents the dependent variable, corporate internal control quality for company i in year t ; $AI_{i,t}$ denotes the core explanatory variable, artificial intelligence; $Controls_{i,t}$ represents the set of control variables; μ_i represents firm fixed effects, and λ_t represents year fixed effects. $\varepsilon_{i,t}$ is the random error term.

To further investigate the mediating mechanisms through which AI affects internal control quality, this study follows T. Jiang (2022) and employs a two-step approach to test the mediation effects.

Testing Model for Testing the Mediating Effect of Human Capital:

$$Wage_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \sum_k \beta_k Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (2)$$

$$Ability_{i,t} = \gamma_0 + \gamma_1 AI_{i,t} + \sum_k \gamma_k Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (3)$$

Testing Model for the Mediating Effect of Agency Costs:

$$MER_{i,t} = \delta_0 + \delta_1 AI_{i,t} + \sum_k \delta_k Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (4)$$

$$ATO_{i,t} = \eta_0 + \eta_1 AI_{i,t} + \sum_k \eta_k Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (5)$$

4.4. Descriptive Statistics

Table 1 presents descriptive statistics for the key variables in this study. The mean value of corporate internal control quality is 6.404, with a standard deviation of 0.647, indicating that the variation in internal control quality across sample firms is relatively limited and mainly reflects subtle differences at relatively high levels, though some dispersion remains. The minimum and maximum values are 3.385 and 7.764, respectively, suggesting that while internal control among listed companies is generally well established, differences still exist in its effectiveness of implementation. The mean value of artificial intelligence is 1.174, with a standard deviation of 1.298, a minimum of 0, and a maximum of 8.060, indicating substantial heterogeneity in the level of AI adoption across firms. Some firms have actively adopted AI technologies and developed relatively extensive technological

layouts, reflecting significant differences in the level of AI development among firms. The remaining control variables are all within reasonable ranges.

Table 1. Descriptive statistics of main variables.

Variables	N	Mean	sd	Min	Median	Max
IC	19,191	6.404	0.647	3.385	6.489	7.764
AI	19,191	1.174	1.298	0.000	0.693	5.193
Size	19,191	22.280	1.236	20.148	22.064	26.263
Age	19,191	1.906	0.963	0.000	1.946	3.401
ROA	19,191	0.027	0.063	−0.243	0.031	0.180
Lev	19,191	0.404	0.196	0.057	0.396	0.875
Cash	19,191	0.849	1.204	0.027	0.430	7.488
Board	19,191	8.237	1.606	5.000	9.000	14.000
Indep	19,191	0.381	0.054	0.333	0.364	0.571
TOP-1	19,191	0.322	0.145	0.079	0.300	0.720
Dual	19,191	0.341	0.474	0.000	0.000	1.000
SOE	19,191	0.280	0.449	0.000	0.000	1.000
Big 4	19,191	0.061	0.239	0.000	0.000	1.000

5. Empirical Analysis

5.1. Baseline Regression Results

To examine whether the application of artificial intelligence (AI) improves corporate internal control quality and to test Hypothesis 1, this study conducts baseline regression analyses based on the variable definitions and econometric models established above. The results are reported in Table 2.

Table 2. Baseline regression results.

	(1)	(2)	(3)	(4)
Variables	IC	IC	IC	IC
AI	0.081 *** (0.004)	0.062 *** (0.004)	0.035 *** (0.009)	0.032 *** (0.009)
Constant	6.309 *** (0.006)	5.185 *** (0.110)	6.364 *** (0.011)	5.830 *** (0.499)
Controls	No	Yes	No	Yes
Year FE	No	No	Yes	Yes
Firm FE	No	No	Yes	Yes
N	19,191	19,191	19,191	19,191
Adjusted-R ²	0.027	0.160	0.223	0.289

Note: Standard errors clustered at the firm level are reported in parentheses. *** indicate significance at the 1% levels.

Columns (1) and (2) of Table 2 present the regression results without fixed effects. The coefficient on the core explanatory variable is significantly positive, indicating that higher levels of AI are associated with better internal control quality. Columns (3) and (4) report the results after including both time and firm fixed effects. The coefficient on AI remains positive and significant at the 1% level, further confirming that improvements in AI are conducive to enhancing corporate internal control quality, thereby supporting Hypothesis 1. By improving firms' capabilities in data processing and information integration, AI strengthens the standardization of business processes and real-time monitoring, while constraining managerial discretion in accounting estimates and accounting policy choices. This helps reduce information asymmetry and agency costs, thereby inhibiting opportunistic earnings management by managers. The findings suggest that AI not only

enhances operational efficiency but also plays a positive role in improving accounting information quality and strengthening internal corporate governance, providing empirical evidence for firms seeking to advance intelligent management practices and for regulators aiming to guide the standardized application of AI technologies.

5.2. Robustness Tests

5.2.1. Alternative Variable

To further examine the robustness of the baseline regression results, this study replaces the core explanatory variable with three alternative measures of artificial intelligence. First, following prior studies that identify firms' AI engagement based on textual information and AI-related disclosures, this study uses the frequency of AI-related terms in firms' annual reports to measure corporate AI attention (H. Wu et al., 2025). Second, considering that AI is often embedded in automation, intelligent equipment, and technological upgrading in production processes, this study further constructs a variable for firms' AI adoption level. Specifically, the book value of machinery and equipment disclosed in fixed asset details is divided by the total number of employees to measure the intensity of production-related intelligent equipment. This indicator captures the extent to which firms substitute or complement labor input with intelligent capital and integrate automation, intelligent equipment, and AI-enabled technologies into production and operational processes (J. Zhang et al., 2025). Finally, this study uses firms' AI investment level as another alternative measure to reflect their resource inputs and financial commitments to AI-related technological upgrading, because AI investment represents firms' strategic resource allocation toward intelligent transformation, technological innovation, and AI-driven growth (Babina et al., 2024; Q. Wu et al., 2025). Columns (1)–(3) of Table 3 report the corresponding regression results. The results show that the coefficients of the three alternative AI measures remain significantly positive, indicating that the positive effect of AI on corporate internal control quality is not driven by a specific measurement method. Overall, these findings further verify the robustness of the baseline regression results.

Table 3. Robustness tests for replacing key explanatory variables.

	(1)	(2)	(3)
	IC	IC	IC
AI	0.018 ** (0.009)	0.108 *** (0.005)	2.070 *** (0.799)
Constant	5.658 *** (0.494)	4.548 *** (0.457)	5.587 *** (0.493)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	19,191	19,191	19,191
Adjusted-R ²	0.289	0.387	0.289

Note: Standard errors clustered at the firm level are reported in parentheses. *** and ** indicate significance at the 1% and 5% levels, respectively.

5.2.2. High-Dimensional Fixed Effects

To further test the robustness of the empirical results, this study incorporates interaction fixed effects into the regression analysis. We controlled for the interaction fixed effects of province and year (Province $\times$ Year), city and year (City $\times$ Year), and industry and year (Industry $\times$ Year) to eliminate the potential influence of systematic differences across provinces, cities, and industries during different periods on the regression results, and to mitigate the interference caused by differences in the macroeconomic environment, regional

policies, or local governance. The regression results are presented in columns (1)–(3) of Table 4. The results show that under different fixed-effect specifications, the coefficient of the core explanatory variable remains significantly positive, confirming the robustness of the empirical findings.

Table 4. Robustness tests for models with fixed effects.

	(1)	(2)	(3)
Variables	IC	IC	IC
AI	0.031 *** (0.009)	0.033 *** (0.010)	0.038 *** (0.009)
Constant	5.876 *** (0.498)	6.285 *** (0.551)	6.276 *** (0.524)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Province-Year FE	Yes	No	No
City-Year FE	No	Yes	No
Industry-Year FE	No	No	Yes
N	19,191	19,191	19,191
Adjusted-R ²	0.295	0.299	0.299

Note: Standard errors clustered at the firm level are reported in parentheses. *** indicate significance at the 1% levels.

5.2.3. Alternative Sample Periods

As an unexpected public health event, the COVID-19 pandemic not only exerted broad impacts on corporate operations but may also have altered firms' transformation and upgrading strategies. To account for the potential effects of the pandemic, the sample is divided into two sub-periods: the pre-pandemic period (2016–2019) and the post-pandemic period (2020–2024), and regressions are conducted separately for each period. The results are reported in columns (1) and (2) of Table 5. The results show that in the pre-pandemic sample, the coefficient of AI is significantly positive, indicating a significant positive relationship between AI and corporate internal control quality. In the post-pandemic period, the relationship remains significantly positive and consistent with that observed before the pandemic. Overall, the regression coefficients maintain the same sign and remain significant across both periods, suggesting that the conclusion that AI improves corporate internal control quality is robust and not substantially affected by exogenous shocks at specific points in time.

Table 5. Robustness tests for changing sample intervals and regression methods.

	Alternative Sample Periods		Dual Machine Learning
Variables	(1) IC	(2) IC	(3) IC
AI	0.071 *** (0.020)	0.028 ** (0.011)	0.045 *** (0.005)
Constant	2.358 (1.543)	6.588 *** (0.810)	−0.058 *** (0.004)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	5673	13,518	19,191
Adjusted-R ²	0.424	0.305	

Note: Standard errors clustered at the firm level are reported in parentheses. *** and ** indicate significance at the 1% and 5% levels, respectively.

5.2.4. Alternative Empirical Method

Because corporate internal control is a complex system rather than a directly observable variable, it is inherently abstract, and the factors affecting internal control are numerous and interact in complex ways. As a result, traditional regression models may not fully capture their underlying mechanisms. To address this concern, and following Chernozhukov et al. (2018), this study employs a double machine learning approach as a robustness check. The results are reported in column (3) of Table 5. The estimated coefficient on AI patents is 0.042 and remains significant at the 1% level. This finding indicates that, after using random forests to account for the nonlinear effects of high-dimensional control variables and applying cross-fitting to mitigate overfitting, AI still significantly improves corporate internal control quality. This result further confirms the robustness of the conclusion that AI enhances internal control quality.

5.3. Endogeneity Analysis

5.3.1. Instrumental Variable Approach

To mitigate the potential effects of omitted variable bias and reverse causality on the research conclusions, this study further employs an instrumental variable approach for estimation. Following the identification logic of Borusyak et al. (2022), which constructs instrumental variables by interacting predetermined exposure with exogenous technological shocks, this study uses the interaction between the city level Internet user ratio in 2002 and the one period lagged level of firm AI application as the instrumental variable.

In terms of relevance, AI is a data intensive and network dependent technology, and its adoption relies on regional digital infrastructure, network connectivity, and accumulated information resources. Prior studies show that China's digital economy has strong advantages in information infrastructure, including mobile Internet, fiber optic networks, and digital platforms, which provide an important foundation for firms' digital applications (H. Jiang & Murmann, 2022). Broadband and information infrastructure upgrading can further promote firms' digital transformation, technological innovation, and productivity improvement (L. Zhang et al., 2022; Xu et al., 2023; M. Li et al., 2025), while AI adoption is closely related to firm size, organizational capabilities, and the regional technological environment (McElheran et al., 2024). Therefore, the city level Internet user ratio in 2002 captures the historical foundation of local information infrastructure and can affect firm AI application by shaping subsequent digital technology diffusion, data resource accumulation, and technological absorptive capacity. Its interaction with the one period lagged level of firm AI application thus helps identify variations in AI application generated by the joint effect of historical regional digital infrastructure and firms' pre-existing AI technological foundation. In terms of exogeneity, the 2002 city level Internet user ratio was formed before the sample period and is unlikely to be affected by the internal control quality of individual firms during the sample period. Moreover, prior studies suggest that digital technologies affect internal control quality mainly through firm internal mechanisms, such as reducing information asymmetry, lowering agency costs, and improving governance efficiency (Zhao et al., 2023), rather than through a direct effect of historical regional Internet penetration.

To further examine the exclusion restriction, this study regresses internal control quality on AI application, extracts the residual term, and tests whether the instrumental variable significantly explains this residual. The coefficient of the instrumental variable has a p value of 0.188, which is not statistically significant at conventional levels, indicating that the instrument is not significantly associated with the residual component of internal control quality after removing the effect of AI application. This result further supports the argument that the instrumental variable affects internal control quality mainly through firm AI application, rather than through an obvious direct channel.

The two-stage regression results are reported in columns (1) and (2) of Table 6. Column (1) of Table 6 presents the first-stage regression results of the IV estimation. The results show a significant positive relationship between instrumental variable and the level of AI, indicating a strong correlation between the instrumental variable and the endogenous explanatory variable. The Kleibergen–Paap rk Wald F-statistic is 34.149, which exceeds the Stock–Yogo critical value, ruling out the possibility of weak instruments and confirming the validity of the instrumental variable. Column (2) of Table 6 reports the second-stage estimation results. Even after correcting for the potential endogeneity of AI, the AI variable still exerts a significantly positive effect on corporate internal control quality. This result is consistent with the baseline regression findings and further supports the hypothesis that AI positively affects corporate internal control quality.

Table 6. Instrumental variable two-stage regression and DID regression results.

Variable	Instrumental Variable Approach		DID Approach
	(1) AI	(2) IC	(3) IC
IV	0.002 *** (0.000)		
AI		0.231 ** (0.113)	
DID			0.071 *** (0.023)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Kleibergen–Paap rk Wald F		34.149	
N	11,419	11,419	18,597

Note: Standard errors clustered at the firm level are reported in parentheses. *** and ** indicate significance at the 1% and 5% levels, respectively.

5.3.2. Difference-in-Differences Approach

To further identify the causal effect of AI on corporate internal control quality and alleviate potential endogeneity concerns, this study follows Wen et al. (2025) and treats the implementation of the National New Generation Artificial Intelligence Innovation and Development Pilot Zone policy as an exogenous shock to construct a difference-in-differences (DID) model. The establishment of pilot zones promotes the application and industrialization of AI technologies through policy support and resource allocation. Accordingly, a policy shock dummy variable is constructed: if the city where a firm is located is designated as a pilot zone, the variable takes the value of 1 in the year of designation and thereafter, and 0 in previous years; for firms located in cities that were not designated as pilot zones, the variable is always set to 0.

The regression results are presented in column (3) of Table 6. The coefficient of the exogenous policy shock variable is 0.071 and passes the statistical significance test. This result indicates that after the policy implementation, firms in pilot regions exhibit significantly higher internal control quality than those in non-pilot regions, with a difference of approximately 7.1 percentage points. This finding suggests that AI-related policies improve corporate internal control quality by promoting the adoption and application of AI technologies. The results confirm the validity of AI policy as an exogenous shock and support the conclusion that AI significantly improves corporate internal control quality. This evidence not only demonstrates the robustness of the baseline regression results but also indicates that the findings are unlikely to be driven by reverse causality or omitted variables.

5.3.3. Omitted Variable Bias Test

To further examine the potential problem of omitted variable bias, this study follows Oster (2019) and conducts an omitted variable sensitivity analysis using the Oster method. The results show that, when δ is set to 1 and $R_{\max}$ is set to $1.3R^2$, the calculated estimate β^* falls within the 95% confidence interval of the baseline regression estimate, indicating that the test is passed. When β is set to 0 and $R_{\max}$ is set to $1.3R^2$, the value of δ is 1.9822, which is greater than 1, also indicating that the test is passed. These results suggest that this study does not suffer from serious omitted variable bias and further support the hypothesis that artificial intelligence improves corporate internal control quality.

6. Further Analysis

6.1. Mechanism Testing

To further examine the mechanisms through which artificial intelligence (AI) improves corporate internal control quality and to test Hypotheses 2 and 3, this study conducts mechanism analyses based on the models constructed above.

First, the human capital mechanism. Columns (1) and (2) of Table 7 report the regression results of AI with employee compensation and employee capability, respectively. The results show that AI has a significantly positive effect on both variables. Specifically, the coefficient of AI on employee compensation is 0.320 and is significant at the 1% level, while the coefficient on employee capability is 0.005, also significant at the 1% level. These findings indicate that the adoption of AI technologies increases firms' demand for data analysis, system operation, and risk identification capabilities, prompting firms to raise compensation levels, strengthen employee training, and recruit high-skilled talent to optimize the human capital structure. As a result, the overall capability level of employees improves. Employees with stronger knowledge and professional expertise are better able to understand the intended design of internal control systems, implement control requirements more consistently in operational processes, and actively contribute to risk identification, information feedback, and audit support, thereby improving the effectiveness of internal control. At the same time, the accumulation of human capital enhances internal information communication, facilitates improvements in the control environment, and supports the effective operation of monitoring mechanisms, ultimately strengthening overall internal control quality. These results suggest that AI improves internal control quality by promoting human capital upgrading and reinforcing the organizational foundations for the implementation of internal control systems.

Table 7. Mechanism test results.

Variables	Capability Mechanism		Constraint Mechanism	
	(1) Wage	(2) Ability	(3) MER	(4) ATO
AI	0.320 *** (0.076)	0.005 ** (0.002)	−0.001 * (0.001)	0.006 ** (0.003)
Constant	5.314 (5.788)	0.095 (0.127)	−0.582 *** (0.061)	2.183 *** (0.203)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	19,191	19,191	19,191	19,191
Adjusted-R ²	0.861	0.854	0.870	0.852

Note: Standard errors clustered at the firm level are reported in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Second, the agency cost mechanism. Columns (3) and (4) of Table 7 report the regression results of AI with the management expense ratio and asset turnover ratio, respectively. The results indicate that AI significantly restrains agency costs. The coefficient of AI on the management expense ratio is -0.001 and is significant at the 10% level, suggesting that AI adoption effectively reduces firms' management expenses. Meanwhile, the coefficient of AI on asset turnover is 0.006 and is significant at the 5% level, indicating that AI improves the efficiency of asset utilization. These findings imply that the application of AI helps curb managerial opportunistic behavior arising from information asymmetry and insufficient supervision, thereby reducing agency costs. In addition, by embedding control rules into business processes, AI enables continuous monitoring and anomaly detection in key operational activities, making managerial practices more standardized and transparent while improving resource allocation and execution efficiency. The resulting reduction in agency costs creates favorable conditions for improving internal control quality. When agency costs are lower, managers have fewer incentives to weaken internal control systems, making it more likely that internal controls are genuinely established and effectively implemented. Moreover, reductions in management expenses and improvements in asset utilization further strengthen the effectiveness of control activities and monitoring mechanisms, preventing internal controls from becoming merely formalistic. Therefore, by reducing agency costs and strengthening internal oversight and governance constraints, AI promotes improvements in corporate internal control quality.

6.2. Heterogeneity Analysis

To further explore the heterogeneous effects of artificial intelligence on corporate internal control quality, this study conducts subsample regressions from three perspectives: industry type, digital infrastructure level, and information transparency.

6.2.1. Industry Heterogeneity

Business process complexity and risk management requirements differ substantially across industries, which may lead to variations in the application scope and governance effects of AI in internal control. Therefore, the sample is divided into manufacturing and non-manufacturing firms to examine industry heterogeneity in the impact of AI on internal control quality. The regression results are reported in columns (1) and (2) of Table 8.

Table 8. Heterogeneity test results.

	(1)	(2)	(3)	(4)	(5)	(6)
	Manufacturing	Non-Manufacturing	High Level of Digital Infrastructure	Low Level of Digital Infrastructure	High Information Transparency	Low Information Transparency
AI	0.048 *** (0.011)	0.022 (0.015)	0.034 ** (0.014)	0.022 (0.014)	0.033 *** (0.012)	0.018 (0.016)
Constant	6.755 *** (0.522)	5.434 *** (0.888)	5.026 *** (0.770)	5.920 *** (0.738)	6.615 *** (0.682)	6.096 *** (0.871)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	12,672	6519	9412	9779	9849	9342
Adjusted-R ²	0.289	0.296	0.283	0.318	0.303	0.254

Note: Standard errors clustered at the firm level are reported in parentheses. *** and ** indicate significance at the 1% and 5% levels, respectively.

The results show that in manufacturing firms, the coefficient of AI is 0.048 and statistically significant, indicating that AI significantly improves internal control quality in manufacturing firms. In contrast, the coefficient is not statistically significant for non-manufacturing firms. This heterogeneity may be explained by the stronger fit between AI technologies and the internal control scenarios of manufacturing firms. Compared with non-manufacturing firms, manufacturing firms usually have more standardized production processes, more structured operational data, and more quantifiable control points, such as procurement, inventory management, production scheduling, quality inspection, equipment maintenance, and logistics tracking. These characteristics make it easier for AI to be embedded into business processes and control procedures, thereby supporting real-time risk identification, exception detection, process monitoring, and responsibility tracing (Dalenogare et al., 2018; Frank et al., 2019; Dubey et al., 2020; Büchi et al., 2020). Therefore, in manufacturing firms, AI can generate a stronger marginal governance effect by transforming internal control from experience-based and ex post supervision toward data-driven, process-embedded, and continuous monitoring. By contrast, non-manufacturing firms often rely more on flexible business models, service interactions, human judgment, and tacit knowledge, and their control targets are relatively implicit and less standardized. Although AI can improve information processing and decision support in these firms, its application is less easily transformed into measurable control procedures and enforceable monitoring mechanisms. This may weaken the marginal effect of AI on internal control quality in non-manufacturing firms. Accordingly, the results suggest that the governance effect of AI depends not only on whether firms adopt AI technologies, but also on the degree of fit between AI applications, data characteristics, and internal control scenarios.

6.2.2. Digital Infrastructure Heterogeneity

The effective operation of AI technologies relies heavily on digital infrastructure, including capabilities for data collection, transmission, storage, and processing. Significant differences exist in the digital infrastructure environments across regions and firms, which may affect the depth of AI application and its governance effects in internal control. To further examine this heterogeneity, this study following Chao et al. (2021) measures the level of digital infrastructure in the region where each firm is located and divides the sample into high and low digital infrastructure groups based on the mean value. Subsample regressions are then conducted, and the results are reported in columns (3) and (4) of Table 8.

The results show that in the subsample with higher digital infrastructure levels, the coefficient of AI is 0.034 and significant at the 5% level, indicating that AI significantly improves internal control quality in firms operating within a favorable digital environment. In contrast, in the subsample with lower digital infrastructure levels, the coefficient remains positive but is not statistically significant. This finding suggests that digital infrastructure affects the degree of integration between AI and internal control processes, thereby shaping the strength of its governance effects. Improvements in internal control quality depend not merely on the adoption of AI technology but also on whether firms possess the necessary data infrastructure and system integration capabilities to support its operation. Firms with well-developed digital infrastructure are better able to integrate business, financial, and management systems, enabling AI to be embedded in key control nodes and improving the efficiency of anomaly detection, process monitoring, and risk warning. In contrast, in firms with inadequate digital infrastructure, issues such as data silos and fragmented systems hinder the continuous support of AI in control processes, limiting its effectiveness in enhancing internal control quality.

6.2.3. Information Transparency Heterogeneity

Information plays a crucial role in all economic activities and is essential for market participants to make optimal decisions. Firms operating in environments with higher information transparency have stronger incentives to improve internal control systems, and managerial misconduct is more effectively constrained (J. Chen et al., 2016). Therefore, differences in firms' information transparency environments may influence the effectiveness of AI in improving internal control quality. Following H. Wu et al. (2025), this study adopts the information transparency rating disclosed by the Shanghai and Shenzhen Stock Exchanges. Firms rated at "qualified" or above are classified as having relatively high information transparency and assigned a value of 1; otherwise, they are assigned a value of 0. The regression results are presented in columns (5) and (6) of Table 8.

The results indicate that in the subsample with higher information transparency, the coefficient of AI is 0.033 and significant at the 1% level, suggesting that AI significantly improves internal control quality in environments with higher information transparency. In contrast, although the coefficient remains positive in the low-transparency subsample, it is not statistically significant. This finding implies that information transparency influences the governance effects of AI by shaping the effectiveness of its information recognition and monitoring mechanisms. In firms with higher transparency, data records and disclosures are more complete and managerial discretion is more limited, enabling AI to more effectively identify anomalies, detect control deviations, and strengthen supervisory constraints. In contrast, in firms with lower transparency, incomplete data and insufficient disclosure limit the ability of AI to obtain reliable signals, weakening its functions in risk warning and process monitoring and reducing its effectiveness in improving internal control quality.

7. Conclusions and Implications

7.1. Conclusions

Enhancing corporate governance capacity is a crucial foundation for promoting high-quality development, and the accelerated application of artificial intelligence (AI) provides a new technological pathway for optimizing internal governance structures and improving internal control quality. Using data from Chinese A-share listed companies from 2016 to 2024, this study systematically examines the impact of AI on corporate internal control quality and its underlying mechanisms. The main findings are as follows. First, AI significantly improves corporate internal control quality, and this conclusion remains robust after a series of robustness checks and endogeneity tests. Second, AI enhances internal control quality by promoting the upgrading of human capital structure and reducing agency costs. Third, the effect of AI on internal control quality exhibits significant heterogeneity, with stronger effects observed in manufacturing firms, firms with higher levels of digital infrastructure, and firms operating in environments with greater information transparency. Based on these findings, this study proposes policy and managerial implications on how firms can strengthen governance capacity to support high-quality development.

7.2. Implications for Policy and Practice

First, from the government perspective, the AI policy framework should be further improved to guide the deeper application of artificial intelligence in corporate governance and internal control. Current policies mainly focus on the role of AI in promoting industrial upgrading and technological innovation. In the future, institutional design should place greater emphasis on the governance functions of AI in areas such as risk prevention, compliance management, and internal supervision. By improving supporting regulations and incentive mechanisms, policymakers can encourage firms to integrate AI technologies

with the construction of internal control systems, thereby promoting the coordinated development of new quality productive forces and the modernization of governance capacity.

Second, from the corporate perspective, the application of AI should be elevated from a tool for improving operational efficiency to an important driver of internal governance optimization. In the process of intelligent transformation, firms should embed AI into key management processes such as budgeting, internal auditing, risk identification, and process control, thereby enhancing the timeliness, precision, and traceability of internal control through data-driven and intelligent analysis. At the same time, firms should promote adjustments in organizational structures and management models and strengthen human-machine collaboration, avoiding an overemphasis on technology while neglecting governance, to fully realize the institutional benefits of AI for improving internal control quality.

Third, greater attention should be paid to the supporting role of digital infrastructure and human capital in enabling the governance effects of AI. The results show that the improvement in internal control quality driven by AI is more pronounced in firms with stronger digital infrastructure, indicating that the governance effect of AI exhibits certain threshold characteristics. Governments and firms should therefore increase coordinated investment in digital infrastructure and AI-related talent development. By strengthening data governance capabilities, algorithm application capabilities, and the digital literacy of managers, a solid foundation can be established for AI to effectively empower internal control systems.

Fourth, while promoting the application of AI, it is also important to address the potential governance risks associated with technology and ensure the coordinated development of technological application and institutional regulation. Although AI can improve the efficiency of internal control, it may also introduce new challenges, such as algorithmic opacity, data compliance issues, and unclear accountability. Regulators and firms should therefore improve internal accountability mechanisms and risk assessment systems alongside the adoption of AI technologies, ensuring that AI operates within a framework that is secure, controllable, and explainable, thereby achieving a balance between efficiency improvement and risk prevention.

7.3. Limitations and Future Research

Despite providing new evidence on the relationship between artificial intelligence (AI) and corporate internal control quality, this study has several limitations that suggest directions for future research.

First, this study uses AI patents as a proxy for firm-level AI adoption. Although AI patents can reflect firms' technological accumulation and innovation activities related to artificial intelligence, they may not fully capture the actual extent to which AI technologies are adopted and embedded in firms' daily operations, management processes, and internal control systems. Some firms may adopt AI through external procurement, cloud-based platforms, software services, or cooperation with technology providers without generating AI patents. Conversely, some AI patents may reflect technological reserves rather than actual business application. Therefore, the measurement of AI adoption in this study may not fully capture the intensity, depth, and specific scenarios of firm-level AI use. Future research could address this limitation by constructing more comprehensive and multidimensional measures of AI adoption. For example, researchers may combine AI patent data with textual information from annual reports, AI-related software investment, digital technology expenditure, AI-related job postings, procurement data, survey data, or case-based evidence. Such measures would help distinguish between AI innovation, AI

adoption, and AI application intensity, and would provide a more accurate understanding of how AI is integrated into corporate governance and internal control processes.

Second, the sample of this study is limited to Chinese A-share listed companies. Listed firms generally possess stronger governance structures, better information disclosure, and more abundant technological resources than small and medium-sized enterprises (SMEs). Therefore, the findings of this study may have limited applicability to non-listed firms or SMEs. Future research could incorporate data from non-listed firms to provide a more comprehensive understanding of how AI affects internal control across different types of enterprises.

Finally, the analysis is confined to the Chinese. China has a unique stage of digital transformation, which may influence both the adoption of AI and the functioning of internal control systems. As a result, the conclusions drawn in this study may not be directly generalized to other countries. Future studies could extend this research framework to firms operating in different institutional and economic environments in order to conduct cross-country comparisons and examine whether the governance effects of AI vary across contexts.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Main variables and definitions.

Variables	Variable Name	Definitions and Measurement Methods
Dependent Variable	Internal control quality (IC)	Internal Control Index/100
Independent Variable	Artificial intelligence (AI)	$\ln(\text{AI patent applications} + 1)$
Mediating Variables	Employee compensation (Wage)	(cash paid to and on behalf of employees-total executive compensation)/(number of employees on duty-number of executives)
	Employee capability (Ability)	Number of employees with a bachelor’ degree or above/number of employees on duty
	Management expense ratio (MER)	Administrative Expenses/Revenue
	Asset turnover ratio (ATO)	Revenue/ Average Total Assets

Table A1. Cont.

Variables	Variable Name	Definitions and Measurement Methods
Control Variables	Firm size (Size)	Ln(Total Assets)
	Firm age (Age)	Ln(listed years)
	return on assets (ROA)	Net Income/Total Assets
	Leverage (Lev)	Total Liabilities/Total Assets
	Cash ratio (Cash)	Ending Balance of Cash and Cash Equivalents/Current Liabilities
	Board size (Board)	Number of Board Members
	Independent directors (Indep)	Number of Independent Directors/Total Number of Board Members
	Concentration of shareholding (TOP-1)	Largest shareholder's ownership percentage
	Two roles combined (Dual)	1 if The chairman and the general manager are the same
	Nature of ownership (SOE)	1 if it is a state-owned enterprise, 0 otherwise
	Audit quality	Set to 1 if audited by the Big Four, otherwise set to 0

References

- Abernethy, M. A., Li, W., Zhang, Y., & Shi, H. (2023). Firm culture and internal control system. *Accounting & Finance*, 63, 3095–3123. [\[CrossRef\]](#)
- Agnese, P., Arduino, F. R., & Di Prisco, D. (2025). The era of artificial intelligence: What implications for the board of directors? *Corporate Governance: The International Journal of Business in Society*, 25, 272–287. [\[CrossRef\]](#)
- Ahdadou, M., Aajly, A., & Tahrouch, M. (2025). Enhancing corporate governance through AI: A systematic literature review. *Technology Analysis & Strategic Management*, 37, 1753–1766. [\[CrossRef\]](#)
- Almaqoushi, W., & Powell, R. (2021). Audit committee quality indices, reporting quality and firm value. *Journal of Business Finance & Accounting*, 48, 185–229. [\[CrossRef\]](#)
- Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, 151, 103745. [\[CrossRef\]](#)
- Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-experimental shift-share research designs. *The Review of Economic Studies*, 89(1), 181–213. [\[CrossRef\]](#) [\[PubMed\]](#)
- Büchi, G., Cugno, M., & Castagnoli, R. (2020). Smart factory performance and Industry 4.0. *Technological Forecasting and Social Change*, 150, 119790. [\[CrossRef\]](#)
- Chao, X., Lian, Y., & Luo, L. (2021). Impact of new digital infrastructure on high-quality development of manufacturing. *Finance and Trade Research*, 32(10), 1–13. [\[CrossRef\]](#)
- Chen, H., Chen, Y., Lin, B., & Wang, Y. (2019). Can short selling improve internal control? An empirical study based on the difference-in-differences model. *Accounting & Finance*, 58, 1233–1259. [\[CrossRef\]](#)
- Chen, J., Cumming, D., Hou, W., & Lee, E. (2016). Does the external monitoring effect of financial analysts deter corporate fraud in China? *Journal of Business Ethics*, 134(4), 727–742. [\[CrossRef\]](#)
- Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., & Robins, J. (2018). Double/debiased machine learning for treatment and structural parameters. *The Econometrics Journal*, 21(1), C1–C68. [\[CrossRef\]](#)
- COSO. (2013). *Internal control—Integrated framework: Executive summary*. Committee of Sponsoring Organizations of the Treadway Commission. Available online: <https://www.coso.org/guidance-on-ic> (accessed on 8 June 2026).
- Czarnitzki, D., Fernández, G. P., & Rammer, C. (2023). Artificial intelligence and firm-level productivity. *Journal of Economic Behavior & Organization*, 211, 188–205. [\[CrossRef\]](#)
- Dalenogare, L. S., Benitez, G. B., Ayala, N. F., & Frank, A. G. (2018). The expected contribution of Industry 4.0 technologies for industrial performance. *International Journal of Production Economics*, 204, 383–394. [\[CrossRef\]](#)
- Doshi, A. R., Bell, J. J., Mirzayev, E., & Vanneste, B. S. (2025). Generative artificial intelligence and evaluating strategic decisions. *Strategic Management Journal*, 46, 583–610. [\[CrossRef\]](#)
- Doyle, J., Ge, W., & McVay, S. (2007). Determinants of weaknesses in internal control over financial reporting. *Journal of Accounting and Economics*, 44, 193–223. [\[CrossRef\]](#)

- Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., Roubaud, D., & Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *International Journal of Production Economics*, 226, 107599. [CrossRef]
- Estep, C., Griffith, E. E., & MacKenzie, N. L. (2024). How do financial executives respond to the use of artificial intelligence in financial reporting and auditing? *Review of Accounting Studies*, 29, 2798–2831. [CrossRef]
- Fedyk, A., Hodson, J., Khimich, N., & Fedyk, T. (2022). Is artificial intelligence improving the audit process? *Review of Accounting Studies*, 27, 938–985. [CrossRef]
- Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies. *International Journal of Production Economics*, 210, 15–26. [CrossRef]
- Giczy, A. V., Pairolero, N. A., & Toole, A. A. (2022). Identifying artificial intelligence (AI) invention: A novel AI patent dataset. *The Journal of Technology Transfer*, 47, 476–505. [CrossRef]
- Han, M., Shen, H., Wu, J., & Zhang, X. (2025). Artificial intelligence and firm resilience: Empirical evidence from natural disaster shocks. *Information Systems Research*, 36, 2116–2133. [CrossRef]
- He, Y. (2025). Digital transformation, internal control quality and equity financing costs. *Communication of Finance and Accounting*, 19, 49–53. [CrossRef]
- Hu, J., Xu, C., & Yin, J. (2025). The impact of artificial intelligence on high-quality development of enterprises. *Journal of Industrial Technological Economics*, 44(10), 59–69. [CrossRef]
- Huang, L., Tang, C., & Li, M. (2025). Internal control quality and boardroom backscratching. *Evaluation Review*, 49, 599–624. [CrossRef] [PubMed]
- Jiang, H., & Murmann, J. P. (2022). The rise of China's digital economy: An overview. *Management and Organization Review*, 18, 790–802. [CrossRef]
- Jiang, T. (2022). Mediating effects and moderating effects in causal inference. *China Industrial Economics*, 5, 100–120. [CrossRef]
- Jin, Y., Li, X., Tian, G., Shi, J., & Wang, Y. (2025). Employee education level and efficiency of corporate investment. *Journal of Accounting Literature*, 47, 277–297. [CrossRef]
- Keding, C., & Meissner, P. (2021). Managerial overreliance on AI-augmented decision-making processes: How the use of AI-based advisory systems shapes choice behavior in R&D investment decisions. *Technological Forecasting and Social Change*, 171, 120970. [CrossRef]
- Khan, S. A. R., Sheikh, A. A., Shamsi, I. R. A., & Yu, Z. (2025). The implications of artificial intelligence for small and medium-sized enterprises' sustainable development in the areas of blockchain technology, supply chain resilience, and closed-loop supply chains. *Sustainability*, 17, 334. [CrossRef]
- Kim, S. M., & Kim, Y. (2017). Product market competition on the effectiveness of internal control. *Asia-Pacific Journal of Accounting & Economics*, 24, 163–182. [CrossRef]
- Kumar, S., Vandana, V., Kumar, V., Chatterjee, S., Mariani, M., & De Massis, A. (2025). The role of artificial intelligence capabilities in enhancing export performance: A study of ambidexterity and dynamic capabilities. *International Marketing Review*, 42, 698–714. [CrossRef]
- Law, K. K. F., & Shen, M. (2025). How does artificial intelligence shape audit firms? *Management Science*, 71, 3641–3666. [CrossRef]
- Lee, Y., & Tulcanaza-Prieto, A. B. (2024). The effect of corporate governance on the degree of agency cost in the Korean market. *Risks*, 12, 59. [CrossRef]
- Li, J. (2026). Artificial intelligence innovation and financial report quality. *International Review of Economics & Finance*, 105, 104832. [CrossRef]
- Li, M., Wang, Z., Shu, L., & Gao, H. (2025). Broadband infrastructure and enterprise digital transformation: Evidence from China. *Research in International Business and Finance*, 73, 102645. [CrossRef]
- Li, Z., Yang, H., & Zhang, T. (2025). Impact of enterprise artificial intelligence development on human capital structure. *Finance Research Letters*, 82, 107600. [CrossRef]
- Lin, B. H., & Li, B. X. (2024). Impact of managerial ability on the quality of accounting information disclosure: Empirical evidence from China. *SAGE Open*, 14, 21582440241281203. [CrossRef]
- Lisic, L. L., Neal, T. L., Zhang, Y., & Zhang, Y. (2016). CEO power, internal control quality, and audit committee effectiveness in substance versus in form. *Contemporary Accounting Research*, 33, 1199–1237. [CrossRef]
- Liu, X., & Wang, Y. (2025). Artificial intelligence technology, risk taking, and financing costs of technology-based firms. *Finance Research Letters*, 85, 107873. [CrossRef]
- Luo, Y. (2020). Employee compensation incentive, knowledge and ability and quality of internal control quality: Empirical evidence from listed manufacturing companies in China. *Journal of Nanjing Audit University*, 17(5), 51–60. Available online: https://xbbjb.nau.edu.cn/sjxyxb/article/issue/2020_17_5 (accessed on 16 January 2026).
- McElheran, K., Li, J. F., Brynjolfsson, E., Kroff, Z., Dinlersoz, E., Foster, L., & Zolas, N. (2024). AI adoption in America: Who, what, and where. *Journal of Economics & Management Strategy*, 33(2), 375–415. [CrossRef]

- Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, 58, 103434. [CrossRef]
- Monteiro, A., Cepêda, C., Da Silva, A. C. F., & Vale, J. (2023). The relationship between AI adoption intensity and internal control system and accounting information quality. *Systems*, 11, 536. [CrossRef]
- Naveed, K., Farooq, M. B., Zahir-Ul-Hassan, M. K., & Rauf, F. (2025). AI adoption, ESG disclosure quality and sustainability committee heterogeneity: Evidence from Chinese companies. *Meditari Accountancy Research*, 33, 708–732. [CrossRef]
- Neiroukh, S., Emeagwali, O. L., & Aljuhmani, H. Y. (2025). Artificial intelligence capability and organizational performance: Unraveling the mediating mechanisms of decision-making processes. *Management Decision*, 63, 3501–3532. [CrossRef]
- Njoku, O. E., & Lee, Y. (2025). Agency costs, ownership structure, and cost stickiness: Implications for sustainable corporate governance. *Sustainability*, 17, 5144. [CrossRef]
- Ong, T. S., Zhou, J., The, B. H., Soh, W. N., & Di Vaio, A. (2024). Equity ownership concentration's impact on corporate internal control: The moderating effects of female directors and board compensation. *Environment, Development and Sustainability*, 26, 12309–12337. [CrossRef]
- Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, 37(2), 187–204. [CrossRef]
- Rahman, M. J., Zhu, H., & Yue, L. (2024). Does the adoption of artificial intelligence by audit firms and their clients affect audit quality and efficiency? Evidence from China. *Managerial Auditing Journal*, 39, 668–699. [CrossRef]
- Schneider, J., Abraham, R., Meske, C., & vom Brocke, J. (2023). Artificial intelligence governance for businesses. *Information Systems Management*, 40, 229–249. [CrossRef]
- Song, H., Han, M., & Shen, L. (2024). How does AI play a role in shaping supply chain resilience: A case study based on Maitrox's global after-sales supply chain management practice. *China Industrial Economics*, 5, 174–192. [CrossRef]
- Wang, X., Zhang, Z., & Chun, D. (2021). The influencing mechanism of internal control effectiveness on technological innovation: CSR as a mediator. *Sustainability*, 13, 13122. [CrossRef]
- Wang, Z., Zhang, T., Ren, X., & Shi, Y. (2024). AI adoption rate and corporate green innovation efficiency: Evidence from Chinese energy companies. *Energy Economics*, 132, 107499. [CrossRef]
- Wen, W., Xiao, Y., & Niu, Y. (2025). Artificial intelligence technology level and corporate investment efficiency. *Economic Management Journal*, 47(6), 103–122. [CrossRef]
- Wu, H., Liu, J., Gao, X., & Gao, C. (2025). Do China Securities Investor Services Center's exercise of rights improve internal control quality of enterprises? *Audit & Economy Research*, 40(4), 74–83. Available online: <https://xbbjb.nau.edu.cn/sjyjyj/article/html/20250204008> (accessed on 10 June 2026).
- Wu, Q., Qalati, S. A., Tajeddini, K., & Wang, H. (2025). The impact of artificial intelligence adoption on Chinese manufacturing enterprises' innovativeness: New insights from a labor structure perspective. *Industrial Management & Data Systems*, 125, 849–874. [CrossRef]
- Xu, S., Chen, H., Dong, S., & Guo, Z. (2023). Can upgrading information infrastructure improve the innovation ability of companies? Empirical evidence from China. *Telecommunications Policy*, 47(6), 102569. [CrossRef]
- Xue, F., & Jin, S. (2025). Artificial intelligence adoption, innovation efficiency, and governance mechanisms: Evidence from China. *Systems*, 13, 1062. [CrossRef]
- Yang, B., & Wang, Y. (2026). Employee compensation and firm performance: An empirical study from the perspective of human capital in listed companies. *Finance Research Letters*, 98, 109841. [CrossRef]
- Zhang, B., Zhao, Y., Yang, M., & Liu, T. (2025). Economic policy uncertainty and litigation risk: Evidence from China. *Pacific-Basin Finance Journal*, 92, 102773. [CrossRef]
- Zhang, J., Chen, C., Zheng, C., & Taylor, G. (2025). Artificial intelligence innovation and stock price crash risk. *Journal of Financial Research*, 48, 503–543. [CrossRef]
- Zhang, L., Tao, Y., & Nie, C. (2022). Does broadband infrastructure boost firm productivity? Evidence from a quasi-natural experiment in China. *Finance Research Letters*, 48, 102886. [CrossRef]
- Zhao, T., Yan, N., & Ji, L. (2023). Digital transformation, life cycle and internal control effectiveness: Evidence from China. *Finance Research Letters*, 58, 104223. [CrossRef]
- Zhong, K., & Song, L. (2025). Artificial intelligence adoption and corporate green innovation capability. *Finance Research Letters*, 72, 106480. [CrossRef]
- Zhou, W., & Liu, Y. (2022). Managerial ability, enterprise digitalization and internal control quality. *Research on Economics and Management*, 43, 110–127. [CrossRef]

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