The Impact of Artificial Intelligence Adoption on Corporate Governance in Chinese Listed Companies: An Empirical Study Based on Agency Costs

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Abstract: In the era of rapid digital transformation, artificial intelligence (AI) has emerged as a transformative force with broad applications across industries. However, its impact on corporate governance—particularly in Chinese enterprises—remains under-researched. This study addresses this gap by empirically examining how AI adoption influences corporate governance in Chinese A-share listed firms from 2010 to 2024, utilizing financial data from the CSMAR database. By measuring AI application through text-based proxy variables and assessing governance via agency costs, the research reveals that higher levels of AI adoption are significantly associated with lower agency costs. The study theoretically extends traditional governance determinants by integrating artificial intelligence, and, in practice, highlights AI's role in reducing agency costs and enhancing governance efficiency. This work underscores the importance of technological innovation in shaping modern corporate governance and provides insights for firms and regulators navigating digital transformation. The research acknowledges unexplored mediating mechanisms, offering avenues for future studies on heterogeneous effects and operational pathways.

Keywords: Artificial intelligence, corporate governance, agency costs, digital transformation

1. Introduction

In the era of accelerating digital transformation, artificial intelligence (AI) has emerged as a transformative force in corporate operations, with enterprises increasingly leveraging AI technologies to enhance decision-making quality and operational efficiency. While existing research recognizes AI's potential to reshape corporate governance by addressing information asymmetry and strengthening oversight mechanisms, empirical evidence tailored to Chinese enterprises— characterized by unique ownership structures and regulatory environments—remains scarce. This study bridges this research gap through a rigorous empirical analysis of how AI adoption influences corporate governance in Chinese listed firms, with a focus on its effects on agency costs and governance effectiveness.

This research makes two key contributions to the academic field. First, it empirically examines the relationship between the degree of AI adoption and corporate governance, demonstrating that AI reduces agency costs. Second, the research integrates AI into the determinants of governance, complementing traditional studies on governance elements, thereby highlighting the mechanism

through which technological innovation interacts with institutional environments to shape governance outcomes.

The paper is structured as follows. Section 2 reviews theories of corporate governance and AI's role in business contexts, followed by the development of research hypotheses. Section 3 details the empirical design, including econometric models, descriptive statistics, mean-difference tests, and regression results. The conclusion summarizes the research implications and proposes future research directions to further explore the heterogeneous effects of AI on corporate governance.

2. Literature review and hypothesis development

Corporate governance focuses on resolving agency problems stemming from the separation of ownership and management in enterprises. In 1932, Berle and Means published Modern Corporations and Private Property, highlighting how the equity diversification of large modern joint-stock companies led to the separation of ownership and control and the principal-agent problem, marking the beginning of corporate governance research [1].

2.1. Definition of corporate governance and its evolution

2.1.1. Type I and type II agency problems

Jensen and Meckling proposed agency theory, which posits that information asymmetry between shareholders and managers leads to conflicts of interest [2]. Managers, driven by self-interest, may engage in behaviors such as seeking excessive compensation or over-investing, which harm shareholders' interests and generate agency costs. In addition, La Porta and colleagues found that controlling shareholders can hold control rights that exceed their cash-flow rights to extract extra private benefits. For instance, motivated by the preservation of socioemotional wealth and the goal of facilitating intergenerational succession, controlling shareholders [3]. Consequently, these controlling shareholders may expropriate the wealth of minority shareholders, highlighting the second type of agency problem in corporate governance, where the interests of large and small shareholders diverge significantly.

2.1.2. Stakeholder theory

In corporate governance, stakeholder theory carries significant implications. Williamson noted that managers represent various stakeholders beyond shareholders. Tirole and Vives emphasized the importance of incorporating stakeholder welfare into governance objectives. The long-standing debate between shareholder-value maximization and stakeholder-value maximization underscores the complexity of applying this theory.

2.2. Research on corporate governance concerning independent directors, executive compensation, and equity pledges

2.2.1. Board structure and independence

The board of directors plays a crucial role in corporate governance. A larger board can bring diverse expertise but may also face coordination challenges. Independent directors are expected to monitor management. Research shows that firms with a higher proportion of independent directors often exhibit better financial reporting quality and reduced earnings management. However, in closely held firms, the influence of controlling shareholders can compromise the independence of independent directors [4].

2.2.2. Executive compensation

Executive compensation is a central topic in corporate governance research. Rooted in agency theory, performance-based pay, such as stock options, aims to align managers' interests with those of shareholders [5]. Scholars argue that incentive compensation, such as stock options, aligns CEOs' interests with those of shareholders, as tying CEO wealth to stock prices motivates value maximization [6]. In China, restricted stock has long been the dominant incentive mechanism, influenced by factors such as the firm's development stage, executive power, and the severity of agency problems [7]. However, as Jensen and Murphy pointed out, if not properly structured, executive pay-to-performance sensitivity may encourage managers to take excessive risks. Moreover, issues such as gender pay gaps and the debated impact of board diversity on pay-performance sensitivity remain active areas of research within the executive compensation literature.

2.2.3. Controlling shareholders' equity pledges

The implications of controlling shareholders' equity pledges for corporate governance are multifaceted. While such pledges can facilitate tax-motivated investment, they also introduce risks, such as the separation of cash-flow and control rights and the potential transfer of control rights. In China, given that most funds from equity pledges are diverted to controllers themselves or non-listed enterprises, combined with high pledge ratios, the overall effect on corporate operations tends to be adverse.

2.3. The evolution of artificial intelligence and recent advancements

Artificial intelligence (AI) established itself as an independent academic discipline in the mid-20th century. The 1956 Dartmouth Conference marked its formal inauguration, during which scholars first systematically explored the feasibility of machine-based human intelligence simulation. Since then, AI development has undergone multiple paradigmatic shifts: beginning with rule-based symbolic logic systems, progressing through the resurgence of connectionist neural networks, and culminating in the contemporary era of data-driven deep learning-each evolutionary phase driven by breakthroughs in computational efficiency and algorithmic innovation. Current AI research exhibits multidimensional breakthroughs. In 2022, OpenAI advanced robust language interaction capabilities, marking a new phase in AI development. Multimodal large models, such as GPT-4V and Gemini, achieve unified text-image-video understanding and generation through cross-modal alignment, enabling creative assistance in industrial design. Embodied intelligence systems, exemplified by Unitree's G1 humanoid robot's autonomous navigation in complex terrains via bionic motion control algorithms, integrate reinforcement learning and physical simulation to advance robotic applications. Significant improvements in model training efficiency have also been achieved. Between 2024 and 2025, DeepSeek Inc. made major breakthroughs: DeepSeek-V3 demonstrated performance comparable to mainstream large language models such as GPT-40 across multiple metrics, while DeepSeek-R1 achieved performance comparable to OpenAI-o1 at only one-thirtieth of the cost. Driven by the "AI+" strategy, AI is increasingly integrated into healthcare for clinical decision support, science education for immersive learning experiences, finance for predictive analytics, and judiciary systems for procedural automation. These advancements signify AI's transition from technical exploration to large-scale implementation, underscoring its transformative impact on social productivity and governance systems.

AI technologies are reshaping corporate operations across production, marketing, financial management, and governance, driving transformative efficiency gains and data-driven decision-making. In production and manufacturing, AI optimizes supply chain logistics through predictive analytics and machine learning, enabling proactive adjustments in inventory management, demand

forecasting, and real-time defect detection [8]. For instance, industrial robots and multi-axis force sensors enhance precision in production processes, reducing waste and improving resource allocation. In marketing, large language models (LLMs) automate perceptual analysis, generate consumer insights, and replace human respondents in surveys, accelerating data collection and enabling tailored strategies to address evolving preferences [9]. AI technologies are increasingly being used to perform a wide range of economic activities with greater accuracy, reliability, and scalability than human workers [10]. Financial management benefits from AI-driven automation of repetitive tasks such as data entry and reconciliations, while advanced algorithms augment auditing, risk assessment, and strategic financial decisions through market trend forecasting and anomaly detection in ESG reporting. At the governance level, explainable AI (XAI) ensures transparency and accountability by tracing audit decisions and mitigating algorithmic bias. These applications collectively enhance governance by providing real-time, objective insights, reducing human error, and fostering cross-departmental collaboration. As AI continues to evolve, its integration redefines industry standards, necessitating workforce adaptability in data literacy and ethical AI governance to maximize its strategic value [11].

2.4. Theoretical analysis and hypothesis development

Jensen and Meckling highlight information asymmetry as a key driver of agency costs, whereby managers may prioritize self-interest over shareholder welfare. AI technologies can reduce this asymmetry by providing transparent, timely, and objective insights into managerial actions. For instance, AI-driven predictive models can identify operational inefficiencies or financial irregularities, enabling proactive oversight and reducing the likelihood of managerial opportunism. Similarly, explainable AI (XAI) enhances audit transparency by tracing algorithmic decision-making processes, aligning with stakeholder theory's emphasis on accountability.

Moreover, AI strengthens both internal and external governance mechanisms. Independent directors and audit committees can leverage AI to analyze complex datasets, improving their ability to monitor managerial performance and strategic decisions. Externally, regulatory bodies may use AI to enforce compliance more effectively, deterring controlling shareholder expropriation. By bridging information gaps and enhancing oversight, AI reduces both Type I and Type II agency costs. Thus, this study hypothesizes:

H1: The adoption of AI technologies is negatively associated with agency costs.

3. Empirical research

3.1. Sample source

This study uses financial data from Chinese A-share listed companies between 2010 and 2024 to investigate the relationship between the degree of artificial intelligence (AI) application and the level of corporate governance. The data are primarily sourced from the CSMAR Corporate Financial Database. The following data processing steps are implemented: Companies in the financial and real estate industries are excluded. Companies under ST, ST, SST, and SST status are excluded. Samples with missing data are removed. To mitigate the impact of extreme values, continuous variables are winsorized at the 1st and 99th percentiles. After processing, a total of 30,767 sample observations are obtained.

3.2. Model specification

This paper constructs the following multiple regression model to examine the impact of enterprises' AI application on corporate governance:

 $Corporate_Governancei, t=\beta0+\beta1AIi, t+\sum controls+\sum ID+\sum Year+\epsilon i, t$

where:

Corporate_Governancei,t represents the governance level of listed company i in year t. Ali,t represents the degree of AI application by enterprise i in year t. The regression controls for individual (firm) and year fixed effects.

3.3. Variable definitions

Explained Variable is Corporate Governance Level (Corporate_Governance). This study measures the corporate governance level using agency costs. Following the approach of Liu Qi et al., the management expense ratio is employed as a proxy for agency costs.

Explanatory Variables are PAF_DT and PAF_DINT. Drawing on the methodology of Xiao Tusheng, Sun Ruiqi, and Yuan Chun, this study uses the proportion of digital technology-related and digital infrastructure construction-related word frequencies in the Management Discussion and Analysis (MD&A) section as proxy variables [12]. Specifically: For PAF_DT, when keywords related to digital technologies (e.g., "artificial intelligence technology," "blockchain technology," "cloud computing technology," "big data technology") appear in the MD&A section of corporate annual reports, the total frequency of these keywords is calculated and divided by the total MD&A text volume. Similarly, for PAF_DINT, keywords related to digital infrastructure construction (e.g., "artificial intelligence technology," "big data technology") appear in the MD&A section of corporate annual reports, the total frequency of these keywords is calculated and divided by the total MD&A text volume. Similarly, for PAF_DINT, keywords related to digital infrastructure construction (e.g., "artificial intelligence technology," "big data technology," "broad digital technology") are counted and divided by the total MD&A text volume.

Key Variables		Variable Symbols	Variable Definitions
Explained Variable	ed Variable Agency Cost		Management Expense Ratio = management expenses / operating income
Explanatory Variable	Proportion of Aggregated Word Frequency of Digital Technologies	PAF_DT	Proportion of Aggregated Word Frequency of Digital Technologies = aggregated word frequency of digital technologies / text volume of Management Discussion and Analysis Section
	Proportion of Aggregated Word Frequency of Digital Infrastructure Construction	PAF_DINT	Proportion of Aggregated Word Frequency of Digital Infrastructure Construction = aggregated word frequency of digital infrastructure construction / text volume of Management Discussion and Analysis Section
	Return on Assets	ROA	Return on Assets = net profit / total assets
Control Variable	Asset - Liability Ratio	Lev	Asset - Liability Ratio = total liabilities / total assets
	Operating Income Growth Rate	Growth	Operating Income Growth Rate = (current period operating income - previous period operating income) / previous period operating income
	Proportion of Independent Directors	Indep	Proportion of Independent Directors = number of independent directors / board size
	Board Size	B_Size	Board Size = natural logarithm of the number of board members

Table	1:	Key	variable	definitions
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3.4. Analysis process

3.4.1. Descriptive statistics

Table 2 presents the descriptive statistical results of the sample. The results show: The mean of AC is 0.080, with a standard deviation of 0.061. The mean of ROA is 0.054, with a standard deviation of 0.041, indicating some variability among companies. The mean of Lev is 0.392, with a standard

deviation of 0.190, indicating moderate dispersion. The mean of Growth is 0.164, with a standard deviation of 0.316, indicating greater variability. The mean of Indep is 37.651, with a standard deviation of 5.323, indicating obvious differences among companies. The mean of B_Size is 2.117, with a standard deviation of 0.198, suggesting relative stability. The means of PAF_DT and PAF_DINT are close to zero, with extremely low standard deviations, indicating very low dispersion.

1		25	2.61	
Obs	Mean	SD	Mın	Max
30767	0.080	0.061	0.008	0.453
30767	0.054	0.041	0.002	0.227
30767	0.392	0.190	0.048	0.845
30767	0.164	0.316	-0.410	1.766
30767	37.651	5.323	33.330	57.140
30767	2.117	0.198	1.609	2.708
30767	0.000	0.001	0.000	0.041
30767	0.000	0.000	0.000	0.001
	Obs 30767 30767 30767 30767 30767 30767 30767 30767 30767 30767 30767 30767 30767	ObsMean307670.080307670.054307670.392307670.1643076737.651307672.117307670.000307670.000	ObsMeanSD307670.0800.061307670.0540.041307670.3920.190307670.1640.3163076737.6515.323307672.1170.198307670.0000.001307670.0000.000	ObsMeanSDMin307670.0800.0610.008307670.0540.0410.002307670.3920.1900.048307670.1640.316-0.4103076737.6515.32333.330307672.1170.1981.609307670.0000.0010.000307670.0000.0000.000

Table 2	: De	escriptive	e statis	stics
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3.4.2. Mean-difference test

To preliminarily examine the relationship between the degree of AI application and AC, a meandifference test is conducted for PAF_DT and PAF_DINT with AC, respectively. Specifically, observations where the explanatory variables are greater than the median are assigned a value of 1 (defined as the higher-digitization group), and those less than the median are assigned a value of 0 (defined as the lower-digitization group).

For the group divided by PAF_DT (obs1 = 15,746), the average AC of the higher-digitization group is 0.079. The t-test results show that the difference in AC between this group and the comparison group is significant at the 1% level (p-value = 0), indicating that the AC of the higher PAF_DT group is significantly lower. For the group divided by PAF_DINT (obs1 = 25,167), the average AC of the higher-digitization group is also 0.079, and the difference is again significant at the 1% level (p-value = 0).

These results provide preliminary support for the hypothesis that a higher degree of AI application is negatively correlated with AC.

	obs1	obs2	Mean1	Mean2	dif	StErr	tvalue	pvalue
AC	15746	15021	0.079	0.082	- 0.003	0.001	-3.7	0.00
AC	25167	5600	0.079	0.088	- 0.011	0.001	-11.55	0.00
					01011			

Table 3: Two-sample t test with equal variances

3.4.3. Regression results

Table 4 presents the main regression results: Columns (1) and (3) report the univariate regression results of PAF_DT and PAF_DINT on AC, respectively. The regression coefficients are -6.296 and -28.279, both significant at the 1% level. This indicates that when only the direct relationship between the explanatory and explained variables is considered, higher PAF_DT and PAF_DINT values are associated with lower AC, preliminarily supporting the study's hypothesis.

Columns (2) and (4) present the multivariate regression results incorporating control variables (ROA, Lev, Growth, Indep, and B_Size). The regression coefficients of PAF_DT and PAF_DINT on

AC are -5.896 and -27.310, respectively, remaining significant at the 1% level. This further validates the study's hypothesis.

	(1)	(2)	(3)	(4)		
VARIABLES	AC					
	PAF_DT	PAF_DT	PAF_DINT	PAF_DINT		
AI	-6.296***	-5.896***	-28.279***	-27.310***		
	(1.347)	(1.308)	(5.120)	(5.102)		
ROA		-0.182***		-0.179***		
		(0.0158)		(0.0159)		
Lev		-0.0788***		-0.0810***		
		(0.00523)		(0.00529)		
Growth		-0.00862***		-0.00851***		
		(0.000981)		(0.000989)		
Indep		-0.000188		-0.000179		
		(0.000122)		(0.000124)		
B_Size		0.00548		0.00635		
		(0.00442)		(0.00446)		
Constant	0.0827***	0.120***	0.0813***	0.117***		
	(0.000528)	(0.0129)	(0.000202)	(0.0130)		
Observations	30,767	30,767	30,767	30,767		
NumberofStkcd	5,000	5,000	5,000	5,000		
R-squared	0.012	0.077	0.004	0.071		

Table 4: Regression results

Robust standard errors in parentheses.

***p<0.01,**p<0.05,*p<0.1

4. Conclusions

This study employs an empirical approach, using financial data from Chinese A-share listed companies from 2010 to 2024 sourced from the CSMAR database, to examine the relationship between AI adoption and corporate governance. By measuring AI application through text-based proxy variables and assessing governance via agency costs, the research finds that higher AI adoption is significantly associated with lower agency costs, indicating improved corporate governance. This finding aligns with the hypothesis, presumably due to AI's ability to mitigate information asymmetry and strengthen monitoring mechanisms—both critical for addressing principal-agent problems.

The research makes several important contributions. Theoretically, it integrates AI into the determinants of corporate governance, and provides empirical evidence of technology's role in reducing agency costs within Chinese enterprises. Methodologically, it innovatively employs textual analysis of MD&A to capture AI adoption, offering a new perspective on measuring digital transformation in governance research. Future research could focus on two key directions. First, it is essential to investigate the mediating mechanisms through which AI influences corporate governance, such as the specific pathways of information processing and monitoring enhancement that drive the reduction in agency costs. Second, exploring the heterogeneous effects of AI across different industries, ownership structures, and regulatory contexts would provide a more comprehensive understanding of how technological innovation interacts with institutional environments to shape

governance outcomes. These avenues will deepen the theoretical and practical insights into AI's role in modern corporate governance.

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