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The Impact of Artificial Intelligence on Executive Compensation in Listed Companies

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Abstract: As artificial intelligence is elevated to a national strategic level and deeply integrated into the real economy, its core role in driving industrial upgrading and economic growth has become increasingly prominent. Executives, as key decision-makers in corporate strategy, have compensation levels that not only relate to agency costs and incentive effectiveness but also influence the fairness and efficiency of internal income distribution within enterprises against the backdrop of technological change. Based on data from A-share listed companies from 2007 to 2023, this study employs textual analysis to construct a firm-level indicator of AI application and systematically examines the impact of AI on executive compensation. The findings are as follows: First, AI significantly increases the compensation levels of executives in listed companies. This conclusion remains robust after addressing endogeneity concerns through methods such as instrumental variable approaches and conducting a series of robustness tests. Second, mechanism tests reveal that AI indirectly promotes the growth of executive compensation through three pathways: alleviating financing constraints, enhancing enterprise total factor productivity, and increasing the level of executive human capital. Third, the level of corporate governance plays a negative moderating role between AI and executive compensation, suggesting that sound internal governance mechanisms can effectively curb the potential expansion of managerial power and the capture of excess returns by executives during technological change.

Keywords: Artificial Intelligence; Executive Compensation; Corporate Governance; Compensation Distribution.

1. Introduction

Artificial intelligence, as a strategic technology leading a new round of technological revolution and industrial transformation, has developed rapidly in recent years. It has become a key force in advancing technological progress, driving industrial optimization and upgrading, and achieving a significant leap in overall social productivity. In response to this trend, major countries around the world have elevated artificial intelligence to a national strategic level, competing to establish its presence to strengthen their core position in the global economy and industrial competition.

At the micro level, the impact of AI technology development on micro-enterprises has permeated all aspects of their operations. In corporate governance and management practices, AI directly alters a companys management model, thereby influencing its governance structure. In capital markets, AI can broaden the financing channels for listed companies and reduce the difficulty of external financing, enabling companies to obtain more stable financial support. This profound and multi-dimensional impact of AI on corporate operations will ultimately be reflected in business performance, further affecting the companys distribution system, compensation structure, and compensation levels. A reasonable compensation structure and level, in turn, can positively influence business performance, contributing to its continuous improvement and the sustainable development of the entire enterprise organization. Among these factors, top executives are the core decision-makers in corporate governance, responsible for crucial aspects such as strategy formulation, resource coordination, and risk control for the entire organization, directly determining its development direction. Reasonable executive compensation helps alleviate principal-agent problems, motivates executives to focus on the long-term sustainable development of the organization, and simultaneously attracts and retains core talent, facilitating the achievement of the enterprises strategic goals. Therefore, investigating whether the development of AI technology affects the compensation structure and levels of top executives, and if so, through what channels or mechanisms and the specific nature of this impact, holds certain theoretical value and practical significance.

However, scant literature has focused on the impact of AI on executive compensation. As mentioned earlier, corporate executives, as managers, are the core of the operational governance structure, and the structure and level of executive compensation are crucial for the effective functioning of this governance structure. Under the impetus of the Fourth Industrial Revolution, represented by AI, its impact on executive compensation may not only, in turn, influence senior managers decisions regarding AI adoption in their own firms, ultimately affecting the application of AI in enterprises, but also affect corporate performance and long-term sustainable development. Therefore, exploring the impact of AI on executive compensation not only possesses theoretical value and practical significance but also highlights a certain necessity and urgency, given the current scarcity of related research. Furthermore, in the context of Chinas current drive to promote common prosperity, narrowing the income gap between different groups is an unavoidable issue. At the corporate governance level, this issue is concretely manifested in how to effectively narrow the pay gap between executives and ordinary employees within a firm. When executive compensation is affected by AI technology, how do the compensation levels of ordinary employees in the same firm change? Compared to executives, what are the direction and magnitude of change in ordinary employees compensation levels? Does the pay gap between executives and ordinary employees change significantly? Research on these questions can provide valuable insights for further examining the formation factors and constraint mechanisms of pay gaps, and can deepen the understanding of AIs impact on micro-enterprises.

Therefore, from the perspective of corporate finance, this study attempts to deeply analyze how AI, as an emerging technological factor, is integrated into the considerations of top-level compensation design within enterprises. It focuses on examining how companies adjust their compensation strategies in the context of the AI era to address the challenges and opportunities brought by technological innovation, ensuring that management behavior aligns with shareholder interests and promoting sustained corporate value growth. Specifically: First, to explore the impact of AI on the executive compensation of listed companies. Second, to analyze the mechanistic pathways through which AI affects executive compensation. Based on existing literature and relevant theories, this study will analyze the impact mechanism of AI on executive compensation from different perspectives. For example, does the impact of AI on corporate financing constraints further affect executive compensation? Does AI affect executive compensation by influencing corporate productivity? Third, to analyze the impact of AI on the internal pay gap within listed companies. This involves examining whether the impact of AI on the compensation levels of ordinary employees differs from that on executives, and analyzing AIs influence on the internal income distribution of enterprises. Fourth, to analyze how the effectiveness of executive compensation contracts might change—that is, whether AI affects the performance sensitivity of executive compensation. Through investigating these issues, this study aims to provide a reference for enterprises making AI-related decisions and offer valuable suggestions for the government in promulgating and implementing relevant policies.

2. Research Hypotheses

According to optimal contract theory, to address the principal-agent problem and reduce the agency costs for firm owners, it is necessary to design an optimal compensation contract that incentivizes management to act in the interests of maximizing firm value [1]. Compensation contracts link executive pay to firm performance; that is, executive compensation increases with improved firm performance. To maximize their own interests, executives will reduce opportunistic behavior, thereby aligning the goal of maximizing their personal interests with the objective of maximizing firm value. It is evident that a prerequisite for compensation contracts, which base managerial rewards on firm performance, to function effectively is that both firm performance and managerial effort can be accurately observed [2]. AI technology can precisely record all business operational processes and production operating results. Various data are processed through information systems to generate new information resources, which are then provided to information users. This helps companies acquire and analyze data more efficiently, optimize business processes, and reduce decision-making costs [3]. Simultaneously, being data-driven, AI can grasp the relationships between things and objective laws. Through more objective indicators and real-time decision simulations provided by AI, companies can make more accurate and timely strategic plans and operational decisions, making it easier to achieve strategic goals and improve firm performance. On the other hand, AI technology enhances a firms ability to predict environmental uncertainties, reduces risks beyond executives control, facilitates precise management in production and operations, and promotes performance improvement. Research by Aghion et al. based on Finnish firm data found that corporate managers could capture 44% of innovation returns, indicating a trend of innovation returns concentrating towards management [4]. Gabaix and Landier pointed out from the perspectives of firm expansion that these factors would push up the compensation levels of management, especially CEOs [5]. Frydman and Papanikolaou, using a general equilibrium model, predicted that technological innovation would widen the pay gap between management and ordinary employees [6]. Compensating wage differentials theory emphasizes that compensation needs to offset the disutility of work. For instance, when job requirements become more stringent or the work environment grows more complex and volatile, workers demand higher pay to compensate for the resulting utility loss. As a rapidly evolving emerging technology, AIs deep integration with corporate strategy significantly raises the comprehensive requirements for executives—they must not only navigate increasingly complex technological scenarios and strategic decisions but also bear the higher decision-making risks stemming from technological uncertainty. In this process, AI also reshapes executives capability sets, driving the continuous accumulation and upgrading of their human capital. To adapt to the intelligent transformation, executives need to proactively invest in enhancing their technological understanding, data-driven decision-making abilities, and other competencies, thereby forming a more scarce human capital advantage. According to human capital theory, the knowledge and skills individuals accumulate through education and experience constitute their human capital, and the level of human capital is a key determinant of compensation returns. Therefore, when executives continuously enhance their human capital and ability to contribute to firm value through the application of AI, their compensation levels correspondingly increase. Furthermore, the introduction of AI not only increases decision-making complexity but also significantly raises the potential losses and reputational risks associated with strategic misjudgments. To compensate executives for the additional risks and pressures borne and to incentivize their continued investment in human capital, firms need to offer a comprehensive compensation package that includes both a skill premium and a risk premium, collectively driving up executive compensation levels.

Based on the above analysis, this paper proposes the following research hypothesis:

Hypothesis 1: Artificial intelligence increases the compensation level of executives in listed companies.

Financing constraints are a significant cause of corporate capital shortages, which can lead to underinvestment. In such situations, firms lack channels to obtain sufficient funds to support R&D and technological innovation, potentially causing technological progress to stagnate, thereby weakening competitiveness and sustainable development capabilities [7]. In capital markets, information asymmetry is often a major obstacle hindering firms from obtaining external financing. Particularly for high-tech firms, information transmission losses between the firm and its stakeholders reduce information transparency, thereby increasing the difficulty of obtaining financing [8]. AI, due to its powerful data processing and analysis capabilities, plays a significant role in enhancing corporate information transparency [9]. First, AI is not limited to analyzing traditional financial statements; it can also analyze nonfinancial data, such as unstructured data from social media, news reports, and transaction records, to conduct more comprehensive credit assessments and more accurately evaluate a firms cr edit risk. Financial institutions can better understand the firms use of funds based on various indicators generated by AI, reducing risks associated with information asymmetry, thereby easing the firms financing constraints. Second, based on big data analytics, AI can improve the transparency and efficiency of transactions. For the financing process, this means that the flow and use of funds can be monitored in real-time, reducing the possibility of fraudulent activities, helping to build investor trust, and lowering the risk of information asymmetry.

Beyond mitigating information asymmetry, AI can also ease corporate financing constraints by reducing transaction costs and increasing policy subsidies. Transaction costs manifest as both internal and external types. Internal transaction costs refer to costs incurred within the firm during organization, coordination, and management, including coordination costs between departments and management costs for maintaining organizational operations. External transaction costs refer to expenses borne by the firm when interacting with external entities in market transactions, including search costs, negotiation costs, and enforcement costs. From the perspective of internal transaction costs, AI applications not only affect a firms operational methods but also its organizational structure. AI can reduce redundant internal layers, promote a flatter and more networked organizational structure, strengthen the efficiency of information exchange between departments, and thus lower internal transaction costs [10]. From the perspective of external transaction costs, the application of AI technology helps firms more openly and transparently showcase their operational status and development prospects, enabling more efficient matching with suitable investors and reducing search costs. Lower transaction costs further alleviate corporate financing constraints. Firms benefiting from policy support often find it easier to obtain credit, thereby easing financing constraints [11]. With the advent of the new technological wave, the Chinese government also highly values the development of the AI industry. The "Notice on the Development Plan for the New Generation of Artificial Intelligence" issued in 2017 emphasized: "It is necessary to accelerate the deep application of AI, cultivate and expand the AI industry, and inject new momentum into Chinas economic development." The 2024 "Government Work Report" pointed out: "Continue to promote the AI+ action, better integrating digital technology with manufacturing advantages and market strengths." It is evident that the Chinese government strongly supports the application of AI technology by enterprises, thereby promoting AI as a new engine for economic development. Therefore, firms actively applying AI are likely to receive more government subsidies and more favorable financing conditions, which in turn eases their financing constraints.

AI can improve firm performance by reducing financing constraints, leading to greater returns that can be distributed to executives. Luo Chuliang and Li Shi confirmed that a firms profitability significantly influences welfare subsidies and wages [12]. When firms are forced to rely on retained profits for internal financing due to financing constraints, the profits available for distribution decrease, thereby reducing the labor income share [13]. Consequently, when a firms financing constraints are relaxed, executive compensation tends to increase.

Based on the above analysis, this paper proposes the following research hypothesis:

Hypothesis 2: Artificial intelligence increases executive compensation by alleviating the financing constraints of listed companies.

Research by Ding Feng found that AI technology has been permeate and applied in various aspects of enterprise production and manufacturing, and can stimulate the potential for total factor productivity improvement [14]. Yao Jiaquan et al. also pointed out that the application of AI technology can significantly enhance a firms total factor productivity [15].

From the perspective of labor structure optimization, the application of AI reduces a firms demand for repetitive, low - skilled labor positions and increases the demand for high-skilled, highly educated talent [16]. This change in labor structure occurs because AI inherently possesses automation attributes. Through machine learning and robotic automation, it can efficiently perform tasks with clear rules and high repetitiveness, which are typically carried out by medium- and low-skilled labor. AI directly substitutes the labor performing these tasks, and the freed-up human resources can be redeployed to higher-value or more creative activities, thereby optimizing the internal labor structure. Simultaneously, AI typically performs tasks faster and more accurately than humans, reducing rework and correction costs and improving task completion efficiency. Research by Frey and Osborne indicates that with the development of AI, the risk of routine labor being substituted will gradually increase, while the demand for non-routine labor will further rise [17]. For firms, this means they may not need to incur additional costs for training low-skilled labor, and can use intelligent machines to ensure consistency in production processes and business operations, thereby improving productivity. Beyond the substitution effect on low-skilled routine labor, AI also has a complementary effect on high-skilled non-routine labor. On one hand, AI substitutes part of the labor force, freeing up human resources to focus on more creative R&D and innovation activities, promoting technological progress and driving productivity gains. On the other hand, AI, through algorithms like machine learning and deep learning, empowers non-routine and innovative work, helping high-skilled talent perform tasks better. For executives, AI can help them transcend the original cognition and experience, enabling them to make more scientific and reasonable decisions [18]. Furthermore, research by Acemoglu and Restrepo and others found that as firms appl ication of AI deepens, AI can also catalyze the creation of new types of jobs [19]. These positions often demand high-skilled talent (such as AI technology consultants and digital management personnel), further integrating AI with the firms production and operational activities and enhancing productivity.

By improving firm productivity, AI can enhance corporate performance, thereby increasing the profit distribution received by executive [20]. In the process of optimizing the labor structure, firms need to lay off low-skilled labor and bring in more high-skilled labor to adapt the application of AI within the enterprise. This process requires systematic decision-making by executives, whose enhanced status and voice grant them greater leeway for autonomous decisions, contributing to an increase in their compensation levels.

Based on the above analysis, this paper proposes the following research hypothesis:

Hypothesis 3: Artificial intelligence increases executive compensation by improving the productivity of enterprises.

The application of AI within a firm can, to a certain extent, enhance the level of executive human capital. According to the task model proposed by Acemoglu and Autor, the proliferation of automation technology increases the demand for high-skilled labor engaged in complex tasks such as management and decision-making [21]. Theoretically, a firms deepening application of AI technology prompts an upgrade of its production technology and equipment systems. In this process, executives, as the core decision-makers, need to master the matching advanced knowledge and skills to achieve effective "technology complementarity"[22]. Specifically, the deep integration of digital technologies, represented by AI, with a firms business operations promotes capital deepening, manifested as an expansion in fixed asset investment embodying higher technological content [23]. This process raises the skill threshold for equipment use and management, requiring executives to possess a higher level of human capital to navigate technological changes. On the other hand, as a firms application of AI deepens, its R&D and innovation activities tend to increase further [24]. AI, as an emerging technology emerging from the wave of intelligentization, requires firms seeking to deeply apply it and transform it into their own competitiveness to increase innovation investment, intensify R&D efforts, and integrate AI with their internal governance and business operations. Innovation investment demands substantial knowledge reserves and skill mastery, exhibiting a clear skill-biased characteristic. Therefore, executives, as the leaders of innovation investment, need profound technological understanding and professional expertise to guide the integration of AI with corporate governance and business models, achieving an effective linkage between human capital investment and innovation activities.

An increase in the level of executive human capital will lead to higher compensation returns. As core members of business decision-making, executives with stronger capabilities optimize operational decisions and bring greater economic benefits to the firm. Li Shicong proposed that an executive incentive mechanism based on human capital contribution can effectively motivate them to create greater value for the enterprise [25]. Research by Fan Yadong et al. found that the higher the educational attainment of executives, the higher the compensation returns they expect to receive [26]. During the intelligent transformation process, executives undertake more complex tasks requiring more diverse knowledge. Shareholders need to compensate for this human capital investment by increasing compensation, a direct and effective incentive tool. In this process, executives, by virtue of their capability value, possess higher bargaining power regarding their compensation, thereby driving up their compensation levels.

Based on the above analysis, this paper proposes the following research hypothesis:

Hypothesis 4: Artificial intelligence increases executive compensation by enhancing the level of executive human capital.

Corporate compensation contracts can link executive pay to shareholder interests, thereby encouraging executives to act in the goal of maximizing shareholder value. However, according to managerial power theory, in practice, corporate compensation contracts are not entirely effective [27]. Based on the assumption of rational economic man, executives always have the motivation to pursue the maximization of their own interests, and managerial power grants them sufficient practical capability to do so. Consequently, executives may engage in opportunistic behavior. Li Linfang and Wang Ye et al. proposed that when a firms governance mechanisms are weak and internal control quality has significant deficiencies, managerial power tends to be greater [28]. The greater the managerial power, the more pronounced the information asymmetry problems within the company become, and the less oversight executives face when making decisions, thereby enabling them to extract additional benefits.

Internal corporate governance mechanisms are designed to monitor and urge agents to act in pursuit of maximizing shareholder wealth. When a firms governance level is high, the impact of AI on executive compensation may be weakened. Specifically, when a companys governance mechanisms are relatively well-developed, the organizational structure tends to be flatter and more decentralized, with fewer redundant layers and higher information transmission efficiency. In this context, executive decisions are subject to greater scrutiny, making it difficult for them to treat the company as their own "fiefdom." The decision-making position of executives diminishes, leading to a smaller positive effect of AI on executive compensation. Simultaneously, when the corporate governance structure is more networked, information asymmetry problems within the firm are mitigated. Grassroots employees are more willing to participate in company decisions, and the benefits brought by AI to the firm rely more on collective wisdom. The decision-making influence of executives decreases, and the increased profit distribution resulting from improved firm performance tends to be shared more broadly among all employees, thereby reducing the positive impact of AI on executive compensation.

Based on the above analysis, this paper proposes the following research hypothesis:

Hypothesis 5: An improvement in the level of corporate governance significantly weakens the positive impact of artificial intelligence on executive compensation.

3. Research Design

3.1. Data Source

This paper selects Chinas A -share listed companies on the Shanghai and Shenzhen stock exchanges from 2007 to 2023 as the research sample to investigate the impact of artificial intelligence on executive compensation in listed companies. The choice of 2007 as the starting point is primarily based on the following reasons: First, from a technological perspective, in 2006, Geoffrey Hinton proposed deep learning algorithms, solving the challenge of training deep neural networks and laying the foundation for modern AI. The year 2007 also became a critical node for algorithms transitioning from theory to engineering application. AI technology gradually entered the era driven by big data, making its application prospects for enterprises clearer and broader. Second, from a policy perspective, the "National Medium- and Long-Term Science and Technology Development Plan Outline (2006-2020)" included "intelligent perception technology" and "artificial intelligence" among the key frontier technology areas for the first time, channeling research funding towards AI technology and providing enterprises with better conditions and capabilities to leverage the advantages of AI. Third, regarding data availability, relevant data for listed companies became more accessible after 2007, with relatively fewer missing values, which benefits the robustness of the empirical estimations in this paper.

The annual reports of listed companies used in this paper are sourced from CNINFO; basic information and financial data of listed companies are obtained from the Chinese Research Data Services Platform (CNRDS) and the RESSET database. To ensure data quality, this paper processes the sample as follows: (1) Excluding samples from the financial industry; (2) Excluding samples with missing data for main variables; (3) Excluding samples that were in ST, *ST, or PT status during the year; (4) Excluding enterprises with liabilities exceeding assets; (5) To mitigate the impact of extreme values, all continuous variables are winsorized at the 1% level on both tails, finally yielding 44,642 observations.

3.2. Construction of Artificial Intelligence Indicator

Existing research primarily employs three methods to construct AI indicators at the micro-enterprise level: using industrial robot penetration based on robot stock, using AI patent indicators, and conducting word frequency statistics of AI-related keywords in listed company annual reports as a proxy variable for AI. Using industrial robot data to measure AI has limitations. On one hand, the sample objects studied using industrial robot indicators are confined to manufacturing enterprises, making it difficult to measure the degree of AI application in non-manufacturing firms. On the other hand, industrial robots and AI differ significantly at a technological level: industrial robots are essentially pre-programmed machinery that follow fixed logic to perform simple, repetitive tasks (such as welding, handling), representing "automation." In contrast, the core of AI technology is data-driven iterative learning and autonomous decision-making, representing "intelligentization." Their application scenarios differ, and using industrial robots to proxy for AI would conflate "automation" and "intelligentization." Although AI patent indicators can reflect, to some extent, a firms degree of AI application, firms applying for AI patents often possess inherently high technological levels and typically belong to the information technology industry. Therefore, AI patent indicators struggle to reflect the AI application status of enterprises outside the information technology sector. Listed company annual reports showcase the application of AI by listed firms. Consequently, this paper draws on the method of Yao Jiaquan et al. (2024), using textual analysis to construct an AI indicator for listed companies, aiming for a more comprehensive measure of their AI technology application level.

The specific steps for constructing the AI indicator in this paper are as follows: ① Convert the annual reports of listed companies crawled from CNINFO into txt format. ② Use the Jieba module in Python for word segmentation of the annual reports. Since Chinese contains many new words and ambiguous terms, direct segmentation might misidentify some proper nouns. Therefore, this paper incorporates the AI feature dictionary into the Jieba segmentation module. ③ Referring to the AI feature dictionary constructed by Yao Jiaquan et al., count the frequency of AI keywords in the "Management Discussion and Analysis" (MD&A) section of the annual reports, and calculate the ratio of the number of AI keywords to the total number of words in that section as the enterprise AI indicator (AI)[15].

3.3. Variable Selection and Data Description

(1) Dependent Variable. The dependent variable in this paper is executive compensation (lnPay), measured by the natural logarithm of the total actual compensation of the top three executives in the listed company for the year. It needs clarification that there is a distinction between executives and management. A companys management includes directors (excluding independent directors), supervisors, and executives. Executives hold the power to allocate core corporate resources, engage in strategy formulation and decision-making, and are directly accountable to the board of directors, encompassing positions such as manager and chief financial officer. To ensure the robustness of the estimation results, this paper will replace the dependent variable with other proxy variables for executive compensation in robustness tests, including total executive compensation, total compensation of the top three directors, number of shares held by executives, and number of shares held by management.

Table 1. Variable Definitions

Variable Type	Variable Name	Symbol	Variable Definition
Dependent Variable	Executive Compensation	lnPay	Natural logarithm of the total actual compensation of the top three executives
Core Explanatory Variable	Artificial Intelligence	AI	Ratio of the frequency of AI keywords to the total word frequency in the MD&A section of listed company annual reports
Control Variables	Firm Size	Size	Natural logarithm of total assets
	Firm Age	Age	Natural logarithm of (number of years since establishment + 1)
	Leverage Ratio	Leverage	Total liabilities / Total assets
	Growth Potential	Growth	Natural logarithm of sales revenue growth rate
	Board Size	BoardSize	Natural logarithm of the number of board members
	Ownership Concentration	Top1	Shareholding ratio of the largest shareholder
	Executive Compensation	lnPay	Natural logarithm of the total actual compensation of the top three executives

(2) Core Explanatory Variable. The core explanatory variable is artificial intelligence (AI). Referring to the dictionary containing 73 AI keywords constructed by Yao Jiaquan et al., this paper conducts textual analysis on listed company annual reports and calculates word frequency [15]. The ratio of the number of AI keywords to the total number of words in the "Management Discussion and Analysis" (MD&A) section of the annual report is used as the AI indicator. Considering instances where this variable takes the value of "0" in many samples, this paper will also construct a new AI indicator for robustness testing based on whether AI keywords are mentioned in the MD&A section of the annual

reports.

(3) Control Variables. To control for factors other than AI that might cause variations in executive compensation, this paper includes firm-level control variables in the baseline regression model. The control variables selected in this paper include Firm Size (Size), Firm Age (Age), Leverage Ratio (Leverage), Growth Potential (Growth), Board Size (BoardSize), and Ownership Concentration (Top1).

Specific variable definitions are shown in Table 1.

3.4. Model Specification

To investigate the impact of artificial intelligence on executive compensation, this paper establishes the following baseline regression model (1):

$$lnPAY_{i,t} = \alpha + \beta AI_{i,t} + \gamma Controls_{i,t} + year + ind + \varepsilon_{i,t} \quad (1)$$

In the baseline regression model, i represents the firm, and t represents the year. lnPayi,t is the dependent variable, representing the executive compensation level of firm i in year t. AIi,t is the core explanatory variable, representing the application of artificial intelligence by firm i in year t. Controlsi,t represents a set of firm-level control variables, including Firm Size (Size), Firm Age (Age), Leverage Ratio (Leverage), Growth Potential (Growth), Board Size (BoardSize), and Ownership Concentration (Top1). In robustness tests, control variables at the industry level and regional level will also be added for further examination. To avoid omitted variable problems caused by unobservable factors, this paper controls for year fixed effects (year) and industry fixed effects (ind). εi,t is the random disturbance term, α is the constant term, and β and γ are parameters to be estimated. In the baseline regression results, this paper focuses on the estimated coefficient β. If β is significantly positive, it indicates that artificial intelligence has a significant positive promoting effect on the executive compensation of listed companies.

4. Empirical Analysis

4.1. Baseline Regression Analysis

To investigate the impact of artificial intelligence on executive compensation, this paper adopts a method of gradually adding control variables in the baseline regression, and includes industry fixed effects and year fixed effects to prevent potential issues such as heteroskedasticity, serial correlation, and omitted variable bias in the estimation results, thereby ensuring the robustness of the findings. Table 2 presents the regression results of executive compensation on artificial intelligence. Column (1) shows the regression results without control variables, column (2) includes control variables, and column (3) further controls for industry fixed effects and year fixed effects based on column (2). In column (1), column (2), and column (3), the regression coefficient of the core explanatory variable, the level of artificial intelligence (AI), is significantly positive at the 1% statistical level, indicating that artificial intelligence can significantly increase the compensation level of executives. Therefore, Hypothesis 1 of this paper is verified. The regression results for the control variables are consistent with expectations. For example, firms with higher ownership concentration, better growth potential, longer establishment, lower leverage ratios, and larger scales tend to have higher executive compensation levels.

Table 2. Benchmark regression results

	(1)	(2)	(3)
Variable Name	LnPay	LnPay	LnPay
AI	1.661***	1.245***	0.169***
	(32.313)	(28.489)	(3.453)
Growth		0.106***	0.128***
		(10.898)	(14.026)
Boardsize		-0.267***	-0.017*
		(-26.181)	(-1.706)
Top1		-0.345***	-0.192***
		(-16.615)	(-9.878)
Leverage		-0.686***	-0.483***
		(-41.263)	(-29.576)
age		0.492***	0.061***
		(53.146)	(5.919)
Size		0.314***	0.292***
		(114.032)	(107.618)
Constant	14.363***	7.006***	8.043***
	(3,769.054)	(121.841)	(130.588)
Ind	NO	NO	YES
Year	NO	NO	YES
Observation	44,642	44,642	44,642
R2	0.023	0.321	0.443

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with t-statistics in parentheses.

4.2. Robustness Tests

4.2.1. Endogeneity Test

Table 3. Two-Stage Least Squares Regression Results

	(1)	(2)
	first stage	second stage
Variable Name	AI	LnPay
AI_prov_mean	0.405***	
	(8.024)	
AI		13.833***
		(6.66)
Growth	-0.003***	0.169***
	(-2.908)	(8.83)
Boardsize	-0.003***	0.038
	(-1.746)	(1.09)
Top1	-0.018***	0.046
	(-4.512)	(0.57)
Leverage	0.001	-0.467***
	(0.223)	(-8.15)
age	-0.000	0.064
	(-0.084)	(1.58)
Size	0.003***	0.251***
	(4.472)	(20.83)
Constant	-0.048***	7.807***
	(-3.882)	(27.78)
Ind	YES	YES
Year	YES	YES
Observation	44,642	44,642
first-stage F-statistic	64.367	

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with t-statistics in parentheses.

The baseline regression model in this paper may suffer from two aspects of endogeneity issues. First, there is the issue of omitted variables. Although this paper has controlled for a considerable number of firm-level variables, due to data availability constraints and the complexity of factors influencing executive compensation, there may still be some unobservable omitted variables affecting executive compensation levels. Second, there is the issue of reverse causality. While artificial intelligence may increase executive compensation, executives with higher compensation levels might, in turn, have greater confidence and motivation to promote the advancement of AI within their firms. This bidirectional causal relationship could potentially lead to biases in the estimation results of this paper. This paper employs the common instrumental variable (IV) method to address potential endogeneity problems. Specifically, referring to the research methods of Yin Zhifeng et al., this paper selects the annual mean AI level of the region where the firm is located, excluding the firm itself, as the instrumental variable, and performs estimations using the two-stage least squares (2SLS) method [29].

The higher the annual mean level of artificial intelligence in the region where an enterprise is located, the better the economic conditions and the higher the overall technological level of that region, making it more likely that the enterprises own AI level is relatively high. Conversely, an enterprises own AI level does not directly affect the AI level of its surrounding region. Therefore, this instrumental variable reasonably satisfies the relevance and exogeneity requirements for instrumental variable selection. The estimation results of the instrumental variable method are shown in Table 3. Column (1) presents the first-stage regression results, where the instrumental variable is significantly positive at the 1% statistical level. Additionally, the F-statistic from the first-stage regression is 64.367, exceeding the critical value of 10, verifying the correlation between the selected instrumental variable and the core explanatory variable. Column (2) displays the second-stage regression results, where the estimated coefficient of the core explanatory variable is significantly positive at the 1% significance level, consistent with the baseline regression results. This indicates that after controlling for potential endogeneity issues, artificial intelligence still has a positive impact on executive compensation levels.

4.2.2. Changing Model Specifications

Table 4. Benchmark Regression Results After Changing Model Specifications

	(1)	(2)	(3)	(4)
	Firm-Level Clustered Standard Errors	Adding Province Fixed Effects	Adding Control Variables	Explanatory Variable Lagged by One Period
Variable Name	LnPay	LnPay	LnPay	LnPay
AI	0.169*	0.096**	0.170***	
	(1.936)	(1.994)	(3.420)	
d_AI				0.146***
				(2.790)
Growth	0.128***	0.115***	0.122***	0.119***
	(11.820)	(12.798)	(12.972)	(12.304)
Boardsize	-0.017	0.040***	-0.015	-0.013
	(-0.727)	(4.052)	(-1.464)	(-1.226)
Top1	-0.192***	-0.210***	-0.184***	-0.205***
	(-3.609)	(-10.898)	(-9.124)	(-9.882)
Leverage	-0.483***	-0.423***	-0.480***	-0.470***
	(-12.632)	(-26.039)	(-28.460)	(-26.983)
age	0.061**	0.009	0.055***	0.085***
	(2.210)	(0.913)	(5.167)	(7.465)
Size	0.292***	0.292***	0.294***	0.292***
	(38.161)	(107.539)	(104.636)	(101.382)
Gdp_growth			0.002**	
			(2.225)	
HHI			0.051	
			(1.546)	
Constant	8.043***	8.060***	8.023***	7.980***
	(46.679)	(130.862)	(124.148)	(119.961)
Ind	YES	YES	YES	YES
Year	YES	YES	YES	YES
Pro	NO	YES	NO	NO
Observation	44,642	44,642	44,642	39,411
R2	0.443	0.477	0.425	0.427

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with t-statistics in parentheses.

This paper has already controlled for year fixed effects and industry fixed effects in the baseline regression. To address potential model specification errors, this paper conducts tests by altering the model specifications. Specifically, this paper examines the robustness of the regression results of AI on executive compensation by controlling for firm-level clustered standard errors and adding province fixed effects, respectively. The results are shown in columns (1) and (2) of Table 4. After adding firm-level clustered standard errors, the regression coefficient of Artificial Intelligence (AI) is 0.169, significantly positive at the 10% level. After adding province fixed effects, the regression coefficient of Artificial Intelligence (AI) is 0.096, significantly positive at the 5% level. Additionally, since the control variables in the baseline model are all at the micro-firm level, potentially overlooking the impact of industry and regional factors on executive compensation, this paper further adds industry-level and regional-level control variables to the baseline model. These include the Herfindahl-Hirschman Index and the GDP growth rate of the city where the firm is located. The Herfindahl-Hirschman Index (HHI) is measured by the sum of squares of the percentage of each firms total assets within its industrys total assets; this index reflects the market concentration of the industry in which the listed company operates. Column (3) of Table 4 presents the estimation results after adding these control variables. The regression coefficient of Artificial Intelligence (AI) is 0.170, significantly positive at the 1% level, indicating that the baseline regression results remain robust.

On the other hand, the application of AI by enterprises is not an overnight process. The disclosure of AI-related information in annual reports by a company does not necessarily mean it has already begun applying AI. Furthermore, there is typically a lag period from R&D investment to the actual integration of AI into a firms production and operations. Therefore, this paper posits that the impact of AI on executive compensation might exhibit a certain time lag. This paper alters the regression window by lagging the AI indicator by one period for estimation. The estimation results are shown in column (4) of Table 4. The study finds that the regression coefficient of the lagged AI variable (d_AI) is significantly positive at the 1% level. Moreover, when executive compensation is led by one period, the regression coefficient of AI remains significantly positive at the 1% level. This suggests that the positive impact of AI on executive compensation is effective over a longer time horizon, further validating the establishment of Hypothesis 1 in this paper.

4.3. Mechanism Testing

To verify the remaining four hypotheses and explore the mechanisms through which artificial intelligence affects executive compensation, this paper further conducts empirical research to examine the potential mediating and moderating effects within the influence pathways.

Regarding the testing of mediating mechanisms, this paper constructs a mediation effect model to discuss the roles played by three channels—financing constraints, innovation investment, and productivity—in the process where artificial intelligence increases executive compensation. The specific model specifications are as follows:

$$Med_{i,t} = \alpha + \beta AI_{i,t} + \gamma Controls_{i,t} + year + ind + \varepsilon_{i,t} \quad (2)$$

$$lnPAY_{i,t} = \alpha + \beta_1 AI_{i,t} + \beta_2 Med_{i,t} + \gamma Controls_{i,t} + year + ind + \varepsilon_{i,t} \quad (3)$$

Here, Med represents the mediating variable. The other parameters and variable settings in the model are the same as those in the baseline model (1). To test the mediating effects of each channel, it is necessary to focus on the coefficients β,β_1 and β_2 in the model. When both coefficients β and β_2 are significant, it indicates the existence of a mediation effect. If, at the same time, coefficient β_1 is also significant, it suggests that the mediating variable exerts a partial mediation effect.

This paper further constructs a model to explore the moderating role of corporate governance level in the pathway through which artificial intelligence affects executive compensation. The specific model specification is as follows:

$$lnPAY_{i,t} = \alpha + \delta_1 AI_{i,t} + \delta_2 Gov_{i,t} + \delta_3 (Gov_{i,t} * AI_{i,t}) + \gamma Controls_{i,t} + year + ind + \varepsilon_{i,t} \quad (4)$$

Here, Gov represents the level of corporate governance. The interaction term between corporate governance level (Gov) and artificial intelligence (AI) is included in the model. The other parameters and variable settings in the model are the same as those in the baseline model (1). The focus is on the coefficient δ_3. If δ_3 is significantly positive, it indicates that the level of corporate governance has a positive moderating effect on the main effect. Conversely, if δ_3 is significantly negative, it suggests that the level of corporate governance weakens the main effect.

4.3.1. Testing the Financing Constraint Effect

When enterprises face obstacles in obtaining external financing, they may fall into the predicament of underinvestment, which subsequently hinders their ability to engage in R&D and innovation, and may even affect normal production and operations. In capital markets, information asymmetry is often a significant factor preventing enterprises from obtaining external financing. Artificial intelligence, with its powerful data processing and analytical capabilities, plays a crucial role in enhancing corporate information transparency. It can mitigate risks arising from information asymmetry and ease corporate financing constraints. Furthermore, AI can alleviate corporate financing constraints by reducing transaction costs and increasing policy subsidies, thereby improving firm performance and boosting executive compensation.

This paper uses the SA index to measure the degree of corporate financing constraints. This index is constructed using two exogenous variables—firm size and firm age—thereby avoiding the influence of endogenous financial indicators. Its calculation method is as follows:

$$SA = -0.737 * ln(Size) + 0.043 * [ln(Size)]^2 - 0.040 * Age \quad (5)$$

Where SizeSize represents the firms total assets in millions, and AgeAge represents the firms age. The SA index is generally negative; a larger SA index (i.e., smaller absolute value) indicates more severe financing constraints faced by the firm.

Table 5. Mechanism Testing: Financing Constraint Effect

	(1)	(2)	(3)
Variable Name	LnPay	SA	LnPay
AI	0.169***	-0.045***	0.161***
	(3.453)	(-4.724)	(3.281)
SA			-0.188***
			(-7.737)
Growth	0.128***	-0.014***	0.125***
	(14.026)	(-8.140)	(13.727)
Boardsize	-0.017*	-0.012***	-0.019*
	(-1.706)	(-6.076)	(-1.929)
Top1	-0.192***	-0.001	-0.192***
	(-9.878)	(-0.176)	(-9.891)
Leverage	-0.483***	-0.014***	-0.485***
	(-29.576)	(-4.366)	(-29.749)
age	0.061***	-0.728***	-0.076***
	(5.919)	(-364.529)	(-3.728)
Size	0.292***	0.016***	0.295***
	(107.618)	(30.143)	(107.701)
Constant	8.043***	-2.015***	7.664***
	(130.588)	(-168.023)	(97.411)
Ind	YES	YES	YES
Year	YES	YES	YES
Observation	44722	44722	44722
R2	0.443	0.832	0.444

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with t-statistics in parentheses.

Table 5 presents the regression results for the mediating effect of financing constraints. Holding other conditions constant, the estimated coefficient of Artificial Intelligence (AI) in column (2) is -0.045, significant at the 1% level. This indicates that AI alleviates corporate financing constraints, consistent with the previous analysis. In column (3), the estimated coefficient of the SA index is significantly negative at the 1% level, suggesting that financing constraints play a mediating role in the process of AI influencing executive compensation. Meanwhile, the coefficient of Artificial Intelligence (AI) remains significantly positive at the 1% level, indicating the presence of a partial mediation effect. Based on the above results, Hypothesis 2 of this paper is verified.

4.3.2. Testing the Productivity Effect

The application of artificial intelligence technology can significantly enhance a firms total factor productivity. From the perspective of labor structure optimization, the application of AI reduces a firms demand for repetitive, low -skilled labor positions and increases the demand for high-skilled, highly educated talent. AI can empower traditional intelligent equipment to efficiently execute tasks with clear rules and high repetitiveness, substituting for low-skilled labor and improving enterprise production efficiency. Simultaneously, AI also generates a complementary effect on high-skilled non-routine labor, assisting high-skilled talent in performing tasks better and helping executives transcend their original cognition and experience, thereby enabling more scientific and reasonable decision-making. AI optimizes the enterprises labor structure, strengthens the core decision-making position of executives, promotes productivity improvement, and consequently increases executive compensation.

Table 6. Mechanism Testing: Productivity Effect

	(1)	(2)	(3)
Variable Name	LnPay	TFP	LnPay
AI	0.169***	0.441***	0.084*
	(3.453)	(9.704)	(1.736)
TFP			0.193***
			(38.333)
Growth	0.128***	0.337***	0.062***
	(14.026)	(39.953)	(6.804)
Boardsize	-0.017*	-0.007	-0.015
	(-1.706)	(-0.785)	(-1.539)
Top1	-0.192***	0.353***	-0.261***
	(-9.878)	(19.572)	(-13.568)
Leverage	-0.483***	0.400***	-0.561***
	(-29.576)	(26.462)	(-34.625)
age	0.061***	0.024**	0.056***
	(5.919)	(2.513)	(5.496)
Size	0.292***	0.603***	0.176***
	(107.618)	(239.533)	(43.376)
Constant	8.043***	1.897***	7.681***
	(130.588)	(33.264)	(125.063)
Ind	YES	YES	YES
Year	YES	YES	YES
Observation	44,642	44,584	44,584
R2	0.443	0.741	0.461

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with t-statistics in parentheses.

This paper employs the LP method to measure the level of enterprise total factor productivity. Specifically, the enterprise TFP indicator is obtained by estimating the logarithmic Cobb-Douglas production function model shown in equation (6):

$$lnY_{i,t} = \beta_0 + \beta_1 lnK_{i,t} + \beta_2 lnL_{i,t} + \beta_2 lnM_{i,t} + \varepsilon_{i,t} \quad (6)$$

In model (6), i and t represent the listed company and year, respectively. Y is the total output of the listed company, measured by operating revenue. K is the capital input of the listed company, measured by the net value of fixed assets. L is the labor input of the listed company, measured by the number of employees. M is the intermediate input of the listed company, measured by cash paid for purchasing goods and receiving labor services. The residual ε measures the enterprises total factor productivity, denoted as TFP. Table 6 presents the regression results for the mediating mechanism of productivity. Holding other conditions constant, the estimated coefficient of Artificial Intelligence (AI) on productivity (TFP) in column (2) is significantly positive at the 1% level, indicating that AI promotes an increase in enterprise productivity. In column (3), the estimated coefficient of productivity (TFP) is significantly positive at the 1% level, suggesting that AI increases executive compensation by enhancing enterprise productivity. The estimated coefficient of Artificial Intelligence (AI) remains significantly positive at the 10% level, indicating the presence of a partial mediation effect. Based on the above results, Hypothesis 3 of this paper is verified.

4.3.3. Testing the Executive Human Capital Level Effect

The deep application of artificial intelligence within enterprises raises the skill threshold for equipment use and management, requiring executives to master matching advanced knowledge and skills to achieve effective "technology complementarity". Concurrently, innovation investment represents an investment activity with significant skill bias, demanding substantial knowledge reserves and skill proficiency. Therefore, executives, as leaders of innovation investment, need profound technological understanding and professional expertise to achieve an effective linkage between human capital investment and innovation activities. Company shareholders need to increase executive compensation returns to compensate for and incentivize executives human capital investment.

Table 7. Mechanism Testing: Executive Human Capital Level Effect

	(1)	(2)	(3)
Variable Name	LnPay	Edu	LnPay
AI	0.169***	0.340***	0.105**
	(3.453)	(7.189)	(2.031)
Edu			0.149***
			(26.941)
Growth	0.128***	0.013	0.129***
	(14.026)	(1.511)	(13.352)
Boardsize	-0.017*	0.160***	-0.038***
	(-1.706)	(16.834)	(-3.596)
Top1	-0.192***	-0.051***	-0.187***
	(-9.878)	(-2.676)	(-9.034)
Leverage	-0.483***	-0.021	-0.504***
	(-29.576)	(-1.323)	(-28.769)
age	0.061***	0.038***	0.067***
	(5.919)	(3.846)	(6.224)
Size	0.292***	0.085***	0.284***
	(107.618)	(31.932)	(95.518)
Constant	8.043***	1.054***	7.729***
	(130.588)	(17.458)	(116.376)
Ind	YES	YES	YES
Year	YES	YES	YES
Observation	44,642	39,313	39,313
R2	0.443	0.145	0.446

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with t-statistics in parentheses.

This paper measures the level of executive human capital using the average educational level (Edu) of the enterprises executive team. The specific values are assigned as follows: 1 = Technical secondary school or below, 2 = Associate degree, 3 = Bachelors degree, 4 = Masters degree, 5 =

Doctoral degree.

Table 7 presents the regression results for the mediating mechanism of executive human capital level. Holding other conditions constant, the regression coefficient of Artificial Intelligence (AI) in column (2) is significantly positive at the 1% level, indicating that AI forces an increase in the human capital level of executives within the enterprise. In column (3), the regression coefficient of executive human capital level (Edu) is significantly positive at the 1% level, and the regression coefficient of Artificial Intelligence (AI) is significantly positive at the 5% level. This demonstrates that AI promotes an increase in executive compensation by enhancing the level of executive human capital, and that a partial mediation effect exists. Based on the above results, Hypothesis 4 of this paper is verified.

4.3.4. Testing the Moderating Effect of Corporate Governance Level

Table 8. Test Results for the Moderating Effect of Corporate Governance Level

	(1)	(2)
Variable Name	LnPay	LnPay
AI	0.262***	0.270***
	(4.896)	(5.332)
Gov	-0.022***	
	(-7.761)	
Gov * AI	-0.110***	
	(-3.933)	
Gov2		0.356***
		(63.787)
Gov2 * AI		-0.466***
		(-7.442)
Growth	0.131***	0.082***
	(14.308)	(9.394)
Boardsize	-0.067***	0.171***
	(-5.939)	(17.445)
Top1	-0.249***	0.134***
	(-12.076)	(6.944)
Leverage	-0.496***	-0.339***
	(-30.266)	(-21.557)
age	0.047***	0.122***
	(4.548)	(12.378)
Size	0.285***	0.286***
	(101.851)	(110.054)
Constant	8.383***	7.387***
	(119.051)	(123.336)
Ind	YES	YES
Year	YES	YES
Observation	44,483	44,483
R2	0.444	0.492

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with t-statistics in parentheses.

Referring to the research method of Hu Nan et al., this paper employs principal component analysis to construct a comprehensive corporate governance level indicator [30]. This indicator systematically measures the corporate governance level from three dimensions: supervision mechanism, incentive mechanism, and decision-making mechanism. Specifically, the incentive mechanism is measured by two indicators: executive compensation level and executive shareholding ratio. The supervisory function of the board of directors is measured by the proportion of independent directors and board size. The supervisory role of the ownership structure is measured by the shareholding ratio of institutional investors and the degree of ownership checks and balances (i.e., the ratio of the total shares held by the second to fifth largest shareholders to the shareholding ratio of the largest shareholder). The decision-making role of the general manager is measured by whether the positions of chairman and general manager are combined. Based on these seven key indicators, principal component analysis is used to synthesize the corporate governance level indicator. A larger value of this indicator indicates a better level of corporate governance.

This paper selects the first principal component (Gov) and the first five principal components (Gov2) from the principal component analysis as comprehensive indicators of corporate governance level for regression. Table 8 presents the test results for the moderating effect of corporate governance level. Holding other conditions constant, the estimated coefficients of the interaction terms between corporate governance level and artificial intelligence (Gov*AI and Gov2*AI) in columns (1) and (2) are both significantly negative at the 1% level. This indicates that a higher level of corporate governance weakens the positive impact of artificial intelligence on executive compensation, meaning that the corporate governance level exerts a negative moderating effect. This verifies Hypothesis 5 of this paper.

5. Research Conclusions

Based on data from Chinas A -share listed companies from 2007 to 2023, this paper constructs a firm-level indicator of artificial intelligence application through textual analysis, systematically investigates the impact of AI on executive compensation and its underlying mechanisms, and further analyzes its effects on the internal pay structure and the effectiveness of executive compensation contracts within enterprises. The main research conclusions are as follows:

First, artificial intelligence significantly increases the compensation level of executives in listed companies. This core conclusion remains robust after a series of robustness tests. This indicates that AI technology, as an important factor of production and a driver of organizational change, has become deeply embedded in business operations and profit distribution processes, exerting a significant positive pulling effect on executive remuneration.

Second, AI influences executive compensation through three mediating pathways: alleviating financing constraints, enhancing the level of executive human capital, and improving productivity. On one hand, by enhancing information transparency, reducing transaction costs, and strengthening policy support, AI effectively eases corporate financing constraints, creating conditions for improved firm performance and increased executive compensation. On the other hand, AI also provides a performance foundation for the growth of executive compensation by boosting enterprise total factor productivity. Furthermore, AI imposes higher knowledge and technical requirements on executives, elevating their human capital level, which in turn raises their compensation.

Third, the level of corporate governance plays a negative moderating role in the relationship between artificial intelligence and executive compensation. The study finds that in enterprises with more well-developed governance mechanisms and more effective internal supervision, the positive effect of AI on executive compensation is significantly weakened. This suggests that a sound corporate governance structure can curb the potential expansion of managerial power and opportunistic behavior during technological change, promoting a broader distribution of technological dividends across the entire organization rather than concentrating them solely on individual executives.

In summary, this paper confirms at the micro-enterprise level that AI indirectly shapes the compensation distribution pattern through multiple pathways such as financing constraints, executive human capital level, and productivity, and is moderated by the firms internal governance environment. It provides new empirical evidence for understanding organizational change and corporate governance under technological shocks.

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