International Review of Economics and Finance 105 (2026) 104832

Contents lists available at ScienceDirect

International Review of Economics and Finance

journal homepage: www.elsevier.com/locate/iref

Artificial intelligence innovation and financial report quality

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ARTICLE INFO

JEL classification:
M20
M21
M40
M41
D21
D82

Keywords:
Artificial intelligence
Mandatory disclosure
Information quality
Governance effect
AI Patent

ABSTRACT

This paper examines the effect of artificial intelligence adoption on firms' annual report disclosure quality. I employ a text analysis approach and use MD&A section texts to measure the precision and readability of corporate annual reports. Using a panel dataset of Chinese listed firms from 2010 to 2023, I find that corporate AI adoption effectively enhances the readability and accuracy of text in the MD&A section. Specifically, corporate AI adoption could increase management efficiency and enhance internal control over information processing which reflects its governance effect on disclosure. Furthermore, the main effect of corporate AI adoption was more pronounced when AI patents are more closely related to firms' core business and when firms' monopoly power is relatively weak. The above conclusions remain robust after employing the DID model and instrumental variable approach. I provide further evidence of the theoretical link between corporate AI adoption and disclosure behaviour, while extending the literature on determinants of management disclosure and AI outcomes in capital markets.

1. Introduction

In recent years, artificial intelligence (AI) technology has advanced significantly. According to a survey by McKinsey & Company, approximately 50 % of companies worldwide used AI in 2022. In particular, since the release of the generative large language model ChatGPT in November 2022, AI has emerged as a key focus in both daily life and the capital market. In fact, AI applications extend beyond conversational large language models to encompass machine learning, deep learning algorithms, image recognition techniques, among others. For governments, firms and individuals, the profound changes brought about by AI primarily manifest in the transformation of information collection and processing methods. For example, capital market regulators can employ machine learning to predict and monitor accounting fraud (Bao et al., 2020). Firms could use machine learning to enhance accounting estimates (Ding et al., 2020). Moreover, AI could also impact information exchange and communication among capital market participants (Bertomeu et al., 2025). However, few studies have examined AI's impact on the disclosure activities of information providers, despite its significance. This study therefore investigates the effect of AI on information disclosure.

With the advancement of digital and intelligent technologies, several studies explore their role in information disclosure. Early research primarily examined the impact of digital transformation on corporate disclosure. Digital transformation improves the accuracy of management performance forecasts (Zeng, & Wang, 2025) and encourages firms to disclose action-oriented, micro-level information (Mao, 2025). Digital technologies also reduce tone manipulation in mandatory disclosures (Gui, 2025). As a result of recent growth in AI technologies, some literature has begun to address the role of AI within the capital market information environment. For instance, AI adoption reduces information asymmetry and mitigates the risk of stock price crashes (Zhang et al., 2025). ChatGPT enhances analysts' processing of firm- and industry-specific information (Bertomeu et al., 2025). Artificial intelligence also

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https://doi.org/10.1016/j.iref.2025.104832
Received 18 April 2025; Received in revised form 10 November 2025; Accepted 11 December 2025
Available online 11 December 2025

improves the quality of corporate environmental disclosures (Zhao et al., 2025). However, this study identifies two theoretical gaps in the existing literature. First, prior research focuses primarily on AI's value for information intermediaries and demand-side investors. Second, prior studies do not analyse AI in the context of mandatory disclosure. Thus, this study contributes theoretically by examining AI's impact on mandatory disclosure from the information supply side.

High-quality information disclosure safeguards the healthy development of capital markets. AI affects information disclosure in two ways: by improving the efficiency and effectiveness of information processing. On the one hand, artificial intelligence streamlines information acquisition, processing, and decision-making (Bertomeu et al., 2025; Duan et al., 2019), thereby enhancing managerial efficiency in information processing (Liu, 2022; Brynjolfsson et al., 2025). AI relies on algorithms and models trained on large volumes of historical data, enabling it to process existing information efficiently, generate data-driven predictions, and provide managers with references and decision support (Cao, & Chen, 2022). Additionally, AI's powerful computing capabilities augment human data processing abilities so that enhancing information processing efficiency. On the other hand, artificial intelligence strengthens oversight of the information processing process and its outcomes. Unlike human subjective decision-making, AI-based information processing is traceable which could facilitate subsequent audits. Moreover, AI adoption enhances directors' oversight of managerial performance (Bao et al., 2020; Monteiro et al., 2023), and thus to improve information disclosure quality (Armstrong et al., 2014). In short, AI may contribute to improvements in the quality of mandatory disclosures.

However, AI may also have a negative impact on corporate disclosure activities. In terms of efficiency, AI hallucinations may reduce the efficiency of information acquisition, processing and analysis, as well as provide inaccurate and incomplete information, which may even mislead information providers and thus impair the quality of mandatory corporate disclosures. In terms of effectiveness, overuse of artificial intelligence may diminish the validity of information supply and supervisory activities, and potentially absolve management of disclosure pressures and responsibilities, which could subsequently induce moral hazard in information disclosure. Accordingly, corporate AI adoption may increase 'noise' in information flows to capital markets, and thus damage the quality of mandatory disclosures. Such adverse effects may manifest immediately or gradually emerge as the intensity of AI adoption increases. Therefore, I have conducted separate tests and identifications using both linear and non-linear formulas.

I select the textual disclosures in the Management's Discussion and Analysis (MD&A) section of Chinese listed firms as the research setting. Firstly, China is the world's second-largest economy and the largest emerging market. Unlike developed capital markets, the A-share market is characterized by higher information asymmetry between supply and demand, which implies lower market efficiency. In such a context, the role of artificial intelligence in improving the quality of information disclosure is particularly effective and significant. Exploring the importance of AI adoption in this scenario is highly representative. Secondly, China's AI sector is in a stage of rapid development. On the one hand, the scale of China's artificial intelligence development is gradually expanding, with a large number of large language models and multi-modal algorithms emerging rapidly. On the other hand, the artificial intelligence industry is also experiencing high-speed growth. As of June 2024, there were 4331 AI companies in China. In addition, nearly half of the public firms hold AI patents developed independently, which provides ample data support for the research.

I initially examine the effect of corporate AI adoption on mandatory disclosure quality. Based on the data of artificial intelligence (AI) patent registered by Chinese A-share listed firms from 2010 to 2023, I find that corporate AI adoption could effectively improve the quality of disclosure in the Management's Discussion and Analysis (MD&A) section of annual reports. Specifically, the higher AI adoption leads to greater readability and accuracy of the text in the MD&A section. The results were also confirmed by tests based on the level of AI investment. I employ the DID model and instrumental variable approach to cope with endogeneity issues and the main results are robust.

Additionally, I examine the mechanism through which corporate AI adoption affects disclosure quality which could be recognized as governance effect. I find that corporate AI adoption could significantly decrease the ratio of management expenditure which reflects an improvement in management efficiency. Meanwhile, I employ internal control index as the proxy and then find that the corporate AI adoption will increase firms' internal control quality so that the regulations on information processing will be enhanced as well. The mediation effect tests have demonstrated the reliability of the aforementioned model and its findings.

Finally, I identify which factors will lead to discrepant impacts of corporate AI adoption on the quality of information disclosure. Using deep learning algorithms, I assess the relevance of AI patents held by listed firms to their core business. I find that when the AI patents are highly relevant to firms' core business, the positive impact of corporate AI adoption on the quality of information disclosure is more pronounced. Moreover, for firms with relatively weaker market competitiveness, the proprietary costs of information disclosure are higher. Therefore, I use the Lerner Index to measure the market power of companies. I find that, compared with companies that have stronger market power, those in a relatively disadvantaged position in competition are more inclined to improve the quality of their information disclosure with the help of AI.

This paper contributes to multiple strands of the literature. First of all, this is the first paper to identify the impact of artificial intelligence adoption at the firm level on corporate information disclosure activities. Prior research has already recognized the significant role that artificial intelligence plays in information transmission within capital markets (Bertomeu et al., 2025; Zhang et al., 2025). Meanwhile, AI has been shown to facilitate information mining and processing in human decision making (Choi et al., 2025; Doshi et al., 2025). Regarding the application of AI at the firm level, most previous studies have focused on production activities, exploring the revolutionary impact of AI on productivity (Zhai, 2023; Li et al., 2024). However, no prior literature has directly examined the impact of corporate AI adoption on information processing and disclosure. I confirm the positive impact of artificial intelligence on information providers and provide empirical evidence for a more balanced assessment of the contributions of AI.

Secondly, the novel patent relevance approach provides a more enriched methodological framework for research in the fields of corporate innovation and governance. Based on deep learning algorithms, I developed an indicator of the relevance between AI patents and the core business of public firms from both textual and semantic similarity perspectives, offering new insights for further in-depth study on the impact of patent technology on corporate development. Additionally, the heterogeneity analysis shows that the relevance of patent technology to core business affects the economic consequences of AI adoption. This conclusion provides a reference for analyzing the economic value of innovation and avoiding blind innovation by enterprises.

Finally, this paper extends the research on the determinants of mandatory information disclosure. Compared with studies on the impact of technological factors such as digital transformation on information disclosure, the role of artificial intelligence, especially generative AI, in corporate management practices is revolutionary. Unlike previous research, this paper expands the research direction of technological factors and corporate information governance into the field of artificial intelligence, providing a more novel perspective for future studies.

The rest of this manuscript is organized as follows. Section 2 introduces the institutional background, discusses the relevant literature and develops the hypotheses. Section 3 shows all the details about methodology and sample. Section 4 reports and discusses the main results and robustness. Section 5 presents mechanism test. Section 6 introduces the results of heterogeneity factors and Section 7 concludes.

2. Background & hypothesis development

2.1. Artificial intelligence development in China

Artificial intelligence refers to the ability of "intelligent entities to understand data, learn from it, and use knowledge to achieve specific goals and tasks" (Russell, 2016). Since the "neuron" model in 1943 and the "Turing Test" in 1950, the concept of artificial intelligence has taken shape. Since 2010, with the development of information technologies such as big data, cloud computing, the Internet, and the Internet of Things, ubiquitous sensing data and computing platforms like graphical processors have driven the rapid development of artificial intelligence technologies represented by deep neural networks. These technologies have significantly bridged the gap between science and application, leading to major breakthroughs in fields such as image classification, speech recognition, knowledge Q&A, human-machine games, and autonomous driving, ushering in a new surge of explosive growth (Jordan & Mitchell, 2015).

Since 2014, artificial intelligence has become one of China's national development strategies. On one hand, the government has gradually introduced various industrial policies to support AI development; on the other hand, Chinese firms have played a prominent role in AI innovation. I have compiled the AI patent application data for A-share public firms from 2010 to 2023. As shown in **Appendix A**, the number of AI patents has significantly increased, with an average annual growth rate of about 13.54 %, and the majority of these patents are invention patents, reflecting the substantial contributions of Chinese firms to AI innovation. Furthermore, the number of firms applying for AI patents has also increased year by year, with an average annual growth rate of approximately 11.43 %, indicating that the scope of AI innovation is expanding and no longer limited to individual firms. Among the 427,249 AI patents I analyzed, patents related to data acquisition, processing, and disclosure consistently accounted for about 50 % in each year. This also reflects the value of AI in improving corporate data governance. Since data is the foundation and evidence for information disclosure, AI's role in data governance will ultimately help firms improve their information disclosure.

In addition, the contribution of artificial intelligence technology to information disclosure in public firms has become increasingly prominent. For example, SUS-FIN has used large language models to reduce the cost of ESG information disclosure and improve disclosure efficiency.[1] NariTech (600406.SH) has applied AI to address the inefficiencies and standardization issues in processing structured data in power market information disclosure. Yutong (600066.SH) has utilized AI to enhance the accuracy of carbon data acquisition and improve the transparency of its disclosure. In summary, artificial intelligence has become an important driver for promoting the development of the capital market in China in recent years. Therefore, the role of AI innovation in disclosure quality is an issue that warrants further investigation.

2.2. AI innovation and annual report disclosure quality

According to information economics, information, as an economic product, could mitigate and even eliminate internal issues of firms such as moral hazard and adverse selection (Akerlof, 1970). Previous studies have confirmed that digital technologies based on big data will influence information asymmetry between information suppliers and users (Sachan et al., 2024). For instance, digital transformation could exert a "governance effect" on information asymmetry, thus enhancing the accuracy of corporate earnings forecasts (Zeng, & Wang, 2025). However, the memory capacity of large language models regarding historical data can also severely undermine information credibility and then generate a "noise effect" on firms' information (Lopez-Lira et al., 2025). In recent years, the rapid development and adoption of artificial intelligence technologies has progressively reshaped the information environment within capital markets (Bertomeu et al., 2025), which profoundly alter the interaction patterns between information providers and users (Calzolari et al., 2025). Nevertheless, there is still a scarcity of studies that examine the impact of AI on corporate information disclosure. Since artificial intelligence, particularly generative AI and machine learning approaches, rely on extensive datasets and precise algorithmic training, their impact on corporate disclosures may manifest as "governance effect" or "noise effect".

[1] https://i.ifeng.com/c/8cjWtFerKzC.

2.2.1. Governance effect

According to agency theory (Jensen & Meckling, 1976), management has incentives to increase information asymmetry through ambiguous disclosure so as to conceal the opportunistic behavior. However, artificial intelligence adoption could reduce agency costs and enhance information transparency by strengthening supervision and improving managerial efficiency so that exerting its governance effects.

Firstly, the AI adoption enhances the supervision of internal management processes by abolishing internal information barriers (Wu, 2025), and thus reduces the scope for rent-seeking in corporate disclosure. Previous studies have confirmed that AI technology could effectively mitigate information asymmetry between firms and external stakeholders through strengthening internal controls (Xu et al., 2025). Specifically, automated internal controls are able to enhance financial reporting quality (Musaib, 2025). In corporate management practice, AI adoption could effectively improve the quality of internal controls (Monteiro et al., 2023; Zhang et al., 2025) and then lead to better corporate financial transparency (Zhang et al., 2025). Meanwhile, artificial intelligence could curb potential financial fraud by improving corporate governance as well (Rehman, 2022). Finally, the use of artificial intelligence to mitigate information asymmetry is technically feasible. For example, machine learning algorithms have already demonstrated their effectiveness in the prediction of financial fraud (Qiu, 2024).

Secondly, AI adoption expands management's breadth of knowledge so that it will reduce subjective errors and omissions and improve the quality of information disclosure. According to prior studies, AI technology alters human learning patterns (Marios et al., 2020) and significantly boosts knowledge acquisition efficiency (Bhatt, 2022). During business management activities, AI could ensure that firms correctly implement complex accounting standards, such as GAAP-FAS133 (Le Guyader, 2020). Simultaneously, machine learning could also increase the accuracy of accounting estimates, decrease the impact of objective estimation bias on accounting information quality and reduce the possibility of significant accounting errors (Bertomeu et al., 2021; Ding et al., 2020). Finally, AI raises the efficiency and accuracy of firms' routine data processing and reduces manual mistakes (Liu, 2022). Specifically at the operational level, artificial intelligence has improved insurers' forecasting of loss probabilities (Eling et al., 2022).

2.2.2. Noise effect

Artificial intelligence is not ideal. The hallucinations inherent to AI and the data upon which it relies during training process may impair the quality of information it provides. Additionally, contemporary AI ethicists have expressed concerns in response to the over-reliance upon and misuse of AI technologies (Xie et al., 2025). Consequently, the AI adoption may also exert a detrimental influence upon the quality of information provision.

First of all, AI may lead to the contamination of information content. The black-box nature of AI algorithms leads to the phenomenon of 'hallucinations' during information processing (Messeri, 2024). AI hallucination refers to the generation of false, inaccurate or contextually irrelevant information by an AI system, thereby affecting the veracity of the information (Sun et al., 2024). For example, large language models possess perfect memories of economic and financial data from the training period, which results in their historical predictions being indistinguishable from actual forecasts or data recall and severely undermines the credibility of economic forecasting and strategy back-testing (Lopez-Lira et al., 2025). According to Vectara's AI model hallucination ranking,[2] most AI systems exhibit hallucination levels ranging from 0.7 % to 30 %. The randomness and invisibility of AI hallucinations cause high uncertainty in their impact on decision-making, and may lead to issues such as misidentification of information and judgement bias among users (Ji et al., 2022). For instance, in 2015, Amazon's AI recruitment tool exclusively recommended male candidates, which provided management with erroneous information. In March 2016, Microsoft's chat-bot posted over 95,000 racially discriminatory tweets within 16 h, and thus conveyed egregiously flawed information to the market. The above examples have showed that AI models are able to impair information quality and managerial decision-making. Furthermore, if management adopts and discloses inaccurate or even unethical information induced by disillusionment, it will directly contaminate the source of the disclosure and compromise its accuracy, fairness and reliability. Meanwhile, it will reduce investors' trust in the corporate disclosure when the capital market identifies these deficiencies, which in turn pulls down its perceived disclosure quality as a whole.

Secondly, AI may induce the impairment of the information procedure. Referring to the existing studies, management may rely on information provided by artificial intelligence and reduce their own responsibilities (Parasuraman, 2010). For instance, while making strategic decisions, management often over-relies on AI-based advisory systems for data analysis and forecasting (Keding, 2021). However in reality, the role of AI in supporting decision-making may be inaccurate (Lebovitz et al., 2021). AI models are frequently trained and make predictions based on historical data, but the decision-making references provided by AI may become highly misleading if market conditions have changed, which consequently impacts management's outlook on and estimate of the firm's prospects within the MD&A section. Moreover, AI adoption by management lacks adequate supervision and insufficiently constrained artificial intelligence may give rise to cognitive biases and ethical dilemmas according to the prior study (Walter et al., 2025; Xue, & Pang, 2022). Specifically, the inappropriate use of AI models may compromise the accuracy of ESG ratings and give rise to ethical risks (Monfort et al., 2025). Furthermore, management may employ artificial intelligence to harvest consumer data and manipulate purchasing behaviour (Kanungo et al., 2022). Therefore, AI adoption may increase information asymmetry between firms and market from this above perspective. Therefore, over-reliance on AI may induce the first type of agency problem, thereby weakening the effectiveness and motivation managerial duties and increasing uncertainty in the source and processing of information, and thus may impair the quality of disclosure. For external users, the nature of the information asymmetry problem shifts from "availability" to

[2] Vectara is a Gen AI platform which provides robust retrieval, abstraction and creation capabilities as well as a user-friendly developer interface. In August 2024, the platform has ranked the degree of "hallucination" exhibited by existing large language models (LLMs) still in active use globally.

"verifiability", which may also have a negative impact on the quality assessment of firms' information.

The analysis of artificial intelligence's governance and noise effects on information disclosure suggests that AI may exert diametrically opposed impacts in mitigating information asymmetry within firms and capital markets. On the one hand, AI's role in promoting information processing efficiency and reinforcing information processing supervision contributes to the improvement of information disclosure quality. Empirical studies indicate that the reduction in the probability of significant internal control deficiencies could markedly improve financial reporting quality (Musaib, 2025). This is because effective governance mechanisms not only enhance information quality (Lem, 2024) but also mitigate the adverse impact of external factors on disclosure quality (Bao et al., 2022). Alternatively, whilst intelligent technologies furnish data support for corporate disclosure, their inherent black-box decision-making mechanisms may exacerbate information asymmetry. Naturally, these dual effects may coexist and mutually obscure one another. Based on the above analysis, I propose the following two opposing hypotheses to identify and test the specific impact and extent of AI on information disclosure.

H1a. Corporate AI adoption could enhance the quality of information disclosure.

H1b. Corporate AI adoption could decrease the quality of information disclosure.

3. Data & methodology

3.1. Sample and data sources

The sample consists of all Chinese public firms which are listed on SZSE and SHSE. Firstly, I used Python to obtain more than 2.7 million patents applied by public enterprises in China from 1988 to 2023 from the official website of China National Intellectual Property Office (CNIPA), and cross-checked them with the patent data of Wanfang Patent Database (WFPD), and then I refer to the 'Patent Classification System of Key Digital Technologies (2023)' issued by CNIPA to determine whether the patents are AI patents according to the IPC classification number of the category in its 'Table of Patent Classification System of Artificial Intelligence Technologies'. Non-AI patents were excluded. I don't include 'Industrial Design' patents in the selection process for AI patents because they are classified under the Locarno Classification Number (LOC) rather than the IPC Classification Number. In addition, I remove patents filed by firms in non-Mainland China regions such as Taiwan and Hong Kong, where the application number starts with 'TW' or 'HK'. Finally, I extract a total of 427,249 AI patent observations distributed over the years 2010–2023.

I obtain the text of the MD&A section of the annual reports of firms which are not labeled ST and have not been unlisted for the years 2010–2023 from the China Stock Market and Accounting Research (CSMAR) database. The remaining financial and non-financial data are obtained from the CSMAR and WIND databases, respectively. The final sample is aggregated and computed according to the firm-year panel and contains a total of 44,771 observations. All continuous variables are winsorized at the upper and lower 1 % levels.

3.2. Variable measurement

3.2.1. Dependent variables

Follow the prior studies (Loughran, 2014; Busee, & GowTaylor, 2018), I employ two proxies to measure the textual quality of annual report. *Precision* designates the informational accuracy of the MD&A section, which is defined the reciprocal of the ratio of ambiguous words in the MD&A text. *Readability* denotes the comprehensibility of the text of the MD&A section, which is specified as the reciprocal of the ratio of complex words in the text. Below I will detail the construction and validation of the underlying dictionaries in a Chinese-language setting.

I firstly obtain the annual reports of Chinese listed firms from 2010 to 2023 from GTIN and the official websites of the Shanghai and Shenzhen Stock Exchanges, and then extract the MD&A sections from these reports. Second, I segment the Chinese MD&A text with Python's "jieba" package and remove all the stop words using the list provided by the Natural Language Processing Laboratory of Harbin Institute of Technology, which covers all uppercase and lowercase Latin letters, numerals, punctuation marks and other prepositions, pronouns and modal particles that are used in Chinese contexts. After pre-processing, the corpus contains on average 4942 unique tokens per MD&A.

Based on the above text, I respectively construct Chinese fuzzy words and complex words lexicons. Referring to previous study (Xu et al., 2021), I adopt commonly used Chinese adverbs and conjunctions as fuzzy-word candidates. Typical adverbs include "very", "especially", "approximately" and "almost", which are mainly used to modify degree and scope of behaviors. Typical conjunctions include "however", "but" and "or", which are mainly used to express the logical relationship within and between sentences. The list of adverbs and conjunctions above is taken from the Modern Chinese Dictionary of Function Words (2005). In addition, referring to previous literature (Li et al., 2023), I employ accounting and financial terminologies contained in MD&A texts to represent readability. Specifically, I use the "Financial Accounting and Finance Lexicon" provided by Sogou Input Method, an authoritative and widely used Chinese input method provider, as the main terminology database and supplement it with relevant terms from Chinese enterprise accounting standards and finally lead to 7631 independent words. **Appendix B** presents typical samples of fuzzy words and complex words in Chinese.

3.2.2. Independent variables

I measure the extent of AI adoption at the firm level using the number of AI patent applications according to prior studies (Zhang

Table 1
Descriptive statistics and Univariate Analysis
Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

Panel A: Descriptive Statistic

Variable	N	Mean	SD	P1	P50	P99
Precision	44,771	94.69	35.53	50.42	86.56	277.0
Readability	44,771	39.38	18.97	18.67	34.97	149.5
$Num\_AI_{i,t\ [0,0]}$	44,771	3.882	13.27	0.000	0.000	99.00
$Num\_AI_{i,t\ [-4,0]}$	44,771	15.10	52.89	0.000	0.000	398.0
$Num\_AI_{i,t\ [-2,2]}$	44,771	17.23	60.40	0.000	0.000	462.0
Age	44,771	9.729	7.953	0.000	8.000	28.00
EPS	44,771	0.452	0.748	−1.748	0.320	3.793
TOP1	44,771	0.339	0.150	0.082	0.315	0.746
Separation	44,771	0.0434	0.071	0.000	0.000	0.283
Dual	44,771	0.297	0.457	0.000	0.000	1.000
Indep	44,771	0.377	0.053	0.333	0.364	0.571
Growth	44,771	0.136	0.329	−0.577	0.095	1.705
Lev	44,771	0.423	0.217	0.050	0.409	0.943
ROA	44,771	0.041	0.069	−0.243	0.040	0.235
Size	44,771	22.19	1.399	19.62	21.96	26.84
MB	44,771	0.605	0.253	0.000	0.611	1.154
Tobin	44,771	2.018	1.337	0.000	1.608	8.757

Panel B: Univariate Test

Variables	No AI Patents		With AI Patents		Mean_Diff	T-Value
	N	Mean	N	Mean		
Precision	30,428	91.81	14,343	100.8	−9.035	−25.325***
Readability	30,428	36.76	14,343	45.00	−8.235	−43.835***
$Num\_AI_{i,t\ [0,0]}$	30,428	0.000	14,343	12.20	−12.20	−100.580***
$Num\_AI_{i,t\ [-4,0]}$	30,428	0.000	14,343	47.47	−47.47	−97.681***
$Num\_AI_{i,t\ [-2,2]}$	30,428	0.000	14,343	54.16	−54.16	−97.592***
Age	30,428	10.61	14,343	7.833	2.782	35.056***
EPS	30,428	0.404	14,343	0.555	−0.151	−20.045***
TOP1	30,428	0.343	14,343	0.329	0.014	9.363***
Separation	30,428	0.045	14,343	0.041	0.004	5.066***
Dual	30,428	0.274	14,343	0.347	−0.073	−15.898***
Indep	30,428	0.375	14,343	0.379	−0.004	−6.992***
Growth	30,428	0.132	14,343	0.143	−0.011	−3.418***
Lev	30,428	0.435	14,343	0.397	0.038	17.481***
ROA	30,428	0.038	14,343	0.049	−0.011	−15.576***
Size	30,428	22.13	14,343	22.32	−0.188	−13.290***
MB	30,428	0.613	14,343	0.589	0.025	9.595***
Tobin	30,428	2.001	14,343	2.054	−0.052	−3.876***

et al., 2025) and define the variable $Num\_AI_{i,t}$ where i represents the firm and t represents the year. In view of the stage-specific nature of the output of R&D activities, I define three different time windows to calculate the number of AI patents. I.t $\in$ [0,0] indicates the number of AI patents that firm i has filed in each single year; II.t $\in$ [−4,0] indicates the weighted cumulative number of AI-related patents that firm i has registered from past 5 years till the statistical year; and III.t $\in$ [−2,2] indicates the weighted cumulative number of AI-related patents that firm i has registered in 2 years around the statistical year before and after. I use declining weight method to design the weights because of the temporal decay feature of previous patents' ability to reflect current technology, and the weights $W_t = 1+(t/5)$.

3.2.3. Control variables

Following the prior literature (Czarnitzki et al., 2023; Zhang et al., 2025), I include both financial and non-financial control variables. Besides I also control the year and firm level fixed effects to exclude endogeneity due to individual-level and time-level influences. The detailed definitions and data sources of these control variables are listed in **Appendix C**.

3.3. Model specification

I employ a multidimensional fixed-effects panel data model to identify the impact of AI adoption on the textual disclosure characteristics of annual reports. Additionally, I employ the same model to test the mechanism of AI's role in improving corporate governance and reinforcing external concerns, and whether this role is moderated by external factors such as patents and market competition. The standard errors of the regression coefficients are corrected for heteroskedasticity based on clustering to the firm level. The specific regression models are as follows, where Model① refers to the baseline regression model and the heterogeneity test model, and Model② and Model③ refer to the mechanism test model. In those models coefficient α_i and λ_t respectively indicate the firm and

Table 2
Main results of precision.

Dep. Vars	Precision					
Window	t ∈ [0,0]		t ∈ [-4,0]		t ∈ [-2,2]	
Models	(1)	(2)	(3)	(4)	(5)	(6)
$Num\_AI_{i,t}$	**0.173*****	**0.148*****	**0.067*****	**0.058*****	**0.033*****	**0.027****
	(4.57)	**(3.89)**	**(4.91)**	**(4.24)**	**(2.89)**	**(2.34)**
Age		0.166		0.165		0.163
		(0.15)		(0.15)		(0.14)
EPS		0.432		0.477		0.451
		(0.69)		(0.76)		(0.72)
TOP1		0.277		0.387		0.289
		(0.07)		(0.10)		(0.08)
Separation		−5.479		−5.188		−5.533
		(-0.98)		(-0.93)		(-0.99)
Dual		0.209		0.234		0.219
		(0.32)		(0.36)		(0.34)
Indep		−8.548		−8.889*		−8.498
		(-1.61)		(-1.67)		(-1.60)
Growth		0.513		0.557		0.466
		(1.12)		(1.22)		(1.02)
Lev		−2.024		−1.976		−2.067
		(-1.04)		(-1.01)		(-1.06)
ROA		−12.256**		−11.663**		−12.388**
		(-2.27)		(-2.17)		(-2.29)
Size		5.731***		5.598***		5.788***
		(9.04)		(8.80)		(9.12)
MB		−2.266		−2.105		−2.373
		(-1.43)		(-1.34)		(-1.50)
Tobin		0.624***		0.625***		0.626***
		(2.71)		(2.72)		(2.71)
Constant	94.070***	−30.159*	93.735***	−27.611	94.163***	−31.230*
	(642.39)	(-1.70)	(458.21)	(-1.56)	(473.05)	(-1.76)
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	*44,771*	*44,771*	*44,771*	*44,771*	*44,771*	*44,771*
Adj.R^2	*0.506*	*0.511*	*0.507*	*0.511*	*0.506*	*0.510*

All specification controlled for Firm and Year fixed effect to handle the unobservable homogeneity in the time dimension. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

year level fixed effect, and the residuals are represented by ϵ_{it}. I mainly focus on the estimated coefficient β_1 and its t-value.

$$\mathrm{Disc_{it}} = \alpha_i + \lambda_t + \beta_1 \mathrm{Num\_AI_{it}} + \gamma \mathrm{Controls_{it}} + \epsilon_{it} \tag{1}$$

$$\mathrm{Mechanism_{it}} = \alpha_i + \lambda_t + \beta_1 \mathrm{Num\_AI_{it}} + \gamma \mathrm{Controls_{it}} + \epsilon_{it} \tag{2}$$

$$\mathrm{Disc_{it}} = \alpha_i + \lambda_t + \beta_1 \mathrm{Num\_AI_{it}} + \beta_2 \mathrm{Mechanism_{it}} + \gamma \mathrm{Controls_{it}} + \epsilon_{it} \tag{3}$$

4. Empirical results

4.1. Descriptive statistics

Panel A of Table 1 presents the descriptive statistics for the main variables. The mean values of *Precision* and *Readability* are 94.69 and 39.38, respectively, with medians of 86.56 and 34.97. The means are slightly higher than the medians, indicating a right-skewed distribution that nonetheless approximates a normal distribution. The standard deviations of *Precision* and *Readability* are relatively large, indicating significant variability in the disclosure quality of MD&A sections across different companies. The minimum and median values of Num_AI_{it} across different time windows are both 0, which means some companies did not produce any AI-related innovations during the sample period. The distribution of other control variables is generally consistent with previous literature (Li et al., 2024).

Panel B of Table 1 presents the results of the univariate analysis. I divide the sample into two sub-samples based on whether the company holds AI patents. The treated group (With AI Patents) contains 14,343 observations, while the control group (No AI Patents) contains 30,428 observations. This distribution aligns with the descriptive statistics presented earlier. The mean values of Precision and Readability in the treated group are significantly higher than those in the control group, with T-values being significant at the 1 % level, which indicates that there are substantial differences between the two sub-samples. As shown in Appendix B, the Pearson

Table 3
Main results of readability.

Dep. Vars	Readability					
Window	t ∈ [0,0]		t ∈ [-4,0]		t ∈ [-2,2]	
Models	(1)	(2)	(3)	(4)	(5)	(6)
$Num\_AI_{i,t}$	**0.085*****	**0.071*****	**0.039*****	**0.034*****	**0.017*****	**0.013*****
	(5.09)	**(4.22)**	**(6.17)**	**(5.42)**	**(3.74)**	**(3.01)**
Age		1.297***		1.306***		1.297***
		(2.59)		(2.59)		(2.60)
EPS		0.561*		0.583*		0.569*
		(1.86)		(1.93)		(1.89)
TOP1		−1.162		−1.091		−1.154
		(-0.70)		(-0.66)		(-0.70)
Separation		−2.583		−2.431		−2.614
		(-1.11)		(-1.04)		(-1.12)
Dual		0.207		0.220		0.211
		(0.66)		(0.71)		(0.68)
Indep		−3.191		−3.436		−3.175
		(-1.33)		(-1.44)		(-1.33)
Growth		−0.931***		−0.896***		−0.953***
		(-4.50)		(-4.37)		(-4.61)
Lev		−5.613***		−5.582***		−5.634***
		(-6.47)		(-6.45)		(-6.49)
ROA		−8.854***		−8.475***		−8.914***
		(-3.59)		(-3.45)		(-3.61)
Size		3.492***		3.396***		3.517***
		(11.09)		(10.78)		(11.16)
MB		−0.227		−0.098		−0.273
		(-0.32)		(-0.14)		(-0.38)
Tobin		0.102		0.103		0.103
		(0.97)		(0.99)		(0.98)
Constant	38.971***	−46.996***	38.709***	−45.269***	39.009***	−47.488***
	(604.05)	(-5.82)	(404.23)	(-5.60)	(501.44)	(-5.88)
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	*44,771*	*44,771*	*44,771*	*44,771*	*44,771*	*44,771*
Adj.R^2	*0.651*	*0.657*	*0.652*	*0.658*	*0.651*	*0.657*

All specification controlled for Firm and Year fixed effect to handle the unobservable homogeneity in the time dimension. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

correlation coefficients between the number of AI patents in three different time windows and *Precision/Readability* are all significantly positive at the 1 % level, which preliminarily supports hypothesis H1a and simultaneously deny the alternative hypothesis H1b.

4.2. Main results

Table 2 reports the main results of baseline regression which employs *Precision* as the dependent variable. Column (1) and (2) add the *Num_AI* within time window [0,0] as the independent variable and detects the main effect of AI adoption on management disclosure quality. In column (1) and (2) the coefficients on *Num_AI* ($\beta_1 = 0.173$ & 0.148, t = 4.57 & 3.89), whether or not all control variables are considered, are all significantly positive at 1 % level, which indicates that the AI adoption could improve the accuracy of management's information disclosure. Column (3) and (4) adds the *Num_AI* within time window [−4,0] as the independent variable. The estimated coefficients of *Num_AI* in column (3) and (4) are 0.067 and 0.058 respectively, which are significantly positive at 1 % level with *Precision*. Within column (5) and (6), I use the same proxy within time window [−2,2] as a substitution and the empirical results is as the same, which demonstrates that the AI adoption in firms' business management and corporate governance could effectively increase the quality of disclosure. The above results are also economically significant as well. Taking columns (1) and (2) as examples, one standard deviation increase in *Num_AI* leads to an increase in *Precision* by 229.57 % (196.40 %).

Table 3 reports the empirical results of the relationship between *Num_AI* and *Readability*. In columns (1) and (2), the coefficients of *Num_AI* are 0.085 and 0.071 respectively and the significance level is 1 %, which indicates that the AI adoption can successfully improve the readability of the MD&A section of the annual report. In Columns (3) and (4), I use the new time window [−4,0] to identify the role of AI in disclosure quality, and the coefficients of *Num_AI* are 0.039 and 0.034, respectively, and both of them are significantly positive at 1 % level. Columns (5) and (6) add the number of AIs (*Num_AI*) calculated in the [−2,2] window as an explanatory variable. The coefficient of *Num_AI* is significantly positive at the 1 % level, regardless of whether control variables are considered or not. The above results reveal that AI adoption could effectively improve the readability of MD&A section of annual reports, which is an important dimension of information disclosure quality. Thus Hypothesis H1a is supported. Under the current

Table 4
The boundary of AI in enhancing disclosure quality.

Dep. Vars	Precision	Readability	Precision	Readability	Precision	Readability
Window	t ∈ [0,0]		t ∈ [-4,0]		t ∈ [-2,2]	
Models	(1)	(2)	(3)	(4)	(5)	(6)
$Num\_AI_{i,t}$	0.278***	0.080*	0.104***	0.053***	0.040	0.009
	(3.11)	(1.94)	(3.17)	(3.22)	(1.48)	(0.72)
$Num\_AI_{i,t}$-squared	−0.002	−0.000	−0.000	−0.000	−0.000	0.000
	(-1.55)	(-0.24)	(-1.50)	(-1.28)	(-0.55)	(0.42)
Constant	38.971***	−46.996***	38.709***	−45.269***	39.009***	−47.488***
	(604.05)	(-5.82)	(404.23)	(-5.60)	(501.44)	(-5.88)
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	*44,771*	*44,771*	*44,771*	*44,771*	*44,771*	*44,771*
Adj.R^2	*0.449*	*0.614*	*0.450*	*0.615*	*0.449*	*0.614*

All specification controlled for Firm and Year fixed effect to handle the unobservable homogeneity in the time dimension. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

research design and sample, the analysis reveals no significant evidence supporting H1b, which posits that the application of artificial intelligence introduces a "noise effect" on corporate information disclosure quality.

In summary, AI is a useful tool to decrease information asymmetry within firms' routine managerial activities. By providing management with adequate, decision-supporting information, AI effectively reduces management's workload in processing information and further enhances the efficiency of management activities. AI enhances automation in management activities and optimizes management processes through intelligent technology. AI, driven by massive amounts of data, is likely to enhance the oversight of details in management activities. As a result, AI adoption could improve the quality of corporate information supply, which is directly reflected in the improved quality of disclosure in annual reports. I go on to test the specific path of action of this result and the potential adverse effects of AI.

4.3. The boundary of AI in enhancing disclosure quality

Referring to prior studies (Aghion et al., 2005), I further employ a nonlinear relationship model to investigate that whether AI will lead to a detrimental influence on the quality of corporate annual report information and its boundary conditions. I generate quadratic terms for the independent variables across different time windows and subsequently incorporated them into the regression equation.

Table 4 reports the results of nonlinear model. The coefficients of the independent variables and their quadratic terms are indeed of opposite sign, however, the estimated coefficient for the quadratic terms are not statistically significant. Therefore, it could be concluded that there is no clear inverted U-shaped relationship between AI adoption and the quality of corporate annual report information. In other words, the consistent non-significance of the nonlinear terms across specifications further solidifies the rejection of H1b, which suggests that the underlying mechanism and economic effect of AI in corporate information disclosure is not characterized by the misusing or hallucination-induced deterioration that a curvilinear relationship would imply. The above results are more consistent with a view of AI as a scalable enhancer of information processing, which supports disclosure quality without evident adverse effects at higher adoption levels. Therefore, alternative hypothesis H1b could not be fully tested within this sample. Consequently, these results provide a compelling case for policymakers and managers to primarily encourage and support AI adoption, given its currently prominent positive influence on corporate disclosure. However, a stance of cautious vigilance is warranted regarding the potential emergence of noise effects as the technology evolves.

4.4. A quasi-natural experiment

The impact of AI adoption on corporate information disclosure behaviour may be influenced by endogeneity issues arising from other factors. Referring to prior studies (Huang et al., 2024), I employ a quasi-natural experiment based on the 'Artificial Intelligence Innovation Application Pilot Zone' (AIIAPZ) as a new research setting. Since 2019, China's Ministry of Industry and Information Technology has established AIIAPZs in 11 provinces and cities to encourage the development of AI, particularly promoting its integration with corporate growth. While selecting pilot cities for the AIIAPZ, policymakers primarily considered factors such as infrastructure, scientific and educational resources, industrial ecology and transportation. Besides, the policy was gradually implemented in different cities over several years so that leads to a high degree of randomness that satisfies the exogeneity assumption.

I employ the difference-in-differences (*DID*) method to assess the impact of AIIAPZ establishment on information disclosure. The variable Treat is used to distinguish the treatment and control groups: if firm i is located in an AIIAPZ, it is assigned to the treatment group with *Treat* taking a value of 1; otherwise, it is assigned to the control group with *Treat* equal to 0. *Post* is a dummy variable indicating the policy intervention period. If the region where firm i is located was deployed as an AIIAPZ in year t, *Post* takes a value of 1 for that year and all subsequent years; otherwise, it remains 0. Given the random timing of policy implementation, pilot zones

Table 5
AIIAPZ quasi-natural experiment.

Models	(1)	(2)
Dep. Vars	Precision	Readability
DID	5.034***	2.128***
	(5.22)	(4.32)
Controls	Yes	Yes
Constant	−34.037*	−48.123***
	(-1.87)	(-5.87)
Year	*Yes*	*Yes*
Firm	*Yes*	*Yes*
N	*43,114*	*43,114*
Adj. R^2	*0.439*	*0.579*

All specification controlled for Firm and Year fixed effect to handle the unobservable homogeneity in the time dimension. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

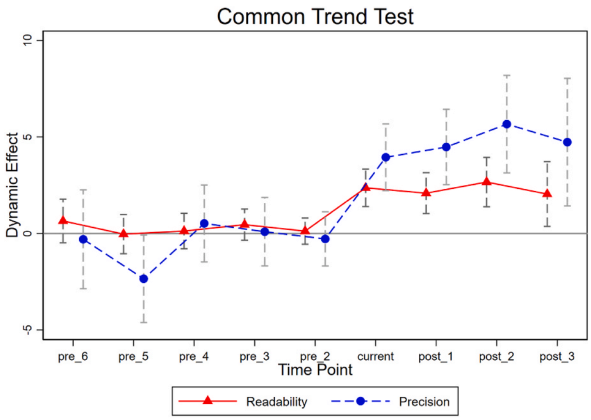

Fig. 1. Common Trend Test
Fig. 1 shows the β coefficient estimates and 95 % confidence intervals from the following regression model mentioned below, where i indicates firms and t indicates year. The β coefficients captures average treatment effect (ATT) estimates. Standard errors are clustered at the firm level.

launched in the first half of the year are considered effective from the beginning of that year, while those launched in the second half are treated as effective from the following year. The variable *DID* represents the interaction term between *Treat* and *Post*. Referring to the existing literature (Callaway, 2021), I employ robust DID model to estimate the weighted average treatment effects of AIIAPZ.

In order to exclude potential endogeneity issues, I drop samples that were listed in the AIIAPZ implementation region within three years prior to the pilot year. This is partly because of the inconsistent quality of information disclosure by newly listed firms, and partly due to the inherent lag in China's industrial policies. A prerequisite for being a pilot region may well be significant advancements in AI within that region over recent years. Since the model already controls for year- and firm-level fixed effects, I no longer focus on the estimated coefficients on *Treat* and *Post*, especially because of the strong covariance.

Table 5 reports the estimated results of AIIAPZ on firms' disclosure quality. In columns (1), the coefficient of *DID* on *Precision* is significantly positive ($\beta_1 = 5.034$, $t = 5.22$), which indicates that the pilot of AIIAPZ improves the accuracy of corporate information disclosure. In columns (2), the coefficient of *DID* is also significantly positive at the 1 % level ($\beta_1 = 2.128$, $t = 4.32$), which reveals that firms' AI adoption enhance the readability of their annual reports which is consistent with the hypothesis.

I further validate the trends of the above DID model prior to policy implementation by drawing time trend graphs. Specifically, I generate interaction terms between year and treatment group dummy variables and regress these interaction terms as explanatory variables.

As shown in Fig. 1, the confidence intervals of the estimated coefficients include zero before the policy intervention, whereas this is no longer the case after the policy implementation. This indicates that there were no significant differences between the treatment and control groups prior to the establishment of AIIAPZ. The DID design follows the basic rules on common trend.

Table 6
Instrumental variable.

Window	t ∈ [0,0]			t ∈ [-4,0]			t ∈ [-2,2]		
Dep. Vars	$Num\_AI_{i,t}$	Precision	Readability	$Num\_AI_{i,t}$	Precision	Readability	$Num\_AI_{i,t}$	Precision	Readability
Models	Stage 1	Stage 2	Stage 2	Stage 1	Stage 2	Stage 2	Stage 1	Stage 2	Stage 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RD	**11.898*** **			**57.208*** **			**40.995*** **		
	(4.39)			**(4.79)**			**(3.51)**		
$Num\_AI_{i,t}$		**3.452*** **	**3.021*** **		**0.718*** **	**0.628*** **		**1.001*** **	**0.877*** **
		(3.03)	**(3.83)**		**(3.27)**	**(4.22)**		**(2.72)**	**(3.19)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
CD-F	*76.56*			*143.93*			*67.75*		
KP-LM	*0.000*			*0.000*			*0.000*		
AR	*0.000*			*0.000*			*0.000*		
F	*19.26*			*22.94*			*12.33*		
Endogeneity	*0.000*			*0.001*			*0.000*		
N	*44,771*			*44,771*			*44,771*		

All specification controlled for Firm and Year fixed effect to handle the unobservable homogeneity in the time dimension. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

Table 7
Alternative measurement of AI adoption.

Dep.Vars	Precision			Readability		
Models	(1)	(2)	(3)	(4)	(5)	(6)
AI_Text	1.204***			0.443***		
	(4.14)			(3.22)		
AI_Invest		259.970***			98.714***	
		(4.71)			(3.72)	
AI_Robot			0.062*			0.033**
			(1.77)			(1.98)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−29.299*	−32.697*	−32.185*	−46.894***	−48.151***	−47.968***
	(-1.65)	(-1.86)	(-1.80)	(-5.82)	(-6.03)	(-5.94)
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	*44,771*	*44,771*	*44,771*	*44,771*	*44,771*	*44,771*
Adj. R^2	*0.449*	*0.449*	*0.448*	*0.614*	*0.614*	*0.613*

All specification controlled for Firm and Year fixed effect to handle the unobservable homogeneity in the time dimension. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

4.5. Instrumental variable: absorptive capacity

Corporate R&D investment helps develop a firm's absorptive capacity and enhance its R&D innovation capabilities (Cohen, 1990), thus promoting innovation in AI. However, as an element measured with accounting indicators, absorptive capacity may not directly affect the accuracy and readability of corporate annual reports. Therefore, it satisfies the assumptions of relevance and exogeneity when employing absorptive capacity as an instrumental variable. Following previous literature (Hsu et al., 2024), I use the ratio of corporate R&D expenditure to operating revenue (*RD*) to measure corporate absorptive capacity.

Table 6 reports the empirical results of instrumental variable. Specifically, I conduct 2SLS tests based on three different statistical windows of *Num_AI*. Columns (1), (4), and (7) report the first-stage regression results, where the estimated coefficients of *RD* on *Num_AI* are all significant at the 1 % level, which indicates that higher corporate absorptive capacity will promote firms' AI adoption. In the second-stage regression results, the estimated coefficients of *Num_AI* remain significantly positive and are consistent with the main results. These findings suggest that the positive impact of AI adoption on annual report disclosure quality is not subject to endogeneity concerns arising from reverse causality. I test another indicators of 2SLS regression. The F-values for each model are 19.26, 22.94, and 12.33, all of which are greater than 10, thus passing the weak instrumental variable test. The Cragg-Donald Wald F statistics for the instrumental variable are 76.56, 143.93, and 67.75, all exceeding the 10 % critical value threshold, so that passing weak identification test (Cragg & Donald, 1993; Stock & Yogo, 2005).The p-values of the Kleibergen-Paap rk LM statistic and the Anderson-Rubin Wald test are both less than 0.1, which means that the 2SLS results pass the under-identification test and weak-instrument-robust inference. Finally, p value of endogeneity test are less than 0.1 which indicates that *RD* are strictly exogenous.

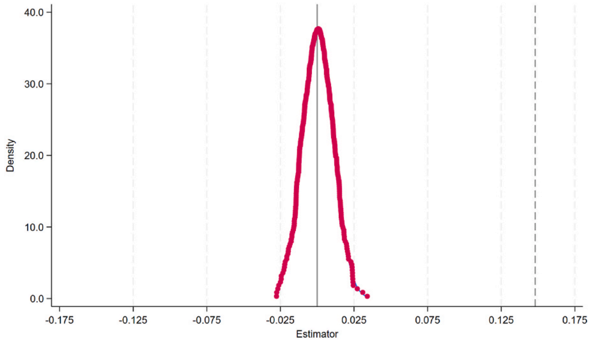

Fig. 2. Placebo Test
Fig. 2 presents the placebo test results after randomly reset value of independent variables and then regress for 500 times. It can be seen that the random sampling coefficient has a mean of 0 and exhibits an approximate normal distribution. In placebo test I also control for firm and year level fixed effect. Standard errors are clustered at the firm level.

Table 8
Lagged variables.

Dep. Vars	Precision	Readability	Precision	Readability	Precision	Readability
Window	t ∈ [0,0]		t ∈ [-4,0]		t ∈ [-2,2]	
Models	(1)	(2)	(3)	(4)	(5)	(6)
L.Num_AI$_{i,t}$	**0.125*****	**0.082*****	**0.049*****	**0.031*****	**0.039*****	**0.024*****
	(2.84)	**(3.93)**	**(3.10)**	**(4.19)**	**(2.99)**	**(4.34)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−29.970	−47.918***	−28.040	−46.777***	−29.732	−47.848***
	(-1.57)	(-5.52)	(-1.47)	(-5.39)	(-1.56)	(-5.50)
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	*39,083*	*39,083*	*39,083*	*39,083*	*39,083*	*39,083*
Adj.R^2	*0.531*	*0.675*	*0.531*	*0.676*	*0.531*	*0.675*

All specification controlled for Firm and Year fixed effect to handle the unobservable homogeneity in the time dimension. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

4.6. Alternative measurement of AI adoption

Although the number of AI patents could effectively reflect firms' innovation achievements in AI, it may not accurately reflect their AI adoption, especially for firms with only a single AI patent, thus the baseline regression model may overestimate its impact on financial reporting quality. Therefore, I employ three more types of variables to further measure AI adoption.

Referring to prior study (Cheng et al., 2025; Wu, 2025), I use the natural logarithm of the number of AI keywords in the MD&A section plus one as the first proxy variable (*AI_Text*). Then I use the proportion of AI-related intangible and fixed assets to total assets (*AI_Invest*) provided by the CSMAR database as the second proxy. Finally, referring to previous studies (Acemoglu, 2019; Chin et al., 2025), I employ the penetration rate of industrial robots (*AI_Robot*) as the third proxy.

Table 7 reports the empirical results with new independent variables. The coefficients of *AI_Text*, *AI_Invest* and *AI_Robot* are all significantly positive which indicates that firms' AI adoption could effectively improve the accuracy and readability of their annual report disclosures. Meanwhile, the results of baseline regression are also relatively robust.

4.7. Other robustness tests

First of all, I employ a placebo test referring to existing study (Cao, & Chen, 2022). Specifically, I randomly scramble the values of the independent variable Num_AI_{it} and then re-estimated model① 500 times. Fig. 2 reports the kernel density and p-values of the corresponding 500 regression estimate coefficients. The estimated coefficients of Num_AI_{it} are mostly concentrated around zero and show an approximate normal distribution and most of the estimated p-values are greater than 0.1, which exclude the possibility of the estimation results being obtained by chance. Therefore, the results pass the robustness test.

In addition, I lag the explanatory variable by one period and reduce the sample size. Specifically, I lag the explanatory variable *Num_AI* by one period and incorporate it into regression model ①. The estimated coefficient results are presented in Table 8. Regardless of the statistical window of *Num_AI*, its estimated coefficients with *Precision* and *Readability* are all significantly positive at the 1 % level.

Table 9
Mechanism test.

Panel A: Management Efficiency									
Dep. Vars	OR	Precision	Readability	OR	Precision	Readability	OR	Precision	Readability
Window	t ∈ [0,0]			t ∈ [-4,0]			t ∈ [-2,2]		
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Num\_AI_{i,t}$	**−0.000*****	**0.149*****	**0.070*****	**−0.000*****	**0.058*****	**0.034*****	**−0.000*****	**0.027****	**0.013*****
	(-4.12)	**(3.90)**	**(4.17)**	**(-4.30)**	**(4.26)**	**(5.38)**	**(-3.43)**	**(2.35)**	**(2.95)**
OR		2.274	−3.293*		2.770	−2.921		2.036	−3.396*
		(0.57)	(-1.80)		(0.69)	(-1.61)		(0.51)	(-1.86)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.469***	−31.226*	−45.451***	0.466***	−28.901	−43.909***	0.470***	−32.187*	−45.891***
	(8.94)	(-1.74)	(-5.58)	(8.87)	(-1.62)	(-5.39)	(8.96)	(-1.79)	(-5.63)
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	*44,771*	*44,771*	*44,771*	*44,771*	*44,771*	*44,771*	*44,771*	*44,771*	*44,771*
Adj.R^2	*0.745*	*0.511*	*0.657*	*0.745*	*0.511*	*0.658*	*0.745*	*0.510*	*0.657*
Panel B: Internal Control									
Dep. Vars	IC	Precision	Readability	IC	Precision	Readability	IC	Precision	Readability
Window	t ∈ [0,0]			t ∈ [-4,0]			t ∈ [-2,2]		
Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Num\_AI_{i,t}$	**0.353****	**0.146*****	**0.070*****	**0.155*****	**0.057*****	**0.034*****	**0.088***	**0.026****	**0.013*****
	(2.13)	**(3.84)**	**(4.19)**	**(2.98)**	**(4.20)**	**(5.39)**	**(1.76)**	**(2.30)**	**(2.97)**
IC		0.006***	0.002***		0.006***	0.002***		0.006***	0.002***
		(8.12)	(6.08)		(8.04)	(5.98)		(8.15)	(6.10)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−1452.534***	−21.518	−43.912***	−1445.040***	−19.102	−42.263***	−1454.325***	−22.546	−44.386***
	(-9.85)	(-1.21)	(-5.36)	(-9.81)	(-1.07)	(-5.16)	(-9.86)	(-1.26)	(-5.42)
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	*44,771*	*44,771*	*44,771*	*44,771*	*44,771*	*44,771*	*44,771*	*44,771*	*44,771*
Adj.R^2	*0.348*	*0.512*	*0.658*	*0.348*	*0.512*	*0.659*	*0.348*	*0.511*	*0.657*

All specification controlled for Firm and Year fixed effect to handle the unobservable homogeneity in the time dimension. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

Finally, I conduct additional robustness tests: I. Excluding samples from 2020 to 2022 that were affected by the public health crisis. II. Excluding samples from 2018 due to the impact of the U.S.-China trade conflict. III. Further controlling for provincial fixed effects based on regression model ①. Those tests all prove that the main results are reliable.

5. Mechanism tests

I propse two mechanisms to support the argument that firms' AI adoption will influence their disclosure behaviour. Specifically, I further test the plausibility of these two mechanisms with Models②and Models③identifying the effect of the independent variables on the mechanism variable and the change in the initial treatment effect after adding the mechanism variable.

5.1. Management efficiency

I firstly employ managerial efficiency to measure the level of corporate governance. Specifically I use overhead rate (*OR*) which is calculated as ratio of management expenditures divided by revenue (Ang et al., 2000).

Panel A of Table 9 reports the mediation effect of *OR* between AI adoption and disclosure quality of MD&A. The estimated coefficients of *OR* in column (1), (4) and (7) are all significantly negative even though the absolute effect is slight ($\beta_1 = -0.000$, t = 4.12 & 4.30 & 3.43), which indicates that the AI adoption could decrease management cost level of public firms and improve management efficiency as well. Meanwhile the coefficients of *Num_AI* on *Precision* and *Readability* are still significantly positive while *OR* had been controlled. The above results imply AI adoption of public firms could enhance disclosure quality through improving the level of corporate governance.

5.2. Internal control

Previous research has found that automation can improve financial reporting quality by strengthening internal controls (Musaib, 2025). As a cutting-edge achievement in the development of digital technology, artificial intelligence encompasses technologies such as automation and digitization. Therefore, it can enhance internal controls, thereby improving the quality of information disclosure. Then I define the other proxy from the prospect of internal control and I use the Index of internal control (*IC*) issued by DIB database to define it according to the previous study (Hu et al., 2024).

Panel B of Table 9 reports results of internal control as a proxy. Within time window [0,0] the number of AI patents could effectively improve internal control at 5 % level significance ($\beta_1 = 0.353$, t = 2.13). The coefficients of *Num_AI* on *IC* are still significant at 1 % and 10 % level respectively within time window [−4,0] and [−2,2]. After controlling *IC* in the regression model the coefficients of *Num_AI* on *Precision* and *Readability* are still significant at 1 % and 5 % level which indicates that *IC* plays a partial mediator role between AI adoption and disclosure quality.

The above empirical results fully confirm the rationality and feasibility of the two channels, namely, strengthening internal control and enhancing management efficiency. Within the framework of agency theory and information economics, effective incentives and supervision mechanisms help to mitigate information asymmetry. Therefore, corporate AI adoption could improve the disclosure quality of annual reports by enhancing the supervision and incentive of information supply activities. This result is consistent with the basic logic of agency theory and supports hypothesis H1a as well.

6. Further analysis

6.1. Disclosing capability: relevance of AI patents

The extent to which technology can be practically applied to a company's daily operations determines the impact on information disclosure practices. When a company's AI patents are closely related to its core business, the technology significantly enhances production and management efficiency, which in turn positively influences the quality of information disclosure by management. Vice versa.

I determine whether patents are related to a company's core business through the following steps: First, I used the Latent Semantic Analysis (LSA) model to calculate the text similarity between patent abstracts and the company's main business activities. Using a threshold of 0.5, I randomly select 1000 patents from AI patent samples of public firms between 2000 and 2023 using simple random sampling. Based on the actual relevance between patent abstracts and business activities, I manually label the relevance of these 1000 patents to business and management activities as the initial training text (Text1) for machine learning. Next, based on the initial training text (Text1), I apply the Torch-BERT model for machine learning to label all AI-related patents from 1995 to 2010, creating the training set (Text_trained). The relevance label rationality and accuracy were manually verified. Furthermore, based on the trained database (Text_trained), I perform multiple rounds of self-supervised machine learning training. After each round of training, I use a validation set to check the accuracy of the labels to ensure the quality of the labeling. If the validation set results met expectations, the model progressed to the next training round; if the results were unsatisfactory, adjustments were made, and retraining was conducted. The final labeled target set is Text_Target.

Table 10
Heterogeneity analysis - patent relevance.

Panel A: Dependent Variable = Precision

Dep. Vars	Precision					
Group	More Relevant			Less Relevant		
Window	t ∈ [0,0]	t ∈ [-4,0]	t ∈ [-2,2]	t ∈ [0,0]	t ∈ [-4,0]	t ∈ [-2,2]
Models	(1)	(2)	(3)	(4)	(5)	(6)
$Num\_AI_{i,t}$	0.107**	0.044***	0.025*	0.123*	0.052*	0.031
	(2.42)	(2.71)	(1.93)	(1.78)	(1.89)	(1.30)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−48.474	−35.943	−48.750	−1.430	2.205	−1.770
	(-0.96)	(-0.72)	(-0.97)	(-0.02)	(0.03)	(-0.03)
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Fisher's P	*0.100*					
N	*6363*			*6152*		
Adj.R^2	*0.609*	*0.610*	*0.609*	*0.648*	*0.649*	*0.648*

Panel B: Dependent Variable = Readability

Dep. Vars	Readability					
Group	More Relevant			Less Relevant		
Window	t ∈ [0,0]	t ∈ [-4,0]	t ∈ [-2,2]	t ∈ [0,0]	t ∈ [-4,0]	t ∈ [-2,2]
Models	(1)	(2)	(3)	(4)	(5)	(6)
$Num\_AI_{i,t}$	0.060***	0.029***	0.015***	0.055*	0.028**	0.017*
	(2.96)	(4.01)	(2.76)	(1.84)	(2.03)	(1.68)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−76.779***	−67.314***	−76.280***	−56.840**	−54.872*	−56.973**
	(-3.30)	(-2.92)	(-3.28)	(-1.97)	(-1.88)	(-1.97)
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Fisher's P	*0.300*					
N	*6363*			*6152*		
Adj.R^2	*0.719*	*0.721*	*0.719*	*0.755*	*0.755*	*0.755*

All specification controlled for Firm and Year fixed effect to handle the unobservable homogeneity in the time dimension. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

I calculate the weighted average of patent relevance for each public firm based on the number of AI patents filed by public firms each year, and then divided the sub-sample according to the annual-industry median. Since this indicator does not exist for firms without AI patents, I exclude the observations of firms without AI patents.

Table 10 reports the results of the heterogeneity test. In the "More Relevant" sub-sample, the coefficients of Num_AI with respect to Precision are significantly positive at the 5 %, 1 %, and 10 % levels, respectively. In contrast, the coefficient in the "Less Relevant" sub-sample is only significant at the 10 % level, especially when the time window for Num_AI is [−2,2], where the estimated coefficient is not significant. Additionally, in the "More Relevant" sub-sample, the coefficients of Num_AI with respect to Readability are significantly positive at the 1 % level, while in the "Less Relevant" sub-sample, they are significantly positive at the 5 % and 10 % levels.

This suggests that when the AI patents of public firms are more relevant to their core business, AI technology has a stronger positive impact on the firm's operations and information disclosure quality. This result also reveals that firms should not only pursue a quantity advantage in AI innovation but also consider the practicality and applicability.

6.2. Disclosing costs: market monopoly power

According to previous studies (Nathan et al., 2021), information disclosure with high proprietary costs may lead to the loss of competitive advantage for firms. Therefore, a firm's market power may play a moderating role between AI adoption and the quality of information disclosure.

I use the Lerner index to measure the market power of firms, which is calculated as (revenue - operating costs - selling expenses - administrative expenses) divided by revenue. I divide the sample into two sub-samples based on the industry-year median and then perform regression according to Model (1). The empirical results are shown in Table 11.

In the "More Monopoly Power" group, the estimated coefficients for *Num_AI* and *Precision* are significantly positive at the 5 % level only within the time window [−4, 0]. When the time windows are [0, 0] and [−2, 2], the coefficients for *Num_AI* and *Precision* are not significant. When the time windows are [0, 0] and [−4, 0], the coefficients for *Num_AI* and *Readability* are significantly positive at the 5

Table 11
Heterogeneity analysis - market power.

Panel A: Dependent Variable = Precision						
Dep. Vars	Precision					
Group	More Monopoly Power			Less Monopoly Power		
Window	t ∈ [0,0]	t ∈ [-4,0]	t ∈ [-2,2]	t ∈ [0,0]	t ∈ [-4,0]	t ∈ [-2,2]
Models	(1)	(2)	(3)	(4)	(5)	(6)
$Num\_AI_{i,t}$	0.083	0.037**	0.002	0.175***	0.069***	0.042***
	(1.55)	(1.97)	(0.11)	(3.45)	(4.10)	(2.58)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−61.163*	−58.303*	−63.521**	−8.228	−6.793	−8.752
	(-1.90)	(-1.80)	(-1.97)	(-0.34)	(-0.28)	(-0.36)
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Fisher's P	*0.000****					
N	*21,360*			*22,265*		
Adj.R^2	*0.565*	*0.566*	*0.565*	*0.547*	*0.547*	*0.546*
Panel B: Dependent Variable = Readability						
Dep. Vars	Readability					
Group	More Monopoly Power			Less Monopoly Power		
Window	t ∈ [0,0]	t ∈ [-4,0]	t ∈ [-2,2]	t ∈ [0,0]	t ∈ [-4,0]	t ∈ [-2,2]
Models	(1)	(2)	(3)	(4)	(5)	(6)
$Num\_AI_{i,t}$	0.053**	0.027***	0.004	0.055***	0.032***	0.016***
	(2.18)	(3.05)	(0.67)	(2.61)	(4.47)	(2.99)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−78.601***	−76.233***	−79.790***	−18.527*	−17.804*	−18.702*
	(-5.20)	(-5.03)	(-5.28)	(-1.77)	(-1.69)	(-1.78)
Year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Fisher's P	*0.000****					
N	*21,360*			*22,265*		
Adj.R^2	*0.693*	*0.693*	*0.693*	*0.677*	*0.678*	*0.677*

All specification controlled for Firm and Year fixed effect to handle the unobservable homogeneity in the time dimension. T-statistics based on standard errors clustered at the industry level are shown in parentheses below the coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively.

% and 1 % levels, respectively. In contrast, in the "Less Monopoly Power" group, the coefficients of *Num_AI* with respect to *Precision* and *Readability* are both significantly positive at the 1 % level. Although the coefficient of *Num_AI* in the time window [−4,0] remains significant at the 1 % level in both sub-samples, its coefficient and t-value are higher in the "Less Monopoly Power" group. I conduct a Fisher's permutation test with 1000 times of sampling for the difference in coefficients between the groups, and the empirical p-value is significant at the 1 % level.

The above results indicate that when a company has stronger market power, it enjoys greater competitive advantages and disclosure costs. In such cases, the management's motivation to improve the quality of information disclosure is weaker, and thus the impact of AI adoption on enhancing disclosure is relatively smaller. In contrast, when market power is weaker, the external competitive environment becomes more intense, giving management a stronger incentive to use AI technology to improve the quality of information disclosure.

7. Conclusions and recommendations

Since the introduction of the concept of artificial intelligence in the 1950s, AI has gained widespread adoption across various industries, creating tremendous opportunities for society and generating substantial value. Evidence indicates that AI serves as a key information-processing facilitator within developed capital markets, substantially enhancing productivity in information dissemination and communication (Bertomeu et al., 2025). However, in emerging capital markets, the influence of AI on information supply remains ambiguous. In particular, under conditions of insufficient regulatory oversight, how companies utilize AI to shape their information disclosure practices remains an important question that warrants further investigation. As the world's second-largest economy and the largest emerging market, China's A-share listed firms provide an appropriate context to explore this issue.

I examine the impact of listed firms' adoption of artificial intelligence (AI) on the quality of their annual report disclosures. Using AI patents as a proxy for firms' AI adoption levels, I find that AI adoption significantly improves disclosure accuracy and textual readability in the MD&A section of annual reports, which demonstrates the governance effect of AI adoption on mandatory corporate disclosure. However, the non-linear relationship test cannot provide sufficient evidence for the noise effect. I also investigate the underlying mechanisms through which AI influences firms' information processing activities. Specifically, the findings indicate that AI adoption substantially enhances the efficiency of internal information processing and decision-making, while also strengthening oversight within internal information management processes. Lastly, I conduct heterogeneity analyses from the perspectives of firms' disclosure capacity and associated costs. The results show that the positive effects of AI adoption on disclosure quality are more pronounced when there is a stronger alignment between firms' AI technology and managerial activities, and when firms possess weaker market power. Robustness checks, including difference-in-differences approaches, further confirm the validity of the results.

According to the above conclusions, I propose the following policy recommendations. Firstly, firms should be encouraged to use AI orderly. The government could provide subsidies or tax incentives to guide firms, particularly those with weaker disclosure capabilities and lower market status, to integrate AI deeply with management routines and optimize internal information processing. Secondly, the regulatory framework for disclosure should be enhanced to align with AI adoption. Capital market regulators should clarify management responsibilities for information generated or co-generated by AI, strengthen internal control supervision requirements, guard against novel risks arising from potential misuse of the technology, and ensure that AI adoption genuinely enhances rather than compromises information quality. Moreover, the government should guide firms whose AI patents are disconnected from their business operations to focus on AI innovations relevant to their core activities, so as not to blindly pursue intelligent technologies.

However, this paper only provides a preliminary exploration of the relationship between artificial intelligence and information disclosure quality. On one hand, while annual report texts constitute the main content of mandatory disclosures, further research is necessary to examine whether AI's positive effects on information disclosure quality can extend to voluntary disclosure contexts. On the other hand, whether AI adoption exerts a long-term impact remains an open question for future inquiry. Finally, subsequent research should delve deeper into the progressive relationship between artificial intelligence and digitization, aiming to better distinguish between these two streams of literature.

$$Depvar_{i,t} = \alpha + \beta_1 DID_{i,t} + \beta_2 Controls_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t}$$

Acknowledgments

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The author would like to thank the editor and anonymous reviewers for their valuable comments.

Appendix A: AI Patent Categories and Annual Statistics

Year	Number of AI Patents			Num. Public Firms			Relevance		
	Invention Disclosure	Invention Grant	Utility Model	Total	Num. Firms with AI Patents	Aver. AI patents	Rel	Non. Rel	Per%
2010	5968	2942	2213	11123	554	20.078	6122	5001	55.04 %
2011	6362	3089	2427	11878	729	16.294	6125	5753	51.57 %
2012	6296	3248	2785	12329	843	14.625	6609	5720	53.61 %
2013	7257	3367	2909	13533	921	14.694	7049	6484	52.09 %
2014	9500	4249	3171	16920	1051	16.099	8332	8588	49.24 %
2015	11331	4805	3557	19693	1137	17.320	9652	10041	49.01 %
2016	14629	5926	4239	24794	1341	18.489	11854	12940	47.81 %
2017	14778	6690	4519	25987	1538	16.897	12773	13214	49.15 %
2018	17509	8007	4772	30288	1669	18.147	14778	15510	48.79 %
2019	22941	9835	5410	38186	1849	20.652	18530	19656	48.53 %
2020	31611	10336	7008	48955	2047	23.915	24687	24268	50.43 %
2021	41604	7230	6870	55704	2135	26.091	28632	27072	51.40 %
2022	53973	3354	6800	64127	2260	28.375	33103	31024	51.62 %
2023	46920	1840	4972	53732	2192	24.513	27431	26301	51.05 %
Total	290679	74918	61652	427249	20266	21.082	215677	211572	50.48 %

Appendix B: Examples of Fuzzy and Complex Words

Fuzzy Words	Complex Words
很(very)	现金流(Cash Flow)
差不多(almost)	资本化(Capitalization)
一些(some)	资本比率(Capital Ratio)
几个(several)	资本结构(Capital Structure)
许多(many)	提前赎回条款(Call Provision)
左右(around)	累计折旧(Accumulated Depreciation)
很久(long)	应计项目(Accrued Items)
马上(soon)	应付账款(Accounts Payable)

(*continued on next page*)

(*continued*)

Fuzzy Words	Complex Words
附近(nearby)	企业内部责任(Internal Responsibility)
旁边(beside)	企业合并(Business Combination)
周围(around)	企业兼并(Merger & Acquisition, M&A)
可能(possibly)	账面价值(Book Value)
大概(roughly)	账面损失(Book Loss)
也许(perhaps)	账面收益(Book Profit)
似乎(seems)	应付债券(Bonds Payable)

Appendix C: Variable Definition

Variable	Definition
Dep. Vars	
Precision	The reciprocal of the word frequency ratio of fuzzy words in MD&A chapters of annual reports.[CSMAR]
Readability	The reciprocal of the word frequency ratio of complex words in MD&A chapters of annual reports.[CSMAR]
Indep. Vars	
$Num\_AI_{i,t}$	The weighted cumulative number of AI-related patents registered by a firm i in a specific time window t. In total, I use three different time windows to count the number of AI patents: I. [0,0], the year of registration; II. [-4, 0], past 5 years of the registration; and III. [-2, 2], from past two years to the after two years of registration.[CNIPA]
Control. Vars	
Age	The difference of reporting year and listed year of the firms.[WIND]
EPS	The ratio of net profit divided by paid-in capital.[WIND]
TOP1	Percentage of shareholding of the largest shareholder (%).[CSMAR]
Separation	Difference between control and ownership of listed companies by beneficial owners.[CSMAR]
Dual	One if the Chairman of the Board of Directors is also the Managing Director, zero otherwise.[CSMAR]
Indep	The ratio of number of independent directors divided into number of all directors.[CSMAR]
Growth	Year-over-year growth rate of operating income.[WIND]
Lev	The ration of total liability divided into total assets.[WIND]
ROA	Net income for frm i's year t scaled by total assets for the same frm-year.[WIND]
Size	The log of the market value of total assets.[WIND]
MB	The market-to-book ratio.[CSMAR]
Tobin	Market Capitalization/Total Assets. Market capitalization = RMB ordinary A shares * today's closing price of A shares at the end of the period + domestically listed foreign shares B shares * today's closing price of B shares at the end of the period * exchange rate on that day + (total shares - RMB ordinary A shares - domestically listed foreign shares B shares) * (total owners' equity at the end of the period/paid-in capital at the end of the period) + total liabilities at the end of the period.[CSMAR]

Appendix D: Pearson Correlation Matrix

	I.Precision	II.Readability	III.Num AI[0,0]	IV.Num AI[-4,0]	V.Num AI[-2,2]	VI.Age	VII.EPS	VIII.TOP1	XI.Separation	X.Dual	XI.Indep	XII.Growth	XIII.Lev	XIV.ROA	XV.Size	XVI.MB	XVII.Tobin
I	**1**																
II	**0.549*****	**1**															
III	**0.160*****	**0.159*****	**1**														
IV	**0.163*****	**0.167*****	**0.924*****	**1**													
V	**0.153*****	**0.137*****	**0.950*****	**0.943*****	**1**												
VI	0.052***	-0.152***	-0.037***	-0.027***	-0.033***	1											
VII	0.065***	0.104***	0.104***	0.083***	0.106***	-0.135***	1										
VIII	-0.015***	-0.048***	-0.033***	-0.045***	-0.032***	-0.069***	0.131***	1									
IX	-0.008	-0.019***	-0.022***	-0.027***	-0.022***	0.097***	0.037***	0.168***	1								
X	-0.020***	0.111***	0.044***	0.043***	0.040***	-0.254***	0.038***	-0.045***	-0.065***	1							
XI	-0.016***	0.013***	0.037***	0.041***	0.036***	-0.013***	0.007	0.035***	-0.073***	0.103***	1						
XII	0.028***	0.006	0.016***	0.006	0.025***	-0.107***	0.249***	-0.011**	-0.007	0.034***	-0.009*	1					
XIII	0.074***	-0.126***	0.001	0.001	0.008	0.354***	-0.152***	0.001	0.045***	-0.169***	-0.015***	0.011**	1				
XIV	-0.005	0.023***	0.046***	0.024***	0.050***	-0.223***	0.725***	0.166***	0.028***	0.058***	-0.018***	0.281***	-0.379***	1			
XV	0.185***	0.029***	0.159***	0.157***	0.166***	0.375***	0.199***	0.133***	0.069***	-0.194***	-0.004	0.010**	0.497***	-0.039***	1		
XVI	0.028***	-0.001	-0.024***	-0.026***	-0.023***	0.152***	-0.059***	0.120***	0.040***	-0.109***	-0.026***	-0.116***	0.297***	-0.208***	0.525***	1	
XVII	0.006	-0.020***	0.028***	0.031***	0.029***	0.036***	0.021***	-0.137***	-0.021***	0.039***	0.039***	0.097***	-0.182***	0.112***	-0.323***	-0.713***	1

Data availability

Data will be made available on request.

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