Research On the Impact of Artificial Intelligence on Corporate Earning Management

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Abstract. With the widespread integration of artificial intelligence (AI) into enterprise management, its impact on corporate financial behaviour—particularly earnings management—has garnered growing scholarly interest. This study employs panel data from A-share non-financial listed firms in Shanghai and Shenzhen (2005–2024) to empirically examine how AI-related discourse in annual reports influences Real Activities Manipulation (RM) and Accrual-Based Earnings Management (AM). Utilizing text analysis and fixed-effect panel regressions, the findings reveal that higher frequency of AI-related terms corresponds to more convergent RM behaviours, suggesting that digital strategy expressions may exert normative constraints on managerial financial decisions. For AM, while the influence of AI discourse is not statistically significant, a weak negative association emerges, implying a potential inhibitory effect. Furthermore, control variables such as audit quality, cash flow status, and profitability demonstrate consistent and significant effects across both models. These results highlight the moderating role of AI language embeddedness in shaping corporate earnings management practices. The study offers theoretical contributions to the discourse on digital governance and practical implications for improving financial disclosure, enhancing regulatory foresight, and guiding AI-informed corporate strategy.

1 Introduction

Relying on its technical advantages in data analysis, process automation, and predictive modelling, AI has gradually penetrated key management links such as finance, accounting, and auditing. AI technology not only improves the efficiency of decision-making and resource allocation but also shows significant potential in improving the financial transparency and reporting quality of enterprises [1].

At the same time, as an important part of enterprise management, earnings management has attracted continuous attention from the academic community. On the one hand, enterprises can achieve legal profit adjustment through earnings management to meet the purposes of contract performance, tax burden planning or information transmission. On the other hand, excessive or malicious earnings manipulation can undermine the reliability of financial reporting and investor trust. In the context of accelerating digital transformation, the means and motivations of corporate earnings

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management have undergone profound changes, and the application of digital tools has not only improved financial transparency but also compressed the earnings manipulation space [2].

In this context, whether AI can inhibit earnings management behaviour to a certain extent by improving the information quality and audit verifiability of enterprises has become an important topic worthy of in-depth discussion. Previous studies have explored the impact path of AI on earnings management drivers from the dimensions of R&D capitalization and government subsidies and preliminarily revealed the theoretical possibilities of AI in influencing earnings management motivations and behavioural mechanisms [3]. In addition, AI can improve the audit quality and the accuracy of audit opinions through audit process automation and risk assessment models, thereby restricting earnings manipulation [4].

However, there are still some gaps in the current research on AI and earnings management. First, most of the research focuses on the impact of AI on macro governance or accounting system and lacks systematic evidence at the micro level. Second, the heterogeneous paths of AI for different types of earnings management (such as Real Activities Manipulation and Accrued-Based Earnings Management) have not yet been distinguished. Therefore, this paper intends to extract the frequency of AI-related words from corporate text disclosure as a proxy variable and combine the fixed-effect regression model to empirically test the impact of AI embeddedness on corporate earnings management behaviour.

The goal of this study is to systematically identify the degree to which AI technology is embedded in the financial context, and whether it can have a constraining or incentive effect on true earnings management (RM) and Accrued-Based Earnings Management (AM) by enhancing the verifiability and audit quality of corporate financial information. The research can not only deepen our understanding of the AI-finance intersectional mechanism but also provide policy recommendations for regulators and corporate managers and improve the transparency of information disclosure and the efficiency and standardization of earnings management.

2 Literature review and hypotheses development

2.1 The impact of AI on Real Activities Manipulation

In the context of the deep integration of digital economy and intelligent governance, the embedding of artificial intelligence technology in the financial and operation systems of enterprises has significantly reconstructed the motivation and realization path of traditional earnings management. On the one hand, AI-enabled digital transformation has improved the transparency of corporate financial and operational information, reshaped the information collaboration and responsibility structure between internal organizations, and made management face higher exposure risks when implementing true earnings management, thereby reducing the room for manipulation [5].

On the other hand, the digital economy not only improves the internal control environment of enterprises, but also effectively alleviates the resource constraints of management in the face of external financing pressure, and the structural optimization of this governance environment reduces the incentive for managers to rely on actual business activities to manipulate earnings [6]. Therefore, the two studies together show that artificial intelligence, as the core force of digital governance, is systematically inhibiting the Real Activities Manipulation behaviour of enterprises through the path of "improving transparency, strengthening control mechanism, and alleviating manipulation motivation".

H1: The extent to which the use of AI inhibits Real Activities Manipulation

2.2 The impact of AI on Accrued-Based Earnings Management:

The wide application of artificial intelligence in corporate financial management has effectively weakened the subjective operation space of management in accounting estimation and policy choice by improving the automation degree of accounting information processing, standardizing the accounting process, strengthening the internal control system and reconstructing the structure of financial job responsibilities, thereby forming a substantial constraint on the Accrued-Based Earnings Management [7]. Specifically, AI technology improves financial transparency and traceability through the standardization of data processing and the proceduralizing of processes, making earnings manipulation easier to identify. At the same time, the dehumanization of posts and the decentralization of control further reduce the possibility of collaborative control. Therefore, the embedding of artificial intelligence not only improves the efficiency of financial governance at the technical level, but also enhances the prevention and control ability of Accrued-Based Earnings Management at the institutional level

H2: The extent to which the use of AI inhibits Accrued-Based Earnings Management

3 Data and methodology

The sample selects non-financial and non-ST companies in Shanghai and Shenzhen A-shares from 2005 to 2024

3.1 Dependent variables: Real Activities Manipulation *(RM)* measurement

3.1.1 Estimate $PROD_t$ and $AbPROD_t$

There are two approaches to calculate Real Activities Manipulation [8].

The first approach is to over-produce inventory, i.e., produce goods that far exceed the actual sales demand, so that fixed costs are spread over more products, short-term inventory unit costs are lowered, and reported profits are higher.

$$COGS_t/A_{t-1} = \alpha_0 + \alpha_1(1/A_{t-1}) + \alpha_2(S_t/A_{t-1}) + \varepsilon_t \quad (1)$$

$COGS_t$ is the cost of the main business. A_{t-1} is the total asset of the company at the end of the previous year, which is used to standardize the data and facilitate comparison between enterprises. ε_t reflects the deviation between the actual cost of the main business and the normal cost of the main business, and represents the abnormal cost of the main business.

For the cost of the main business $COGS_t$, When the inventory is sold, the revenue is recognized immediately, so it is affected by the main business income of the year S_t. $1/A_{t-1}$ is the reciprocal term of the total asset, which captures the non-linear impact of asset size on cost changes. If this option is not set, due to economies of scale, the fixed costs of large firms are allocated to the cost of each commodity lower, and the model will mistakenly think that the abnormal costs of large firms ε_t lower, while small-scale businesses have unusual costs ε_t higher, making the model less interpretable.

$$\Delta INV_t/A_{t-1} = \alpha_0 + \alpha_1(1/A_{t-1}) + \alpha_2(\Delta S_t/A_{t-1}) + \alpha_3(\Delta S_{t-1}/A_{t-1}) + \varepsilon_t \quad (2)$$

ΔINV_t represents the increase in inventory of the enterprise in the current year, that is, the increase or decrease in the inventory of the current year compared with the previous year. ε_t reflects the deviation between the actual inventory increase of the enterprise and the normal inventory increase predicted according to the trend of sales revenue, and represents the abnormal inventory increase. For inventory changes ΔINV_t, A company's inventory is usually affected by changes in sales during the year ΔS_t and the change in sales of the previous year ΔS_{t-1}, because companies tend to rationalize inventory production and storage based on current and historical sales trends.

Combining the above models results in the following model:

$$PROD_t/A_{t-1} = \alpha_0 + \alpha_1(1/A_{t-1}) + \alpha_2(S_t/A_{t-1}) + \alpha_3(\Delta S_t/A_{t-1}) + \alpha_4(\Delta S_{t-1}/A_{t-1}) + \varepsilon_t \quad (3)$$

Normal Production Costs in Model $PROD_t$ represents the cost of sales in the t year plus the increase in inventory compared to the previous year. The model regards the normal production cost as a linear function of the main business income of the current year and the increase of the main business income of the current year compared with the previous year, and regresses by year and industry. The value of the residual ε_t estimated by the model is the abnormal production cost $AbPROD_t$, the higher the value indicates the tendency of the firm to manage the Real Activities Manipulation by expanding production, etc.

3.1.2 Estimate $DISX_t$ and $AbDISX_t$

This study estimates the normal discretionary expenditures as follows [8]:

$$DISX_t/A_{t-1} = \alpha_0 + \alpha_1(1/A_{t-1}) + \alpha_2(S_{t-1}/A_{t-1}) + \varepsilon_t \quad (4)$$

$DISX\text{-}t$ represents the discretionary expenditure of the enterprise in the T year, including sales, management, research and development, financial expenses and other expenditures that are of positive significance to the long-term development of the enterprise. The controllable expenses of the enterprise usually depend on the business scale and profitability of the enterprise in the previous year, so the standardized variables of sales revenue in the previous year (S_{t-1}/A_{t-1}) are introduced in the model to reflect the impact of the size of the enterprise on the controllable expenses of the year. ε_t reflects the deviation between the actual discretionary expenditure of the enterprise and the normal discretionary expenditure, representing the abnormal inventory increase $AbDISX_t$

3.1.3 Estimate the level of Real Activities Manipulation RM_t

The residuals derived from the first two major regression models are set as Abnormal Production Cost $AbPROD_t$ and Abnormal Discretionary Expenditure $AbDISX_t$, respectively. Since companies that engage in Real Activities Manipulation usually have higher levels of abnormal production costs and lower levels of abnormal discretionary expenditures, they can be used as proxy variables for true earnings management [9]. The research can construct a composite variable for Real Activities Manipulation RM_t.It will multiply $AbDISX_t$ by (-1) so the management direction is consistent. And the $(-AbDISX_t)$ and $AbPROD_t$ are added together to find RM_t.

$$RM_t = AbPROD_t + (-1)AbDISX_t \tag{5}$$

3.2 Dependent variables: Accrual-based Earnings Management（AM）measurement

Accrual-based Earnings Management (AM) is the behaviour of an enterprise to adjust the reported profit by manipulating accounting estimates, accounting policies or recognition points within the scope permitted by accounting standards without changing actual business activities. The calculation is mainly based on the difference between accrued profit and operating cash flow, and $Normal\ Accurals_t$ is often estimated by the model. $Normal\ Accurals_t$ subtracts the "total accrual" equals to the "abnormal accrual" $AbTACC_t$, which is an estimate of the level of earnings management [10].

3.2.1 Estimate $Total\ Accurals_t$

$$Total\ Accurals_t = Net\ Income_t - CFO_t \tag{6}$$

3.2.2 Estimate $Normal\ Accurals_t$ *and* $AbTACC_t$

$$\frac{Normal\ Accurals_t}{A_{t-1}} = \alpha_0 + \alpha_1\left(\frac{1}{A_{t-1}}\right) + \alpha_2\left(\frac{\Delta S_t}{A_{t-1}}\right) + \alpha_3(-\Delta TR_t/A_{t-1}) + \alpha_4(PPE_t/A_{t-1}) + \varepsilon_t \tag{7}$$

3.2.3 Estimate AM_t

ε_t reflects the deviation $AbTACC_t$ between the total accrued earnings of the enterprise and the management of the normal accrued earnings, which represents the degree of abnormal earnings management. The model finds the level of the Accrued-Based Earnings Management of the enterprise, AM_t is:

$$AM_t = AbTACC_t \tag{8}$$

3.3 Independent variable: *RobetFreq_z*

The frequency of AI occurrence in the annual reports of listed companies is taken as the degree of AI use $RobetFreq\_z$ (Text indicator standardized by Z-score).

3.4 Select controllable variables

AUD_t is used to measure whether the audit institution hired by the enterprise has a high audit quality. Specifically, if the company's annual financial report is issued by the "top 10 firms", it will be recorded as 1, otherwise it will be 0. The introduction of such dummy variables aims to control the constraining effect of audit quality on earnings management behaviour.

In terms of company characteristics, ROA_{it} is the return on total assets, and a higher ROA usually means that the company is in good operating condition and the quality of earnings is higher.

For the company's financial leverage LEV_{it}, a higher level of leverage is often accompanied by stronger debt repayment pressure, which may motivate the company to adjust its financial performance through earnings management to avoid contractual risks (such as breach of loan agreement, debt default clause, etc.).

Set operating cash flow CFO_{it}/A_{it-1}. Cash flow is more difficult to manipulate through accounting operations than profits, so the introduction of this variable controls the impact of company performance.

4 Empirical results

According to Xiang Hao's (2019) research, many scholars use earnings quality to measure audit quality.

4.1 The impact of artificial intelligence on Real Activities Manipulation

After the maturity of the measurement model of earnings quality, many scholars use Real Activities Manipulation and Accrued-Based Earnings Management quality to measure audit quality, so this paper also sets up the following Real Activities Manipulation *(RM)* regression equation to explore, regression by year and industry dimension, and regression by fixed-effect model:

$$RM_{\mathrm{it}} = \alpha_0 + \alpha_1 RobotFreq_{z_{\mathrm{it}}} + \alpha_2 AUD_{\mathrm{it}} + \alpha_3 ROA_{\mathrm{it}} + \alpha_4 LEV_{\mathrm{it}} + \alpha_5 \frac{CFO_{\mathrm{it}}}{A_{\mathrm{it}-1}} + Industry_t + Year_i + \varepsilon_{\mathrm{it}} \quad (9)$$

4.1.1 RM_{it} model regression results

The model yields the following results.

Table 1. RM_{it} Model Regression results

	Regression Coefficient	Standard Deviation
RobetFreq_z	-0.015***	0.002
AUD	-0.009***	0.002
ROA	-0.349***	0.046
LEV	0.054***	0.007
CFO_A	-0.644***	0.083
Constant	0.030***	0.004
Observations	38833	
R-squared	0.186	
Adjusted R-squared	0.185	

According to the results in Table 1, the regression coefficient of *RobotFreq_z* is -0.015, which is significantly negative ($p < 0.01$), indicating that the more frequently the enterprise uses the term "robot" in the annual report, the more convergent its Real Activities Manipulation behaviour becomes, and the stronger the financial standardization. The results remain stable after controlling for industry and year fixed effects, which supports the research view of "language embedding digital strategy", which means that the more companies express their emphasis on intelligence in public texts, the weaker their earnings manipulation motivation in financial reports.

In terms of control variables, *AUD* 's coefficient of -0.009 is also significantly negative ($p < 0.01$), indicating that companies audited by the Big Four accounting firms are more likely to follow auditing practices and market constraints, thereby reducing their earnings management propensity. The coefficient of *ROA* is -0.349, which is also significantly negative ($p < 0.01$), indicating that the more profitable the company, the more likely it is to express its financial position and not rely on manipulation to achieve its earnings target. The LEV showed a positive coefficient (0.054, $p < 0.01$), indicating that firms with higher financial leverage are more likely to adopt earnings management strategies due to debt covenant pressure or market expectations. The coefficient of *CFO_A* is -0.644, which is significantly negative at the 1% level, which further indicates that when the operating cash flow of enterprises is abundant, their motivation to adjust their financial statements through artificial means is significantly reduced.

From the perspective of the overall fitting effect, *R-squared* =0.186, and the *Adjusted R-squared* = 0.185, indicating that the fixed-effect model can still explain about 18.5% of the true earnings management heterogeneity after controlling for industry and year differences. This is of moderate intensity in accounting and corporate governance research, indicating that the selected variables are reasonable in constructing the explanatory framework of financial behaviour drivers, and the model fitting effect is consistent with the results of the existing literature.

4.1.2 RM_{it} model descriptive statistics

Descriptive statistics of the above variables yielded the following results:

Table 2. RM_{it} Model descriptive statistics

Stats	***RM***	***RobetFreq_z***	***AUD***	***ROA***	***LEV***	***CFO_A***
N	49067	44235	49067	49067	49067	43286
Mean	2.49E-06	-9.30E-09	0.512789	0.034531	0.440932	0.056364
p50	0.023789	-0.33639	1	0.034657	0.435757	0.051455
p75	0.999251	-0.09028	1	0.067419	0.59016	0.098189
p25	-0.06081	-0.36715	0	0.010446	0.281596	0.010528
Min	-9.1879	-0.36715	0	-2.08945	0.00708	-3.25389
Max	6.553203	16.46045	1	1.28476	3.919121	6.409492
SD	0.212489	1	0.499842	0.080485	0.207199	0.118685

According to the descriptive statistical results in Table 2 above, the sample enterprises have a reasonable overall distribution in terms of Real Activities Manipulation behaviour, robot discourse frequency and various financial characteristics, and have a strong analytical basis. Among them, the RobetFreq_z is 0, the standard deviation is 1, and the maximum value is as high as 6.55, which shows that there are significant differences in the degree of "artificial intelligence" discourse embeddedness. The mean AUD is 0.51, indicating that more than half of the companies have hired high-quality auditors such as the "Big Four". ROA and LEV are concentrated in the middle range, but there are still some fluctuations. Although the average value of CFO_A is positive, the extreme minimum value is -3.25, indicating that some enterprises have tight cash flow or abnormal operation.

Overall, the statistical characteristics of each variable were stable, and the differences were moderate.

4.1.3 RM_{it} correlation analysis results

Here are the results of the correlation analysis:

Table 3. RM_{it} Model Spearman correlation coefficient (top half) and Pearson correlation coefficient (bottom half)

	RM	***RobetFreq_z***	***AUD***	***ROA***	***LEV***	***CFO_A***
RM	1	-0.0876***	-0.0478***	-0.3466***	0.1252***	-0.3337***
RobetFreq_z	-0.0391***	1	0.1005***	-0.0026	-0.0875***	-0.0320***
AUD	-0.0461***	0.0580***	1	0.0546***	-0.0157***	0.0640***
ROA	-0.2559***	-0.0534***	0.0544***	1	-0.3746***	-0.4691***
LEV	0.1129***	-0.0787***	-0.0263***	-0.3458***	1	-0.1610***
CFO_A	-0.3889***	-0.0327***	0.0515***	0.3454***	-0.1200***	1

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

The correlation analysis results in Table 3 show that there is a significant relationship between multiple variables and Real Activities Manipulation (RM) with economic explanatory power.

First, there is a stable and strong negative correlation between *CFO_A* and *RM* (Pearson = -0.3889, Spearman = -0.3337), indicating that enterprises with abundant cash flow are less dependent on adjusting earnings through actual business operations, reflecting that their financial soundness has an inhibitory effect on earnings behavior. Second, *ROA* is also negatively correlated with *RM* (Spearman = -0.3466), indicating that the higher the level of profitability, the more inclined the company is to disclose its true performance. At the same time, *LEV* is positively correlated with *RM* (Spearman = 0.1252), suggesting that highly leveraged firms may be more inclined to engage in earnings management due to debt repayment pressure or contractual incentives. In addition, there is a slight negative correlation between *RobetFreq_z* and *RM* (Spearman = -0.0876), suggesting that the higher the degree of expression of the digital strategy, the weaker the motivation to adjust earnings may be.

The above relationships are consistent with theoretical expectations and form an important basis for subsequent regression analysis.

4.2 The Impact of artificial intelligence on Accrued-Based Earnings Management

After the measurement model of earnings quality matures, many scholars use Real Activities Manipulation and Accrued-Based Earnings Management quality to measure audit quality, so this paper can also set up the following regression equation to explore, and use the fixed-effect model of year and industry to regress:

$$AM_{it} = \alpha_0 + \alpha_1 RobotFreq_{z_{\mathrm{it}}} + \alpha_2 AUD_{\mathrm{it}} + \alpha_3 ROA_{\mathrm{it}} + \alpha_4 LEV_{\mathrm{it}} + \alpha_5 \frac{CFO_{\mathrm{it}}}{A_{\mathrm{it}-1}} + Industry_t + Year_i + \varepsilon_{\mathrm{it}} \quad (10)$$

4.2.1 $\mathrm{AM}_{\mathrm{it}}$ model regression results

Table 4. AM_{it} Model regression results

	Regression Coefficient	Standard Deviation
RobetFreq_z	-0.001*	0.000
AUD	-0.002***	0.001
ROA	0.699***	0.029
LEV	0.000	0.003
CFO_A	-0.490***	0.048
Constant	0.002	0.002
Observations	44,180	
R-squared	0.533	
Adjusted R-squared	0.533	

From the regression results in Table 4, it can be seen that the coefficient of *RobetFreq_z* is -0.001, and the significance is at the 10% level, indicating that enterprises use intelligent terms such as "robots" more frequently in their annual reports, which shows a certain degree of negative correlation with their Accrued-Based Earnings Management behaviour, indicating that digital language embedding may have a positive effect on improving the quality of accounting information. In terms of control variables, *AUD* is significantly negative, indicating that the companies subject to the Big Four audits are more prudent and have a lower degree of earnings control. A significantly positive *ROA* may indicate that companies with strong profitability will still use accruals to adjust to maintain performance; *LEV* is not significant, indicating a weak relationship between financial leverage and Accrued-Based Earnings Management; *CFO_A* is significantly negative, indicating that the more abundant the cash flow, the less earnings manipulation the company can use accounting estimates.

Overall, the *R-squared* and *Adjusted R-squared* models are both 0.533, which have strong explanatory power, indicating that the selected variables can effectively describe the Accrued-Based Earnings Management behaviour of enterprises.

4.2.2 AM_{it} model descriptive statistics

Table 5. AM_{it} Model descriptive statistics

Stats	***AM***	***RobetFreq~z***	***AUD***	***ROA***	***CFO_A***	***LEV***
N	55185	50105	55185	55185	49012	55185
Mean	1.95E-11	-1.80E-08	0.504213	0.03615	0.056253	0.433351
p50	0.000444	-0.32997	1	0.036367	0.051612	0.426864
p75	0.036678	-0.11082	1	0.069634	0.098947	0.584635
p25	-0.03698	-0.36128	0	0.011262	0.010214	0.269054
Min	-2.03753	-0.36128	0	-2.08945	-4.05031	0.005927
Max	3.340339	16.76339	1	1.28476	6.409492	9.698812
SD	0.089086	1	0.499987	0.081714	0.119912	0.214726

According to the descriptive statistical results in Table 5, the mean value of the *AM* variable of Accrued-Based Earnings Management is close to zero, but its standard deviation is 0.089, and the difference between the maximum and minimum values is significant (3.34 and -2.03), indicating that the sample enterprises have significant differences in the degree of earnings manipulation, which has research value. The average value of *ROA* and *CFO_A* is positive, indicating that the overall financial performance of the sample enterprises is acceptable. Among them, the minimum value of *CFO_A* reached -4.50, indicating that some companies are seriously short of cash flow and may face high financial pressure. At the same time, the standard deviation of the *RobetFreq_z* in the sample is 1, and the distribution range is wide (the maximum value is 16.76), reflecting the large heterogeneity of enterprises in the degree of AI discourse embeddedness.

4.2.3 AM_{it} model correlation analysis

Here are the results of the correlation analysis:

Table 6. AM_{it} Model Spearman correlation coefficient (top half) and Pearson correlation coefficient (bottom half)

	AM	***RobetFreq_z***	***AUD***	***ROA***	***CFO_A***	***LEV***
AM	1	-0.0127***	-0.0038	0.3096***	-0.4117***	-0.1714***
RobetFreq_z	-0.0127***	1	0.1152***	-0.0041	-0.0337***	-0.0899***
AUD	-0.0068	0.0671***	1	0.0549***	0.0625***	-0.0238***
ROA	0.3754***	-0.0497***	0.0568***	1	0.4686***	-0.3790***
CFO_A	-0.4329***	-0.0339***	0.0503***	0.3563***	1	-0.1568***
LEV	-0.1538***	-0.0748***	-0.0356***	-0.3719***	-0.1167***	1

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

In the Pearson-Spearman correlation analysis in Table 6, several key variables showed significant relationships with *AM*. First, *CFO_A* is negatively correlated with *AM* (Pearson = -0.4298, Spearman = -0.4117), and the value is relatively the largest among the two correlation coefficients, indicating that the tighter the cash flow, the more likely it is that the company will manipulate the earnings through accounting methods. Second, *ROA* is positively correlated with *AM* (Spearman = 0.3096), indicating that the stronger the profitability, the more inclined management is to use accounting estimates for earnings management operations. In addition, *LEV* is negatively correlated with *AM* (Spearman = -0.1714), which may reflect that highly leveraged companies face stricter accounting supervision or audit constraints, which in turn reduces the room for Accrued-Based Earnings Management. It is worth noting that the Spearman coefficient between *RobetFreq_z* and *AM* is -0.0127, which is statistically significant (p = 0.0075), which suggests that there may be a slight downward trend in the hierarchical order of the Accrued-Based Earnings Management behaviour of enterprises in the context of more AI discourse expression.

5 Conclusion

Based on the panel data of A-share non-financial listed companies in Shanghai and Shenzhen from 2005 to 2024, this paper empirically tests the influence mechanism of enterprise AI discourse embeddedness on Real Activities Manipulation and Accrued-Based Earnings Management.

The results show that, on the one hand, the more digital strategic discourses such as "artificial intelligence" are expressed in the annual reports, the more their Real Activities Manipulation level shows a downward trend, indicating that the embedding of AI at the discourse level enhances financial standardization and transparency to a certain extent. On the other hand, in the Accrued-Based Earnings Management model, although the AI discourse frequency has a weak impact on earnings manipulation, it still shows a slight negative correlation, suggesting that the expression of digital strategy may form a weak normative constraint. In addition, variables such as cash flow and profitability of operating activities show the same directional effect in the two models, which further confirms the moderating effect of internal operational soundness on earnings manipulation motivation.

Based on the research results, enterprises can deepen the application and value release of AI technology from three aspects: strategic expression, information governance, and financial norms.

First, it is recommended that enterprises actively build a credible image of digital governance by enhancing the consistency of AI-related discourse and practice, improving the strategic clarity and financial transparency of information disclosure such as annual reports.

Second, it is recommended that enterprises use AI to optimize the financial management process, reduce the subjectivity and manipulation space of human judgment in accounting estimates, and improve the traceability of accounting information.

Third, the audit supervision department can also use natural language processing technology to conduct structured analysis of the annual report text to identify the earnings manipulation characteristics of high-risk enterprises, so as to improve the ability of risk early warning and financial compliance supervision.

There are still some limitations in sample selection and variable construction in this study.

First, the degree of use of artificial intelligence is only measured by the frequency of "robot" keywords in the annual report text, which is representative, but it may underestimate the substantial impact of the practical application of AI on enterprise management.

Second, the measurement of earnings management still relies on the model residual method, which is affected by industry heterogeneity and time cycle, and its explanatory power is limited. In the future, multi-dimensional indicators such as AI investment intensity and technology adoption path can be further introduced, combined with semantic analysis technology to finely measure discourse content, and the interaction mechanism between different governance structures, external regulatory environment and the role of AI can be discussed, so as to systematically reveal the boundary effects and conditional variables of AI in the standardization of corporate financial behaviour.

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