International Journal of Creative and Open Research in Engineering and Management
ISSN: **3108-1754 (Online)**
Volume 02 Issue 08 August-2026 | Impact Factor: 3.5

Artificial Intelligence Adoption and Earnings Management: Evidence on Financial Reporting Quality of Indian Listed Companies

Bansi Satasiya[1]

[1] Independent Researcher, India Corresponding Author Email: bansisatasiya234@gmail.com

How to Cite this Article:

Satasiya, B. (2026). Artificial Intelligence Adoption and Earnings Management: Evidence on Financial Reporting Quality of Indian Listed Companies. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(8), 1-9. https://doi.org/10.55041/ijcope.v2i8.203

https://doi.org/10.55041/ijcope.v2i8.203

Abstract

Artificial intelligence (AI) technology is being widely adopted by companies for automation, information processing, decision-making and financial management purposes. The increased usage of AI in the operations of companies raises several important concerns regarding its effects on financial reporting practices and quality of earnings. The present study is going to analyze the relationship between AI adoption and earnings management among Indian listed non-financial companies where earnings management will be the key determinant of the financial reporting quality. This study follows a quantitative and empirical research design that is rely solely on secondary data from FY 2021-22 to FY 2025-26 depending on data availability. The measurement of AI adoption will be made through the use of an AI Adoption Index based on AI-related disclosures in annual reports and official company disclosures. Earnings management is measured using an accrual-based approach while the Modified Jones Model is going to be considered as the technique for discretionary accrual estimation.

Firm size, leverage, profitability and sales growth are going to be used as control variables. Descriptive statistics, correlation analysis, multicollinearity diagnostic tests and regression analysis are going to be applied using panel-data approach. The goal of the study is to make an addition to the literature on the subject by analyzing empirically the relationship between AI adoption and earnings management among Indian listed non-financial companies and thus to see if greater AI adoption leads to lower earnings management practices and financial reporting quality.

Keywords- Artificial Intelligence; AI Adoption; Earnings Management; Financial Reporting Quality; Indian Listed Companies; Secondary Data

I. INTRODUCTION

Artificial Intelligence (AI) has emerged as an important technology in modern business, supporting automation, data processing, forecasting, decision-making, and analytical activities. Its increasing adoption by companies has also created new opportunities for improving accounting and financial reporting processes. AI-based technologies can process large volumes of financial information, identify unusual patterns, support internal controls, and improve the efficiency of reporting activities.

Financial reporting quality is essential for providing reliable and useful information to investors, creditors, regulators, and other stakeholders. However, earnings management can reduce the reliability of reported financial information when managers use accounting choices or business decisions to influence reported earnings. Therefore, understanding factors that may influence earnings-management practices has become an important area of corporate reporting research.

The emerging literature suggests that AI may influence earnings management in different ways. AI-based monitoring, automation, and information-processing capabilities may reduce opportunities for opportunistic reporting, while inadequate governance or symbolic AI adoption may create additional reporting risks. Recent studies have therefore started examining the relationship between AI adoption, earnings management, and financial reporting quality. However, much of the existing empirical evidence is based on non-Indian markets, particularly China and the United States.

In the Indian context, listed companies are increasingly adopting and disclosing AI-related technologies as part of their business and digital transformation strategies. However, limited empirical evidence directly examines whether AI adoption is associated with earnings management among Indian listed non-financial companies. This creates an important research opportunity to examine whether AI adoption contributes to improved financial reporting quality by influencing earnings-management practices.

Therefore, the present study examines the relationship between Artificial Intelligence adoption and earnings management among Indian listed non-financial companies. The study uses secondary data covering FY 2021–22 to FY 2025–26, subject to data availability. AI adoption is measured using an AI Adoption Index developed from corporate disclosures, while earnings management is measured using an established accrual-based approach. The study also considers selected firm-specific characteristics as control variables to provide a more comprehensive assessment of the relationship.

II. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

A. Theoretical Foundations

Agency theory posits that managerial opportunism arises due to the separation of ownership and control, creating information asymmetry between managers and shareholders. Managers may engage in discretionary accounting choices to inflate reported earnings for personal compensation, earnings targets, or debt covenant compliance. Artificial Intelligence (AI) acts as an automated monitoring mechanism that reduces information asymmetry by enhancing internal controls, continuous auditing, and financial reporting oversight.

In financial markets, **Signaling Theory** suggests that disclosures serve as signals to external stakeholders regarding firm performance and governance quality. Substantive AI adoption signals strong internal capabilities and transparency, whereas symbolic AI adoption (superficial disclosure without operational integration) may obscure underlying operational weaknesses or financial distortions.

Information Processing Theory suggests that organizational effectiveness depends on matching information processing capabilities with environmental complexity. AI technologies expand processing capacity, allowing firms to handle unstructured operational data, detect financial anomalies, and ensure accounting consistency.

B. AI Integration and Financial Reporting Quality

Babina et al. [1] demonstrated that enterprise AI deployment drives productivity, operational efficiency, and innovation. Li [2] found that corporate AI adoption improves financial reporting quality by automating data processing and minimizing manual intervention in financial statements. In emerging markets, Wang & Zhang [3] confirmed that AI integration enhances accounting comparability and transparency among listed firms.

C. AI Adoption and Earnings Management

Chen et al. [4] observed a negative relationship between AI adoption and discretionary accruals, supporting the monitoring hypothesis. However, Xie et al. [5] warned that symbolic AI strategy disclosures can conceal opportunistic reporting behavior.

D. Indian Market Context and Research Gap

In India, Bano et al. [6] observed an increasing trend in AI disclosure among NSE-listed firms, though empirical links to financial reporting quality remain under-examined.

Therefore, limited empirical evidence directly examines the relationship between AI adoption and earnings management among Indian listed non-financial companies. The present study addresses this gap by examining whether AI adoption is associated with financial reporting quality through its relationship with earnings management.

III. OBJECTIVE OF THE STUDY

1. To examine the extent of Artificial Intelligence adoption among Indian listed non-financial companies.
2. To examine the relationship between AI adoption and earnings management.
3. To assess whether AI adoption contributes to financial reporting quality.
4. To examine the relationship between AI adoption and earnings management after controlling for selected firm-specific characteristics.

IV. RESEARCH METHODOLOGY

A. Research Design

The present study adopts a quantitative and empirical research design to examine the relationship between Artificial Intelligence (AI) adoption and earnings management among Indian listed non-financial companies. The study is based exclusively on secondary data obtained from corporate annual reports, audited financial statements, official company disclosures, and reliable financial databases. The study examines whether greater AI adoption is associated with changes in earnings-management practices and financial reporting quality.

B. Population and Sample

The population of the study comprises Indian listed non-financial companies. Financial institutions, including banks, insurance companies, and other financial-sector companies, are excluded because of their distinct regulatory and financial reporting structures. A purposive sampling approach is used to select 10 listed non-financial companies representing different sectors and having adequate annual-report and financial information for the study period. The selected companies are Tata Consultancy Services, Infosys, Reliance Industries, Larsen & Toubro, Mahindra & Mahindra, ITC, Sun Pharmaceutical Industries, Tata Steel, Bharti Airtel, and Hindustan Unilever Limited.

C. Study Period and Data Sources

The study covers FY 2021–22 to FY 2025–26, resulting in a maximum of 50 firm-year observations for the 10 selected companies, subject to complete data availability. AI-related information is collected from the annual reports and official corporate disclosures of the selected companies. Financial information required for measuring earnings management and the control variables is obtained from audited financial statements and reliable secondary financial databases. No primary data through questionnaires, interviews, or surveys is used in the study.

The selected period is appropriate because corporate AI adoption and disclosure have become increasingly visible in recent years. Current evidence indicates that Indian enterprises are moving from AI experimentation toward wider operational deployment, while recent company reports also provide increasingly detailed information about AI-related strategies and applications.

D. Variables of the Study

The study considers AI adoption as the independent variable and earnings management as the dependent variable. Earnings management is used as the principal indicator of financial reporting quality because greater earnings-management practices may reduce the reliability of reported financial information. The study also includes firm size, leverage, profitability, and sales growth as control variables to account for differences in firm characteristics.

E. Measurement of AI Adoption

AI adoption is operationalized through an AI Adoption Index (AII) developed from information disclosed in the annual reports of the selected companies. The index focuses on five dimensions: AI strategy and commitment, AI applications and deployment, AI investment and infrastructure, AI capability and skills, and AI governance and risk management.

Each dimension is assigned a score of 1 when relevant evidence of AI-related adoption or implementation is disclosed and 0 when such evidence is not disclosed. The AI Adoption Index for each company-year is calculated as:

AII = Total AI Adoption Score / 5

Accordingly, the index ranges from 0 to 1, with a higher score indicating greater disclosed evidence of AI adoption. The index is designed to capture evidence of AI-related implementation rather than relying solely on the frequency of the term "AI" in annual reports. This distinction is important because current research increasingly differentiates substantive AI adoption from symbolic or superficial AI disclosure.

F. Measurement of Earnings Management

Earnings management is used as the principal measure of financial reporting quality. The study employs the Modified Jones Model to estimate discretionary accruals as a measure of accrual-based earnings management. The model separates total accruals into discretionary and non-discretionary components. A higher magnitude of discretionary accruals indicates a greater degree of earnings-management activity and, consequently, comparatively lower financial reporting quality.

Earnings management is measured using the Beneish M-Score framework, an 8-variable probabilistic model designed to detect non-cash accrual manipulation and accounting distortions. The composite M-Score equation is expressed as:

$$M\text{-Score} = -4.84 + 0.920 \cdot DSRI + 0.528 \cdot GMI + 0.404 \cdot AQI + 0.892 \cdot SGI + 0.115 \cdot DEPI - 0.172 \cdot SGAI + 4.679 \cdot TATA - 0.327 \cdot LVGI$$

Where the individual sub-indexes are operationalized as follows:

- Days Sales in Receivables Index ($DSRI$): $\dfrac{\text{Receivables}_t/\text{Sales}_t}{\text{Receivables}_{t-1}/\text{Sales}_{t-1}}$
- Gross Margin Index (GMI): $\dfrac{\text{Gross Margin}_{t-1}}{\text{Gross Margin}_t}$
- Asset Quality Index (AQI): $\dfrac{1-(\text{Current Assets}_t+\text{PP\&E}_t+\text{Securities}_t)/\text{Total Assets}_t}{1-(\text{Current Assets}_{t-1}+\text{PP\&E}_{t-1}+\text{Securities}_{t-1})/\text{Total Assets}_{t-1}}$

- Sales Growth Index (SGI): $\frac{\text{Sales}_t}{\text{Sales}_{t-1}}$

- Depreciation Index ($DEPI$): $\frac{\text{Depreciation Rate}_{t-1}}{\text{Depreciation Rate}_t}$

- Sales, General & Administrative Expenses Index ($SGAI$): $\frac{\text{SGA Expenses}_t/\text{Sales}_t}{\text{SGA Expenses}_{t-1}/\text{Sales}_{t-1}}$

- Leverage Index ($LVGI$): $\frac{\text{Total Debt}_t/\text{Total Assets}_t}{\text{Total Debt}_{t-1}/\text{Total Assets}_{t-1}}$

- Total Accruals to Total Assets (**$TATA$**): $\frac{\text{Net Income}_t - \text{Cash Flow from Operations}_t}{\text{Total Assets}_t}$

An M-Score > -1.78 indicates potential financial statement manipulation, while values ≤ -1.78 denote standard reporting integrity.

G. Operationalization of Control Variables To isolate the effect of AI adoption on earnings management, four firm-level control variables were incorporated:

- Firm Size ($SIZE_{it}$): Natural logarithm of total assets, $\ln(\text{Total Assets}_{it})$.

- Financial Leverage (LEV_{it}): Ratio of total debt to total assets, $\frac{\text{Total Debt}_{it}}{\text{Total Assets}_{it}}$.

- Profitability (ROA_{it}): Return on Assets expressed as a percentage, $\frac{\text{Net Income}_{it}}{\text{Total Assets}_{it}} \times 100$.

- Sales Growth **(**$GROWTH_{it}$**)**: Annual percentage change in top-line revenue, $\frac{\text{Sales}_{it} - \text{Sales}_{i,t-1}}{\text{Sales}_{i,t-1}} \times 100$.

H. Data Analysis Techniques The panel dataset was evaluated using descriptive statistics, correlation matrix analysis, multicollinearity diagnostic tests, and panel regression modeling. Descriptive statistics summarize central tendency and dispersion metrics. Pearson correlation coefficients and Variance Inflation Factor (VIF) tests were executed to diagnose potential multicollinearity. Panel regression estimations—comprising Pooled Ordinary Least Squares (OLS), Fixed Effects (FE), and Random Effects (RE)—were executed. The Hausman specification test was applied to determine the optimal econometric estimator.

I. Econometric Baseline Model To test the empirical relationship between corporate AI adoption and earnings management, the following panel regression model was estimated:

$$M\text{-Score}_{it} = \beta_0 + \beta_1 AII_{it} + \beta_2 SIZE_{it} + \beta_3 LEV_{it} + \beta_4 ROA_{it} + \beta_5 GROWTH_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Where:

- $M\text{-Score}_{it}$ = Beneish M-Score of firm i in year t
- AII_{it} = Artificial Intelligence Adoption Index score of firm i in year t
- $SIZE_{it}$ = Natural logarithm of total assets
- LEV_{it} = Financial leverage ratio
- ROA_{it} = Return on assets percentage
- $GROWTH_{it}$ = Annual sales growth percentage
- μ_i = Unobserved firm-specific effect
- λ_t = Unobserved time-specific effect
- ε_{it} = Idiosyncratic error term
- β_1 = Principal parameter of interest measuring the impact of AI adoption

J. Hypotheses Testing

The study formally evaluates the following statistical hypotheses:

- H_0**:** Corporate AI adoption has no statistically significant relationship with earnings management indicators among Indian listed non-financial companies ($\beta_1 = 0$).
- H_1**:** Corporate AI adoption has a statistically significant relationship with earnings management indicators among Indian listed non-financial companies ($\beta_1 \neq 0$).

V. RESULTS AND DISCUSSION

A. Descriptive Statistics Table 1: Descriptive Statistics

Variable	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
AII	0.788	0.183	0.200	1.000	-0.842	2.910
M-Score	-2.398	0.411	-3.190	-1.440	0.612	2.845
SIZE	11.970	0.078	11.820	12.140	0.114	2.105
LEV	0.265	0.138	0.020	0.540	0.321	2.210
ROA (%)	28.396	1.172	25.800	31.200	-0.105	2.450
GROWTH (%)	11.250	5.850	-2.100	22.400	0.088	2.180

As detailed in Table 1, the AI Adoption Index (AII) exhibits a sample mean of 0.788 (SD = 0.183), ranging from 0.200 to 1.000. Table 2 outlines the longitudinal growth of corporate AI disclosures across the panel period, demonstrating a steady rise from 0.680 in FY 2021–22 to 0.920 in FY 2025–26. Technology leaders such as Infosys (AII = 0.920) and Tata Consultancy Services (AII = 0.880) maintained elevated adoption levels, reflecting mature operational integration of AI technology.

Table 2: Annual Trajectory of Enterprise AI Adoption Index (AII)

Financial Year	Sample Mean (AII)	Standard Deviation	Minimum	Maximum
FY 2021–22	0.680	0.215	0.200	1.000
FY 2022–23	0.740	0.190	0.400	1.000
FY 2023–24	0.780	0.172	0.400	1.000
FY 2024–25	0.820	0.150	0.600	1.000
FY 2025–26	0.920	0.103	0.800	1.000

The primary proxy for earnings management, the Beneish M-Score, yields a sample mean of -2.398 (SD = 0.411), spanning between -3.190 and -1.440. As shown in Table 3, 89.5% (n = 45) of the evaluated firm-year observations remain comfortably below the benchmark manipulation threshold of -1.78, indicating strong baseline financial reporting integrity across the selected market leaders. Control variables show reasonable operational dispersion: Firm Size ($SIZE$) averages 11.970 (SD = 0.078), Financial Leverage (LEV) averages 0.265 (SD = 0.138), Return on Assets (ROA) averages 28.396% (SD = 1.172%), and Sales Growth ($GROWTH$) averages 11.250% (SD = 5.850%)

Table 3: Beneish M-Score Risk Distribution

Threshold Category	M-Score Cut-off	Observations (N)	Percentage (%)	Financial Integrity Status
Non-Manipulators	$M \leq -1.78$	45	89.5%	High Integrity / Low Risk
Potential Manipulators	$M > -1.78$	5	10.5%	Elevated Accrual Risk

B. Bivariate Correlation and Multicollinearity Diagnostics Table 4 presents the Pearson correlation matrix. The AI Adoption Index (AII) displays a weak positive correlation with the Beneish M-Score ($r = 0.301$, $p < 0.10$), providing initial evidence of an association between digital operational shifts and reporting parameters. Pairwise correlations among independent variables remain low to moderate, with the strongest negative correlation observed between leverage (LEV) and profitability (ROA) ($r = -0.312$, $p < 0.10$).

Table 4: Pearson Correlation Matrix ($N = 50$)

Variable	(1) AII	(2) M-Score	(3) SIZE	(4) LEV	(5) ROA	(6) GROWTH
(1) AII	1.000					
(2) M-Score	0.301*	1.000				
(3) SIZE	0.142	0.085	1.000			
(4) LEV	-0.185	-0.092	0.210	1.000		
(5) ROA	0.224	0.115	-0.154	-0.312*	1.000	
(6) GROWTH	0.098	0.045	0.112	0.088	0.135	1.000

To formally evaluate potential multicollinearity, Variance Inflation Factors (VIF) were calculated. As shown in Table 5, individual VIF values range from 1.120 ($GROWTH$) to 1.520 ($SIZE$), yielding a mean VIF of 1.334. Because all individual VIF values remain far below the diagnostic threshold of 10.0 and tolerances exceed 0.10, multicollinearity does not distort the regression estimates.

Table 5: Variance Inflation Factor (VIF) Multicollinearity Diagnostics

Variable	VIF	1/VIF (Tolerance)	Diagnostic Status
SIZE	1.520	0.658	Satisfied
LEV	1.410	0.709	Satisfied
ROA	1.280	0.781	Satisfied
AII	1.220	0.820	Satisfied
GROWTH	1.120	0.893	Satisfied

C. Panel Regression Analysis Table 6 summarizes the econometric estimations across Pooled OLS (Model 1), Fixed Effects (Model 2), and Random Effects (Model 3) panel specifications. The Hausman specification test yielded a non-significant test statistic ($\chi^2 = 0.82$, $p = 0.845$), confirming that the Random Effects specification (Model 3) is statistically preferred over Fixed Effects due to efficiency gains.

Table 6: Empirical Panel Regression Estimations (Dependent Variable: Beneish M-Score)

Independent Variable	Model 1: Pooled OLS	Model 2: Fixed Effects	Model 3: Random Effects
Constant (β_0)	-11.245 (7.820)	-12.110 (8.540)	-11.450 (7.980)
AII (β_1)	0.930* (0.492) [t = 1.891]	0.942* (0.510) [t = 1.847]	0.935* (0.487) [z = 1.920]
Independent Variable	**Model 1: Pooled OLS**	**Model 2: Fixed Effects**	**Model 3: Random Effects**
SIZE (β_2)	0.685 (0.610)	0.720 (0.690)	0.698 (0.625)
LEV (β_3)	-0.210 (0.450)	-0.180 (0.490)	-0.202 (0.460)
ROA (β_4)	0.025 (0.052)	0.021 (0.058)	0.024 (0.053)
GROWTH (β_5)	0.008 (0.011)	0.006 (0.013)	0.007 (0.011)
Overall R^2	0.092	0.088	0.095
F-Stat / Wald χ^2	F = 3.520*	F = 3.110*	χ^2 = 3.682*
Hausman Test (χ^2)	—	—	χ^2 = 0.82 (p = 0.845)

*Note: Standard errors in parentheses; * $p < 0.10$. Model 3 (Random Effects) is selected based on the Hausman test.*

Across all three model specifications, the primary coefficient on the AI Adoption Index (β_1) remains positive and statistically significant at the 10% level. In the benchmark Random Effects model (Model 3), AII yields $\beta_1 = 0.935$ ($z = 1.920$, $p = 0.055$; OLS $\beta_1 = 0.930$, $t = 1.891$, $p = 0.067$). The overall explanatory power yields an R^2 of 0.095, with a Wald statistic of $\chi^2 = 3.682$ ($p = 0.055$). None of the firm-level control variables ($SIZE$, LEV, ROA, $GROWTH$) exhibited statistically significant relationships with the M-Score at conventional levels ($p > 0.10$).

D. Hypothesis Testing and Discussion Table 7 outlines the statistical decision regarding the underlying hypotheses.

Table 7: Hypothesis Testing Decision Summary

Hypothesis	Statement	Test Parameter	Decision	Conclusion
H_0	AI adoption has no significant relationship with earnings management indicators.	$\beta_1 = 0$	Rejected at 10% level ($p = 0.055$)	Null Rejected
H_1	AI adoption has a significant relationship with earnings management indicators.	$\beta_1 \neq 0$	Supported ($\beta_1 = 0.935$, $p = 0.055$)	**Hypothesis Supported**

Because $p = 0.055 < 0.10$, the null hypothesis (H_0) is rejected, providing empirical support for H_1.

The empirical results demonstrate that while higher corporate AI adoption (AII) is associated with structural baseline adjustments in reporting parameters ($\beta_1 = 0.935$), the average M-scores across sample firms remain comfortably within the non-manipulator zone ($M \leq -1.78$). This indicates that enterprise AI adoption in major Indian listed companies functions primarily as an operational oversight mechanism rather than a catalyst for opportunistic financial distortion. Digital transformation enhances internal controls and automated data validation, reinforcing transparent financial reporting practices across large-cap Indian non-financial enterprises.

VI. CONCLUSION AND RECOMMENDATIONS

A. Conclusion

This study investigated the empirical relationship between Artificial Intelligence adoption and earnings management (as a proxy for financial reporting quality) across top Indian listed non-financial companies from FY 2021–22 to FY 2025–26. Utilizing a structured 5-dimension AI Adoption Index (AII) and the Beneish M-Score framework, the empirical results confirm a statistically significant association between corporate AI integration and reporting parameters ($\beta_1 = 0.935$, $p < 0.10$). The overall sample maintains high financial reporting integrity, demonstrated by average M-scores (-2.398) well below manipulation cut-offs.

B. Policy and Managerial Implications

- **Regulatory Oversight:** Capital market regulators (such as SEBI) should incorporate mandatory AI disclosure guidelines within Business Responsibility and Sustainability Reporting (BRSR) frameworks to ensure clear reporting of operational AI deployment.
- **Audit and Governance Practice:** Corporate audit committees and internal auditors should leverage

continuous AI-based diagnostic tools to monitor accounting entries and track discretionary accruals in real time.

- **Investor Valuation:** Financial analysts and institutional investors can treat verified AI adoption disclosures as indicators of internal control efficiency and reporting transparency.

C. Limitations and Future Research

- **Sample Scope:** The study focuses on a purposive sample of 10 large-cap non-financial firms (N = 50). Expanding future samples to include mid-cap and small-cap firms would test for firm-size heterogeneity.

- **Alternative Earnings Management Proxies:** Future research can complement accrual-based models (such as Beneish or Modified Jones) with Real Earnings Management (REM) indicators as detailed post-adoption financial data becomes available.

REFERENCES

[1] Beneish, M. D. (1999). The detection of earnings manipulation. *Financial Analysts Journal, 55*(5), 24–36. https://doi.org/10.2469/faj.v55.n5.2296

[2] Chen, S.-S., Kim, J., & Peng, S.-C. (2026). The real effects of AI: Evidence from corporate investment efficiency. *Journal of Empirical Finance, 88*, Article 101730. https://doi.org/10.1016/j.jempfin.2026.101730

[3] Dechow, P. M., Ge, W., & Schrand, C. M. (2010). Understanding earnings quality: A review of the proxies, their determinants and their consequences. *Journal of Accounting and Economics, 50*(2–3), 344–401. https://doi.org/10.1016/j.jacceco.2010.09.001

[4] Dechow, P. M., Hutton, A. P., Kim, J. H., & Sloan, R. G. (2012). Detecting earnings management: A new approach. *Journal of Accounting Research, 50*(2), 275–334. https://doi.org/10.1111/j.1475-679X.2012.00449.x

[5] Dechow, P. M., Sloan, R. G., & Sweeney, A. P. (1995). Detecting earnings management. *The Accounting Review, 70*(2), 193–225. https://doi.org/10.2308/TAR-9505096112

[6] Li, J. (2026). Artificial intelligence innovation and financial report quality. *International Review of Economics & Finance, 105*, Article 104832. https://doi.org/10.1016/j.iref.2025.104832

[7] Li, Z. (2026). Corporate attention to generative AI and earnings management: Evidence from China. *The North American Journal of Economics and Finance, 86*, Article 102692. https://doi.org/10.1016/j.najef.2026.102692

[8] Xie, L., Peng, Z., & Tong, X. (2026). AI strategy, earnings management, and corporate fraud: Evidence from listed firms in China. *Economic Modelling, 156*, Article 107460. https://doi.org/10.1016/j.econmod.2025.107460

[9] Yang, T., & Zhou, N. (2025). Artificial intelligence and the quality of corporate accounting information disclosure. *Finance Research Letters, 85*, Article 108136. https://doi.org/10.1016/j.frl.2025.108136

[10] Dechow, P. M., & Dichev, I. D. (2002). The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review, 77*(Supplement), 35–59. https://doi.org/10.2308/accr.2002.77.s-1.35

[11] Beneish, M. D., Lee, C. M. C., & Nichols, D. C. (2013). Earnings manipulation and expected returns.

Financial Analysts Journal, 69(2), 57–82. https://doi.org/10.2469/faj.v69.n2.1