

AI, Earnings Management and Audit Committee

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Abstract

In the rapidly evolving landscape of financial reporting, traditional corporate governance frameworks centered on monitoring human managerial decisions are increasingly shifting toward AI governance, which focuses on overseeing algorithmic design and automated data processing. This study investigates the empirical effect of artificial intelligence (AI) implementation on earnings management and examines the moderating role of audit committee oversight mechanisms. Utilizing a sample of 217 manufacturing firms listed on the Indonesia Stock Exchange over the 2023–2024 period (comprising 434 firm-year observations), this research employs fixed-effects panel regression analysis with robust controls for firm-level heterogeneity. AI implementation is operationalized through a comprehensive text-mining disclosure index in annual reports, while earnings management is evaluated across two distinct dimensions of accrual and real earnings management. The empirical findings reveal that AI implementation exerts a statistically significant negative impact on both accrual and real earnings management, confirming that AI adoption serves predominantly as an automated internal control and monitoring-enhancing mechanism that mitigates managerial opportunistic behavior rather than as an instrument for algorithmic manipulation. Crucially, moderation analysis demonstrates that both audit committee technology expertise and meeting frequency significantly amplify this negative relationship, indicating that the efficacy of AI in curbing financial statement distortions is strictly contingent upon governance quality. The primary originality of this research lies in extending agency theory into the digital era by illustrating that digital transformation mitigates information asymmetry only when backed by strong governance that bridges algorithmic opacity.

Keywords: Accrual Earnings Management, Artificial Intelligence, Audit Committee, Real Earnings Management.

Introduction

The era of artificial intelligence (AI) promotes significant transformation in accounting practice and financial reporting (1, 2). Global and national standards provide responses to technology integration in the accounting system. International Financial Reporting Standards (3) regulate digital reporting by using digital taxonomies of the filing system. In Indonesia, technology involvement in financial reporting is regulated in the Financial Services Authority Regulation (Peraturan Otoritas Jasa Keuangan) No. 14 /POJK.04/2022 for public companies. Conceptually, the relationship between AI and earnings management can be explained by using two main perspectives. First, the efficiency and monitoring perspectives suggest that AI increases accounting system quality, promotes better internal control and detects anomalies by using big data analysis (4), which can lead to lower earnings management. Second, the opportunistic perspective argues that a controlled algorithm allows managers to optimize accounting

estimation and create a new strategy called algorithmic earnings management (5). The impact of AI on earnings management depends on corporate governance, managerial ethics and technology transparency.

There are some reporting manipulation cases that indicate that earnings management is a serious problem. In China, the Evergrande company inflated its revenues over two years (2019-2020) up to RMB 564.1 billion (6). In Brazil, the Americanas company has accounting inconsistencies of approximately R\$ 20 billion in 2023 (7). In Germany, the Wirecard company has an accounting manipulation of €1.9 billion in cash on its balance sheet (8). In Indonesia, the Efishery company is suspected of improperly inflating its financial performance (9). In the digital era, earnings management is not limited to manual manipulation, but also to information systems and technology-based data processing. AI relates to the feature of “black box” that can complicate auditors

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and regulators in tracing the accounting process decision-making (10).

AI plays an important role since technology is more widely adopted in functions of accounting, internal audit and risk management. From the perspective of agency theory, earnings management occurs when there is a conflict of interest between managers and shareholders. AI integration has the potential to reduce asymmetrical information between managers and shareholders by improving the rapidity and accuracy of data processing. However, on the other hand, AI can also be utilized to optimize accounting estimates by beating earnings targets without explicitly violating the accounting standards. In this case, AI has ambivalent characteristics where it can be used as a monitoring mechanism, but also can be an opportunistic tool in earnings management.

Previous studies, in general, focus on the role of technology in reporting quality (11–13) and the role of AI in audit and fraud detection (14, 15). Previous studies of earnings management mostly investigate aspects of corporate governance (16, 17). Some studies also find that the audit committee has a critical role in reducing information asymmetry between managers and shareholders (18) by holding more meetings (19). However, there are previous gaps. First, some digitalization studies treat technology as a general monolith instead of isolating the AI-specific functions of algorithms and predictive analytics. Second, accounting studies put AI to detect fraud from the perspective of external auditors instead of the AI role internally can lead managers to engage in earnings management. Third, there are limited studies that investigate the role of AI in both accruals (AEM) and real (REM) earnings management to capture comprehensive managerial behavior.

Previous limitations promote a crucial research gap where, although theoretical debate increases, there is limited empirical evidence of AI on whether as a monitoring mechanism or an opportunistic tool to engage in earnings management in emerging markets. There is also limited evidence about boundary conditions to determine AI-generated reporting. In the context of contract efficiency, AI reduces information asymmetry by processing data in real time and detecting anomalies automatically (4). In the context of opportunistic behavior, a designed AI

algorithm allows managers to use algorithmic earnings management by calibrating the model (20). It is important to examine the interaction between AI and corporate governance, especially the role of the audit committee to ensure algorithmic transparency and AI ethics.

The audit committee plays an important role in determining whether AI is used as a monitoring mechanism or an opportunistic tool. The audit committee has responsibilities to supervise the financial reporting process and ensure compliance with standards and regulations (21). In this case, the audit committee must ensure that AI is used to improve accounting estimation accuracy and reporting efficiency.

This research aims to examine the effect of AI implementation on earnings management and the role of the audit committee as a moderating variable. This research proposes some novelties. Theoretically, this research brings agency theory into the digital era by showing that digital transformation does not remove the agency conflict but shifts managerial opportunistic behavior from manual reporting discretion into algorithm design, data selection and model parametrization (22). Methodologically and empirically, this research provides evidence in emerging markets such as Indonesia by showing the practice of AEM and REM comprehensively through AI implementation. This research also introduces algorithm governance to show that AI effectiveness can reduce reporting distortions by optimizing the audit committee. This research gives practical insights for boards, auditors and regulators to integrate the technology implementation with financial reporting.

Methodology

Research Sample

This research uses a purposive sampling method to select the sample with certain criteria. First, the sample is a manufacturing company that is listed on the Indonesian Stock Exchange. The manufacturing sector has more accrual components than other sectors, including recognition for inventory, receivables, depreciation and production costs. This leads to a higher probability for managers to manage earnings through discretionary accruals. Manufacturing companies also involve production activities, which lead to wider real earnings management, including over-

production, oversales and discretionary expenses reduction. Second, the company is listed in 2023–2024. In 2023, Indonesia regulates the principle of AI ethics through Circular Letter of the Ministry of Communication and Informatics (Surat Edaran

Menteri Komunikasi dan Informatika) no. 9 of 2023 about Ethics of Artificial Intelligence. The total sample is 217 manufacturing companies, as in Table 1 (23).

Table 1: Research Sample

Criteria	Companies	Observation
Manufacturing Companies on the Indonesian Stock Exchange 2023-2024	219	438
Minus incomplete data	2	4
Total	217	434

Research Variable

The independent variable is AI implementation. AI implementation is measured by the disclosure level of AI in the annual report by using structured manual content analysis. This research performs some steps to identify, code and measure AI-related disclosure systematically to ensure objectivity, reliability and replicability. First, this research selects keywords that relate to digital transformation literature (24) and adjusts them with aspects of accounting, internal control and managerial decision-making. This research determines words that relate to AI, including artificial intelligence (AI), machine learning, deep learning, big data analytics, natural language processing (NLP), robotic process automation (RPA), automation, predictive analytics, data mining, intelligent systems, cloud-based analytics, algorithmic decision-making and other relevant terms (24). Second, this research performs content analysis manually by reviewing the electronic annual report word-by-word and using the standard “find” feature in PDF. Manual extraction specifically focuses on narratives where technology implementation is disclosed, which are

the Management Discussion and Analysis, Corporate Governance Report and Notes to the Financial Statements. To avoid false positives, this research excludes the negative context (for example, there is no plan for AI adoption), boilerplate, or conditions that are not related to corporate activities. Third, to verify coding consistency and reliability, this research performs a validation procedure. An independent sub-sample of 10% of annual reports (43 firm-year observations) was randomly selected and manually coded by two independent researchers. Inter-coder agreement was calculated using Krippendorff’s alpha, yielding a score of 0.92 (well above the conventional 0.80 reliability threshold), confirming high consistency across independent manual coders. Minor coding discrepancies were discussed and resolved through consensus before running the full sample analysis. Fourth, to mitigate positive skewness and zero-inflation in the raw number of words for non-implementing corporations, the AI score is operationalized as in Equation [1] (24).

$$\text{AI Score} = \ln (1 + \text{number of words that relate to AI}) \quad [1]$$

The dependent variable is earnings management, including AEM and REM. AEM is calculated by using the Modified Jones Model as in Equations [2-5] (25).

$$\text{TAC} = \text{Net Income} - \text{Operating Cash Flow} \quad [2]$$

$$\frac{\text{TAC}}{A_{t-1}} = a + b_1 \frac{1}{A_{t-1}} + b_2 \frac{\Delta \text{REV}}{A_{t-1}} + b_3 \frac{\text{PPE}}{A_{t-1}} + e \quad [3]$$

$$\text{NDACC} = a + \widehat{b_1} \frac{1}{A_{t-1}} + \widehat{b_2} \frac{\Delta \text{REV} - \Delta \text{REC}}{A_{t-1}} + \widehat{b_3} \frac{\text{PPE}}{A_{t-1}} \quad [4]$$

$$\text{DACC} = \frac{\text{TAC}}{A_{t-1}} - \text{NDACC} \quad [5]$$

TAC is total accruals. Notation of ΔREV is the change in revenues. Notation of ΔREC is a change in receivables. PPE is net fixed assets. A_{t-1} is the total assets in period t-1. NDACC is non-discretionary accruals. DACC is discretionary accruals. Accrual earnings management is the absolute value of DACC. REM includes oversales

(abnormal cash flow from operations), overproduction (abnormal production cost) and discretionary expenses reduction (abnormal discretionary expenses). Real earnings management is calculated by combining these 3 abnormal activities as in Equations [6-9] (26).

$$\frac{CFO}{A_{t-1}} = a + b1 \frac{1}{A_{t-1}} + b2 \frac{REV}{A_{t-1}} + b3 \frac{\Delta REV}{A_{t-1}} + e \quad [6]$$

$$\frac{PROD}{A_{t-1}} = a + b1 \frac{1}{A_{t-1}} + b2 \frac{REV}{A_{t-1}} + b3 \frac{\Delta REV}{A_{t-1}} + b3 \frac{\Delta REV_{t-1}}{A_{t-1}} + e \quad [7]$$

$$\frac{DISC}{A_{t-1}} = a + b1 \frac{1}{A_{t-1}} + b2 \frac{REV}{A_{t-1}} + e \quad [8]$$

$$REAL \ EARNINGS \ MANAGEMENT = -Abnormal \ CFO + Abnormal \ PROD - Abnormal \ DISC \quad [9]$$

CFO is cash flow from operations. PROD is production cost. DISC is discretionary expenses. Notation of e in equation 6 is abnormal cash flow from operations. Notation of e in Equation [7] is abnormal production. Notation of e in equation 8 is abnormal discretionary expenses.

The moderating variable is the audit committee. There are some measurements of audit committee effectiveness. First, an audit committee is effective in ensuring AI reduces earnings management if there are members who have expertise in technology. It is measured by calculating the proportion of audit committee members who have experience or an educational background in technology (27). Second, an audit committee is effective in ensuring AI reduces earnings management if there is more evaluation and discussion by holding more meetings. It is

measured by the number of audit committee meetings in 1 year (19).

Control variables include company size and leverage. The company's size is measured by the natural logarithm of total assets. A company's size aims to control for the fact that bigger companies tend to have more complex internal control systems and political pressure that affect earnings management. Leverage is measured by the debt-to-assets ratio. Leverage aims to control for debt covenant motivation that affects earnings management.

Data Analysis

This research uses fixed-effect regression to test hypotheses. Fixed effects aim to control for the fact that different companies have different accounting systems and internal controls. The regression model is as in Equations [10, 11].

$$AEM = a + b1AI + b2AI \times AUDIT + b3AUDIT + b4SIZE + b5LEV + e \quad [10]$$

$$REM = a + b1AI + b2AI \times AUDIT + b3AUDIT + b4SIZE + b5LEV + e \quad [11]$$

AEM is accrual earnings management. REM is real earnings management. AI is AI implementation. AUDIT is the audit committee. SIZE is the company's size. LEV is leverage. H1 is accepted if the coefficient of b1 is significant. H2 is accepted if the coefficient of b2 is negative and significant.

Results

Descriptive Statistics

Table 2 shows that AI implementation has an average value of 2.876 with a deviation of 1.421. The range of AI implementation is between 0.000 and 6.732. AEM has an average value of 0.087 with a deviation of 0.064. The range of AEM is between

0.002 and 0.354. REM has an average value of 0.094 with a deviation of 0.071. The range of REM is between 0.005 and 0.389. Audit committee technology expertise has an average value of 0.031 with a deviation of 0.109. The range of audit committee technology expertise is between 0.000 and 0.500. Audit committee meetings have an average value of 6.842 with a deviation of 2.114. The range of audit committee meetings is between 2.000 and 15.000. Size has an average value of 28.745 with a deviation of 1.432. The range of size is between 25.201 and 32.114. Leverage has an average value of 0.421 with a deviation of 0.214. The range of leverage is between 0.052 and 0.891.

Table 2: Descriptive Statistics

Variable	Minimum	Maximum	Mean	Standard Deviation
AI Implementation	0.000	6.732	2.876	1.421
Accrual Earnings Management	0.002	0.354	0.087	0.064
Real Earnings Management	0.005	0.389	0.094	0.071
Audit Committee Technology Expertise	0.000	0.500	0.031	0.109
Audit Committee Meetings	2.000	15.000	6.842	2.114
Size	25.201	32.114	28.745	1.432
Leverage	0.052	0.891	0.421	0.214

Preliminary Test

To ensure the best linear unbiased estimator, this research performs classical assumptions as a preliminary test. Based on Table 3, the multicollinearity test uses the Variance Inflation Factor (VIF), which has a value range between 1.121 and 2.154. The VIF values are below 5, which indicates that there is no multicollinearity problem (28). The heteroskedasticity test uses White test, which has a significance value of 0.238 (above 0.05), indicating that residual has a homogeneous

variance (29). Serial-correlation uses the Run test which as which has a significance value of 0.516 (above 0.05), indicating that the residual is distributed randomly and free from autocorrelation (30). Cross-sectional dependence uses Pesaran's Cross-Sectional Dependence (CD) Test, which has a significance of 0.142 (above 0.05), indicating that each company is independent in the context of cross-section and does not have a spillover effect (31).

Table 3: Preliminary Test

Diagnostic Test	Method	Result	Benchmark
Multicollinearity	Variance Inflation Factor (VIF)	1.121 to 2.154	Below 5
Heteroskedasticity	White Test	Significance = 0.238	Above 0.05
Serial Correlation	Run Test	Significance = 0.516	Above 0.05
Cross-Sectional Dependence	Pesaran's Cross-Sectional Test	Significance = 0.142	Above 0.05

Regression Analysis

Based on Table 4, in the model where the audit committee is measured by audit committee technology expertise, the effect of AI on AEM has a coefficient value of -0.012 with a t-statistic of -3.214 (significant at 0.01) and a significance value of 0.001. In the model where the audit committee is measured by audit committee technology expertise, the effect of AI on REM has a coefficient value of -0.015 with a t-statistic of -3.642 (significant at 0.01) and a significance value of 0.000.

In the model where the audit committee is measured by audit committee meetings, the effect of AI on AEM has a coefficient value of -0.010 with a t-statistic of -2.554 (significant at 0.05) and a significance value of 0.011. In the model where the audit committee is measured by audit committee meetings, the effect of AI on REM has a coefficient value of -0.013 with a t-statistic of -3.112 (significant at 0.01) and a significance value of 0.002. In general, AI reduces both AEM and REM.

Table 4: Regression Analysis

Independent Variable	Coefficient t-Statistics Significance			
	Moderating Role of Audit Committee Technology Expertise		Moderating Role of Audit Committee Meeting	
AI	-0.012	-0.015	-0.010	-0.013
	-3.214*	-3.642*	-2.554**	-3.112*
	0.001	0.000	0.011	0.002
Audit Committee Technology Expertise	-0.041	-0.037		
	-2.118**	-2.067**		
	0.035	0.039		
	-0.028	-0.031		

AI × Audit Committee	-2.476**	-2.581**		
Technology Expertise	0.014	0.010		
Audit Committee Meeting			-0.003	-0.004
			-1.899***	-2.234**
			0.058	0.026
AI × Audit Committee			-0.002	-0.002
Meeting			-2.214**	-2.408**
			0.027	0.017
Size	-0.006	-0.004	-0.006	-0.003
	-1.872***	-1.244	-1.861***	-1.017
	0.062	0.214	0.063	0.310
Leverage	0.053	0.061	0.052	0.059
	3.441*	3.982*	3.427*	3.856*
	0.001	0.000	0.001	0.000
Constant	0.241	0.198	0.233	0.187
	4.992*	4.103*	4.874*	3.962*
	0.000	0.000	0.000	0.000
Dependent Variable	Accrual Earnings	Real Earnings	Accrual Earnings	Real Earnings
	Management	Management	Management	Management
F-Stat.	18.477*	21.051*	16.922*	19.761*
Adjusted R-Squared	0.312	0.337	0.298	0.321

Note: *Significant at 0.01, **Significant at 0.05, ***Significant at 0.10.

The interaction variable of AI and audit committee technology expertise on AEM has a coefficient value of -0.028 with a t-statistic of -2.476 (significant at 0.05) and a significance value of 0.014. The interaction variable of AI and audit committee technology expertise on REM has a coefficient value of -0.031 with a t-statistic of -2.581 (significant at 0.05) and a significance value of 0.010. The interaction variable of AI and audit committee meetings on AEM has a coefficient value of -0.003 with a t-statistic of -1.899 (significant at 0.10) and a significance value of 0.058. The interaction variable of AI and audit committee meetings on REM has a coefficient value of -0.004 with a t-statistic of -2.234 (significant at 0.05) and a significance value of 0.026. In general, the audit committee strengthens the role of AI to reduce AEM and REM.

Robustness Test

The potential of an endogeneity problem occurs when there is omitted variable bias and reverse

causality in the relationship between AI and earnings management. Companies with stronger corporate governance and resources can actively adopt AI, but at the same time, have lower financial report manipulation, which can lead to a biased relationship. This research performs two-stage least squares (2-SLS) to mitigate the problem.

This research chooses industry-average AI implementation as an instrumental variable by excluding the observed company. Industry-average AI implementation is relevant to give institutional pressure and spillover effects that encourage companies to implement AI, also exogenous to an individual company's idiosyncratic accounting choices and discretionary accruals (exclusion restriction). The first-stage regression examines industry-average AI implementation on company-level AI implementation. The second-stage regression examines the predicted AI implementation in the first-stage model on AEM and REM. The result can be seen in Table 5.

Table 5: Two-Stage Least Squares

Variable	Coefficient		t-statistics	
	First-Stage Regression		Second-Stage Regression	
Industry-Year AI Average	0.642			
	4.985*			
Predicted AI		-0.014		-0.017
		-2.258**		-2.833*

Audit Committee Technology	0.812	-0.038	-0.035
Expertise	2.104**	-2.015**	-2.002**
Audit Committee Meeting	0.085	-0.003	-0.004
	1.812***	-1.842***	-2.105**
Size	0.214	-0.005	-0.003
	2.341**	-1.789***	-1.085
Leverage	-0.152	0.051	0.058
	-0.985	3.312*	3.741*
Constant	0.412	0.228	0.185
Dependent Variable	AI	Accrual Earnings Management	Real Earnings Management
Sample	434	434	434
Cragg-Donald Wald F-stat	24.850*		
Adjusted R-Squared	0.285	0.301	0.324
Fixed Effects	Yes	Yes	Yes

Note: *Significant at 0.01, **Significant at 0.05, ***Significant at 0.10.

Based on Table 5, in the first-stage regression, the instrumental variable of industry-average AI implementation has a positive effect on company-level AI implementation with a Cragg-Donald Wald F-statistic of 24.85, which is above the weak instrument benchmark of 10. In the second-stage regression, predicted AI implementation still has a negative effect on AEM and REM. The result confirms that self-selection bias does not contaminate primary inference, which is that AI adoption genuinely serves as a structural control mechanism that mitigates earnings management rather than merely reflecting superior unobserved firm governance.

Discussion

Data analysis shows that AI implementation has a negative effect on both AEM and REM. This result indicates that AI has a function more as a mechanism of internal control and monitoring than an opportunistic instrument. In the context of agency theory, AI integration in financial reporting contributes to information asymmetry reduction between managers and shareholders by providing accurate estimation, accounting automation and data-driven anomaly detection. This empirical finding aligns with and reinforces prior digital transformation literature from developed markets, which demonstrates that continuous automated transaction monitoring restricts discretionary accounting adjustments. AI also supports operational visibility and internal control in real-time through integrated ERP or predictive analysis.

There are some internal control mechanisms that are related to one another in how AI can restrict opportunistic managerial discretion in financial

reporting. First, automatic transaction monitoring and sustainable audit allow tracing of operational and accounting entries in real time. This mechanism reduces the time lag that can be used as a loophole to make discretionary adjustments. Second, machine learning-based anomaly detection algorithms systematically identify uncommon entries, non-routine transactions and abnormal accruals compared to historical patterns. Third, predictive analysis increases the estimation accuracy for complex accounting elements. This mechanism reduces the reliance on subjective managerial assumptions and arbitrary discretionary choices. Fourth, the integration between algorithmic capacities and the ERP system allows AI to improve overall internal control. This mechanism creates fixed digital audit trails and enforces standardized accounting rules that directly limit managerial opportunism in both AEM and REM.

The role of the audit committee ensures that algorithm complexity does not lead to AI manipulation. Audit committee technology expertise and meeting frequency strengthen the negative effect of AI on earnings management. Instead of working deterministically, AI effectiveness depends on corporate governance quality. This empirical divergence can be explained by contextual factors within the Indonesian emerging market setting, where listed manufacturing firms are characterized by concentrated ownership structures and varying digital maturity, rendering technological tools vulnerable to managerial override unless actively monitored. An audit committee with high technology literacy can evaluate model

assumptions, understand algorithm parameter implications and ensure compatibility between AI and accounting standards. Audit committee meetings indicate intensive procedural monitoring, especially in the digital era. Frequent discussions by the audit committee increase the possibility of early detection of manipulation in technology-based financial reporting.

The results give a distinct incremental contribution to accounting and technology literature. While previous studies emphasize analytical big data in operational scale, data storage capabilities and broad efficiency gains (32–34), this research specifically finds how advanced cognitive capabilities directly restrict opportunistic accounting choices. Moreover, although robotic process automation can perform regulated and routine administrative tasks automatically to mitigate human error (35), this technology does not have cognitive evaluation capability. This research shows that AI performs beyond basic automation by utilizing a machine learning algorithm that can detect complex anomalies to restrict opportunistic managerial discretion in AEM and operational manipulation in REM. While prior accounting technology literature often assumes a deterministic, direct link between technology adoption and reporting quality, our evidence reveals that AI acts as a governance-enabling tool whose efficacy in emerging markets is strictly contingent upon human oversight, specifically audit committee technology expertise and meeting frequency.

Practically, this research confirms that investment in AI must be followed by strong corporate governance. The company must ensure that there is a monitoring structure for algorithm model design, validation and sensitivity. For corporate boards and executive leadership, these empirical findings provide actionable guidance on operationalizing and strengthening internal AI governance. To ensure that AI implementation functions as an effective monitoring mechanism rather than an opaque operational risk, organizations must fortify their governance infrastructure across four key pillars. First, boards should institute continuous technology training programs and digital literacy workshops tailored for board and audit committee members, empowering them to decode machine learning outputs, critically evaluate model assumptions and

interpret algorithmic flags. Second, organizations need to adopt formal AI governance frameworks that explicitly delineate oversight roles, establish clear lines of algorithmic accountability and define ethical standards for data usage in financial reporting. Third, executive management must formulate robust AI risk management policies that encompass pre-deployment model validation, periodic bias and drift assessments, data privacy compliance and continuous sensitivity testing of financial algorithms. Finally, boards should enforce enhanced oversight procedures, such as mandatory independent algorithmic audits, real-time tracking of automated anomaly flags and formal escalation protocols whenever discrepancies emerge between automated outputs and human accounting judgments. By embedding these structured mechanisms into corporate practices, boards can safeguard financial reporting integrity against algorithmic opacity and managerial override.

Beyond its practical contributions to corporate boards, this study offers critical policy implications for regulatory bodies and standard-setters, such as capital market authorities and corporate governance councils. Current corporate governance codes predominantly emphasize financial, accounting and legal expertise when defining the composition and mandate of audit committees. However, given our empirical evidence that AI efficacy in constraining earnings management depends strictly on active governance oversight, existing regulatory frameworks must evolve to incorporate explicit guidelines on AI governance, digital oversight and technology literacy. Specifically, regulators should consider updating national corporate governance guidelines to mandate at least one audit committee member with verifiable digital or IT expertise. Furthermore, standard-setters need to establish formal regulatory frameworks covering algorithmic risk management, mandatory algorithm auditing, model validation standards and digital audit trail integrity. Updating regulatory guidelines in this manner will ensure that public firms maintain robust oversight over automated reporting tools and prevent algorithmic complexity from being exploited to obscure financial manipulation.

Conclusion

This study examines the effect of artificial intelligence (AI) implementation on earnings management and the moderating role of the audit committee in Indonesian manufacturing firms. The findings provide consistent evidence that AI implementation is negatively associated with both AEM and REM. These results suggest that, within the observed institutional context, AI functions primarily as a monitoring-enhancing mechanism rather than as an opportunistic tool for managerial manipulation.

From a theoretical perspective, the findings extend agency theory by demonstrating that digital transformation reshapes the structure of information asymmetry and monitoring mechanisms. AI reduces discretionary space in accounting estimation and operational decision-making by increasing automation, standardization, predictive analytics and anomaly detection. Importantly, the reduction in both AEM and REM indicates that AI influences not only reporting techniques but also operational behavior embedded in financial outcomes.

The study further shows that the effectiveness of AI is conditional on governance quality. Audit committee technology expertise and meeting frequency significantly strengthen the negative relationship between AI and earnings management. This evidence highlights that AI does not automatically guarantee higher reporting quality. Instead, its impact depends on whether governance mechanisms can oversee algorithm design, parameter calibration and system transparency. In the digital era, monitoring must extend beyond financial statement outputs to include algorithm governance and digital infrastructure accountability.

Practically, the results imply that firms should complement AI investment with enhanced digital literacy within audit committees and structured oversight procedures for AI systems. Regulators may also consider encouraging more transparent disclosure of AI governance practices to maintain investor confidence in technology-driven financial reporting.

Despite its contributions, this study is subject to limitations, including disclosure-based measurement of AI and the focus on a single sector and country context. Future research could explore

causal identification strategies, cross-country comparisons and the emerging phenomenon of algorithmic earnings management as AI systems become increasingly autonomous.

Abbreviations

None.

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Author Contributions

Ghina Fitri Ariesta Susilo: Conceptualization, Methodology, Validation, Formal Analysis, Investigation, Data Curation, Writing - Original Draft Preparation, Supervision, Funding Acquisition, Muhamad Wahyudi: Conceptualization, Software, Validation, Resources, Writing - Review and Editing, Visualization, Agustina Prativi Nugraheni: Validation, Writing - Review and Editing, Project Administration, Funding Acquisition, Alex Johanes Simamora: Methodology, Visualization, Project Administration.

Conflict of Interest

The authors declare no conflicts of interest.

Data Availability

The datasets can be accessed from www.idx.co.id.

Declaration of Artificial Intelligence (AI) Assistance

During the preparation of this work, the authors used Grammarly in order to improve the language flow and grammar accuracy. After using this tool, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Ethics Approval

None

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