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Detecting Financial Statement Fraud in Indonesian Companies: The Beneish M-Score Model

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Abstract:. This study aims to detect financial statement fraud in Indonesian companies using the Beneish M-Score model. The research covers 622 companies from ten sectors listed on the Indonesia Stock Exchange (IDX) during the period 2021–2024, with a total of 2,488 financial statements. The data was obtained from the IDX's published financial reports and analysed using eight Beneish M-Score ratios to classify companies into manipulator and non-manipulator categories. The results show that 34.03% of companies were identified as manipulators, while the remaining 65.97% were classified as non-manipulators. The technology sector had the highest percentage of manipulators (45%), followed by the raw materials sector (37%) and energy (36.49%). Conversely, the transportation (24.04%) and health (27.68%) sectors had the lowest percentages. These findings confirm that financial statement fraud remains a serious problem, with varying levels of risk across sectors. The implications of the study emphasise the importance of strengthening corporate governance, the role of external audits, and regulatory oversight to prevent manipulative practices. In addition, this study contributes to academic literature by providing a comprehensive overview of cross-sector manipulation trends in Indonesia.
Keywords: Financial statement fraud, Beneish M-Score, profit manipulation, corporate governance, Indonesia Stock Exchange.

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1. INTRODUCTION

Financial statements are important documents for every company that serve to present information about the company's financial position, performance, and changes in financial position (Sudarma & Wulandari, 2025). The goal is to give different users of the statements relevant information to help them make financial decisions.(Nugraha et al., 2024). These reports must be prepared periodically and submitted to interested parties (Hayuningrum & Sari, 2023). In addition to providing a basis for decision-making, financial reports also demonstrate management's stewardship of the company's resources entrusted to them (Tio & Kuswanto, 2025). Although financial reports contain very important information, there is always a risk of misstatement, which can be caused by errors or fraud committed by company management (Monica et al., 2023;Lasdin & Ratnawati, 2023). In order to deceive users of financial statements, such fraud frequently takes the form of intentional modification of financial data. As a result, it's critical to learn more about financial statement fraud and its several manifestations.

Financial statement fraud is the act of manipulating financial statements in order to benefit oneself or others, but at the expense of certain parties. (Warseno et al., 2023). This practice not only deviates from basic accounting principles but is also illegal. Asset theft, corruption, and financial statement fraud are the three primary types of fraud that are the subject of international scrutiny, according to the Association of Certified Fraud Examiners' (ACFE) 2016 Report to the Nations. Financial statement fraud is the falsification or manipulation of information in a company's or organization's financial statements; asset misappropriation is the theft or misuse of an organization's assets; and corruption is the abuse of power or influence in business transactions to obtain personal gain. (ACFE, 2016).

Various cases of financial statement fraud that have come to light show that this practice often causes significant financial losses and has a serious impact on the reputation and sustainability of companies. The Association of Certified Fraud Examiners (2024) notes that asset misappropriation is the most common type of fraud, accounting for 89% of all cases, followed by corruption at 48%, while financial statement fraud accounts for only 5% of the total cases analysed. Although financial statement fraud cases are the least common, the losses incurred are significantly the highest. The average loss (median loss) from this type of fraud reaches around $660,000 to $799,000, which is much higher than corruption and asset misappropriation, which only result in median losses of $170,000 and $120,000 respectively (ACFE, 2024). This fact underlines that although financial statement fraud is less common, its impact on the sustainability and financial integrity of organisations is far greater. Similar conditions are also reflected in a number of cases in Indonesia, which show that financial statement fraud remains a serious threat to the transparency and accountability of business entities and state institutions. One such phenomenon was seen in the case involving PT Indofarma Tbk. and its subsidiaries in 2024, which caused state losses of up to Rp371.38 billion.

In 2024, PT Indofarma Tbk and its subsidiaries were indicated to have committed financial statement fraud, causing state losses of up to Rp371.83 billion. This fraud included financial statement manipulation practices carried out by individuals in the previous management, one of which was by creating fictitious receivables and transactions in an attempt to cover up the actual financial condition. Additionally, Indofarma was also involved in various other irregularities, such as procuring medical equipment without feasibility studies, selling products without customer feasibility analysis, which resulted in large amounts of bad debts, and using online loans (fintech) for operational purposes. This case highlights the weakness of governance and internal controls, which not only harms state finances but also impacts the delay in employee salary payments and a decline in public trust in this state-owned enterprise. Various efforts need to be made to prevent financial statement fraud. One of the most effective efforts is through detection by applying company financial statement analysis (Aros et al., 2024;Zhou et al., 2024).

The necessity for corporate transparency and the growing complexity of accounting procedures are driving the ongoing evolution of research on financial statement fraud detection. Due to its capacity to identify signs of profits manipulation using eight financial ratios, Beneish's (1999) Beneish M-Score model has grown to be one of the most often used methods. This approach has worked well in a number of situations, including significant cases like Enron. (MacCarthy, 2017), as well as cross-country empirical studies(Hugo, 2019;Khatun et al., 2022). Research using the Beneish M-score model has also been conducted in Indonesia..

The efficacy of the Beneish M-Score in Indonesian businesses has been the subject of earlier empirical research, but the majority of these studies are sector-specific. For example, Nurjanah et al. (2023) focused on the insurance sector,Widowati & Oktoriza (2021) researched the raw materials and manufacturing sectors, Ramadhan et al. (2025) focused on the health sector, and Ginting & Daljono (2023) focused on the consumer sector. This fragmentation of research indicates that the use of the Beneish M-Score in Indonesia is still limited to certain areas and does not yet reflect a general picture across industrial sectors.

Research conducted by Hugo (2019) on cross-sector companies on the US Stock Exchange shows a more comprehensive approach to detecting financial statement fraud. Meanwhile, previous studies in Indonesia have generally been limited to a specific industrial sector. This indicates that no research has been done on financial statement fraud in Indonesian cross-sector businesses. Thus, this study covers companies from ten different industries on the Indonesia Stock Exchange (IDX) between 2021 and 2024 in an effort to more thoroughly identify possible financial statement fraud.

The selection of the ten sectors that were the subject of the study was based on methodological considerations to maintain consistency and validity in the application of the Beneish M-Score Model. The Beneish Model (1999) was developed based on financial ratios that are highly suitable for detecting profit manipulation in real or non-financial sector companies, as covered by the ten sectors in the sample, because they have financial report structures that enable accurate calculation of the eight Beneish index ratios, such as the Days Sales in Receivable Index (DSRI) and Asset Quality Index (AQI). Thus, this study not only provides a comprehensive picture of cross-sector manipulation trends in Indonesia, but also serves as a practical early warning system for stakeholders, while enriching academic literature.

2. LITERATURE REVIEW

Agency Theory

This study is based on Agency Theory introduced by Jensen & Meckling (1976), which explains the contractual relationship between company owners (principals) and management (agents). In this theory, the principal delegates authority to the agent to manage company resources, but differences in interests and objectives often give rise to agency conflicts. Managers, as agents, have a tendency to maximise their personal interests, such as maintaining their position, obtaining bonuses, or improving their performance image, which can encourage financial statement manipulation. This condition is exacerbated by information asymmetry, where managers have more access to information than owners or investors, creating opportunities for earnings manipulation(Scott, 2015:265-270). In this study, the Beneish M-Score Model is used as a tool to identify such opportunistic behaviour through eight financial ratios that reflect deviations in reporting practices.

The application of Agency Theory in this study provides a theoretical framework for understanding the motives and mechanisms of financial statement fraud in public companies in Indonesia. External pressure from shareholders and the capital market to show positive performance after the pandemic can create pressure that encourages managers to engage in earnings management. In this study, the Beneish M-Score model serves to detect manifestations of such opportunistic behaviour through financial ratio analysis, so that the classification results between manipulators and non-manipulators reflect the effectiveness of agency control mechanisms such as good corporate governance, external audits, and regulatory oversight. Thus, this study not only provides empirical evidence regarding the relevance of Agency Theory in explaining deviant management behaviour, but also strengthens the academic literature on the use of financial models as instruments for mitigating conflicts of interest between agents and principals in the context of corporate financial reporting in Indonesia.

Financial Statement Fraud

Financial statement fraud is one of the most serious types of fraud in the accounting world because it can mislead stakeholders and undermine public confidence in company information. According to Rezaee (2010:33-34), this fraud is defined as a deliberate act of misstatement or omission of material information in financial statements with the main purpose of deceiving users of the statements. This element of intentional misstatement clearly distinguishes it from unintentional accounting errors.

Wells (2017:364) and Albrecht et al. (2016:402-404) reinforce this definition by emphasising the role of company management as the main perpetrators. They manipulate and falsify information to make the company's financial condition appear better than it actually is. The objectives of this fraud vary, such as attracting investors, increasing share prices, or obtaining performance-based bonuses. These forms of fraud include recognition of fictitious income, manipulation of expenses, inflation of asset values, or presentation of liabilities that are lower than their actual value.

Based on this explanation, financial statement fraud is defined as a deliberate act of presenting false or misleading financial information, either through misrepresentation or omission of material facts, with the intent to deceive users of the report in order to obtain specific benefits.

Financial Statement Fraud Detection Models

Various financial statement fraud detection models have been developed by researchers around the world. One of the most well-known is the F-Score Model introduced by Dechow et al. (2011). This model combines eight financial and accrual variables to identify potential profit manipulation through analysis of accrual quality and company financial performance. Although the F-Score has a good level of accuracy, its application is relatively more complex because it requires specific data and advanced regression testing. Furthermore, the Altman Z-Score (Altman, 1968) was originally designed to predict bankruptcy, but it is also often used as an early indicator of financial distress that can trigger financial statement manipulation practices. This model focuses on liquidity, profitability, and solvency ratios, but it is less capable of directly detecting accounting manipulation. Compared to the complex F-Score Model and the Altman Z-Score, which is less specific in detecting accounting manipulation, the Beneish M-Score Model offers a more focused and practical approach to this research.

The Beneish M-Score has the main advantage of being quantitative, objective, and based on accounting ratios that directly represent indications of financial statement manipulation. This model is not only easy to apply using public secondary data, but has also been proven effective in various empirical contexts, including detecting major manipulation cases such as Enron (MacCarthy, 2017) and cross-sector research in various countries (Hugo, 2019; Khatun et al., 2022). Therefore, the M-Score is considered the most appropriate for use in this study because it is capable of providing accurate and replicable results in detecting potential cross-sector financial statement fraud in Indonesia.

Beneish M-Score

A model for identifying potential profit manipulation in a company's financial statements is the Beneish M-Score. The likelihood that the business will conduct fraud increases with the M-Score score. The Beneish M-Score approach was selected due to its shown efficacy in detecting deceptive reporting techniques and accounting manipulation.

The Beneish M-Score model was developed by Beneish (1999) using eight financial ratios aimed at detecting possible fraud in financial statements. The Beneish M-Score is calculated using the following formula:

$$\begin{aligned}\mathrm{MScore} = {} & -4{,}840 + 0{,}920 \times \mathrm{DSRI} + 0{,}528 \times \mathrm{GMI} + 0{,}404 \times \mathrm{AQI} + 0{,}892 \times \mathrm{SGI} \\ & + 0{,}115 \times \mathrm{DEPI} - 0{,}172 \times \mathrm{SGAI} - 0{,}327 \times \mathrm{LVGI} + 4{,}679 \times \mathrm{TATA}\end{aligned}$$

Description
DSRI *: Days Sales in Receivable Index*
GMI *: Gross Margin Index*
AQI *: Asset Quality Index*
SGI *: Sales Growth Index*
DEPI *: Depreciation Index*
SGAI *: Sales, General, and Administrative Expenses Index*
LVGI *: Leverage Index*
TATA *: Total Accruals to Total Assets*

Companies with an M-Score of more than -2.22 are seen to be indicative of fraud, whereas those with an M-Score of less than -2.22 are not indicative of financial statement manipulation. This is how the Beneish M-Score is evaluated.

Beneish (1999) argues that there are a number of ratios that can indicate negative signs of financial statement manipulation. These ratios, known as the Beneish Ratio Index, include:

1. **Days Sales in Receivable Index (DSRI)**

Days' Sales in Receivables Index (DSRI) is one of the components in the Beneish M-Score model used to detect possible profit manipulation. DSRI measures changes in the ratio of accounts receivable to net sales from the previous year to the current year. An increase in DSRI may indicate management's efforts to accelerate revenue recognition through an increase in accounts receivable, for example by relaxing credit policies or recording fictitious sales. In other words, a high DSRI reflects the potential that the company is trying to present better sales performance than the actual conditions, which may be a signal of financial statement manipulation.

$$\mathrm{DSRI} = \frac{Account\ Receivable\ (t)/Sales\ (t)}{Account\ Receivable\ (t-1)/Sales\ (t-1)}$$

2. **Gross Margin Index (GMI)**

The gross profit index is a ratio that measures a company's profitability and reflects its future prospects. According to Beneish (1999), a decline in gross profit margin is a negative signal for a company's prospects. Therefore, companies with poor prospects tend to be more vulnerable to manipulation. If the GMI value is greater than 1, it means that the gross profit margin is declining, which is a negative indication for the company. An increase in GMI indicates the company's drive to inflate profits, so there is a positive relationship between GMI and the possibility of manipulation when the company's performance declines.

$$\mathrm{GMI} = \frac{Sales(t-1) - Cost\ of\ Sales(t-1)/Sales(t-1)}{Sales(t) - Cost\ of\ Sales(t)/Sales(t)}$$

3. **Asset Quality Index**

The Asset Quality Index (AQI) is used to assess the quality of a company's assets by comparing the ratio of fixed assets, particularly Property, Plant and Equipment (PPE), to total assets. According to Beneish (1999), the higher this ratio, the greater the likelihood that the company will increase deferred costs or expand intangible assets that can be used to manipulate income. The AQI measures asset risk in year t compared to year t-1. An AQI value greater than 1 indicates that the company has the potential to improve cost control. In addition, the AQI indicates the proportion of total assets to future profits that may be uncertain, so there is a positive relationship between the AQI and the possibility of financial statement manipulation.

$$\mathrm{AQI} = \frac{1 - ((Current\ Asset(t) + Property\ Plant\ Equipment\ (t)) : Total\ Asset\ (t))}{1 - ((Current\ Asset(t-1) + Property\ Plant\ Equipment\ (t-1)) : Total\ Asset\ (t-1))}$$

4. Sales Growth Index (SGI)

The Sales Growth Index (SGI) is a ratio that compares sales in the current year (t) with the previous year (t-1). An SGI value greater than 1 indicates an increase in sales compared to the previous year. SGI can be used to identify companies that may be recording fictitious sales. An increase in SGI indicates the potential for fictitious revenue recognition, as companies attempt to exceed normal expected growth for the period. Although increased sales do not directly indicate manipulation, if this growth is accompanied by a decline in share prices, it may trigger manipulation practices by companies.

$$\mathrm{SGI} = \frac{Sales\ (t)}{Sales\ (t-1)}$$

5. Depreciation Index (DEPI)

The Depreciation Index (DEPI) is a ratio that compares depreciation expense to the value of fixed assets before depreciation in the current year (t) with the previous year (t-1). If the DEPI value is greater than 1, this indicates that the rate of asset depreciation is decreasing, which may be due to the company extending the estimated useful life of the asset or using a new depreciation method to increase profits. Based on Beneish's (1999) research, there is a positive relationship between the DEPI value and the likelihood of financial statement manipulation.

$$\mathrm{DEPI} = \frac{[Depreciation\ (t-1)/(PPE\big(t-1\big) + Depreciation\big(t-1\big))]}{[Depreciation\ (t)/(PPE(t) + Depreciation(t))]}$$

6. Sales, General and Administrative Expenses Index (SGAI)

The Sales, General and Administrative Expenses Index (SGAI) is a ratio that measures the comparison of sales, general and administrative expenses to sales in the current year (t) and the previous year (t-1). SGAI shows that an increase in expenses that is not balanced with an increase in sales can be a bad indication for the company's future prospects. Beneish (1999) argues that there is a positive relationship between SGAI and the risk of financial statement manipulation.

$$\mathrm{SGAI} = \frac{(SGA\ Expense(t)/Sales(t))}{(SGA\ Expense(t-1)/Sales(t-1))}$$

7. Leverage Index (LVGI)

The Leverage Index (LVGI) is a ratio that compares total debt to total assets in the current year (t) and the previous year (t-1). LVGI reflects a company's ability to meet its obligations. If the LVGI value is greater than 1, this indicates an increase in leverage, so companies experiencing an increase in leverage tend to have a higher risk of income manipulation. An LVGI exceeding 1 aims to identify incentives in debt covenants that could trigger profit manipulation. Beneish (1999) states that changes in leverage in a company's capital structure are associated with technical default risk in the stock market.

$$\mathrm{LVGI} = \frac{(Long\ Term\ Debt(t) + Current\ Liabilities(t)) \div Total\ Asset(t)}{\big(Long\ Term\ Debt(t-1) + Current\ Liabilities(t-1)\big) \div Total\ Asset(t-1)}$$

8. Total Accruals to Total Assets (TATA)

The Total Accrual to Total Assets (TATA) index is used to measure the proportion of accrual income in a company's total assets. A high total accrual value reflects the high level of accrual profit earned by the company. In addition, if the total accrual is positive, this may indicate greater potential for income manipulation. Beneish (1999) utilised TATA to identify accounting profits that did not originate from the company's actual cash flow.

$$\text{TATA} = \frac{(Net\ Income\ From\ Continuing\ Operations(t) - Cash\ Flow\ from\ Operations(t))}{Total\ Asset\ (t)}$$

3. RESEARCH METHOD

This study utilises a descriptive quantitative approach. According to Creswell (2014:155), a descriptive quantitative approach is a research method that aims to objectively and systematically describe the characteristics of a phenomenon or variable based on numerical data. This study utilises the documentation method to collect secondary data. The secondary data collected were in the form of financial reports of companies listed on the Indonesia Stock Exchange (IDX) for the period 2021–2024, which were accessed through the official website www.idx.co.id. The reason for selecting financial reports from 2021 to 2024 as the sample was because this period was identified as the post-pandemic recovery phase. During this period, it is assumed that there was greater pressure on companies to manipulate their financial reports in order to present more attractive financial performance to investors. The research population included all companies that published financial reports during that period, with a total of 955 companies based on data from the IDX website. The sampling technique used purposive sampling, with the criteria being companies that published financial reports for the 2020–2024 period and provided the data required by the researcher. Based on these criteria, 622 companies from 10 industrial sectors were obtained as samples, with a total of 2,488 financial reports. Companies from the financial sector (such as banking and insurance) were explicitly excluded from the research sample. This exclusion was based on the fundamental nature of the Beneish M-Score, which was developed to detect manipulation in non-financial companies. The structure of financial statements in the financial sector, especially banking, is very different from that of industrial companies in general, so that some of the eight ratios in the Beneish M-Score Model such as Days Sales in Receivable Index (DSRI) and Total Accruals to Total Assets (TATA) become difficult to interpret or less relevant (Patmawati & Rahmawati, 2023).

Data analysis using the ratio index method on the financial statement data of the companies sampled in the study. Ratio index calculations were performed to classify companies into manipulator or non-manipulator categories. The classification was determined based on the ratio index value compared to the Beneish M-Score parameter. The steps in calculating the ratio index to determine the company category include:

a) Calculate the Beneish M-Score
b) Classify companies that engage in manipulation (manipulators) and those that do not (non-manipulators) based on the M-Score parameter
c) Calculate the percentage of manipulator and non-manipulator companies in each sector and among all companies

4. RESULTS AND DISCUSSION

Descriptive Analysis

Descriptive analysis shows variations in data characteristics across the eight Beneish M-Score ratios. The DSRI, AQI, DEPI, and SGAI variables have very high standard deviations, indicating data deviation and potential outliers. Meanwhile, GMI, SGI, and LVGI show a more stable data distribution. TATA has a positive mean close to zero. The detailed results are presented in Table 1 below.

Table 1. Descriptive Analysis Results

No	Variabel	Min	Max	Mean	Standar Deviasi
1.	DSRI	0,007048	2078,759	2,309519009	42,55839
2.	GMI	0,006101	14,96429	0,777726168	0,725438
3.	AQI	-26,1574	736,7775	1,977314701	16,12736
4.	SGI	0,014914	16,25045	1,225088623	0,882924
5.	DEPI	0,007921	533,6512	1,561901235	11,01251
6.	SGAI	-584,8302	904,8684	1,25117606	23,07002
7.	LVGI	0,052398	9,367778	0,996086426	0,38022
8.	TATA	-11,2924	4,634249	0,038905991	0,396897

Source: Processed data (2025)

Descriptive statistical analysis shows diverse characteristics in each variable. The average Days' Sales in Receivables Index (DSRI), Asset Quality Index (AQI), Depreciation Index (DEPI), and Sales, General and Administrative Expenses Index (SGAI) vary significantly. This can be seen from the very high standard deviation values for these four variables, indicating data deviation and potential outliers. Conversely, the Gross Margin Index (GMI), Sales Growth Index (SGI), and Leverage Index (LVGI) variables show a more stable data distribution with averages close to one and lower standard deviations. Meanwhile, Total Accruals to Total Assets (TATA) has a negative mean (-0.04), indicating that accrual values tend to be close to zero.

Percentage of Manipulative Companies in Each Sector

An analysis of 2,488 company financial reports using the Beneish M-Score shows that 34.03% of companies in Indonesia are indicated to have manipulated their financial reports. This risk varies across sectors, with the Technology Sector recording the highest percentage of manipulators at 45%, followed by Raw Materials (37%) and Energy (36.49%). Conversely, the Transportation Sector (24.04%) and Health Sector (27.68%) have the lowest percentages. Details of the percentage of manipulating companies from ten sectors on the IDX are presented in Table 2.

Tabel 2. Percentage Calculation Results

No	Sector	Number Of Companies	Percentage Of Manipulators	Percentage Of Non-Manipulators
1.	Technology	136,00	45,00%	55,00%
2.	Raw Materials	332,00	37,00%	63,00%
3.	Energy	296,00	36,49%	63,51%
4.	Industry	212,00	36,00%	64,00%
5.	Primary Consumption	440,00	35,00%	65,00%
6.	Non-Primary Consumption	428,00	33,00%	67,00%
7.	Infrastructure	188,00	30,43%	69,57%
8.	Property	240,00	29,00%	71,00%
9.	Health	112,00	27,68%	72,32%
10.	Transportation	104,00	24,04%	75,96%
Total		**2.488,00**	**34,03%**	**65,97%**

Source: Processed data (2025)

The results of this study reveal significant differences in the level of corporate manipulation across various sectors, with the technology sector recording the highest percentage at 45%; this figure implies that nearly half of technology companies tend to manipulate their financial reports. This high percentage can be attributed to the unique characteristics of the technology sector, which is marked by uncertainty, fierce competition, and the need to maintain investment appeal, so that companies often face enormous pressure to show positive performance and increase the chances of manipulation. The most striking difference from previous studies is the identification of the Technology Sector as the highest manipulator, surpassing traditional sectors such as Raw Materials (37%), which previously dominated fraud risk in Indonesia (as shown by the findings of Widowati & Oktoriza, 2021). This shift signals a new trend in fraud risk, where post-pandemic market conditions and pressure to maintain high valuations in growth sectors have created far greater incentives for Technology sector managers to engage in earnings management compared to other sectors.

Furthermore, traditional sectors such as Raw Materials, Energy, and Industry also occupy a fairly high risk position, with manipulator percentages of 37%, 36.49%, and 36% respectively. The high percentages in these sectors are largely due to commodity price fluctuations and intense competition, which directly affect income stability. These uncertain conditions then encourage companies to engage in earnings management to make their financial reports look more profitable in the eyes of stakeholders. In addition, the Primary and Non-Primary Consumption sectors also show fairly high percentages, at 35% and 33% respectively. Although the consumption sector is known to have relatively stable demand, this high figure indicates that the sector still faces pressure to maintain growth, making it prone to manipulation. In particular, the finding of high risk in the Raw Materials Sector is in line with the assumptions of the study by Widowati & Oktoriza (2021), which states that commodity price fluctuations are the main trigger for profit management.

In contrast to the previously mentioned high-risk sectors, the Infrastructure (30.43%) and Property (29%) sectors show lower levels of manipulation, below the overall average. One of the main reasons for this low figure is the nature of the business, which is oriented towards long-term projects, and the relatively strict supervision by regulators, which limits the scope for manipulation, as supported by the research by Aryani et al. (2023). Furthermore, the Health (27.68%) and Transportation (24.04%) sectors ranked lowest in terms of percentage of manipulators. In the health sector, this low risk is believed to be influenced by strict regulations and social sensitivity in the provision of public services, which significantly suppress manipulation. As for the transportation sector, despite being highly competitive, it recorded the lowest rate, possibly because relatively thin profit margins make it difficult for companies to significantly manipulate their reports. The percentage of manipulators in the Health Sector (27.68%) is even very similar to the findings of Ramadhan et al. (2025) (28.57%), which consistently show that the level of fraud risk in this sector is relatively stable and low compared to the market average.

This study found that a significant majority of companies on the Indonesia Stock Exchange (IDX) during the 2021–2024 period were classified as non-manipulators (65.97% or 1,641 financial reports). This high percentage indicates that most entities have successfully maintained integrity and transparency in financial reporting, reflecting success in mitigating financial statement fraud risk. The majority of non-manipulators is interpreted as the result of prudent management, the implementation of solid good corporate governance (GCG), and an optimal internal control system. Specifically, sectors such as Transportation (75.96%) and Health (72.32%) showed the highest percentage of non-manipulators, indicating that their industry characteristics—such as strict regulations or thin margins—actually create a higher accountability environment that does not encourage earnings management practices. Thus, these findings provide a positive outlook and empirical evidence that accurate and reliable financial reporting remains the standard practice for the majority of public companies in Indonesia, serving as a counterbalance to post-pandemic pressures.

Overall, this study shows that 34.03% of companies in Indonesia are indicated to have manipulated their financial statements, while the remaining 65.97% are classified as non-manipulators, in line with the Agency Theory (Jensen & Meckling, 1976) which emphasises the conflict of interest between owners (principals) and managers (agents). The finding that one-third of companies still show indications of manipulation indicates that some managers behave opportunistically by exploiting information asymmetry to embellish financial performance and obtain personal gains, such as profit-based bonuses or a positive image in the eyes of investors. This is consistent with Scott's (2015: 265–280) statement that information asymmetry provides opportunities for agents to engage in earnings management and financial reporting distortion.

Meanwhile, the dominant proportion of non-manipulative companies (65.97%) illustrates that most companies have successfully managed agency conflicts through the implementation of effective agency control mechanisms, such as good corporate governance, independent external audits, and strict regulatory oversight. These results also support the assumption that transparency and accountability in financial reporting can serve as a mitigation tool against opportunistic management behaviour. Thus, the findings of this study reinforce the relevance of Agency Theory in the empirical context of public companies in Indonesia, where the effectiveness of governance and oversight systems has been proven to reduce the level of financial statement manipulation across sectors.

The findings of this study also show that the risk of manipulation is not evenly distributed across all sectors, but is influenced by industry characteristics, market pressures, and applicable regulations. Therefore, supervision and manipulation prevention policies should be tailored to the conditions of each sector in order to be more effective in reducing financial statement fraud.

5. CONCLUSION

An extensive analysis of companies in Indonesia using the Beneish M-Score Model confirms that financial statement fraud remains a serious and persistent problem in the domestic corporate environment. These findings reaffirm the research objective of detecting potential earnings manipulation and indicate that there are substantial variations in risk levels across industry sectors. The identified sectoral disparities, with some sectors showing higher vulnerability than others, imply that unique industry characteristics, market volatility, and competitive pressures play a significant causal role in the tendency towards financial statement manipulation. The results of this study reinforce the relevance of Agency Theory by providing empirical evidence of opportunistic management behaviour that exploits information asymmetry to embellish financial performance. However, it should be noted that this study relies solely on the Beneish M-Score Model, which focuses primarily on accrual-based manipulation and may not fully capture other forms of financial statement fraud, such as real earnings management, off-balance-sheet transactions, or governance-related misconduct. In addition, the research sample is limited to companies listed on the Indonesia Stock Exchange (IDX), thereby restricting the generalisability of the findings to other types of entities, including state-owned enterprises, non-public companies, and start-ups that operate under different regulatory and disclosure environments. Moreover, the use of secondary quantitative data does not allow for deeper exploration of managerial motives, internal control effectiveness, or regulatory enforcement practices that may influence fraudulent behaviour. Despite these limitations, the findings not only contribute theoretically by providing empirical evidence regarding fraud detection and agency conflicts, but also serve as a practical early warning system for stakeholders. The implications of this study emphasise the urgency of strict supervision through effective external audits, the implementation of good corporate governance (GCG), and the strengthening of regulations by relevant institutions, particularly by adjusting supervision and prevention policies to sector-specific conditions in order to suppress manipulation practices.

The results of this study have practical implications for several parties. For the government, it is necessary to strengthen regulations and supervision of financial reporting, especially in high-risk sectors, by utilising early detection technology and imposing strict sanctions. For company management, it is important to apply the principles of good corporate governance and strengthen internal control systems so that financial reports remain transparent and trusted by the public. Meanwhile, for investors, these findings can serve as an early warning to conduct more careful analysis before making investment decisions.

For future research, it is recommended that the development of fraud detection models be expanded, not only relying on the Beneish M-Score, but also integrating it with other methods such as the F-Score, Fraud Pentagon, or machine learning techniques. This combination aims to improve detection accuracy. The scope of future research should be expanded to include study objects outside companies listed on the Indonesia Stock Exchange (IDX), covering state-owned enterprises, non-public companies, and start-ups. This expansion aims to provide a more comprehensive picture of the issues under study. In addition, it is recommended to adopt a qualitative approach, such as interviews with auditors, regulators, and management, to enrich quantitative findings and produce more holistic conclusions.

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