Integrating the Altman Z-Score, Beneish M-Score, and Granular Financial Ratios at PT Tiga Pilar Sejahtera Food Tbk for Early Fraud Detection

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Abstract
This research investigates the early detection of financial statement fraud at PT Tiga Pilar Sejahtera Food Tbk (AISA) by identifying quantitative traces of manipulation years before public exposure. Although accounting-based fraud screening models are well established, prior evidence provides limited insight into how fraud risk accumulates over time at the account level, particularly in emerging markets where high-quality fraud labels are scarce. Employing a quantitative case study approach, the study investigates the early detection of financial statement fraud at AISA using secondary audited data from 2012 to 2016. Data analysis integrates the Altman Z-Score model for financial distress, the Beneish M-Score model for earnings manipulation, and granular financial ratios. Results show that while the composite manipulation score remained in the non-manipulator range, several M-Score indices exhibit red-flag classifications, the Z-score declined to 1.806 in 2015, accounts receivable-to-sales increased to 0.366 by 2016, and inventory days rose to 153. The practical implication is that aggregate manipulation scores may mask subtle but material account-level anomalies. Therefore, auditors and market participants should adopt integrated monitoring that combines distress screening with targeted forensic attention to receivables, inventory, and depreciation-related accounts to improve early detection of potential misstatements.

1. Introduction

Fraudulent financial reporting is among the most challenging forms of fraud to detect because it is perpetrated through engineered recording and presentation choices that make the financial statements appear reasonable to users, at least in the short run. The literature emphasizes that material misstatements due to fraud often involve manipulation of revenue recognition, accounting estimates, cost capitalization, or asset inflation to portray performance and financial position as stronger than the underlying reality (COSO, 2010). From the fraud triangle perspective, pressure (performance targets, debt pressure, financing needs), opportunity (weak governance, internal control), and rationalization recurrently appear as drivers in corporate fraud cases (Cressey, 1953). Because such fraud can mislead investors, creditors, and regulators, research that identifies early warning signals (red flags) before fraud becomes public is increasingly important (Shahana et al., 2023).

The urgency of early detection is even greater for listed firms, as financial statements are the primary basis for investment decisions and risk assessment. Forensic accounting studies suggest that, prior to the eventual revelation of material misstatements, firms often exhibit recognizable red-flag patterns, such as increases in receivables and inventories that are not aligned with cash flows, deteriorating earnings quality, spikes in accruals, abnormal margin changes, and mounting leverage and liquidity pressure (Beneish, 1999; Dechow et al., 2011; Munteanu et al., 2024). In line with this, ratio-based models have been developed to help identify traces of manipulation in reported numbers well before scandals become widely known (Shahana et al., 2023; Hájek et al., 2026). One of the most widely used is the Beneish M-Score, which combines multiple financial indices to estimate the likelihood of earnings manipulation or reporting misstatement (Beneish, 1999; Hájek et al., 2026). Accordingly, the M-Score offers a relevant quantitative framework for interpreting anomalous signals in corporate performance and financial position.

Beyond manipulation detection, financial distress is also important in the fraud context, because pressure to maintain performance and avoid debt covenant violations is often cited as a trigger for reporting manipulation. For this purpose, the Altman Z-Score is commonly used to gauge bankruptcy risk and distress through a combination of liquidity, profitability, leverage, and activity ratios (Altman, 1968; Özari et al., 2025). When distress indicators deteriorate, managerial incentives to polish financial statements may intensify. Therefore, a joint analysis using the Beneish M-Score (manipulation signals) and Altman Z-Score (distress pressure) may provide a more comprehensive understanding of pre-fraud red flags (Özari et al., 2025).

The case of PT Tiga Pilar Sejahtera Food Tbk (AISA) provides an important context for testing the proposed approach on non-financial and non-service companies listed on the Indonesia Stock Exchange (IDX). Based on media reports referring to investigative findings, AISA's 2017 financial statements allegedly contained an overstatement of approximately IDR 4 trillion in accounts such as trade receivables, inventories, and fixed assets, along with alleged overstatement of sales of around IDR 662 billion and EBITDA of around IDR 329 billion in the food segment (Wareza, 2019; Forddanta & Prasetyo, 2019). These findings indicate that the irregularities were not merely clerical errors but rather exhibit the characteristics of material misstatements consistent with common patterns of reporting fraud—namely, inflating current asset accounts and/or revenue accounts to shape perceptions of stronger profitability and solvency than the underlying reality (Beasley et al., 2010; Beneish, 1999). In the legal domain, the court decision further provides context that the case concerned the submission of information/statements that were materially incorrect or misleading, with the potential to affect investor decisions in the capital market (Pengadilan Negeri Jakarta Selatan, 2021).

From a chronological perspective, it is important to clarify when and how the misstatements entered the realm of public reporting. The court decision documents a sequence of 2017 financial reporting/publication and communications to the capital market authority (Pengadilan Negeri Jakarta Selatan, 2021). Subsequently, the alleged irregularities attracted broad public attention when the investigative results and related discussions were reported in 2019 (Wareza, 2019; Forddanta & Prasetyo, 2019). The time lag between the allegedly problematic reporting period (fiscal year 2017) and the period when the issue became widely public (2019) creates an opportunity to assess whether financial indicators had already produced warning signals in the preceding years (Shahana et al., 2023).

A primary gap in current forensic accounting literature is the over-reliance on aggregate scoring models, such as the Beneish M-Score, which may fail to detect manipulation at the composite level during the early, subtle stages of fraud (Musanovic & Halilbegović, 2021). While large-scale statistical studies establish general probabilities of misstatement, they often lack the longitudinal depth required to track how specific quantitative traces evolve in individual accounts over a multi-year pre-event period (Capraş et al., 2025; Tarjo et al., 2023). Furthermore, although financial distress is conceptually linked to the pressure element of the fraud triangle, there is a lack of integrated research that maps exactly how a declining Z-Score translates into specific account-level anomalies, such as inventory bloating, before a public scandal occurs (Arum et al., 2023; Aviantara, 2021).

To address these limitations, this research employs a quantitative descriptive case study design focused on PT Tiga Pilar Sejahtera Food Tbk. By utilizing a case study approach, the study moves beyond aggregate classification to examine the specific intersections of manipulations signals, financial pressure, and account-level evidence over a five-year observation period (2012–2016). Operationally, the study can trace pre-event red-flag patterns through: (1) manipulation indicators using the Beneish M-Score (Beneish, 1999), (2) distress pressure indicators using the Altman Z-Score (Altman, 1968), and (3) supporting indicators, namely Cash Flow from Operation to Net Income (CFO/NI), Account Receivable to Sales (AR/S), Inventory to Cost of goods sold (Inv/COGS), and gross margin (GM), that commonly emerge as early markers of misstatement (Dechow et al., 2011; Özari et al., 2025; Sodnomdavaa et al., 2025). By focusing on the five-year pre-fraud window, the study is expected to provide practical contributions for investors, auditors, and regulators in strengthening early warning systems, while also enriching Indonesian empirical evidence (Narsa et al., 2023) on financial reporting misstatements. Therefore, the study is guided by the following research question: "to what extent do the Beneish M-Score, Altman Z-Score, and supporting financial ratios provide early warning red flags in the five years preceding the alleged fraud/misstatement (2012–2016)?"

Literature Review

Fraudulent Financial Reporting and Material Misstatement

Fraudulent financial reporting is an intentional act that results in material misstatements in financial statements that are misleading to financial statement users (Yadav & Sora, 2021). Such misstatements often involve the manipulation of financial data, concealment of information, or misapplication of accounting principles, ultimately distorting the true financial position and performance of a company (Jaswadi et al., 2022). In auditing and reporting contexts, material misstatements arising from fraud differ from errors because fraudulent activities inherently involve deception, whereas errors are unintentional (Shahana et al., 2023).

A conceptual framework most frequently used to explain the emergence of fraud is the fraud triangle, which posits that opportunity, pressure, and rationalization are the three conditions generally present when fraud occurs. Financial pressure such as the need to meet earnings targets, protect reputation, or avoid violations of debt covenants can incentivize individuals to commit financial statement fraud (Aviantara, 2021). Opportunity arises when internal controls are weak or nonexistent, allowing individuals to exploit vulnerabilities in financial systems (Achmad et al., 2022). While rationalization serves as the cognitive bridge, enabling perpetrators to justify their illicit actions as acceptable or necessary under certain circumstances (Ridwan, 2023). This framework is relevant for red-flag-based research because it positions financial pressure as a primary driver that is often reflected in distress indicators and financial ratio.

Financial Red flags as Early Indicators of Fraud

The misstatement-detection literature suggests that fraudulent financial reporting often leaves detectable traces or red flags in a company's financial statements, which can be identified through careful analysis (Aviantara, 2021), such as scrutinizing unusual trends in financial ratios or identifying inconsistencies in reported data (Tümmler & Quick, 2025). The red-flag concept is grounded in the premise that although figures can be manipulated, manipulation typically requires changes to specific components that ultimately become visible in financial ratios and relationships among financial statement line items (Beneish, 1999).

Specifically, Dechow et al. emphasize that material misstatements can be predicted using a combination of performance- and accrual-based variables, including signals of deteriorating accrual quality, abnormal changes in certain balance-sheet accounts, and intensifying incentives driven by performance pressure (Dechow et al., 2011). This supports the view that pre-event analysis of financial indicators can reveal patterns consistent with an elevated risk of fraudulent activities (Burcă et al., 2022; Schneider & Brühl, 2023).

Agency Theory and Managerial Incentives in Fraud

Under agency theory, the separation between ownership and control creates information asymmetry and conflicts of interest. Managers have incentives to present stronger performance in order to obtain compensation, retain their positions, or facilitate access to financing, while shareholders rely on financial statements as a monitoring mechanism (Jensen & Meckling, 1976). Under financial pressure or market targets, these conflicts may escalate from aggressive earnings management to material misstatement (Healy & Wahlen, 1999). Accordingly, financial red flags can be interpreted as quantitative manifestations of the incentives and pressures faced by management.

Beneish M-Score as a Proxies for Opportunistic Behaviour

The Beneish M-score is a widely recognized statistical model designed to identify companies that may be manipulating their reported earnings, functioning by analyzing a combination of eight financial ratios to produce a score that indicates the likelihood of earnings manipulation (Musanovic & Halilbegović, 2021). The model uses eight main components such as the day's sales in receivables index (DSRI), gross margin index (GMI), asset quality index (AQI), sales growth index (SGI), depreciation index (DEPI), selling, general and administrative expenses index (SGAI), leverage index (LVI), and total accruals to total assets (TATA) (Musanovic & Halilbegović, 2021). Conceptually, DSRI tests whether receivables are growing faster than sales, which may indicate aggressive revenue recognition. GMI and DEPI capture margin deterioration or changes in depreciation that may motivate management to polish reported earnings. AQI assesses shifts in asset quality (a higher proportion of assets that are harder to verify). SGI reflects growth pressure, high-growth firms often face market expectations that can trigger manipulation. SGAI and LVGI capture cost pressure and leverage. TATA measures total accruals relative to assets, which is associated with earnings quality (Beneish, 1999). These indices function as proxies for opportunistic behavior, identifying where management has exploited accounting flexibility to mask deteriorating performance (Fenyves et al., 2023; Musanovic & Halilbegović, 2021).

The relevance of the M-Score for a pre-fraud case study lies in its ability to act as an early warning system, highlighting financial characteristics that often precede documented cases of accounting fraud and providing a quantitative measure of a company's susceptibility to earnings manipulation (Tarjo et al., 2023). In contexts where misstatements involve alleged overstatement of balance-sheet accounts such as receivables and inventories, M-Score components that capture anomalies in receivables growth, asset quality, and accruals become particularly important (Beneish, 1999).

Altman Z-Score as an Indicator for Fraud Pressure

The Altman Z-Score was developed to predict bankruptcy potential through a combination of ratios representing liquidity, profitability, leverage/solvency, and activity (Altman, 1968). Theoretically, distress increases the likelihood of financial statement fraud, as companies facing severe financial difficulties may resort to fraudulent activities to conceal their precarious situation or to attract new investment (Arum et al., 2023). Therefore, the Z-Score is relevant as a proxy for financial pressure that may serve as an early trigger of misstatement.

Empirically, studies have shown that a low Z-score, indicating higher financial distress, correlates with an increased propensity for fraudulent financial reporting (Chakrabarty et al., 2024; Maniatis, 2021). This connection between financial distress and fraudulent reporting solidifies the Z-score's utility in a red-flag framework for fraud detection (Steingen & Löw, 2025). This aligns with the notion that companies under duress may manipulate financial statements to project a healthier image, thereby avoiding negative market reactions or regulatory scrutiny (Chakrabarty et al., 2024). Accordingly, using the Z-Score alongside the M-Score strengthens the detection framework by providing a comprehensive view of both the financial health and potential for manipulation within an organization, a critical consideration for grey-area companies that exhibit characteristics of both healthy and fraudulent entities (Thanathamathee et al., 2024).

Financial Ratio as Observable Proxies of Fraud Risk

Financial ratios function as observable proxies for fraud risk by capturing red flags, quantitative anomalies that signal underlying manipulation or severe financial distress (Musanovic & Halilbegović, 2021; Tümmler & Quick, 2025). Because fraudulent entities often struggle to maintain consistent performance across all metrics simultaneously, combining financial ratios provide the diagnostic traces necessary to detect potential fraud before it is publicly revealed (Thanathamathee et al., 2024; Yadav & Sora, 2021).

Framework Integration: Pre-Fraud Red Flags Over a Five-Year Horizon

Integrating the M-Score and Z-Score in a pre-event analytical framework provides a more comprehensive approach. The M-Score targets patterns consistent with manipulation (e.g., anomalies in receivables, asset quality, and accruals), whereas the Z-Score tests whether the firm exhibits distress trends that may reinforce incentives to manipulate (Beneish, 1999; Altman, 1968). In misstatement prediction frameworks, combining performance, accrual, and financial pressure signals is also consistent with approaches that assess misstatement probability using quantitative indicators before the event is revealed (Dechow et al., 2011).

A five-year pre-fraud horizon is relevant because many scandals do not occur instantaneously but rather develop over a prolonged period as financial pressures mount and managerial discretion erodes ethical boundaries, often showing predictive signals within this timeframe (Lokanan & Ramzan, 2024). By analyzing indicator patterns across several years prior to the problematic fiscal year, research can identify gradual deteriorations or sudden anomalies that might signal impending fraud (Capraş et al., 2025; Musanovic & Halilbegović, 2021).

Theoretical Basis

This research starts from two main pillars. First, agency theory states that information asymmetry and conflicts of interest between managers and shareholders create incentives for management to present better performance than actual conditions, especially when compensation, reputation, or access to funding are dependent on accounting figures (Jensen & Meckling, 1976). Second, the fraud triangle emphasizes that fraud occurs when there are pressure, opportunity, and rationalization (Cressey, 1953). In the context of financial reporting, pressure often manifests as financial distress or unrealistic performance targets; opportunity is related to governance/control weaknesses, while rationalization is psychological (Cressey, 1953; COSO, 2010).

This theoretical foundation underpins the application of the Beneish M-Score and Altman Z-Score, as they quantitatively measure elements contributing to the opportunity and pressure facets of the fraud triangle, thereby offering predictive insights into potential financial statement manipulation. Beneish M-Score reflects opportunistic managerial behavior by identifying quantitative traces left behind when managers prioritize personal or institutional goals, such as meeting earnings targets or securing bonuses, over reporting accuracy (Fenyves et al., 2023; Musanovic & Halilbegović, 2021). Under Agency Theory, the separation of ownership and control creates incentives for managers to use their discretion to polish financial reports, especially when the firm faces performance pressure (Yadav & Sora, 2021). While, the Altman Z-Score serves as a quantitative proxy for the pressure element of the fraud triangle by measuring the heightened incentive for management to engage in manipulative reporting when a firm faces severe financial difficulties (Arum et al., 2023). Under the fraud triangle framework, pressure arises from financial targets, debt covenant requirements, or the need to maintain access to capital, conditions that become increasingly acute when a company's Z-Score declines toward the distress zone ($Z < 1.81$) (Braunsberger & Aschauer, 2025; Burcă et al., 2022). Research demonstrates that financial distress possesses strong relationship with pressure factor, as failing companies face a substantially higher risk of default and are compelled to manipulate earnings, defer costs, or record premature sales to project a healthier financial position (Aviantara, 2021; Musanovic & Halilbegović, 2021).

In addition to these two indicators, supporting indicators are often associated with misstatement pattern. In this study, four specific ratios serve as critical proxies for detecting material misstatement:

- Cash Flow from Operations to Net Income: This ratio serves as a proxy for the quality of earnings. A significantly low or declining ratio suggests that reported profits are not supported by actual cash inflows but are instead driven by non-cash accruals (Musanovic &

Halilbegović, 2021; Tarjo et al., 2023). When net income grows while cash flow remains stagnant or negative, it indicates a high risk of earnings inflation (Tarjo et al., 2023).
- Accounts Receivable to Sales: This ratio acts as a proxy for revenue manipulation. An abnormal increase in receivables relative to sales indicates that the company may be recording fictitious revenue or "channel stuffing" to meet targets, as the growth in reported sales is not being converted into cash (Fenyves et al., 2023; Tarjo et al., 2023).
- Inventory to Cost of Goods Sold: This serves as a proxy for inventory overvaluation or the concealment of obsolescence. If inventory levels rise significantly faster than the cost of goods sold, it suggests that management may be artificially inflating asset values or deferring cost recognition to boost current-period margins (Musanovic & Halilbegović, 2021).
- Gross Margin: Fluctuations in the gross margin function as a proxy for manipulation in either the sales or production cost accounts. A deteriorating gross margin index often signals a loss of competitive advantage, which may create the pressure for management to engage in aggressive accounting to mask falling profitability (Fenyves et al., 2023; Musanovic & Halilbegović, 2021).

Critical Gaps and Inconsistencies in Existing Forensic Models

While models like the Beneish M-Score and Altman Z-Score are foundational, contemporary research reveals several critical limitations and inconsistencies in their application for early fraud detection:

- A significant inconsistency in existing literature is the over-reliance on aggregate thresholds. Studies have found that aggregate indices, such as the Beneish M-Score, may return a safe classification even when underlying accounts show clear evidence of manipulation (Fenyves et al., 2023; Musanovic & Halilbegović, 2021). For example, a firm may manipulate specific ratios, like Days Sales in Receivables, while other components of the index remain stable, allowing the total score to stay below the traditional -1.78 threshold (Fenyves et al., 2023). This creates a false sense of security for auditors who rely solely on composite scores rather than granular account-level forensic monitoring (Musanovic & Halilbegović, 2021; Tarjo et al., 2023).
- Most previous research employs cross-sectional designs that categorize firms as fraud or non-fraud at a single point in time (Chakrabarty et al., 2024). This approach fails to capture the gradual progression of fraud, where financial distress slowly erodes a firm's integrity over several years (Capraş et al., 2025; Tarjo et al., 2023). There is a lack of research that tracks the longitudinal transition of a firm and maps how this specific pressure triggers opportunistic behavior in accounts like Inventory and Accounts Receivable.
- There is evidence that the predictive accuracy of these models varies significantly across different regulatory environments and industries (Fenyves et al., 2023). For instance, while the M-Score is highly effective in developed markets, its sensitivity can be inconsistent in emerging markets like Indonesia, where corporate governance structures and reporting pressures may lead to different manipulative patterns (Arum et al., 2023; Fenyves et al., 2023).

By highlighting these limitations, this study justifies its multi-layered approach. Rather than relying on a single aggregate score, this research integrates distress indicators as proxies for pressure, manipulation signals as proxies for opportunistic behaviour, and supporting granular financial ratios, thereby addressing the detection delay inherent in traditional models.

2. Research Method

This study uses a quantitative-descriptive case study design with a forensic financial analysis approach to identify financial red flags at PT Tiga Pilar Sejahtera Food Tbk in the five years prior to the financial statement period suspected of containing misstatements. A case study helps fraud-detection research in three main ways. First, it explains how red-flag numbers relate to real actions and accounting choices, so the signals are not treated as black box statistics (Beneish, 1999; Dechow et al., 2011). Second, it shows how fraud risk can build up over time, which helps evaluate whether early-warning indicators appear before a case becomes public (Dechow et al., 2011). Third, it provides a practical, replicable example of how to apply screening tools in a real setting, which can guide future studies and audit practice (Eisenhardt, 1989).

Investigating AISA case is valuable for fraud-detection research for three key reasons. First, the allegations are linked to clear accounts in the financial statements, so we can connect changes in ratios to specific areas where manipulation may happen. Second, the case allows us to look at several years before the problem became public, which is exactly what an "early warning" study needs. Third, the firm's audited financial statements and disclosures are available, so our analysis can be based on verifiable documents, not only media stories.

The unit of analysis is annual data (time-series) sourced from audited annual financial statements and company information disclosure documents published through the Indonesia Stock Exchange (IDX). The event year (t) is defined as the fiscal year of the alleged problematic financial statements, while the observation period of the study covers t−5 to t−1. All data used are consistently aligned across years; if restatement figures are available, the study prioritizes the use of figures after the restatement to avoid biased cross-time comparisons.

Red flags were measured using two primary indicators and several supporting indicators. First, the study calculated the Beneish M-Score as a composite indicator of the risk of earnings manipulation/reporting misstatement, constructed from eight indices according to the Beneish formula (Beneish, 1999). Second, the study calculated the Altman Z-Score to capture the level of financial distress, which represents the pressure within the fraud triangle (Altman, 1968; Cressey, 1953). In addition to these two indicators, the study uses supporting indicators that are often associated with misstatement patterns, namely Cash Flow from Operation to Net Income (CFO/NI) to assess the quality of cash-based earnings, Account Receivable to Sales (AR/S) to evaluate the aggressiveness of revenue recognition or collectability risk, Inventory to Cost of goods sold (Inv/COGS) to detect potential inventory abnormalities and COGS distortions, and gross margin (GM) to observe operating profitability pressures that can trigger aggressive reporting behavior. These additional metrics provide a more granular view of potential anomalies beyond what the M-score and Z-score alone might reveal, aiding in the identification of specific areas of financial statement manipulation (Musanovic & Halilbegović, 2021).

3. Results and Discussions

This section presents the results of an early-warning analysis for the 2012–2016 pre-event period to assess potential misstatement prior to the alleged 2017 overstatement and indications of financial pressure. Based on the table 1, AISA's aggregate M-Score remains below −2.22 in every year from 2012 to 2016, indicating that, at the aggregate level, the firm is consistently classified as closer to the non-manipulator group during the pre-event window (Beneish, 1999). This finding is important for two reasons. First, the aggregate M-Score, despite its widespread application, might not be sufficiently sensitive to capture subtle, early-stage manipulative activities within a specific case study, particularly when the underlying variables do not reach critical thresholds (Musanovic & Halilbegović, 2021). Second, it highlights the analytical need to examine component-level signals and account-specific diagnostics, because an aggregate score can mask concentrated risks in particular accounts if movements in certain indices offset others within the weighted sum, and because screening models can exhibit false negatives when applied outside their original estimation setting (Beneish, 1999).

Table 1. Result of Beneish M Score

	2012	2013	2014	2015	2016
Beneish M	-2,598	-2,752	-2,902	-3,025	-3,431
DSRI	0,754	1,094	1,173	1,259	1,111
GMI	1,094	0,978	1,112	0,9556	0,824
AQI	1,087	0,803	0,965	1,139	0,312
SGI	0,568	0,476	0,267	0,169	0,089
DEPI	0,984	1,089	1,052	1,024	1,094
SGAI	0,999	1,126	1,027	1,191	1,136
LVGI	0,969	1,119	0,966	1,097	0,959
TATA	0,086	0,053	0,003	-0,003	0,028

Source: authors' compilation

A closer examination of the component indices indicates that, despite safe aggregate classifications, several indices exhibit red-flag classifications in selected years. The following is a further analysis of the ratio indices applied to the Beneish model on PT Tiga Pilar Sejahtera Food 's financial statements.

A DSRI of 1.031 or lower indicates that sales are not fabricated, and a value above 1.465 indicates that sales have been fabricated (Khatun et al., 2022). A DSRI value between 1.031 and 1.465 suggests a moderate risk of revenue manipulation. The DSRI rises from 0.754 (2012) to 1.094 (2013), remains above one in 2014 (1.173) and 2015 (1.259), and stays elevated in 2016 (1.111). This pattern suggests that, after 2012, receivables tended to grow faster than sales, an empirical signal commonly associated with heightened revenue-recognition risk (Fenyves et al., 2023).

The benchmark established by Beneish (1999) is that a GMI value of 1.041 or below indicates that the current period's gross profit is not manipulated. However, a value greater than or equal to 1.193 indicates that the company's gross profit is manipulated. Meanwhile, a GMI value between 1.041 and 1.193 suggests a moderate risk of gross profit manipulation. the GMI is above one in 2012 (1.094) and 2014 (1.112), but falls below one in 2013 (0.978), 2015 (0.956), and more markedly in 2016 (0.824). Interpreted within the Beneish logic, the performance pressure channel related to shrinking margins appears more pronounced in 2012 and 2014, while it is less evident in later years (Beneish, 1999).

A company is classified as a manipulator if its AQI is ≥ 1.254. Conversely, an AQI of 0.817 or less suggests a low probability of asset manipulation, with values between these thresholds indicating a moderate risk (Tarjo et al., 2023). For AISA, AQI is above one in 2012 (1.087) and 2015 (1.139), below one in 2013 (0.803) and 2014 (0.965), and drops sharply in 2016 (0.312). This suggests that, in 2012 and 2015, the balance sheet composition shifted toward asset categories where capitalization and valuation judgments could be more influential, while 2016 reflects the opposite direction

Beneish (1999) states that an SGI ratio of 1.134 or below indicates that sales revenue is not fabricated, and an SGI value above 1.607 indicates that sales revenue is likely fabricated (Dyck et al., 2023; Khatun et al., 2022). An SGI ratio between these thresholds suggests a moderate risk of revenue manipulation. For AISA, SGI is below one in every year, 0.568 (2012), 0.476 (2013), 0.267 (2014), 0.169 (2015), and 0.089 (2016), indicating persistent contraction rather than growth. Under the Beneish framework, this means the growth pressure mechanism is not the dominant channel here (Beneish, 1999). Nevertheless, this sustained decline in SGI, falling below the non-manipulation threshold and consistently decreasing over the period, suggests a lack of top-line expansion, which often incentivizes aggressive accounting practices to mask underlying operational weaknesses (Musanovic & Halilbegović, 2021).

A DEPI ratio of 1.001 or below indicates that the DEPI is not engineered (Tarjo et al., 2023). A DEPI ratio above 1.077 indicates that the company has increased the estimated useful life of the asset or that the asset value has been revalued, resulting in slower depreciation (Fenyves et al., 2023). Conversely, a DEPI between 1.001 and 1.077 suggests a moderate likelihood of depreciation manipulation. For AISA, the DEPI is close to one in 2012 (0.984) and then remains above one in 2013 (1.089), 2014 (1.052), 2015 (1.024), and 2016 (1.094). This sustained elevation of the DEPI above one, especially in the later years, strongly indicates a consistent pattern of reduced depreciation expenses, potentially through the extension of asset useful lives or revaluation, thereby artificially inflating reported earnings (Fenyves et al., 2023). This manipulation of depreciation is a common tactic for earnings management, as companies may attempt to avoid reporting decreases in earnings (Khatun et al., 2022; Thanathamathee et al., 2024).

A value of 1.001 or below indicates that SGAI is not manipulated, while a value of 1.041 or above indicates that sales, general, and administrative expenses are manipulated (Beneish, 1999), with values between these thresholds suggesting a moderate risk of manipulation. The SGAI for AISA is approximately one in 2012 (0.999) but exceeds one thereafter: 1.126 (2013), 1.027 (2014), 1.191 (2015), 1.136 (2016). This persistent increase in SGAI, particularly above the 1.041 threshold, suggests that the company may be experiencing cost inefficiencies or that aggressive revenue recognition practices are being offset by proportionally higher operating expenses (Fenyves et al., 2023).

An LVGI of 1.037 or below indicates non-manipulated leverage, and a value above 1.111 indicates manipulated leverage (Beneish, 1999). For PT Tiga Pilar Sejahtera Food Tbk, the LVGI is below one in 2012 (0.969), 2014 (0.966), and 2016 (0.959), but above one in 2013 (1.119) and 2015 (1.097). This fluctuating pattern, particularly the increases in 2013 and 2015, could signify an attempt to window-dress the balance sheet by altering debt levels, potentially to meet covenant requirements or present a more favorable financial position, consistent with findings that financially distressed companies often increase leverage (Musanovic & Halilbegović, 2021).

According to Beneish (1999), a TATA value of 0.018 or below indicates no non-financial manipulation. However, a TATA value of 0.031 or above indicates that the company is likely to have engaged in non-financial manipulation, with values between these thresholds suggesting a moderate risk of manipulation (Ebaid, 2023). For AISA, the TATA is positive in 2012 (0.0857), 2013 (0.0533), 2014 (0.0033), and 2016 (0.0276), and slightly negative in 2015 (-0.0028). The comparatively higher TATA in 2012–2013 indicates that earnings were more accrual-driven in those years, a phenomenon often associated with earnings management practices where non-cash adjustments inflate reported profits (Ponce et al., 2023).

Table 2. Results of Altman Z Score

	2012	2013	2014	2015	2016
Altman Z	2,347	2,565	2,645	1,806	2,635

Source: authors' compilation

Then, we analyse the results of the Altman Z-Score for AISA over the 2012-2016 pre-event period. In its classic form for publicly traded manufacturing firms, Z-scores are commonly interpreted using three zones: a distress zone ($Z < 1.81$), a grey zone ($1.81 \leq Z \leq 2.99$), and a safe zone ($Z > 2.99$) (Altman, 1968). The 2012 Z-score of 2.347 falls within the grey zone, indicating that the firm's financial condition is neither clearly safe nor unequivocally distressed under the original Altman classification (Altman, 1968). Empirically, the grey zone is interpreted as a range where firms exhibit intermediate bankruptcy risk.

In 2013, the Z-score increases to 2.565 and remains in the grey zone. This upward trend, while still within the grey area, might suggest a marginal improvement in financial stability during that year, though not enough to exit the zone of uncertainty (Marsenne et al., 2023). By 2014, the Z-score for AISA rises significantly to 2.645, still positioning the company within the grey zone, yet closer to the safe threshold, indicating a slightly reduced probability of financial distress (Do et al., 2023). However, this continued presence in the grey zone, even with an increasing Z-score, still signals a need for caution and further scrutiny of the company's financial health, as the risk of bankruptcy remains elevated compared to firms in the safe zone (Thanathamathee et al., 2024).

The 2015 Z-score declines sharply to 1.806, which places it just below the 1.81 distress cutoff, thereby classifying the firm in the distress zone under the original model (Altman, 1968). This precipitous drop suggests a rapid deterioration of financial health, increasing the likelihood of bankruptcy (Song et al., 2024). This shift is economically meaningful because crossing into the distress zone is typically interpreted as a marked increase in bankruptcy risk, consistent with deterioration in one or more of the underlying dimensions captured by the model (Altman, 1968). Given evidence that model performance can vary across settings, the safest inference is that 2015 represents a year of heightened financial distress risk and warrants deeper examination of the firm's financing constraints, operating shocks, or major accounting changes during the period (Grice & Ingram, 2001).

In 2016, the Z-score rebounds to 2.635, returning to the grey zone. This improvement suggests that the firm's distress risk decreased from the 2015 trough, though the firm still does not reach the safe zone threshold of 2.99 (Altman, 1968). In empirical applications, such rebounds are often interpreted as partial recovery rather than full financial stabilization, meaning the firm may remain exposed to renewed stress if macro conditions worsen or if the recovery is driven by temporary factors (Braunsberger & Aschauer, 2025; Saraiva et al., 2024). Specifically, a Z-score between 1.81 and 2.99 indicates an ambiguous financial position, prompting the need for closer scrutiny as the firm's trajectory could either improve or deteriorate (Awwad & Razia, 2021).

While the Beneish M-Score provides a probabilistic screening signal for manipulation and the Altman Z-Score captures the broader context of financial pressure, account-level ratios help identify which specific operating accounts display unusual patterns that frequently precede material misstatements. Accordingly, the analysis focuses on CFO/NI, AR/Sales, Inventory/COGS (Days Inventory), and gross margin, which are directly relevant to the account areas later alleged to be overstated in 2017.

Table 3. Results of Account-Level Ratio

	2012	2013	2014	2015	2016
CFO/NI	0,279	0,227	0,935	1,068	0,645
AR/Sales	0,204	0,223	0,262	0,329	0,366
Inventory/COGS	101	117	109	119	153
Gross Margin	0,220	0,225	0,202	0,212	0,257

Source: authors' compilation

The ratio of operating cash flow to net income (CFO/NI) shows marked volatility. CFO/NI is low in 2012 (0.279) and 2013 (0.227), improves substantially in 2014 (0.935), rises above unity in 2015 (1.068), and declines again in 2016 (0.645). From an earnings-quality perspective, CFO/NI materially below 1 indicates that reported earnings are weakly supported by operating cash flows, which can be an indicator of aggressive accounting policies or even earnings manipulation (Toit, 2023). For PT Tiga Pilar Sejahtera Food, the CFO/NI ratio being below 1 in 2012, 2013, and 2016 raises red flags regarding the sustainability and quality of its reported earnings, suggesting a potential reliance on accruals to bolster profitability rather than genuine cash generation (Musanovic & Halilbegović, 2021). Conversely, a CFO/NI ratio above unity, as observed in 2015, implies that a company's earnings are of higher quality and are backed by strong cash flow, which is typically a positive signal of financial health and operational efficiency (Georgios & Styliani, 2023). However, it is crucial to investigate the underlying reasons for such fluctuations, as a high CFO/NI ratio can sometimes be indicative of unsustainable one-off events rather than consistent operational strength.

Receivables intensity (AR/Sales) increases consistently throughout the pre-event window, from 0.204 (2012) to 0.223 (2013), 0.262 (2014), 0.329 (2015), and 0.366 (2016). This sustained rise in accounts receivable relative to sales revenue could signal aggressive revenue recognition practices, where sales are recorded before cash collection, or the shipment of goods to customers with a questionable ability to pay (Tarjo et al., 2023). This aligned with Beneish's receivables-based signal (DSRI) and frequently emphasized in fraudulent reporting risk discussions (Tarjo et al., 2023). Such a trend often indicates attempts to inflate revenues prematurely, leading to an overstatement of assets and ultimately, a misrepresentation of financial performance (Amin & Cumming, 2023). Given that the subsequent 2017 allegations include overstatement of receivables and sales, the upward AR/Sales trajectory provides economically meaningful pre-event evidence consistent with increasing exposure to misstatement risk in revenue-related accounts.

Inventory risk becomes particularly salient toward the end of the window. The dataset reports Inv/COGS as Days Inventory, which increases from 101 days (2012) to 117 days (2013), decreases to 109 days (2014), rises to 119 days (2015), and then jumps materially to 153 days (2016). A pronounced increase in inventory days can indicate slow-moving inventory, demand weakness, or valuation issues, all of which are frequently implicated in misstatement cases because inventory accounting requires managerial estimates and directly affects reported profitability through cost of goods sold (Thanathamathee et al., 2024). This significant increase in inventory days, particularly the sharp jump to 153 days, could signify a buildup of unsaleable goods or an intentional overstatement of inventory values to inflate assets and earnings, warranting close examination for potential manipulation, again aligning with later allegations involving inventory overstatement.

Gross margin declines from 22.5% (2013) to 20.2% (2014), then recovers to 21.2% (2015) and increases to 25.7% (2016). The 2014 decline is consistent with a period of profitability pressure, which the earnings-management literature associates with greater incentives to manage reported performance (Healy & Wahlen, 1999). Meanwhile, the sharp margin expansion by 2016 may reflect genuine operational improvement; however, in a forensic context it also merits verification because it could be indicative of aggressive revenue recognition or cost capitalization practices, which can artificially inflate gross profit (Foster, 2023; Toit, 2023).

The results from AISA illustrate that financial statement fraud risk can develop through a progressive interaction between financial pressure and localized account distortions, and that this progression is not always captured by aggregate screening classifications. In AISA, the composite Beneish M-Score remained below the commonly cited −2.22 threshold and therefore classified the firm as a non-manipulator, yet several component indices and supporting ratios deteriorated in economically meaningful ways. This pattern is consistent with the argument that composite screening scores, while useful as broad classifiers, can mask concentrated risks when manipulation is localized to specific accounts or executed subtly rather than through pervasive, system-wide distortion (Musanovic & Halilbegović, 2021).

Our finding is supported by Enron case. Prior analyses have highlighted that Enron's early warning profile was not necessarily uniform across all metrics, but manifested prominently in specific components such as the Gross Margin Index, Asset Quality Index, and Sales Growth Index (MacCarthy, 2017). The convergence across AISA and Enron therefore supports the argument that meaningful fraud detection requires moving beyond composite outputs toward component-level diagnostics and account-focused interpretation, especially when the fraud mechanism is sophisticated or concentrated.

In AISA, the Altman Z-Score declined to 1.806 in 2015, placing the firm in the distress zone and indicating elevated financial vulnerability before the alleged misstatement was publicly recognized. This pattern is consistent with the conceptual argument that deteriorating financial conditions can operate as a form of “pressure” that increases incentives for managerial opportunism, particularly when firms face financing constraints, reputational concerns, or performance targets (Arum et al., 2023; Aviantara, 2021). A similar pre-collapse distress signal has been documented in Enron, where Z-scores remained within the distress or ambiguous range for multiple years prior to the firm’s collapse, suggesting that declining fundamentals can coexist with, and potentially motivate, aggressive reporting strategies (MacCarthy, 2017).

However, the comparative evidence also underscores a boundary condition: the Altman Z-Score may fail when fraud is executed through mechanisms that manufacture apparent financial health, particularly the appearance of liquidity. In Satyam, prior research reports that the Z-Score remained in the safe zone during the years preceding exposure, implying that the distress-based proxy did not reflect the true fragility of the firm’s condition (Yadav et al., 2023). This divergence is theoretically important because it indicates that distress proxies are sensitive to the reliability of the underlying accounting inputs. When core balance-sheet items (e.g., cash or current assets) are fabricated or materially misstated, the Z-Score can be fooled, producing a deceptively safe classification (Yadav et al., 2023). Consequently, distress screening should be interpreted as an incentive/pressure proxy rather than a definitive fraud detector, and should be complemented by manipulation-focused tools that are more directly tied to reporting distortions.

Taken together, the ratio evidence suggests that AISA’s pre-event risk profile is account-specific and time-varying rather than concentrated in a single indicator. The early period (2012–2013) is dominated by weak cash support for earnings (low CFO/NI), consistent with elevated accrual-related risk. The later period shows a persistent upward trend in receivables intensity and a sharp inventory-days spike in 2016, signals that map closely to the accounts later alleged to be overstated (receivables and inventory), and that can also plausibly affect sales through revenue and cost recognition pathways. This comprehensive analysis of individual financial ratios provides a nuanced understanding of AISA's financial reporting risks, extending beyond the generalized indicators of the Beneish M-Score and Altman Z-Score.

4. Conclusions

The findings of this research demonstrate that the financial statement fraud at PT Tiga Pilar Sejahtera Food Tbk was a detectable, gradual progression rather than an isolated event. By integrating multiple forensic models, the study reveals that the company's financial health and reporting quality deteriorated significantly between 2012 and 2016. The Altman Z-Score provided an early warning of increasing financial pressure, as the score declined to 1.806 by 2015, moving the firm from a safe position into the grey zone and nearing the "distress zone" two years before the 2017 scandal. This decline indicates that management faced substantial pressure to maintain performance, a key element of the Fraud Triangle that often precedes earnings manipulation.

Furthermore, the results highlight a critical diagnostic limitation of using aggregate scores alone: while the Beneish M-Score remained below the -2.22 threshold, technically labeling the firm as a non-manipulator, several indices exhibit red-flag classifications. Specifically, the Days Sales in Receivables Index and Depreciation Index showed abnormal spikes, signaling potential revenue inflation and expense deferral. These traces were confirmed by other indicators, such as the accounts receivable intensity rising from 0.204 to 0.366 and inventory days surging to 153 days by 2016. The persistent reliance on non-cash accruals, evidenced by a low CFO/NI ratio, further validated that reported profits were not supported by actual cash inflows. This three-tiered approach allowed for the detection of deteriorating metrics, even when the aggregate M-Score appeared safe, thereby offering a more precise diagnostic tool for auditors and investors to identify fraud in its nascent stages

Ultimately, this study concludes that a multi-layered forensic framework is essential for effective early fraud detection. While aggregate models like the M-Score can mask subtle risks, a deep-dive analysis of account-level disparities provides the necessary granularity to identify material misstatements. For auditors, regulators, and investors in the Indonesian market, monitoring the intersection of financial distress and specific indices offers a robust early-warning system capable of uncovering fraud years before it is publicly revealed.

This study is subject to several limitations. First, as a single-case analysis, the findings provide detailed within-firm insights but have limited generalizability beyond the focal firm and period. Second, because the analysis relies on audited financial statements, the indicators may be lagging and potentially affected by the same reporting choices under investigation, which can weaken the sensitivity of ratio-based screening. Future research should test the framework in larger multi-firm samples, incorporate machine-learning approaches, and add non-financial governance proxies to strengthen early-warning inference.

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