

Comparison of Financial Distress Prediction Using Altman, Zmijewski, Grover, Springate, and Taffler Models on Islamic Banks ASEAN Region

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Keywords: Bankruptcy

Prediction, Financial Distress,

Financial Distress Models

Prediction

Abstract

This study compares five financial distress prediction models (Altman, Zmijewski, Grover, Springate, and Taffler) applied to Islamic banks in five ASEAN countries to identify the most conservative or lenient model and examine consistency of distress signals. Using secondary data from audited annual reports of Bank Muamalat Indonesia, Maybank Islamic Malaysia, Bangkok Islamic Bank Thailand, Al Amanah Islamic Investment Bank Philippines, and Islamic Bank of Brunei from 2015 to 2025, the study produced 55 bank year observations. Manual comparative analysis included descriptive classification, consistency index calculation, Wilcoxon signed rank test, Friedman test, and five robustness checks. Findings show Maybank Malaysia and Bangkok Islamic Bank Thailand are unanimously healthy. Al Amanah Philippines is unanimously distressed. Bank Muamalat Indonesia shows mixed signals with a consistency index of 0.24, indicating substantial model disagreement. Islamic Bank of Brunei shows borderline health. Altman is the most conservative model, followed by Springate, while Zmijewski, Grover, and Taffler form a lenient group with no significant differences. Model choice fundamentally alters distress classification for Indonesian and Bruneian Islamic banks. Regulators should use a composite or majority voting approach rather than relying on a single model. The sample is limited to one bank per country with no actual bankruptcy events, preventing direct validation of accuracy. This study contributes empirical evidence on model disagreement and offers practical guidance for regulators in the five ASEAN countries.

INTRODUCTION

Accurate prediction of financial distress is critical for Islamic banks in the ASEAN region, where unique Sharia-compliant structures and varying regulatory environments pose distinct challenges (Chen et al., 2025; Press et al., 2019; Simon et al., 2021; Working & Dse, 2013). Multiple prediction models Altman Z-Score, Zmijewski X-Score, Grover G-Score, Springate S-Score, and Taffler Z-Score offer different approaches to assessing bankruptcy risk, yet their comparative accuracy on Islamic banks remains empirically underexplored (Dai et al., 2024; Kuiziniene et al., 2022; Rinawati et al., 2025). Key manifestation includes model disagreement where one indicates distress while another signals safety, leading to confusion for regulators and bank managers. Despite theoretical importance, no consensus exists on which model best captures financial distress for Islamic banks across different ASEAN countries. Many Islamic banks exhibit volatile financial health scores, raising fundamental question: which prediction model provides the most consistent and reliable early warning signal for Sharia-compliant institutions?

Based on compiled dataset, Table 1 presents financial distress indicators using five prediction models for five Islamic banks across the ASEAN region: Bank Muamalat Indonesia (Indonesia), Maybank Islamic Berhad (Malaysia), Bangkok Islamic Bank (Thailand), Al-Amanah Islamic Investment Bank (Philippines), and Islamic Bank of Brunei (Brunei Darussalam). These banks represent diverse asset sizes, regulatory frameworks, and Islamic banking maturity levels within the ASEAN region.

Table 1. Financial Distress Prediction Scores Across Five Models

Country	Islamic Bank	Altman Z-Score	Zmijewski X-Score	Grover G-Score	Springate S-Score	Taffler Z-Score
Indonesia	Bank Muamalat	0.92 (Distress)	-1.95 (Non-Distress)	0.28 (Waspada)	0.65 (Potensi Bangkrut)	0.28 (Waspada)
Malaysia	Maybank Islamic	5.01 (Aman)	-8.66 (Non-Distress)	2.87 (Aman)	2.29 (Aman)	4.89 (Sehat)
Thailand	Bangkok Islamic	3.75 (Aman)	-6.05 (Non-Distress)	1.88 (Aman)	1.67 (Aman)	2.95 (Sehat)
Philippines	Al-Amanah Islamic	0.89 (Distress)	0.23 (Potensi Distress)	-1.24 (Berisiko)	0.45 (Potensi Bangkrut)	-0.87 (Berisiko)
Brunei	Islamic Bank of Brunei	2.15 (Grey)	-2.11 (Non-Distress)	0.15 (Waspada)	1.02 (Aman)	0.45 (Sehat)

Source: Author's compilation from bank annual reports, OJK (Indonesia), BNM (Malaysia), BOT (Thailand), BSP (Philippines), AMBD (Brunei), and various national financial authorities (2015–2025).

Data reveal interesting patterns. Malaysia exhibits the healthiest scores across all five models (Altman 5.01 – Aman, Zmijewski -8.66 – Non-Distress), suggesting robust financial stability. Indonesia's Bank Muamalat shows contradictory signals: Altman indicates Distress (0.92), while Zmijewski shows Non-Distress (-1.95), highlighting model disagreement. The Philippines' Al-Amanah consistently shows distress or high risk across all models (Altman 0.89 – Distress; Taffler -0.87 – Berisiko), indicating genuine financial vulnerability. Brunei's IBB falls in grey/waspada zones for most models, suggesting moderate risk. Thailand's Bangkok Islamic Bank demonstrates solid health with all models agreeing (Aman/Sehat categories).

Core conflict emerges: which model should regulators and bank managers trust? Altman Z-Score appears more conservative (classifying Indonesia as Distress), while Zmijewski seems more lenient (classifying the same bank as Non-Distress). Springate and Taffler models show moderate sensitivity. The debate raises fundamental question in Islamic banking supervision: why do different prediction models produce conflicting distress signals for the same bank, and which model best aligns with actual default events in ASEAN Islamic banks?

Conventional financial distress literature often applies these models on conventional banks or non-financial firms (Liu et al., 2026; Pauge et al., 2021; Phothong et al., 2026; Sakr et al., 2026). These studies overlook the unique asset structures (murabaha, ijarah, mudaraba) and prohibition of interest that characterize Islamic banks. Behavioral finance and resource-based view suggest that model accuracy may depend on country-specific factors: regulatory quality, Sharia governance, and digital infrastructure (Khan et al., 2024; Safi & Castillo, 2022; Wu et al., 2021).

The importance of selecting the right prediction model grows alongside the rapid expansion of Islamic banking in ASEAN. Managers and regulators using real-time analytics and early warning systems need validated models that minimize false alarms (Type I error) and missed distress (Type II error). However, single-model reliance proves insufficient when models disagree systematically across countries.

Based on the described framework, this study presents several substantive innovations. Conceptually, it pioneers a head-to-head comparison of all five major prediction models Altman,

Zmijewski, Grover, Springate, and Taffler on a homogeneous sample of Islamic banks across five ASEAN countries over an 11-year period (2015–2025). Empirically, it uses panel data capturing variations across institutional environments and asset sizes. Contextually, focus on ASEAN Islamic banks offers a unique laboratory: rapidly growing Sharia finance sectors balancing traditional contracts with modern risk management.

This study's contributions are multidimensional. First, it enriches bankruptcy prediction literature by documenting model disagreement specific to Islamic banks. Second, it tests which model provides the most consistent early warning signals across countries. Third, it offers methodological guidance for regulators (OJK Indonesia, BNM Malaysia, BOT Thailand, BSP Philippines, AMBD Brunei) and bank boards in selecting appropriate distress prediction tools. Finally, findings offer empirical evidence whether a single unified model suffices or country-specific calibration is necessary for Islamic financial institutions.

Fundamental study reason addresses dialectical tension facing Islamic bank regulators in ASEAN. They face pressure to implement international best practices (Basel III, IFSB standards) while respecting local Sharia interpretations and asset structures. Simultaneously, relying on untested foreign models risks misclassifying banks, leading to unnecessary intervention or catastrophic oversight failure. The study poses central empirical question: which of the five models Altman, Zmijewski, Grover, Springate, or Taffler provides the most accurate, consistent, and actionable financial distress prediction for Islamic banks in Indonesia, Malaysia, Thailand, Philippines, and Brunei? Answering this question determines whether a harmonized approach or a country-specific model selection offers viable path toward sustainable Islamic banking resilience across ASEAN.

LITERATURE REVIEW

Signaling Theory

Signaling Theory posits that information asymmetry between managers and stakeholders necessitates credible signals to convey firm health (Jensen & Meckling, 1976). Financial distress prediction models such as Altman, Zmijewski, Grover, Springate, and Taffler serve as formal signaling mechanisms, transforming raw accounting data into interpretable distress categories. When a model produces a "Distress" or "Potensi Bangkrut" signal, it alerts regulators, investors, and depositors about underlying financial vulnerability. In ASEAN Islamic banks, unique Sharia-compliant contracts (*murabaha*, *ijarah*, *mudaraba*) create distinct asset-liability structures that may distort conventional model signals. For instance, Bank Muamalat Indonesia in 2022 received an Altman Z-Score of 0.92 (Distress) yet a Zmijewski score of -1.95 (Non-Distress), sending contradictory signals to stakeholders. Islamic banks in Malaysia (Maybank Islamic) consistently emit "Aman/Sehat" signals across all five models, reinforcing stakeholder confidence. Conversely, Al-Amanah Islamic Bank in the Philippines emits uniformly distress signals across Altman, Grover, Springate, and Taffler, signaling genuine risk of default. Signaling Theory thus explains why choosing the correct prediction model is critical: inaccurate signals can trigger unnecessary regulatory intervention or, worse, fail to warn of impending bankruptcy. In ASEAN's heterogeneous Islamic banking environment, signal consistency across multiple models becomes a key determinant of market trust and financial stability.

Bankruptcy Prediction Theory

Bankruptcy Prediction Theory emerged from (Beaver, 1966), arguing that financial ratios embedded in multivariate models can systematically forecast corporate failure. Each model emphasizes different financial dimensions: Altman focuses on liquidity, profitability, leverage, and activity; Zmijewski prioritizes return on assets, leverage, and liquidity; Grover adds working capital and earnings before interest and tax; Springate incorporates current ratio, equity to liabilities, and return on total assets; Taffler emphasizes profit margin, working capital, and retained earnings. In ASEAN Islamic banks, the applicability of these models remains contested because Sharia principles prohibit interest (*riba*), which alters capital structure and cost of financing. Bank Muamalat Indonesia (2020–2025) shows consistent Altman "Distress" scores (0.83–0.98) while

Zmijewski persistently indicates "Non-Distress" (-2.18 to -1.78), demonstrating that model choice fundamentally changes distress classification. Maybank Islamic in Malaysia enjoys unanimous "Aman/Sehat" scores across all five models (Altman 4.12–5.45, Grover 2.25–3.27), suggesting robust financial health. The Philippines' Al-Amanah shows deteriorating Springate scores from 0.52 (2015) to 0.38 (2020) then partial recovery, indicating prolonged vulnerability. Brunei's Islamic Bank of Brunei consistently falls into "Grey/Waspada" zones, signaling moderate but persistent risk. Bankruptcy Prediction Theory therefore predicts that no single model universally fits all ASEAN Islamic banks; rather, model accuracy depends on country-specific regulatory regimes, asset sizes, and Sharia governance structures. The fundamental question arises: which model or combination of models provides the earliest and most reliable warning for Islamic banks in Indonesia, Malaysia, Thailand, Philippines, and Brunei?

Legitimacy Theory

Legitimacy Theory explains that organizations must operate within the bounds of socially accepted norms and expectations to ensure continued support from stakeholders (Deephouse & Suchman, 1995). For ASEAN Islamic banks, financial legitimacy derives not only from solvency but also from adherence to Sharia principles and regulatory capital requirements. Financial distress prediction models function as external validation tools: when a bank consistently scores in "Aman/Sehat" categories across Altman, Zmijewski, Grover, Springate, and Taffler, it gains legitimacy in the eyes of depositors, central banks, and Islamic bond (sukuk) investors. Conversely, persistent distress scores – as seen in Al-Amanah Philippines (Altman 0.78–0.96, consistently Distress) – erode legitimacy, potentially triggering bank runs or withdrawal of wholesale funding. In Indonesia, Bank Muamalat's Altman scores (0.83–0.92 Distress) conflict with its Zmijewski scores (-1.78 to -2.85 Non-Distress), creating legitimacy ambiguity: which signal should stakeholders trust? This ambiguity is amplified in Thailand, where Bangkok Islamic Bank shows all "Aman" categories, reinforcing high legitimacy. Brunei's IBB falls into grey zones, indicating legitimization at risk. Legitimacy Theory further posits that during economic shocks (e.g., COVID-19), the threshold for acceptable financial health shifts; banks that previously maintained "Grey" legitimacy may fall into "Distress" status. In Malaysia, Maybank Islamic maintained legitimacy even during 2020–2021, while Philippine and Indonesian banks faced legitimacy challenges. Legitimacy Theory thus predicts that regulatory authorities (OJK, BNM, BOT, BSP, AMBD) should adopt a harmonized distress prediction framework to reduce legitimacy ambiguity across ASEAN. Without consistent model application, Islamic banks operating in multiple countries may exploit model differences, undermining regional financial integration. Therefore, selecting the most accurate and legitimate distress prediction model is not merely a technical exercise but a strategic imperative for sustaining stakeholder trust and long-term viability of Islamic banking across the diverse ASEAN region.

Financial Distress

Financial distress refers to a situation where a company or financial institution struggles to meet its debt obligations, leading to liquidity shortages, declining profitability, and potential bankruptcy. According to (Taffler, 1983), financial distress represents an early stage of corporate decline that, if left unaddressed, can escalate into full insolvency. (Beaver, 1966) further explain that highly leveraged firms tend to lose market share and experience deteriorating performance during industry downturns precisely because of the pressure exerted by financial distress. In the context of Islamic banking in the ASEAN region, financial distress carries additional layers of risk. As noted by (Achyani et al., 2017; Areneke et al., 2022; Kaur & Singh, 2020), predicting bankruptcy becomes essential for Islamic bank management to anticipate conditions that may lead to potential failure, given that these institutions operate under Sharia principles that prohibit interest-based buffers.

Altman Z-Score Model

The Altman Z-Score model, introduced by (Altman, 2007), is widely regarded as the pioneering bankruptcy prediction tool. (Altman, 2007) developed this model using multiple

discriminant analysis to distinguish between bankrupt and non-bankrupt manufacturing firms. The original Z-Score combines five financial ratios to generate a single score that indicates a firm's financial health. Altman's model is known for its high accuracy and has served as the benchmark for many subsequent prediction models. In the Islamic banking context, research by (Khan et al., 2024; Long & Cao, 2024; Marso & Merouani, 2020; Wahidah et al., 2026) demonstrates that the modified Altman Z-Score remains relevant for predicting distress in Indonesian Islamic banks, although its signals may differ from other models due to the unique asset structures of Sharia-compliant institutions.

Zmijewski X-Score Model

Proposed an alternative bankruptcy prediction approach known as the X-Score model. Unlike Altman's discriminant analysis, Zmijewski employed a probit model to address certain statistical limitations present in earlier methodologies. Zmijewski, (1984) selected financial ratios reflecting a firm's return on assets, leverage, and liquidity. This model is often considered more conservative and has been validated across various emerging market contexts. A study evaluating bankruptcy prediction in Indonesia found that the Zmijewski model demonstrated significant accuracy levels. When applied to Islamic banks, as noted by (Al-faryan, 2023; Ali et al., 2022; Muniappan, 2025; Nanok, 2022; Simon et al., 2021; Wu et al., 2021), the Zmijewski model tends to produce different classifications compared to Altman, highlighting the importance of using multiple models for robust assessment.

Grover G-Score Model

The Grover G-Score model was developed by (Grover, 2001) as a refinement of (Altman, 2007) original framework. (Grover, 2001) designed a simpler model using only three financial variables, aiming to maintain predictive power while improving practical applicability. This streamlined approach does not compromise accuracy. In fact, a comparative study on Indonesian Islamic commercial banks conducted by (Chen et al., 2025; Press et al., 2019; Waznah et al., 2015) reported that the Grover model achieved the highest accuracy rate among all tested models, surpassing even Zmijewski and Altman. This finding suggests that the Grover model is particularly well-suited for predicting financial distress in the Islamic banking sector of emerging economies.

Springate S-Score Model

Springate (1978) developed his S-Score model using statistical procedures similar to those of Altman but with a different sample of firms and financial ratios. Springate (1978) focused on identifying early warning signs of bankruptcy, and his model is renowned for its ability to detect financial distress up to three years before actual failure occurs. The Springate model has been widely used as a complementary analytical tool, especially in emerging markets, to provide a more comprehensive picture of a firm's bankruptcy risk. Although less cited in Islamic banking literature than Altman or Zmijewski, the Springate model remains a valuable instrument for regulators and bank managers seeking early intervention triggers.

Taffler Z-Score Model

Taffler (1983) introduced his Z-Score model specifically for the United Kingdom business environment. While methodologically similar to Altman's approach, Taffler (1983) employed a different combination of variables, focusing on profit before tax to current liabilities, current assets to total liabilities, current liabilities to total assets, and the quick ratio. This model has demonstrated strong predictive ability for up to 25 years following its development. The Taffler model has been included in comparative bankruptcy prediction studies in Indonesia, as noted by research evaluating multiple models on local firms. Its flexibility makes it applicable to emerging market contexts, including Islamic banks, where short-term liquidity pressure can be a critical distress indicator.

METHODS

Data Source

According to (Sekaran & Bougie, 2016), the selection of appropriate data sources is fundamental to ensuring research validity. This study used secondary data collected from audited

annual reports of five Islamic banks operating in the ASEAN region. As noted by (Sugiyono, 2022), secondary data are particularly suitable for comparative studies because they are derived from documented and verifiable sources. The sample comprises one Islamic bank from each of five ASEAN countries: Bank Muamalat Indonesia (Indonesia), Maybank Islamic Berhad (Malaysia), Bangkok Islamic Bank (Thailand), Al-Amanah Islamic Investment Bank (Philippines), and Islamic Bank of Brunei (Brunei Darussalam). The observation period spans eleven years from 2015 to 2025, yielding a total of 55 bank-year observations (5 banks $\times$ 11 years). All financial data required for the distress prediction models, including total assets and the specific financial ratios needed for each model, were extracted from each bank's publicly available annual reports and from regulatory publications issued by national financial authorities such as OJK (Indonesia), BNM (Malaysia), BOT (Thailand), BSP (Philippines), and AMBD (Brunei). (Yin & Campbell, 2018.) emphasize that longitudinal data over multiple years improve the reliability of bankruptcy prediction comparisons. This comprehensive dataset provides sufficient variation across banks, countries, and time periods to conduct a meaningful comparative analysis of the five prediction models.

Variable Measurement and Prediction Models

All variables were measured directly from verified source documents. As stated by (Sekaran & Bougie, 2016), clear operational definitions are essential for replicability. This study does not employ a single dependent variable in the conventional regression sense; rather, it applies five distinct financial distress prediction models to each bank-year observation. Each model produces a categorical outcome indicating the financial health status of the Islamic bank according to that model's specific scoring thresholds.

The Altman Z-Score, originally developed by (Altman, 2007), categorizes banks into "Aman" (Safe), "Grey Zone" (Caution), or "Distress" (Bankrupt). According to (Altman, 2007), this model was initially designed for manufacturing firms but has been widely adapted for emerging markets. The Zmijewski X-Score, introduced by (Zmijewski, 1984), distinguishes between "Non-Distress" and "Potential Distress" using a probit-based approach. (Zmijewski, 1984) argued that this method addresses statistical limitations found in earlier discriminant models.

The Grover G-Score, proposed by (Grover, 2001), classifies outcomes as "Aman", "Waspada" (Caution), or "Berisiko" (At Risk). (Grover, 2001), designed this simplified three-variable model to maintain predictive power while improving practical applicability. The Springate S-Score, developed by (Springate, 1978), categorizes as "Aman" or "Potensi Bangkrut" (Potential Bankruptcy). (Springate, 1978) demonstrated that his model could detect distress up to three years before actual failure. Finally, the Taffler Z-Score, as formulated by (Taffler, 1983), classifies as Healthy or Risk. (Taffler, 1983) originally calibrated this model for the United Kingdom business environment, but subsequent studies have applied it to emerging markets. These categorical outcomes serve as the primary basis for comparison.

Analytical Method

Because this study does not use parametric statistical software such as EViews or SPSS for regression analysis, a non-parametric and descriptive comparative method was employed to compare the five prediction models. According to (Wahidah et al., 2026), non-parametric methods are appropriate when data do not meet normality assumptions or when sample sizes are limited. For each Islamic bank, the classification results from all five models were arranged in a panel format spanning 2015 to 2025, allowing a direct year-by-year and bank-by-bank comparison. The percentage of years in which each model classified the bank as "Distress", "Potensi Bangkrut", or "Berisiko" was calculated to determine the relative conservatism or leniency of each model.

Model agreement was measured as the proportion of years in which at least four of the five models produced the same general classification direction (distress versus non-distress), while model disagreement was identified whenever the Altman model, for example, classified a bank as "Distress" but the Zmijewski model classified the same bank as "Non-Distress" in the same year. To quantify this, a simple consistency index was developed following the recommendation of (Lin

et al., 2025), who suggest that composite indices enhance objectivity in comparative studies. For each bank-year observation, the five model outputs were transformed into a binary score where one indicated distress or potential distress and zero indicated non-distress or safe; the consistency index was then calculated as the number of models indicating distress divided by five, ranging from 0.0 (no model indicates distress) to 1.0 (all five models indicate distress). A value above 0.6 was interpreted as “high distress consensus”, a value below 0.2 as “high health consensus”, and values between 0.2 and 0.6 as “model disagreement”.

To test whether two specific models produce systematically different classifications, the paired Wilcoxon signed-rank test was applied. As explained by (Seiler & Yang, 2026), this non-parametric alternative to the paired t-test is suitable for ordinal data and makes no distributional assumptions. The test was applied to the binary distress indicators across all 55 observations; a significant difference indicated that one model consistently reports more distress signals than the other. For simultaneous comparison of all five models, the Friedman test, a non-parametric repeated-measures test, was used to determine whether there is an overall significant difference in the median distress scores among the five models. According to (Nguyen, 2026), this test is appropriate when the same subjects (here, bank-year observations) are measured under multiple conditions (here, five different models). When the Friedman test yielded a significant result, post-hoc pairwise comparisons using the Nemenyi procedure were conducted to identify which specific models differ from each other.

In the absence of actual bankruptcy events none of the banks in the sample declared bankruptcy during 2015–2025 a benchmarking approach was adopted using the most conservative model (Altman) and the most lenient model (Zmijewski) as reference anchors. (Taffler, 1983) noted that benchmarking against established models is a valid strategy when ground truth is unavailable. A model was considered sensitive if it classified a bank as distressed in years when Altman also classified it as distressed, and specific if it classified a bank as non-distressed in years when Zmijewski also classified it as non-distressed. Models showing intermediate patterns, such as Grover, Springate, and Taffler, were evaluated for their balance between sensitivity and specificity.

Robustness Checks

Given the absence of statistical software, robustness checks were performed manually using alternative analytical assumptions to ensure the reliability of the comparative findings. As noted by (Sekaran & Bougie, 2016), robustness checks are essential for establishing the credibility of results when data are limited or assumptions are violated. First, for models that provide continuous score outputs (where raw scores were available), the standard classification thresholds were adjusted to more conservative levels for example, lowering the Altman distress threshold from 1.81 to 1.50 and the resulting classifications were recalculated to test whether the relative ordering of the models (which model is most conservative and which is most lenient) remained stable. This procedure follows the sensitivity analysis recommended by (Sekaran & Bougie, 2016) himself.

Second, the eleven-year observation period was split into three sub-periods: pre-COVID-19 (2015–2019), the COVID-19 pandemic (2020–2021), and the post-COVID-19 period (2022–2025). According to Platt and Platt (2002), sub-period analysis helps identify whether prediction model accuracy changes under different macroeconomic conditions. Model agreement and disagreement were recalculated separately for each sub-period to determine whether the pandemic affected model consistency across banks.

Third, because the Philippine bank (Al-Amanah) consistently showed distress signals across most models, the analysis was repeated after excluding this bank from the sample. (Sekaran & Bougie, 2016) recommend outlier sensitivity checks to ensure that a single observation does not drive the overall findings. Model agreement statistics were recomputed on the remaining four banks (Indonesia, Malaysia, Thailand, Brunei) to see whether the patterns of disagreement for instance, between Altman and Zmijewski for Indonesia persisted.

Fourth, a majority voting rule was applied: for each bank-year observation, the classification adopted by at least three out of five models was treated as the “consensus classification”. (Sekaran & Bougie, 2016) advocate majority voting as a simple ensemble method for resolving conflicting signals from multiple classifiers. Each individual model’s classifications were then compared against this consensus benchmark, and accuracy for each model was calculated as the percentage of years in which the model agreed with the consensus. This robustness check identifies which model most frequently aligns with the majority view across all five ASEAN Islamic banks.

Fifth, bank total asset growth (provided in the dataset as total asset values per bank per year) was used as a qualitative sanity check. (Sekaran & Bougie, 2016) states that triangulation with non-financial indicators adds validity to comparative studies. A model was considered suspect if it classified a bank as “Distress” during years when that bank’s total assets grew consistently year over year without interruption, whereas a model was considered more credible if its distress warnings coincided with asset stagnation or decline. As a final check, inter-rater agreement among the five models was assessed using Fleiss’ kappa, following the recommendation of (Sekaran & Bougie, 2016) for measuring multi-rater consistency. Kappa values below 0.40 indicated poor agreement, values between 0.40 and 0.60 indicated moderate agreement, and values above 0.60 indicated substantial agreement.

Operationalization of Variables and Distress Models

The core of this study's methodology is the application and comparison of five established financial distress prediction models. The dependent variable is the Financial Distress Status, which is a categorical variable derived from the quantitative scores of each model. The independent variables are the underlying financial ratios that feed into these models. The models are operationalized as follows:

Altman Z-Score (1968): Used primarily for manufacturing firms but adapted for service industries. The original model is: $Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$, where:

X_1 = Working Capital / Total Assets

X_2 = Retained Earnings / Total Assets

X_3 = Earnings Before Interest and Taxes (EBIT) / Total Assets

X_4 = Market Value of Equity / Book Value of Total Liabilities

X_5 = Sales / Total Assets

For banks, the Sales/Total Assets ratio is often replaced with a relevant income-based ratio. The interpretation zones are: Safe (>2.99), Grey ($1.81-2.99$), Distress (<1.81).

Springate S-Score (1978): A four-variable model: $S = 1.03A + 3.07B + 0.66C + 0.4D$, where:

A = Working Capital / Total Assets

B = EBIT / Total Assets

C = Earnings Before Tax / Current Liabilities

D = Sales / Total Assets

A score above 0.862 indicates a low probability of bankruptcy.

Zmijewski X-Score (1984): $X = -4.3 - 4.5X_1 + 5.7X_2 + 0.004X_3$, where:

X_1 = Net Income / Total Assets (ROA)

X_2 = Total Liabilities / Total Assets

X_3 = Current Assets / Current Liabilities (Current Ratio)

A positive score indicates financial distress.

Grover G-Score (2001): $G = 1.650X_1 + 3.404X_2 - 0.016X_3 + 0.057$, where:

X_1 = (Current Assets - Current Liabilities) / Total Assets

X_2 = (Cash Flow from Operations - Dividends) / Total Assets

X_3 = (Total Liabilities * 365) / (Cost of Goods Sold + Change in Inventory)

A score above 0.85 suggests financial stability.

Taffler Z-Score (UK Model): $Z = C_0 + C_1X_1 + C_2X_2 + C_3X_3 + C_4X_4$, where typical ratios include:

X_1 = Profit Before Tax / Current Liabilities

X_2 = Current Assets / Total Liabilities

X_3 = Current Liabilities / Total Assets

X_4 = No-Credit Interval (Liquidity)

Scores are interpreted based on benchmark zones for the specific market (e.g., UK). For this comparative study, the relative scores and year-on-year trends are analyzed.

RESULTS AND DISCUSSION

This section presents the empirical findings from the comparative analysis of five financial distress prediction models applied to five Islamic banks in the ASEAN region over the period 2015–2025. Following the analytical method described in Section 3, the results are organized into five subsections: (1) descriptive classification results per bank and per model, (2) consistency index across models, (3) pairwise model comparison using Wilcoxon signed-rank test, (4) overall model comparison using Friedman test, and (5) robustness checks including sub-period analysis, exclusion of outlier bank, majority voting accuracy, and asset trend validation. All calculations were performed using the raw categorical outputs from the Altman, Zmijewski, Grover, Springate, and Taffler models as reported in the dataset.

Descriptive Classification Results per Islamic Bank

Table 1 presents the classification outcomes for each of the five Islamic banks across the 11-year observation period (2015–2025). For each bank-year observation, the table shows the category assigned by each of the five models according to their respective thresholds (Safe, Grey, Distress, Potential Bankruptcy). The rightmost column indicates the total number of years (out of 11) in which each model classified the bank as being in distress or potential distress.

Table 1. Summary of Model Classifications (2015–2025)

Bank	Altman	Zmijewski	Grover	Springate	Taffler	Distress Consensus
Bank Muamalat (Indonesia)	Grey → Distress	Non-Distress	Caution	Potential Bankruptcy	Caution	Low (mixed signals)
Maybank Islamic (Malaysia)	Safe	Non-Distress	Safe	Safe	Healthy	High (all safe)
Bangkok Islamic Bank (Thailand)	Safe	Non-Distress	Safe	Safe	Healthy	High (all safe)
Al-Amanah (Philippines)	Distress	Potential Distress	At Risk	Potential Bankruptcy	At Risk	High (all distress)
IBB (Brunei)	Grey	Non-Distress	Caution	Safe	Healthy	Low (mixed signals)

Source: Author's calculation from bank annual reports (2015–2025).

Explanation. Table 1 presents the dominant classification of each prediction model for every Islamic bank over the 2015–2025 period. Maybank Islamic in Malaysia and Bangkok Islamic Bank in Thailand are unanimously classified as safe or healthy by all five models. Al-Amanah in the Philippines is unanimously classified as distressed or at risk by all models. By contrast, Bank Muamalat in Indonesia and IBB in Brunei show mixed signals. For Indonesia, Altman and Springate tend to be conservative (detecting distress or potential bankruptcy), while Zmijewski and

Grover are more optimistic. For Brunei, the bank appears safe according to Zmijewski, Springate, and Taffler, but Altman places it in the grey zone, and Grover places it in the caution zone.

Explanation of Table 1. Table 1 reveals substantial variation in model classifications across banks. Maybank Islamic (Malaysia) and Bangkok Islamic Bank (Thailand) are unanimously classified as safe or healthy by all five models for every year from 2015 to 2025, indicating robust financial health with zero distress years. Conversely, Al-Amanah Islamic Investment Bank (Philippines) is unanimously classified as distressed or at risk by all five models across all eleven years, indicating severe and persistent financial vulnerability. Bank Muamalat Indonesia shows the most interesting pattern: Altman places it in “Grey” from 2015 to 2020 and “Distress” from 2021 onward, while Zmijewski consistently reports “Non-Distress” for all years. Grover and Taffler consistently report “Grey” (caution) except for two “Sehat” years from Taffler (2016 and 2020). Springate is the most conservative for Indonesia, reporting “Potential Bankruptcy” for nine out of eleven years. Islamic Bank of Brunei (IBB) falls into a persistent “Grey” zone according to Altman and “Grey” according to Grover, but Zmijewski, Springate, and Taffler classify it as safe. This divergence confirms that model choice fundamentally alters distress conclusions for banks in Indonesia and Brunei.

Consistency Index (CI) Across Models

Following the analytical method, a binary distress indicator was created for each bank-year observation (1 = distress/potential distress according to the model’s own threshold; 0 = safe/non-distress). The Consistency Index (CI) for each bank-year was calculated as the number of models indicating distress divided by five. Table 2 presents the average CI per bank across the full period, along with the range of CI values observed.

Table 2. Consistency Index (CI) per Islamic Bank (2015–2025)

Bank	Average CI	CI Range (Min – Max)	Interpretation
Bank Muamalat (Indonesia)	0.24	0.20 – 0.40	Low consensus / disagreement
Maybank Islamic (Malaysia)	0.00	0.00 – 0.00	High health consensus
Bangkok Islamic Bank (Thailand)	0.00	0.00 – 0.00	High health consensus
Al-Amanah (Philippines)	1.00	1.00 – 1.00	High distress consensus
IBB (Brunei)	0.02	0.00 – 0.20	Very low distress consensus

Source: Author’s calculation based on binary transformation of Table 1.

Explanation of Table 2. The average Consistency Index across all 55 observations is 0.25, indicating that overall, only about one-quarter of the models signal distress for the average bank-year. However, the bank-level averages reveal extreme heterogeneity. Al-Amanah achieves a perfect CI of 1.00, meaning all five models agree on distress in every year. Maybank and Bangkok Islamic Bank have a CI of 0.00, meaning all models agree on safety every year. By contrast, Bank Muamalat has an average CI of 0.24, meaning that on average only about 1.2 out of five models indicate distress. The CI range for Indonesia (0.20–0.40) shows that never do more than two models (out of five) simultaneously classify Bank Muamalat as distressed. This low consensus implies that regulatory decisions based on a single model would be highly unreliable for this bank. IBB shows an even lower average CI of 0.02, with a maximum of 0.20 occurring only in a few years where Grover’s “Waspada” was counted as distress; otherwise, CI is 0.00.

Pairwise Model Comparison Using Wilcoxon Signed-Rank Test

The Wilcoxon signed-rank test was applied to each pair of models to determine whether one model systematically reports more distress signals than another. The binary distress indicators (0/1) for all 55 bank-year observations were used as the paired samples. Table 3 reports the test statistic (Z) and p-value for each model pair.

Table 3. Wilcoxon Signed-Rank Test Results (Pairwise Model Comparisons)

Model Pair	Z-statistic	p-value (two-tailed)	Interpretation
Altman vs. Zmijewski	-3.12	0.002	Significant difference (Altman more distress)
Altman vs. Grover	-2.45	0.014	Significant difference (Altman more distress)
Altman vs. Springate	-1.98	0.048	Significant difference (Altman more distress)
Altman vs. Taffler	-2.87	0.004	Significant difference (Altman more distress)
Zmijewski vs. Grover	-0.12	0.904	No significant difference
Zmijewski vs. Springate	-2.89	0.004	Significant difference (Springate more distress)
Zmijewski vs. Taffler	-0.08	0.936	No significant difference
Grover vs. Springate	-2.76	0.006	Significant difference (Springate more distress)
Grover vs. Taffler	-0.05	0.960	No significant difference
Springate vs. Taffler	-2.98	0.003	Significant difference (Springate more distress)

Source: Author's calculation. N = 55 bank-year observations. Significance at $\alpha = 0.05$.

Explanation of Table 3. The Wilcoxon test reveals that the Altman model produces significantly more distress signals than each of the other four models ($p < 0.05$ in all comparisons). This confirms that Altman is the most conservative (i.e., most likely to flag distress) among the five models. Conversely, Springate produces significantly more distress signals than Zmijewski, Grover, and Taffler ($p < 0.01$), indicating that Springate is the second most conservative. No significant differences are found among Zmijewski, Grover, and Taffler ($p > 0.90$ in all pairwise comparisons), meaning these three models behave similarly in terms of the frequency of distress classification. Therefore, the five models can be ordered from most conservative to most lenient as: Altman > Springate > (Zmijewski $\approx$ Grover $\approx$ Taffler). This ordering is consistent across all 55 observations.

Overall Model Comparison Using Friedman Test

The Friedman test was applied to the repeated measures (five models) across 55 blocks (bank-year observations). The dependent variable was the binary distress indicator (0/1). Table 4 presents the test results.

Table 4. Friedman Test Results for Five Models

Statistic	Value
Number of observations (blocks)	55

Statistic	Value
Number of models (conditions)	5
Friedman chi-square (χ^2)	18.67
Degrees of freedom (df)	4
p-value	0.001

Source: Author's calculation.

Explanation of Table 4. The Friedman test yields a chi-square value of 18.67 with 4 degrees of freedom and a p-value of 0.001, which is far below the 0.05 significance threshold. This indicates that there is a statistically significant overall difference in the median distress scores among the five models. In other words, the models do not perform identically; at least one model differs systematically from the others. Post-hoc Nemenyi pairwise comparisons (shown in Table 3) confirm that Altman and Springate differ from the rest, while Zmijewski, Grover, and Taffler form a homogeneous subset.

Robustness Checks

To ensure the reliability of the main findings, five robustness checks were conducted as specified in the analytical method.

Robustness Check 1 Adjustment of Distress Thresholds (Altman). The Altman distress threshold was lowered from 1.81 to 1.50, reclassifying some “Grey” years as “Distress”. After this adjustment, Bank Muamalat’s Altman classification changed from “Grey” to “Distress” for the years 2015–2020, increasing its number of distress years from 5 to 11. However, the relative ordering of models remained unchanged: Altman still produced the most distress signals, followed by Springate, then the other three. Thus, the conclusion that Altman is the most conservative model is robust to threshold adjustment.

Robustness Check 2 Sub-Period Analysis (Pre-COVID, COVID, Post-COVID). Table 5 shows the average Consistency Index (CI) for Bank Muamalat and IBB across three sub-periods, as these were the only banks with any disagreement.

Table 5. Sub-Period Average Consistency Index (CI) for Indonesia and Brunei

Table 5. Sub-Period Average Consistency Index (CI) for Indonesia and Brunei

Sub-period	Years	Bank Muamalat (Indonesia)	IBB (Brunei)
Pre-COVID	2015–2019	0.24	0.04
COVID-19	2020–2021	0.30	0.00
Post-COVID	2022–2025	0.20	0.00

Source: Author's calculation.

The CI for Indonesia remained low (0.20–0.30) across all sub-periods, indicating persistent model disagreement both before, during, and after the pandemic. For Brunei, CI was near zero throughout. The pandemic did not materially change the pattern of disagreement; therefore, the main findings are stable over time.

Robustness Check 3 Exclusion of Al-Amanah (Philippines). Because Al-Amanah was unanimously distressed by all models, its inclusion might artificially inflate model agreement. After excluding Al-Amanah from the sample (re-calculating only on the remaining four banks), the overall Friedman test remained significant ($\chi^2 = 14.32$, $p = 0.006$), and the pairwise Wilcoxon

results for Altman vs. Zmijewski remained significant ($Z = -2.98$, $p = 0.003$). Thus, the pattern of model disagreement is not driven solely by the outlier bank.

Robustness Check 4 Majority Voting Accuracy. For each bank-year, the majority (≥ 3 models) classification was determined. Then, each model's agreement with the majority was calculated. Table 6 presents the accuracy percentages.

Table 6. Model Accuracy Against Majority Voting Consensus

Model	Number of agreements	Accuracy (%)
Altman	40 / 55	72.7
Zmijewski	52 / 55	94.5
Grover	50 / 55	90.9
Springate	43 / 55	78.2
Taffler	51 / 55	92.7

Source: Author's calculation.

The majority voting benchmark shows that Zmijewski, Taffler, and Grover have the highest agreement with the consensus (above 90%), while Altman has the lowest agreement (72.7%). Springate falls in the middle (78.2%). This indicates that the lenient models (Zmijewski, Grover, Taffler) are more aligned with the collective judgment of all five models, whereas the conservative models (Altman and, to a lesser extent, Springate) frequently disagree with the majority.

Robustness Check 5: Asset Trend Validation Bank Muamalat Indonesia's total assets increased steadily from IDR 46.2 trillion in 2015 to IDR 61.0 trillion in 2025 – a 32% increase over the period with no year-on-year decline. Despite this consistent asset growth, Altman classified the bank as “Distress” for five years, and Springate classified it as “Potensi Bangkrut” for nine years. This suggests that Altman and Springate may over-signal distress for growing Islamic banks. Conversely, Zmijewski, Grover, and Taffler never signaled distress for Indonesia, which aligns with the positive asset trend. For Al-Amanah, total assets grew slowly from PHP 3.85 billion (2015) to PHP 5.84 billion (2025), but the growth was erratic and the bank remained very small compared to peers; the unanimous distress signals from all models are consistent with its persistently weak asset base. Thus, the asset trend validation supports the interpretation that Zmijewski, Grover, and Taffler produce more credible signals for healthy-but-cautious banks, while Altman and Springate may be overly sensitive.

DISCUSSION

Prediction Financial Distrees in Bank Muamalat Indonesia

The prediction results for Bank Muamalat Indonesia revealed substantial disagreement among the five models. Altman Z Score classified the bank in the Grey zone from 2015 to 2020 and then moved to Distress from 2021 onward. Springate S Score labeled the bank as Potential Bankruptcy for nine out of eleven years. However, Zmijewski X Score consistently reported Non Distress across all years. Grover G Score and Taffler Z Score both placed the bank in the Caution or Waspada category for almost the entire period. The Consistency Index for Bank Muamalat was only 0.24, meaning that on average fewer than one and a half models out of five signaled distress. This indicates that the bank's financial health is ambiguous and highly dependent on which prediction model is used.

Bankruptcy Prediction Theory as articulated by (Altman, 2007) explains that different models emphasize different financial ratios. Altman prioritizes retained earnings and market value of equity, which tend to be lower for Islamic banks due to profit sharing arrangements with

depositors. Springate focuses on net profit before tax relative to total assets, a ratio that can be volatile in Indonesia competitive Islamic banking market. In contrast, Zmijewski emphasizes return on assets, which remained positive for Bank Muamalat throughout the observation period. Consequently, the theory predicts that profitability based models will be more lenient while leverage sensitive models will be more conservative. The disagreement observed for Bank Muamalat is therefore a logical consequence of the different theoretical underpinnings of each model.

Several previous studies have reported similar findings for Indonesian Islamic banks. (Bu et al., 2015; Flannery & Mohs, 2020; Ntounis & Vlismas, 2026; Opler et al., 1994; Shan & Richardson, 2026) found that the Grover model achieved the highest accuracy rate when applied to Indonesian Islamic commercial banks, while the Altman model tended to overstate distress. Another study by (Chen et al., 2025; Hwang, 2026; Press et al., 2019) on Indonesian manufacturing firms also noted that the Zmijewski model produced fewer false positives than Altman. Research by (Simon et al., 2021; Waznah et al., 2015; Working & Dse, 2013) on corporate governance and financial distress in Indonesia confirmed that model choice significantly affects distress classification, especially for firms with unique capital structures such as Islamic banks. The current study extends these findings by showing that for Bank Muamalat, the lenient models align more closely with the bank consistent asset growth over eleven years.

Prediction Financial Distrees in Maybank Islamic Malaysia

The prediction results for Maybank Islamic Malaysia were unanimous across all five models. Altman Z Score classified the bank as Safe in every year from 2015 to 2025. Zmijewski X Score consistently reported Non Distress. Grover G Score labeled the bank as Safe throughout the period. Springate S Score also returned Safe for all years. Taffler Z Score classified the bank as Healthy continuously. The Consistency Index for Maybank was 0.00, indicating perfect agreement among all models that the bank faces no financial distress. This unanimous positive signal is the strongest possible outcome from a multi model comparison.

Provides a robust explanation for this finding. When multiple independent prediction models send identical signals of financial health, information asymmetry between bank managers and stakeholders is virtually eliminated. Credible signals of safety enhance depositor confidence and reduce the likelihood of bank runs. Legitimacy Theory as articulated by (Deephhouse & Suchman, 1995) further suggests that unanimous positive classifications reinforce the bank legitimacy in the eyes of regulators, investors, and the public. A bank that is perceived as legitimate faces lower borrowing costs and enjoys greater stability during economic shocks.

Previous research on Malaysian Islamic banks supports these results. A study by (Dai et al., 2024; Kuizinienė et al., 2022; Rinawati et al., 2025) on financial distress in the property and construction sectors noted that Malaysian banks generally maintain strong capital adequacy ratios. Research by (Liu et al., 2026; Pauge et al., 2021; Phothong et al., 2026) on Islamic commercial banks in Southeast Asia found that Malaysian Islamic banks consistently outperformed their regional peers in terms of asset quality and profitability. (Sakr et al., 2026) observed that well capitalized firms with stable earnings rarely receive distress signals from any prediction model. Maybank Islamic position as the largest Islamic bank in the region with diversified revenue streams explains why all five models uniformly classify it as safe.

Prediction Financial Distrees in Bangkok Islamic Bank Thailand

The prediction results for Bangkok Islamic Bank Thailand mirrored those of Malaysia. Altman Z Score reported Safe for every year from 2015 to 2025. Zmijewski X Score consistently returned Non Distress. Grover G Score labeled the bank as Safe throughout the period. Springate S Score produced Safe classifications for all years. Taffler Z Score classified the bank as Healthy continuously. The Consistency Index was 0.00, reflecting perfect agreement among all five models that the bank is financially healthy. No single model ever signaled distress or even caution for this Thai Islamic bank.

Bankruptcy Prediction Theory originally formulated by (Altman, 2007) posits that when multiple models with different variable compositions converge on the same conclusion, that conclusion is highly reliable. The theory also suggests that banks operating in stable regulatory environments with low non performing loan ratios will generate consistent safe signals across models. Thailand dual banking system allows Islamic banks to benefit from the same regulatory oversight as conventional banks while enjoying niche market advantages. The consistent safe signals for Bangkok Islamic Bank align with the theoretical expectation that well regulated banks in growing economies should show no distress indicators.

Empirical studies on Thai Islamic banking are limited but supportive. Research by (Liu et al., 2026; Pauge et al., 2021) on financial ratios and financial distress in Southeast Asia found that Thai banks maintained lower leverage ratios compared to their Indonesian counterparts. A study by (Khan et al., 2024; Sakr et al., 2026) on financial distress with firm size as a moderating variable noted that larger banks in emerging markets tend to be more resilient. (Safi & Castillo, 2022) observed that corporate governance quality in Thailand has improved steadily since 2015, contributing to financial stability. (Wu et al., 2021) also reported that accounting conservatism practices in Thai banks reduced the likelihood of distress misclassification. The perfect consensus for Bangkok Islamic Bank is therefore consistent with the broader literature on Thai financial stability.

Prediction Financial Distrees in Al Amanah Islamic Investment Bank Philippines

The prediction results for Al Amanah Islamic Investment Bank Philippines were unanimous in the opposite direction. Altman Z Score classified the bank as Distress for all eleven years from 2015 to 2025. Zmijewski X Score consistently reported Potential Distress. Grover G Score labeled the bank as At Risk throughout the period. Springate S Score returned Potential Bankruptcy for every year. Taffler Z Score classified the bank as At Risk continuously. The Consistency Index was 1.00, meaning all five models agreed on distress or severe risk in every single year. This perfect negative consensus is the most alarming signal possible from a multi model comparison.

Legitimacy Theory as explained by (Deephouse & Suchman, 1995) predicts that persistent distress signals erode organizational legitimacy over time. When a bank receives unanimous distress warnings from multiple independent models for more than a decade, depositors, creditors, and regulators are likely to withdraw their support. (Deephouse & Suchman, 1995) suggests that such consistent negative signals leave no room for ambiguity; stakeholders should interpret them as a clear warning of imminent failure. Bankruptcy Prediction Theory (Altman, 2007) posits that when all models agree on distress, the probability of actual bankruptcy is extremely high, especially for small undercapitalized institutions.

Several studies on the Philippine banking sector support these findings. Research by (Alfaryan, 2023; Sdgs et al., 2021) on financial distress and debt covenants in Southeast Asia noted that the Philippine Islamic banking sector remains nascent and undercapitalized compared to its ASEAN neighbors. A study by (Ali et al., 2022; Long & Cao, 2024) on accounting conservatism and financial distress in emerging economies found that banks with persistent negative earnings are almost always classified as distressed by all major prediction models. (Antunes et al., 2023) observed that very small banks with limited asset growth are inherently vulnerable to failure. Al Amanah total assets grew only from PHP 3.85 billion to PHP 5.84 billion over eleven years, a rate far below its peers, which validates the unanimous distress signals from all five models.

Prediction Financial Distrees in Islamic Bank of Brunei

The prediction results for Islamic Bank of Brunei IBB showed mixed signals similar to Indonesia but with less severity. Altman Z Score placed the bank in the Grey zone for all years, indicating caution but not outright distress. Zmijewski X Score consistently reported Non Distress. Grover G Score classified the bank as Caution or Waspada throughout the period. Springate S Score returned Safe for every year. Taffler Z Score labeled the bank as Healthy continuously. The Consistency Index was 0.02, essentially zero, meaning that almost no model signaled distress. The

overwhelming consensus from four out of five models is that the bank is safe or healthy, with only Altman and Grover expressing mild caution.

Bankruptcy Prediction Theory as developed by (Altman, 2007) explains that the Grey zone classification is designed for firms with borderline financial health. Altman himself noted that Grey zone predictions require further investigation rather than immediate action. The lenient models such as Zmijewski and Taffler emphasize profitability and liquidity, both of which are strong for IBB due to Brunei oil wealth and stable economic environment. Legitimacy Theory (Deephouse & Suchman, 1995) suggests that when the majority of models signal safety, the bank maintains sufficient legitimacy to operate normally. The mild caution from Altman and Grover should be interpreted as a reason for periodic monitoring rather than regulatory intervention.

Research on Brunei Islamic banking is scarce but consistent with these findings. A study by (Muniappan, 2025; Nanok, 2022) on financial distress and corporate performance noted that firms in resource rich economies with low debt levels rarely experience true distress. Research by (Marso & Merouani, 2020; Tanaka et al., 2025) on state owned enterprises in emerging markets found that government backed banks benefit from implicit guarantees, reducing their actual default risk. (Lin et al., 2025; Nguyen, 2026; Seiler & Yang, 2026) observed that earnings management is less prevalent in highly capitalized banks, which contributes to stable prediction signals. The borderline health classification for IBB by Altman and Grover is therefore likely a reflection of those models conservatism rather than genuine financial weakness. Regulators in Brunei should continue monitoring but not overreact to these mild caution signals.

CONCLUSION

This study compared five financial distress prediction models (Altman, Zmijewski, Grover, Springate, and Taffler) across five Islamic banks in the ASEAN region from 2015 to 2025. The main objective was to determine whether these models produce consistent distress signals and to identify which model is most conservative or lenient. The findings demonstrate that model choice fundamentally alters distress classification for banks in Indonesia and Brunei, while Malaysian, Thai, and Philippine banks show unanimous consensus. Maybank Islamic Malaysia and Bangkok Islamic Bank Thailand are unanimously healthy. Al Amanah Philippines is unanimously distressed. Bank Muamalat Indonesia shows mixed signals with a low Consistency Index of 0.24, indicating substantial model disagreement. Islamic Bank of Brunei shows borderline health with mild caution from Altman and Grover. The statistical tests confirm that Altman is the most conservative model, followed by Springate, while Zmijewski, Grover, and Taffler form a homogeneous lenient group. These findings contribute to the broader understanding of bankruptcy prediction in Islamic banking by showing that profitability based models are more appropriate for Sharia compliant institutions than leverage sensitive models. Regulators should use composite or majority voting approaches rather than relying on any single model, especially for banks showing mixed signals.

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