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Splitting long-term and short-term financial ratios for improved financial distress prediction: Evidence from Taiwanese public companies

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Abstract

Financial distress occurs when a company cannot meet its financial obligations within a specified timeframe, often owing to prolonged poor operational performance. While studies on financial distress prediction (FDP) use financial ratios (FRs) to forecast distress, they neglect to differentiate long-term (LT) attributes from FRs. To address this gap, our study introduces a novel model that distinguishes between LT and short-term (ST) accounting attributes in FRs. Using data from Taiwanese public companies (1991–2018), our proposed model employs a stacking ensemble classifier to split LT and ST Altman's ratios. This study addresses three key questions: (1) Do models involving split of LT and ST ratios outperform those that combine them? (2) How reliable and robust are these proposed models? (3) What is the proposed model's impact on distress prediction? The results show a significant outperformance of the existing solution, with higher accuracy, lower Type I and Type II errors, and reduced misclassification costs. These models are reliable in handling imbalanced data, proving suitable for real-market investigations. Diverse FR contexts from previous Taiwanese studies validate the distinction between LT and ST features, representing robust performance. This model identifies characteristics of correctly and incorrectly predicted distress in companies, providing nuanced insights into complex distress attributes. This study introduces a pioneering model demonstrating superior predictive accuracy, reliability, and robustness by considering the split between LT and ST accounting attributes. It lays a foundation for future studies to extend and refine the proposed model, offering valuable insights into the complex dynamics of FDP.

KEYWORDS

accounting attributes, financial distress prediction, financial ratios, imbalanced datasets, long-term and short-term financial ratios, stacking ensemble classifier

1 | INTRODUCTION

Financial distress poses significant challenges for both capital market participants and researchers, potentially leading to market loss and disruption. Consequently, predicting financial distress is of paramount importance to both companies and investors (Dinh et al., 2021; Sun & Li, 2012; Wang et al., 2022).

Accounting figures are crucial in assessing a company's financial health, offering insights into operational and financial risks. Financial ratios (FRs), derived from meaningful accounting figures, are the most significant and widely used features for financial distress prediction (FDP) (Barboza et al., 2017; Gepp & Kumar, 2012; Liang et al., 2020). Although financial distress is often triggered by poor long-term (LT) operational performance, existing FDP studies apply FRs without differentiating the LT attribute from these ratios. This omission may hamper predictive performance and inhibit discussions on the varying impacts of different financial attributes on financial distress. Our study addresses this gap and proposes a model to investigate the significance of accounting attributes in both LT and short-term (ST) ratios[1] for predicting financial distress.

By dissecting the distinct attributes of FRs, our model is expected to demonstrate improved predictive ability, reliability, and robustness. Additionally, we aim to provide a detailed interpretation of features influencing a company's financial distress and assist in analyzing distressed companies. This study addresses the following research questions: (1) Do models involving split LT and ST ratios outperform those that combine them? (2) How reliable and robust are these proposed models? (3) What is the proposed model's impact on distress prediction?

This study utilizes data from Taiwanese public companies spanning 1991 to 2018, sourced from the Taiwan Economic Journal (TEJ) database. [2] Referring to Altman's (1968) well-known FDP ratios,[3] we apply these ratios and categorize them according to LT and ST attributes. We adopt the studies of Almamy et al. (2016) and González-Martín et al. (2019), incorporating Altman's ratios in the samples when constructing both baseline and proposed models. The proposed model involves splitting Altman's ratios into LT and ST components by employing a stacking ensemble classifier for prediction. In comparison, the baseline model combines Altman's ratios with an support vector machine (SVM) classifier, a popular single classifier (Doğan et al., 2022; Zeng et al., 2020), for distress prediction.

The findings and implications are as follows. First, the proposed models significantly outperform the baseline models, demonstrating higher accuracy, lower Type I and Type II errors, and lower misclassification costs. This suggests that models splitting LT and ST ratios predict distress more accurately than those combining them. Second, the proposed models exhibit reliability when dealing with imbalanced datasets (1:2, 1:3, and 1:N). They consistently surpass the baseline models with significant differences, making them suitable for real-market data investigations. Furthermore, by applying various FR contexts from previous Taiwanese studies (Huang & Yen, 2019; Liang et al., 2016) to validate the concept of separating LT and ST accounting features, the proposed models demonstrate robustness by consistently surpassing the baseline models in both balanced and imbalanced datasets. Finally, compared with models that do not differentiate between LT and ST, our model can distinctly identify the characteristics of correctly predicted and mispredicted distress companies, interpreting them more precisely. Specifically, the model accurately captures distress in companies facing worsened LT operations and simultaneous ST operational challenges, aligning with the definition of distress. Moreover, the proposed model can identify more distressed companies than simply using LT ratios (commonly applied by financial users), given the similarity in LT levels among many non-distressed companies. However, the model struggles when both the LT and ST ratios are outstanding, indicating that financial distress may be caused by factors other than LT operational difficulties. Therefore, to enhance FDP accuracy, future studies can extend our proposed model setting and consider diverse distress categories, encompassing supplementary features.

In summary, this study bridges existing gaps by introducing a novel predictive model that considers the split of LT and ST accounting attributes. This model demonstrates superior predictive accuracy, reliability, and robustness, offering insights into capturing distressed companies, and provides a foundation for future studies.

The remainder of this paper is organized as follows. Section 2 reviews the theoretical background. Section 3 explains the experimental procedure and Section 4 presents the results and discussion. Finally, Section 5 concludes the study and provides suggestions for future research.

2 | THEORETICAL BACKGROUND

2.1 | LT and ST attributes of FRs

FRs play a crucial role in predicting company distress. The components of each FR can be found in financial statements, providing insights into a company's operating and financial performance (Tulchinsky et al., 2015). Hence, a thorough understanding of financial statements is vital for forecasting company distress.

FRs are frequently employed to analyze financial statements and provide valuable insights into a company's financial health. These have been primary indicators of distress over the past six decades. As different FRs exhibit distinct accounting attributes, we can interpret a company's operating conditions based on these attributes. For instance, retained earnings reflect a company's LT profitability and possess strong predictive power (Ball et al., 2020). Consistent with Ball et al.'s (2020) findings, Jiang and Jones (2018), Lu et al. (n.d.), and Tian and Yu (2017) indicated that retained earnings are one of the crucial features among FRs for predicting distress in Chinese, Japanese, and Taiwanese companies. The accumulated effect indicates that sustained performance results from accumulated LT operations, and a company with higher accumulated profits is less likely to default.

In contrast, FRs with ST attributes have a single-period impact, exerting a substantial influence on a company's operational status. Despite annual performance variations, shifts or deviations in these ST FRs can serve as early indicators of distress. Previous studies attempting to predict distress using 1-year period FRs may address accounting problems specific to a single year. Given the distinct yet substantial roles of LT and ST attributes in FRs, it is crucial to distinguish their individual impacts in predicting financial distress. Consequently, this study proposes predictive models that distinctly consider the LT and ST attributes of FRs, anticipating improved performance compared with models disregarding these distinct attributes.

2.2 | Previous FDP studies

In this section, we discuss considerations from earlier FDP studies, outlined in Table 1, with an emphasis on distinguishing between Taiwan's and other countries' FDP research. We explore concerns related to input feature selection, classifiers, and imbalanced sample treatment. Focusing on LT and ST FRs, we scrutinize previous studies that utilized FRs as input features, emphasizing commonly employed ratios. Additionally, we review prior research incorporating stacking ensemble techniques for constructing distress models by comparing the performances of different stacking models. Finally, we explore how earlier studies addressed the challenges posed by imbalanced samples when predicting financial distress.

2.2.1 | FRs on prior studies

Table 1 presents studies that utilized FRs, classified into two groups based on the number of ratios employed. While some studies with a substantial number of ratios employ the entire set, several studies, like Chou et al. (2017) and Huang and Yen (2019), use a feature selection approach to identify the most effective ratios. In contrast, studies with a smaller set of ratios, exemplified by Almamy et al. (2016) and Altman (1968), typically incorporate all ratios into the model. Additionally, most studies as Almamy et al. (2016), Altman (1968), Barboza et al. (2017), González-Martín et al. (2019), Ko et al. (2017), and Qiu et al. (2020), including Taiwanese studies (Huang & Yen, 2019; Ko et al., 2017) that employ a smaller set of ratios include Altman's ratios.

Despite originating in 1968, Altman's ratios are prominent in contemporary distress prediction research globally, including the United States (Barboza et al., 2017; Liang et al., 2020; Qiu et al., 2020), the United Kingdom, Spain (Almamy et al., 2016; González-Martín et al., 2019), and Taiwan (Huang & Yen, 2019; Ko et al., 2017). Altman's ratios are also employed either with other FRs or non-financial features when constructing predictive models, as shown in Table 1. This emphasizes the extensive use of Altman's (1968) five ratios for global distress prediction, including in Taiwan. This review motivated our study to employ Altman's ratios for distress prediction.

The split FRs column in Table 1 highlights our study's aims to fill a research gap. The existence or absence of splitting FRs into LT and ST accounting attributes within studies is highlighted in bold. Some studies utilize FRs with both LT and ST attributes but fail to distinguish between them, opting for a combined approach. Acknowledging the distinct roles of LT and ST ratios in accounting theory, our model was designed to align more closely with accounting principles.

This study introduces a framework that categorizes Altman's ratios into distinct groups based on their LT and ST attributes to predict financial distress in companies. Altman's ratios, comprising both LT and ST attributes, serve as suitable FRs for distress prediction. In our model, the ratio of retained earnings to total assets (Z2) was designated as an LT attribute, whereas the remaining four ratios suggested by Altman were classified as ST attributes. This approach has the potential to improve predictive accuracy compared with previous studies that collectively analyzed all ratios. Additionally, we evaluated the models' robustness by applying FRs from two earlier FDP studies in Taiwan (Huang & Yen, 2019; Liang et al., 2016).

TABLE 1 List of prior FDP studies employing LT/ST-based attributes of FRs—including classifiers used to construct the distress model and numerous sample data: either balance or imbalance (real-market) data.

Works	Features	Split FRs (√/X)	Data; matching rule (√/X)	Balance (B)/ imbalance (Imb)	Classifier
Global distress studies					
Altman (1968)	5 **Altman** (LT and ST)	**X**	US: 33 pairs in 1946–1960 (√)	B	Multivariate analysis
Almamy et al. (2016)	6 FRs, including **Altman** (LT and ST)	**X**	UK: around 90:1000 data in 2000–2013 (**X**)	Imb-**1:N**	Univariate analysis, multiple-DA
Barboza et al. (2017)	11 FRs, including **Altman** (LT and ST)	**X**	US: 449 pairs in 1985–2005 (√)	B	Linear-DA, LR, NN, **SVM**, boosting, bagging, RF
Veganzones and Séverin (2018)	50 FRs (ST)	**X**	French: 1500 to 4,000 data published in 2013–2014 (X)	Imb-**1:N** (RO, EasyEnsemble, RU, **SMOTE**)	LDA, LR, NN, **SVM**, RF
González-Martín et al. (2019)	5 **Altman** (LT and ST)	**X**	Spanish: 79:5824 data in 2007–2015 (X)	Imb-**1:N**	GA
Qiu et al. (2020)	5 **Altman** (LT and ST)	**X**	US: 110668 (3.7% are distress) data in 1961–2015	Imb	LR
Liang et al. (2020)	40 FRs, including **Altman** (LT and ST), 21 CG	**X**	US: 143 pairs in 1996–2014 (√)	B	**SVM**, **stacking**
Zeng et al. (2020)	161 FRs (LT and ST), 10 market, 8 CG	**X**	China: 188 pairs in 2012–2019 (√)	B	KNN, **SVM**
Doğan et al. (2022)	24 FRs (ST)	**X**	Turkey: 71:101 data in 2010–2017 (**X**)	Imb-**1:N** (mostly **1:2**)	LR, **SVM**
Kim et al. (2022)	8 FRs (ST)	**X**	US: 1858:381757 data	Imb-1:3 (SMOTE)	LR, **SVM**, RF, recurrent-NN, LSTM, ensemble
Taiwanese distress studies					
Liang et al. (2016)	95 FRs (LT and ST), 95 CG	**X**	Taiwanese: 239 pairs in 1999–2009 (√)	B	**SVM**, KNN, CART, MLP, NB
Ko et al. (2017)	5 **Altman** (LT and ST)	**X**	Taiwanese: 20:28 data in 2009–2014 (**X**)	B	Evidential analysis
Chou et al. (2017)	64 FRs (LT and ST)	**X**	Taiwanese: 150/450 (√)	Imb-**1:3**	GA-fuzzy, BackpropagationNN
Liang et al. (2018)	95 FRs (LT and ST) (Liang et al., 2016)	**X**	Taiwanese: 220 pairs in 1999–2009; (including China's bankruptcy, Australian, and German credit) (√)	B	**SVM**, KNN, CART, MLP, NB, ensemble bagging, boosting, **stacking**, and majority voting.
Lin et al. (2019)	95 FRs (LT and ST) (Liang et al., 2016)	**X**	(Liang et al., 2018) (√)	B	DT, GA, IG, KNN, LR, NB, **SVM**

TABLE 1 (Continued)

Works	Features	Split FRs (√/X)	Data; matching rule (√/X)	Balance (B)/ imbalance (Imb)	Classifier
Huang and Yen (2019)	16 FRs including **Altman** (LT and ST)	**X**	Taiwanese: 32 pairs in 2010–2016 (√)	B	Supervised (**SVM**, HACT, HGA-fuzzy, XGBoost)
Chen et al. (2020)	9 FRs (ST), 7 CG	**X**	Taiwanese: 83:249 in 1995–2016 (√)	Imb-**1:3**	LR, 2SLS
Tsai et al. (2021)	95 FRs (LT and ST) (Liang et al., 2016)	**X**	Taiwanese: 220:6599; imb of Liang et al. (2018) data[a] (**X**)	Imb-**1:N**	Bagging DT, ANN, DT, LR, **SVM**, bagging, and boosting
Aljawazneh et al. (2021)	95 FRs (LT and ST) (Liang et al., 2016)	**X**	Taiwanese imb of Liang et al. (2018) data (**X**)	Imb-**1:N** (**SMOTE**-based)	KNN, **SVM**, RF, Adaboost, and XGBoost; DL: DBN, LSTM, MLP-6L
Wang and Liu (2021)	95 FRs (LT and ST) (Liang et al., 2016)	**X**	Taiwanese imb of Liang et al. (2018) data (**X**)	Imb-**1:N** (TL, ENN, RENN, OSS, NCR, CCMUT)	**SVM**, LR, LDA, NB, XGboost, ANN, KNN, RF.
Sue et al. (2022)	95 FRs (LT and ST) (Liang et al., 2016)	**X**	Taiwanese imb of Liang et al. (2018) data (**X**)	Imb-**1:N** (SMOTE)	DeepNN, RF, **SVM**
Sue et al. (2023)	95 FRs (LT and ST) (Liang et al., 2016)	**X**	Taiwanese imb of Liang et al. (2018) data (**X**)	Imb-**1:3** (RU, **SMOTE**)	LR, **SVM**, NN, and DT

Abbreviation: 2SLS, two-stage least squares; ANN, artificial neural network; AP, affinity propagation; CG, corporate governance; DA, discriminant analysis; DBN, deep belief network; DES-MI, dynamic ensemble selection-multi class imbalance; DL, deep learning; DT, decision tree; ENN, edited N-N; FDP, financial distress prediction; GA, genetic algorithm; GAM, generalized additive model; GBDT, gradient boosting DT; GBM, gradient boosting machine; HACT, hybrid associative memory with translation; IG, information gain; KNN, *k*-N-N; LR, logistic regression; MARS, multivariate adaptive regression splines; MLP-6L, multi-layer perceptron with six layers; N-N, nearest neighbors; NN, neural network; NCR, neighborhood cleaning rule; OSS, TL + condensed N-N; PCA, principal component analysis; RENN, repeated N-N; RF, random forest; RO, random oversampling; RU, random under-sampling; SMOTE, synthetic minority oversampling technique; SOM, self-organizing map; TL, Tomek Links; XGBoost, eXtreme gradient boosting.
[a]Liang et al.'s (2018) data can be found at https://archive.ics.uci.edu/dataset/572/taiwanese+bankruptcy+prediction.

2.2.2 | Stacking ensemble models in FDP

Numerous classifiers can be used to construct highly effective distress models. Stacking, an advanced ensemble classifier, is widely recommended for improved predictive performance in distress prediction (Liang et al., 2020), as well as other binary classification topics, such as credit risk assessment (Hou et al., 2020; Xia et al., 2018; Yin et al., 2023) and financial fraud identification (Zhang et al., 2022). Liang et al. (2020) applied a stacking ensemble to predict financial distress by employing two distinct features: FRs and corporate governance indicators. The results demonstrate that the distress model, which utilizes stacking base learners with two different features, outperforms the model that relies solely on FRs. In a credit risk assessment study by Hou et al. (2020), they used a stacking ensemble to build a benchmark model, resulting in the second-lowest Type I error rate compared with five other enhanced ensemble tree-based classifiers. The differences in performance between stacking and the other ensemble classifiers were found to be insignificant. Yin et al. (2023) found that stacking yields more accurate credit default risk predictions and achieves a lower error rate than single classifiers. Notably, the base learners of stacking, as indicated in these studies, were constructed using several classifiers with the same data or input features. These reviews demonstrate that stacking has become a popular and valuable classifier for constructing models to address binary problems, including distress prediction. However, few studies, such as Liang et al.'s (2020), have focused on stacking with distinct input features.

For base and meta learners in stacking, we reviewed the single classifiers used to predict distress. SVM stands out prominently in this regard. Recent distress studies report that SVM's post-performance feature selection surpasses other classifiers, such as logistic regression (Doğan et al., 2022) and k-nearest neighbor (Zeng et al., 2020), in terms of predictive performance. Zeng et al. (2020) selected SVM for distress prediction due to its ability to handle small samples, solve nonlinear problems, and provide a desirable predictive accuracy compared with artificial neural networks. Barboza et al. (2017) also found that linear SVM has the highest true positive rate (distressed companies are correctly predicted) and the lowest Type I error rate (misidentified distressed as a non-distressed company) among seven other classifiers. Interestingly, the Taiwanese FDP studies in Table 1 commonly use SVM to predict distress (Liang et al., 2016; Lin et al., 2019; Sue et al., 2023; Tsai et al., 2021). These reviews underscore SVM's value in enhancing predictive performance for FDP. Therefore, we employed SVM as both the base learners and meta learner in our stacking ensemble model, which is a suitable methodology to construct a distress model exploring the distinctive attributes of LT and ST ratios.

2.2.3 | Imbalanced sample in FDP

FDP researchers often encounter the challenge of imbalanced datasets owing to significant differences in sample sizes between opposing classes. This makes it challenging to predict minority classes.[4] However, using imbalanced datasets can better reflect the real-world ratios of distressed and non-distressed companies. Table 1 presents previous studies that employed imbalanced datasets to forecast distress. This subsection reviews FDP studies with various imbalanced ratios, the utilization of matching rules, and a well-known technique to address the imbalance issue.

The imbalanced ratio of each prior study is provided in the Balance/Imbalance column of Table 1. The imbalanced ratio Imbalanced ratios 1:3 (Chen et al., 2020; Chou et al., 2017; Kim et al., 2022; Sue et al., 2023) and 1:N appear to be commonly used (Aljawazneh et al., 2021; Almamy et al., 2016; González-Martín et al., 2019; Sue et al., 2022; Tsai et al., 2021; Veganzones & Séverin, 2018; Wang & Liu, 2021). However, Doğan et al. (2022) claimed to use a 1:N imbalanced ratio but aligned more closely with a 1:2 imbalanced ratio based on total samples. Notably, as the imbalanced ratio increases, the model's improvement may decrease, presenting a challenge for this study. In our study, we assess the reliability of prior models in real-market scenarios using these imbalance ratios.

We review the utilization of matching rules on imbalanced datasets in each distress study in the Data and Balance/Imbalance columns in Table 1. Matching rules, pioneered by Altman (1968), are commonly applied in FDP studies. Techniques like stratified random sampling can reduce sampling errors and enhance sample representativeness (Hens & Tiwari, 2012). For the 1:3 imbalanced ratios listed in Table 1, the matching rules are often applied. However, this is different for studies that use 1:N ratios, which rarely apply matching rules to find non-distressed companies. Hence, this study uses matching rules for various imbalanced ratios to construct better real-market models.

Table 1's Balance/Imbalance column highlights the popular technique for addressing imbalanced datasets, which is the synthetic minority oversampling technique (SMOTE) (Aljawazneh et al., 2021; Hou et al., 2020; Sue et al., 2022; Veganzones & Séverin, 2018). Veganzones and Séverin (2018) revealed that SMOTE outperforms other sampling techniques, indicating its high potential for dealing with imbalance issues when predicting distress. Additionally, SMOTE balances imbalanced samples by creating new synthetic samples rather than copying the original samples. The advantage of this is that it avoids the overfitting problem to some extent (Veganzones & Séverin, 2018). Thus, our study uses SMOTE along with matching rules to select non-distressed companies and handle imbalanced datasets. In addition, we investigate the reliability and impact of the imbalanced model on FDP by implementing various imbalance ratios (1:2, 1:3, and 1:N).

Overall, this study considers the distinct implications of FRs represented by Altman's ratios, in both LT and ST contexts. It also adopts a more appropriate methodology to incorporate these attributes in predicting distress. In addition, we assess the reliability and robustness of our distress model by evaluating its performance on real-market data with different imbalanced ratios.

2.3 | Stacking ensemble for the LT and ST attributes

The concept of stacking as an ensemble classifier was initially proposed by Wolpert (1992) and has been shown to provide prominent predictive performance compared with single classifiers in various domains, including distress prediction and credit risk assessment (Liang et al., 2020; Yin et al., 2023). To address the implications of both LT and ST FRs in predicting distress, we employ a stacking ensemble classifier following Liang et al.'s (2020) approach.

Stacking consists of two primary steps: base learner and meta learner prediction. Base learners create various models using the same or different classifiers to generate multiple prediction results. In this study, we aim to address two distinct attributes: LT and ST FRs. To accomplish this, we adopt Liang et al.'s (2020) approach, which involved modifying two different inputs for two base learners (see Figure 1).

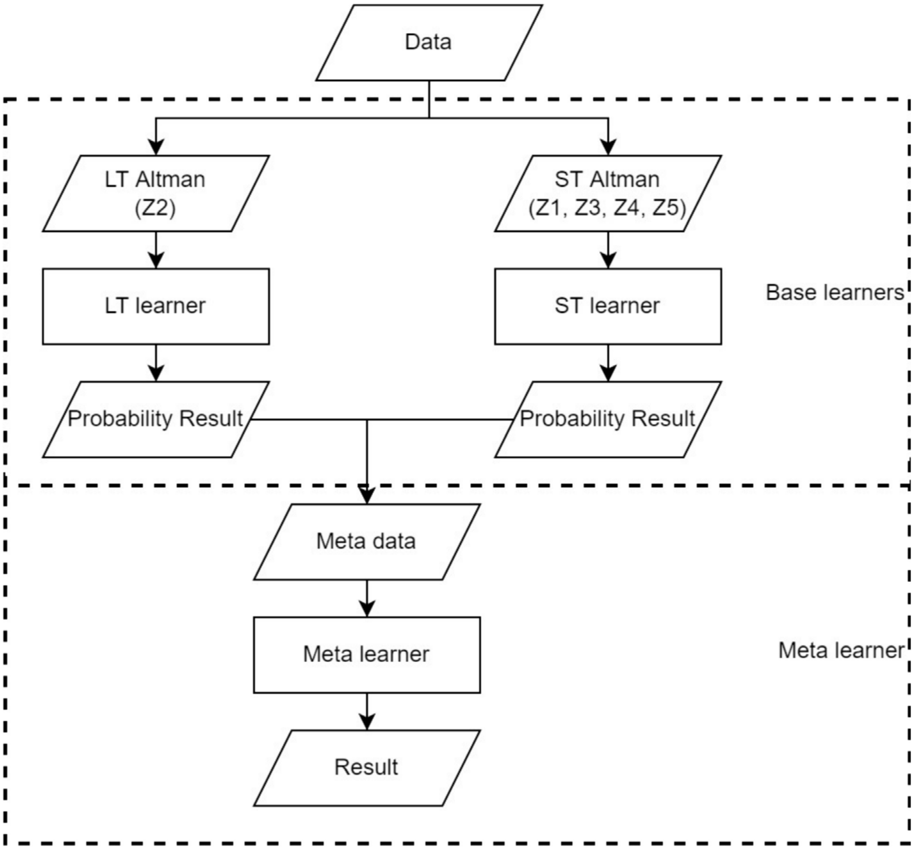


FIGURE 1 Stacking procedure for two different accounting attributes, long-term (LT) and short-term (ST), of Altman's ratios for building the proposed distress model.

Two models with distinct attributes produced different performances, biases, and errors. These predictions were merged as metadata, serving as inputs for the meta learner. The meta learner uses a classifier to produce a final prediction. This last step of stacking helps reduces the impact of biases and errors from individual base models by learning their strengths and weaknesses, ensuring a more stable and accurate final prediction. Unlike other common ensemble methods, stacking employs a meta learner instead of simple methods like a major vote or average, providing an advantage in correcting prediction results that are not achievable with other ensemble methods. In this study, we employ a stacking ensemble classifier with SVM as the single classifier for base learners and a meta learner, following Liang et al. (2020).

SVM's superiority in solving nonlinear problems was proven based on the above review. However, the SVM model still uses a hyperplane and a straight line (linear) to build the model. Despite its ability to handle nonlinear problems, the SVM-RBF kernel model still uses a linear continuity line. Meanwhile, two distinct attributes, LT and ST FRs, have nonlinear relationships that may be inappropriate if these attributes are combined. This causes a decrease in the model performance owing to the failure to capture nonlinear relationships. For example, if a company has a good LT, reflecting that the company is consistently good in LT, then it must be non-distressed regardless of the fluctuation in the ST value. To address these issues, stacking SVM to predict these distinct attributes can be a powerful tool in understanding and predicting financial performance. Using stacking SVM, two different linear SVM models with distinct attributes are generated to capture each model's strength. Finally, these models are combined to capture the nonlinear relationships and provide better insights into the data. The complementary information captured by stacking leads to an optimal final prediction.

3 | EXPERIMENTAL PROCEDURE

3.1 | Data

We collected data from the TEJ database to obtain samples of distressed and non-distressed companies. This database encompasses two datasets from 1991 to 2018: a finance dataset comprising FRs, including Altman's five ratios, and an event dataset comprising distress events (including financial distress and the company's corrective response).[5]

The TEJ's financial data were preprocessed to derive distressed and non-distressed samples through the following steps:

Step 1: We selected distressed samples based on distress events, indicating situations in which a company experiences substantial losses and financial distress.[6] Specifically, we identified a company in the distressed sample[7] if it has experienced at least one distress event in a given year. Relevant information was collected from the year preceding the distress.

Step 2: We obtained non-distressed samples by identifying matched pairs. Non-distressed companies do not experience any distress. A non-distressed company was selected when finding a distressed company's matched pairs based on the following criteria: the same year, the same industry, and comparable total assets. By ensuring similar total assets, we obtained imbalance ratios, including 1:1, 1:2, 1:3, and 1:N, which closely mirror real-market data.

Step 3: We deleted the samples to ensure that there were no missing values for Altman's five ratios. The total sample size was as follows: 368 for a 1:1 balanced ratio (184 distressed and 184 non-distressed), 552 for a 1:2 imbalanced ratio (184 distressed and 368 non-distressed), 732 for a 1:3 imbalanced ratio (183 distressed and 549 non-distressed), and 5908 for a 1:N imbalanced ratio (184 distressed and 5724 non-distressed).

3.2 | Model building

We constructed a baseline model (M_0) for comparison with the proposed model (M_1). We implemented 10-fold cross-validation and ran five times with the sample randomized each time for M_1 and M_0. This implies that each company was tested five times for each model. We incorporated Altman's ratios into the sample while building both M_0 and M_1 models, referencing Almamy et al. (2016) and González-Martín et al. (2019). M_0 was constructed by combining Altman's five ratios with the SVM classifier, whereas M_1 was constructed by splitting Altman's ratios based on the LT (Z_2) and ST attributes (Z_1, Z_3, Z_4, and Z_5) with the stacking ensemble classifier. The stacking ensemble classifier employed both base and meta learners, leveraging the promising SVM classifier (Figure 1).

In this study, we examined the reliability of our distress model by evaluating the performance of a model that splits Altman's ratios based on LT and ST attributes compared with a baseline model (M_0). We conducted experiments under various imbalanced ratios (1:2, 1:3, and 1:N). To address imbalances in datasets with varying ratios between the two classes, we used SMOTE, a technique introduced by Chawla et al. (2002) during data preprocessing before model construction. We then compared M_1 with M_0 for each imbalanced ratio. The goal was to determine whether splitting Altman's five ratios consistently improves upon M_0, showcasing its reliability using real-market data.

3.3 | Evaluation measures

We evaluated prediction outcomes using two main metrics outlined in Table 2. The first was accuracy, measuring the correctness of predictions calculated using $((a+d)/(a+b+c+d))$. The second was Type II error used to assess the misidentification of distressed companies, calculated using $(b/(a+b))$. These measures were designed to gauge a model's effectiveness sample classification accuracy and prevent the misprediction of distressed companies. Additionally, we evaluated the models using the data error trade-off (DET) curve, misclassification cost (misCost), and Wilcoxon signed-rank test.

The DET curve visualizes error outcomes of compared models when different thresholds are applied based on the probability results.[8] A powerful model should consistently exhibit a lower Type II error rate compared with others at the same Type I error rate, demonstrating its capability to prevent inaccurate predictions. This is evident when the area on the bottom-left side of the curve is minimized. Moreover, we identified the superior model based on the equal error rate (EER) when the Type I error equals the Type II error on the DET curve.

However, we cannot determine a superior model by simply considering Type I and II errors, which are equally critical in our context. Consequently, to reduce Type II errors, we utilized the cost ratio and misCost. These measures strike a balance by imposing a higher penalty for Type I errors. For example, a cost ratio of 3 implies that we sacrificed misclassifying non-distressed companies three times higher than misclassifying distressed companies. We evaluated the models using cost ratios ranging from 1 to 7 (1, 1.5, 2, 2.5, 3, 4, 4.5, 5, 6, and 7). A higher cost ratio indicates a smaller Type II error, suggesting that the error is greater to the left of the DET curve. The superior model was determined by demonstrating a lower misCost across various cost ratios. The misCost calculation is given in Equation 1.

$$misCost = (TypeIIerror * totalDistress * Cost) + (TypeIerror * totalNonDistress). \quad (1)$$

We applied the Wilcoxon signed-rank test to analyze the significant differences between the model performances. This test provides a p value that indicates the difference between a model and a superior model, denoted as 1, which has a lower average misCost.

4 | EXPERIMENTAL RESULTS AND DISCUSSION

4.1 | Do models involving the split LT and ST ratios outperform those that combine them?

For the first evaluation, we compared the performances of the proposed with baseline models to determine whether a model that splits Altman's five ratios based on two different attributes (LT and ST) outperforms one that uses a combination of LT and ST to predict distress. To reiterate, a lower Type II error is a crucial metric for studying distress. Figure 2 presents the DET curves representing the error outcomes (Type I and II errors) for both models. The majority of the points on M_1's curve are below those of M_0, except for a small area on the right side. The M_1 model's strength lies in consistently lower Type II errors, particularly on the far-left side of the DET curve. For instance, with a Type I error rate of 0.5, the Type II error rate of M_1 was 0.11, which was lower than M_0's Type II error rate of 0.14. Furthermore, the EER point of M_1 demonstrated a lower Type II error rate (0.247) than that of M_0 (0.263). This indicates that M_1 captures up to 1.5% fewer misidentified distress companies than M_0. Consequently, M_1 outperforms M_0 by exhibiting lower Type I and Type II errors across all cost ratios. This suggests that the model splitting LT and ST is less likely to misidentify companies than those that combine them.

Table 3 presents the misCost results for both models, including all performance measures. The results indicate that when the Type I error equals the Type II error (cost = 1), M_1's accuracy improves by more than 1.5%, and the crucial Type II error decreases by more than 2.5%. This implies that our model can correctly detect more companies while avoiding the failure to detect distressed or non-distressed companies. Additionally, the most significant increase in M_1's accuracy occurs when the cost equals 7, showing a 5% improvement over M_0. The corresponding values in Table 3 are highlighted in bold. Improved performance metrics such as higher

TABLE 2 Confusion metrics used for labeling prediction result.

Predicted → ↓Actual	Distressed	Non-distressed
Distressed	a	b; (Type II)
Non-distressed	c; (Type I)	d

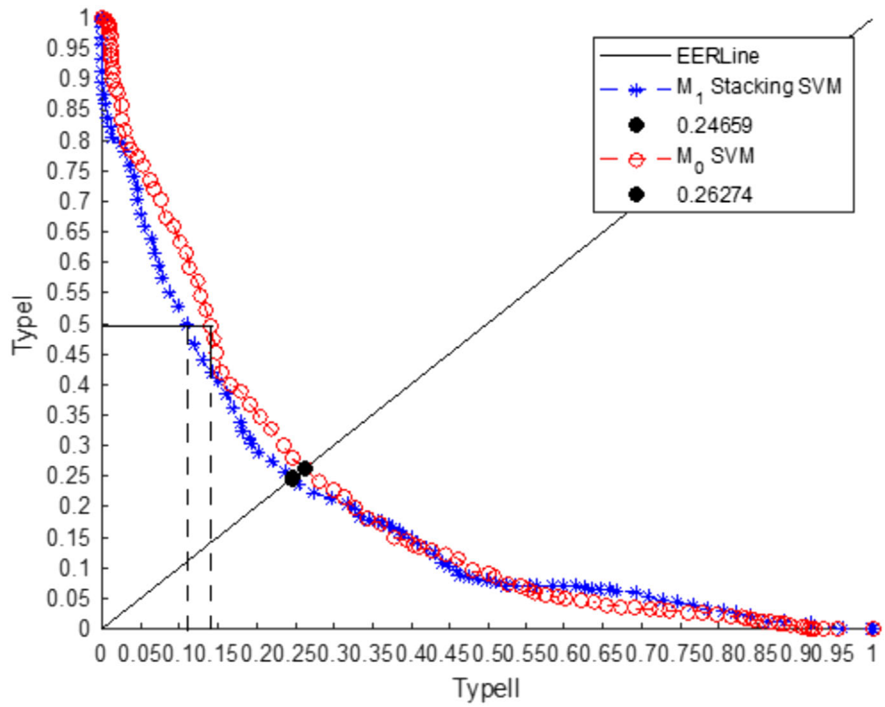


FIGURE 2 Evaluating M_1 and M_0 based on the data error trade-off (DET) curve.

TABLE 3 Measures to evaluate prediction results of M_1 and M_0 for each cost applied.

	Cost list									
Average	**1**	**1.5**	**2**	**2.5**	**3**	**4**	**4.5**	**5**	**6**	**7**
Proposed (M_1)										
Acc(%)	**75.3**	75.2	73.5	72.3	71.5	69.7	69.7	68.6	68.1	**67.3**
Type I	0.257	0.303	0.360	0.405	0.440	0.497	0.497	0.528	0.550	0.574
Type II	**0.237**	0.193	0.169	0.150	0.130	0.109	0.109	0.099	0.088	0.079
misCost	90.99	108.99	128.64	143.34	152.70	172.00	182.06	188.62	197.96	207.33
Baseline (M_0).										
Acc(%)	**73.7**	72.5	71.6	71.3	70.0	66.4	65.3	64.8	63.3	**62.4**
Type I	0.263	0.347	0.389	0.421	0.452	0.545	0.570	0.591	0.634	0.659
Type II	**0.263**	0.204	0.180	0.154	0.148	0.128	0.123	0.113	0.100	0.093
misCost	96.69	120.03	137.74	148.08	165.03	194.25	206.97	213.04	227.60	241.00

TABLE 4 Significant difference between M_1 and M_0 for each cost ratio—per p value of Wilcoxon signed-rank test results.

Cost list	M_1	M_0
1	1	0.061*
1.5	1	0.003***
2	1	0.083*
2.5	1	0.363
3	1	0.047**
4	1	0.001***
4.5	1	0.001***
5	1	0.006***
6	1	0.006***
7	1	0.005***

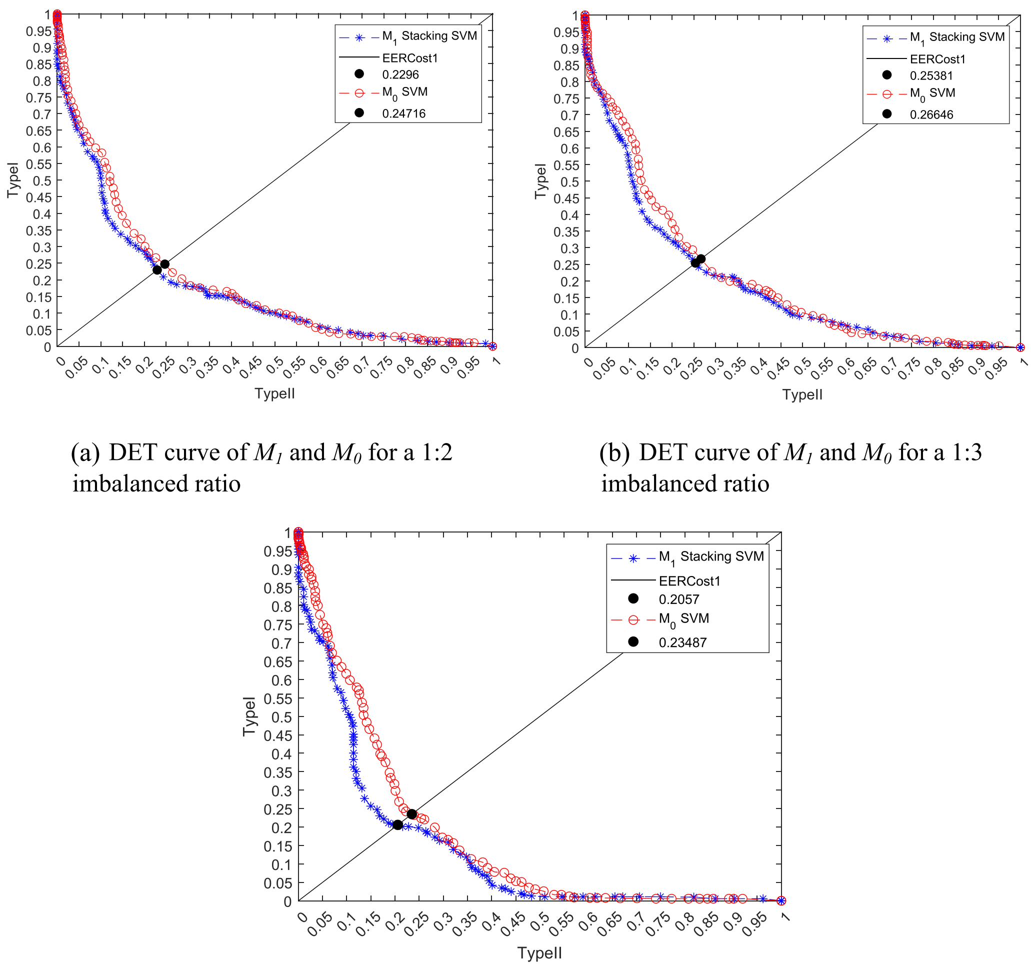
*= $0.05 < p \leq 0.1$.**= $0.01 < p \leq 0.05$.***= $p \leq 0.01$.

accuracy, lower Type I and Type II errors, and reduced misCost across all cost ratios highlight the superiority of M_1 over M_0. This implies that by splitting LT and ST, the model enhances the accuracy in predicting companies and avoids more mispredictions compared with a model that combines these attributes.

Table 4 presents the results of the Wilcoxon signed-rank test comparing M_0 and M_1. M_1 consistently outperformed M_0, as indicated by the presence of "1" over M_1 across all cost ratios. The p value results in M_1's column further confirm its significant superiority over M_0, with consistently lower misCost at all cost ratios. In summary, M_1 surpasses M_0 by achieving higher accuracy, lower Type I error, lower Type II error, and lower misCost, with significant differences. This indicates that our proposed model is more effective at identifying distressed and non-distressed companies, and preventing misclassifications than the baseline model, which utilizes the LT and ST combination.

4.2 | How reliable are the LT and ST models?

As previously established, the proposed model outperformed the baseline model. We subsequently investigated whether M_1 was consistently superior to M_0 across various imbalanced ratios (1:2, 1:3, and 1:N). Figure 3 shows three DET curves comparing M_1 and M_0 models for these imbalanced ratios (Figure 3a–c representing ratios of 1:2, 1:3, and 1:N, respectively). Across all imbalanced ratios, M_1s consistently outperformed M_0s, as evidenced by the widening performance gap between the models. This was particularly noticeable in the 1:N ratio, which resembles real-market data. M_1 consistently maintained a lower Type II error in most areas of the DET curve, especially in the far-left sections where it had a lower EER point than M_0. For the 1:2 imbalanced ratio, M_1 had an EER of 0.230, which was lower than M_0 (0.247). In other ratios, each M_1 had a lower EER than M_0 including a 1:3 imbalanced ratio ($M_1 = 0.254$, $M_0 = 0.266$) and a 1:N imbalanced ratio ($M_1 = 0.206$, $M_0 = 0.235$). The Wilcoxon test results for various imbalanced ratios are presented in Table 5. For each imbalanced ratio, M_1s consistently outperformed M_0s, exhibiting a significant difference at most cost ratios. Specifically, 8 out of 10 cost ratios (2, 2.5, 3, 4, 4.5, 5, 6, and 7) were below 0.05.[9] As a result, M_1s consistently outperformed M_0s with a reduction in lower Type I and Type II errors across all cost ratios for each imbalanced ratio, with significant differences. In summary, the



(a) DET curve of M_1 and M_0 for a 1:2 imbalanced ratio

(b) DET curve of M_1 and M_0 for a 1:3 imbalanced ratio

(c) DET curve of M_1 and M_0 for a 1:N imbalanced ratio

FIGURE 3 Evaluating M_1 and M_0 according to the data error trade-off (DET) curves on various imbalanced ratios. (a) DET curve of M_1 and M_0 for a 1:2 imbalanced ratio; (b) DET curve of M_1 and M_0 for a 1:3 imbalanced ratio; (c) DET curve of M_1 and M_0 for a 1:N imbalanced ratio.

proposed models for splitting LT and ST exhibited reliability in avoiding misclassifications when addressing imbalanced datasets (1:2, 1:3, and 1:N). The proposed models are well-suited for investigations involving real-market data as they consistently surpassed the baseline models with notable distinctions.

4.3 | How robust are the LT and ST models?

The models were previously built using Altman's five ratios, and we evaluated the resilience of M_1 to various and substantial sets of FRs from two prior studies (Huang & Yen, 2019; Liang et al., 2016)[10] both in balanced and imbalanced datasets.

Samples with Huang and Yen's (2019) 16 ratios and Liang et al.'s (2016)[11] 94 ratios contained 183 (183 distressed and 183 non-distressed) and 164 pairs for the balanced ratio, respectively. Additionally, Huang and Yen (2019) used 5905 sample (183 distressed and 5722 non-distressed), whereas Liang et al. (2016) used 5081 (164 distressed and 4917 non-distressed) for the 1:N imbalanced ratio. Regarding the features of M_1 and M_0 in these two studies, Huang and Yen (2019) built M_0 using all 16 ratios, whereas M_1 was constructed by splitting LT (retained earnings ratio) and ST (with 15 remaining ratios). Liang et al. (2016) constructed M_0 using 94 ratios. Meanwhile, M_1 was built using the retained earnings ratio as LT and the remaining 93 ratios as ST. The classifiers for M_1 and M_0 in these two studies remained consistent: SVM for M_0 and stacking ensemble for M_1.

4.3.1 | Comparison models regarding balanced samples

Table 6 presents the comparison results of the distress models by employing ratios from prior studies by Huang and Yen (2019) and Liang et al. (2016) for the balanced dataset. Utilizing 16 FRs from Huang and Yen (2019) to predict distress, M_1, which splits these ratios into LT and ST, outperforms M_0, incorporating a combination of LT and ST FRs. The improvement in M_1 compared with M_0 was in terms of higher accuracy and lower Type I and Type II errors. Similar results were obtained by comparing the models of Liang et al. (2016). Rigorous testing revealed the effectiveness of M_1s over M_0s by securing higher accuracy and lower Type I and Type II errors when the Type I error rate was closer to that of Type II. These results suggest that by employing different FRs from various prior Taiwanese studies, distress models that split FRs into LT and ST exhibit resilience and continue to provide reliable predictions, showcasing their robust nature.

TABLE 5 Significant difference between M_1 and M_0 for each cost ratio on various imbalanced ratios—per p value of Wilcoxon signed-rank test results.

	1:2		1:3		1:N	
Cost list	M_1	M_0	M_1	M_0	M_1	M_0
1	1	0.001***	1	0.077*	1	0.000***
1.5	1	0.027**	1	0.080*	1	0.000***
2	1	0.023**	1	0.000***	1	0.000***
2.5	1	0.017**	1	0.000***	1	0.000***
3	1	0.003***	1	0.002***	1	0.000***
4	1	0.002***	1	0.002***	1	0.000***
4.5	1	0.000***	1	0.002***	1	0.000***
5	1	0.000***	1	0.003***	1	0.000***
6	1	0.000***	1	0.000***	1	0.000***
7	1	0.003***	1	0.000***	1	0.000***

*= $0.05 < p \leq 0.1$.**= $0.01 < p \leq 0.05$.***= $p \leq 0.01$.

4.3.2 | Comparison models regarding imbalanced samples

Furthermore, this study presents model comparison results from prior Taiwanese distress studies using a 1:N imbalanced ratio. According to Table 7, M_1s, splitting FRs into two distinct attributes, LT and ST, outpaced M_0s, which employed a combination of LT and ST FRs for all studies. The Altman's FRs (ours) column in Table 7 corresponds to Figure 3c, displaying results of a model 1:N imbalanced ratios employing Altman's ratios. Compared with M_0s, M_1s' efficacy is proven by increasing the accuracy and diminishing Type I and Type II errors when using imbalanced data. These results suggest that the capability of splitting FRs into LT and ST remains stable, underscoring their robustness in handling different ratios compared with prior Taiwanese studies when using real-market data.

Overall, the efficacy of splitting LT and ST models was tested across diverse and substantial set ratios from previous Taiwanese studies for both balanced and imbalanced datasets. The superior models' consistent ability to adapt and perform well reinforces its robustness in FDP applications, even when using imbalanced data. In summary, the results in Sections 4.2 and 4.3 answer our second research question: How reliable and robust are the proposed models?

4.4 | What is the impact of an LT and ST model on FDP?

The previous section suggested that the proposed models exhibited a better performance than the baseline models.

TABLE 6 Comparison of models with (M_1) and without (M_0) splitting FRs into LT and ST, where various FRs are from prior Taiwanese FDP studies.

		Various FRs	
Models	**Metrics**	**Sixteen FRs (Huang & Yen, 2019)**	**Ninety-four FRs (Liang et al., 2016)**
M_1 (Split FRs: LT and ST)	Acc(%)	76.63	74.99
	Type I	0.233	0.255
	Type II	0.234	0.245
M_0 (combined: LT and ST)	Acc(%)	75.26	64.22
	Type I	0.243	0.267
	Type II	0.252	0.449

Abbreviations: FDP, financial distress prediction; FRs; financial ratios; LT, long-term; ST, short-term.

TABLE 7 Comparison of models with (M_1) and without (M_0) splitting FRs into LT and ST, where various FRs are from prior Taiwanese distress studies for a 1:N imbalanced ratio.

Models	Metrics	Various FRs[a] Altman's FRs (ours)	16 FRs (Huang & Yen, 2019)	94 FRs (Liang et al., 2016)
M_1 (split FRs: LT and ST)	Acc(%)	81.59	80.08	79.21
	Type I	0.190	0.200	0.208
	Type II	0.178	0.198	0.208
M_0 (combined: LT and ST)	Acc(%)	77.09	78.77	53.98
	Type I	0.237	0.208	0.636
	Type II	0.221	0.217	0.284

Abbreviations: FRs; financial ratios; LT, long-term; ST, short-term.
[a]The settings to construct M_1 and M_0 models in all prior studies were the same. Thus, the observed decrease in results for models employing a large number of FRs might be due to the availability of higher correlation ratios.

In this section, we provide a supplemental analysis to identify the conditions under which a model that splits Altman's five ratios based on two attributes outperforms a model that does not.

To perform the analysis, we established two schemes for distressed companies. The first scheme was characterized by distressed companies correctly identified by M_1, whereas the second scheme was characterized by distressed companies correctly identified by M_0. For each scheme, we compared the companies characterized (correctly identified distress companies) under the scheme with the misclassified companies based on the ST over LT attributes. The detailed steps for acquiring these companies under the first scheme (M_1) are outlined as follows:

Step 1: We selected a threshold near the EER point: Type I error rate = Type II error rate. The EER of the DET curve in Figure 3c (1:N) is 0.18. The threshold nearest to the EER was 0.43, whose Type II error rate was 0.17. Companies below the aforementioned thresholds were observed. Each company was tested five times due to the implementation of cross-validation.

Step 2: We selected a unique company if it was correctly identified as distressed by M_1 consistently. Accordingly, we obtained 155 characterized distressed companies that satisfied the first scheme, and 29 companies misclassified as non-distressed.

Step 3: We performed the same process to obtain the second scheme's characterized companies: 150 distressed companies and 34 misclassified as non-distressed companies.

After following the aforementioned procedure, we plotted the companies characterized under the first scheme and the misclassified ones based on the split features LT and ST, as displayed in Figure 4. On the basis of Figure 4, we have the following three discussions.

4.4.1 | Interpretation of M_1 based on LT and ST attributes versus M_0

To compare M_1 with M_0, we first plotted the companies characterized under the first and second schemes and their misclassified companies in Figures 4 and 5,[12] respectively. Figures 4 and 5 show the limited LT value ranges used to highlight the differences between the two figures. A comparison of these figures indicates two clear differences between M_1 and M_0. First, Figure 4 shows a distinct pattern, illustrated by a green dotted line, whereas M_0 does not. The presence of a distinct pattern in M_1 indicates its superior performance in splitting FRs into LT and ST attributes. Meanwhile, the absence of a specific pattern in Figure 5 is likely because M_0 treats all FRs equally without distinguishing between the LT and ST performances, such as prior common models by Barboza et al. (2017), Doğan et al. (2022), and González-Martín et al. (2019). Therefore, the baseline model's approach (M_0) poses a risk, as it fails to recognize patterns that could lead to the misclassification of a company's financial condition. Identifying the cause of misclassification becomes challenging using a single SVM classifier, particularly when distressed companies exhibit poor ST performance.

Second, the companies characterized under the first scheme are predominantly situated in the bottom-left area of Figure 4, representing poorer LT performance, whereas Figure 5 exhibits a higher number of misclassified companies within the same range. This suggests that M_1 effectively predicts distress when companies exhibit unfavorable performance in both the LT and ST. This implies that companies with insufficient LT profits, such as retained earnings, and poor ST performance are more likely to experience distress. This observation aligns with the fundamental concept of distress.

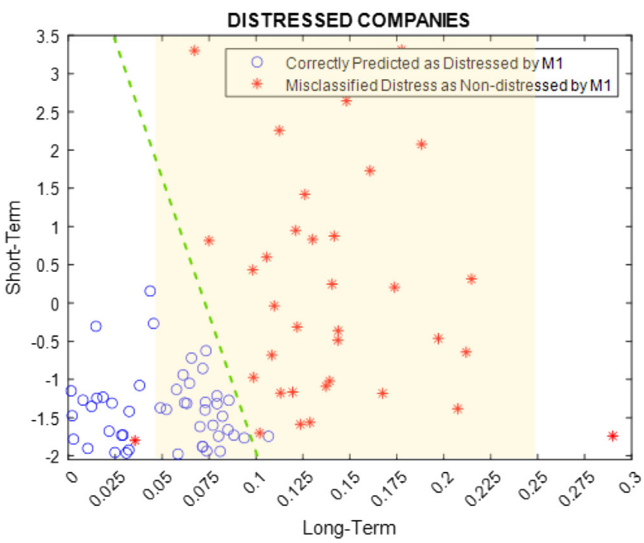


FIGURE 4 Distribution of distressed companies characterized under the first scheme (M_1) and its misclassified companies, based on the long-term (LT) over short-term (ST) accounting attributes.

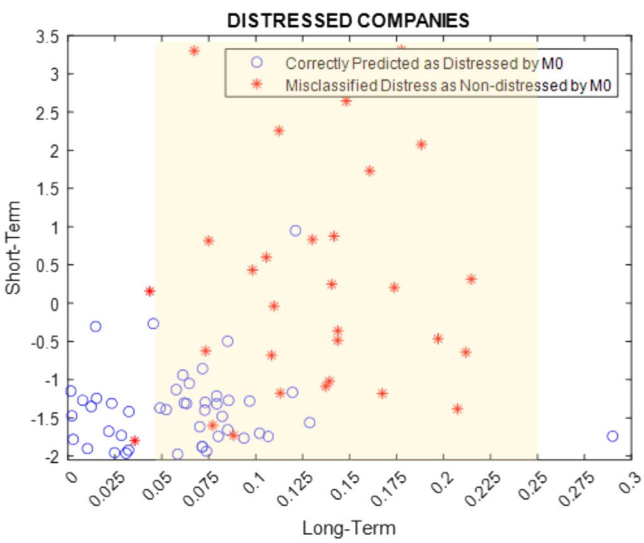


FIGURE 5 Distribution of distressed companies characterized under the second scheme (M_0) and its misclassified companies, based on the long-term (LT) over short-term (ST) accounting attributes.

4.4.2 | Interpretation of M_1 misidentifications versus M_0

Focusing specifically on Figure 4, we find that M_1 misclassifies a few companies in the top-right area where both LT and ST exhibit desirable performance, and no consistent pattern is evident in Figure 5. Theoretically, these companies are less likely to experience distress, and numerous classifiers may encounter difficulties in identifying them. These distressed companies should be identified by factors irrespective of FRs, such as distressed companies with financial report manipulation. In summary, by splitting LT and ST attributes, M_1 provides a clearer and more effective understanding of the intricate dynamics involved in predicting financial distress than M_0. We suggest improving predictive performance using our proposed model to incorporate factors beyond FRs.

4.4.3 | Interpretation of M_1 based on LT and ST attributes versus using LT ratio alone

Recognizing the significance of LT attributes in distress prediction, we compared M_1, which distinguishes between LT and ST, with the LT ratio alone, as shown in Figure 6. It displays the distribution of original distressed and non-distressed companies based on their LT performance. Focusing solely on LT values revealed that the most distressed companies occur when the LT value is less than 0.05, confirming the importance of LT. However, we also observed that when the LT value is greater than 0.05 ($0.05 < LT < 0.25$), highlighted by the yellow box in Figure 6, the highest number of non-

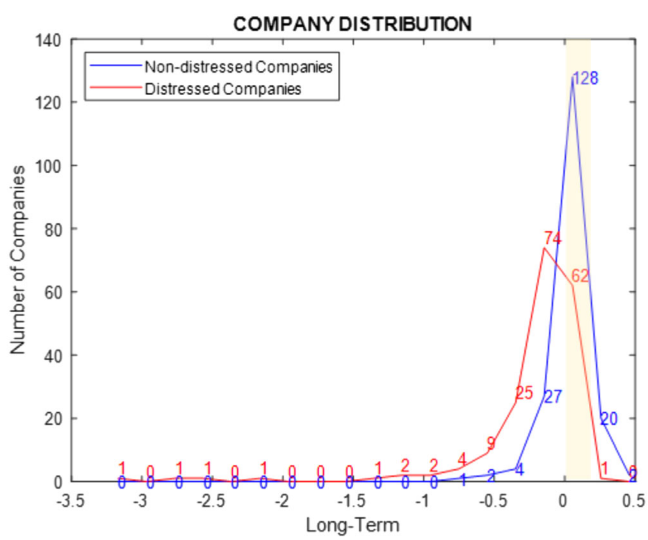


FIGURE 6 Distribution of distressed and non-distressed companies regarding the long-term (LT) value range.

distressed companies occurs (128). Within the same LT value range, there were relatively high numbers of distressed companies (62). Therefore, relying solely on the LT value makes it challenging to differentiate distinctly between distressed and non-distressed companies when the LT value is close to 0.05.

However, within the same LT value range highlighted by the yellow box in Figure 4, there are companies characterized under the first scheme (correct identification of distress companies by M_1). This demonstrates the distinctive capabilities of our model, which cannot be achieved using the LT ratio alone. To achieve a clear distinction, it is necessary to construct a reliable and robust distress prediction model by incorporating ST FRs. This integration can enhance distress prediction performance. The findings in Figure 6 validate the discussions in Sections 4.4.1 and 4.4.2.

5 | CONCLUSION AND FUTURE WORK

This study effectively addresses the challenge of predicting financial distress by introducing an innovative model that distinguishes between LT and ST accounting attributes within FRs. Our objective was to assess the significance of these attributes in predicting financial distress. By leveraging Altman's well-established FDP ratios, the proposed model splits the LT and ST Altman's ratios by employing a stacking ensemble classifier for prediction, in contrast to a baseline model that utilizes Altman's ratios and an SVM classifier.

The results demonstrate notable advancements in the predictive accuracy, reliability, and robustness of the proposed models over baseline models. Specifically, models splitting the LT and ST ratios outperformed those combining them, emphasizing the importance of considering these attributes separately. The proposed models exhibited reliability in handling imbalanced datasets and demonstrated robustness across various contexts from previous Taiwanese distress studies.

Furthermore, the model's ability to differentiate between correctly and incorrectly predicted distress in companies provides nuanced insights. It identifies companies facing deteriorating LT operations and simultaneous ST operational challenges. While surpassing the identification of distressed companies compared with relying solely on LT ratios, the model still faces challenges when both the LT and ST ratios are outstanding. This suggests that factors other than operational difficulties contribute to financial distress. Given the constraints of traditional FRs in recognizing various types of financial distress, this model establishes a foundation for future studies to extend and explore different distress categories. Researchers can distinguish financial distress from FRs and factors not observable in FRs, such as financial manipulations involving accounting figures in financial reports. By incorporating supplementary features, our proposed model can enhance the predictive performance of financial distress in future research.

AUTHOR CONTRIBUTIONS

Asyrofa Rahmi: Visualization; methodology; writing—original draft. **Chia-chi Lu**: Supervision; resources; conceptualization; validation. **Deron Liang**: Supervision; investigation; methodology; validation. **Ayu Nur Fadilah**: Investigation; software; methodology; validation.

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DATA AVAILABILITY STATEMENT

The datasets generated and/or analyzed during the current study are publicly available in the FDP repository, which can be accessed at https://github.com/FinanceISSL/FDP, reference number FOR-23-0248.

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ENDNOTES

[1] Typically, LT ratios provide a picture of a company's LT condition (Ball et al., 2020). Meanwhile, ST ratios offer their current operational status. A study by Huang and Xu (1999) investigated the financial crisis of financial institutions in East Asia. They showed that the cause of the financial crisis started from LT's accumulated problems in fundamental areas, such as the large amount of bad loans (Huang & Xu, 1999). This indicates that financial distress in companies is caused by the negative performance in the LT, as reflected in LT ratios.

[2] Taiwan data are commonly used to predict financial distress, not exclusively company bankruptcy (Chen et al., 2020; Huang & Yen, 2019), due to a limited number of companies. Consulting Liang et al. (2016), a key source for studies like Tsai et al. (2021), confirms their focus on distressed companies rather than solely on bankruptcy.

[3] Altman's ratios definitions: Z1: working capital/total assets, Z2: retained earnings/total assets, Z3: earnings before interest and tax/total assets, Z4: market value of equity/total liabilities, Z5: sales/total assets.

[4] In real-market data, there are more non-distressed companies than distressed companies. Zhou (2013) validated that the ratio of distressed to non-distressed companies for the US dataset is between 1:100 and 1:1000.

[5] Distress events refer to occurrences, including the company's immediate corrective actions, that take place when the company is experiencing financial distress.

[6] An event dataset in the TEJ contains the Taiwan Corporate Credit Risk Index (TCRI) category. Common distress events that are used to predict distress when using data from Taiwan (Chou et al., 2017; Ko et al., 2017) include RD01_Bounced check (listed as dishonored accounts), RD02_Bailout of financial crisis, RD03_Restructuring, RD04_Bankruptcy, RD05_Taking over, RD07_Net value is negative, RD08_Full-cash delivery stock with delisting, and RD09_Financial tight stoppage.
Each company has a record of distress events occurring at specific times. Companies may have multiple distress events, and we counted the number of events per year for each company. We created a dataset that lists companies along with the count of distress events for each year. These data were then used to identify distressed companies.

[7] Determining distressed companies is more critical than determining non-distressed companies because of the former's limited number.

[8] The prediction process of a model, such as the SVM model, generates probability results. Owing to 100 adjusted thresholds (range: 0–1), the probability generates 100 various classification results (errors: Type I and Type II errors) that become the points on a curve of the model. The more appropriate the threshold, the better the result achieved.

[9] We do not include a table of evaluation measures, like Table 3, for each imbalanced ratio result. It will be provided solely for review.

[10] In prior Taiwanese distress studies, Huang and Yen (2019) included a limited set of FRs after Altman's ratios, whereas Liang et al. (2018) covered the most extensive set of FRs. It is assumed that other studies, including Chou et al. (2017) fall within the set used by Liang et al. (2018). Furthermore, being widely utilized by researchers to date, the ratios from Liang et al. (2018) can be considered representative of the prevalent Taiwanese distress model. Table 1 illustrates six Taiwanese FDP studies that employ the same ratios as Liang et al.'s (2018) study.

[11] We used 94 out of the 95 ratios proposed by Liang et al.'s (2016) study. We eliminated the "no-credit interval" ratio due to an unexplainable ratio and uncommon term in the financial domain.

[12] Please refer to the Appendix A to view Figures 7 and 8, which include the complete LT value of all samples.

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APPENDIX A

Distribution of distressed companies characterized under the first and second schemes, which include the complete LT value of all samples.

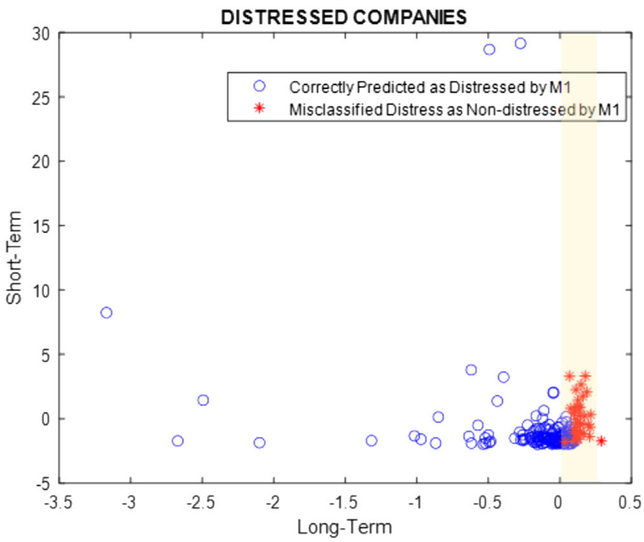

FIGURE A1 Distribution of distressed companies characterized under the first scheme (M_1) and its misclassified companies, based on the long-term (LT) over short-term (ST) accounting attributes (all sample).

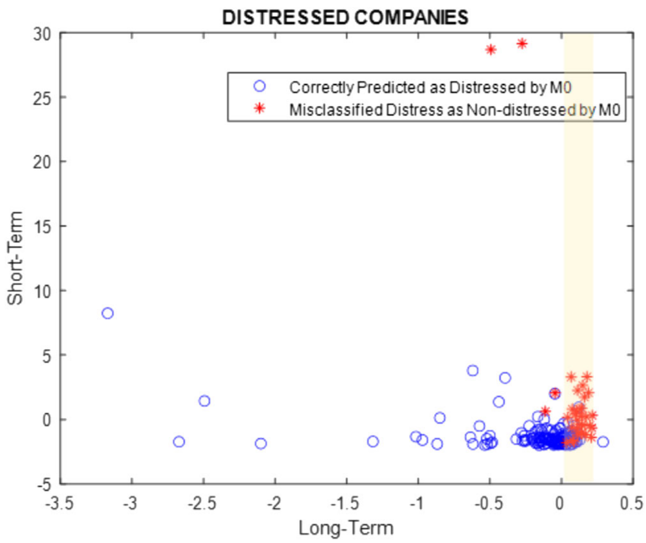

FIGURE A2 Distribution of distressed companies characterized under the second scheme (M_0) and its misclassified companies, based on the long-term (LT) over short-term (ST) accounting attributes (all sample).