ISSN 2783-8692

Predicting Financial Distress among Listed Hotels in Post-War Sri Lanka

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Abstract

This study examines the financial indicators associated with financial distress among listed hotel companies in Sri Lanka and develops a model for predicting distress in a post-war tourism context. The analysis uses 21 hotel companies over the period 2013–2022. Financial distress is measured as a binary variable that takes the value of one when a company reports negative operating earnings, negative operating cash flow, or both, and zero otherwise. Profitability, liquidity, activity, leverage, market-based and firm-specific indicators are examined using logistic regression with company-clustered standard errors. The revised model is statistically significant and demonstrates satisfactory predictive performance, with an overall classification accuracy of 83.50 per cent and an area under the receiver operating characteristic curve of 0.913. The findings show that return on assets has a significant negative association with the probability of financial distress, indicating that hotels generating stronger earnings from their asset base are less likely to experience financial difficulty. In contrast, working capital to total assets has a significant positive association with distress probability, suggesting that a higher level of net current assets does not necessarily indicate financial strength when those resources are inefficiently employed or concentrated in less liquid operating assets. The remaining profitability, liquidity, activity, leverage, market and firm-specific variables are not statistically significant. The findings highlight the importance of asset profitability and effective working capital management in assessing financial vulnerability within the hotel sector. The model assists managers, investors, lenders and policymakers in identifying financially vulnerable hotel companies and taking timely corrective action.

***JEL Classification**: G17, G32, G33*

Keywords: *likelihood of financial distress, listed hotels, Colombo Stock Exchanges, financial ratios, distress model*

1. Introduction

Predicting financial distress is fundamental to evaluating a company's financial condition and future prospects. In economics, corporate bankruptcy prediction is critically important. According to Altman (1969), bankruptcies signify market imperfections, and the frequency of bankruptcies indicates the resilience of an economy. Bernanke (1981) further argued that bankruptcies increase net social costs. Therefore, it is in the public interest to identify insolvency cases as early as possible to take preventive measures. This can help reduce the direct costs associated with insolvency, such as legal fees and diminishing assets, as well as the indirect costs, like declining productivity and loss of market share (Almeida & Philippon,

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2007; Chalupka & Kopecsni, 2009). These costs can potentially result in losses for investors and creditors.

Further, investors, suppliers, and retailers involved in the business require financial distress prediction. Before making an investment or credit-granting decision, lenders and investors must evaluate the financial bankruptcy risk of a company to mitigate potential losses. Credit transactions between a company and its suppliers or retailers necessitate a thorough comprehension of the company's financial position, which enables these stakeholders to make informed decisions regarding credit transactions. As such, accurate prediction of a company's financial distress is important for the diverse stakeholders invested in the company. Hence, the financial stability of a company holds significant importance for a diverse range of stakeholders, such as policymakers, investors, banks, internal management, and the general public (Ogachi et al., 2020).

Situm (2023) asserts that numerous companies face crises, which are often not accurately reflected in official statistics. The term insolvency signifies a critical stage of the crisis, and if left unresolved, it ultimately leads to bankruptcy (Haber, 2011), resulting in foreclosure and the company's departure from the market. Therefore, insolvency and bankruptcy reflect a point at which the crisis has already become highly advanced. From a business management standpoint, it is more desirable to detect crisis phases earlier on, when they are less severe (Situm, 2023).

According to Zhang et al. (2013), financial distress is a universal occurrence that can impact companies operating within any industry across the global economy. Since the tourism industry is considered a high-risk sector, early crisis and insolvency detection within this context is relevant (Situm, 2023). The hotel industry plays a pivotal role in the economy, contributing to employment and overall economic growth. In the past, tourism was the third-largest foreign exchange earner for Sri Lanka. Sri Lanka experienced a peak in tourism receipts with 2.5 million tourist arrivals in 2018. In contrast, the year 2021 witnessed a significant decline, with only approximately 194,500 tourists arriving, a drastic reduction of 92% compared to previous years (International Trade Administration, 2022).

Tourism in Sri Lanka has evolved significantly since the 1960s, when the government began promoting it as part of the economic development strategy. The establishment of the Ceylon Tourist Board in 1966 marked the formal beginning of structured tourism development. By the late 1970s, Sri Lanka was attracting a growing number of international visitors, driven by its rich cultural heritage, tropical climate, and diverse landscapes. However, the outbreak of the civil war in 1983 initiated a period of volatility.

Over the next 26 years, the industry faced setbacks due to the conflict and security threats. Tourist arrivals during this period remained volatile, and several hotel operations, particularly in Northern and Eastern provinces, were either suspended or scaled down due to instability. The end of the civil war in 2009 marked a turning point. With peace restored, Sri Lanka experienced a tourism boom. Tourist arrivals increased from 447,000 in 2009 to over 2.5 million in 2018, while tourism receipts reached a peak of USD 5.61 billion (SLTDA, 2022). The period saw rapid expansion in hotel infrastructure, increased foreign investment, and the integration of previously conflict-affected regions into the national tourism circuit.

However, the tourism industry in Sri Lanka has been severely impacted by a series of shocks since 2018. In April 2019, the Easter Sunday terror attacks in Sri Lanka had a significant impact on the industry. Subsequently, the onset of the COVID-19 pandemic in 2020 and 2021 led to unprecedented border closures and affected the global tourism industry (SLTDA, 2022).

Unlike many post-war countries, Sri Lanka integrated the Northern and Eastern provinces into its tourism strategy after 2009. These regions, once theatres of war, were rebranded with historical, religious, and ecological attractions. Community-based tourism initiatives empowered local populations, especially war-affected communities, offering them economic inclusion and opportunities to engage in national narratives of peace. Hence, this study addresses the Tourism Industry in Sri Lanka, considering its significant contribution to the economy and the ongoing crisis the sector faces.

The literature suggests that there are two research gaps. First, most studies have concentrated on a limited number of countries. Therefore, this study utilizes data from Sri Lanka's listed hotels to determine whether findings from other countries can be generalized to Sri Lanka. Second, most of the research has focused on bankruptcy failure and insolvency, which are considered to be the end stages of the business life cycle. However, financial distress is an upstream crisis phase that differs significantly from bankruptcy and insolvency. Therefore, the study aims to formulate a model and predict financial distress using logistic regression.

The study examines the association between financial distress and a range of financial indicators representing profitability, liquidity, activity, leverage, market performance and firm characteristics. The analysis covers 21 listed hotel companies over the period from 2013 to 2022. Financial distress is classified using negative operating earnings and negative operating cash flow. To avoid definitional overlap, operating profit margin and operating cash flow to total assets are not included as explanatory variables. The final model incorporates return on assets, return on equity, current ratio, current assets to total assets, working capital to total assets, inventory turnover, receivable turnover, payable turnover, debt to total assets, dividend payout ratio, price-to-earnings ratio, firm size and firm age.

The findings indicate that return on assets is negatively associated with financial distress, suggesting that hotels generating stronger earnings from their asset base are less likely to experience financial difficulty. In contrast, working capital to total assets shows a positive association with distress probability, indicating that a higher level of net current assets does not necessarily represent greater financial strength when those resources are not efficiently utilised. The model demonstrates strong predictive performance, with an overall classification accuracy of 83.50 per cent and an area under the receiver operating characteristic curve of 0.913.

The subsequent section of the research paper includes a literature review, covering both theoretical and empirical works. It is followed by a detailed description of the methodology, including model specification and data collection procedures. The results are presented and discussed in the subsequent section, which concludes with remarks on the study's limitations and suggestions for future research.

2. Literature Review

Financial distress is generally defined as a condition wherein a firm faces difficulty in fulfilling its financial obligations, often due to deteriorating profitability, cash flow constraints or excessive leverage. It is considered a transitional phase preceding insolvency or bankruptcy and is marked by reduced financial flexibility and heightened operational risk (Platt & Platt, 2012; Altman et al., 2017). Common symptoms include sustained operating losses, negative operating cash flows, declining liquidity ratios, high debt to equity levels, constrained access to capital markets and adverse movements in stock valuation (Bukalska & Maziarczyk, 2023; Metaxas & Romanopoulos, 2023; Pratiwi et al., 2024).

At the firm level, financial distress can erode investor confidence, reduce workforce and damage long-term stakeholder relationships (Dimitras et al., 1996). In the tourism and hospitality industry, highly sensitive to macroeconomic shocks and external crises, financial distress has far-reaching implications. It can destabilize regional employment, disturb supply chains, and depress national GDP contributions, particularly in economies heavily reliant on tourism (Shukla & Elias, 2023; Watson & Deller, 2022). Therefore, timely identification of distress in this sector is important for corporate recovery strategies, policy interventions and macroeconomic stability.

From a theoretical standpoint, multiple theories support this concept. Financial ratios are widely acknowledged as significant indicators for explaining bankruptcy, failure, and financial distress in companies. Although there are criticisms regarding their limitations, such as their retrospective nature and susceptibility to manipulation by managers (Anderson, 2007; Madrid-Guijarro et al., 2011; Situm, 2023; Viana et al., 2022), previous studies have demonstrated their efficacy in distinguishing underperforming and financially distressed companies from their counterparts (Hensher et al., 2007; Ogachi et al., 2020; Situm, 2023). Further, capital structure theory examines how financial distress can arise from excessive debt levels or poor financing decisions. The Modigliani-Miller theory, trade-off theory, and pecking order theory are commonly referenced in this context. In addition, corporate restructuring and turnaround literature focus on strategies and approaches for managing financial distress and revitalizing troubled companies. It covers debt restructuring, asset divestment, cost reduction, operational improvements, and organizational restructuring. These theories collectively provide a rationale for the widespread use of financial indicators in the empirical modelling of distress.

Over time, many models were developed to assess the likelihood of financial distress. One of the earliest models is the Altman Z-score model (Altman, 1968), which uses a linear discriminant analysis to classify firms into healthy and distressed categories. The model incorporates five key financial ratios, namely working capital to total assets, retained earnings to total assets, EBIT to total assets, market value of equity to book value of liabilities and sales to total assets, to generate a score that indicates the firm’s likelihood of bankruptcy. Although widely used, the model’s applicability is limited by its original calibration to U.S. manufacturing firms.

Logistic regression, which is considered an extension of linear discriminant analysis, was initially introduced by Day and Kerridge (1967) and Lancaster and Cox (1971). To address the limitations of discriminant analysis, Ohlson (1980) proposed this logistic regression model, known as the O-score, which introduced probabilistic classification of firms using nine financial and firm specific variables. Logistic regression allows for more flexible assumptions and has been widely adopted across industries. Similarly, Zmijewski (1984) developed a probit model incorporating profitability (ROA), financial leverage and liquidity as predictors of distress. Both models showed improved predictive capabilities over traditional linear classifiers and are particularly useful in emerging markets where financial statement data are accessible, but market data may be sparse.

Shumway (2001) extended the statistical modelling approach by integrating market-based indicators into a dynamic logit framework. This model addressed time dependence in bankruptcy risk and demonstrated that combining accounting ratios with firm-specific market information, such as stock return volatility and market capitalization, could significantly enhance predictive accuracy. This advancement bridged the gap between traditional accounting-based models and forward-looking frameworks.

Recognizing the practical limitations of traditional financial distress models, such as their complexity, data intensity and firm type specificity, Hadlock and Pierce (2010) developed a model to measure financial vulnerabilities. Their model, known as the HP score, is based on the premise that younger and smaller firms are systematically more financially constrained, a concept that is grounded in asymmetric information and agency theories.

The model relies on just two explanatory variables, namely firm size and firm age, excluding volatile earnings-based or market-based variables that are often unreliable or unavailable in less developed markets. Despite its simplicity, the HP score has shown predictive power comparable to more complex alternatives, particularly in out-of-sample tests. While initially framed to measure financial constraints rather than bankruptcy prediction, the HP model has since been adopted in studies assessing firm fragility, creditworthiness, and distress likelihood.

Beyond the classical models discussed, several alternative frameworks have been developed to address sectoral and regional differences. The Springate model, based on the discriminant analysis (Springate, 1978) and the Grover model, a refinement of Altman's Z score, were both designed to improve bankruptcy prediction in small and medium-sized enterprises (Grover, 2001). Similarly, the Fulmer model incorporated nine financial ratios and was tailored for privately held industrial firms, offering strong predictive capacity in environments where market data are scarce or unreliable (Fulmer et al., 1984). Further, early warning systems have been developed by financial regulators to monitor sector-wide distress, especially in vulnerable industries such as tourism during economic downturns. These frameworks often integrate firm-level financial ratios, macroeconomic indicators and qualitative assessments, offering a more comprehensive approach to systematic risk detection (Sun et al., 2016).

In recent years, the rise in machine learning models has added a new dimension to financial distress prediction. Techniques such as decision trees, support vector machines, random forests, and neural networks showed strong predictive performance when applied to large datasets (Elhoseny et al., 2025; Rahman & Zhu, 2024).

While each model offers unique strengths, no single approach universally outperforms others across all sectors and geographies. Model choice must be guided by data availability, sector characteristics, firm size and the economic environment.

Over the years, financial ratios have been employed as indicators for predicting bankruptcy or financial distress. Various models, including Multi-Variant Discriminant Analysis (Altman, 1968; Barreda et al., 2017), Logit Analysis (Barreda et al., 2017; Becerra-Vicario et al., 2020; Belda & Cabrer-Borrás, 2021; Zainol Abidin et al., 2021), Probit Analysis (Vivel-Búa & Lado-Sestayo, 2023), and Neural Network Analysis (Becerra-Vicario et al., 2020; Kim, 2011), have been devised to assess and predict the financial distress status of companies.

In general, the probability of insolvency in tourism businesses tends to increase with higher levels of debt (Axioglou & Christodoulakis, 2021; Zainol et al., 2021). Additionally, profitability measured through various metrics such as OPM, NPM, ROA, and ROE, is found to be a relevant explanatory variable. Situm (2023) suggests that higher profitability indicates managerial efficiency and is associated with a lower likelihood of insolvency. Moreover, liquidity ratios, encompassing metrics like Working Capital and Current ratio, are considered significant explanatory variables in the early detection of crises and insolvencies, as demonstrated in studies (Amoa-Gyarteng, 2021; Habib & Kayani, 2022).

In the study conducted in Sri Lanka, Samarakoon and Hasan (2003) examined the original Altman's Z-score models and concluded that the third version, known as the Z-score model, exhibited the highest overall success rate. This finding suggests that Z-score models hold significant potential for accurate predictions. Notably, the most prominent model developed in the United Kingdom, which utilizes different variables compared to Altman's Model, was also analyzed. In conclusion, it can be inferred that the Z-score model, when utilized with Multiple Discriminant Analysis (MDA), remains a valid approach for predicting financial distress within the context of Sri Lanka, despite existing criticisms concerning MDA (Nanayakkara & Azeez, 2015). This study is further supported by other researchers who indicated that the Altman model exhibits higher accuracy and significance in identifying financial distress in Sri Lanka. (Gunathilaka, 2014; Senevirathne & Kuruppu, 2018).

Vivel-Búa and Lado-Sestayo (2023) conducted a study on the impact of contagion on business failure within the Spanish hotel sector. The study focuses on a sample of 3,948 hotel micro-, small- and medium-sized enterprises operating between 2012 and 2015. Various variables of hotel characteristics and tourist destinations such as Income to Total asset, Asset efficiency, Distance in kilometers to the nearest airport, Concentration, Seasonality, Hotel rooms to number of hotels and occupancy rates were considered, and analysis was carried out using Probit regression. The findings indicate a significant contagion effect, which enhances the model's explanatory power. Additionally, the results demonstrate that the analysis of the contagion effect should encompass its immediate influence and its deferred impact over time on the likelihood of failure. Consequently, the study reveals that following the initial shock, the contagion effect diminishes and undergoes a change in direction from negative to positive in the fourth year.

In a study conducted by Zainol Abidin et al. (2021), the researchers examined a sample of 634 bankrupted firms and 634 financially healthier firms in Malaysia spanning the period from 2000 to 2016. They utilized a logistic regression model to analyze various variables, including Age, Gender, Board size, Subsidiary, and return on assets (ROA). The study's findings indicated that both ROA and age significantly contributed to predicting bankruptcy conditions among small and medium-sized enterprises (SMEs).

Another study, which also focuses on Spain, used Logit regression and Cox proportional hazard model to analyze 6,809 active and 1,179 inactive hospitality enterprises from 2009 to 2015. Size, Age, Workers, Financial Leverage, Positive profitability, and Positive cash flow are taken as the variables of the study and concluded that the survival of hospitality enterprises is positively influenced by factors such as size, age, productivity, financial leverage and liquidity. These elements contribute to the longevity and success of the businesses. Additionally, effective management practices play a crucial role in ensuring good performance and supporting the survival of hospitality enterprises (Belda & Cabrer-Borrás, 2021).

The primary objective of Agrawal and Maheshwari (2019) was to examine the potential influence of a sensitivity metric called industry beta on firms' probability of default. The logistic regression and multiple discriminant analysis were applied to a dataset comprising publicly listed companies in India. The study results indicated that the sensitivity metric related to industry factors, specifically industry beta, demonstrated a statistically noteworthy correlation with the prediction of defaults. Notably, a heightened sensitivity to industry factors is associated with an amplified likelihood of default occurrence.

Situm (2023) analyzed the conditions of financial distress by utilizing financial and non-financial indicators of the tourism industry of Austria. In this study, 776 observations were used from 2005 to 2015. The study employed resource-based and network-based views as theoretical frameworks to identify the variables that impact the likelihood of financial distress. The findings indicated that variables related to the endogenous unsystematic risk at both the firm-specific and destination levels significantly explained financial distress among tourism businesses. Conversely, variables related to exogenous unsystematic and exogenous systematic risk demonstrated minimal or no relevance in this context.

Based on the reviewed theoretical and empirical evidence, financial ratios remain widely used in identifying and predicting financial distress. Logistic regression is particularly appropriate when financial distress is represented as a binary outcome because it estimates the probability that a company belongs to either the distressed or non-distressed category. It also does not require the strict distributional assumptions associated with multiple discriminant analysis and can provide reliable estimates when explanatory variables are not normally distributed (Situm, 2023). Accordingly, the present study applies logistic regression to examine whether profitability, liquidity, activity, leverage, market-based, and firm-specific indicators distinguish financially distressed hotel companies from financially healthy companies in Sri Lanka.

3. Data and Methodology

The secondary data utilized in the study were obtained from the annual reports of 21 companies spanning ten years, from 2013 to 2022. In Sri Lanka, the hotel industry is categorized under the consumer discretionary sector in the consumer services (CS) industry in the Colombo Stock Exchange as per the GICS code of 2520. As of May 2023, the hotel and tourism industry comprises approximately 36 listed companies. A purposive sampling method was employed to ensure the inclusion of both financially distressed and financially healthy companies in the analysis.

This study employs logistic (logit) regression to forecast the financial distress model since the dependent variable is categorical. This simplifies the calculation of bankruptcy probabilities, eliminating the need for independent variable distribution, and directly yields the probability of bankruptcy.

The definitions and measurements of the dependent and explanatory variables are presented in Table 1. The dependent variable is the financial distress position of a company during a reporting period. The hotel companies included in the study were classified into two groups using a dummy variable coded as zero for non-financially distressed observations and one for financially distressed observations. Consistent with Poston et al (1994), financial distress was considered to have occurred when one or both of two conditions were observed during a reporting year. The first condition was negative operating cash flow during the reporting period (Ragab and Saleh, 2022; Situm, 2023), while the second condition was negative operating earnings during the same accounting period (Gilbert et al., 1990; Ragab and Saleh, 2022; Situm, 2023).

The study incorporates seven categories of explanatory variables, namely profitability, liquidity, activity, leverage, market-related variables, firm size, and firm age. Return on assets and return on equity represent the profitability position of the companies, while the current ratio represents liquidity. Current assets to total assets, working capital to total assets, inventory turnover, receivable turnover, and payable turnover represent activity-related characteristics. Debt to total assets is used to capture leverage. Dividend payout and the price-to-earnings ratio represent market-related characteristics. Firm size and firm age are included as control variables.

Table 1: Variable definitions and measurements.

Variables	**Indicators**	**Measurement**	**References**
Financial Distress	Dichotomous Groups (Z)	1 if negative operating earnings, negative operating cash flow, or both are reported; 0 otherwise	Poston et al. (1994); Gilbert et al. (1990); Ragab and Saleh (2022); Situm (2023)
Profitability ratios	Return On Equity (ROE)	Net Profit/ Average Equity	Zhai et al. (2015)
	Return On Asset (ROA)	Net Profit/ Average Total Assets	Acosta-González et al. (2019)
Liquidity ratios	Current Ratio (CR)	Current Assets/ Current Liabilities	Zhai et al. (2015)
Activity ratios	Current Asset Utilization (CA_TA)	Current Asset/ Total Assets	Zhai et al. (2015) Barreda et al. (2017)
	Working Capital Utilization (WC_TA)	(Current Asset- Current Liabilities)/ Total Asset	Kim (2011)
	Inventory Turnover Ratio (ITO)	Cost of Sales/ Average Inventory	Kim (2011)
	Receivable Turnover Ratio (RTO)	Revenue/ Average Receivables	Kim (2011)
	Payable Turnover Ratio (PTO)	Cost of Sales/Average Payables	Kim (2011)
	Debt to Total Assets Ratio (D_TA)	Debt/Total Asset	Belda & Cabrer-Borrás (2021)
Market Ratios	Dividend Pay-out Ratio (DPO)	Dividend Per Share/ Earnings Per Share	Park & Hancer (2012)
	Price to Earnings Ratio (PE)	Market Price Per Share/ Earnings Per Share	Park & Hancer (2012)
Size	Firm size (SIZE)	Ln(Total Assets)	Kim (2011)
Age	Firm age (LNAGE)	Financial Year - Establishment Year	Kim (2011)

Note: OPM and OCF_TA are used to construct financial distress and are excluded from the explanatory variables. NPM, QR, and D_E are also excluded from the final model.

Operating profit margin and operating cash flow to total assets are excluded from the explanatory variables because operating earnings and operating cash flow are already used to classify the dependent variable. Including these variables in the model would create a mechanical overlap between the dependent and explanatory variables. Net profit margin, quick ratio, and debt to equity are also excluded from the final specification following the preliminary multicollinearity assessment. The following model guided the study.

$$z = \beta_0 + \beta_1 ROA + \beta_2 ROE + \beta_3 CR + \beta_4 CA\_TA + \beta_5 WC\_TA + \beta_6 ITO + \beta_7 RTO + \beta_8 PTO + \beta_9 D\_TA + \beta_{10} DPO + \beta_{11} PE + \beta_{12} SIZE + \beta_{13} LNAGE + \varepsilon_{i,t}$$

The financial distress position of a company is determined using the predicted probability generated by the logistic regression model. A firm-year observation is classified as financially distressed when the predicted probability is equal to or greater than 0.50. A predicted probability below 0.50 indicates that the company is financially healthy.

4. Empirical Findings

Table 2 presents the frequency distribution of the financial distress variable which was conducted to confirm that the dependent variable consists only of financially distressed situations (equal to 1) and non-financially distressed situations (equal to 0) . Of the 201 firm-year observations, 129 observations, representing 64.18 per cent of the sample, were classified as non-financially distressed. The remaining 72 observations, representing 35.82 per cent, were classified as financially distressed. These results confirm that the dependent variable contains only the two intended categories, coded as zero for non-distressed observations and one for distressed observations. The distribution also shows that both categories are adequately represented, although non-distressed observations account for a larger proportion of the sample.

Table 2: Frequency Test

Variables	Frequency	Percent	Cum.
Non-distress (0)	129	64.18	64.18
Distress (1)	72	35.82	100
Total	201	100	

Table 3 presents the descriptive statistics for the variables used to classify financial distress and the explanatory variables included in the revised model. Panel A reports the operating profit margin and operating cash flow to total assets, which are used only to classify financial distress. Panel B reports the descriptive statistics for the explanatory variables in the same order as they appear in the regression model.

The descriptive results show clear differences between financially distressed and non-distressed hotel observations. Non-distressed firms report positive average return on assets and return on equity, whereas distressed firms report negative average profitability. Distressed firms also record lower average current ratios, current assets to total assets, working capital to total assets, and turnover ratios. In contrast, the average debt-to-total-assets ratio is higher among distressed firms, indicating greater reliance on debt financing. Dividend payout and price-to-earnings ratios are also negative, on average, among distressed observations. The average firm age is lower among distressed firms. However, the average firm size is higher among distressed observations, indicating that financial distress was not confined to smaller hotel companies during the study period. Overall, the descriptive evidence indicates that weaker profitability, liquidity, activity performance, and higher leverage are associated with financial distress, consistent with previous research on crisis detection and insolvency prediction in the tourism industry (Ogachi et al., 2020; Ragab & Saleh, 2022; Situm, 2023).

Table 3: Descriptive Statistics

Variables	Symbol	Healthy companies (n=129)		Distress Companies (n=72)	
		Mean	Std. Error	Mean	Std. Error
Panel A. Variables used to classify financial distress					
Operating profit margin	OPM	0.0918	0.2939	-0.5128	0.0667
Operating cash flow to total assets	OCF_TA	0.0797	0.0058	-0.0184	0.0074
Current asset utilization	CA_TA	0.1736	0.0089	0.1354	0.0150
Panel B. Explanatory variables included in the revised model					
Return on assets	ROA	0.0387	0.0052	-0.0440	0.0069
Return on equity	ROE	0.0456	0.0073	-0.2832	0.1775
Current ratio	CR	3.1334	0.4584	2.5141	0.7093
Current assets to total assets	CA_TA	0.1736	0.0089	0.1354	0.0150
Working capital to total assets	WC_TA	0.0428	0.0185	-0.0222	0.0223
Inventory turnover ratio	ITO	34.5641	1.4067	28.2798	1.5992
Receivable turnover ratio	RTO	8.5441	0.4042	7.6653	0.8719
Payable turnover ratio	PTO	6.6752	0.4960	3.4591	0.3357
Debt to total assets	D_TA	0.1580	0.0142	0.2620	0.0226
Dividend payout ratio	DPO	0.2584	0.0442	-0.1326	0.1302
Price-to-earnings ratio	PE	9.8113	2.9439	-0.6699	8.8188
Firm size	SIZE	17.1239	0.2809	18.2276	0.4160
Firm age	LNAGE	3.5591	0.0622	3.3052	0.1029

Table 4 presents the correlations among the explanatory variables. The correlations are generally moderate, and none exceeds the threshold of 0.80 suggested by Burns (2008). The highest correlations are observed between return on assets and working capital to total assets, return on assets and debt to total assets, and working capital to total assets and debt to total assets. These coefficients remain below the specified threshold, suggesting that severe multicollinearity is not present among the variables retained in the revised model.

Table 5 presents the results of the revised logistic regression model. The analysis is based on 200 firm-year observations because the price-to-earnings ratio for one observation was unavailable before the company was listed. Company-clustered standard errors were used to account for repeated observations of the same hotel companies over time. The overall model is statistically significant, with a likelihood-ratio chi-square value of 120.326 (p < .001). This indicates that the explanatory variables jointly improve the prediction of financial distress compared with an intercept-only model. The McFadden pseudo (R^2) is 0.460, indicating a substantial improvement in model fit. The area under the receiver operating characteristic curve is 0.913, demonstrating strong ability to distinguish between financially distressed and non-distressed observations.

Table 4: Correlations

No.	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1	ROA	1.000												
2	ROE	0.416***	1.000											
3	CR	0.314***	0.071	1.000										
4	CA_TA	0.385***	0.107	0.505***	1.000									
5	WC_TA	0.570***	0.146**	0.500***	0.469***	1.000								
6	ITO	0.224***	0.055	-0.187***	0.009	-0.105	1.000							
7	RTO	0.062	0.003	0.066	-0.028	0.101	-0.058	1.000						
8	PTO	0.327***	0.077	-0.044	0.116	0.189***	0.109	0.258***	1.000					
9	D_TA	-0.570***	-0.303***	-0.401***	-0.394***	-0.541***	0.008	0.029	-0.004	1.000				
10	DPO	0.151**	0.028	0.043	0.144**	0.101	0.045	0.055	0.074	-0.068	1.000			
11	PE	0.122*	0.027	0.058	0.091	0.103	0.024	0.126*	0.068	-0.098	0.375***	1.000		
12	SIZE	-0.092	0.028	0.255***	-0.012	-0.059	-0.276***	-0.099	-0.079	-0.156**	-0.111	0.090	1.000	
13	LNAGE	0.102	-0.007	-0.021	0.075	0.104	-0.184***	0.176**	0.186***	-0.267***	0.057	0.198***	0.153**	1.000

Variable order: 1 = ROA; 2 = ROE; 3 = CR; 4 = CA_TA; 5 = WC_TA; 6 = ITO; 7 = RTO; 8 = PTO; 9 = D_TA; 10 = DPO; 11 = PE; 12 = SIZE; 13 = LNAGE

ISSN 2783-8692

Return on assets has a negative and statistically significant relationship with financial distress at the 1 per cent level. This indicates that companies generating higher net income relative to their asset base are less likely to experience financial distress. The finding is consistent with the view that stronger asset profitability reflects greater operating efficiency and financial resilience. It also supports previous studies that identify profitability as an important predictor of financial difficulty and business failure (Situm, 2023; Zainol Abidin et al., 2021).

Working capital to total assets has a positive and statistically significant relationship with financial distress at the 1 per cent level. This result indicates that a higher proportion of net working capital relative to total assets is associated with a greater probability of financial distress in the sample. Although positive working capital is generally expected to strengthen liquidity, the finding may reflect inefficient allocation of resources into receivables, inventories, or other current assets that did not generate sufficient earnings or operating cash flows during periods of weak tourism activity. Therefore, the composition and productivity of working capital may be more important than its absolute level in the hotel industry.

The coefficients of return on equity, current ratio, current assets to total assets, inventory turnover, receivable turnover, payable turnover, debt to total assets, dividend payout ratio, price-to-earnings ratio, firm size, and firm age are not statistically significant at conventional levels. Therefore, the revised results do not provide sufficient evidence that these variables independently explain the probability of financial distress after controlling for the other variables in the model.

Table 5: Logistic Regression Model

Variables	Coef.	Std. Err.	Z	p>z	[95% Confidence Interval]	
ROA	-39.886	11.871	-3.360	0.001	-63.154	-16.618
ROE	-0.745	2.921	-0.255	0.799	-6.471	4.981
CR	0.040	0.045	0.884	0.377	-0.049	0.129
CA_TA	-1.600	2.804	-0.571	0.568	-7.095	3.895
WC_TA	6.088	1.794	3.393	0.001	2.572	9.605
ITO	0.002	0.025	0.077	0.939	-0.048	0.052
RTO	-0.033	0.044	-0.743	0.458	-0.119	0.054
PTO	-0.109	0.098	-1.109	0.267	-0.301	0.083
D_TA	1.231	2.587	0.476	0.634	-3.839	6.301
DPO	-0.917	0.712	-1.288	0.198	-2.313	0.479
PE	0.003	0.003	1.180	0.238	-0.002	0.009
SIZE	0.122	0.093	1.314	0.189	-0.060	0.304
LNAGE	-0.293	0.489	-0.600	0.548	-1.251	0.665
Constant	-1.437	2.867	-0.501	0.616	-7.056	4.182
Log- likelihood	-70.521				*LR* $chi^2(13)$	120.326
Number of obs	200				Prob > chi^2	<0.001
Area under ROC curve	0.913				Pseudo R^2	0.460

4.1 Marginal Effect Analysis

Table 6 presents the average marginal effects of the explanatory variables. In logistic regression, the estimated coefficients indicate the direction of the relationship between each explanatory variable and the log odds of financial distress. However, these coefficients do not directly show how much the probability of financial distress changes when an explanatory variable changes. Marginal effects convert the estimated coefficients into changes in predicted probability, making the results easier to interpret in practical terms. This analysis is important because it provides additional information about the magnitude of each relationship rather than only indicating whether the relationship is positive or negative. The average marginal effect shows the average change in the probability of financial distress associated with a one-unit increase in an explanatory variable, while the remaining variables are held at their observed values. Therefore, marginal effect analysis complements the logistic regression results by showing the practical importance of each explanatory variable in probability terms.

Return on assets has a negative and statistically significant average marginal effect of (-4.5166). Because return on assets is expressed as a ratio, a one-unit change is not economically realistic. A 0.01 increase in return on assets is associated with an average reduction of approximately 0.0452, or 4.52 percentage points, in the predicted probability of financial distress.

Working capital to total assets has a positive and statistically significant average marginal effect of 0.6894. Accordingly, a 0.01 increase in working capital to total assets is associated with an average increase of approximately 0.0069, or 0.69 percentage points, in the predicted probability of financial distress. The remaining marginal effects are not statistically significant, consistent with the logistic regression results.

Table 6: Marginal Effect Analysis

Variable	dy/dx	Std. Err.	z	P>z	[95% Confidence Inerval]	
ROA	-4.5166	1.0266	-4.3994	0.0000	-6.5288	-2.5044
ROE	-0.0843	0.3330	-0.2533	0.8001	-0.7370	0.5683
CR	0.0045	0.0049	0.9174	0.3589	-0.0051	0.0142
CA_TA	-0.1812	0.3116	-0.5815	0.5609	-0.7920	0.4296
WC_TA	0.6894	0.1425	4.8382	0.0000	0.4101	0.9687
ITO	0.0002	0.0029	0.0769	0.9387	-0.0054	0.0059
RTO	-0.0037	0.0049	-0.7598	0.4474	-0.0133	0.0059
PTO	-0.0123	0.0112	-1.1023	0.2703	-0.0342	0.0096
D_TA	0.1394	0.2853	0.4886	0.6251	-0.4198	0.6986
DPO	-0.1039	0.0836	-1.2426	0.2140	-0.2677	0.0600
PE	0.0004	0.0003	1.2171	0.2236	-0.0002	0.0010
SIZE	0.0138	0.0104	1.3352	0.1818	-0.0065	0.0341
LNAGE	-0.0332	0.0549	-0.6047	0.5454	-0.1409	0.0744

4.2 Goodness of fit test

The Hosmer Lemeshow goodness-of-fit test was used to assess whether the predicted probabilities generated by the logistic regression model were consistent with the observed outcomes. The test compares the observed and expected frequencies of financial distress across groups of predicted risk.

The test produced a chi-square value of 2.609 and a p-value of 0.956. Because the p-value is greater than 0.05, the null hypothesis that the model fits the observed data cannot be rejected. Therefore, there is no evidence of a significant difference between the observed and model-predicted outcomes, indicating that the revised logistic regression model provides an acceptable fit to the data.

4.3 Type I and II error classification

Table 7 presents the classification performance of the revised model using a predicted probability threshold of 0.50. The model correctly classifies 53 of the 72 financially distressed observations, resulting in a sensitivity rate of 73.61 per cent. It also correctly classifies 114 of the 128 financially healthy observations, producing a specificity rate of 89.06 per cent. The overall classification accuracy is 83.50 per cent, indicating that the model correctly identifies a substantial proportion of both distressed and healthy hotel observations.

A Type I error occurs when a financially distressed observation is incorrectly classified as financially healthy. The model misclassifies 19 of the 72 distressed observations, resulting in a Type I error rate of 26.39 per cent. This error is particularly important because failing to identify a financially distressed company may expose lenders, investors, and other stakeholders to unexpected financial losses.

A Type II error occurs when a financially healthy observation is incorrectly classified as financially distressed. The model misclassifies 14 of the 128 healthy observations, producing a Type II error rate of 10.94 per cent. This error may result in the rejection of a financially viable company or the loss of a potentially profitable lending or investment opportunity.

The area under the receiver operating characteristic curve is 0.913, further confirming that the model has strong discriminatory ability in distinguishing financially distressed observations from financially healthy observations.

Table 7: Classification

	Distressed Firms	Healthy Firms	Total	Percentage Correct
Distressed firms	53	19	72	73.61%
Healthy firms	14	114	128	89.06%
Total	67	133	200	
Overall percentage				83.50%

Note: Threshold = 0.50. Sensitivity = 73.61%; specificity = 89.06%; Type I error = 26.39%; Type II error = 10.94%; AUC = 0.913.

5. Conclusions

This study examined whether financial statement variables can distinguish financially distressed hotel companies from financially healthy hotel companies in Sri Lanka. Logistic regression was employed to identify the financial indicators associated with the probability of financial distress.

The findings show that return on assets has a significant negative relationship with financial distress. This indicates that hotel companies generating higher earnings from their asset base are less likely to experience financial difficulty. In contrast, working capital to total assets has a significant positive relationship with financial distress. This suggests that a higher level of net working capital does not necessarily reflect financial strength when current assets are not efficiently managed or converted into earnings and operating cash flows.

The remaining variables, including return on equity, current ratio, current assets to total assets, inventory turnover, receivable turnover, payable turnover, debt to total assets, dividend payout ratio, price-to-earnings ratio, firm size and firm age, do not show statistically significant independent relationships with financial distress. Therefore, the findings highlight asset profitability and the efficient management of working capital as the most relevant indicators for distinguishing financially distressed hotel observations from financially healthy observations in the study.

The model demonstrates satisfactory predictive performance. It correctly classifies 83.50 per cent of the observations and records an area under the receiver operating characteristic curve of 0.913, indicating strong discriminatory ability. A predicted probability equal to or greater than 0.50 classifies a company as financially distressed, while a probability below 0.50 classifies it as financially healthy.

Estimating the probability of financial distress may support credit rating agencies and financial institutions when evaluating loan applications and credit risk. The model may also assist investors in identifying financially vulnerable hotel companies and avoiding unsuitable investments. Managers and regulatory institutions can use the findings as an early warning mechanism to identify declining asset profitability and inefficient working capital management. Timely identification may enable corrective action before financial difficulties develop into insolvency or business failure.

6. Limitations and Scope for Future Studies

This study is limited to hotel companies listed on the Colombo Stock Exchange, which may restrict the generalisability of the findings to companies operating in other industries. The hotel industry was selected because it was severely affected by several external shocks, including the Easter Sunday attacks in 2019, the COVID-19 pandemic and related airport closures, and the broader economic crisis in Sri Lanka. The study also applies only logistic regression. Future research may compare its predictive performance with multiple discriminant analysis, probit models, survival analysis, neural networks and other machine learning techniques. Further studies may extend the analysis to all companies listed on the Colombo Stock Exchange or examine other industries separately. Additional firm-specific and macroeconomic variables may also be incorporated, including corporate governance, gross domestic product growth, interest rates, unemployment, leadership characteristics, corporate reputation, ownership structure, hotel location and business diversification. Future research may also include non-financial indicators and forward-looking information to capture financial vulnerability more comprehensively. In addition, the positive relationship between working capital to total assets and financial distress may be examined further by considering the composition, liquidity and efficiency of current assets.

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