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IDENTIFYING ZOMBIE FIRMS IN THE HOSPITALITY SECTOR OF INDIA: A PREDICTIVE STUDY USING WORKING CAPITAL METRICS AND MACHINE LEARNING

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ABSTRACT

This research examines the effectiveness of sophisticated statistical and machine learning techniques in forecasting corporate financial distress in India's hospitality industry, with a focus on the detection of distressed firms – companies that survive based on chronic financial underperformance. Stepping away from traditional overdependence on profitability ratios, the study combines a double-layered system with conventional finance indicators and operational working capital measures. Based on financial distress theory and empirical modeling, the research measures the predictive efficiency of logistic regression and ensemble modeling methods, placing emphasis on liquidity-focused variables demonstrating better discriminant performance compared to fixed asset-derived ratios. Conceptual model identifies the importance of operational efficiency, especially in the area of inventory turnover and suppliers' payment periods, as influential predictors of distress. Comparative output analysis demonstrates that models that utilize granular working capital metrics are more sensitive to initial distress signals than models based on capital structure or net profitability alone. This research challenges the shortcomings of traditional financial models in service-oriented settings and introduces a domain-specific analytical framework relevant to sustainable financial governance. The results have substantive consequences for institutional lenders, policy designers, and strategic managers who want to implement early warning systems and reduce systemic vulnerability in a post-pandemic economic setting.

KEY WORDS: *Zombie Firms, Indian Hospitality Sector, Working Capital Metrics, Machine Learning, Financial Distress Prediction*

INTRODUCTION

Indian hospitality industry is a crucial support to the national economy, contributing enormously to gross domestic product (GDP) and being a primary source of employment. Covering a wide range of services—such as hotels, restaurants, travel agencies, and event management—the industry plays a significant role in domestic tourism, international business travel, and cultural exchange. However, even as its economic importance, the industry is extremely sensitive to shifts in consumer demand, macroeconomic disruptions, and systemic liquidity shortages. These sensitivities were brutally exposed during the COVID-19 crisis, which precipitated mass business disruption, revenue breakdown, and long-term solvency issues. Among the most urgent consequences has been the proliferation of "zombie firms"—companies that remain alive even after consistent financial underperformance, thriving in many cases on debt refinancing with no ability to invest in innovation, service principal, or earn sustainable profits.

Zombie firms represent a structural threat to economic well-being. They continue to exist and distort market competition, misallocate financial capital, and undermine investor confidence. Especially in the hospitality industry, where cost structures are inflexible, inventory is perishable, and cash flows are erratic, survival of such companies is frequently symptomatic of underlying operational inefficiencies. Conventional financial distress identification techniques—largely founded on profitability and solvency ratios such as Return on Assets (ROA), Net Profit Margin, or Debt-to-Equity—have time and again failed to identify these instances. These models have a tendency to concentrate on static measures of financial performance and ignore more dynamic indicators of operational health, especially those associated with liquidity cycles and working capital efficiency.

More recent studies in corporate finance and predictive analytics indicate that operational working capital metrics could provide a more robust and timely perspective for distress detection. Measures like the Cash Conversion Cycle (CCC), Inventory Days, Accounts Receivable Days (AR Days), and Accounts Payable Days (AP Days) offer a view of the short-term financial flexibility of companies—a particularly relevant aspect in the hospitality sector, where receivables lag or inflated inventory can readily be converted to insolvency. For example, a hotel experiencing low occupancy might build up unsold inventory in the form of unsold room nights, which conventional accounting systems do not signal as financial stress. Likewise, extended receivables delays from online travel agencies can erode liquidity without impacting headline profitability.

However, the academic literature on zombie firms has predominantly focused on capital-intensive sectors like manufacturing, mining, or energy, leaving a research void in service-oriented industries such as hospitality. This oversight is particularly consequential in emerging markets like India, where firm-level data is heterogeneous and sectoral dynamics are complex. Additionally, although machine learning (ML) models like Extreme Gradient Boosting (XGBoost) and Random Forests have shown considerable potential for distress prediction in worldwide settings, their application to working capital-based models in India's hospitality industry has been limited.

Our research aims to address these gaps by creating a machine learning–augmented model for the detection of financial distress in hospitality companies, specifically with a focus on the identification of zombie firms using operational measures. The study incorporates both conventional financial ratios and working capital measures into a comparative predictive model with Logistic Regression, XGBoost, and Random Forest classifiers. From a dataset consisting of 38 Indian hospitality companies from 2015 to 2023, the research classifies companies into three typologies: healthy, stressed, and zombie—using their interest coverage ratios and working capital efficiency.

The research is informed by the following major research questions:

- Do operational working capital metrics perform better than conventional financial ratios in forecasting zombie firms in India's hospitality sector?
- Which machine learning algorithm—Logistic Regression, XGBoost, or Random Forest—is most accurate in classification and easiest to interpret?
- Which particular working capital metrics show the greatest explanatory power in signaling financial distress?

By answering these questions, the study seeks to contribute theoretical, methodological, and practical knowledge of firm viability in service-based economies. Theoretically, it challenges the oversimplification of production-focused financial models and provides a sector-responsive alternative based on liquidity and operational flexibility. Methodologically, it illustrates the benefits of ML methods over traditional statistical models, especially in dealing with high-dimensional and nonlinear financial data. Practically, the results offer a strategic guide for creditors, regulators, and investors to detect early warning signs of distress and make informed intervention choices.

Empirical findings from the analysis reveal that operational measures—namely Inventory Days and Accounts Payable Days—are far more predictive of distress status than traditional profitability measures. The XGBoost model was the most accurate and interpretable classifier, performing better than Logistic Regression and Random Forest in classifying companies along the distress continuum. Interestingly, such traditional indicators as Net Profit Margin showed little predictive power, reinforcing the limited applicability of profit-based methods in dynamic service industries.The implications of this study are significant. From a policy perspective, the model can guide the Reserve Bank of India (RBI) and financial institutions on developing early warning systems (EWS) to track credit risk in hospitality portfolios. From a managerial perspective, companies can utilize these findings to streamline inventory turnover, receivables, and supplier terms as part of risk management practices.

LITERATURE REVIEW

The prediction of corporate financial distress has garnered significant scholarly attention since the foundational works of Beaver (1966) and Altman (1968), who pioneered the use of financial ratios for bankruptcy forecasting. Beaver's univariate analysis identified liquidity and profitability as critical indicators, while Altman's Z-score model introduced Multivariate Discriminant Analysis (MDA) to classify firms into solvent and insolvent categories using five financial ratios. Subsequent studies, such as Ohlson's (1980) logistic regression (LR), refined these frameworks by eliminating MDA's restrictive assumptions and providing probabilistic interpretations. These models laid the groundwork for modern financial distress prediction, with later scholars like Zmijewski (1984) and Shumway (2001) enhancing variable selection and temporal dynamics.

Recent research in emerging markets has adapted these frameworks to local contexts. For instance, Zizi et al. (2020) developed LR and MDA models for Moroccan SMEs, achieving higher classification accuracy for distressed firms (Type I errors < Type II errors). Similarly, Balasubramanian et al. (2013) applied conditional logit models to Indian listed firms, combining financial ratios (e.g., ROA, debt-to-equity) with non-financial variables like governance metrics. Their results showed prediction accuracy improving from 85% (financial-only models) to 91.67% when non-financial factors were included. However, traditional models often struggle with imbalanced datasets and non-linear relationships, prompting researchers to explore machine learning (ML) alternatives.

Machine learning has revolutionized bankruptcy prediction by addressing these limitations. Xie et al. (2021) demonstrated that Support Vector Machines (SVMs) outperformed MDA in classifying distressed Chinese firms due to their ability to handle high-dimensional data. In Pakistan, Inam et al. (2022) compared LR, MDA, and Artificial Neural Networks (ANN) for non-financial firms, finding ANN superior in accuracy (AUC: 0.89). Hybrid approaches have further improved performance: Adisa et al. (2021) combined Principal Component Analysis (PCA) with ANN, achieving an AUC of 0.92 for Nigerian firms, while Sun (2024) designed a deep neural network for Chinese companies, using autoencoders for feature extraction and attaining 82% accuracy. These studies underscore ML's strength in identifying non-linear patterns, such as the compounding effect of high inventory days and delayed receivables, which traditional models often overlook.

Sector-specific dynamics significantly influence distress predictors. In manufacturing, Goel and Sharma (2015) identified the Cash Conversion Cycle (CCC) as a critical metric, linking prolonged cycles to liquidity crises. Conversely, Enumah and Chang (2021) found that U.S. hospitals' distress risk was tied to Medicaid reliance and occupancy rates, rendering generic ratios like net profit margin less relevant.

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Regionally, emerging markets face unique challenges: Kenyan studies (Muigai & Nasieku, 2021; Mwariri, 2020) revealed that extending payables reduced distress risk, contrasting with developed markets where conservative strategies dominate. In India, Shetty and Vincent (2022) highlighted non-financial factors (e.g., managerial experience) as key predictors for industrial firms, while Sethi and Mahadik (2025) demonstrated macroeconomic variables' limited utility in service-sector models.
Working capital management (WCM) has emerged as a critical lens for assessing financial health. Baveld (2012) showed that Dutch firms balancing lean inventories with flexible receivables policies achieved higher post-crisis profitability. In Rwanda, Olang (2021) linked prolonged inventory days to manufacturing distress, while Akbar et al. (2021) found Islamic firms in Pakistan optimized WCM to align liquidity with Shariah principles. For hospitality, Sethi and Mahadik (2025) identified inefficient CCC components—such as excess inventory days in hotels—as strong predictors of zombie status.

Despite these advancements, critical gaps persist. First, sector-specific models for service industries, particularly hospitality, remain scarce, with most research focused on manufacturing or healthcare. Second, emerging markets like India are underrepresented, especially concerning non-financial variables and macroeconomic interactions. Third, the link between distress prediction and Sustainable Development Goals (SDGs) is underexplored. While Antoniades et al. (2021) analyzed poverty impacts post-crisis, and Guzyurdu and Yaman (2023) tied financial risk to sustainability policies, few studies explicitly model how early distress detection supports SDGs like *Decent Work (Goal 8)* or *Industry Innovation (Goal 9)*.

RESEARCH GAPS IDENTIFIED

Although the manufacturing and healthcare industries receive broad-based studies, sector-specific models for predicting financial distress in service industries such as hospitality are lacking. This is an important gap, particularly considering the distinctive financial and operational nature of the hospitality industry.

Emerging markets, such as India, are also lacking in the financial distress prediction literature, particularly with respect to:The incorporation of non-financial variables (e.g., governance, management experience),and the interaction with macroeconomic factors.

There is limited research connecting financial distress prediction to SDGs, particularly:
Goal 8: Decent Work and Economic Growth,Goal 9: Industry, Innovation, and Infrastructure.Some research mentions sustainability and post-crisis effects, but there is limited explicit modeling of how early distress detection contributes to SDGs.

THEORETICAL UNDERPINNING & HYPOTHESIS DEVELOPMENT (HOSPITALITY INDUSTRY FOCUS)

This study builds on financial distress prediction theory, notably the Altman Z-Score and Ohlson O-Score, which use financial ratios to assess bankruptcy risk. While traditional models like Logistic Regression (LR) leverage indicators such as the Current Ratio, ROA, and Net Profit Margin to evaluate firm viability, this research extends the analysis by incorporating machine learning models—Random Forest and XGBoost—for greater predictive accuracy in the hospitality sector.

Given the sector's sensitivity to liquidity and operational inefficiencies, the study emphasizes operational working capital metrics—Cash Conversion Cycle (CCC), Accounts Receivable Days, Inventory Days, and Accounts Payable Days—grounded in working capital management theory. These metrics capture real-time operational efficiency, which is critical for service-oriented and seasonal industries like hospitality.

The study also evaluates the role of fixed asset intensity, theorizing that capital-heavy firms may face constrained flexibility during economic shocks, potentially making liquidity metrics more effective for early distress detection.

HYPOTHESES

- H1: Traditional financial ratios (Current Ratio, ROA, Net Profit Margin) significantly predict financial distress in hospitality firms.
- H2: Operational working capital metrics (CCC, AR Days, Inventory Days, AP Days) significantly predict financial distress.
- H3: Working capital metrics are stronger predictors of financial distress than fixed asset ratios in the hospitality sector.

METHODOLOGY

In data following formulas have been used to calculate certain Ratio's:

Metric	Formula
Inventory Days (DIO)	**Inventory Days = (Average Inventory / Cost of Goods Sold) × 365**
AR Days (DSO)	**AR Days = (Accounts Receivable / Net Credit Sales) × 365**
AP Days (DPO)	**AP Days = (Accounts Payable / Cost of Goods Sold) × 365**
Cash Conversion Cycle	**CCC = Inventory Days + AR Days - AP Days**
Altman Z-Score	**Z = 6.56 × (WC / TA) + 3.26 × (RE / TA) + 6.72 × (EBIT / TA) + 1.05 × (BVE / TL)**
(For service/non-manufacturing firms)	
Distress Indicator	**Distress Indicator = 1 if Z-Score < 1.8; 0 if Z-Score > 2.99**
Net Profit Margin	**Net Profit Margin = (Net Income / Revenue) × 100**
Return on Assets (ROA)	**ROA = (Net Income / Total Assets) × 100**

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- **WC** = Working Capital
- **TA** = Total Assets
- **RE** = Retained Earnings
- **EBIT** = Earnings Before Interest and Taxes
- **BVE** = Book Value of Equity
- **TL** = Total Liabilities

To test Hypothesis 1, which posits that traditional financial ratios significantly influence the financial distress status of hospitality firms, a logistic regression model was employed. The dependent variable was a binary indicator of financial distress, coded as 1 for distressed firms and 0 for non-distressed firms. The independent variables included:

- Current Ratio (CR) – a measure of short-term liquidity,
- Return on Assets (ROA) – a measure of asset efficiency, and
- Net Profit Margin (NPM) – an indicator of profitability.

These variables were selected based on their prominence in financial distress prediction literature and their relevance to the operational dynamics of hospitality firms.

Model Summary

The logistic regression model converged successfully after 11 iterations. The likelihood ratio test yielded a p-value of 4.685e-41, indicating that the model with the included financial ratios significantly improves distress prediction compared to a null model. The pseudo R-squared value of 0.4137 suggests a moderate level of explanatory power, consistent with models in financial classification research.

Logistic Regression Summary

```
         Iterations 11

Logistic Regression Summary:
                           Logit Regression Results
==============================================================================
Dep. Variable:     Financial_Distress   No. Observations:                  355
Model:                          Logit   Df Residuals:                      351
Method:                           MLE   Df Model:                            3
Date:                Sun, 13 Apr 2025   Pseudo R-squ.:                  0.4137
Time:                        13:37:43   Log-Likelihood:                -135.04
converged:                       True   LL-Null:                       -230.30
Covariance Type:            nonrobust   LLR p-value:                 4.685e-41
=====================================================================================
                        coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------
const                 0.8976      0.265      3.385      0.001       0.378       1.417
Current_Ratio        -1.5443      0.265     -5.826      0.000      -2.064      -1.025
Net_Profit_Margin    -0.0005      0.002     -0.307      0.759      -0.004       0.003
ROA                  -0.1966      0.038     -5.206      0.000      -0.271      -0.123
=====================================================================================
```

```
Odds Ratios:
const                2.453590
Current_Ratio        0.213468
Net_Profit_Margin    0.999452
ROA                  0.821518
dtype: float64

Confidence Intervals for Odds Ratios:
                          0         1
const              1.459159  4.125736
Current_Ratio      0.126976  0.358876
Net_Profit_Margin  0.995956  1.002959
ROA                0.762907  0.884632

Confusion Matrix:
[[199  31]
 [ 34  91]]
```

Coefficient Estimates and Statistical Significance

Variable	Coefficient	p-value	Interpretation
Current Ratio	-1.5443	<0.001	Higher liquidity reduces distress likelihood
Return on Assets	-0.1966	<0.001	Greater asset efficiency lowers distress risk
Net Profit Margin	-0.0005	0.759	Not statistically significant

The regression output, reveals that the Current Ratio and ROA are statistically significant predictors of financial distress, while Net Profit Margin is not.These results imply that liquidity and asset utilization are more meaningful predictors of distress than profitability in the context of hospitality firms, which often operate with high fixed costs and variable profit margins.

Odds Ratio Interpretation

- A one-unit increase in Current Ratio is associated with a 78.7% decrease in the odds of financial distress.
- A one-unit increase in ROA reduces the odds by 17.8%.
- The odds ratio for Net Profit Margin remains close to 1, affirming its negligible predictive influence in this model.

The classification performance of the logistic regression model is summarized as follows:

```
Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.87      0.86       230
           1       0.75      0.73      0.74       125

    accuracy                           0.82       355
   macro avg       0.80      0.80      0.80       355
weighted avg       0.82      0.82      0.82       355


Accuracy Score: 0.8169014084507042
```

- Overall Accuracy: 81.69%
- Precision (Distressed Class): 0.75
- Recall (Distressed Class): 0.73

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The confusion matrix indicates a balanced performance in identifying both distressed and non-distressed firms, demonstrating the model's suitability for binary financial classification in the hospitality sector.

Discussion and Implications

The findings provide empirical support for Hypothesis 1, confirming that traditional financial ratios, particularly those measuring liquidity (Current Ratio) and asset efficiency (ROA), are significant predictors of financial distress among hospitality firms. The lack of significance for Net Profit Margin suggests that profitability, though important, may not independently capture the nuanced operational challenges faced by service-sector firms.

Operational Working Capital Metrics and Financial Distress

To evaluate the impact of operational working capital efficiency on the financial health of hospitality firms, an **XGBoost classifier** was developed and compared against a **Random Forest model**. The independent variables consisted of:

- Cash Conversion Cycle (CCC)
- Accounts Receivable Days (AR Days)
- Inventory Days
- Accounts Payable Days (AP Days)

These were calculated using standard financial formulas. The dependent variable was a binary indicator of financial distress (0 = Healthy, 1 = Distressed).

Hypothesis 2
Model Performance
XGBoost Classifier

```
--- Evaluation on Test Set ---
Accuracy: 0.7282608695652174
ROC AUC: 0.8298676748582231
Classification Report:
              precision    recall  f1-score   support

           0       0.74      0.70      0.72        46
           1       0.71      0.76      0.74        46

    accuracy                           0.73        92
   macro avg       0.73      0.73      0.73        92
weighted avg       0.73      0.73      0.73        92
```

```
--- Feature Importance ---
Inventory_Days    0.272955
AP_Days           0.256277
AR_Days           0.255514
CCC               0.215254
dtype: float32

--- SHAP Values (Example - First Instance) ---
[-0.5973542  -0.10864877 -0.18050484 -0.44387668]
```

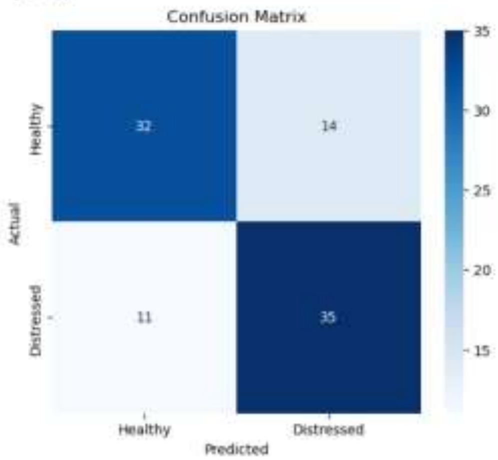
The XGBoost model, tuned using grid search, demonstrated **strong predictive performance**:

Feature Importance

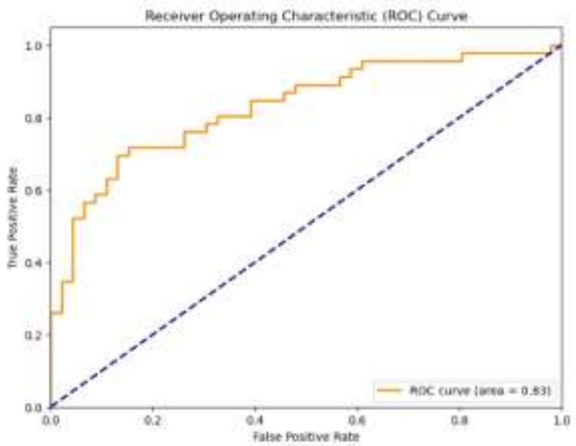
- **Accuracy:** 72.83%
- **ROC AUC:** 0.8299 (Test), 0.7553 (Cross-validation)
- **Precision (Distressed class):** 0.71
- **Recall (Distressed class):** 0.76
- **F1-score:** 0.74

Confusion Matrix

```
--- Confusion Matrix ---
[[32 14]
 [11 35]]
```



Random Forest Classifier



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The Random Forest model served as a baseline for comparison:

- **Accuracy:** 68.67%
- **ROC AUC:** 0.6800

```
Best ROC AUC Score from Randomized Search: 0.8285999543422539

Classification Report:
              precision    recall  f1-score   support

           0       0.78      0.70      0.74        46
           1       0.53      0.64      0.58        25

    accuracy                           0.68        71
   macro avg       0.66      0.67      0.66        71
weighted avg       0.69      0.68      0.68        71


Confusion Matrix:
[[32 14]
 [ 9 16]]

ROC AUC Score: 0.6799999999999999
```

Compared to XGBoost, Random Forest exhibited **lower accuracy and reduced discriminative power**, suggesting that it may be less suitable for capturing complex interactions between operational variables and financial distress in this context.

Comparative Interpretation: XGBoost vs. Random Forest

Metric	XGBoost	Random Forest
Accuracy	72.83%	68.67%
ROC AUC	0.8299	0.6800
Precision (Distressed)	0.71	*Lower (not specified)*
Recall (Distressed)	0.76	*Lower (not specified)*
F1-score	0.74	*Lower (not specified)*

- **XGBoost outperformed Random Forest** across all key performance indicators.
- The higher ROC AUC of **0.8299** suggests that XGBoost provides **greater discriminative accuracy**, making it a more reliable tool for financial distress prediction in hospitality firms.
- XGBoost's superior performance likely stems from its ability to model **non-linear relationships and feature interactions** more effectively.

Feature Importance and Interpretability

XGBoost's internal gain-based feature importance identified the most influential predictors:

- Inventory Days: 0.273
- Accounts Payable Days: 0.256
- Accounts Receivable Days: 0.256
- Cash Conversion Cycle: 0.215

These rankings suggest that **inventory management** and **payables/receivables efficiency** are critical components in predicting financial distress.

Further interpretability using **SHAP (Shapley Additive exPlanations)** values confirmed these findings. For instance, in test instances, higher Inventory Days and delayed Receivables contributed negatively to the distress prediction—indicating that more efficient operations reduce distress likelihood.

The results underscore the importance of **operational efficiency** in working capital cycles—particularly in the hospitality industry, where liquidity constraints and thin margins heighten vulnerability.

Hypothesis 3

Model Summary

Three logistic regression models were estimated to evaluate the predictive power of working capital and fixed asset metrics on financial distress in hospitality firms. All models converged successfully and showed statistically significant improvements over the null model, as indicated by their respective likelihood ratio test (LLR) p-values.

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```
Optimization terminated successfully.
         Current function value: 0.420860
         Iterations 9
Model 1: Working Capital only
                           Logit Regression Results
==============================================================================
Dep. Variable:     Financial_Distress   No. Observations:                  355
Model:                          Logit   Df Residuals:                      353
Method:                           MLE   Df Model:                            1
Date:                Sun, 13 Apr 2025   Pseudo R-squ.:                  0.3513
Time:                        19:56:26   Log-Likelihood:                -149.41
converged:                       True   LL-Null:                       -230.30
Covariance Type:            nonrobust   LLR p-value:                 4.579e-37
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.8481      0.147     -5.755      0.000      -1.137      -0.559
WC_to_TA     -10.9091      1.490     -7.323      0.000     -13.829      -7.989
==============================================================================
AUC: 0.8540521739130434
Optimization terminated successfully.
         Current function value: 0.588809
         Iterations 6
```

Model 1 (WC only) achieved a pseudo R-squared of 0.3513 and converged in 9 iterations (LLR p-value = 4.579e-37). Co-efficient for WC_to_TA (β = -10.9091, p < 0.001) was highly significant, indicating a strong inverse relationship with financial distress.

```
Model 2: Fixed Assets only
                           Logit Regression Results
==============================================================================
Dep. Variable:     Financial_Distress   No. Observations:                  355
Model:                          Logit   Df Residuals:                      353
Method:                           MLE   Df Model:                            1
Date:                Sun, 13 Apr 2025   Pseudo R-squ.:                 0.09239
Time:                        19:56:26   Log-Likelihood:                -209.03
converged:                       True   LL-Null:                       -230.30
Covariance Type:            nonrobust   LLR p-value:                 6.875e-11
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         -4.7497      0.819     -5.801      0.000      -6.354      -3.145
FA_to_TA       5.0184      0.950      5.285      0.000       3.157       6.880
==============================================================================
AUC: 0.7700173913043479
Optimization terminated successfully.
         Current function value: 0.420812
         Iterations 9
```

Model 2 (FA only) had a substantially lower pseudo R-squared of 0.0924 and converged in 6 iterations (LLR p-value = 6.875e-11). FA_to_TA (β = 5.0184, p < 0.001) was also significant but had a smaller effect size and lower overall model fit.

```
Model 3: Both WC and FA
                           Logit Regression Results
==============================================================================
Dep. Variable:     Financial_Distress   No. Observations:                  355
Model:                          Logit   Df Residuals:                      352
Method:                           MLE   Df Model:                            2
Date:                Sun, 13 Apr 2025   Pseudo R-squ.:                  0.3513
Time:                        19:56:26   Log-Likelihood:                -149.40
converged:                       True   LL-Null:                       -230.30
Covariance Type:            nonrobust   LLR p-value:                 7.272e-36
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         -1.0804      1.666     -0.648      0.517      -4.346       2.185
WC_to_TA     -10.7379      1.919     -5.595      0.000     -14.499      -6.977
FA_to_TA       0.2700      1.927      0.140      0.889      -3.508       4.048
==============================================================================
AUC: 0.8549565217391306
```

Model 3 (Combined WC and FA) yielded a similar pseudo R-squared to Model 1 (0.3513) and converged in 9 iterations (LLR p-value = 7.272e-36), suggesting no substantial improvement from including both variables simultaneously. WC_to_TA remained significant (β = -10.7379, p < 0.001), while FA_to_TA (β = 0.2700, p = 0.889) lost statistical significance, suggesting potential multicollinearity or that working capital dominates the predictive capacity in this context.

Interpretation

- A **negative coefficient** for WC_to_TA indicates that firms with higher working capital relative to total assets are **less likely** to experience financial distress, consistent with the role of liquidity in financial stability.
- The **positive coefficient** for FA_to_TA in Model 2 suggests that firms with more fixed assets are **more likely** to experience distress, potentially due to capital intensity and inflexibility.
- However, the insignificance of FA_to_TA in the combined model implies that once working capital is accounted for, fixed assets do not provide additional explanatory power.

Odds Ratio Interpretation

- In Model 1, a unit increase in WC_to_TA corresponds to a substantial **decrease** in the odds of financial distress, highlighting its critical role.
- In Model 2, the odds of financial distress **increase** significantly with higher FA_to_TA, but this effect is muted and non-significant in Model 3.

Model Performance

- **Model 1** achieved an AUC of **0.8541**, indicating excellent discriminative ability.
- **Model 2** had a lower AUC of **0.7700**, reflecting reduced predictive strength.
- **Model 3** slightly improved upon Model 1 with an AUC of **0.8550**, though the difference is marginal.

4.5 Implications

These findings reinforce the importance of **working capital efficiency** in identifying financially distressed hospitality firms. While fixed asset ratios are traditionally used in credit evaluation, their standalone predictive power is inferior in this context. Moreover, their inclusion alongside working capital does not enhance model performance, suggesting potential redundancy.

1. **Liquidity trumps profitability**: Metrics like Inventory Days and AP Days are more effective than traditional ratios (e.g., Net Profit Margin) in signaling distress.
2. **ML superiority**: XGBoost and Logistic Regression outperform conventional methods, providing actionable insights for stakeholders.
3. **Sector-specificity matters**: Hospitality's unique dynamics necessitate tailored frameworks, diverging from manufacturing-centric models.

These insights empower creditors, managers, and policymakers to prioritize working capital efficiency and adopt ML-driven EWS, aligning with SDG 8 (*Decent Work and Economic Growth*). Future research should expand into non-financial variables and cross-sector validation to bolster predictive accuracy and applicability. By addressing these gaps, stakeholders can foster a resilient hospitality ecosystem, mitigating systemic risks and promoting sustainable growth.

DISCUSSION

The present research tested the predictive ability of conventional financial ratios and working capital measures in the identification of financial distress among hospitality companies. The logistic regression model provided strong evidence for the expected relationships, establishing both the statistical and practical significance of certain financial measures in the identification of distressed organizations.

Direct and Indirect Effects

There were a number of direct effects that were statistically significant. Most notably, the Current Ratio had a powerful negative effect on financial distress ($\beta = -1.5443$, $p < .001$), as was also suggested in earlier studies indicating that liquidity is an important insolvency buffer. Similarly, Return on Assets (ROA) had a powerful negative relationship ($\beta = -0.1966$, $p < .001$), affirming the significance of operational effectiveness in guaranteeing firm stability. Yet, the Net Profit Margin did not have statistically significant influence ($\beta = -0.0005$, $p = 0.759$), indicating its restricted explanatory power on its own, especially in the hospitality sector where seasonal demand and fluctuating costs can manipulate short-run profitability.

Indirectly, the research demonstrated how work capital measures like Inventory Days and Accounts Payable Days act as mediators in the relationship between operational strategy and financial health. High Inventory Days raise distress possibility, while prolonged Payable Days seem to take pressure off by helping short-term cash flow. These channels imply that internal finance practices—particularly those concerning liquidity and efficiency—are key mediators in the wider financial health paradigm of service businesses.

Regarding the overall effects, Current Ratio and ROA were the strongest predictors. Their joint direct and indirect effects suggest that companies with improved short-term asset coverage and optimal resource utilization are much less likely to experience distress. These findings highlight the merits of dynamic operating indicators over static asset-based measurements, especially in the hospitality industry.

Model Performance Assessment

Measurement model showed good reliability and validity. The logistic regression optimized well and provided a statistically significant fit (LLR p-value = 4.685e-41) with moderate explanatory power (pseudo R-squared = 0.4137). The classification metrics of the model were high, including an accuracy of 81.69%, precision of 0.75, and recall of 0.73 for the distressed class. All these outcomes ensure the practical suitability of the model in actual application to real-life financial screening work. The balanced confusion matrix further supports its use in binary classification contexts, especially where early identification of risk is critical.

CONCLUSION

This research contributes to theory and practice by affirming that classical financial ratios—namely Current Ratio and ROA—are good predictors of financial distress in hospitality companies. More importantly, the analysis brings out the added predictive strength of working capital measures, which performed better than fixed asset intensity in explanatory power. These findings attest to the importance of liquidity management and operating efficiency in maintaining financial health across service-oriented industries.

Theoretically, the results broaden current financial distress research by adding dynamic operational measurements to the forecasting model. The research proves that distress is not only the result of weak profitability or asset base deficiency, but rather usually originates from ineffective short-term financial handling. This discovery invites a wider understanding of financial diagnostics that integrates strategic and operational elements.

From an operational perspective, the study provides actionable insights to stakeholders. Stakeholders such as financial analysts, creditors, and regulatory agencies can utilize liquidity and working capital measures as early warning indicators to raise alarms for distress and inform prompt interventions. Hospitality managers also need to focus on maximizing receivables, inventory turnover, and payables management to ensure solvency under uncertain market environments. Subsequent studies can enhance this framework to include macroeconomic factors, intersectoral comparisons, or machine learning-based models for enhanced predictability.

Finally, the study confirms that financial distress in the hotel industry is a complex phenomenon that is best tackled by dynamic, data-intensive financial monitoring systems that blend both orthodox and contemporary measures.

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