Interdisciplinary Journal of Information, Knowledge, and Management

An Official Publication of the Informing Science Institute InformingScience.org

IJIKM.org

Volume 18, 2023

MULTIPLE MODELS IN PREDICTING ACQUISITIONS IN THE INDIAN MANUFACTURING SECTOR: A PERFORMANCE COMPARISON

Venkateswaran Vinod	VIT Business School, Chennai, India	venkateswaran.vinod2017@vitstudent.ac.in
Sudarsanam, S. K.*	VIT Business School, Chennai, India	Sudarsanam.sk@vit.ac.in

* Corresponding author

ABSTRACT

Aim/Purpose	Acquisitions play a pivotal role in the growth strategy of a firm. Extensive resources and time are dedicated by a firm toward the identification of prospective acquisition candidates. The Indian manufacturing sector is currently experiencing significant growth, organically and inorganically, through acquisitions. The principal aim of this study is to explore models that can predict acquisitions and compare their performance in the Indian manufacturing sector.
Background	Mergers and Acquisitions (M&A) have been integral to a firm's growth strategy. Over the years, academic research has investigated multiple models for predicting acquisitions. In the context of the Indian manufacturing industry, the research is limited to prediction models. This research paper explores three models, namely Logistic Regression, Decision Tree, and Multilayer Perceptron, to predict acquisitions.
Methodology	The methodology includes defining the accounting variables to be used in the model which have been selected based on strong theoretical foundations. The Indian manufacturing industry was selected as the focus, specifically, data for firms listed in the Bombay Stock Exchange (BSE) between 2010 and 2022 from the Prowess database. There were multiple techniques, such as data transformation and data scrubbing, that were used to mitigate bias and enhance the data reliability. The dataset was split into 70% training and 30% test data. The performance of the three models was compared using standard metrics.

Accepting Editor Dimitar Grozdanov Christozov │ Received: July 25, 2023 │ Revised: September 26, October 10, October 22, 2023 │ Accepted: October 23, 2023.

Cite as: Vinod, V., & Sudarsanam, S. K. (2023). Multiple models in predicting acquisitions in the Indian manufacturing sector: A performance comparison. *Interdisciplinary Journal of Information, Knowledge, and Management, 18,* 791-818. https://doi.org/10.28945/5205

Contribution The research contributes to the existing body of knowledge in multiple dimensions. First, a prediction model customized to the Indian manufacturing sector has been developed. Second, there are accounting variables identified specific to the Indian manufacturing sector. Third, the paper contributes to prediction modeling in the Indian manufacturing sector where there is limited research.

Findings The study found significant supporting evidence for four of the proposed hypotheses indicating that accounting variables can be used to predict acquisitions. It has been ascertained that statistically significant variables influence acquisition likelihood: Quick Ratio, Equity Turnover, Pretax Margin, and Total Sales. These variables are intrinsically linked with the theories of liquidity, growth-resource mismatch, profitability, and firm size. Furthermore, comparing performance metrics reveals that the Decision Tree model exhibits the highest accuracy rate of 62.3%, specificity rate of 66.4%, and the lowest false positive ratio of 33.6%. In contrast, the Multilayer Perceptron model exhibits the highest precision rate of 61.4% and recall rate of 64.3%.

Recommendations for Practitioners The study findings can help practitioners build custom prediction models for their firms. The model can be developed as a live reference model, which is continually updated based on a firm's results. In addition, there is an opportunity for industry practitioners to establish a benchmark score that provides a reference for acquisitions.

Recommendations for Researchers Researchers can expand the scope of research by including additional classification modeling techniques. The data quality can be enhanced by cross-validation with other databases. Textual commentary about the target firms, including management and analyst quotes, provides additional insight that can enhance the predictive power of the models.

Impact on Society The research provides insights into leveraging emerging technologies to predict acquisitions. The theoretical basis and modeling attributes provide a foundation that can be further expanded to suit specific industries and firms.

Future Research There are opportunities to expand the scope of research in various dimensions by comparing acquisition prediction models across industries and cross-border and domestic acquisitions. Additionally, it is plausible to explore further research by incorporating non-financial data, such as management commentary, to augment the acquisition prediction model.

Keywords Indian manufacturing industry acquisitions, mergers and acquisitions modeling, predictive modeling, machine learning, artificial neural networks

INTRODUCTION

Growth is essential for an organization to survive in a highly competitive, globalized, volatile, uncertain, complex, and ambiguous environment. There are two options for firms to grow, either organically or inorganically, through Mergers and Acquisitions (M&A) (Meghouar, 2016). The Indian manufacturing industry will contribute 16-17% of India's Gross Domestic Product (GDP) in 2023 and is expected to export goods worth US $1 trillion by 2023 (Mehta & Rajan, 2017). There are 24 activities, as defined by the National Industrial Classification (NIC), that constitute the manufacturing sector in India. The industry has been one of the growth engines for the country in the five decades since independence; however, it seems to have slowed down after the economic reforms of 1991 (Kalirajan, 2004). There are recommendations for policy changes by increasing research and development (R&D) and technical training. In the Indian context, M&A can be categorized into pre-liberalization and post-liberalization phases (Goyal & Rathi, 2020). The manufacturing sector has been accounting for over 75% of the total transactions between 2000 and 2009 (Pandya, 2017). It is argued that another reason for acquisitions is the increase in Foreign Direct Investment (FDI), which shows that 46.65% of the overall inflow in the manufacturing sector is acquisition FDI inflows (Chalapati Rao & Dhar, 2011).

The motivations for acquisitions can be categorized into synergistic, non-synergistic, and strategic reasons (Kode et al., 2003). The theories include economies of scale, diversification into new products and markets, operational efficiencies, and revenue enhancement. Analyzing the historical patterns reveals that M&A happen in waves, each defined by attributes, triggers, and commercial models (Yaghoubi et al., 2016). Seven waves have been identified. While it is not a discrete cutover to the next wave, multiple events have triggered the beginning and end of a phase (Cho & Chung, 2022). There are three phases in a typical M&A cycle: pre-acquisition (which includes identifying potential candidates and performing due diligence); acquisition (initial offer is made and negotiations happen); and post-acquisition (when the integration of the acquired firm happens). The process can last from a few months to years, depending on the industry, firm size, and other parameters. However, the results vary based on the individual firms, industry, geography, and other factors.

Predicting acquisitions has been a research topic that has evolved over the past five decades. There are four broad phases of prediction evolution, each building on the previous phase, correcting methodological flaws, and introducing newer techniques (Tunyi, 2021). The fundamental premise is that models can identify suitable targets from a candidate pool based on determinants (Espahbodi & Espahbodi, 2001). Classifying firms as potential acquisition candidates based on accounting, financial, and market data is valuable to management, investors, policymakers, and shareholders (Tunyi, 2019). In this paper, the authors aim to build a predictive model to determine the acquisition likelihood of firms in the Indian manufacturing industry. In addition, there is a comparison of three models – Logistic Regression (LR), Decision Tree (DT), and Multilayer Perceptron (MLP) – on standard metrics. By building a predictive model, the authors will understand the factors that predict if a firm is fit for acquisition. The paper's contribution to the body of knowledge is the application of the three models to predict acquisition, identify the acquisition determinants, and contextualize it to the Indian manufacturing industry. This research paper's uniqueness is that it applies prediction modeling to the Indian manufacturing industry, which is under-researched.

The paper is organized as follows. The first section provides a literature review of the acquisition determinants and prediction modeling methods, which helps to identify research gaps. The next section explains the research methodology, detailing the research objectives, hypotheses, and process. The subsequent section comprehensively analyzes the performance of the three methods – LR, DT, and MLP – following which research findings and their implications are summarized and discussed. The paper provides a unique perspective in comparing traditional statistical models with advanced models like Artificial Neural Networks (ANN) models. Finally, the authors conclude by providing an overview of the results, research limitations, and recommendations for further research.

LITERATURE REVIEW

OVERVIEW

This section discusses a detailed literature review across multiple topics that guided the research, informed the research gaps, and supported the research objectives. The literature review was based on research articles from various sources, including, but not limited to, ProQuest Dissertations & Theses, Emerald Management Journals, ProQuest Central, EBSCO Host, LexisNexis, SAGE, SpringerLink, and Google Scholar. The key topics of the literature review were:

- *Mergers and Acquisitions:* To gain an understanding of the motivations for M&A, transaction attributes, patterns across time periods, a perspective of M&A in India, and comparison with global phenomena.
- *Prediction Modeling for Acquisitions:* Evolution of prediction modeling over the years, associated theories, and acquisition determinants. The literature review was done globally and in the Indian industry context to compare and contrast the two.
- *Machine Learning and Neural Networks:* Review of the various techniques used to understand their applications, process of developing models, and application in predicting acquisitions.

Mergers and Acquisitions (M&A) are integral to a firm's corporate, operational, and financial restructuring strategy. It is common in literature to use the terms *mergers* and *acquisitions* interchangeably, so it is vital to have a clear definition that sets them apart. A merger is a combination of two or more firms where one ceases to exist legally; the combined organization continues under the original name of the existing firm (DePamphilis, 2010). When a firm purchases a controlling interest in another or specific assets of another firm, it is referred to as an acquisition (Coates, 2014). An explanation of the different types of M&A is beyond the scope of this paper. There are several motivations for a firm to pursue acquisitions as a strategic choice. These include achieving economics of scale and scope, access to lower cost of capital, diversification of products and markets, operational efficiencies, and access to technology and resources (Ghauri & Buckley, 2003). M&A are like tides in business, influenced by the economy, regulations, and technology. They create a dynamic landscape for companies to navigate (Andrade et al., 2001). There have been seven waves of M&A identified, and the cyclical pattern was observed by Golbe and White (1988). The waves are abstract patterns to understand the history and evolution of mergers; they are not meant to be precise start and endpoints (Cho & Chung, 2022). In India, the latter part of the 1990s was when M&A activity gained momentum. The slow growth can be attributed to several factors, such as restrictive regulations and the trend that has increased since liberalization (Kumar & Rajib, 2007). The motivations behind M&A deals in India are like those globally. These include expanding into emerging markets like India, consolidating companies to improve financial stability, and streamlining shareholdings by merging investment subsidiaries among promoters within a group (Patel & Shah, 2016). The manufacturing sector has been attracting acquisition-related Foreign Direct Investment (FDI) inflow, as 50% of the total inflow in the industry (Irfan et al., 2016). The pace of expansion is expected to increase, given a significant push to improve the infrastructure, transform archaic laws, and remove other bottlenecks.

Simkowitz and Monroe (1971) conducted pioneering research in predicting M&A targets using financial characteristics. Tunyi (2021) analyzed M&A between 1986 to 2002 to understand the evolution of prediction modeling using financial attributes. The implications of prediction modeling are relevant to multiple stakeholders: management assessing the risk, investors interested in the market returns, policymakers for the regulatory impact, and researchers exploring newer prediction modeling techniques (Naik et al., 2010). It is common knowledge that a target firm's financial health is a good indicator of its acquisition likelihood. Most researchers have used the financial attributes of target companies as predictive variables on which the models are developed (Brar et al., 2009; Rodrigues & Stevenson, 2013). The variables and statistical techniques used in past research studies have been summarized (Meador et al., 1996). The variables were characterized by: (1) growth, (2) leverage, (3) liquidity, (4) size, (5) dividend policy, (6) profitability, and (7) stock market characteristics. Froese (2013) associated the theories for acquisition and the variables' direction of influence; most variables were firm and industry-specific (Dietrich & Sorensen, 1984; Froese, 2013). The selection of the statistical model and sampling methodology influences the accuracy of the acquisition likelihood (Barnes, 1998; Powell, 2004). An analysis of research papers published from the 1970s shows the distribution of various statistical models used to predict acquisitions. As shown in Figure 1, 65% of the papers have used Logit regression as either the primary model or one of the models to predict acquisition.

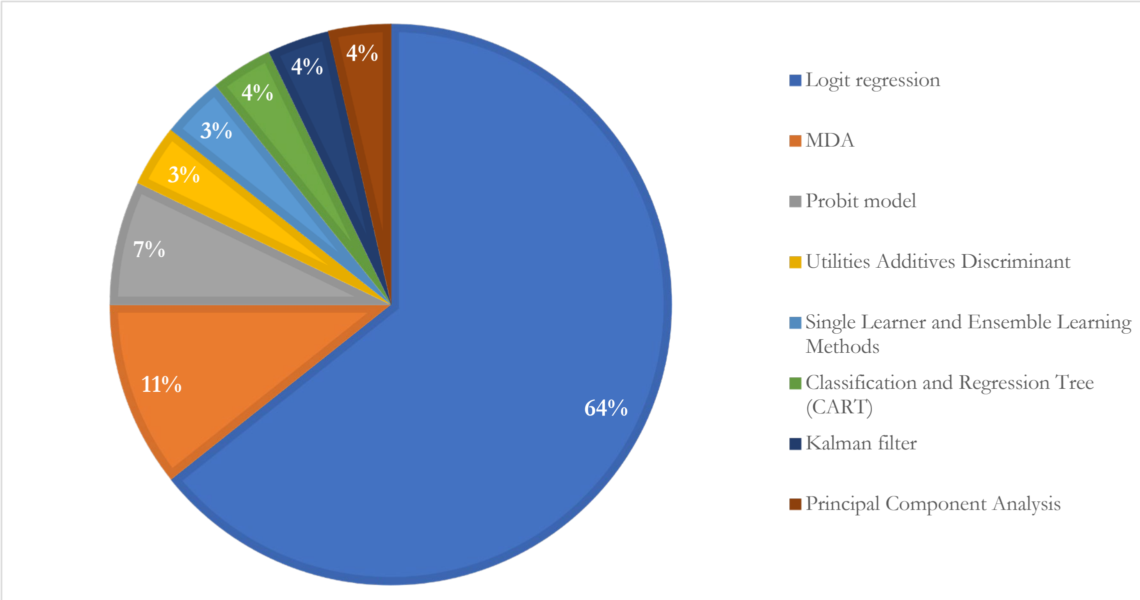


Figure 1. Statistical models used in past studies

There is limited research on predicting acquisitions in the Indian industry. M&A, as a corporate strategy, have been maturing over the last two decades; hence, the available research is based on empirical studies outside India. Thus, creating a model for predicting acquisitions in the Indian manufacturing sector is a gap in the existing research.

The availability of computing power combined with massive data volume has increased the application of Artificial Intelligence (AI) and Machine Learning (ML) across multiple domains such as process design, legal writing, insurance underwriting, process automation, and the finance industry (von Lilienfeld, 2020). Jiang (2021), in his research paper, has asked fundamental questions: “Can machine learning algorithms analyze more than thousands of companies and predict patterns?”, “Can machine learning automate spotting potential candidates for M&As replacing human analysis?”. The classification method under supervised learning was considered one of the best-fit models for predicting acquisitions (Handhika et al., 2019). DTs are considered one of the most straightforward supervised classification algorithms; they are quite easy to interpret and require minimal data preparation (Weinberg & Last, 2019). ANNs have promising applications across multiple fields – engineering, science, healthcare, and business. Their inspiration is from the human brain, which processes large amounts of data to make decisions (McMenamin, 1997). Multiple factors are considered to select an algorithm, including the quantity of data, the quality of data, and the type of problem being solved (Rafique & Velasco, 2018).

Research Gaps

A detailed literature review helped identify gaps that guided the research further. The research gaps were identified at three levels. First, geographically in the Indian context, in prediction modeling, and manufacturing industry. After a thorough literature review, it is clear that mergers and acquisitions in India are progressing and adopting international standards within the industry. Second, while statistical modeling has been used for prediction, AI and ML-based acquisition prediction are limited. Consequently, the comparison of model performance between statistical and AI/ML algorithms is non-existent. Last, the research on applying acquisition prediction modeling in the Indian manufacturing industry is limited.

CONCEPTUAL FRAMEWORK OF PREDICTIVE FEATURES

As discussed in the previous section, a firm's financial attributes can be used to determine the acquisition likelihood. Figure 2 provides a conceptual framework of the associated theories and accounting variables that impact the acquisition likelihood. The variables were used by all three methods, i.e., Logistic Regression, Decision Trees, and Multilayer Perceptron, after a few data cleansing steps that removed variables that did not have sufficient data.

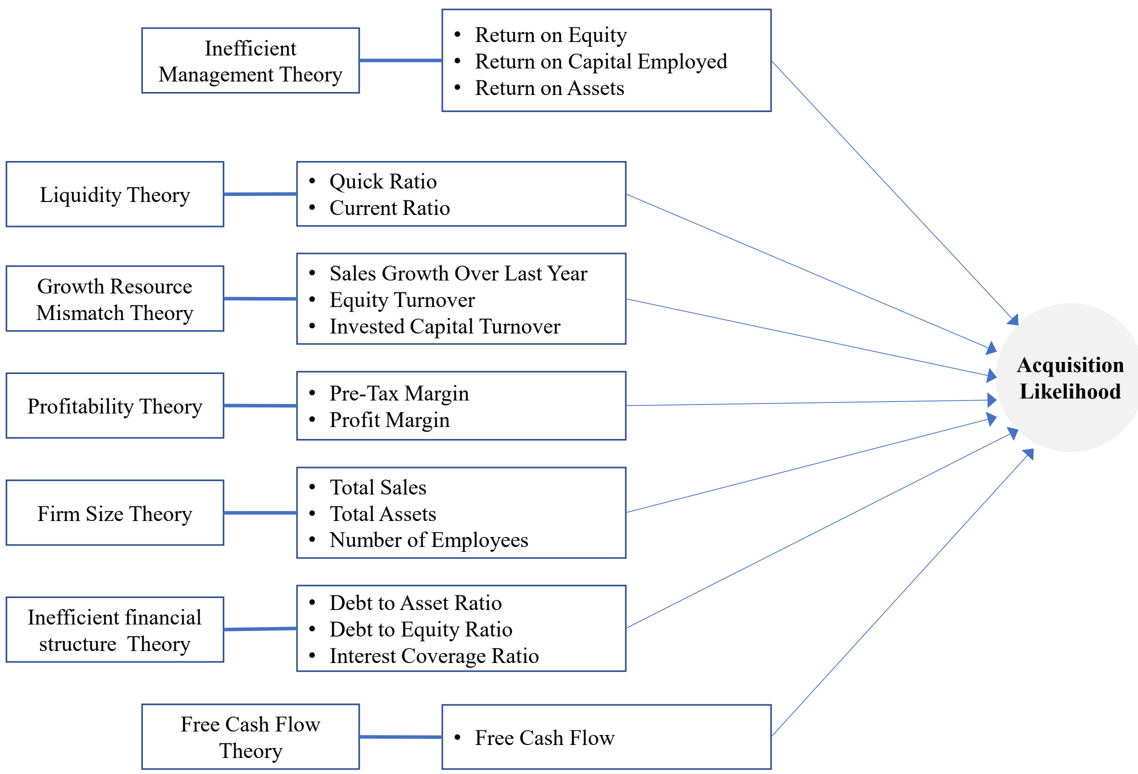


Figure 2. Conceptual framework

RESEARCH OBJECTIVES

This study has multiple objectives, including investigating statistical and machine learning algorithms that predict acquisitions, specifically in the manufacturing industry. The primary objective of the research is to build models that can predict acquisitions in the Indian manufacturing industry and support decision-making on acquisitions. The secondary objectives are the comparison of three different models, namely LR., DT, and MLP, and understanding the factors influencing acquisition likelihood. It is imperative to incorporate multiple models to enhance the accuracy of prediction theory and facilitate the comparison of results from diverse models. The primary and secondary research objectives are complementary and guide the research journey, data gathering and analysis, and inferences from the research.

Three prediction models are included in this investigation based on the problem, which is to identify whether a firm will be acquired. After considering various regression techniques, including linear, logistic, and regression discontinuity, it was determined that LR was the most appropriate given the nature of the problem (Maravelakis, 2019). LR is particularly well-suited for binomial targets or dependent variables, with values of either 0 (not acquired) or 1 (acquired), and where the independent variables are continuous. Machine learning involves preparing the data, splitting it into training and test data, and fitting the model. DTs are a non-parametric supervised learning algorithm that can be applied to classification and regression tasks (Quinlan, 1996).

Meanwhile, ANNs have been found to have promising applications across various fields, including engineering, science, healthcare, and business. ANNs are inspired by the human brain's data processing capabilities and consist of an input layer, nodes, and an output layer. Each neuron or node in the ANN is a compute element that receives inputs from other neurons (McMenamin, 1997). MLP, a feedforward ANN, includes one or more hidden layers, and the weights are adjusted through backpropagation.

METHODOLOGY

The present research is based on data from the Center for Monitoring Indian Economy (CMIE) Prowess IQ v1.96 database. The manufacturing industry was selected as the focus, specifically firms listed on the Bombay Stock Exchange (BSE) between 2010 and 2022. Listed companies were chosen due to regulatory requirements necessitating the filing and informing of any corporate event. The manufacturing industry incorporates a range of categories, including Construction Materials, Metals and Metal Products, Food and Agro-Based Products, Textiles, Transport Equipment, Chemicals and Chemical Products, Machinery, Miscellaneous Manufacturing, Diversified Manufacturing, and Consumer Goods. The selected time period accounts for seasonal effects and accommodates the high activity observed in the manufacturing sector over the last decade (Mishra & Jaiswal, 2012). The research focuses specifically on the sale of assets and acquisition of shares, as opposed to mergers, given the paper's scope for predicting acquisitions.

The initial query for firms in the manufacturing sector listed in BSE resulted in 1,869 companies. There are multiple events in the acquisition journey of a target firm, and each of these is reported. In this context, only the approval events which finally resulted in an acquisition were considered. Event types that indicated management decisions, investments, restructuring, qualified institutional placements, and preferential allotment were not considered (Gantumur & Stephan, 2012). There were 596 firms that were acquired in the Indian manufacturing sector between 2010 and 2022 that were considered for further analysis. The distribution between the sale of assets and the acquisition of shares is shown in Figure 3.

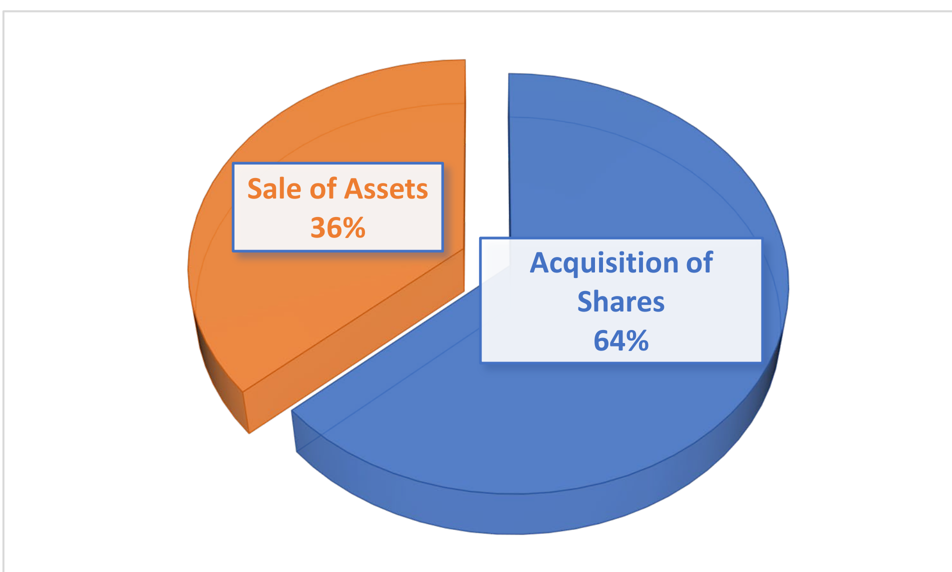


Figure 3. Acquisition type analysis

DATA PROCESSING AND ANALYSIS

Data cleansing is essential before applying any algorithm; the output quality is proportional to the data quality. The following data cleansing and transformation techniques were used to enhance data integrity – removing duplicate data, and missing data was carefully addressed, filtering unwanted outliers, and data transformation. Similarly, to mitigate bias pooled sampling and matching techniques, measurement bias was reduced by choosing a time period sufficient to address industry trends and choosing the acquisition type to reduce data bias and model bias by using three different models. The initial dataset consisted of 1,869 manufacturing firms listed in BSE. Seventeen independent variables were initially chosen for the analysis; however, IV13 (Number of Employees) was dropped since it had over 80% missing values across the years. Similarly, an analysis of missing values across each company for 13 years revealed that 492 companies did not have sufficient data, so they were dropped. After further scrubbing for invalid data, 27 more companies were not considered. The final data for LR, DT, and MLP analysis contained 796 firms, of which 398 were not acquired, and 398 were acquired. As suggested in earlier research papers, the matching technique was used as a sampling methodology (Pasiouras et al., 2007).

DESCRIPTIVE ANALYSIS

The first step of the analysis was to explore the data using descriptive analysis output from SPSS software. An analysis of the values in Appendix A indicates extreme variance and highly skewed data. Therefore, the baseline data must be prepared for modeling based on descriptive statistical analysis. There were data transformation rules that included excluding variables that had over 50% missing values, outliers beyond three standard deviations were replaced with outlier values, missing values for nominal variables were replaced with mode, ordinal variables with median, and continuous variables with mean and continuous fields were rescaled using z-score transformation so that all variables were on a common scale. The descriptive statistics after data transformation are shown in Appendix B and do not show extreme variation.

LOGISTIC REGRESSION ANALYSIS

The SPSS tool was used for LR analysis; the model determines the target firm's acquisition likelihood. Equations 1 and 2 were used within the tool to compute the probability.

$$P(Y_i) = \frac{1}{(1+e^{-Y}i)} \qquad (1)$$

$$Y_i = \alpha + \sum_{i=1} \beta_i X_i \qquad (2)$$

P(Y) is the probability of firm *i* being acquired.

α is the intercept.

β is the coefficient of the variables.

X_i is the independent variable for each firm.

The number of iterations before the backward stepwise (Likelihood Ratio) model was stopped was 12, as shown in Appendix C. The initial set of independent variables was 16, and in iteration 12, four were statistically significant. The p-value is 0.000, and hence the model is statistically significant. Appendix D shows the Cox & Snell R Square, Nagelkerke R Square, and -2 Log Likelihood in the final iteration and how it has gradually improved with every iteration. The explained variation in the "Acquired" field, which is the dependent variable, is between 3% to 4%.

The confusion matrix in Table 1 shows the LR model's accuracy in the final iteration number 12, which is 55.9%. The True Negatives (TN) are when the predicted and acquisition flags are "not acquired" which is in the top left quadrant. False Positives (FP) are in the top right quadrant when the prediction is acquired but the actual value is not acquired. True Negatives (TN) are when the prediction is not acquired but the actual value is acquired is shown in the bottom left quadrant (FN). The True Positives (TP) are when the predicted and acquisition flags are 1 which is in the lower right quadrant. Given a new dataset, the accuracy indicates that the model can predict whether a firm in the Indian manufacturing sector will be acquired or not. The classification table is computed with each iteration; Appendix E outlines the classification table values for each iteration.

Table 1. Logistic regression confusion matrix

	Observed		Predicted		
			Acquisition Flag		Percentage Correct
			0	1	
Step 12	Acquisition Flag	0	204 (TN)	194 (FP)	51.3
		1	157 (FN)	241 (TP)	60.6
	Overall Percentage				55.9

Table 2 outlines the variables that remained after 12 iterations of the backward stepwise method. The statistically significant variables are Quick Ratio (IV4), Equity Turnover (IV7), Pretax margin (IV9), and Total Sales (IV11) at a 95% confidence interval. The Quick Ratio provides an indication of short-term liquidity which is the ability to pay short-term liabilities. Equity Turnover measures a firm's ability to generate revenue from equity. Pretax margin measures a firm's operating efficiency, while Total Sales measures the revenue generated from sales. The statistically significant variables address different dimensions of a firm's financial health and performance, thus providing an indicator for an acquisition likelihood.

The odds ratio is shown under column Exp (B), which indicates that the acquisition likelihood increases when there is an increase in the independent variables of Equity Turnover and Pretax Margin. In other words, every unit increase in equity turnover is associated with a 21.7% increase in the odds of acquisition. Similarly, every unit increase in Pretax margin is associated with a 28.1% increase in the odds of acquisition. Conversely, the acquisition likelihood decreases when the Quick Ratio and Total Sales variables increase. According to the data, for every increase in Quick Ratio by one unit, the odds of acquisition decrease by 28.2%. Similarly, for every increase in Sales of one unit, the odds of acquisition decrease by 19.5%. Appendix F shows the LR coefficients for each of the 11 steps as variables get dropped from the analysis.

Table 2. Logistic regression coefficients

		B	SE	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step 12	QR_transformed	-.332	.103	10.442	1	.001	.718	.587	.878
	ET_transformed	.196	.077	6.511	1	.011	1.217	1.047	1.414
	PrM_transformed	.248	.091	7.443	1	.006	1.281	1.072	1.531
	ICR_transformed	.167	.095	3.054	1	.081	1.181	.980	1.424
	Log_Sales_ transformed	-.217	.082	6.891	1	.009	.805	.685	.947
	Constant	-.002	.072	.000	1	.983	.998		

The regression equation is:

Predicted Acquisition = -.002 -.332 * Quick Ratio + .196 * Equity Turnover + .248 * Pretax Margin - .217 * Total Sales

DECISION TREE ANALYSIS

The decision tree algorithm was implemented using SPSS. The dataset of 1350 firms was split into 70% training and 30% test samples. The depth of nodes considered was 5, and the Classification and Regression Tree (CRT) option was chosen. The CRT method splits the data into homogenous segments based on the dependent variable. The decision tree output for the training and test sample is included in Appendix G and Appendix H. The DT model's accuracy is shown in Table 3 and is computed for training and test datasets. The accuracy for the training dataset is 60.9%, and the test dataset is 62.3%. The accuracy of the test data shown is higher and indicates the best fit of the model based on the training. The model's performance metrics, such as precision, recall, sensitivity, and false positive rate, can be calculated from the confusion matrix.

Table 3. Decision tree confusion matrix

Sample	Observed	Predicted		
		0	1	Percent Correct
Training	0	160	116	58%
	1	106	186	63.7%
	Overall Percentage	46.8%	53.2%	60.9%
Test	0	81	41	66.4%
	1	45	61	57.5%
	Overall Percentage	55.3%	44.7%	62.3%

The feature importance, i.e., the relative importance of each of the sixteen variables in predicting the acquisition, is shown in Figure 4. The top variables with the maximum influence on acquisition are Free Cash Flow (FCF), Interest Coverage Ratio (ICR), Return on Assets (ROA), and Return on Equity (ROE). Similarly, Debt to Equity Ratio, Sales, and Sales Growth over the Last Year are the three variables with the least influence on acquisition.

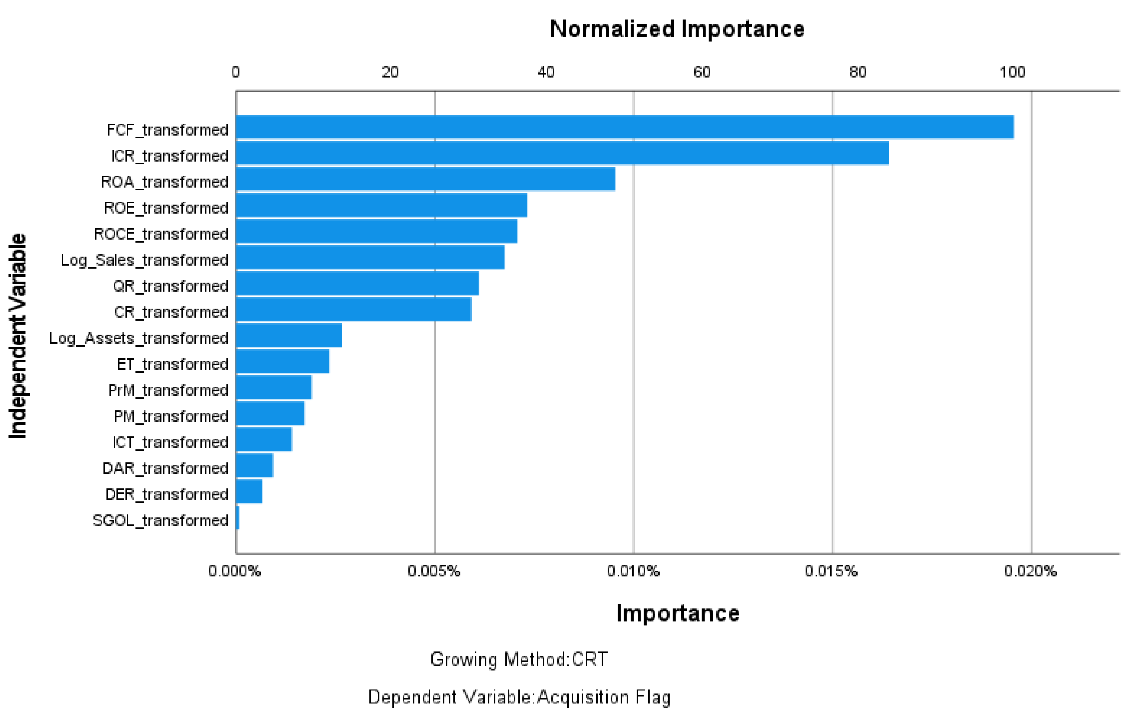


Figure 4. Decision tree variable importance

The top variables with the maximum influence on acquisition are Free Cash Flow (FCF), Interest Coverage Ratio (ICR), Return on Assets (ROA), and Return on Equity (ROE). Similarly, Debt to Equity Ratio, Sales, and Sales Growth over the Last Year are the three variables with the least influence on acquisition. Analyzing the variables highlights a firm's ability to pay off its debt, measured by ICR, which indicates robust financial health. FCF is the second most important variable that validates the argument since FCF measures the amount of free cash flow generated from operations used to address debt repayment ability. ROA and ROE measure a firm's efficiency in generating profits and indicate that the management can generate income.

Multilayer Perceptron Analysis

MLPs are feedforward networks where the signal flows through the input layer and hidden layers, and decisions are made in the output layer (Figure 5).

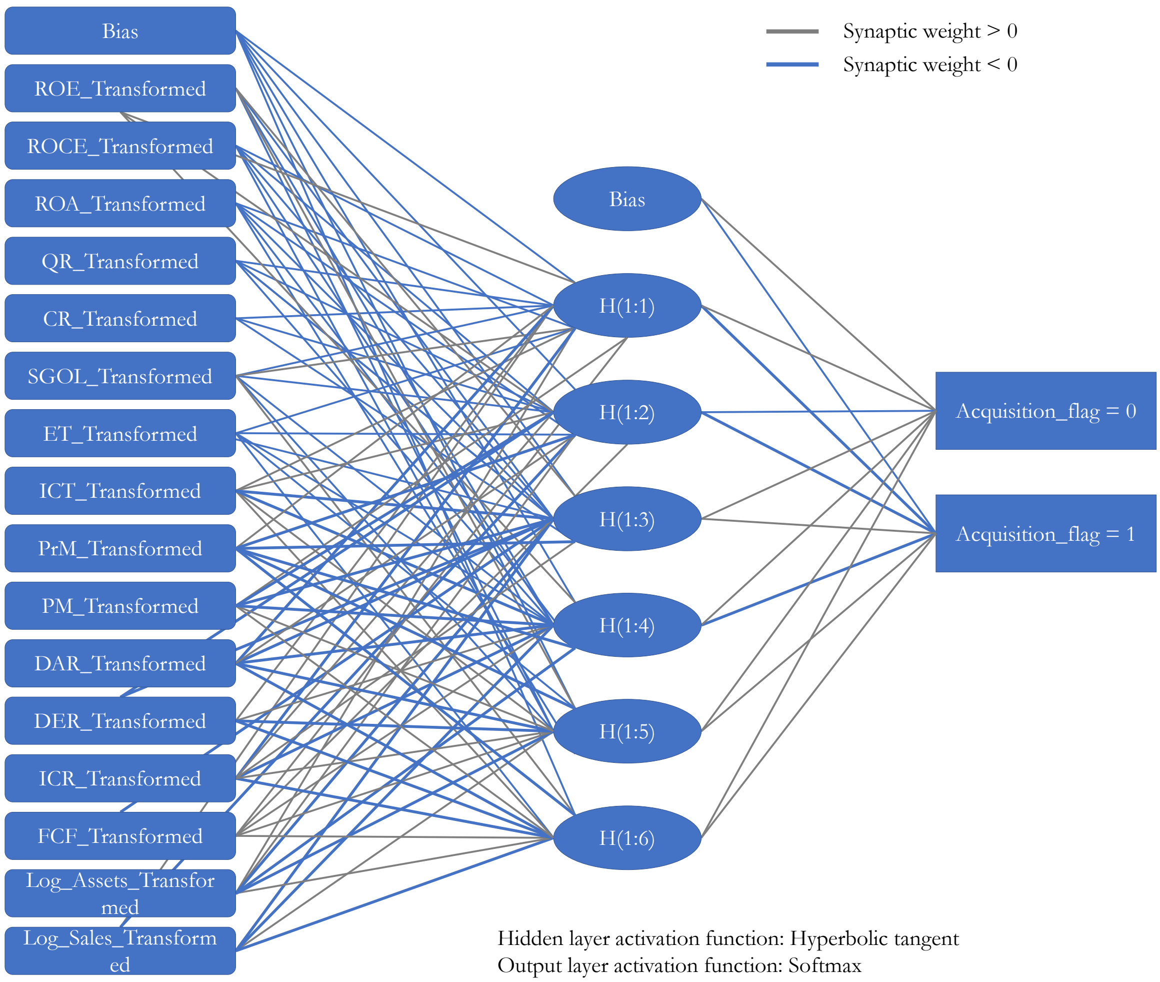


Figure 5. Multilayer perceptron output

The neural network has three layers: input, hidden, and output. The input layer accepts the input, the output layer does the actual classifications, and the hidden layer does the computation. The backward propagation is based on the computed and actual results; the error difference is used to adjust the weights. The process continues until the algorithm decides reducing the error is no longer feasible.

The MLP model's accuracy is shown in Table 4 and is computed for training and test datasets. The accuracy for the training dataset is 58.5%, and the test dataset is 61.9%. The model's performance metrics, such as precision, recall, sensitivity, and false positive rate, can be calculated from the confusion matrix.

Table 4. Multilayer perceptron classification table

Sample	Observed	Predicted		
		0	1	Percent Correct
Training	0	158	114	58.1%
	1	112	160	58.8%
	Overall Percent	49.6%	50.4%	58.5%
Testing	0	75	51	59.5%
	1	45	81	64.3%
	Overall Percent	47.6%	52.4%	61.9%

The feature importance of MLP is shown in Figure 6. Profit Margin, Current Ratio, and Sales are the top three variables that are valuable in predicting acquisitions. These three variables are associated with Profitability, Liquidity, and Size theories; the first two theories are consistent with the LR results.

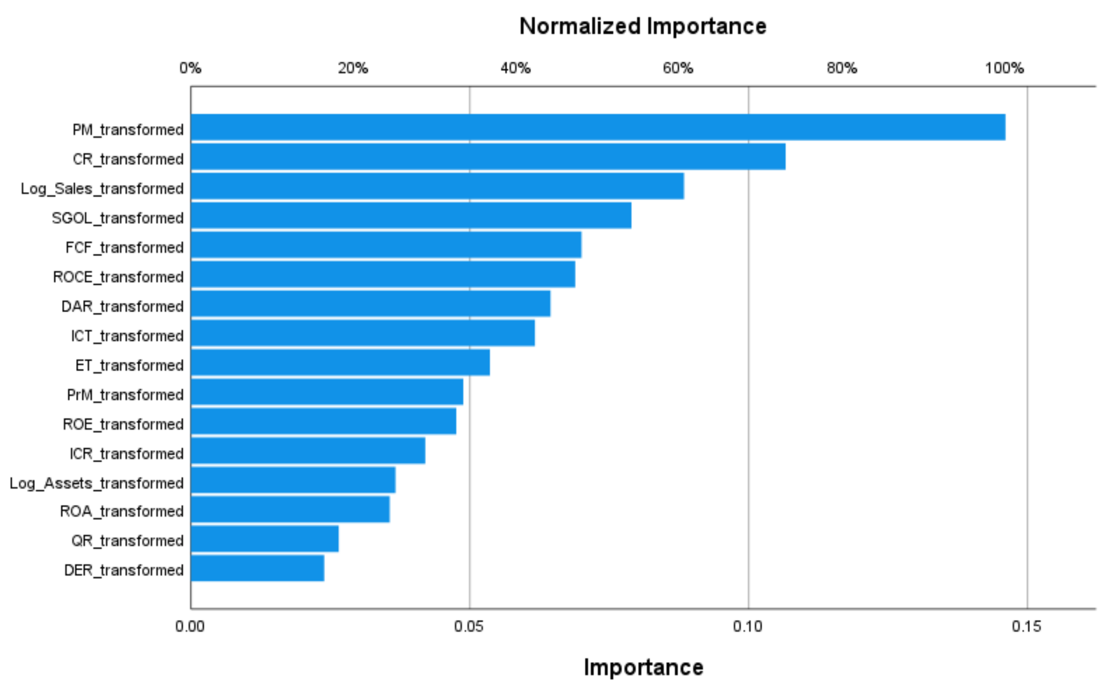


Figure 6. Multilayer perceptron variable importance

RESULTS AND DISCUSSION

The results of hypothesis testing are shown in Table 5; four of the seven hypotheses were not rejected. The associated variables are Quick Ratio, Equity Turnover, and Pretax margin. Based on the testing, the inferences are:

(i) There is a statistically significant relationship between QR and acquisition likelihood. The acquisition likelihood will decrease when the target firm has higher liquidity.

(ii) There is a statistically significant relationship between ET and acquisition likelihood. One of two scenarios is likely to exist high growth using low resources or low growth using high resources. Either of these scenarios increases the acquisition likelihood.
(iii) There is a statistically significant relationship between PrM and acquisition likelihood. When there is higher profitability, the target firm' acquisition likelihood is lower.
(iv) There is a statistically significant relationship between Total Sales and acquisition likelihood. When the firm size increases, the acquisition likelihood decreases.

Table 5. Hypothesis testing results

Hypothesis	Variables to test the hypothesis	Statistical Significance	Testing Results
H1: Inefficient management increases the target firm's acquisition likelihood in the Indian manufacturing sector	IV1: Return on equity (ROE)	p = .498, B = -.086 (Removed in Step 5)	H0 is not rejected, H1 is rejected
	IV2: Return on capital employed (ROCE)	p = .246, B = .358 (Removed in Step 8)	
	IV3: Return on Assets (ROA)	p = .490, B = -.094 (Removed in Step 9)	
H2: Higher liquidity decreases the target firm's acquisition likelihood in the Indian manufacturing sector	IV4: Quick ratio (QR)	p = .001, B = -.332	H0 is rejected, H2 is not rejected
	IV5: Current ratio (CR)	p = .437, B = -.130 (Removed in Step 6)	
H3: Target Firms that have a mismatch between growth and resources have a higher acquisition likelihood in the Indian manufacturing sector	IV6: Sales Growth Over Past Year (SGOL)	p = .128, B = .113 (Removed in Step 12)	H0 is rejected, H3 is not rejected
	IV7: Equity Turnover (ET)	p = .011, B = .196	
	IV8: Invested Capital Turnover (ICT)	p = .882, B = .014 (Removed in Step 4)	
H4: Higher profitable target firms have a lower acquisition likelihood in the Indian manufacturing sector	IV9: Pretax margin (PrM)	p = .006, B = .248	H0 is rejected, H4 is not rejected
	IV10: Profit margin (PM)	p = .348, B = .1717 (Removed in Step 8)	
H5: The larger the size of a target firm, the lower the target firm's acquisition likelihood in the Indian manufacturing sector	IV11: Sales (Log_sales)	p = .009, B = -.217	H0 is rejected, H5 is rejected
	IV12: Total assets (Log_assets)	p = .793, B = .092	
	IV13: Number of employees (NOE)	Removed before the analysis	
H6: Inefficient financial structure increases the acquisition likelihood of a target firm in the Indian manufacturing	IV14: Debt to asset ratio (DAR)	p = .131, B = .176 (Removed in Step 11)	H0 is not rejected, H6 is rejected
	IV15: Debt to equity ratio (DER)	p = .851, B = -.027 (Removed in Step 2)	
	IV16: Interest coverage ratio (ICR)	p = .081, B = .167	

Hypothesis	Variables to test the hypothesis	Statistical Significance	Testing Results
H7: The higher the cash flows, the lower the target firm's acquisition likelihood in the Indian manufacturing sector	IV17: Free cash flow return (FCF)	p = .466, B = -.067 (Removed in Step 7)	H0 is not rejected, H7 is rejected

A comparison of the variable's importance between DT and MLP does not indicate any overlap. ET, a statistically significant variable in the LR model, is also of the highest importance in MLP. In the DT model, all four statistically significant variables in the LR model have low significance. The performance metrics of all three models are shown in Table 6. One of the reasons for computing multiple metrics is to assess a model's performance holistically. A short description of each of the metrics is provided below.

- Accuracy measures the number of correct predictions to the total number of observations.
- Specificity measures the model's ability to correctly predict true negatives.
- FPR measures the false positives which have been incorrectly predicted by the model.
- Precision measures the model's ability to correctly predict true positives.
- Recall measures the model's ability to correctly identify the true positives.

The DT model is the best among the three based on accuracy and specificity, while MLP has the highest precision and recall, and LR has the best FPR ratio. One way to interpret the results is that a hybrid model might yield better results.

Table 6. Performance metrics comparison

Model	Accuracy	Specificity	FPR	Precision	Recall
Logistic Regression	55.9%	51.3%	48.7%	55.4%	60.6%
Decision Tree	62.3%	66.4%	33.6%	59.8%	57.5%
Multilayer Perceptron	61.9%	59.5%	40.5%	61.4%	64.3%

CONCLUSION

The Indian manufacturing sector is an integral part of the Indian economy employing over 27 million workers and contributing to 17% of the nation's GDP (Mehta & Rajan, 2017). The industry is embracing technology modernization, adopting Industry 4.0 technologies, and expanding, driven by exports. Many factors, including government initiatives, increasing domestic consumption, a vast labor pool, and international investments, drive the growth. The National Manufacturing Policy was announced to enhance the manufacturing sector's share to 25% and create over 100 million jobs (Dutta et al., 2020). Acquisitions have fueled growth in the manufacturing sector and contributed to 75% of the overall acquisitions between 2000 and 2009. The acquirer firm invests significant time, money, and people resources to identify potential candidates, investigate if they align with the firm's philosophy, and create the required synergies. Using prediction models assists the decision-makers in filtering out candidate firms that need further analysis.

In this paper, we have developed three models – LR, DT, and MLP based on sixteen variables for a period of thirteen years. Four of the seven alternate hypotheses were not rejected, and four variables – QR, ET, PrM, and Sales – were statistically significant. The associated theories are:

(i) A target firm with high liquidity has a lower probability of being acquired.

(ii) A target firm with high growth using low resources or low growth using high resources has a higher probability of being acquired.
(iii) A target firm with high profitability has a lower probability of being acquired and
(iv) A target firm with a large size has a lower probability of being acquired.

In the DT model, the top three variables with the maximum influence on acquisition are FCF, ICR, and ROA. In contrast, in the MLP model, PM, CR, and Sales are the top three variables with maximum influence in predicting acquisitions. Comparing the metrics of the three models highlights that the DT model's performance is better in accuracy, specificity, and false positive ratio. While the MLP model does better on precision and recall.

Research Limitations

The research is based on domestic acquisitions in the Indian manufacturing sector and does not consider cross-border acquisitions (CBA). There have been many instances of Indian firms expanding beyond the borders allowing Indian companies to attain economies of scale and be globally competitive (Lawrence et al., 2010). Therefore, the research is limited in not considering CBAs and focusing on domestic acquisitions. The Prowess database is considered a comprehensive database of Indian companies; there is always an opportunity to cross-validate and use other databases.

Research Contribution

This research paper contributes to the existing body of knowledge in multiple ways. Firstly, developing a prediction model for acquisitions in the Indian manufacturing sector is a significant contribution. The models, influencing variables, and associated theories add to the entire body of knowledge. The comparison of performance metrics of the three models is another unique contribution of the paper. There are many applications of AI across industries, and leveraging them for predicting acquisitions helps to expand the research continuum.

Scope for Further Research

There is scope to extend the research in multiple dimensions, such as making an industry comparison of prediction models, thereby considering the best predictive ability. While a target firm's financial health is crucial, additional factors, such as leadership and culture, must be considered for acquisition. So, while the models can serve as an initial filter, there is scope to extend beyond the financial parameters. Expanding the models to include management commentary captures the non-financial aspects, and using advanced machine learning algorithms can capture the sentiments. A combined model that uses both financial and non-financial data will enhance efficiency. There are industry, geo-political, and other global events that trigger acquisitions – exploring the impact of these events and capturing them in the model will help researchers and practitioners on how to respond. Developing a threshold based on the three models will provide a quantitative measure that can be continuously updated.

References

Andrade, G., Mitchell, M., & Stafford, E. (2001). New evidence and perspectives on mergers. *Journal of Economic Perspectives*, *15*(2), 103–120. https://doi.org/10.1257/jep.15.2.103

Barnes, P. (1998). Can takeover targets be identified by statistical techniques? Some UK evidence. *Journal of the Royal Statistical Society Series D: The Statistician*, *47*(4), 573–591. https://doi.org/10.1111/1467-9884.00156

Brar, G., Giamouridis, D., & Liodakis, M. (2009). Predicting European takeover targets. *European Financial Management*, *15*(2), 430–450. https://doi.org/10.1111/j.1468-036X.2007.00423.x

Chalapati Rao, K., & Dhar, B. (2011). India's FDI inflows: Trends and concepts. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1770222

Cho, S., & Chung, C. Y. (2022). Review of the literature on merger waves. *Journal of Risk and Financial Management*, *15*(10), 432. https://doi.org/10.3390/jrfm15100432

Coates, J. C. (2014). Mergers, acquisitions, and restructuring: Types, regulation, and patterns of practice. In J. N. Gordon, & W.-G. Ringe (Eds.), *Oxford handbook on corporate law and governance* (pp. 570-602). Oxford Handbooks. https://doi.org/10.1093/oxfordhb/9780198743682.013.29

DePamphilis, D. (2010). *Mergers and acquisitions basics.* Academic Press. https://doi.org/10.1016/B978-0-12-374878-2.00017-9

Dietrich, J. K., & Sorensen, E. (1984). An application of logit analysis to prediction of merger targets. *Journal of Business Research*, *12*(3), 393–402. https://doi.org/10.1016/0148-2963(84)90020-1

Dutta, G., Kumar, R., Sindhwani, R., & Singh, R. K. (2020). Digital transformation priorities of India's discrete manufacturing SMEs – A conceptual study in perspective of Industry 4.0. *Competitiveness Review*, *30*(3), 289–314. https://doi.org/10.1108/CR-03-2019-0031

Espahbodi, H., & Espahbodi, P. (2001). Predicting corporate takeovers. *The Journal of Business Forecasting*, *20*(3), 25.

Froese, H. G. (2013). *Predicting takeover targets. An empirical analysis of the European market* [MSc Thesis, University of St. Gallen, Switzerland].

Gantumur, T., & Stephan, A. (2012). Mergers & acquisitions and innovation performance in the telecommunications equipment industry. *Industrial and Corporate Change*, *21*(2), 277–314. https://doi.org/10.1093/icc/dtr052

Ghauri, P. N., & Buckley, P. J. (2003). International mergers and acquisitions: Past, present and future. In S. Finkelstein & C. Cooper (Eds.), *Advances in Mergers and Acquisitions*, *Volume 2* (pp. 207–229). Emerald Group Publishing Limited.

Golbe, D., & White, L. (1988). A time-series analysis of mergers and acquisitions in the US economy. In A. J. Auerbach (Ed.), *Corporate takeovers: Causes and consequences* (pp. 265-310). University of Chicago Press.

Goyal, K. A., & Rathi, M. (2020). A flashback of mergers and acquisition trends in India. *Pacific Business Review International*, *13*(4), 177–186.

Handhika, T., Lestari, D. P., & Sari, I. (2019). Multivariate time series classification analysis: State-of-the-art and future challenges. *IOP Conference Series: Materials Science and Engineering*, *536*, 12003. https://doi.org/10.1088/1757-899X/536/1/012003

Irfan, M., Saha, S. K., & Singh, S. K. (2016). Determinants of being acquired in Indian manufacturing sector: A panel data analysis. *Journal of Indian Business Research*, *8*(4), 246–263. https://doi.org/10.1108/jibr-11-2015-0118

Jiang, T. (2021). Using machine learning to analyze merger activity. *Frontiers in Applied Mathematics and Statistics*, *7*, Article 649501. https://doi.org/10.3389/fams.2021.649501

Kalirajan, K. (2004). *Is the manufacturing sector in India an engine of growth?* (Working Paper No. 151). Institute for Social and Economic Change.

Kode, G., Ford, J., & Sutherland, M. (2003). A conceptual model for evaluation of synergies in mergers and acquisitions: A critical review of the literature. *South African Journal of Business Management*, *34*(1), 27–38. https://doi.org/10.4102/sajbm.v34i1.675

Kumar, B. R., & Rajib, P. (2007). Characteristics of merging firms in India: An empirical examination. *Vikalpa*, *32*(1), 27–44. https://doi.org/10.1177/0256090920070103

Lawrence, S., Duppati, G., & Locke, S. (2010). Emerging global giants: Foreign investment by Indian companies. *Social Science Research Network*. https://doi.org/10.2139/ssrn.3283508

Maravelakis, P. (2019). The use of statistics in social sciences. *Journal of Humanities and Applied Social Sciences*, *1*(2), 87–97. https://doi.org/10.1108/jhass-08-2019-0038

McMenamin, J. S. (1997). Why not Pi? A primer on neural networks for forecasting. *The Journal of Business Forecasting Methods and Systems*, *16*(3), 1-20.

Meador, A. L., Church, P. H., & Rayburn, L. G. (1996). Development of prediction models for horizontal and vertical mergers. *Journal of Financial and Strategic Decision*, *9*(1), 11–23.

Meghouar, H. (2016). *Corporate takeover targets acquisition probability*. John Wiley & Sons. https://doi.org/10.1002/9781119292234

Mehta, Y., & Rajan, A. J. (2017). Manufacturing sector in India: Outlook and challenges. *Procedia Engineering*, *174*, 90–104. https://doi.org/10.1016/j.proeng.2017.01.173

Mishra, P., & Jaiswal, N. (2012). Mergers, acquisitions and export competitiveness: Experience of Indian manufacturing sector. *Journal of Competitiveness*, *4*(1), 3–19. https://doi.org/10.7441/joc.2012.01.01

Naik, B., Ragothaman, S., & Ramakrishnan, K. (2010). Application of classification models. *International Journal of Business, Accounting and Finance*, *4*(2), 70–84.

Pandya, V. U. (2017). Mergers and acquisitions trends – The Indian experience. *International Journal of Business Administration*, *9*(1), 44–54. https://doi.org/10.5430/ijba.v9n1p44

Pasiouras, F., Tanna, S., & Zopounidis, C. (2007). The identification of acquisition targets in the EU banking industry: An application of multicriteria approaches. *International Review of Financial Analysis*, *16*(3), 262–281. https://doi.org/10.1016/j.irfa.2006.09.001

Patel, R., & Shah, D. (2016). Mergers and acquisitions: A pre-post risk-return analysis for the Indian banking sector. *Journal of Applied Finance & Banking*, *6*(3), 99–113.

Powell, R. G. (2004). Takeover prediction models and portfolio strategies: A multinomial approach. *Multinational Finance Journal*, *8*(1/2), 35–72. https://doi.org/10.17578/8-1/2-2

Quinlan, J. R. (1996). Learning decision tree classifiers. *ACM Computing Surveys*, *28*(1), 71-72. https://doi.org/10.1145/234313.234346

Rafique, D., & Velasco, L. (2018). Machine learning for network automation: Overview, architecture, and applications [Invited Tutorial]. *Journal of Optical Communications and Networking*, *10*(10), D126–D143. https://doi.org/10.1364/JOCN.10.00D126

Rodrigues, B. D., & Stevenson, M. J. (2013). Takeover prediction using forecast combinations. *International Journal of Forecasting*, *29*(4), 628–641. https://doi.org/10.1016/J.IJFORECAST.2013.01.008

Simkowitz, M., & Monroe, R. J. (1971). A discriminant analysis function for conglomerate targets. *Southern Journal of Business*, *6*(1), 1–15. https://doi.org/10.1016/0007-6813(72)90026-2

Tunyi, A. A. (2019). Firm size, market conditions and takeover likelihood. *Review of Accounting and Finance*, *18*(3), 483–507. https://doi.org/10.1108/RAF-07-2018-0145

Tunyi, A. A. (2021). Fifty years of research on takeover target prediction: A historical perspective. *Qualitative Research in Financial Markets*, *13*(4), 482–502. https://doi.org/10.1108/QRFM-08-2020-0169

von Lilienfeld, O. A. (2020). Introducing machine learning: Science and technology. *Machine Learning: Science and Technology*, *1*(1), 10201. https://doi.org/10.1088/2632-2153/ab6d5d

Weinberg, A. I., & Last, M. (2019). Selecting a representative decision tree from an ensemble of decision-tree models for fast big data classification. *Journal of Big Data, 6*, Article 23. https://doi.org/10.1186/s40537-019-0186-3

Yaghoubi, R., Yaghoubi, M., Locke, S., & Gibb, J. (2016). Mergers and acquisitions: A review. Part 1. *Studies in Economics and Finance*, *33*(1), 147–188. https://doi.org/10.1108/SEF-03-2015-0078

APPENDICES

APPENDIX A: DESCRIPTIVE STATISTICS BEFORE DATA TRANSFORMATION

	N Statistic	Range Statistic	Min Statistic	Max Statistic	Mean Statistic	Mean Std Error	Std. Devia-tion
ROE	796.00	3469.21	-171.03	3298.18	12.26	4.24	119.58
ROCE	796.00	221.98	-69.10	152.88	6.24	.43	12.12
ROA	796.00	57.82	-29.94	27.88	4.32	.22	6.15
QR	796.00	11.33	.05	11.38	1.02	.04	1.26
CR	796.00	21.87	.23	22.11	1.77	.07	1.85
SGOL	796.00	7623.07	-31.40	7591.67	40.91	11.56	326.14
ET	796.00	576.70	-481.27	95.43	2.12	.91	25.65
ICT	796.00	46.77	-36.19	10.58	1.77	.07	2.12
PrM	796.00	846.08	-796.62	49.47	2.49	1.20	33.79
PM	796.00	4490.59	-4448.03	42.55	-8.51	6.40	180.44
DAR	796.00	5.11	.00	5.11	.29	.01	.27
DER	796.00	33.38	.00	33.38	1.44	.10	2.87
ICR	796.00	5870.64	.16	5870.80	94.12	16.26	458.68
FCF	796.00	2.13	-1.83	.30	.07	.00	.09
Log_Sales	796.00	14.41	.64	15.06	8.06	.07	1.85
Log_Assets	796.00	12.67	2.92	15.59	8.13	.07	1.89

	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Std. Error	Statistic	Std. Error
ROE	14298.77	26.18	.09	719.75	.173
ROCE	146.96	2.03	.09	35.41	.173
ROA	37.77	-.07	.09	2.49	.173
QR	1.58	4.74	.09	27.79	.173
CR	3.44	5.74	.09	44.11	.173
SGOL	106369.04	19.37	.09	411.11	.173
ET	658.08	-16.91	.09	315.36	.173
ICT	4.48	-9.29	.09	162.57	.173
PrM	1141.97	-17.80	.09	400.81	.173
PM	32559.34	-21.05	.09	484.79	.173
DAR	.07	7.91	.09	135.12	.173
DER	8.25	5.93	.09	46.73	.173
ICR	210390.14	8.68	.09	86.16	.173
FCF	.01	-11.68	.09	228.38	.173
Log_Sales	3.44	.01	.09	.73	.173
Log_Assets	3.57	.23	.09	.24	.173
Valid N	796				

APPENDIX B: DESCRIPTIVE STATISTICS AFTER TRANSFORMATION

	N	Range	Minimum	Maximum	Mean	
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
ROE_transformed	796.00	6.36	-3.19	3.18	.00	.04
ROCE_transformed	796.00	5.33	-2.66	2.67	.00	.04
ROA_transformed	796.00	5.40	-2.76	2.64	.00	.04
QR_transformed	796.00	4.08	-1.36	2.72	.00	.04
CR_transformed	796.00	4.36	-1.56	2.81	.00	.04
SGOL_transformed	796.00	6.22	-2.39	3.84	.00	.04
ET_transformed	796.00	6.46	-3.24	3.22	.00	.04
ICT_transformed	796.00	5.74	-2.89	2.85	.00	.04
PrM_transformed	796.00	5.40	-2.63	2.77	.00	.04
PM_transformed	796.00	7.67	-3.87	3.80	.00	.04
DAR_transformed	796.00	4.26	-1.47	2.79	.00	.04
DER_transformed	796.00	3.67	-.96	2.71	.00	.04
ICR_transformed	796.00	3.72	-.50	3.22	.00	.04
FCF_transformed	796.00	5.43	-2.63	2.80	.00	.04
Log_Sales_transformed	796.00	5.35	-2.67	2.67	.00	.04
Log_Assets_transformed	796.00	5.41	-2.72	2.69	.00	.04
Valid N (listwise)	796.00					

	Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
ROE_transformed	1.00	1.00	-.75	.09	3.33	.17
ROCE_transformed	1.00	1.00	.04	.09	.77	.17
ROA_transformed	1.00	1.00	.05	.09	.68	.17
QR_transformed	1.00	1.00	1.39	.09	1.27	.17
CR_transformed	1.00	1.00	1.50	.09	1.59	.17
SGOL_transformed	1.00	1.00	2.43	.09	6.76	.17
ET_transformed	1.00	1.00	.77	.09	2.99	.17
ICT_transformed	1.00	1.00	1.06	.09	1.27	.17
PrM_transformed	1.00	1.00	-.23	.09	1.25	.17
PM_transformed	1.00	1.00	-1.86	.09	6.23	.17
DAR_transformed	1.00	1.00	.49	.09	-.20	.17
DER_transformed	1.00	1.00	1.44	.09	1.30	.17
ICR_transformed	1.00	1.00	2.47	.09	4.84	.17
FCF_transformed	1.00	1.00	.02	.09	.46	.17
Log_Sales_transformed	1.00	1.00	-.01	.09	-.06	.17
Log_Assets_transformed	1.00	1.00	.13	.09	-.11	.17

APPENDIX C: OMNIBUS TESTS OF MODEL COEFFICIENTS

		Chi-square	df	Sig.
Step 1	Step	32.722	16	.008
	Block	32.722	16	.008
	Model	32.722	16	.008
Step 2[a]	Step	-.036	1	.851
	Block	32.686	15	.005
	Model	32.686	15	.005
Step 3[a]	Step	-.069	1	.793
	Block	32.617	14	.003
	Model	32.617	14	.003
Step 4[a]	Step	-.022	1	.882
	Block	32.595	13	.002
	Model	32.595	13	.002
Step 5[a]	Step	-.460	1	.497
	Block	32.135	12	.001
	Model	32.135	12	.001
Step 6[a]	Step	-.607	1	.436
	Block	31.528	11	.001
	Model	31.528	11	.001
Step 7[a]	Step	-.533	1	.465
	Block	30.995	10	.001
	Model	30.995	10	.001
Step 8[a]	Step	-.893	1	.345
	Block	30.102	9	.000
	Model	30.102	9	.000
Step 9[a]	Step	-1.419	1	.234
	Block	28.684	8	.000
	Model	28.684	8	.000
Step 10[a]	Step	-.480	1	.488
	Block	28.204	7	.000
	Model	28.204	7	.000
Step 11[a]	Step	-1.839	1	.175
	Block	26.365	6	.000
	Model	26.365	6	.000
Step 12[a]	Step	-2.333	1	.127
	Block	24.033	5	.000
	Model	24.033	5	.000

a - A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step

APPENDIX D: MODEL SUMMARY

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1070.768[a]	.040	.054
2	1070.804[a]	.040	.054
3	1070.873[a]	.040	.054
4	1070.895[a]	.040	.053
5	1071.355[a]	.040	.053
6	1071.962[a]	.039	.052
7	1072.495[a]	.038	.051
8	1073.388[a]	.037	.049
9	1074.806[b]	.035	.047
10	1075.287[b]	.035	.046
11	1077.125[b]	.033	.043
12	1079.458[b]	.030	.040

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.
b. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

APPENDIX E: CLASSIFICATION TABLE

	Observed		Predicted		
			Acquisition Flag		Percentage Correct
			0	1	
Step 1	Acquisition Flag	0	234	164	58.8
		1	152	246	61.8
	Overall Percentage				60.3
Step 2	Acquisition Flag	0	235	163	59.0
		1	153	245	61.6
	Overall Percentage				60.3
Step 3	Acquisition Flag	0	237	161	59.5
		1	153	245	61.6
	Overall Percentage				60.6
Step 4	Acquisition Flag	0	237	161	59.5
		1	153	245	61.6
	Overall Percentage				60.6
Step 5	Acquisition Flag	0	234	164	58.8
		1	152	246	61.8
	Overall Percentage				60.3
Step 6	Acquisition Flag	0	239	159	60.1
		1	156	242	60.8
	Overall Percentage				60.4

	Observed		Predicted		
			Acquisition Flag		Percentage Correct
			0	1	
Step 7	Acquisition Flag	0	237	161	59.5
		1	158	240	60.3
	Overall Percentage				59.9
Step 8	Acquisition Flag	0	236	162	59.3
		1	160	238	59.8
	Overall Percentage				59.5
Step 9	Acquisition Flag	0	224	174	56.3
		1	165	233	58.5
	Overall Percentage				57.4
Step 10	Acquisition Flag	0	225	173	56.5
		1	160	238	59.8
	Overall Percentage				58.2
Step 11	Acquisition Flag	0	218	180	54.8
		1	174	224	56.3
	Overall Percentage				55.5
Step 12	Acquisition Flag	0	204	194	51.3
		1	157	241	60.6
	Overall Percentage				55.9

APPENDIX F: LOGISTIC REGRESSION COEFFICIENTS

		B	SE.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	ROE_transformed	-.089	.130	.470	1	.493	.915	.710	1.180
	ROCE_transformed	.384	.327	1.378	1	.240	1.468	.773	2.785
	ROA_transformed	-.355	.333	1.132	1	.287	.701	.365	1.348
	QR_transformed	-.189	.174	1.182	1	.277	.828	.589	1.164
	CR_transformed	-.123	.169	.525	1	.469	.885	.635	1.232
	SGOL_transformed	.117	.078	2.232	1	.135	1.124	.964	1.311
	ET_transformed	.174	.099	3.076	1	.079	1.190	.980	1.445
	ICT_transformed	.033	.119	.076	1	.783	1.033	.818	1.306
	PrM_transformed	.224	.211	1.127	1	.288	1.250	.828	1.889
	PM_transformed	.173	.186	.861	1	.353	1.189	.825	1.712
	DAR_transformed	.209	.155	1.808	1	.179	1.232	.909	1.670
	DER_transformed	-.027	.144	.035	1	.851	.973	.734	1.290
	ICR_transformed	.226	.106	4.564	1	.033	1.254	1.019	1.543
	FCF_transformed	-.077	.094	.676	1	.411	.926	.770	1.113
	Log_Sales_trans-formed	-.308	.353	.762	1	.383	.735	.368	1.467
	Log_Assets_trans-formed	.098	.351	.078	1	.780	1.103	.555	2.193
	Constant	.000	.072	.000	1	.995	1.000		

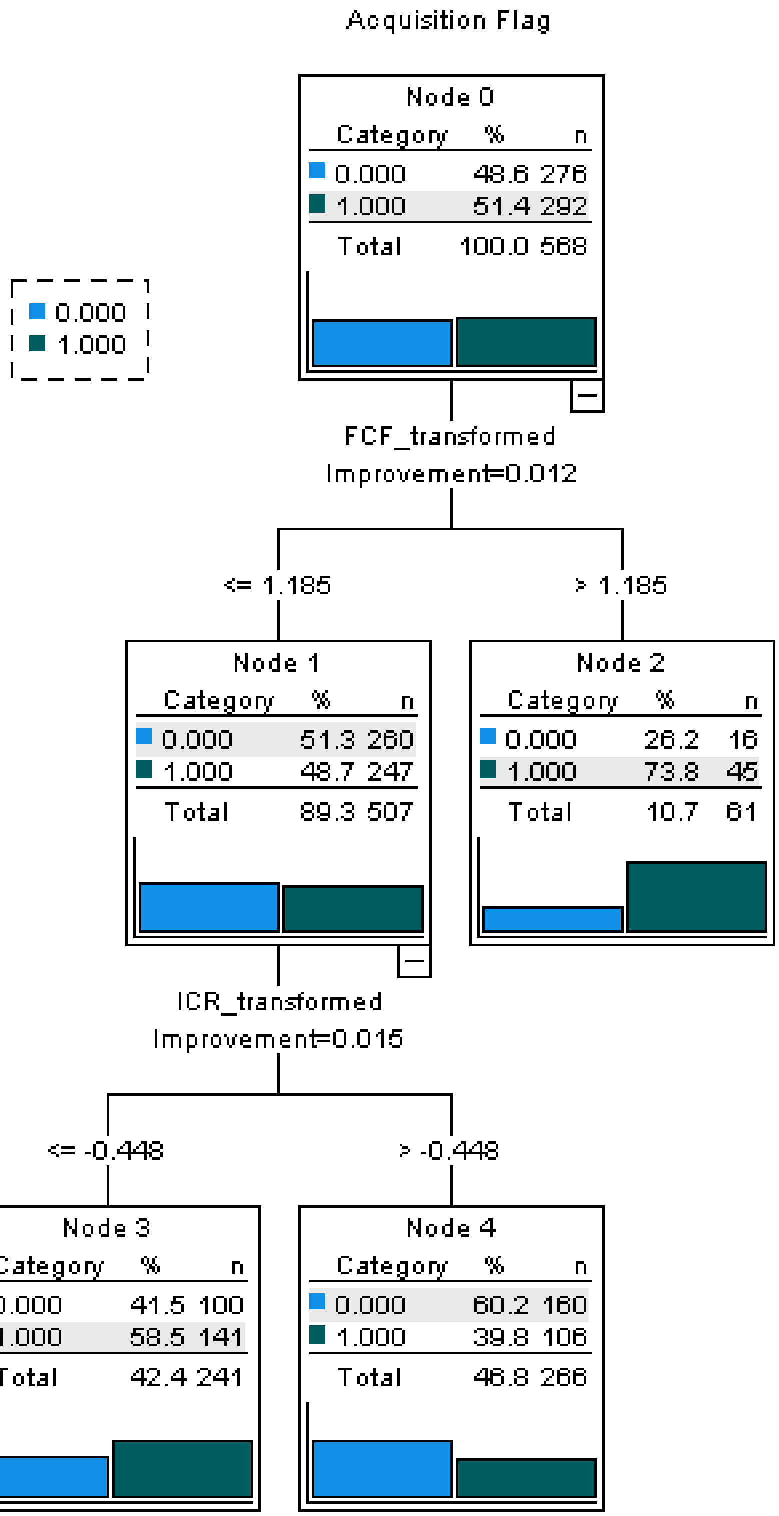
		B	SE.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 2[a]	ROE_transformed	-.084	.127	.438	1	.508	.919	.716	1.180
	ROCE_transformed	.380	.326	1.355	1	.244	1.462	.771	2.772
	ROA_transformed	-.349	.332	1.104	1	.293	.705	.368	1.353
	QR_transformed	-.192	.173	1.231	1	.267	.825	.588	1.158
	CR_transformed	-.119	.168	.503	1	.478	.888	.638	1.234
	SGOL_transformed	.117	.078	2.254	1	.133	1.125	.965	1.311
	ET_transformed	.168	.094	3.219	1	.073	1.183	.985	1.421
	ICT_transformed	.033	.119	.076	1	.783	1.033	.818	1.305
	PrM_transformed	.225	.210	1.143	1	.285	1.252	.829	1.892
	PM_transformed	.171	.186	.846	1	.358	1.186	.824	1.708
	DAR_transformed	.188	.111	2.872	1	.090	1.207	.971	1.501
	ICR_transformed	.223	.104	4.565	1	.033	1.249	1.019	1.533
	FCF_transformed	-.078	.094	.682	1	.409	.925	.769	1.113
	Log_Sales_trans-formed	-.302	.351	.740	1	.390	.739	.371	1.472
	Log_Assets_trans-formed	.092	.349	.069	1	.793	1.096	.553	2.172
	Constant	.000	.072	.000	1	.996	1.000		
Step 3[a]	ROE_transformed	-.087	.127	.465	1	.495	.917	.715	1.176
	ROCE_transformed	.389	.326	1.422	1	.233	1.475	.779	2.796
	ROA_transformed	-.365	.329	1.233	1	.267	.694	.365	1.322
	QR_transformed	-.189	.172	1.197	1	.274	.828	.591	1.161
	CR_transformed	-.124	.167	.555	1	.456	.883	.636	1.225
	SGOL_transformed	.119	.078	2.301	1	.129	1.126	.966	1.312
	ET_transformed	.166	.093	3.169	1	.075	1.181	.983	1.418
	ICT_transformed	.014	.097	.022	1	.882	1.014	.839	1.226
	PrM_transformed	.240	.203	1.391	1	.238	1.271	.853	1.892
	PM_transformed	.163	.183	.792	1	.374	1.177	.822	1.687
	DAR_transformed	.185	.110	2.808	1	.094	1.203	.969	1.493
	ICR_transformed	.225	.104	4.663	1	.031	1.252	1.021	1.535
	FCF_transformed	-.081	.093	.765	1	.382	.922	.768	1.106
	Log_Sales_trans-formed	-.213	.086	6.079	1	.014	.808	.683	.957
	Constant	.000	.072	.000	1	.996	1.000		
Step 4[a]	ROE_transformed	-.086	.127	.460	1	.498	.917	.715	1.177
	ROCE_transformed	.395	.325	1.479	1	.224	1.484	.785	2.805
	ROA_transformed	-.368	.329	1.247	1	.264	.692	.363	1.320
	QR_transformed	-.188	.172	1.195	1	.274	.828	.591	1.161
	CR_transformed	-.126	.167	.567	1	.451	.882	.636	1.223
	SGOL_transformed	.119	.078	2.324	1	.127	1.126	.967	1.313
	ET_transformed	.174	.080	4.717	1	.030	1.190	1.017	1.391
	PrM_transformed	.232	.197	1.387	1	.239	1.262	.857	1.858
	PM_transformed	.166	.183	.823	1	.364	1.180	.825	1.688
	DAR_transformed	.181	.107	2.848	1	.092	1.198	.971	1.479
	ICR_transformed	.225	.104	4.686	1	.030	1.252	1.022	1.535
	FCF_transformed	-.080	.093	.749	1	.387	.923	.769	1.107
	Log_Sales_trans-formed	-.212	.086	6.063	1	.014	.809	.683	.958
	Constant	.000	.072	.000	1	.996	1.000		

		B	SE.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 5[a]	ROCE_transformed	.335	.315	1.133	1	.287	1.398	.754	2.590
	ROA_transformed	-.387	.330	1.377	1	.241	.679	.356	1.296
	QR_transformed	-.179	.172	1.089	1	.297	.836	.597	1.170
	CR_transformed	-.130	.167	.605	1	.437	.878	.634	1.218
	SGOL_transformed	.113	.078	2.139	1	.144	1.120	.962	1.304
	ET_transformed	.170	.080	4.561	1	.033	1.186	1.014	1.386
	PrM_transformed	.231	.197	1.376	1	.241	1.260	.856	1.855
	PM_transformed	.162	.182	.788	1	.375	1.176	.823	1.680
	DAR_transformed	.173	.107	2.648	1	.104	1.189	.965	1.466
	ICR_transformed	.234	.103	5.131	1	.024	1.263	1.032	1.546
	FCF_transformed	-.076	.092	.674	1	.412	.927	.773	1.111
	Log_Sales_trans-formed	-.207	.086	5.827	1	.016	.813	.687	.962
	Constant	.000	.072	.000	1	.999	1.000		
Step 6[a]	ROCE_transformed	.380	.310	1.500	1	.221	1.462	.796	2.687
	ROA_transformed	-.436	.325	1.797	1	.180	.647	.342	1.223
	QR_transformed	-.280	.112	6.278	1	.012	.755	.607	.941
	SGOL_transformed	.108	.077	1.955	1	.162	1.114	.957	1.296
	ET_transformed	.170	.080	4.539	1	.033	1.185	1.014	1.385
	PrM_transformed	.225	.197	1.302	1	.254	1.252	.851	1.841
	PM_transformed	.166	.182	.827	1	.363	1.180	.826	1.686
	DAR_transformed	.179	.106	2.829	1	.093	1.196	.971	1.473
	ICR_transformed	.229	.103	4.953	1	.026	1.257	1.028	1.538
	FCF_transformed	-.067	.092	.532	1	.466	.935	.781	1.119
	Log_Sales_trans-formed	-.194	.084	5.324	1	.021	.824	.698	.971
	Constant	.000	.072	.000	1	.998	1.000		
Step 7[a]	ROCE_transformed	.370	.310	1.427	1	.232	1.448	.789	2.658
	ROA_transformed	-.467	.322	2.106	1	.147	.627	.334	1.178
	QR_transformed	-.269	.111	5.907	1	.015	.764	.615	.949
	SGOL_transformed	.116	.077	2.293	1	.130	1.123	.966	1.305
	ET_transformed	.168	.080	4.449	1	.035	1.183	1.012	1.383
	PrM_transformed	.218	.197	1.231	1	.267	1.244	.846	1.830
	PM_transformed	.171	.182	.882	1	.348	1.187	.830	1.696
	DAR_transformed	.165	.105	2.499	1	.114	1.180	.961	1.448
	ICR_transformed	.222	.102	4.703	1	.030	1.249	1.022	1.526
	Log_Sales_trans-formed	-.199	.084	5.656	1	.017	.819	.695	.966
	Constant	.000	.072	.000	1	.999	1.000		
Step 8[a]	ROCE_transformed	.358	.309	1.344	1	.246	1.431	.781	2.623
	ROA_transformed	-.424	.318	1.779	1	.182	.654	.351	1.220
	QR_transformed	-.280	.110	6.509	1	.011	.756	.609	.937
	SGOL_transformed	.111	.076	2.145	1	.143	1.118	.963	1.298
	ET_transformed	.177	.079	4.974	1	.026	1.193	1.022	1.394
	PrM_transformed	.355	.135	6.949	1	.008	1.426	1.095	1.856
	DAR_transformed	.162	.104	2.412	1	.120	1.176	.958	1.443
	ICR_transformed	.210	.101	4.261	1	.039	1.233	1.011	1.504
	Log_Sales_trans-formed	-.199	.084	5.626	1	.018	.820	.695	.966

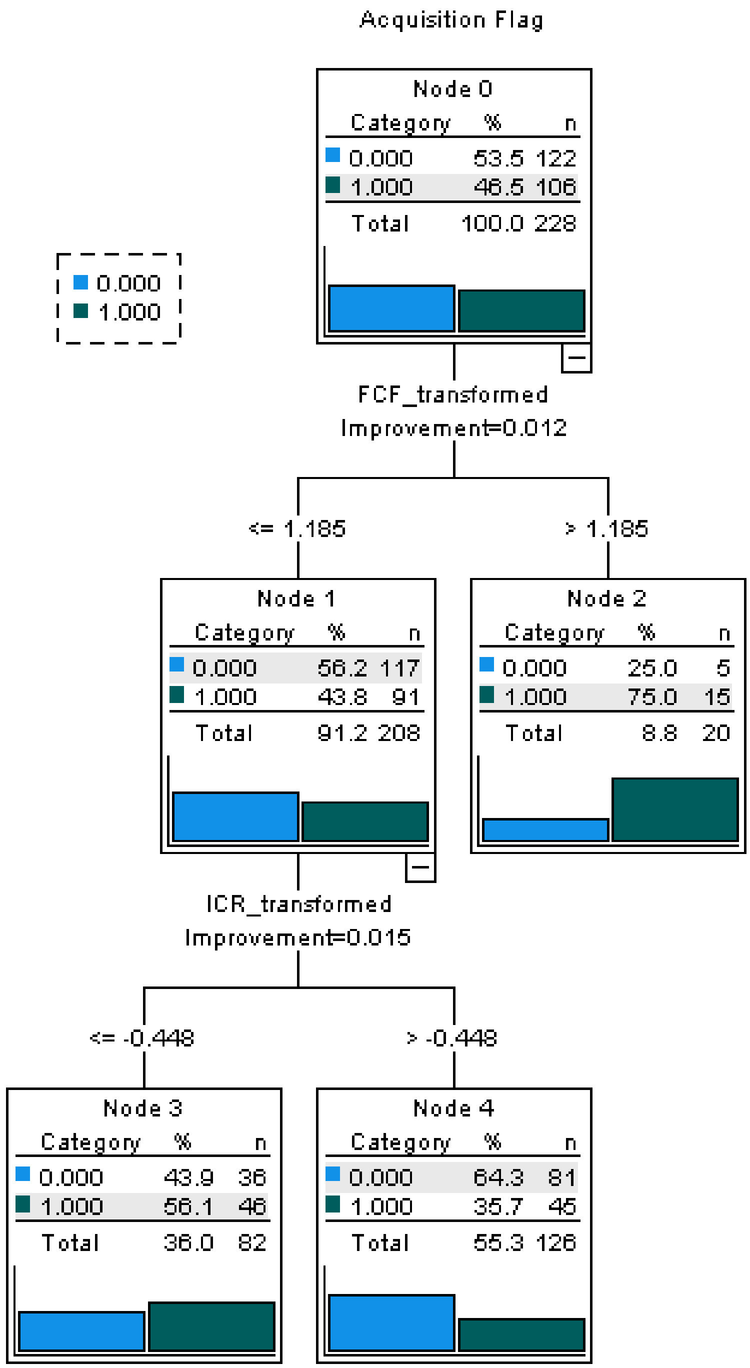
		B	SE.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
	Constant	.001	.072	.000	1	.994	1.001		
Step 9[a]	ROA_transformed	-.094	.135	.477	1	.490	.911	.698	1.188
	QR_transformed	-.309	.107	8.335	1	.004	.734	.595	.906
	SGOL_transformed	.121	.076	2.562	1	.109	1.129	.973	1.309
	ET_transformed	.194	.078	6.146	1	.013	1.214	1.041	1.415
	PrM_transformed	.351	.134	6.917	1	.009	1.421	1.094	1.846
	DAR_transformed	.120	.098	1.490	1	.222	1.127	.930	1.366
	ICR_transformed	.221	.101	4.795	1	.029	1.247	1.023	1.519
	Log_Sales_trans-formed	-.200	.084	5.743	1	.017	.818	.695	.964
	Constant	-.001	.072	.000	1	.994	.999		
Step 10[a]	QR_transformed	-.307	.107	8.261	1	.004	.736	.597	.907
	SGOL_transformed	.112	.074	2.293	1	.130	1.119	.967	1.294
	ET_transformed	.185	.077	5.773	1	.016	1.203	1.035	1.398
	PrM_transformed	.287	.095	9.162	1	.002	1.333	1.106	1.605
	DAR_transformed	.131	.097	1.832	1	.176	1.140	.943	1.378
	ICR_transformed	.206	.099	4.375	1	.036	1.229	1.013	1.491
	Log_Sales_trans-formed	-.208	.083	6.326	1	.012	.812	.690	.955
	Constant	-.001	.072	.000	1	.994	.999		
Step 11[a]	QR_transformed	-.344	.103	11.124	1	.001	.709	.579	.868
	SGOL_transformed	.113	.074	2.315	1	.128	1.119	.968	1.294
	ET_transformed	.192	.077	6.205	1	.013	1.211	1.042	1.408
	PrM_transformed	.252	.091	7.676	1	.006	1.287	1.077	1.539
	ICR_transformed	.175	.096	3.340	1	.068	1.191	.987	1.437
	Log_Sales_trans-formed	-.211	.083	6.478	1	.011	.810	.689	.953
	Constant	-.001	.072	.000	1	.990	.999		
Step 12[a]	QR_transformed	-.332	.103	10.442	1	.001	.718	.587	.878
	ET_transformed	.196	.077	6.511	1	.011	1.217	1.047	1.414
	PrM_transformed	.248	.091	7.443	1	.006	1.281	1.072	1.531
	ICR_transformed	.167	.095	3.054	1	.081	1.181	.980	1.424
	Log_Sales_trans-formed	-.217	.082	6.891	1	.009	.805	.685	.947
	Constant	-.002	.072	.000	1	.983	.998		

a. Variable(s) entered on step 1: ROE_transformed, ROCE_transformed, ROA_transformed, QR_transformed, CR_transformed, SGOL_transformed, ET_transformed, ICT_transformed, PrM_transformed, PM_transformed, DAR_transformed, DER_transformed, ICR_transformed, FCF_transformed, Log_Sales_transformed, Log_Assets_transformed.

APPENDIX G: TRAINING SAMPLE DECISION TREE



APPENDIX H: TEST SAMPLE DECISION TREE



AUTHORS

Venkateswaran Vinod is a Ph.D. Research Scholar at the Vellore Institute of Technology Business School, Chennai. His research areas include strategic management, organizational strategy, and the application of emerging technologies, such as machine learning and artificial intelligence, in the field of management. Specifically, he has been working on building prediction models using statistical techniques and machine learning to predict acquisitions.

Venkateswaran Vinod completed his Bachelor in Engineering degree from the Birla Institute of Technology and Science, Pilani, India. He completed his Master's in Business Administration from the California State University, Sacramento, USA.

Dr. Sudarsanam is a Professor at VIT Business School, VIT Chennai. His research areas include Information Systems, Business Analytics, Machine Learning, Fuzzy Systems, Multicriteria Decision Making, and Knowledge Management. He has more than 15 years of IT industry experience and more than 14 years of research and teaching experience.

Dr. Sudarsanam completed his Master's degree and Ph.D. degree in Mathematics from the Indian Institute of Technology, Chennai.