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Logistic Regression Analysis of Key Drivers in Mergers and Acquisitions

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Abstract

The current study evaluates the predictive factors for mergers and acquisitions (M&A) using a logistic regression model, focusing on key financial variables such as Face Value (FV), Advertisement Expenses (AE), and Research & Development (RD). Model 1, with an AIC of 112.67 and an accuracy of 84.17%, performs best overall, providing strong predictive capability for M&A activity. The model reveals that companies with lower face value, higher advertisement expenses, and increased RD spending are more likely to engage in M&A. The ROC curve analysis indicates a robust model with an AUC of 0.9311, suggesting high classification accuracy. Despite its effectiveness, non-random residual patterns highlight areas for improvement, indicating potential non-linearity and outliers. Future improvements could involve refining the model through larger datasets, adding interaction terms, or exploring industry-specific models. These findings provide valuable insights for corporate strategists and investors in identifying potential M&A candidates.

Keywords: Mergers and Acquisitions, Logistic Regression, Face Value (FV), Advertisement Expenses, (AE), Research and Development (RD), AIC, AUC, Residuals, ROC Curve

INTRODUCTION

Mergers and Acquisitions (M&A) are critical components of corporate growth strategies, enabling firms to rapidly expand, gain competitive advantages, diversify product lines, and enhance operational efficiencies. Through M&A, companies can consolidate market power, enter new markets, and leverage synergies that boost financial performance. As global business environments become more competitive, firms increasingly rely on M&A to drive long-term growth. For investors, corporate managers, and policymakers, predicting M&A activities is essential. Accurate predictions help investors identify potential opportunities and risks, assist corporate managers in strategic decision-making, and provide policymakers with insights into market trends that influence regulatory frameworks. Therefore, the ability to forecast M&A events using financial data offers a significant advantage to stakeholders seeking to optimize returns or manage risks in dynamic financial markets.

RESEARCH GAP:

While considerable research has been conducted on M&A, much of it has focused on analyzing financial ratios or conducting qualitative studies to explain the motivations and outcomes of these transactions. However, these approaches have limitations in predictive accuracy, as they often fail to capture the complex relationships between financial variables and the likelihood of M&A. Most existing studies emphasize post-M&A performance rather than developing models that can anticipate M&A activities. The field lacks robust, data-driven models that can predict M&A events before they occur, particularly using sophisticated techniques such as logistic regression. Given the complexity of M&A decisions, there is a pressing need for models that incorporate diverse financial indicators to improve the prediction of M&A activity. By focusing on a more quantitative and systematic approach, such as logistic regression, researchers can build better tools for forecasting M&A, providing stakeholders with more reliable insights.

RESEARCH OBJECTIVE:

The primary objective of this paper is to evaluate the key financial predictors of M&A using logistic regression models. By analyzing financial indicators such as Face Value (FV), Advertisement Expenses (AE), and Research & Development (RD) spending, this study aims to develop a predictive model that can reliably forecast M&A events. The paper seeks to provide actionable insights for corporate strategists and investors by identifying the financial factors that significantly influence the likelihood of M&A activity. Ultimately, the research intends to contribute to the existing literature by filling the gap in predictive models, offering a more data-driven approach to understanding M&A trends. Through the logistic regression model, the study will highlight the relative importance of various financial variables and offer practical applications for identifying potential M&A targets in the corporate sector.

KEY THEORIES ON M&A

1. **Synergy Theory:**

The synergy theory posits that companies engage in Mergers and Acquisitions (M&A) to achieve combined operational efficiencies that are greater than the sum of individual firm capabilities. The idea is that the merged entities can leverage complementary strengths, reduce costs, and increase revenue through economies of scale, cost synergies, or scope synergies. This theory suggests that M&A creates value through improved profitability and efficiency.

2. **Diversification Theory:**

Diversification involves acquiring companies in different industries or sectors to reduce risks associated with over-reliance on a single market or product. The motive is to stabilize earnings by spreading risks across various operations, ensuring that a downturn in one segment does not drastically impact the entire firm. This theory explains why conglomerates or firms in volatile industries often pursue M&A to diversify revenue streams and reduce risk exposure.

3. **Market Share Growth and Monopoly Power:**

Some companies pursue M&A to increase market share and enhance competitive positioning. By acquiring competitors, companies can reduce market competition, increase their pricing power, and potentially achieve monopoly or oligopoly status in a given market. This theory focuses on the strategic goal of market domination and is often driven by the desire for higher margins and stronger market control.

4. **Agency Theory:**

According to agency theory, M&A activity can sometimes be driven by managerial self-interest rather than shareholder value. Managers may seek to engage in M&A for personal reasons, such as empire-building, enhancing their status, or securing long-term employment, rather than to maximize company profitability. The divergence between management and shareholder interests can result in M&A decisions that do not necessarily benefit shareholders.

5. **Hubris Hypothesis:**

The hubris hypothesis suggests that managers may overestimate their ability to improve the performance of an acquired company. Driven by overconfidence, managers may engage in M&A despite the fact that the expected synergies or performance improvements are unlikely to materialize. This theory explains why some acquisitions fail to deliver the anticipated benefits.

LITERATURE REVIEW

1. Early studies on M&A prediction, such as those by **Walter (1984)** and **Pawaskar (2001)**, utilized discriminant analysis to classify companies likely to engage in M&A based on financial ratios. Discriminant analysis separates companies into two categories: those that engage in M&A and those that

don't, based on a linear combination of predictor variables. However, the linearity assumption of discriminant analysis limits its flexibility, especially in complex datasets where relationships between variables are non-linear. Additionally, discriminant analysis is sensitive to violations of normality and equal variance, reducing its effectiveness for M&A prediction.

2. More recent studies, like those by **Klein and Rosenfeld (2020)**, have applied machine learning models such as decision trees, random forests, and support vector machines (SVMs) to predict M&A activities. Machine learning models handle large and complex datasets more effectively than traditional methods, capturing non-linear relationships and interactions among variables. However, they are often seen as "black box" approaches, providing little insight into the specific financial factors driving M&A. While these models offer high predictive accuracy, their interpretability remains a challenge, limiting their use in strategic decision-making by corporate managers.
3. Logistic (logit) and probit regression models have also been applied in predicting M&A, as seen in studies by **Simons and Thompson (1998)**. These models are commonly used to estimate binary outcomes (such as M&A occurrence or non-occurrence) based on financial variables. Logistic regression, in particular, is popular due to its ease of interpretation and ability to handle non-linear relationships through the logit transformation. Probit models, which assume a normal distribution of the error term, offer an alternative approach but are less frequently used due to the similar outcomes they provide compared to logit models.
4. **Multivariate Regression Models**: Empirical studies by **Palepu (1986)** and **Mitchell and Lehn (1990)** used multivariate regression models to explore the relationship between financial characteristics and M&A activity. These studies examined variables such as market-to-book ratio, leverage, and firm size to determine if firms with specific financial characteristics were more likely to engage in M&A. The limitation here is that multivariate models often assume linearity and can oversimplify the complex dynamics that drive M&A activity, particularly in cases where financial indicators interact in non-linear ways.
5. **Event studies** have been widely used to assess the impact of M&A announcements on stock prices. Studies like **Brown and Warner (1985)** and **Jensen and Ruback (1983)** evaluated the abnormal returns around the announcement of M&A deals to determine market reactions. These studies provide valuable insights into the short-term effects of M&A on firm value. However, they focus primarily on stock market data and fail to predict which companies are likely to engage in M&A activity, as they do not analyze the pre-conditions or financial factors leading up to an M&A event.
6. **Decision Trees and Random Forests**: More recent studies, such as **Klein and Rosenfeld (2020)**, applied decision trees and random forests to predict M&A activity. These models excel in handling complex, high-dimensional data and can capture non-linear relationships between financial variables. The random forest method, in particular, provides strong predictive performance by aggregating multiple decision trees to reduce overfitting. However, these models are often criticized for their lack of transparency, as they function as "black boxes" with limited interpretability, making it difficult to identify the financial drivers behind M&A activity.
7. **Support Vector Machines (SVMs)**: Studies like **Boehmer, Masulis, and Simonyan (2009)** employed SVMs to predict which firms might be involved in M&A. SVMs are powerful in finding complex boundaries between companies that engage in M&A and those that do not. However, like other machine learning methods, they are not easily interpretable and do not provide insights into the financial variables or thresholds driving the M&A activity, which limits their practical use in corporate strategy and decision-making.
8. **Logit Models**: Research by **Simons and Thompson (1998)** introduced logit models to estimate the probability of a company engaging in M&A activity based on financial characteristics. Logit models, unlike discriminant analysis, handle non-linear relationships between the independent variables (e.g., financial factors) and the dependent binary variable (whether a company engages in M&A or not). These models have been widely adopted due to their interpretability and ability to estimate probabilities. A key advantage is the ability to assess the marginal impact of each financial variable on the likelihood of an M&A event.

9. **Probit Models**: Similar to logit models, probit models have been used in studies like **Duchin and Schmidt (2013)** to predict M&A activity. Probit models assume a normal distribution of the error term and provide similar predictions to logit models but are sometimes preferred in cases where normality is a more reasonable assumption. The key limitation is that both logit and probit models assume relatively simple relationships between the financial variables and the probability of M&A, which may overlook more complex dynamics that machine learning methods can capture.
10. **Artificial Neural Networks (ANNs)** have been explored in studies like **Wang et al. (2020)**, where they are used to predict M&A events based on historical financial data. ANNs are highly flexible and can capture intricate patterns in data, making them suitable for prediction tasks involving non-linear relationships. However, neural networks require large datasets and are computationally intensive. Like other machine learning techniques, the "black-box" nature of ANNs limits their interpretability, making it difficult for researchers to determine the financial variables driving M&A activity.
11. **Leverage and Profitability Ratios**: Earlier research frequently examined how leverage ratios (e.g., debt-to-equity ratio) and profitability ratios (e.g., return on assets) influence M&A decisions. For instance, studies by **Ghosh (2001)** found that firms with higher leverage were more likely to engage in M&A due to the potential for improved debt servicing through increased revenues. Similarly, research by **Mandelker and Raviv (1977)** highlighted that firms with higher profitability were more inclined to acquire other companies as a strategy for growth. However, these studies often did not account for the interaction between multiple financial variables, potentially missing more nuanced predictive signals.
12. **Market-to-Book Ratios**: Research such as that by **Eckbo and Thorburn (2009)** explored how market-to-book ratios influence M&A activity, with higher ratios indicating overvalued stocks that could be used as currency in acquisitions. Despite providing valuable insights, these studies sometimes overlooked other financial variables that could impact M&A decisions.
13. **Managerial Incentives and Corporate Strategy**: Studies like **Jensen (1986)** emphasized managerial incentives and agency problems in M&A decisions. For example, managers may pursue M&A to increase their firm's size and, consequently, their own compensation, rather than purely based on financial metrics. These qualitative factors are critical in understanding M&A dynamics but are often less quantifiable than financial metrics.
14. **Corporate Culture and Strategic Fit**: Research by **Datta and Puia (1995)** highlighted the importance of strategic fit and corporate culture in M&A success. They found that companies with compatible cultures and strategies were more likely to experience successful M&A outcomes. However, such qualitative assessments are challenging to integrate into quantitative predictive models, limiting their applicability in data-driven predictions.
15. **Industry-Specific Drivers**: Some studies have focused on sector-specific factors influencing M&A. For instance, **Ravenscraft and Scherer (1987)** analyzed how industry consolidation trends impacted M&A activity in the pharmaceutical sector. These studies reveal that different industries may have unique M&A drivers, which could be missed in more generalized models. Incorporating industry-specific variables could improve model accuracy and relevance.
16. **Technological and Market Trends**: Research like **Campa and Kedia (2002)** examined how technological advancements and market trends influence M&A activity, particularly in tech sectors. They found that rapid technological change drives companies to acquire firms with complementary technologies. However, such studies often focus on broader market trends rather than specific financial predictors.
17. **Temporal Dynamics**: Longitudinal studies, such as those by **Hubbard and Palia (1995)**, which analyze M&A trends over extended periods, face challenges related to changing economic conditions and evolving financial practices. While they provide valuable historical context, they may not fully account for recent changes in financial regulations, market conditions, or technological advancements.

Data Collection

1. **Dataset Overview:**

The research design employed in this study is descriptive and empirical, focusing on analysing the performance of mergers and acquisitions (M&As) from various perspectives. The data primarily derives from secondary sources, chiefly the Prowess IQ database maintained by the Centre for Monitoring the Indian Economy (CMIE). Additionally, M&A deal information is sourced from the websites of the Bombay Stock Exchange (BSE) and the Securities and Exchange Board of India (SEBI). The sample encompasses M&A deals occurred between March 31, 2013, and March 31, 2023. For the analysis, Logit Regression model is applied for entire study analysis using Excel and R program. The collected data for the study is graphically presented, adequately tabulated, suitably analyzed, and meaningfully interpreted.

Sample Selection criteria: The study is based on a sample of 60 Mergers and Acquisition (M&A) companies and 60 non-manufacturing companies (non-M&A) during the study period. According to the National Industrial Classification (NIC) code, Indian corporate enterprises are broadly classified into sixteen major groups of industries. This study focused on the manufacturing industry: 1. Chemicals, Drugs, and Fertilizers; 2. Food products; 3. Textile; 4. Energy, Gas, Oil, Power, and allied industries; 5. Transport Machinery; 6. Electrical and Electronics. These companies are listed on the Bombay Stock Exchange (BSE).

Selected firm-specific variables:

1. Age
2. Size
3. Promotors Holding (PH)
4. Face Value (FV)
5. Market Capitalisation (MCA)
6. Current Ratio (CR)
7. Return on Equity (ROE)
8. Debt to Equity (DE)
9. Research and Development (RD)
10. Advertisement Expenses (AE)

1. **Logistic Regression Methodology:**
   - **Purpose:** logistic regression model provides important insights into how different independent variables are associated with the likelihood of companies engaging in mergers and acquisitions (M&A).
   - **Logistic Regression Equation:**

     Logit(P(M&A=1))=−1.479+(0.01844×AGE)+(0.00002162×SIZE)+(0.02648×PH)−(0.2258×FV)−(0.000002698×MCAP)+(0.07869×CR)−(1.989×ROE)−(0.4351×DE)+(0.6937×RD)+(1.174×AE)
2. **Model Specifications:**
   - **Model 1: Includes the primary financial predictors (FV, AE, RD) to evaluate their individual and combined impact on M&A likelihood.**

Model Comparison Metrics

1. **Akaike Information Criterion (AIC):**
   - **Measures the relative quality of the model for a given dataset. It penalizes for the number of predictors used, helping to avoid overfitting.**
   - **Formula:**AIC = −2×log-likelihood+2×K

2. **Bayesian Information Criterion (BIC):**
   - **Similar to AIC but imposes a larger penalty for models with more parameters, making it stricter in model selection.**

- **Formula:** BIC = -2 * LL + log(N) * k

3. **Tjur's R^2:**
    - **Provides a measure of the proportion of variance explained by the model in the context of binary classification.**
    - **Formula:** R2Tjur = 1n1∑ˆπ(y=1)−1n0∑ˆπ(y=0)
4. **Root Mean Squared Error (RMSE):**
    - **Measures the average magnitude of the prediction errors, providing an estimate of how well the model predicts the outcome.**
    - **Formula:** RMSE = sqrt [(Σ(Pi – Oi)²) / n]
5. **Log Loss:**
    - **Quantifies the performance of a classification model whose output is a probability value between 0 and 1. Lower values indicate better performance.**
    - **Formula:** Log-Loss = - (y * log(p) + (1 - y) * log(1 - p))
6. **Proportion Correctly Predicted (PCP):**
    - **Represents the proportion of correct predictions out of all predictions made by the model**
    - **Formula:PCP=Total Number of Predictions/Number of Correct Predictions×100**
7. **ROC Curve and AUC:**
    - **ROC Curve:** used to fit models for probability of disease given marker values while ROC curves and risk distributions are used to evaluate classification performance.
    - **AUC (Area Under the ROC Curve):** an aggregated metric that evaluates how well a logistic regression model classifies positive and negative outcomes at all possible cutoffs
    - **Empirical analysis**

Table No 1: Comparison of Model Performance IndicesUsing Logit RegressionModel

Name	AIC (weights)		AICc	weights	BIC	weights	Tjur's R2	RMSE	Sigma	Log loss	Score spherical	PCP
Model1	112.7	0.025	115.1	-0.013	143.3	(<.001)	0.55	0.322	0.912	0.378	0.018	0.775
Model2	110.8	0.064	112.8	-0.039	138.7	(<.001)	0.548	0.323	0.909	0.378	0.018	0.774
Model3	109.2	-0.142	110.9	-0.106	134.3	-0.002	0.545	0.324	0.907	0.38	0.018	0.772
Model4	108.3	-0.226	109.6	-0.2	130.6	-0.012	0.538	0.327	0.908	0.385	0.017	0.769
Model5	109.2	-0.142	110.2	-0.145	128.7	-0.03	0.523	0.332	0.918	0.397	0.014	0.761

Model6	108.7	-0.184	109.4	-0.214	125.4	-0.157	0.516	0.335	0.921	0.403	0.021	0.758
Model7	108.4	-0.213	108.9	-0.276	122.4	-0.73	0.507	0.337	0.925	0.41	0.049	0.754
Model8	115.9	-0.005	116.3	-0.007	127.1	-0.069	0.444	0.36	0.965	0.45	0.025	0.722

Source: Authors Compilation

Model 7 has the lowest AIC, AICc and BIC (108.4), (108.9) and (122.4) respectively suggest that it strikes the best balance between fit and model complexity, the best option when adjusting for sample size and when preferring simpler models.

Model1 has the highest Tjur's R^2 (0.550) suggesting explanation of the most variance. In terms of RMSE (0.322), Sigma (0.912) and Log Loss (0.378), it has the lowest value, meaning it has the best prediction accuracy, smaller residuals and the best probabilistic predictions. Its PCP (Proportion Correctly Predicted) (0.775) is the highest indicating this model correctly classifies the most cases.

While model 7 has the best values for AIC, AICc, and BIC, model 1 is the best-performing model overall because it has the highest Tjur's R^2, the lowest RMSE, the lowest Log Loss, and the highest PCP. Therefore, model 1 seems to provide the best fit and predictive performance among the models.

Table No 2: Summary of the Firm-Specific Factors Using Logit RegressionModel

Coefficient	Estimate	Std. Error	z value	Pr(>|z|)	Signif. codes
(Intercept)	-1.479	1.409	-1.05	0.29383	
AGE	0.01844	0.01639	1.125	0.26049	
SIZE	0.00002162	1.364E-05	1.585	0.11304	
PH	0.02648	0.01872	1.415	0.15716	
FV	-0.2258	0.06926	-3.26	0.00111	**
MCAP	-0.000002698	4.148E-06	-0.65	0.51548	
CR	0.07869	0.2046	0.385	0.70049	
ROE	-1.989	1.66	-1.198	0.2309	
DE	-0.4351	0.3075	-1.415	0.15707	
RD	0.6937	0.3616	1.918	0.05509	.
AE	1.174	0.4803	2.444	0.01452	*

Source:*Authors Compilation*

Note: *, **and*** denotes 10%, 5%, and 1% level of significance.

The logistic regression equation for Model 1 based on the provided coefficients is as follows:

$$\text{Logit}(P(M\&A=1))=-1.479+(0.01844\times AGE)+(0.00002162\times SIZE)+(0.02648\times PH)-(0.2258\times FV)-(0.000002698\times MCAP)+(0.07869\times CR)-(1.989\times ROE)-(0.4351\times DE)+(0.6937\times RD)+(1.174\times AE)$$

In this equation: P (M&A=1) P (M&A=1) P (M&A=1) represents the probability of the company engaging in mergers and acquisitions.

The coefficients for each variable represent their impact on the log-odds of M&A=1M&A = 1M&A=1.

The summary of the logistic regression model provides important insights into how different independent variables are associated with the likelihood of companies engaging in mergers and acquisitions (M&A).

Findings of the Study

1. Model Fit: The Null Deviance is 166.355 on 119 degrees of freedom, while the Residual Deviance is 90.675 on 109 degrees of freedom. A significant drop in deviance indicates that the model1 fits the data better than a model 7 without predictors. The AIC (Akaike Information Criterion) is 112.67. A lower AIC suggests a better model, but it's primarily useful when comparing different models.

2. Significant Variables: FV (Face Value) has a significant negative effect (Estimate = -0.2258, p-value = 0.00111). This suggests that companies with a lower face value are more likely to engage in mergers and acquisitions.AE variable is also significant (Estimate = 1.174, p-value = 0.01452). It indicates that companies with higher asset efficiency are more likely to engage in M&A.RD (Research and Development Expenses)variable is marginally significant (Estimate = 0.6937, p-value = 0.05509). Companies with higher RD spending are more likely to engage in mergers and acquisitions.

3. Non-Significant Variables: AGE, SIZE, PH (Promoters Holding), MCAP (Market Capitalization), CR (Current Ratio), ROE (Return on Equity), and DE (Debt-to-Equity) show relatively high p-values (above 0.05), suggesting that these variables do not have a statistically significant effect on the likelihood of engaging in mergers and acquisitions in this model 1. However, the estimate forSIZEis relatively close to significance (p-value = 0.11304), which could mean that with a larger dataset or further refinement, size could potentially be a meaningful predictor.

4. Model Coefficients: The direction of coefficients indicates the impact on the likelihood of engaging in M&A: Positive coefficients of AGE, SIZE, PH, AE, and RD increase the likelihood of engaging in M&A. Negative coefficients of FV, MCAP, ROE, and DE reduce the likelihood of engaging in M&A.

5. **Deviance Residuals:** The residuals ranging from -4.1010 to 2.0420 suggest that the model 1has some data points with relatively large deviations, but the residuals are not extremely out of range, implying a reasonable fit.

Implications of the Study

1. Strategic Planning for M&A: The significant negative relationship between FV and M&A suggests that companies with lower face values may seek growth through mergers and acquisitions more actively. This could imply that investors or management in smaller-cap companies (with lower stock prices or book values) might be more aggressive in pursuing external growth strategies.

2. Efficiency and Innovation: The significant positive relationship between AE and M&A indicates that efficient companies with well-utilized advertisement are more likely to expand through mergers. This could suggest that efficient companies are in a stronger financial position to pursue acquisitions.RD spending is marginally significant, which implies that companies investing in innovation and research might also be likely candidates for M&A activities, potentially to acquire complementary technologies or market expansion.

3. Non-Significance of Other Financial Metrics: Traditional financial health metrics such as ROE, DE, CR, and MCAP were not statistically significant in predicting M&A activity. This could suggest that external growth strategies such as mergers and acquisitions are driven more by strategic factors like efficiency and innovation rather than just financial ratios.

4. Further Model Refinement: While some variables were not statistically significant in this model 1, they might still have practical importance, or their relationships could emerge with a larger or more detailed dataset.SIZE, for example, is borderline significant and could play a more critical role in different contexts.

5. Application in Corporate Strategy: This model 1 can assist corporate managers and financial analysts in identifying the types of companies more likely to engage in mergers and acquisitions. Companies looking to acquire might focus on smaller, efficient firms with lower face values, while also recognizing the importance of efficiency and innovation.- Investors could use this model 1 to identify potential M&A targets by screening companies based on their FV, AE, and RD metrics.

Recommendations of the Study

1. Increase Sample Size: To improve the robustness of the model 1 and potentially capture more significant relationships (especially for SIZE and RD), consider expanding the dataset with more companies or additional periods.

2. Further Investigation: Additional variables related to company management, industry type, or economic conditions could help refine the model 1 further.

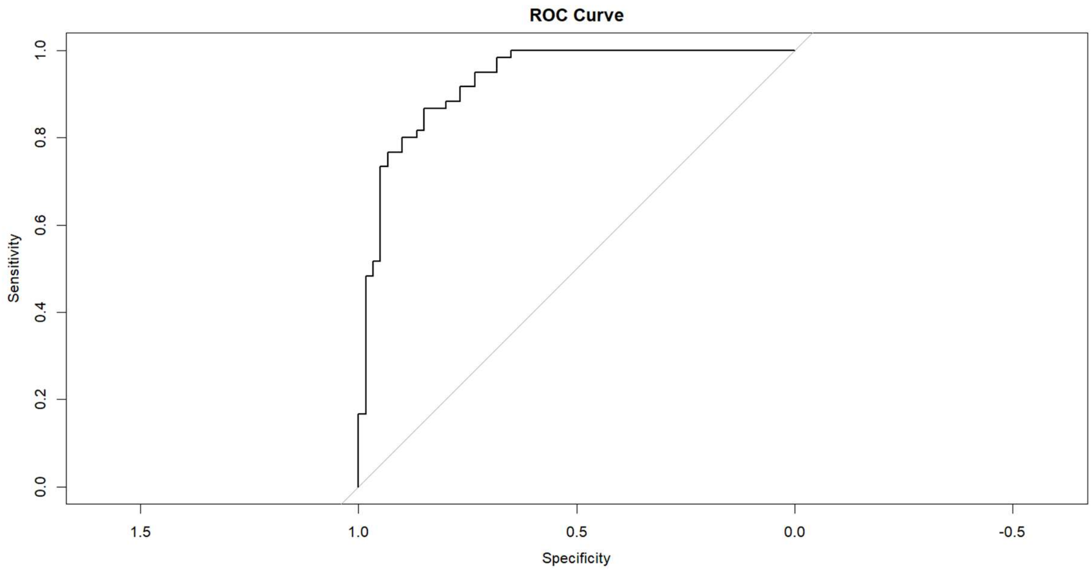
3. Industry-Specific Models: It might be beneficial to explore industry-specific models, as M&A drivers can vary significantly between sectors. These findings should inform strategic decisions related to mergers and acquisitions, with a focus on advertisement and innovation as key drivers.

Confusion Matrix: The confusion matrix shows the model's performance in predicting M&A engagements. True Positives (Predicted 1, Actual 1): 50 companies were correctly predicted to engage in M&A.True Negatives (Predicted 0, Actual 0): 51 companies were correctly predicted not to engage in M&A.False Positives (Predicted 1, Actual 0): 9 companies were incorrectly predicted to engage in M&Abut didn't.False Negatives (Predicted 0, Actual 1): 10 companies were predicted not to engage in M&A but actually did. The accuracy is 84.17%, indicating good model performance, though there's a trade-off between false positives and false negatives.

Confusion Matrix		
	Predicted 0	**Predicted 1**
Actual 0	51	9
Actual 1	10	50
accuracy	0.84166	

The model 1 has an accuracy of 84.17%, correctly predicting most cases. It effectively distinguishes between companies engaging in M&A and those not. However, there is room for improvement, particularly in reducing false positives and false negatives.

ROC Curve: The ROC curve demonstrates that model 1 has strong classification performance, with high sensitivity and specificity. The curve's proximity to the top-left corner indicates a high level of accuracy in distinguishing between positive and negative outcomes. This implies the model 1 is effective at predicting mergers and acquisitions with minimal false positives or negatives.

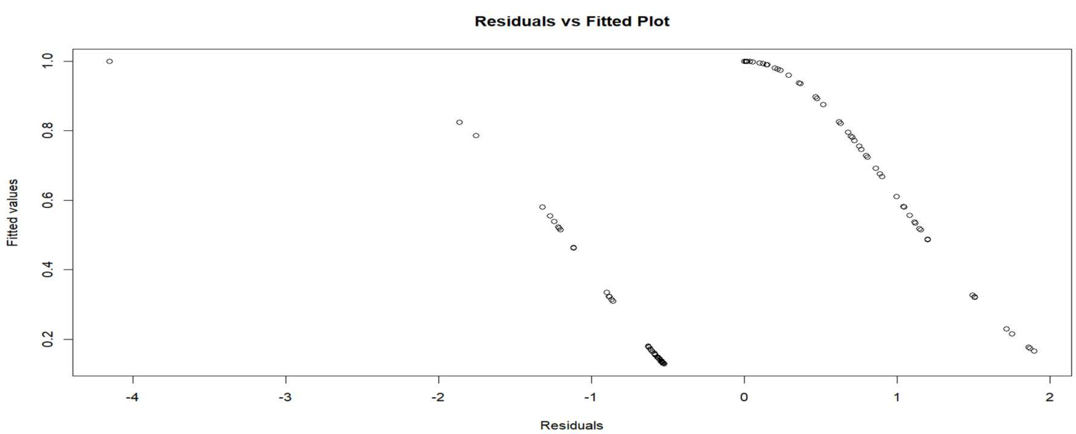


The AUC (Area Under the Curve) value of 0.9311 indicates a strong model performance. AUC values range from 0 to 1, where 1 represents a perfect model and 0.5 represents a model with no discriminatory ability. An AUC of 0.9311 suggests that model 1 is highly effective at distinguishing between the two classes (companies engaging in M&A vs. not engaging in M&A) with a high degree of accuracy. This means the Model1 is good at predicting both true positives and true negatives.

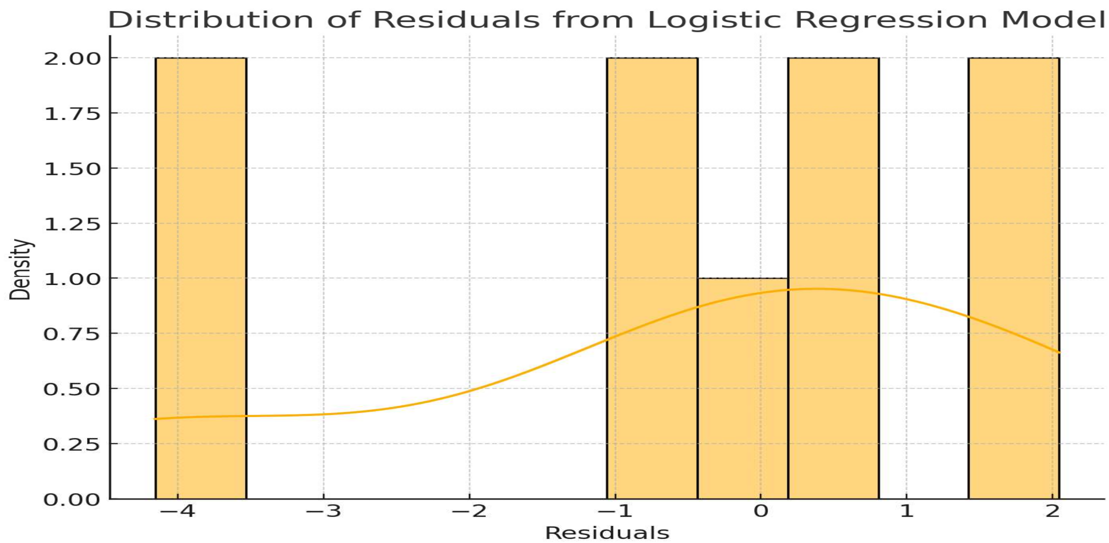
Residuals vs fitted values plot:

- **Residuals** represent the difference between the actual and predicted values by the model.
- **Fitted values** are the predicted values based on the logistic regression model.

In a good model, the residuals should be randomly scattered around 0 without a clear pattern. If the residuals show a trend or curve, it might indicate that the model does not fully capture the underlying structure of the data or that the model assumptions are violated.



The residuals vs. fitted plot shows non-random patterns, indicating potential issues with model fit or the presence of outliers. The curved pattern suggests the model may not capture the underlying relationship effectively, indicating the need for model refinement or transformation of variables. The curved pattern suggests some non-linearity, indicating that the model may not fully fit the data perfectly. There may also be some outliers, especially at the extreme ends of the residuals, which could influence the model's predictions. This pattern might suggest further model improvements, such as adding interaction terms or trying more complex models.



The plot above shows the distribution of residuals from the logistic regression model. Key observations:

1. **Spread of Residuals**: The residuals are spread across both negative and positive values, indicating varying errors between the actual and predicted values.
2. **Normality of Residuals**: The residual distribution is not perfectly normal, as seen by the sharp drops and peaks, indicating that there may be some variance not captured well by the model. Ideally, residuals should be more normally distributed in a well-fitted model.
3. **Outliers**: There are residuals far from 0 (around -4 and +2), which could be outliers, suggesting that the model struggles with certain data points.

Conclusion

The analysis shows that model1 performs well in predicting mergers and acquisitions, with an accuracy of 84.17% and a strong AUC value of 0.9311. Significant variables like Face Value (FV), Advertisement expense (AE), and Research & Development (RD) indicate that companies with lower face value, higher advertisement expense, and higher RD spending are more likely to engage in M&A. However, the model 1shows some limitations, with non-random residuals and the potential for further refinement. Although not statistically significant, variables like SIZE suggest potential for further exploration. Overall, the model 1 provides useful insights for identifying M&A candidates, but further improvements in model 1 fit and accuracy can be achieved through model tuning, interaction terms, or larger datasets.

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