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The Impact of Artificial Intelligence on Financial Ratios Indicating Financial Distress: Evidence from NYSE-Listed Companies

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ABSTRACT
Integrating artificial intelligence (AI) in financial institutions has transformed financial distress prediction by improving risk assessment and operational efficiency. This study analyzes the relationship between AI adoption and key financial and macroeconomic indicators. A generalized linear model (GLM) with a binomial logit function was utilized to evaluate the impact of AI adoption on financial distress and the reverse. The dataset includes 2,000 NYSE-listed firms from 2019 to 2023, obtained from the FMP cloud database. Statistical techniques such as descriptive analysis, correlation analysis, Principal Component Analysis (PCA), and logistic regression with LASSO and Ridge regularization were employed to enhance model accuracy and control for multicollinearity. Findings indicate that AI adoption is negatively correlated with the Debt-to-Equity Ratio (-0.65) and positively correlated with the Current Ratio (0.85) and ROA (0.77), suggesting that AI-adopting firms have stronger financial health. Regression analysis confirms that liquidity, profitability, and market volatility significantly influence AI adoption, while leverage and macroeconomic indicators show weaker predictive power. LASSO regression identifies Stock Market Volatility (0.87) as the strongest predictor of AI adoption. AI adoption is associated with improved financial stability, reinforcing its role in mitigating financial distress. Future studies should explore sectoral differences and incorporate advanced machine learning techniques for predictive modeling.

1. INTRODUCTION

Financial distress prediction has evolved significantly over the decades, beginning with traditional accounting-based models and progressing toward more sophisticated statistical and advanced computational techniques. Early methods, such as Altman's Z-Score (1968), relied on financial ratios to assess a firm's likelihood of bankruptcy (Jiang et al., 2023; Wang et al., 2018). These models provided a foundational framework but were often limited by their reliance on historical financial statements, making them less effective in capturing real-time financial distress signals (Huang et al., 2012; Jiang et al., 2023). Subsequent advancements introduced multivariate statistical techniques, including logistic regression and discriminant analysis, to enhance predictive accuracy. However, these models still suffered from key limitations, such as assumptions of linearity, data stationarity, and the inability to effectively handle large, complex datasets (Al Ali et al., 2023; Wang et al., 2018; Yu & Li, 2023). Furthermore, traditional models could not develop a strong classifier for actual predictions and often lacked adaptability to evolving economic conditions and industry-specific risk factors (Al Ali et al., 2023).

Before the adoption of artificial intelligence (AI), financial distress prediction was largely constrained by these methodological shortcomings. AI-driven approaches, such as machine learning (ML) and deep learning, have since emerged as powerful alternatives, enabling the analysis of vast datasets, uncovering hidden patterns, and improving predictive accuracy through adaptive learning (Bao et al., 2015; Lokanan & Ramzan, 2024; Ramzan & Lokanan, 2024). AI enables financial institutions to analyze enormous amounts of data with exceptional accuracy and velocity (Carmona et al., 2022; Figlioli & Lima, 2022; Lokanan & Ramzan, 2024; Ramzan & Lokanan, 2024). AI systems process vast amounts of data to detect potential risks and provide proactive insights for managing financial risk (Dbouk & Zaarour, 2017; Lokanan & Ramzan, 2024; Ramzan, 2023).

The finance industry identifies and prevents fraudulent activities, manages risks, conducts predictive analytics, and facilitates automated trading while enhancing the identification and prediction of financial degradation (Bartel et al., 2024; Petric, 2024) with the help of AI's data analysis automation, and predictive modelling capabilities (Dbouk & Zaarour, 2017). AI-based technologies enhance data processing efficiency and improve prediction accuracy, reducing false positives (Achakzai & Juan, 2022; Lokanan & Ramzan, 2024; Ramzan, 2023). As such, AI techniques are being utilized by organizations to predict and identify financial distress by using financial indicators to attain higher prediction accuracy and to reduce false positives. AI models, especially ML techniques, detect fraud patterns and anomalies, enhancing the security of transactions (Lokanan & Ramzan, 2024; Ramzan & Lokanan, 2024). Moreover, AI utilizes unconventional data sources such as utility bill payments, rental payment history, social media activity, and online shopping behaviour to enhance the reliability of credit scores (Lokanan & Liu, 2023). AI techniques optimize transactions in algorithmic trading systems by analyzing structured and unstructured data to maximize profits and reduce losses (Lokanan & Liu, 2023; Ramzan & Lokanan, 2024). Based on the extant literature, AI algorithms have the potential to significantly improve financial performance and predict financial distress when implemented effectively (Carmona et al., 2022; Lokanan & Ramzan, 2024; Ramzan & Lokanan, 2024).

2. Literature Review

With the increasing adoption of AI, it is crucial to comprehend its broader impact on organizational financial health and stability, particularly financial distress. Incorporating AI for financial distress prediction aims to enhance the precision of financial crisis forecasts by redefining what factors lead to a financial crisis and employing ML algorithms (Bartel et al., 2024; Petric, 2024). Financial distress occurs when a corporation is unable to meet its financial obligations and has stagnant operations and insufficient cash flows, resulting in either bankruptcy or the need for restructuring (Farooq & Qamar, 2019; Kristanti et al., 2023; Liu et al., 2023). Financial distress is, therefore, a preceding stage before bankruptcy (Kristanti et al., 2023). Adverse wealth effects can arise from the depletion of financial assets and the downward impact on asset values (Bartel et al., 2024). Kristanti and her supporting authors (2023) argue that financial distress occurs when management cannot implement business strategies, determine capital plans, manage debt structures and follow financial markets. When a company fails to manage and handle risks, it will build up and explode, triggering a crisis (Sun et al., 2023; Yu & Li, 2023).

Financial distress is a critical concern for businesses, potentially leading to bankruptcy or significant restructuring (Farooq & Qamar, 2019; Jiang et al., 2023; Kristanti et al., 2023; Liu et al., 2023). Key financial ratios used to assess the likelihood of financial distress include the debt-to-equity ratio, which measures a company's financial leverage by comparing total liabilities to shareholders' equity (Gupta & Mehta, 2024). A high debt-to-equity ratio indicates higher financial risk and potential distress (Gupta & Mehta, 2024; Ramzan & Lokanan, 2024). The current ratio assesses a company's ability to meet short-term obligations with its current assets, where a low current ratio may signal liquidity issues and impending financial distress (Gupta & Mehta, 2024). Return on assets (ROA) measures profitability relative to total assets, with lower ROA values indicating inefficiency and financial problems (Gupta & Mehta, 2024; Ramzan & Lokanan, 2024; Wang et al., 2018). These indicators are critical for investors, creditors, and management in evaluating a company's financial health and risk of distress. Various studies have used financial ratios such as debt-to-equity, current, and ROA ratios to evaluate a company's financial well-being and any potential financial distress (Ding et al., 2023; Farooq & Qamar, 2019; Gupta & Mehta, 2024; Jiang et al., 2023; Kristanti et al., 2023; Liu et al., 2023; Wang et al., 2018; Zhao et al., 2023).

AI can potentially enhance these ratios by enhancing financial management and operational efficiency (Petric, 2024). AI can improve the accuracy and reliability of financial reporting, reducing the risk of errors and enhancing transparency (Dbouk & Zaarour, 2017; Figlioli & Lima, 2022; Ramzan & Lokanan, 2024). By leveraging AI, companies can gain advanced insights into financial risk factors, enabling them to anticipate and respond to potential financial challenges more effectively (Bartel et al., 2024). While considering financial factors, this proactive approach facilitates the development of robust financial strategies that address immediate financial concerns and fortify the company's overall economic foundation (Ramzan & Lokanan, 2024). Gaining insight into how AI enhances financial well-being can enhance investor trust, thereby stimulating investments and fostering market expansion (Liu et al., 2023; Ramzan & Lokanan, 2024; Trabelsi, 2023). Investors may gain more confidence in the financial prospects of firms that integrate AI and enhance capital inflows as they observe potential improvements in risk management, predictive analytics, and operational efficiency (Liu et al., 2023; Ramzan, 2023). Various stakeholders, such as investors, shareholders, creditors, auditors, etc., are interested in early prediction of financial distress as they can make informed decisions about AI investments and implementations to optimize their financial performance and reduce distress risks (Lin et al., 2013; Yu & Li, 2023;

Lokanan & Liu, 2023; Ramzan & Lokanan, 2024; Zhao et al., 2023).

Given these potential benefits, the research aims to examine if there are significant differences in critical financial performance indicators between companies that have adopted AI and those that have not by categorizing them based on their level of AI implementation. This study investigates how adopting AI influences vital financial ratios—debt-to-equity ratio, current ratio, and ROA—associated with financial distress among NYSE-listed companies. The objectives are to assess AI adoption prevalence and early adopter characteristics, analyze the impact on financial ratios over time, compare financial performance between AI adopters and non-adopters, and provide actionable insights for stakeholders. The research aims to contribute valuable knowledge to finance and technology by achieving these objectives, emphasizing AI's transformative potential in enhancing financial health and mitigating distress in the financial landscape.

Hypotheses Development

Financial distress in corporations refers to a state where a firm struggles to meet its financial obligations, often leading to insolvency or bankruptcy (Bao et al., 2015; Farooq & Qamar, 2018). Distressed firms usually face excessive debt burdens and are unable to cover short-term liabilities, thus facing high financial strain (Abdullah et al., 2016).

The hypotheses for this research are formulated based on insights drawn from existing literature on the impact of AI on organizational financial performance and the conceptualization of financial distress. These hypotheses are designed to assess how AI adoption influences vital financial ratios that indicate financial distress among companies listed on the New York Stock Exchange (NYSE). Three types of financial ratios are used in this study to understand the influence of AI adoption due to their predictive power, accessibility and standardization (Ding et al., 2023; Farooq & Qamar, 2019; Figlioli & Lima, 2022). The debt-to-equity ratio is a critical measure of a company's financial leverage, reflecting the proportion of debt used to finance the company's assets relative to shareholders' equity (Ding et al., 2023). High debt-to-equity ratios indicate greater financial risk and potential distress (Ding et al., 2023; Gupta & Mehta, 2024). Studies have shown that optimization of debt levels leads to better forecasting and risk assessment, as debt is positively related to cost fixity and agency cost (Carmona et al., 2022; Ding et al., 2023).

The current ratio measures a company's capacity to fulfil its immediate financial commitments using its existing assets (Figlioli & Lima, 2022). A more excellent current ratio indicates improved liquidity and reduced risk of a financial crisis (Gupta & Mehta, 2024; Jabeur et al., 2023; Ramzan & Lokanan, 2024). ROA measures a company's profitability relative to its total assets. Higher ROA values indicate more efficient use of assets to generate profits, reflecting better overall financial health (Gupta & Mehta, 2024; Lokanan & Ramzan, 2024). Jabeur and his supporting authors (2023) state in their study that high profitability ratios tend to result in low insolvency risk.

Thus, the research aims to examine three hypotheses:

H1: The adoption of AI is associated with a decrease in the debt-to-equity ratio amongst financial institutions in the United States.

H2: The adoption of AI is associated with an increase in the current ratio amongst companies in the United States.

H3: The adoption of AI is associated with an increase in the ROA ratio amongst companies in the United States.

These hypotheses set the foundation for empirical analysis in this research, which aims to understand the impact of AI adoption on key financial ratios indicative of financial distress. By testing these hypotheses, the study seeks to provide statistical evidence on whether AI adoption contributes to improved financial stability and reduced distress among NYSE-listed companies.

3. METHODOLOGY

This article applied a generalized linear model (GLM) with a binomial logit function to assess the impact of AI adoption on key financial ratios associated with financial distress among companies listed on the New York Stock Exchange (NYSE). Our regression model includes multiple independent variables, such as Current Ratio, ROA, Debt-to-Equity Ratio, and principal components (PC1 and PC2) derived from control variables to mitigate multicollinearity concerns. The study utilizes a longitudinal approach, examining financial data for five years (2019, 2020, 2021, 2022 and 2023) to capture changes in financial ratios due to AI adoption. The inclusion of longitudinal data allows for a stronger causal interpretation of AI adoption's effects on financial distress indicators, addressing the limitations of a shorter observation window.

The data collection stage in this study involves gathering financial statements and AI adoption indicators for the selected sample of companies. Data is gathered from the annual financial statements of NYSE-listed companies obtained from the FMP cloud database. Information on AI adoption is sourced from company reports, press releases, and industry databases that track technological implementations.

The sample consists of 2000 companies listed on the NYSE. Companies are selected based on the availability of complete financial and AI adoption information for 2019, 2020, 2021, 2022 and 2023. A mix of companies that have adopted AI and those that have not is included, with a higher proportion of non-adopters to reflect real-world distribution. Furthermore, the analysis employed multiple quantitative techniques, including descriptive statistics, correlation analysis, principal component analysis (PCA), and regression modelling, all of which were conducted using the Python programming language and its statistical libraries. This approach ensured computational efficiency, reproducibility, and robust data handling throughout the study. Moreover, for better results, logistic regression is implemented further in the study with regularization techniques namely Ridge (L1) and Lasso (L2) regularization.

Dependent Variables

The dependent variable in this study is AI_Adoption, represented as a binary variable that indicates whether a company has integrated AI technologies into its operations (1 = Adopted AI, 0 = Did not adopt AI). AI adoption is a dependent variable due to its growing influence on transforming corporate processes, impacting strategic direction, financial performance, and operational capabilities. Companies that have adopted AI are characterized by deploying AI technologies in core business processes, such as predictive analytics, ML algorithms, and automated decision-making systems. They utilize AI-driven tools for tasks like fraud detection, risk management, credit scoring, and financial forecasting and enhance customer interactions through AI chatbots, virtual assistants, and personalized recommendation systems. Additionally, AI adopters integrate AI into supply chain management, logistics, inventory control, and process automation while leveraging AI for big data analytics, sentiment analysis, and market trend predictions. Investment in AI research and development, participation in AI-related projects, and the use of AI in financial management further distinguish these companies. In contrast, companies that have not adopted AI show no evidence of AI technologies in their operations, relying instead on traditional methods for decision-making, customer service, data analysis, and financial management, with minimal investment in AI-related research and development.

$$AI\_Adoption_i = \begin{cases} 1 & if\ company\ i\ has\ adopted\ AI\ technologies \\ 0 & if\ company\ i\ has\ not\ adopted\ AI\ technologies \end{cases} \quad (1)$$

Independent Variables

The primary focus of the study is on three independent financial variables: the Debt-to-Equity Ratio, the Current Ratio, and the ROA. The Debt-to-Equity Ratio quantifies a firm's financial leverage by measuring the proportion of debt relative to shareholder equity. A higher ratio suggests increased reliance on debt financing, which can elevate financial risk and impact a firm's ability to invest in technological advancements such as AI adoption. The relationship is modelled as follows:

$$Debt\ to\ Equity\ Ratio = \beta_0 + \beta_1 AI\_Adoption + \varepsilon \quad (2)$$

The Current Ratio evaluates a company's liquidity position by measuring its ability to cover short-term obligations with available current assets. A higher Current Ratio indicates greater financial flexibility, potentially enabling firms to allocate resources toward AI investments. The equation is specified as:

$$Current\ Ratio = \beta_0 + \beta_1 AI\_Adoption + \varepsilon \quad (3)$$

Finally, ROA assesses a firm's profitability relative to its total assets, reflecting operational efficiency and financial performance. Firms with higher ROA values may have greater capacity to invest in AI, leveraging technological innovations to enhance performance. The model is represented as:

$$Return\ on\ Assets = \beta_0 + \beta_1 AI\_Adoption + \varepsilon \quad (4)$$

By comparing these financial variables, the study examines if differences in firms' leverage, liquidity, and profitability lead to adopting AI compared to those not utilizing AI. Awareness of these impacts may enhance understanding of AI technology's strategic implications and financial benefits.

Table 1: Independent Variables

Indicators	Definition	Formula
Debt-to-Equity Ratio	Measures a firm's leverage while considering the total debt and equity structure of firms. A higher ratio indicates extensive usage of debt, leading to increased financial risk.	$Debt\ to\ Equity\ Ratio = \frac{Total\ Liabilities}{Total\ Shareholder's\ Equity}$
Current Ratio	Assesses a firm's liquidity and ability to meet short-term liabilities using current assets. A higher ratio suggests stronger liquidity.	$Current\ Ratio = \frac{Current\ Assets}{Current\ Liabilities}$
Return on Assets (ROA)	Measures a firm's profitability by assessing how efficiently assets generate net income. Higher ROA indicates better operational efficiency.	$ROA = \frac{Net\ Income}{Total\ Assets}$

Control Variables

Several control variables are incorporated into the model to enhance the robustness of the analysis and control for external factors that may influence financial performance. Larger firms often possess greater financial resources and infrastructure to support AI adoption. Market

Capitalization serves as a proxy for firm size in this study, as firms with higher valuations are more likely to invest in advanced technologies. The broader economic environment influences firms' strategic investment decisions. GDP growth is controlled for, as firms operating in high-growth economies may have greater incentives to integrate AI. Market volatility affects investment risk and capital allocation decisions. Firms operating in high-volatility environments may be more inclined to adopt AI to manage risk and enhance predictive analytics. Inflationary pressures impact operational costs and financial stability. Firms operating in high-inflation economies may prioritize cost-saving technologies, influencing AI adoption. Therefore, the four control variables in this study are market capitalization, GDP growth rate, stock market volatility and inflation rate.

4. Results and Analysis

A. Descriptive Statistics

The descriptive analysis, as shown in Table 2 below, reveals that AI adoption remains relatively low, with only 28.87% of firms integrating AI technologies, suggesting that adoption is concentrated among a subset of firms. The debt-to-equity ratio (mean = 2.13, wide dispersion) indicates diverse financial structures, with some firms highly leveraged while others maintain lower debt levels.

Table 2. Descriptive Statistics

Year	Measure (count of 10,000)	AI Adoption	Debt-to-Equity Ratio	Current Ratio	ROA	GDP Growth Rate	Stock Market Volatility	Inflation Rate	Market Capitalization
	Mean	0.2887	2.13	1.30	5.52	1.51	17.06	2.67	19763
	Std	0.45	1.24	0.87	4.14	2.86	11.24	2.29	17212
2019	min	0	-0.01	0.12	0.75	-5.58	7.32	0.28	252.17
2020	25%	0	1.07	0.70	2.72	1.00	9.37	0.97	7790.2
2021	50%	0	1.90	1.00	4.33	1.34	11.05	1.91	15611
2022	75%	1	3.20	1.55	5.89	2.96	22.85	3.24	23283
2023	max	1	4.73	3.99	18.11	8.82	49.50	10.06	74997

The current ratio (mean = 1.30, median = 0.99) highlights liquidity constraints for many firms, potentially limiting AI investments. Profitability, as measured by ROA (mean = 5.52%), varies significantly, with most firms demonstrating modest returns, which may affect their ability to finance AI initiatives. Macroeconomic conditions, particularly GDP contractions (negative growth periods linked to the COVID-19 crisis), likely influenced AI adoption trends and financial decision-making. Due to uncertainty, stock market volatility (mean = 17.06) may further deter long-term AI investment. With an average inflation rate of 2.67%, firms in high-inflation environments may exhibit greater risk aversion, impacting AI adoption. Market capitalization (mean = $19.76 billion) suggests that larger firms with greater financial resources are more likely to adopt AI, while smaller firms face adoption barriers.

As shown in Table 3 below, AI adoption exhibits positive skewness (0.93) and negative kurtosis (-1.13), indicating a right-skewed distribution with fewer firms adopting AI. Financial indicators such as current ratio (skewness = 1.29), ROA (1.46), and market capitalization (1.50) are also right-skewed, suggesting that most firms have lower values while a subset of firms demonstrates significantly higher financial health. Stock market volatility (1.47) and inflation rate (1.78) display substantial right skewness, reflecting periods of heightened financial instability. Kurtosis values below three indicate relatively flat distributions, with AI adoption (-1.13), debt-to-equity ratio (-1.16), and current ratio (0.60) showing less extreme outliers. However, inflation rate (2.82) and market capitalization (1.64) suggest moderately peaked distributions, implying greater data concentration around central values. Moreover, GDP growth rate shows both positive and negative values, reflecting economic fluctuations. Therefore, through descriptive statistics, firms with stronger financial positions and greater market capitalization are more likely to exhibit AI adoption, while macroeconomic volatility may impact firms' strategic investment decisions.

Table 3. More Descriptive Statistics

Descriptive Statistics	Skewness	Kurtosis	Range	IQR
Company_ID	0	-1.200001	1999	999.5
Year	0	-1.30005	4	2
AI_Adoption	0.93270617	-1.130285	1	1
Debt_to_Equity_Ratio	0.33808221	-1.163593	4.74017	2.132119
Current_Ratio	1.29577728	0.600496	3.879135	0.849276
ROA	1.45783451	1.248286	17.35758	3.177126
GDP_Growth_Rate	-0.0200966	1.249261	14.40555	1.949154

Stock_Market_ Volatility	1.46603788	1.402128	42.18213	13.47856
Inflation_Rate	1.78343809	2.819968	9.775858	2.27228
Market_Capitalization	1.49988403	1.644323	74744.63	15493.25

B. Correlation Analysis

Correlation analysis explores the relationships between AI adoption, financial ratios and control variables to identify potential associations. Based on Figure 1 and Figure 8, the correlation coefficient is -0.6485, indicating a strong negative relationship between AI adoption and Debt to Equity Ratio. This means that companies that have adopted AI tend to have lower debt-to-equity ratios compared to those that have not. As shown in Table 4 below, companies that have not adopted AI (0) have an average debt-to-equity ratio of about 2.65. In contrast, companies that have adopted AI (1) have a lower average ratio of about 0.88. This suggests that companies adopting AI generally maintain lower leverage levels, possibly indicating more conservative financial management or better access to equity financing.

Table 4. AI Adoption VS Debt to Equity Ratio mean values

AI_Adoption	Debt_to_Equity_Ratio
0	2.6456
1	0.8767

Figure 1. AI Adoption VS Debt Equity Ratio Correlation Scatterplot

The findings, as shown in Figure 2 and Figure 8, indicate a rather strong positive correlation (approximately 0.85) between AI adoption and the Current Ratio. This means that companies adopting AI generally have a higher Current Ratio than those that do not adopt AI. The mean values show that companies not using AI have an average Current Ratio of about 0.83, whereas AI-adopting companies have an average of around 2.47, as shown in Table 05. Therefore, AI-adopting companies have higher current ratio signifying greater financial flexibility to fund AI projects.

Table 5. AI Adoption VS Current Ratio mean values

AI_Adoption	Current_Ratio
0	0.827
1	2.469

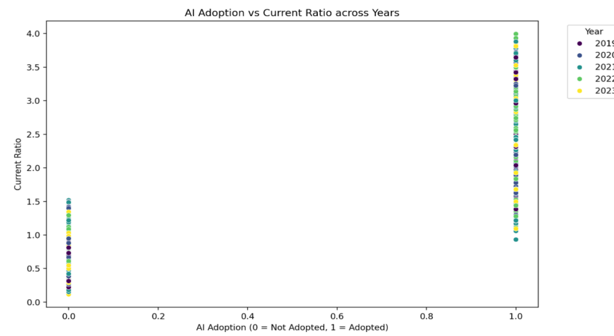

Figure 2. AI Adoption VS Current Ratio Correlation Scatterplot

The findings from Figure 3 and Figure 8 show a strong positive correlation (about 0.77) between AI adoption and ROA, suggesting that companies that have adopted AI tend to have higher ROA than those that have not. As shown in Table 06, firms that have adopted AI exhibit a significantly higher ROA of 10.53%, compared to 3.49% for non-AI adopters, suggesting that AI implementation is associated with enhanced profitability and operational efficiency.

Table 6: AI Adoption VS ROA mean values

AI_Adoption	ROA
0	3.485
1	10.533

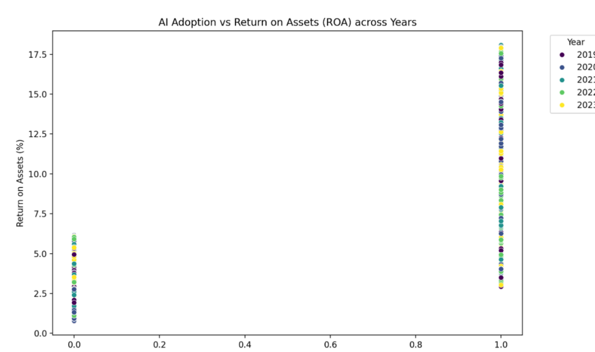

Figure 3. AI Adoption VS ROA Correlation Scatterplot

The output in Figure 4 and Figure 8 shows a moderate positive correlation (approximately 0.30) between AI adoption and GDP growth rate. The mean values, as shown in Table 07, indicate that companies not adopting AI experience an average GDP growth rate of about

0.96%, while those adopting AI are associated with an average of about 2.86% GDP growth. This suggests that firms operating in higher GDP growth environments may be more inclined to invest in AI technologies, potentially due to increased economic stability, greater access to capital, and stronger market demand.

Table 7. AI Adoption VS GDP Growth Rate mean values

AI_Adoption	GDP_Growth_Rate
0	0.961
1	2.864

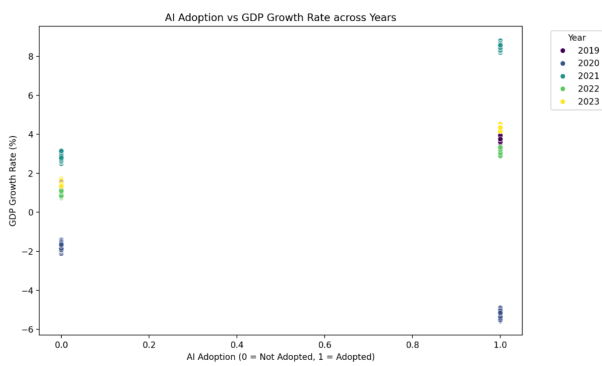

Figure 4. AI Adoption VS GDP Growth Rate Correlation Scatterplot

The analysis reveals a strong positive correlation (approximately 0.87) between AI adoption and Stock Market Volatility as shown in Figure 5 and Figure 8. Moreover, the mean values as shown in Table 8 indicate that companies that have adopted AI tend to experience higher stock market volatility compared to those that have not.

Table 8. AI Adoption VS Stock Market Volatility mean values

AI_Adoption	Stock_Market_Volatility
0	10.805
1	32.473

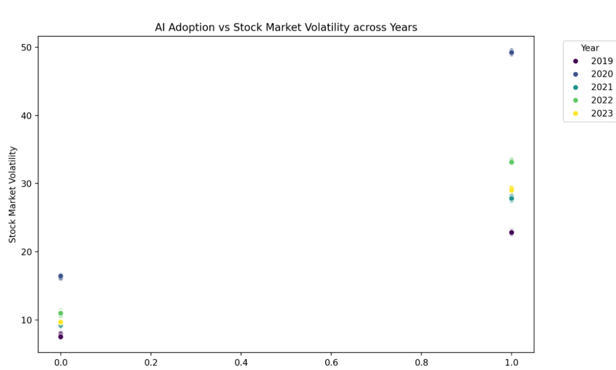

Figure 5. AI Adoption VS Stock Market Volatility Correlation Scatterplot

The analysis in Figure 6 and Figure 8 shows a moderately strong positive correlation (approximately 0.67) between AI adoption and inflation rate. Table 9 shows that companies that have adopted AI are associated with environments having higher inflation rates (mean of about 5.08%) compared to non-adopting companies (mean of about 1.69%).

Table 9. AI Adoption VS Inflation Rate mean values

AI_Adoption	Inflation_Rate
0	1.691
1	5.075

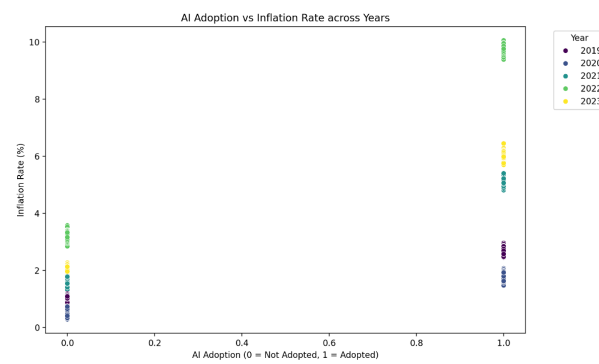

Figure 6: AI Adoption VS Inflation Rate Correlation Scatterplot

The analysis in Figure 7 and 8 shows a moderately strong positive correlation (about 0.66) between AI adoption and Market Capitalization. Moreover, Table 10 further suggests that companies adopting AI tend to have higher market capitalizations than those that do not.

Table 10: AI Adoption VS Market Capitalization mean values

AI_Adoption	Inflation_Rate
0	12568.049
1	37489.375

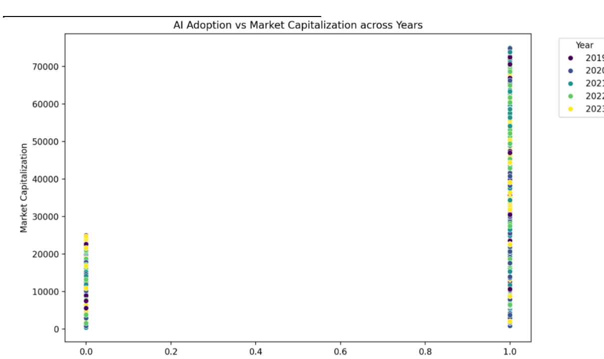

Figure 7. AI Adoption VS Market Capitalization Correlation Scatterplot

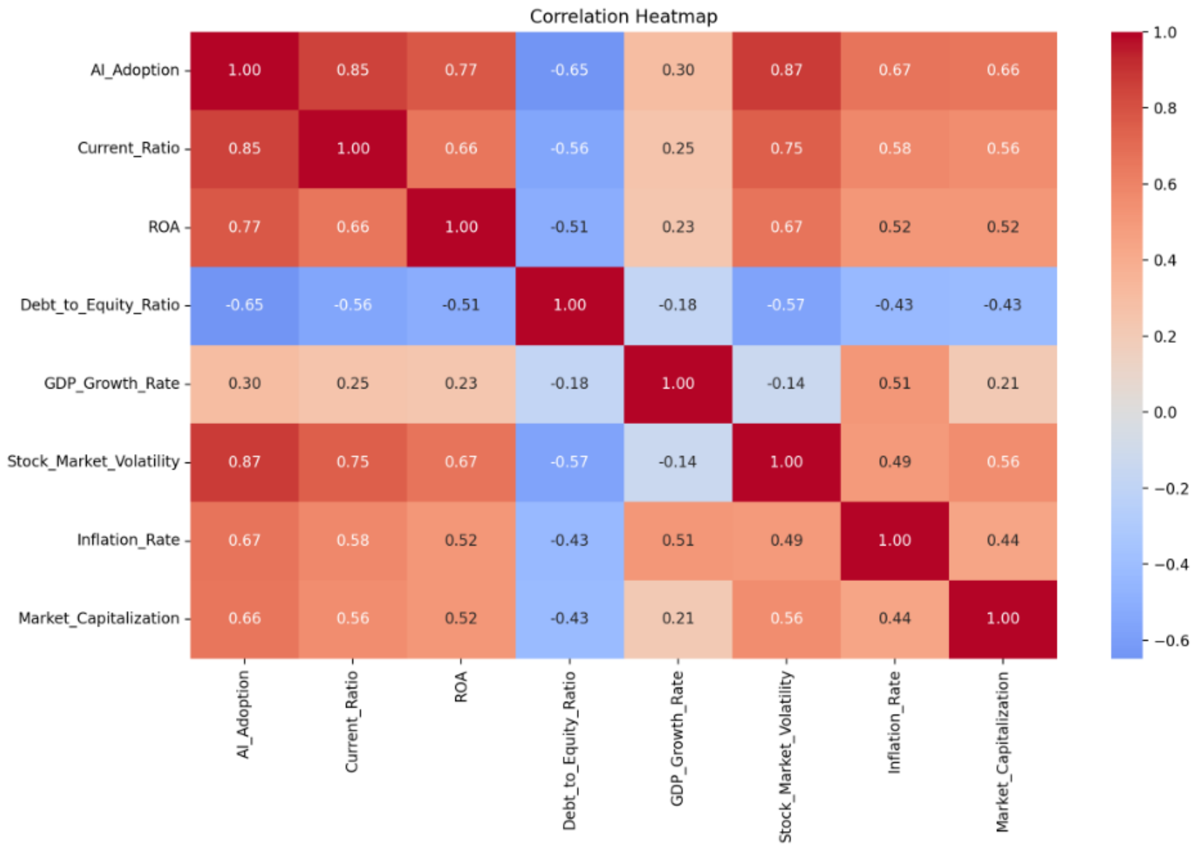

Figure 8. Correlation Heatmap

C. Regression Analysis

Principal Component Analysis

Before conducting a regression analysis, it is essential to examine the correlations between control variables and apply Principal Component Analysis (PCA) to mitigate multicollinearity and reduce dimensionality. Principal Component Analysis (PCA) is a dimensionality reduction technique used in statistics and ML to transform a set of highly correlated variables into a smaller set of uncorrelated components while preserving as much information (variance) as possible and dealing with multicollinearity in regression models to improve computational efficiency in larger datasets (Bao et al., 2015).

The correlation of Stock Market Volatility and Market Capitalization is 56% showcasing that larger firms may experience lower volatility due to greater financial stability. In comparison, smaller firms are more susceptible to market fluctuations. GDP Growth Rate and Inflation Rate has a positive correlation of 51%, which aligns with economic theory, as periods of higher GDP growth often coincide with moderate inflationary pressures. Stock Market Volatility and Inflation Rate has a correlation of 49% which shows that inflationary periods may contribute to heightened stock market uncertainty, influencing firm-level investment decisions. While these correlations are not excessively high, they suggest potential multicollinearity issues in regression models, warranting dimensionality reduction through PCA.

The analysis of the cumulative explained variance of the principal components indicates that the first component accounts for 52.70% of the total variance, while the second component increases the cumulative variance explained to 82.46%. The third and fourth components contribute an additional 12.72% and 4.82%, respectively, leading to a total explained variance of 100%. Given that the first two principal components collectively capture 82.46% of the variance, they were selected for further analysis, as they sufficiently represent the underlying structure of the control variables while allowing for dimensionality reduction. As shown in the scree plot of Figure 9, PC1 alone explains approximately 52.7% of the total variance, indicating that this component captures a significant proportion of the information in the control variables. Adding PC2 increases the cumulative explained variance to 82.46%, meaning that the first two principal components together capture the majority of the variability in the data. The "elbow" in the scree plot occurs at PC2, indicating that the first two components capture most of the variance. PC3 increases the cumulative variance to approximately 95.18%, and PC4 completes it at 100%. These additional components contribute marginally to explaining variance, suggesting that most of the information is contained within the first two components.

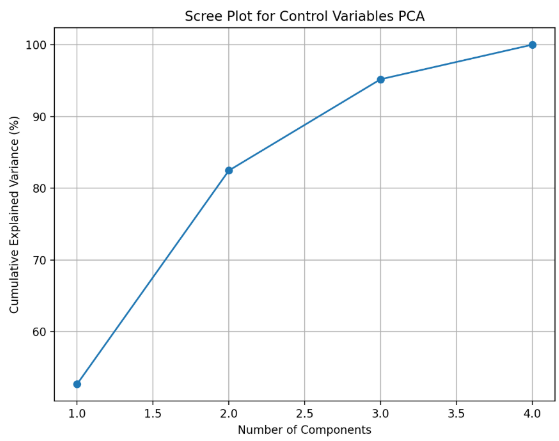

Figure 9: Scree Plot for Control Variables PCA

As shown in Figure 10, the R squared value of the regression model shows that 69.94% of the variance in AI adoption is explained by current ratio, ROA, Debt to Equity Ratio, PC1 and PC2, indicating a relatively strong logistic regression model fit. Moreover, a higher log-likelihood (closer to zero) indicates a better fit. Current Ratio (130.10) and ROA (62.08) have positive coefficients, suggesting that firms with higher liquidity and profitability are more likely to adopt AI. Debt-to-Equity Ratio (-8.21) has a negative coefficient, indicating that higher leverage may discourage AI adoption due to financial constraints. PC1 and PC2, representing macroeconomic factors, positively influence AI adoption, but their effects are not statistically significant. All predictor variables have p-values of 1.000, indicating that none of the independent variables are statistically significant at conventional significance levels (e.g., 0.05). This suggests that while the model explains a larger proportion of the variance (high pseudo R^2), individual predictors do not show statistically meaningful contributions, which means that there are other indicators that may have significant contributions in explaining AI adoption by companies as explained by the financial distress scholarship (Lokanan & Ramzan, 2024). The wide confidence intervals for all variables suggest a high degree of uncertainty in the estimates. The large standard errors indicate possible issues with multicollinearity or data scaling, which may affect coefficient estimation.

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:            AI_Adoption   No. Observations:                10000
Model:                            GLM   Df Residuals:                     9994
Model Family:                Binomial   Df Model:                            5
Link Function:                  Logit   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:            -1.9408e-09
Date:                Thu, 13 Feb 2025   Deviance:                   3.8817e-09
Time:                        06:46:24   Pearson chi2:                 1.94e-09
No. Iterations:                    32   Pseudo R-squ. (CS):             0.6994
Covariance Type:            nonrobust
========================================================================================
                          coef    std err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------------------------
const                  -8.5369   7.76e+04     -0.000      1.000   -1.52e+05    1.52e+05
Current_Ratio         130.0955   1.99e+05      0.001      0.999   -3.91e+05    3.91e+05
ROA                    62.0783    1.1e+05      0.001      1.000   -2.15e+05    2.15e+05
Debt_to_Equity_Ratio   -8.2080   6.95e+04     -0.000      1.000   -1.36e+05    1.36e+05
PC1                   115.5415   1.03e+05      0.001      0.999   -2.03e+05    2.03e+05
PC2                     8.0313    2.2e+04      0.000      1.000   -4.31e+04    4.31e+04
========================================================================================
```

Figure 10: Regression Analysis

Lasso and Ridge Regression Analysis

LASSO (Least Absolute Shrinkage and Selection Operator) performs feature selection by shrinking some coefficients to exactly zero, effectively removing less important variables from the model. As shown in Table 11, Current Ratio of 0.55 indicates a moderate positive association with AI adoption, suggesting liquidity plays a role in AI investment. ROA of 0.10 depicts a smaller coefficient than the Current Ratio but is still positive, indicating profitability's role in AI adoption. Stock Market Volatility of 0.87, the strongest predictor in LASSO, implies that firms operating in volatile markets are more likely to adopt AI. However, the LASSO model assigned zero coefficients to Debt-to-Equity Ratio, GDP Growth Rate, Inflation Rate, and Market Capitalization, deeming them less relevant for explaining AI adoption.

Table 11: Lasso and Ridge regularization coefficients

Feature	L1 (LASSO)	L2 (Ridge)
Current_Ratio	0.554122871	0.53295453
ROA	0.103370242	0.44814712
Debt_to_Equity_Ratio	0	-0.3130552
GDP_Growth_Rate	0	0.19380805
Stock_Market_Volatility	0.875375863	0.60609633
Inflation_Rate	0	0.37009295
Market_Capitalization	0	0.3595648

Ridge regression shrinks coefficients but does not eliminate them, meaning all variables remain in the model but with reduced influence. According to Ridge regression, as shown in Table 11, Stock Market Volatility (0.61) still remains the strongest predictor, indicating market instability has significant influence on AI adoption. Similar to Lasso, current ratio is 0.53 under Ridge regression highlighting the liquidity’s importance. ROA, under Ridge regression, is 0.45 which is higher as compared to Lasso regression, as shown in Figure 11, suggesting that Ridge considers profitability more strongly. Unlike in LASSO (where it was zero), Ridge suggests a negative association with Debt to Equity Ratio of -0.31, meaning firms with higher debt levels are less likely to adopt AI. GDP Growth Rate (0.19), Inflation Rate (0.37), and Market Capitalization (0.36) all have non-zero coefficients, meaning Ridge retains them as relevant predictors. Therefore, Ridge suggests a more balanced view where all factors influence AI adoption to some extent, with liquidity, volatility, and profitability still being key, but macroeconomic conditions and firm size also playing a role.

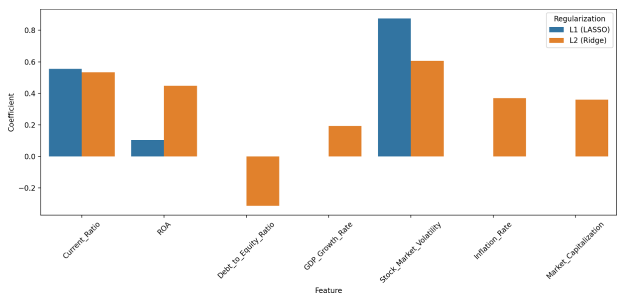

Figure 11. Comparison of L1 and L2 regularization coefficients.

The classification performance of the Ridge (L2) and LASSO (L1) regularized logistic regression models was assessed using confusion matrices, as shown in Figure 12, providing critical insights into the models' predictive capabilities. A confusion matrix offers a structured evaluation of classification accuracy by detailing the distribution of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). This analysis is crucial for assessing the effectiveness of predictive models, particularly in financial and economic applications where classification accuracy directly impacts decision-making. The confusion matrices for both models exhibit identical performance, indicating a highly effective classification system. Specifically, for both Ridge and LASSO models, 2115 instances were correctly classified as non-AI adopters (True Negatives), 885 instances were correctly classified as AI adopters (True Positives), none of the instances were misclassified as AI adopters when they were not (False Positives = 0) and none of the instances were misclassified as non-AI adopters when they were actually adopters (False Negatives = 0). These results indicate that both models achieved perfect classification performance, distinguishing AI-adopting firms from non-adopters with complete accuracy.

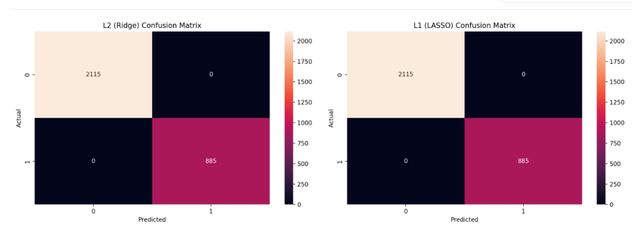

Figure 12. Confusion Matrices of L1 (LASSO) and L2 (Ridge)

5. DISCUSSIONS

The findings of this study provide important insights into the relationship between AI adoption and financial performance, particularly in the context of companies listed on the NYSE. Through a combination of descriptive statistics, correlation analysis, principal component analysis (PCA), and regression modeling, the study systematically examined the financial and macroeconomic determinants of AI adoption. While existing literature extensively examines financial indicators related to AI adoption, there is limited research that focuses on macroeconomic indicators (Figlioli & Lima, 2022; Tang et al., 2020). Furthermore, the macroeconomic indicators identified in the literature are often indirectly associated with financial variables that influence AI adoption (Bao et al., 2015; Figlioli & Lima, 2022).

A. AI Adoption and Financial Characteristics

The descriptive analysis (Table 02) reveals that AI adoption remains relatively low, with only 28.87% of firms integrating AI technologies. This finding aligns with prior studies (e.g., Lokanan & Ramzan, 2024), which suggest that while AI adoption is increasing, it is often concentrated among firms with greater financial stability and higher technological capacity. Firms with stronger financial health, as indicated by higher liquidity (Current Ratio = 1.30), lower leverage (Debt-to-Equity Ratio = 2.13), and higher profitability (ROA = 5.52%), are more likely to adopt AI, suggesting that financial constraints may limit the ability of some firms to engage in digital transformation (Carmona et al., 2022; Ding et al., 2023; Figlioli & Lima, 2022; Jabeur et al., 2023; Yu & Li, 2023).

The correlation analysis further supports these findings, demonstrating a strong negative relationship (-0.65) between AI adoption and the debt-to-equity ratio (Figure 01). Firms that have adopted AI exhibit a significantly lower average debt-to-equity ratio (0.88) compared to non-adopting firms (2.65) (Table 04). This suggests that AI-adopting firms tend to have stronger equity positions and lower financial risk exposure, making them more capable of investing in technological advancements. These findings are consistent with previous research (Bao et al., 2015), which highlights that firms with lower financial leverage are better positioned to engage in AI-driven innovation (Al Ali et al., 2023; Ding et al., 2023; Figlioli & Lima, 2022; Yu & Li, 2023). Moreover, the study identifies a strong positive correlation (0.85) between AI adoption and the Current Ratio (Table 5, Figure 2), indicating that firms with higher liquidity levels are more likely to adopt AI. Firms with AI adoption exhibit a higher average current ratio (2.47) compared to non-adopting firms (0.83). This suggests that financial flexibility plays a crucial role in AI investment decisions, as firms with more liquid assets have greater capacity to allocate resources toward technology adoption (Ding et al., 2023; Figlioli & Lima, 2022). The study also identifies a strong positive correlation (0.77) between AI adoption and ROA (Table 06, Figure 03), suggesting that firms with higher profitability levels are more likely to integrate AI technologies. The findings indicate that AI-adopting firms achieve significantly higher returns on assets (10.53%) compared to non-adopters (3.49%), reinforcing the argument that AI implementation enhances operational efficiency and financial performance. These results are consistent with prior research indicating that AI adoption can lead to cost reductions, improved decision-making, and greater market competitiveness (Lokanan & Ramzan, 2024).

B. AI Adoption and Macroeconomic Conditions

In addition to firm-level financial factors, macroeconomic conditions also appear to influence AI adoption. The study finds a moderate positive correlation (0.30) between AI adoption and GDP growth rate (Table 7, Figure 4). AI-adopting firms are associated with an average GDP growth rate of 2.86%, compared to 0.96% for non-adopters, suggesting that firms in high-growth economic environments are more inclined to invest in AI technologies. This finding is consistent with the literature, which suggests that economic stability and growth facilitate greater investment in innovation and technological infrastructure (Bao et al., 2015; Ding et al., 2023, Wang et al, 2018). Additionally, the analysis identifies a strong positive correlation (0.87) between AI adoption and stock market volatility (Table 8, Figure 5). AI-adopting firms tend to experience higher market volatility (32.47) compared to non-adopting firms (10.81).

This may indicate that firms operating in more volatile financial environments are more likely to adopt AI to manage risk and enhance decision-making capabilities. However, this relationship could also reflect the fact that investors may perceive AI-adopting firms as more speculative or high-risk, leading to increased stock price fluctuations (Farooq & Qamar, 2019). A similar trend is observed in the relationship between AI adoption and inflation rate, with a moderately strong positive correlation (0.67) (Table 9, Figure 6). AI-adopting firms are associated with higher inflation environments (5.08%) compared to non-adopters (1.69%), suggesting that firms in inflationary conditions may seek technological solutions to improve efficiency and offset cost pressures. These findings align with research suggesting that AI can help firms navigate economic uncertainty by optimizing resource allocation and automating processes (Lokanan & Ramzan, 2024).

C. Regression Insights

The regression analysis further confirms the relationship between AI adoption and key financial indicators. The R-squared value of 0.6994 (Figure 10) indicates that the regression model explains approximately 69.94% of the variance in AI adoption, suggesting a strong model fit. The positive coefficients for Current Ratio (130.10) and ROA (62.08) reinforce the argument that firms with higher liquidity and profitability are more likely to adopt AI. Conversely, the negative coefficient for Debt-to-Equity Ratio (-8.21) suggests that higher leverage discourages AI adoption due to financial constraints. However, the statistical insignificance of all independent variables (p-value = 1.000) suggests that additional factors may contribute to AI adoption. The wide confidence intervals and high standard errors indicate potential multicollinearity issues, which were addressed through Principal Component Analysis (PCA) (Figure 9). PCA reduced the dimensionality of control variables while retaining 82.46% of the variance, ensuring a more robust regression model.

The findings from LASSO and Ridge regression (Table 11, Figure 11) provide further insights into the importance of different financial variables in predicting AI adoption. LASSO regression eliminates less significant variables, retaining only Current Ratio (0.55), ROA (0.10), and Stock Market Volatility (0.87) as key predictors. In contrast, Ridge regression retains all variables but assigns lower weights to less important factors. Therefore, the results indicate that liquidity, profitability, and market volatility are the most significant factors influencing AI adoption. In contrast, leverage, GDP growth, and inflation rate show weaker predictive power. One possible explanation for the weak influence of leverage on AI adoption is that lower leverage may facilitate greater acceptance of AI technologies. Conversely, higher leverage might suggest that firms are utilizing this borrowed capital to implement AI solutions. The weaker predictive power of GDP growth on AI adoption may arise from a growing economy encouraging traditional investments over technological change. During strong GDP growth, firms often prioritize expansion, while in downturns, they seek efficiency through AI automation to counteract losses. Thus, while GDP growth establishes the economic backdrop, firm strategies and industry dynamics are more pivotal in determining AI adoption.

6. Conclusion

This study presents a comprehensive empirical analysis of the relationship between AI adoption and financial performance, focusing on key financial indicators such as liquidity, profitability, leverage, and macroeconomic conditions. The findings indicate that firms with higher liquidity, stronger profitability, and lower leverage are more likely to integrate AI technologies, underscoring the role of financial stability in facilitating digital transformation. Furthermore, macroeconomic factors such as GDP growth, inflation, and stock market volatility also exhibit significant associations with AI adoption, suggesting that broader economic conditions influence firms' strategic decisions regarding AI investments. The regression model results reinforce these relationships, highlighting the predictive power of financial ratios in determining AI adoption. Meanwhile, LASSO and Ridge regression analyses provided deeper insights into variable importance, revealing that liquidity, profitability, and market volatility are the most significant determinants of AI adoption, while leverage and macroeconomic indicators play a secondary role.

From a theoretical perspective, this study contributes to the growing literature on AI adoption in US firms by demonstrating the critical role of financial health in enabling technological transformation. From a practical standpoint, these findings offer valuable insights for corporate decision-makers, financial analysts, and policymakers, emphasizing the need for strategic financial planning to support AI-driven innovation. Firms with strong liquidity positions and lower financial risk are better positioned to leverage AI for competitive advantage, while policymakers can design incentives to support AI adoption among firms facing financial constraints. In conclusion, this study provides a strong empirical foundation for understanding AI adoption trends in financial institutions, paving the way for future research to refine predictive models further, explore causal mechanisms, and assess the broader economic implications of AI-driven financial transformation.

Limitations and Future Areas of Research

Despite the valuable insights provided, this study has several limitations that warrant consideration. One major limitation is the reliance on publicly available financial data and AI adoption indicators. While these sources provide a broad overview, they may not capture all nuances of AI implementation and financial performance. For instance, the study does not account for the varying degrees of AI sophistication or the specific areas of AI application within companies, which could influence the financial outcomes. Additionally, the dataset may not fully reflect all dimensions of AI adoption, such as internal AI development versus third-party AI services, which could have different financial implications.

Moreover, while the study's results indicate effective models, further validation techniques should be employed to confirm generalizability across different datasets and ensure the model's applicability in broader financial and economic contexts. Industry-specific factors and market conditions unique to NYSE-listed firms could influence the results, challenging these findings to companies listed on other exchanges or operating in different economic environments. Future research could expand the scope to include companies from diverse sectors and geographical regions to enhance the generalizability of the results. Furthermore, future research should explore the application of advanced predictive ML algorithms to enhance the robustness of the findings and mitigate potential overfitting risks, which may contribute to the perfect classification accuracy observed in the confusion matrices. Specifically, incorporating ensemble techniques, such as Random Forest, Gradient Boosting, or Stacking models, could provide a comparative assessment of classification performance and improve model generalizability. This approach would enable a more comprehensive evaluation of model reliability across different datasets and predictive environments.

Another limitation is the issue of causality. While the study identifies significant associations between AI adoption and financial ratios, it does not establish a causal relationship. The observed improvements in financial performance could be influenced by other factors not controlled for in the analysis, such as broader economic conditions, changes in management strategies, or other technological advancements. To better understand the causal mechanisms underlying these relationships, future research should employ methodologies that can account for endogeneity and potential reverse causality, such as instrumental variable approaches or longitudinal studies with more extended time frames.

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