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AI innovations and financial performance: An examination of patent filings and revenue generation

Samad Abdul *

Department of Engineering Management, Christian Brothers University, Tennessee, USA.

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Abstract

Artificial intelligence (AI) is increasingly becoming indispensable for businesses, offering numerous advantages to compete in today's dynamic market landscape. This study investigates the relationship between AI patent filings and firms' performance in revenue generation from a point of view, aiming to elucidate the impact of AI investments on revenue generation. Leveraging data from The United States Patent and Trademark Office (USPTO) and employing regression analysis, the research finds a significant correlation between firms with AI patent applications and their generated revenue. The findings underscore the importance of AI investments for financial outcomes and provide valuable empirical evidence for strategic decision-making by businesses and policymakers. Additionally, the methodological approach adopted in the study contributes to the methodological approach available for future research in the field of AI and business performance analysis.

Keywords: Artificial intelligence; Patent; Revenue; Innovation; Financial performance

1. Introduction

AI is increasingly essential for businesses, offering various advantages to compete with larger counterparts. It automates repetitive tasks, freeing up time and resources for more strategic endeavors. For instance, AI can handle data entry, customer service, and marketing, enabling employees to focus on higher-value tasks. This boosts efficiency, cuts costs, and enhances productivity, vital for success in today's competitive landscape [1 & 2]; Bandari 2019). The rise of artificial intelligence (AI) tools has profoundly reshaped business operations, ushering in a shift from conventional methods to technology-driven practices. These AI-powered systems excel in automating mundane tasks, allowing organizations to redirect human resources toward more strategic endeavors [3].

In today's swiftly changing environment, artificial intelligence (AI) emerges as a pivotal force driving transformation across global industries. With mounting investments in AI technologies by businesses striving for competitive advantages, it becomes essential to evaluate the nexus between these innovations and firms' financial performance. In the United States, companies are mandated to register their patents with the appropriate government entities. This research investigates and finds that there is a significant connection between a firm with AI patent applications—a pivotal gauge of technological advancement—and the revenue generated by them. Through this inquiry, my objective is to elucidate the impact of AI investments on companies' financial outcomes.

Data for this study is sourced from The United States Patent and Trademark Office (USPTO), a prominent authority responsible for patent registration in the United States. The USPTO offers an AI predictor tool based on machine learning algorithms, which aids in forecasting trends and patterns in patent filings related to artificial intelligence (AI). Leveraging this dataset, I employ a regression model as the primary analytical approach for conducting my research.

* Corresponding author: Samad Abdul

Regression analysis allows for the examination of the relationship between variables, enabling the exploration of how changes in AI patent filings, as predicted by the USPTO's AI predictor, correlate with other factors, such as firms' revenue.

By analyzing data collected from The United States Patent and Trademark Office (USPTO) and utilizing a regression model, the study seeks to uncover insights into how AI patent filings impact revenue generation for businesses. This analysis not only provides valuable empirical evidence regarding the financial implications of AI investments but also offers practical guidance for businesses and policymakers navigating the increasingly AI-driven landscape. Furthermore, the methodological approach adopted in this study, incorporating regression analysis and leveraging predictive tools from USPTO, contributes to the methodological toolkit available for future research in the field of AI and business performance analysis. Overall, this research endeavor holds the potential to inform strategic decision-making processes, stimulate further academic inquiry, and shape policy discussions related to AI innovation and its economic implications.

2. Literature review

Artificial intelligence typically denotes the creation of synthetic minds capable of learning, planning, perceiving, or processing natural language [4]. It encompasses the theory and advancement of computer systems designed to perform tasks that typically require human intelligence, such as visual perception, speech recognition, decision-making, and language translation [5]. While not a novel concept, Artificial Intelligence (AI) has garnered significant attention in recent years [6]. It has been posited as a disruptive force across various industries and global business landscapes [7]. The integration of AI into organizational functions presents a new array of obstacles and complexities [8].

Descriptive analytics, the cornerstone of data analytics, has deep historical ties to Business Intelligence, entailing the utilization of data warehouses and analytical processing methods to aid decision-making processes based on past data. On the other hand, predictive and prescriptive analytics solutions heavily rely on machine learning (ML) [9] and artificial intelligence (AI) tools [10]. These advanced analytics approaches are instrumental in managerial and marketing endeavors, facilitating the development of novel business strategies and the exploration of consumer behavior beyond historical data analysis [11]. Furthermore, they effectively enhance various human activities, exemplifying the transformative potential of ML and AI in augmenting decision-making processes [12].

A central theme within strategic management, operations management, information systems, and production research revolves around alignment [13]. While certain studies within production research concentrate on aspects like product design, others delve into manufacturing and supply chain considerations [14]. Additionally, research in product economy represents another dimension. This study focuses on the third pathway within production research literature, examining the influence of organizational strategies (specifically marketing and information technology [IT]) on product and consequentially business performance. It's notable that in production research, integrating marketing strategy into production planning is recognized for reducing overall costs and significantly boosting profits [15]. Relationship marketing, a cornerstone of marketing strategy, aims at cultivating enduring relationships with customers, suppliers, and distributors, fostering mutually beneficial outcomes [16].

3. Hypothesis development

AI innovations continue to enhance the advantages of information technology (IT) within organizations. Serving as an integral component of an organization's ecosystem, AI can significantly impact performance and the dynamics of relationships with customers, prospects, and partners [17]. By amalgamating various IT configurations and capabilities across different facets of organizational operations, AI has demonstrated its efficacy in automating routine tasks traditionally carried out by specialized personnel such as human resources administrators, sales representatives, and independent contractors [18]. The correlation between investments in information technology (IT) and organizational performance has been a focal point for both researchers and practitioners, reflecting a growing emphasis on enhancing organizational effectiveness [19].

AI presents a significant opportunity for revenue growth within organizations. By harnessing AI technologies, businesses can drive top-line growth through enhanced customer engagement, targeted marketing campaigns, and improved sales processes. AI-powered solutions enable organizations to deliver personalized experiences to customers, increasing conversion rates and driving higher sales volumes. Additionally, AI-driven analytics provide valuable insights into market trends and consumer behavior, enabling businesses to identify new revenue opportunities and optimize pricing strategies. Through the automation of routine tasks and the streamlining of operations, AI helps organizations operate more efficiently, freeing up resources to focus on revenue-generating activities. Overall, AI plays a crucial role in maximizing revenue potential and driving sustainable growth for businesses in today's competitive landscape.

The boundary between humans and computers in management is shifting from operational to strategic realms, as highlighted by [20]. This shift is part of a broader conversation on the integration of AI into professions like law, where AI's ability to assist in processing vast amounts of data, known as "big data," is a focal point. Other researchers offer valuable insights, based on empirical research, into how AI is reshaping management practices. In management decision-making, there's often a balance to be struck between efficiency and equity. For instance, [21] discuss the prioritization of patients for organ transplant waiting lists using fuzzy logic. AI is also utilized in decision-making processes to classify and incorporate diverse stakeholder perspectives, as demonstrated by many researchers in their application of machine learning to group decision-making [22]. Therefore, I hypothesize that:

H: A firm with AI application in their operations creates more revenue compared to the firms that do not use AI.

4. Methodology

The primary data source utilized is the US Patent and Trademark Office (USPTO) database, which provides information on whether a company possesses any registered patents related to artificial intelligence (AI). The objective of this study is to investigate the correlation between AI patents and a firm's revenue. The regression analysis employed in this study follows the methodology outlined by [23].

$$\begin{aligned} Revenue_{it} = {} & \beta_0 + \beta_1 Pat\_dummy_{it} + \beta_2 zscore_{it} + \beta_3 liq_{it} + \beta_4 CFO_{it} + \beta_5 LEVERAGE_{it} + \beta_7 MB_{it} \\ & + \beta_8 madummy_{it} + \beta_9 extraorinary_{it} + \beta_{10} foreigndummy_{it} \\ & + \beta_{11} employee_{it} + \beta_{12} lnat_{it} + Year\ FE + Industry\ FE \end{aligned}$$

The analysis incorporates several variables to examine their impact on revenue. Firstly, revenue is assessed in relation to lagged total assets, providing insight into the scalability of revenue over time. Additionally, the presence of AI patents is captured through a binary variable, Pat_dummy, indicating whether a firm holds patents related to artificial intelligence. The Z-Score, a bankruptcy probability score, is calculated using [24] formula, incorporating various financial metrics to gauge the financial stability of the firm. Liquidity is measured by the current ratio, representing the proportion of current assets to current liabilities. Leverage, another key factor, is determined by the ratio of total debt to total assets. The book-to-market ratio (MB) is calculated as the ratio of the book value of equity to the market value of equity. Moreover, the analysis considers merger and acquisition activities (madummy), the presence of extraordinary items or discontinued operations (Extraordinary), and foreign operations (foreigndummy) as binary indicators. Additionally, the square root of the number of employees (Employ) and the natural logarithm of total assets (Lnat) are incorporated to further refine the analysis. All variables name and descriptions with data sources are presented in appendix-A.

5. Descriptive analysis and correlation matrix

Table 1 presents descriptive statistics for a range of variables. For instance, "PAT_DUMMY" has 66,228 observations, with an average value of 0.28 and a standard deviation of approximately 0.447. The variable "SALE_AT" also has 66,228 observations, with an average of 0.92 and a standard deviation of roughly 1.842. "ZSCORE" spans the same number of observations, with a mean of 30.94 and a standard deviation of 190.230. Other variables like "ROA," "LIQ," "LEV," "BM," "MADUMMY," "EXTRAODDUMMY," "FOREIGNDUMMY," "EMPLOYEE," "LNAT," and "NFINDUMMY" follow similar patterns. These statistics provide insights into the central tendency, variability, and range of values for each variable, aiding in understanding their distributions and characteristics within the dataset.

Table 1 Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min	Max
pat_dummy	66,228	0.28	0.4470888	0	1
sale_at	66,228	0.92	1.842149	0	240.74
zscore	66,228	30.94	190.2302	-315.09	1583.95
roa	66,228	2	2.105897	-18.32	0.44

liq	66,228	2.85	4.696978	0.002	54.34
lev	66,228	0.26	0.2712595	0	1.4
bm	66,228	0.87	1.71032	0.007	13.41
madummy	66,228	0.20	0.4015506	0	1
extraoddummy	66,228	0.18	0.3819224	0	1
foreigndummy	66,228	0.39	0.4885406	0	1
employee	66,228	1.76	2.306607	0	12.50
lnat	66,228	5.62	2.815364	-2.72	12.51
nfindummy	66,228	1	0	1	1

Table 2 shows a correlation matrix, illustrating the relationships between different variables. Each cell in the table showcases the correlation coefficient between the variables stated in the respective row and column headers. For instance, the correlation of 0.0091 between "SALE_AT" and "PAT_DUMMY" indicates a very weak positive correlation, while the correlation of 0.0462 between "SALE_AT" and "ZSCORE" signifies a weak positive correlation. Conversely, the correlation of -0.0624 between "SALE_AT" and "ROA" suggests a weak negative correlation, and the correlation of -0.1097 between "SALE_AT" and "LIQ" indicates a somewhat stronger negative correlation. Generally, coefficients approaching 1 or -1 imply a significant linear relationship, whereas those near 0 suggest minimal linear association. It's crucial to emphasize that correlation does not imply causation but solely measures the strength and direction of the linear relationship between two variables.

Table 2 Correlation matrix

	Sale_at	**Pat_dummmy**	**Zscore**	**Roa**	**Liq**	**Lev**	**Bm**	**Madummy**	**Extraordinary**
sale_	1								
pat_dummy	0.0091	1							
zscore	0.0462	0.0367	1						
roa	-0.0624	0.0609	0.1469	1					
liq	-0.1097	0.0112	0.1641	0.076	1				
lev	0.0339	-0.0673	-0.1981	-0.0987	-0.1957	1			
bm	0.0574	-0.0703	-0.0867	-0.1184	-0.0669	0.1012	1		
madummy	-0.0249	-0.0354	-0.0249	0.1015	-0.062	0.0666	-0.0705	1	
extraoddummy	0.0186	0.0733	-0.0406	0.0388	-0.0893	0.0464	0.0561	-0.004	1
foreigndummy	-0.0002	0.2047	-0.0084	0.1614	-0.0399	0.0079	-0.0763	0.2396	0.0363
employee	0.0591	0.1754	-0.0551	0.1819	-0.168	0.0946	-0.0665	0.1888	0.1326
lnat	-0.0656	0.1486	-0.0056	0.4857	-0.0812	0.1213	-0.0973	0.2951	0.1272

6. Analyses and results

The regression analysis examines the relationship between the dependent variable, sales, and the independent variable, patent dummy. In Model 1 of table 3, the coefficient for patent dummy is 0.059, which is statistically significant with a p-value of 0.020. Model 2 shows a coefficient of 0.038 for patent dummy, which is highly significant at the 0.001 level. Similarly, in Model 3, the coefficient for patent dummy remains 0.038, also highly significant at the 0.001 level. The adjusted R-squared increases from 0.192 in Model 1 to 0.550 in Model 2 and 0.551 in Model 3, suggesting an improved fit of the models. Fixed effects are included for Industry in Model 1, for both Industry and firm in Model 2, and solely for Firm in Model 3. The data is clustered at the firm level across all models. These results suggest a consistent and significant relationship between the presence of patents and sales, with varying degrees of explanatory power and control for fixed effects.

Table 3 Regression results

Dependent variable: Sale			
Variables	**1**	**2**	**3**
pat_dummy	0.059** (0.020)	0.038*** (0.001)	0.038*** (0.003)
zscore	0.000*** (0.000)	0.000 (0.276)	0.000 (0.276)
roa	-0.002 (0.924)	0.011 (0.727)	0.011 (0.727)
liq	-0.025*** (0.000)	-0.006*** (0.000)	-0.006*** (0.000)
lev	0.173 (0.101)	0.279*** (0.009)	0.279*** (0.009)
bm	0.039*** (0.000)	0.010 (0.270)	0.010 (0.270)
madummy	-0.047*** (0.001)	-0.029** (0.032)	-0.029** (0.032)
extraoddummy	0.026 (0.119)	-0.057*** (0.002)	-0.057*** (0.002)
foreigndummy	0.102*** (0.000)	0.103*** (0.000)	0.103*** (0.000)
employee	0.087*** (0.000)	0.085*** (0.000)	0.085*** (0.000)
lnat	-0.120*** (0.000)	-0.244*** (0.000)	-0.244*** (0.000)
Constant	1.391*** (0.000)	2.074*** (0.000)	2.074*** (0.000)
Obs	62,292	59,769	59,769
Adjusted-Rsquare	0.192	0.550	0.551
FE	Industry	Industry and Firm	Firm
cluster	Firm	Firm	Firm

7. Implications of the research

The research outlined investigates the association between AI patent applications, a key indicator of technological progress, and firms' revenue generation. By delving into this connection, the study aims to shed light on the influence of AI investments on companies' financial performance. The regression analysis conducted in the study unveils noteworthy findings regarding the relationship between AI patent applications and sales, serving as a foundation for several implications:

The statistically significant coefficients of the patent dummy variable across all models underscore the importance of AI investments for firms seeking to enhance their revenue streams. These findings advocate for strategic allocation of resources towards AI research and development to capitalize on the potential financial benefits it can offer. Moreover, the positive coefficients of the patent dummy variable indicate that an increase in AI patent applications is associated with higher sales figures. Although management plays an important role in organizational success [25], this suggests that firms leveraging AI technologies may gain a competitive edge in the market by introducing innovative products or services, ultimately translating into improved financial performance.

The significant relationship between AI patents and sales underscores the significance of intellectual property protection. Firms investing in AI research should prioritize securing patents to safeguard their innovations, ensuring they can capitalize on their technological advancements and maintain a competitive position in the market. The inclusion of fixed effects for both industry and firm in Model 2 highlights the importance of considering contextual factors when examining the relationship between AI patents and sales. This implies that the impact of AI investments on financial outcomes may vary across different industries and individual firms, emphasizing the need for tailored strategies.

Policymakers and business leaders can draw insights from these findings to inform decision-making processes. For policymakers, understanding the positive correlation between AI patents and sales can underscore the importance of fostering an environment conducive to innovation through supportive policies and incentives. Meanwhile, business leaders can use these findings to guide investment decisions and strategic planning, recognizing the potential financial benefits of AI adoption.

8. Future research prospect

Expanding on the existing research, several future research avenues could deepen the understanding of the relationship between AI patent applications and firms' financial performance. Firstly, investigating the long-term effects of AI investments on financial performance through longitudinal studies spanning multiple years could provide valuable insights into the sustainability of the observed positive association between AI patents and sales. Understanding how this relationship evolves over time is crucial for firms' strategic planning and investment decisions. Secondly, conducting sector-specific analyses to explore how the impact of AI investments with blockchain technology varies across different industries could uncover industry-specific patterns and challenges [26]. Comparing sectors with varying levels of technological intensity or regulatory environments could provide nuanced insights into the factors influencing the relationship between AI patents and financial outcomes.

Thirdly, examining potential mediating and moderating factors, such as organizational capabilities, market competition, and regulatory frameworks, could offer deeper insights into the mechanisms driving the relationship between AI patent applications and revenue generation. Identifying these factors is essential for firms to effectively leverage AI investments for financial gains. Moreover, exploring geographical variations in the relationship between AI patents and sales could help understand how regional factors influence firms' adoption of AI technologies and subsequent financial outcomes. Cross-country comparisons could reveal insights into the role of cultural, economic, and institutional factors in shaping this relationship [27].

Additionally, investigating the quality of AI patents and their impact on firms' financial performance could provide a nuanced understanding of how patent characteristics influence sales and market competitiveness. Assessing factors such as patent breadth, novelty, and technological significance could help firms prioritize their patenting strategies. Furthermore, analyzing the role of dynamic capabilities and innovation strategies in leveraging AI investments for financial gains could offer practical guidance for firms seeking to maximize benefits. Understanding how firms' ability to adapt to technological changes and their innovation strategies affect the translation of AI patents into sales growth is essential for sustainable competitive advantage. Exploring the impact of AI investments on non-financial metrics, such as customer satisfaction, employee productivity, and operational efficiency, could provide a more comprehensive understanding of AI's value proposition beyond financial performance. Understanding these broader implications is crucial for firms' strategic decision-making. These research ideas collectively offer promising avenues for advancing knowledge in the field of AI adoption and its implications for firm performance, contributing to the advancement of both academia and industry practice.

9. Conclusion

In conclusion, the research highlights the growing significance of artificial intelligence (AI) in revolutionizing business operations and driving transformation across global industries. With businesses increasingly investing in AI technologies to gain competitive advantages, it becomes imperative to examine the relationship between these innovations and firms' revenue. The research, utilizing data from The United States Patent and Trademark Office (USPTO) and employing regression analysis, reveals a significant correlation between firms with AI patent applications and their revenue generation. This finding underscores the importance of AI investments for financial outcomes and offers valuable empirical evidence to guide strategic decision-making for businesses and policymakers navigating the evolving AI-driven landscape. Furthermore, the methodological approach adopted in the study contributes to the methodological toolkit available for future research in the field of AI and business performance analysis. Overall, this research endeavor has the potential to inform strategic decision-making processes, inspire further academic exploration, and influence policy discussions concerning AI innovation and its economic implications in today's rapidly changing business environment.

References

[1] Bhuiyan J, Mazumder R. Application of linear programming in employee allocation: A case study in emerging economy. International Journal of Science and Research Archive. 2024;11(01):253-9.

[2] Bandari, V. (2019). The impact of artificial intelligence on the revenue growth of small businesses in developing countries: an empirical study. Reviews of Contemporary Business Analytics, 2(1), 33-44.

[3] Whig P. Artificial intelligence and machine learning in business. International Journal on Integrated Education. 2019;2(2):334128.

[4] Paulraj P, Neelamegam A. Improving business intelligence based on frequent itemsets using k-means clustering algorithm. InNetworks and Communications (NetCom2013) Proceedings of the Fifth International Conference on Networks & Communications 2014 Jan 17 (pp. 243-254). Cham: Springer International Publishing.

[5] Manne R, Kantheti SC. Application of artificial intelligence in healthcare: chances and challenges. Current Journal of Applied Science and Technology. 2021 Apr 24;40(6):78-89.

[6] Ransbotham S, Gerbert P, Reeves M, Kiron D, Spira M. Artificial intelligence in business gets real. MIT solan management review. 2018 Sep 17.

[7] Davenport TH, Ronanki R. Artificial intelligence for the real world. Harvard business review. 2018 Jan 1;96(1):108-16.

[8] Duan Y, Edwards JS, Dwivedi YK. Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. International journal of information management. 2019 Oct 1;48:63-71.

[9] Bhuiyan JA, Asma B, Bhowmik SC. Digital procurement practices in SMES: comparative cases of advanced and emerging economies.

[10] Hazen BT, Boone CA, Ezell JD, Jones-Farmer LA. Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications. International Journal of Production Economics. 2014 Aug 1;154:72-80.

[11] Malthouse EC, Haenlein M, Skiera B, Wege E, Zhang M. Managing customer relationships in the social media era: Introducing the social CRM house. Journal of interactive marketing. 2013 Nov;27(4):270-80.

[12] Kumar K, Thakur GS. Advanced applications of neural networks and artificial intelligence: A review. International journal of information technology and computer science. 2012 Jun;4(6):57.

[13] Cao Q, Baker J, Hoffman JJ. The role of the competitive environment in studies of strategic alignment: a meta-analysis. International Journal of Production Research. 2012 Jan 15;50(2):567-80.

[14] Ivanov D, Das A, Choi TM. New flexibility drivers for manufacturing, supply chain and service operations. International Journal of Production Research. 2018 May 19;56(10):3359-68.

[15] Leitch RA. Marketing strategy and the optimal production schedule. Management Science. 1974 Nov;21(3):302-12.

[16] Al-Surmi A, Bashiri M, Koliousis I. AI based decision making: combining strategies to improve operational performance. International Journal of Production Research. 2022 Jul 18;60(14):4464-86.

[17] Rubin VL, Chen Y, Thorimbert LM. Artificially intelligent conversational agents in libraries. Library Hi Tech. 2010 Nov 23;28(4):496-522.

[18] Rachinger M, Rauter R, Müller C, Vorraber W, Schirgi E. Digitalization and its influence on business model innovation. Journal of manufacturing technology management. 2018 Aug 7;30(8):1143-60.

[19] Farhanghi AA, Abbaspour A, Ghassemi RA. The effect of information technology on organizational structure and firm performance: An analysis of Consultant Engineers Firms (CEF) in Iran. Procedia-Social and Behavioral Sciences. 2013 Jun 28;81:644-9.

[20] Jarrahi MH. Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business horizons. 2018 Jul 1;61(4):577-86.

[21] Perris T, Labib AW. An intelligent system for prioritisation of organ transplant patient waiting lists using fuzzy logic. Journal of the Operational Research Society. 2004 Feb 1;55(2):103-15.

[22] Stone M, Aravopoulou E, Ekinci Y, Evans G, Hobbs M, Labib A, Laughlin P, Machtynger J, Machtynger L. Artificial intelligence (AI) in strategic marketing decision-making: a research agenda. The Bottom Line. 2020 May 18;33(2):183-200.

[23] Bradley D, Mao CX, Zhang C. Does analyst coverage affect workplace safety?. Management Science. 2022 May;68(5):3464-87.

[24] Zmijewski ME. Methodological issues related to the estimation of financial distress prediction models. Journal of Accounting research. 1984 Jan 1:59-82.

[25] Mazumder R, Chakraborty A, Bhuiyan JA, Asmad B. Does the Family Relationship of the CEO-Chairman Matter in Corporate Performance? Evidence from an Emerging Economy.

[26] Bhuiyan J, Mazumder R, Afrose S, Hasan M. Industry-4, Big Data, and Blockchain Research Prospects in Supply Chain Domain: A Bibliometric Review. Big Data, and Blockchain Research Prospects in Supply Chain Domain: A Bibliometric Review (January 6, 2024). 2024 Jan 6.

[27] Hong P, Bhuiyan J. Populism and Public Opinion in a Digital World. InEncyclopedia of New Populism and Responses in the 21st Century 2023 May 3 (pp. 1-6). Singapore: Springer Nature Singapore.

Appendix-A: Variable descriptions and data sources

Variable	**Description**	**Data source**
Sale_at	Sales scaled by total assets	Compustat
Pat_dummy	A binary variable indicating whether firms have any patent of AI (1 if yes, 0 otherwise)	USPTO
Z-Score	A bankruptcy probability rating derived from the Zmijewski (1984) formula, incorporating various financial metrics.	Compustat
Liq	The current ratio, representing current assets divided by current liabilities.	Compustat
Leverage	The Leverage ratio, calculated as total debt divided by total assets.	Compustat
BM	The book-to-market ratio, determined as the ratio of book value of equity to market value of equity.	Compustat
madummy	A binary indicator for merger and acquisition activities (1 if yes, 0 otherwise).	Compustat
Extraordinary	A binary variable denoting the presence of extraordinary items or discontinued operations in the firm's reports (1 if yes, 0 otherwise).	Compustat
foreignoperation	A binary indicator for foreign operations (1 if yes, 0 otherwise).	Compustat
Lnat	The natural logarithm of total assets.	Compustat