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Article

Optimizing financial success: The synergistic impact of artificial intelligence and R&D investments in U.S. firms

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Abstract: The use of artificial intelligence (AI) and intellectual machines can support businesses in performing various activities. Therefore, it is necessary to examine the performance outcomes by assessing the concentration of AI technologies. To create a quantifiable score of AI concentration, AI-related terms are identified in the annual reports of all listed firms in the U.S. For analysis purposes, a fixed effects model is employed, using firms' panel data from 2003 to 2022. The analysis reveals that AI concentration is beneficial for a company's financial success. Additional analysis examines the moderating role of research and development (R&D). Firms with higher R&D spending experience increased financial benefits from concentrating on AI technologies. The uniqueness of this study lies in analyzing the financial success through the AI and R&D parameters. The findings support a higher concentration on AI, combined with higher R&D spending, to attain greater financial success. The main insights suggest that management must evaluate their existing focus on AI and R&D spending to improve their financial position.

Keywords: artificial intelligence; AI; textual analysis; financial gains; profitability; R&D; fixed effects model
JEL Classification: F65; G30; O32; P33

1. Introduction

Artificial intelligence (AI) systems focus on augmenting human intelligence and applying it to machines so that they can perform tasks like humans (Meske et al., 2022). Theoretical concepts and applied methods can facilitate the formation of intelligent machines that require little to no human involvement in task completion (Gupta et al., 2024). With advanced AI features, machines can analyze their surroundings and determine the most efficient way to complete tasks (Zengyi et al., 2024). Examples of common AI applications include natural language processing tools like Alexa or Siri, ChatGPT, self-driving cars like Tesla, social media marketing, and chatbots. By analyzing complex, unstructured data to make accurate forecasts, AI works in coordination with human intelligence to enable intelligent decision-making (Kim et al., 2022). AI technologies have become increasingly important for attaining and accelerating economic growth and development.

Numerous industries, including healthcare, banking, manufacturing, security and defense, transportation, and technology, have embraced AI. In the financial sector, the development and growth of Financial Technology (FinTech) have driven AI adoption, propelling the expansion of the global financial industry (Li et al., 2022). AI has become a crucial part of military operations, with around 50% of defense companies already implementing it (IBM, 2022). In healthcare, AI plays a significant role by enabling the identification of patients' distinct genetic disorders (Secinaro et al., 2021). AI's application in online and social media marketing has increased the effectiveness of advertising by targeting potential customers more accurately (Arumugam et al., 2024). In transportation, AI is revolutionizing travel by introducing self-driving vehicles equipped with navigation sensors (Charroud et al., 2024).

Andrew Ng, co-founder of Google Brain and a member of the AI team, stated in 2017 that AI has the potential to revolutionize all industries in the same manner that electricity did (Ng, 2017). Numerous sources point out the rising popularity of AI and the significant increase in funding for the cognitive development of machines using AI. According to reports, overall spending on AI systems is predicted to reach over $200 billion by 2025, up from $120 billion in 2023 (Statista, 2023). Moreover, it is anticipated that by the end of 2032, AI spending will surpass $2.5 trillion (Forbes, 2024).

Companies are automating their procedures with the hopes of increasing productivity and cutting expenses. However, research on the effects of automation has yielded conflicting results. On the positive side, AI has been shown to improve processes and increase productivity (Babina et al., 2024). AI facilitates process integration, enhances data exchange, and supports coordinated decision-making. It may also enhance working conditions by lowering workplace accidents and injuries (Johnson et al., 2022). Nonetheless, some research indicates negligible or adverse effects of AI. Due to processing issues with AI technologies, there is no conclusive evidence of increased efficiency in business operations (Aguirre and Rodriguez, 2017). Instead of improving working conditions, AI utilization is reportedly increasing employee stress (Yang, 2022). Companies are often confused about the true benefits of AI, unsure whether it justifies the investment (Khogali and Mekid, 2023). Upfront costs and synchronization issues with current systems require significant restructuring, preventing businesses from realizing gains (Zhang and Liu, 2019).

When firms seek solutions to enhance financial gains, investor returns are primary concerns for managers and shareholders (Lu and Wang, 2024). Metrics such as returns on assets (ROA), and return on equity (ROE) are crucial for evaluating the financial performance growth and the effectiveness of new technology investment (Haque et al., 2024; Qalati et al., 2022). This demonstrates the need for a better comprehension of the potential growth in financial returns AI technologies. Therefore, the main purpose of this study is to identify the influence of AI concentration on firms' financial returns growth.

For companies, the concentration on AI can be defined as their focus on AI technologies, which can be identified through their activities and operations. The most reliable source of disclosures about the company's activities and operations are the publicly available reports they publish. Additionally, observable business attributes can be correlated with AI technologies to predict their association with a firm's financial success. Business characteristics are very crucial to the incorporation of new technologies (Finlay, 2021).

Regarding the concentration on technology, businesses exhibit varying levels depending on their industry, operational needs, and their research and learning scenario. Internal characteristics like research and development (R&D) spending are strategic in identifying the contribution of advanced technologies to the improvement of products and processes (Lu and Wang, 2024). The levels of R&D spending define the innovation speed within an organization. Technology application is targeted when R&D suggestions are implemented (Xiong et al., 2023). Higher R&D spending enables businesses to outperform those that don't (Lin and Xie, 2023). R&D is considered a primary driver that identifies the need to upgrade the systems, procedures, and products. Higher R&D investment can also support the alignment of various technologies together to achieve organizational objectives (Sarpong et al., 2023). Companies with high R&D spending demonstrate great organizational readiness and a strong preference for the newest technology (Sarpong et al., 2023). While R&D may have been important in this regard, the argument is not well supported by the available data. In this context, the purpose of this study is to consider the moderating role of R&D between the concentration of AI and firms' financial gains.

The study's primary contribution lies in its analysis of the connection between monetary gains and concentration on AI. This adds both conceptually and empirically to the expanding body of research on business goals and the application of AI technologies. To expand the comprehension of current theories from the standpoint of AI resources, this study suggests leveraging firm resources in conjunction with AI technologies. In order to increase business profitability, this study supports the endogenous growth theory, which emphasizes the value of aligning internal organizational resources like R&D with AI resources. This study is exceptional in its examination of how AI resources and R&D contribute to the accomplishment of the financial goals of business.

2. Literature review

2.1. Endogenous growth theory

In the middle of the 1980s, economists Kenneth Arrow, Sergio Robelo, Robert Lucas, and Paul Romer noted down the endogenous growth theory. The premise of this approach is that endogenous features are responsible for growth (Romer, 1994). Noting that investments in innovation and knowledge-based systems have a major role in determining economic growth (Jones, 2019; Parker, 2009). This theory emphasizes how knowledge-based and technology-based economies have positive externalities and spillover effects on the economy (Acemoglu and Restrepo, 2019). A knowledge-based economy improves productivity and production efficiency and lowers production costs (Laborda et al., 2020). The endogenous growth theory holds that the involvement of knowledge-based systems can bring growth in the production capacity of businesses (Lui et al., 2022). Nonetheless, the firm's intrinsic qualities, serve as the main catalysts for innovation and change.

2.2. Growth in AI over the years

At a 1956 symposium held at Dartmouth College in Hanover, classical philosophers discussed the possibility of developing human intellect within the symbolic system, which led to the formal recognition of AI in the 1950s (Turing and

Haugeland, 1950). This period marked a significant advancement in AI, including the development of rule-based systems (Feigenbaum and McCorduck, 1983), intelligent chat agents (Wooldridge and Jennings, 1995), and data mining algorithms (Gurcan et al., 2023). These technologies demonstrated capabilities such as solving algebraic word problems, playing games similar to those played by humans, and demonstrating social intelligence (Khogali and Mekid, 2023; Macanovic, 2022).

AI machines are capable of scanning their environment for task completion like self-driving cars, serving food, health scanning, automatics job processing, and understanding of human language (Charroud et al., 2024; Ramirez, 2024). AI encompasses a set of technologies including automation, machine learning, speech recognition, image identification, and trend analysis, which are projected to add an extra $15 trillion in economic output by 2030 (Forbes, 2024). Based on the discussion, the following hypothesis is coined:

H_1: There has been significant growth in concentration on AI in businesses from 2003 to 2022.

2.3. Impact of AI on businesses

Companies are automating their workflows to boost efficiency and productivity (Yang, 2022). Automation facilitates easy process integration for coordinated decision-making (Martinez-Alonso et al., 2023). AI can transform marketing strategies by helping companies target clients more precisely, understand their preferences, and offer personalized experiences (Arumugam et al., 2024). AI systems have the potential to reduce risks, eliminate operational disruptions, and financial losses (Hoque et al., 2024). Additionally, AI can improve working conditions by reducing workplace accidents and injuries (Johnson et al., 2022).

However, previous studies are providing conflicting information about the application of AI and its effects on business outcomes. According to Aguirre and Rodriguez (2017), there has been no improvement in the productivity of corporate operations when it comes to automated machines completing tasks. Due to high initial costs and synchronization challenges with current systems, firms have not produced any financial gains (Zhang and Liu, 2019). Companies are often confused and unsure of the true benefits of AI (Khogali and Mekid, 2023), and many report little to no influence on business growth (Kiron and Schrage, 2019). Therefore, based on the opposing viewpoints in the literature the following hypotheses are coined:

H_2: Concentration on AI technologies significantly affect firms' return on assets.

H_3: Concentration on AI technologies significantly affect firms' return on equity.

2.4. Moderating role of R&D

For businesses, R&D is a critical factor for continuous improvement in products and services (Leung and Sharma, 2021). R&D helps in the identification of the required skills, knowledge, and resources that can create value for the business. It enhances innovative capabilities by identifying the areas of improvement and providing possible solutions (Haque et al., 2024). A company's ability to perform better is positively correlated with an increase in R&D intensity, which is positively correlated with economic success (Lu and Wang, 2024). Businesses that prioritize

R&D over other spending see a constant improvement in their business operations (Johnson et al., 2022). This shows that investing in R&D fosters creativity and improves the understanding of new technology.

However, higher R&D spending does have a drawback: it raises costs, which can lower firm returns (Leung and Sharma, 2021). Some argue that R&D expenditures do not always provide businesses with a competitive advantage; instead, they can drain resources that might be better spent on other crucial tasks (Xiong et al., 2023). Occasionally, R&D-suggested changes take longer to operationalize, fail to keep up with the rapid pace of technological development, and do not produce the intended results or innovation (Johnson et al., 2022).

On the other hand, businesses that invest more in R&D are better able to adopt new technology, which boosts financial performance (Lu and Wang, 2024). Investing in R&D projects also helps businesses combine technology with expansion efforts. Additionally, R&D contributes to the proper application of cutting-edge technologies, greatly improving products and processes (Sarpong et al., 2023). In this context, the following hypotheses are coined:

H_4: R&D significantly moderates the relationship between concentration on AI technologies and firms' return on assets.

H_5: R&D significantly moderates the relationship between concentration on AI technologies and firms' return on equity.

3. Methodology

The study's primary goal is to determine how concentration on AI affects businesses' financial success, guiding the choice of factors. The variables include concentration on AI technologies as the independent variable, the financial performance of the firm as the dependent variable, and R&D spending as a moderating variable. To obtain more accurate results, control variables are also used for all listed companies in the US. A comprehensive description of all variables engaged in this study is provided in the following sub-sections.

3.1. Independent variable

The primary research question, which investigates the relationship between the concentration on AI and financial gains, informs the choice of the independent variable. Consequently, the primary independent variable is the company's emphasis on AI. This study uses text analysis of annual reports using a word search technique with an AI-based lexicon. Generally, the focus on AI is important to identify through any reliable source of information. Previous studies have indicated that annual reports can disclose information on their focus on the latest technologies which are published by all listed companies. Annual reports include information related to all business and financial activities. For every business, these reports can be used to identify the areas of concern and the attention paid to them.

3.1.1. Use of textual analysis

Formal documents have been used to explicitly identify the focus of a firm to a variety of aspects, including customers (Gupta et al., 2024), market information (Andreou et al., 2020), digitalization (Jiang et al., 2023), green concerns (Qalati et al., 2022), and many other concepts. This study is engaging the AI-based lexicon given by Mishra et al. (2022) and Chhaidar et al., (2022) to identify the firm's concentration on AI technologies. This AI lexicon is further improved by using the technique called in-sample availability for AI terms proposed by Babolmorad and Massoud (2020). The amended AI-related terms are presented in **Table 1**.

Table 1. AI wordlist.

AI-related wordlist
AI, ai technology, ai capabilities, ai application, ai innovation, intelligent machine, advance technologies, intelligent machine, modern technology, modern systems, technology advancement, machine ability, high tech, high technology, cost-effective, solution system, automated design, intensive computing, response time, embedded system, interactive system, mobile system, system assistance, machine learning, deep learning, machine thinking, machine behavior, machine intelligence, decision making, rule-based systems, cognitive decision making, algorithms, cognitive algorithms, self-learning, self-learning algorithms, learning algorithm, artificial intelligence algorithm, algorithm, probability algorithm, machine translation, chatbots, machine programs, machine intelligence, machine ability, neural network, and, learning systems, computing, digitization, knowledge reasoning, knowledge-based, knowledge system, artificial neural networks, logic theories, reinforcement learning, supervised learning, unsupervised, learning, augmented learning, augmentation, expert system.

3.1.2. Transformation of annual report's text

For standardization purposes, all frequently reported terms, stop words, and connectors like "the," "of," "and," "to," and "in" are removed from annual reports (Henry, 2008). Additionally, elements like headings, footers, links, tables of contents, exhibits, appendices, signatures, and powers of attorney are eliminated as part of the standardizing process. The text is then transformed to lowercase and stemmed for the query search of the AI lexicon (presented in **Table 1**).

3.2. Measurement of other variables

3.2.1. Dependent variable

Financial performance is measured using a range of metrics. Accounting returns serve as a direct indicator of the effectiveness of management initiatives in performance evaluation. The two most significant accounting metrics for all stakeholders are ROA and ROE. These performance measures are important for both management and stakeholders, as they describe the financial returns of business activities. They have been used in various previous studies to show the company's financial outcomes (Haque et al., 2024; Lu and Wang, 2024).

3.2.2. Moderating variable

This study examines R&D spending's moderating role, with the rationale being that R&D stimulates creativity and focuses on new technologies. R&D encourages the involvement of more efficient and up-to-date technology in product and procedure design (Xiong et al., 2023). Additionally, R&D activities enhance the understanding of the latest technologies by facilitating the identification of appropriate technology (Lu and Wang, 2024).

3.2.3. Control variables

As recommended by the literature, control factors are added to precisely explain the relationship between performance and the explanatory variables (Richards et al., 2019). These factors help distinguish companies that operate in diverse conditions, thereby increasing the quality of the relationship and its explanation. Firm size, financial leverage, market-to-book value of equity, and firm age are the control variables used in this study based on the suggestion from previous studies in similar contexts (Tung and Binh, 2022; Yuanyuan et al., 2023). **Table 2** provides a thorough explanation and measurement of every variable engaged in this study.

Table 2. Description & measurement of variables.

Variable	Proxy	Measurement	Source
FP	Financial performance (a) Return on Assets (ROA) (b) Return on Equity (ROE)	(a) ROA = Income Before Taxes/Total Assets (b) ROE = Income Before Taxes/Total Equity	Compustat
AI_Score	Artificial intelligence Score percentage	Percentage (%) of AI words to total words in a document	Annual reports from the EDGAR website
R&D	Research & development spending (a) R&D_Percent (b) R&D_Dummy	(a) Percentage of R&D (R&D_Percent) Spending to Total Sales (b) R&D_Dummy = 1, if R&D percentage is higher than average otherwise = 0.	Compustat
F_SIZ	Firm size	Natural log of total sales	Compustat
LEV	Financial leverage	Total debt to total assets	Compustat
MBR	Market-to-book ratio	The ratio of the market value of equity to the book value of equity	Compustat
F_AGE	Firm age	Natural log of the number of years the firm appeared in compustat	Compustat

Table 2 presents the details and measurements of the variables used in this study. The main source of financial data is the Compustat available at Wharton Research Data Services (WRDS, 2024). Annual Reports are obtained for all listed companies from Electronic Data Gathering, Analysis, and Retrieval System website (EDGAR, 2024).

3.3. Data sources and data period

Based on the availability of the data, this study uses the data from 2003 through 2022 for all US-listed companies. After the Sarbanes-Oxley act in the year 2002 requiring extended financial information disclosures and uniformity in the format of annual reports. The standardized 10-K reporting format, which started in 2003, is the main reason for selecting this start year. The end year, 2022, is chosen as it is the last available year for annual reports. Additionally, this year allows for the recognition of the growth in the understanding and implementation of AI technologies over time.

The annual reports in the 10-K form for all listed corporations are downloaded from the EDGAR website of the Securities and Exchange Commission (SEC). Additionally, the data for other firm-specific variables is downloaded from the Compustat database available at the WRDS database service. The dataset contains missing values, resulting in an unbalanced panel. Using STATA, which is an statistical analysis tool, regression analysis can be performed with missing observations by taking into account the instances and years with complete data (Greene, 2012). As a result, an unbalanced panel is permissible and takes into account the available annual observations.

3.4. Data analysis technique

The classical linear regression method is effective when all the fundamental requirements of the model are fulfilled by the data. However, in many cases, the fundamental requirements are not satisfied especially when working with panel data using firm-specific variables. In such contexts, there is a high likelihood of error correlations and multi-collinearity, which can lead to unreliable results when using the classical linear regression method. Consequently, the usage of dynamic regression models is suggested when dealing with firm-specific variables.

In this context, the dynamic fixed effects model (FEM) or dynamic random effects model (REM) would be a good choice. The primary difference between these models lies in how they allow the unobserved individual effects to correlate with the independent variables. To ascertain which of the two models is appropriate for the data, a Hausman test is conducted. REM is appropriate, when the null hypothesis is accepted otherwise, FEM is utilized. The regression equation to determine the effect of the AI concentration on financial gains in panel data is expressed in Equation (1).

$$\mathrm{FP}_{it} = \alpha_{\mathrm{o}} + \beta_1 \mathrm{AI\_Score}_{it} + B_i \mathrm{CONT}_{it} + \mu_{it} \quad (1)$$

Equation (2) is the extended form of Equation (1) which extends the control variables (CONT).

$$\mathrm{FP}_{it} = \alpha_{\mathrm{it}} + \beta_1 \mathrm{AI\_Score}_{it} + \beta_2 \mathrm{F\_SIZ}_{it} + \beta_3 \mathrm{LEV}_{it} + \beta_4 \mathrm{F\_AGE}_{it} + \beta_5 \mathrm{MBR}_{it} + \beta_6 (\mathrm{FP}t - 1)_{it} + \mathrm{\mu}_{it} \quad (2)$$

Equations (3) and (4) extend the two performance measures as ROA, and ROE to test the hypothesis H2 and H3 using the regression analysis with control variables.

$$\mathrm{ROA}_{it} = \alpha_{it} + \beta_1 \mathrm{AI\_Score}_{it} + \beta_2 \mathrm{F\_SIZ}_{\mathbf{it}} + \beta_3 \mathrm{LEV}_{it} + \beta_4 \mathrm{F\_AGE}_{it} + \beta_5 \mathrm{MBR}_{it} + \beta_6 (\mathrm{ROA}t - 1)_{it} + \mu_{it} \quad (3)$$

$$\mathrm{ROE}_{it} = \alpha_{it} + \beta_1 \mathrm{AI\_Score}_{it} + \beta_2 \mathrm{F\_SIZ}_{it} + \beta_3 \mathrm{LEV}_{it} + \beta_4 \mathrm{F\_AGE}_{it} + \beta_5 \mathrm{MBR}_{it} + \beta_6 (\mathrm{ROE}t - 1)_{it} + \mu_{it} \quad (4)$$

This regression equation is extended for the analysis of the moderating role using the moderating effect of AI score and R&D (AI_Score × R&D). The extended form is given in Equation (5).

$$\mathrm{FP}_{it} = \alpha_{it} + \beta_1 \mathrm{AI\_Score}_{it} + \beta_2 \mathrm{R\&D}_{it} + \beta_3 \mathrm{AI\_Score}_{it} \times \mathrm{R\&D}_{it} + B_i \mathrm{CONT}_{it} + \mu_{it} \quad (5)$$

Equation (6) express the regression model with two performance indicators and controlling factors (CONT).

$$\mathrm{FP}_{it} = \alpha_{it} + \beta_1 \mathrm{AI\_Score}_{it} + \beta_2 \mathrm{R\&D}_{it} + \beta_3 \mathrm{AI\_Score}_{it} \times \mathrm{R\&D}_{it} + \beta_4 \mathrm{F\_SIZ}_{it} + \beta_5 \mathrm{LEV}_{it} + \beta_6 \mathrm{F\_AGE}_{it} + \beta_7 \mathrm{MBR}_{it} + \mu_{it} \quad (6)$$

Equations (7) and (8) are extended by including two performance indicators. These regression equations are engaged to test hypotheses H4 and H5 respectively.

$$\mathrm{ROA}_{it} = \alpha_{it} + \beta_1 \mathrm{AI\_Score}_{it} + \beta_2 \mathrm{R\&D}_{it} + \beta_3 \mathrm{AI\_Score}_{it} \times \mathrm{R\&D}_{it} + \beta_4 \mathrm{F\_SIZ}_{it} + \beta_5 \mathrm{LEV}_{it} + \beta_6 \mathrm{F\_AGE}_{it} + \beta_7 \mathrm{MBR}_{it} + \mu_{it} \quad (7)$$

$$\mathrm{ROE}_{it} = \alpha_{it} + \beta_1 \mathrm{AI\_Score}_{it} + \beta_2 \mathrm{R\&D}_{it} + \beta_3 \mathrm{AI\_Score}_{it} \times \mathrm{R\&D}_{it} + \beta_4 \mathrm{F\_SIZ}_{it} + \beta_5 \mathrm{LEV}_{it} + \beta_6 \mathrm{F\_AGE}_{it} + \beta_7 \mathrm{MBR}_{it} + \mu_{it} \quad (8)$$

where 'FP' is a vector of financial performance in terms of two financial performance indicators which are return on assets (ROA) and return on equity (ROE). ∴FP ← ROA and ROE. 'AI_Score' is the percentage of AI words frequency to total words in an annual report, CONT is a vector of four control variables, all β's are slopes parameters for explanatory variables, 'u_i' is the unobservable effect covered in the stochastic error term, 'i' and 't' with each variable are for the cross-section and time effects in panel data. The moderating effect of concentration on AI and R&D (AI_Score × R&D) is also included.

4. Results

The results are provided using regression analysis to examine the impact of concentration on AI on the financial gains of firms. Initially, to understand the general features of the data series descriptive statistics and correlation matrix are presented in **Tables 3** and **4** respectively.

Table 3. Descriptive statistics.

Variables	Mean	Min	Max	St. Dev.	Obs.
ROA	−0.16	−1.18	0.26	0.88	80,875
ROE	−0.12	−2.72	0.399	0.80	70,569
AI_Score	0.018	0.012	0.12	0.018	80,952
F_SIZ	5.26	−6.91	13.25	2.71	83,913
LEV	0.21	0.00	0.87	0.26	88,816
MBR	2.67	−71.4	77.6	13.5	71,361
F_AGE	11.2	0	29	7.03	66,191
R&D	0.25	0.00	21.8	2.5	67,890

Note: The table shows descriptive statistics of each variable of the study. This comprises the mean, minimum, maximum, standard deviation, and total number of observations of each variable. The sample includes the years 2003–2022.

Table 4. Correlation matrix.

Variables	ROA	ROE	AI_Score	F_SIZ	LEV	MBR	F_AGE	R&D
ROA	1.00							
ROE	0.21	1.00						
AI_Score	0.09	0.01	1.00					
F_SIZ	0.35	0.20	0.22	1.00				
LEV	−0.05	−0.09	−0.13	0.15	1.00			
MBR	0.17	0.05	0.05	0.05	−0.07	1.00		
F_AGE	−0.03	−0.02	−0.02	0.09	0.02	−0.02	1.00	
R&D	−0.12	−0.07	0.24	0.37	−0.03	−0.001	−0.02	1.00

Note: This table presents the Pearson correlation coefficient value for the variables engaged in this study.

The descriptive statistics show that over the period starting from 2003 to 2022, the firms under investigation performed poorly, as evidenced by the negative mean values of ROA and ROE (−0.16, −0.12). The maximum values of these performance markers were 0.26 for ROA and 0.399 for ROE. Nonetheless, the minimum values of the performance indicators were negative, indicating that during the study period, the majority of the enterprises had at least one instance of subpar performance. The average percentage of AI_score is 1.8, this means that average annual reports contain 1.8 percent of AI words to the total number of words.

After taking the natural logarithm of the firm size proxy using total sales (F_SIZ), descriptive analysis shows a positive mean value of 5.26. Leverage (LEV), the market-to-book value of equity (MBR), and firm age (F_AGE) have mean values of 0.21, 2.67, and 11.2, respectively. Each of these variables, except leverage, has more than one maximum value. Leverage has a maximum value of 0.87 suggesting that the corporation under investigation utilized a maximum of 87 percent debt financing.

The Pearson correlation coefficient is calculated to ascertain the relationship between the variables in the data set, as presented in **Table 4**. It is essential that there is a minor correlation between the variables and there is no existence of high correlation, that could compromise the validity of the results obtained from the dataset utilized in this investigation. If the dataset's Pearson correlation coefficient is less than 0.8, it indicates that high collinearity is not an issue; if not, some highly correlated variables need to be changed. The correlation values are less than 0.8 which supports the basic condition of the absence of multi-collinearity in the dataset.

4.1. Growth in AI technologies over time

In **Figure 1**, the AI score pattern is based on the average annual frequency of AI-related terms that appear in annual reports of all US-listed companies examined here. The AI Score increased steadily and consistently from 774 in 2003 to 1387 in 2022 demonstrating a rising trend of attention being paid to AI (see **Figure 1**). This suggests that interest in AI technologies is expanding, indicating that companies are increasingly investing in these technologies. This growing interest in AI may positively impact their output, effectiveness, data processing capacity, and decision-making ability as noted by Arumugam et al. (2024). The consistent surge in AI scores highlights the potential advantages of AI technologies for businesses. Based on the score of AI-related terms a word cloud of AI-related words is presented in **Figure 2**.

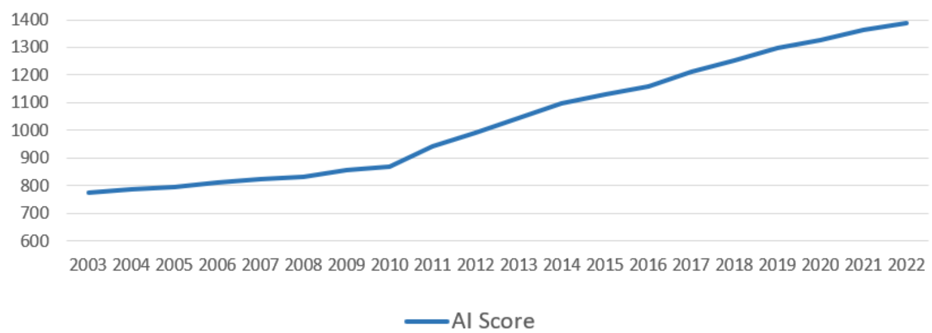

Figure 1. AI score trend from the year 2003 to 2022.

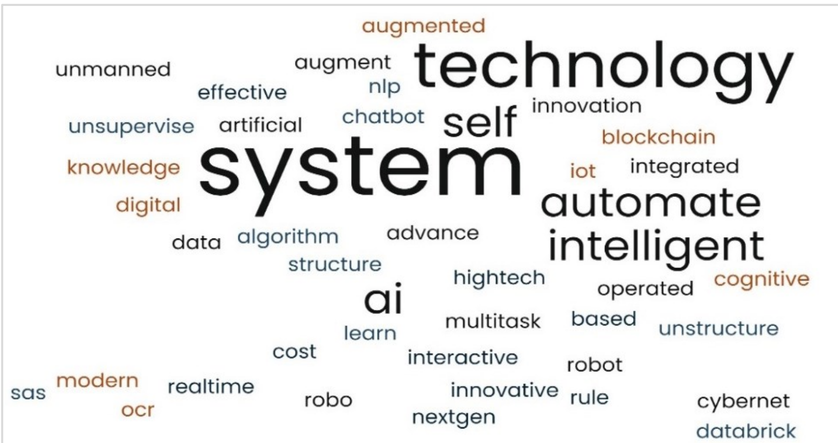

Figure 2. Word cloud of AI-related words in annual reports.

4.2. Results of regression analysis

To identify the appropriate model from the fixed and random effects model, Hausman's test is used. Its *p*-value is less than 0.05 significance level, indicating that the study can proceed with a fixed effects model to inspect the influence of AI technology attention on a firm's financial performance. The Hausman's test's *p*-value is provided in **Table 5**, along with the main findings of the study.

In findings, models 1 and 2 prove that AI concentration affects the ROA. The *p*-value is statistically significant at a 1% significance level, demonstrating the significantly beneficial effect of concentration on AI on returns growth. This indicates that businesses will see a significant boost in return on assets when they devote more attention to AI technologies. Furthermore, models 3 and 4 shed light on how concentration on AI affects ROE, another type of financial performance metric. The findings indicate that AI_Score has a favorably significant influence on ROE at a 1% significance level. This proves that higher AI concentration increases shareholder returns. highlighting the significance of increasing the focus on AI to raise the firms' equity returns.

Table 5. Regression results: Impact of concentration on AI on financial gains of business.

Variables	**Dependent variable (DV): Financial Performance (FP)**			
	DV: ROA		**DV: ROE**	
	Model 1	**Model 2**	**Model 3**	**Model 4**
AI_Score	0.26*** [0.03]	0.095*** [0.025]	0.31*** [0.01]	0.21*** [0.01]
*F*_SIZ		0.21*** [0.005]		0.12*** [0.004]
LEV		−0.46*** [0.025]		−0.18*** [0.018]
MBR		0.01*** [0.00]		0.001*** [0.00]
*F*_AGE		−0.011*** [0.001]		−0.014*** [0.00]
DV (−1)		0.23*** [0.003]		0.176*** [0.004]
Constant	0.48*** [0.11]	−0.96*** [0.07]	0.88*** [0.06]	0.16*** [0.017]
F-stat (*p*-value)	64 (0.00)	397 (0.00)	314 (0.00)	389 (0.00)
Time Effects	Yes	Yes	Yes	Yes
Hausman's *p*-value	0.00	0.00	0.00	0.00
Number of Firms	5832	5832	5749	5749

Note: The fixed effects regression results for the impact of concentration on AI on two financial gains measures (ROA and ROE) are presented in this table. AI_Score is the primary independent variable and control variables are included in the regression analysis. The standard error is presented in large parenthesis [], and the *p*-value is reported in small brackets (). Results at the 1%, 5%, and 10% levels of significance are represented by the symbols ***, **, and *, respectively.

Furthermore, **Table 5** indicates positive coefficient estimates for control variables such as firm size, market value of equity to book value of equity, and performance from the prior year. These results imply that their increase brings positive changes in financial gains for businesses. The *p*-values are statistically significant at a 1% significance level, suggesting that companies can get favorable performance results if they have more sales, a greater market value relative to the book value of equity, and past positive performance. Negative coefficients are found for company age and use of greater debt. This implies that using more debt in a company is a big factor in poor performance and that as a company ages, returns decline. These findings support the notion that younger enterprises outperform older ones and that higher use of debt financing does not offer increased financial gains.

Overall, the results support the idea that a higher concentration on AI leads to increased financial outcomes. This suggests that a heightened emphasis on AI technologies enhances corporate returns and profitability. However, the benefits of emphasizing on AI technology vary on two performance metrics. More focus on AI has a bigger impact on growing shareholder returns than it has on growing return on assets. This indicates that by putting more emphasis on AI technologies, companies can achieve higher growth in returns on equity than returns on assets.

4.3. Results of regression analysis on the moderating role of R&D

The findings on the moderating effect of R&D spending on the link between AI_Score and both performance metrics (ROA and ROE) are shown in **Table 6**. This study engaged two proxies for R&D spending. The first is the R&D dummy (R&D_Dummy), which has a value of 1 when businesses spend more than the average in R&D and 0 when businesses spend less than average. R&D percentage (R&D_Percent), is the second proxy.

Panel A data shows that a concentration on AI can improve a company's financial gains, demonstrating that businesses can profit financially from AI technologies. The findings indicate a substantial positive coefficient for R&D_Dummy, suggesting that returns are improved by higher-than-average R&D spending. This suggests that higher R&D spending can improve the financial metrics. Its higher value greatly increases the financial rewards. Further, the regression results demonstrate that the interaction term (AI_Score × R&D_Dummy) strengthens the relationship between concentration on AI and firm performance. Higher R&D spending enhances a favorable correlation between AI and business performance, suggesting that greater focus on AI technologies leads to higher performance gains in the presence of higher R&D spending. According to Johnson et al. (2022), R&D is a crucial component that encourages the use of AI technology in enterprises. The results support its beneficial influence of focus on AI technology with performance outcomes.

Table 6. Regression results: The moderating role of R&D on the connection between concentration on ai and financial gains of business.

	Panel A: Regression results for the moderating role of R&D_Dummy			
Variables	**DV: ROA**		**DV: ROE**	
	Model 1	**Model 2**	**Model 3**	**Model 4**
AI_Score	0.20*** [0.03]	0.08** [0.03]	0.27*** [0.02]	0.25*** [0.02]
R&D_Dummy	1.14*** [0.22]	0.28*** [0.03]	0.88*** [0.12]	0.72*** [0.12]
AI_Score*R&D_Dummy	0.38*** [0.07]	0.096*** [0.03]	0.34*** [0.04]	0.29*** [0.04]
*F*_SIZ		0.28*** [0.01]		0.07*** [0.004]
LEV		−0.54*** [0.04]		−0.24*** [0.02]
MBR		0.01*** [0.00]		0.001*** [0.00]
*F*_AGE		−0.011*** [0.00]		−0.011*** [0.00]

Table 6. (*Continued*).

Variables	Panel A: Regression results for the moderating role of R&D_Dummy			
	DV: ROA		**DV: ROE**	
	Model 1	**Model 2**	**Model 3**	**Model 4**
Constant	0.29*** [0.11]	0.42*** [0.11]	0.77*** [0.06]	0.41*** [0.07]
F-stat (prob > F)	30 (0.00)	517 (0.00)	134 (0.00)	261 (0.00)
Number of Firms	5762	5762	5578	5578
	Panel B: Regression results for the moderating role of R&D_Percent			
AI_Score	0.23*** [0.03]	0.02 [0.02]	0.31*** [0.02]	0.13*** [0.04]
R&D_Percent	0.24*** [0.02]	0.28*** [0.03]	0.06*** [0.014]	0.20*** [0.03]
AI_Score*R&D_Percent	0.11*** [0.01]	0.095*** [0.01]	0.023*** [0.005]	0.036*** [0.01]
*F*_SIZ		0.31*** [0.04]		0.08*** [0.002]
LEV		−0.60*** [0.03]		−0.30*** [0.02]
MBR		0.01*** [0.00]		0.01*** [0.00]
*F*_AGE		−0.01*** [0.00]		−0.01*** [0.00]
Constant	0.43*** [0.11]	−1.75*** [0.09]	0.86*** [0.07]	−0.10*** [0.04]
F-stat (prob > F)	60 (0.00)	530 (0.00)	112 (0.00)	253 (0.00)
Number of Firms	5734	5734	5578	5578

Note: This table reports the regression results for the moderating effect of R&D spending on the relationship between concentration on AI and financial performance indicators (ROA and ROE,). Including AI_Score, and R&D as the main variables, and AI_Score * R&D as interacting terms to demonstrate moderating effects along with control variables. In large parenthesis [], the standard error is reported and in small brackets (), the *p*-value is reported. Results at the 1%, 5%, and 10% levels of significance are represented by the symbols ***, **, and *, respectively.

On the other hand, Panel B demonstrates the favorable correlation between R&D_Percent and performance metrics. However, the effect of AI_Score on performance measures is not strengthened by the interaction term (AI_Score × R&D_Percent), although its impact greatly enhances ROE and ROA. This indicates that the correlation between interest in AI and performance metrics is not strengthened by merely looking at the R&D spending percentage.

Overall, higher R&D spending supports the striking increase in the influence of AI focus on financial benefits. However, due to its fundamental characteristic of being an expense that is mostly negatively correlated with the company's profit margins, the R&D percentage proxy is unable to positively impact (see Panel B). To achieve the desired results, companies need to appropriately manage their R&D expenses. Studies have shown that investing in R&D can help firms become more innovative (Lin and Xie, 2023; Nguyen-Van and Chang, 2020). The results of this study are consistent with earlier research showing that increased R&D spending is drawing attention to AI technologies that benefit businesses financially.

4.4. Discussion of the findings

The results of the study indicate that a concentration on AI is correlated with financial success, aligning with the conclusions of Qinqin et al. (2023). According to the literature, the application of AI technologies in business operations is advantageous due to cost savings, operational efficiency, and increased profitability

(Arumugam et al., 2024; Babina et al., 2024; Li et al., 2023) As a result, the study's findings confirm previous research findings that businesses can increase their profitability by concentrating more on AI technologies.

However, some studies claim there is no positive contribution of AI technologies (Bharadiya, 2023; Pathak et al., 2023). These studies suggest that firms must first increase their employees' knowledge and skills before realizing the benefits, as AI technologies are linked to high computational devices. Similarly, Vinuesa et al. (2020) emphasized that issues with skill development and initial cost exist. Businesses are still unsure of the precise results and procedures associated (Lundvall and Rikap, 2022). However, as noted by Arumugam et al. (2024), companies that place a greater emphasis on cutting-edge technologies are more likely to see greater financial advantages than their competitors. The findings confirm that increased concentration on AI technologies can significantly improve financial gains. Therefore, hypotheses 2 and 3 are supported.

Furthermore, there is a significant moderating effect of greater R&D spending on the impact of focus on AI on business performance. These results are aligned with previous studies that R&D brings positive outcomes of new technologies (Lu and Wang, 2024; Tung and Binh, 2022). The findings of the study have validated the growth in financial outcomes of focus on AI technologies which are further enhanced in the presence of higher R&D spending. Averagely higher R&D spending amplifies the positive outcomes of AI technology advancement (Sarpong et al., 2023; Xiong et al., 2023). Therefore, hypotheses 4 and 5 are supported.

5. Conclusion

Based on the main findings, there is a significant correlation between financial gains and a focus on AI technologies. This specifies that with increased concentration on AI, business profitability is improved. Additionally, shifts in concentration on AI have a significantly larger outcome for shareholders' returns than assets' returns. This explains that companies that pay more attention to AI typically see larger returns on their shareholders' wealth compared to those that do not.

Furthermore, the findings reveal that a greater emphasis on AI, combined with greater R&D spending, improves business financial gains. R&D endeavors are essential components in fostering innovation that yields financial gains. To promote learning and development, businesses need to allocate more funds to R&D. When research and learning are continuously encouraged, it becomes easy to identify the newest business trends. More investment in R&D is closely associated with the positive outcomes of AI focus on financial growth. Increased R&D spending can provide management with the necessary motivation to leverage cutting-edge technology that may improve the product and process.

Implication and limitations of the study

This study supports the idea that organizational interest in AI technologies needs to be effectively managed due to their influence on performance outcomes. The findings of the study can be useful to shareholders, managers, government authorities, and policymakers. Managers must channel their interest in the right technologies to get the maximum benefit of the business resources. The findings can encourage managers to use AI technologies to foster more rapid growth. Shareholders must invest their money in firms that are proactively focusing on AI technologies because these technologies can benefit firms in achieving their targets.

Government authorities and policymakers need to design policies on the use of AI technologies to ensure their appropriate involvement. They can arrange programs to create more awareness, thereby minimizing the confusion surrounding the use of AI technologies. Furthermore, the findings of this study extend support to the notion of the endogenous growth theory that the benefits of the latest technologies can be increased with the support of internal factors. Businesses that are spending more on R&D are capable of getting higher financial outcomes from AI technologies. However, this study has focused on US-listed companies only and the proxy for the concentration on AI technologies is not entirely exhaustive. Therefore, future research studies can expand by using various other proxies at the micro, and macro levels and to other types of businesses.

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