Artificial Intelligence as a Dynamic Capability: Implications for Sustained Competitive Advantage

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Abstract

Artificial Intelligence (AI) is also becoming not only a tool of technology but also a strategic organizational asset that has helped companies to adjust, innovate, and maintain a competitive advantage in dynamic markets. This study builds on the theory of Dynamic Capability, and the Resource-Based View (RBV): the concept of AI is developed as a higher-order dynamic capability, which upgrades the sensing, seizing, and reconfiguring capacity of firms. The study incorporates financial, operational and AI-specific metrics of innovation by using a cross-sectional dataset of 43 major technology and AI-intensive companies globally in 2024 (including the likes of NVIDIA, Microsoft, Alphabet and Amazon) to empirically test the relationship between AI capability and competitive performance. AI capability is modeled based on AI revenue percentage, AI patent counts, cloud revenue contribution, and GPU market share and sustained competitive advantage is proxied based on market capitalization, revenue growth and valuation metrics. The results indicate that companies that have more powerful AI-based abilities have a much higher growth rate and market valuation, implying that AI helps to bring agility at the firm-level and competitive positioning in the long-term perspective. The findings reveal that AI competence does not only increase the intensity of innovation, but also investor confidence, which supports the position of AI capability as a strategic resource and not an independent technology investment. This study makes a contribution to the literature related to strategy management because it provides empirical data that AI is a dynamic ability, which affects competitive advantage in the digital economy. It provides managerial insights to executives who aim to use AI investments to create sustainable values as well. The study contributes to the knowledge of AI metrics in the context of the firm performance indicators, thus, moving AI metrics in terms of relevant outcomes of the digital transformation to the realms of competitive practices.

Keywords: Artificial Intelligence, Dynamic Capability, Constant Competitive Advantage. Resource-Based View (RBV), AI Capability Index and Strategic Management

I. Introduction

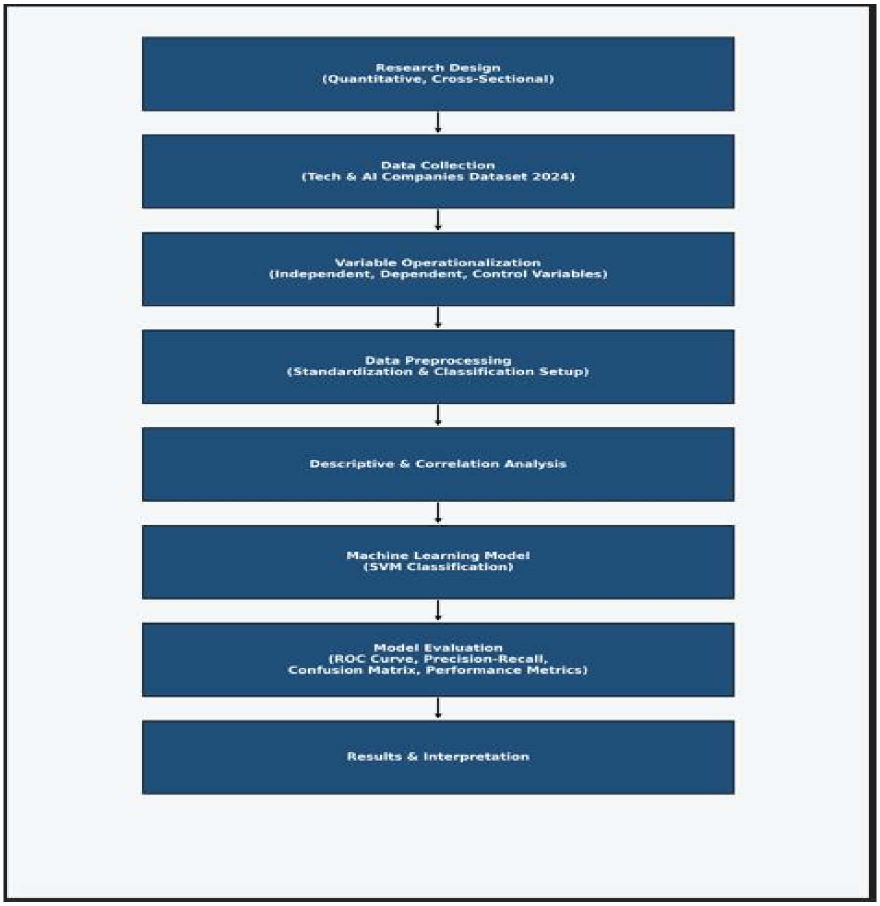
Artificial Intelligence (AI) has rapidly evolved from a specialized computational discipline into a core driver of digital transformation across industries, with firms increasingly embedding AI into strategic and operational processes to improve efficiency, innovation, and decision-making [1-3]. Its applications now extend beyond routine automation to include predictive analytics, intelligent recommendation systems, autonomous operations, and real-time data-driven insight generation, allowing major global technology firms such as NVIDIA, Microsoft, Alphabet, and Amazon to create new revenue streams, strengthen customer engagement, and optimize large-scale operations [4-6]. As competitive environments become more volatile and technology-intensive, AI is no longer viewed merely as an element of IT infrastructure but as a strategic organizational resource with the capacity to reshape long-term firm competitiveness [7]. This perspective is strongly supported by the Resource-Based View and Dynamic Capability Theory, which argue that sustainable competitive advantage arises not only from valuable, rare, and difficult-to-imitate resources, but also from a firm's ability to integrate, build, and reconfigure internal and external competencies in response to changing environments [8-10]. In this context, AI can be understood as a higher-order dynamic capability because it enhances organizational sensing through large-scale data interpretation, strengthens seizing through data-driven innovation and adaptive strategic responses, and supports reconfiguration through workflow automation, supply chain transformation, and scalable digital infrastructure development [11-13]. Despite growing recognition of AI as a strategic enabler, much of the existing literature remains focused on technical performance, adoption barriers, or short-term financial returns, while empirical evidence treating AI as a measurable dynamic capability linked to sustained firm-level competitive advantage remains limited [14]. Prior studies have often relied on qualitative case analyses or narrow industry settings, reducing generalizability and leaving insufficient integration between AI-specific innovation indicators and conventional performance metrics [15]. To address this gap, the present study conceptualizes AI as a dynamic organizational capability and investigates its relationship with long-term competitive advantage in the digital economy by examining whether AI capability positively influences firm growth and valuation, how AI-related indicators such as AI revenue share, patent strength, and cloud-based AI revenue relate to competitive positioning, whether AI can be empirically modeled as a source of sustained advantage, and whether organizational and market factors moderate this relationship [16-18]. Accordingly, this study aims to construct a measurable AI capability index using financial and innovation variables, test its association with firm performance outcomes such as revenue growth and market capitalization, and assess whether capital markets recognize AI capability as a contributor to long-term value creation [19]. By doing so, the study contributes to strategic management theory by extending the dynamic capability perspective into the AI domain and offers practical guidance for executives seeking to align AI investment and implementation with long-term organizational growth, resilience, and sustainable competitive positioning [20].

2. Literature Review

Artificial intelligence has emerged as a strategic technological resource that shapes firm performance and industry structure by enabling organizations to process large volumes of data, extract actionable insights, automate routine decision-making, and continuously improve prediction quality, efficiency, and customer personalization over time [21,22]. Unlike traditional information systems, AI develops through learning, which strengthens its strategic value when it is embedded in organizational routines, combined with proprietary data, and supported by firm-specific human expertise that competitors cannot easily replicate [23,24]. This strategic role aligns closely with Dynamic Capability Theory, which explains how firms sustain competitiveness in turbulent environments by sensing change, seizing new opportunities, and reconfiguring internal resources and processes [25,26]. AI enhances sensing through advanced analytics and machine learning, supports seizing through innovation, automation, and responsive market actions, and facilitates reconfiguration by improving operational flexibility, supply-chain adaptation, production efficiency, and customer interface redesign [27,28]. Firms that cultivate data-driven cultures, invest in AI talent, and integrate AI into governance and decision structures are therefore better positioned to transform technological adoption into continuous strategic renewal and long-term adaptability [29,30]. In technology-intensive industries, sustained competitive advantage increasingly depends on innovation speed, scalability, and the ability to respond rapidly to environmental change, and AI has become central to these capabilities by improving revenue generation, cost efficiency, customer retention, predictive maintenance, intelligent supply chains, and market responsiveness [31,32]. However, the advantages of AI are not automatic, since sustainable benefit depends on complementary resources such as infrastructure, proprietary datasets, organizational learning, and the capacity to create self-reinforcing innovation cycles that raise competitive barriers over time [33,34]. Investor perception also strengthens this effect, as firms with strong AI capabilities are often viewed as more innovative, scalable, and profitable, which can improve valuation and access to capital [35,36]. Existing research has provided useful evidence for the positive relationship between AI and innovation capability, particularly through digital adaptability and market perception within a dynamic capabilities framework, but much of this work has focused more narrowly on innovation outcomes, relied heavily on regional or survey-based samples, and measured AI largely as behavioral adoption rather than through objective firm-level indicators [37,38]. As a result, an important research gap remains in understanding AI as a quantifiable strategic capability that directly influences sustained competitive advantage through market-based and financial performance measures across globally relevant technology-intensive firms [39,40].

3. Methodology

In this study, the quantitative methodological approach has been used to investigate the relationship between Artificial Intelligence (AI) capability and long-term competitive advantage in technology companies throughout the world . The study bases the study on financial, operational, and innovation measures to assess the strategic results using a cross-sectional dataset of AI-intensive firms in the year 2024. Descriptive statistics, correlation analysis and machine learning classification are integrated into the methodology to evaluate the structural relation along with the predictive performance . The operationalization of AI capability by measuring its impact under indicators presents empirical data on how AI can help companies enhance their performance and competitiveness in unstable digital markets.The flowchart below displays the methodological approach followed in the study in a systemic manner. It starts with the research design, which is a quantitative, cross-sectional design. The second stage describes the collection of data through the use of the 2024 Tech & AI Companies dataset. This is followed by variable operationalization where an independent, dependent and control variable are defined in accordance with the conceptual framework. Preprocessing of the data is done by standardizing data features and configuring it with classification to set it up before analysis . The methodology goes ahead to descriptive, correlation analysis to find out the relationships between variables. An SVM classification machine learning model is then used and finally, the model is evaluated using ROC, Precision-Recall, and Confusion Matrix as well as performance metrics. Results interpretation is the last step in the process.

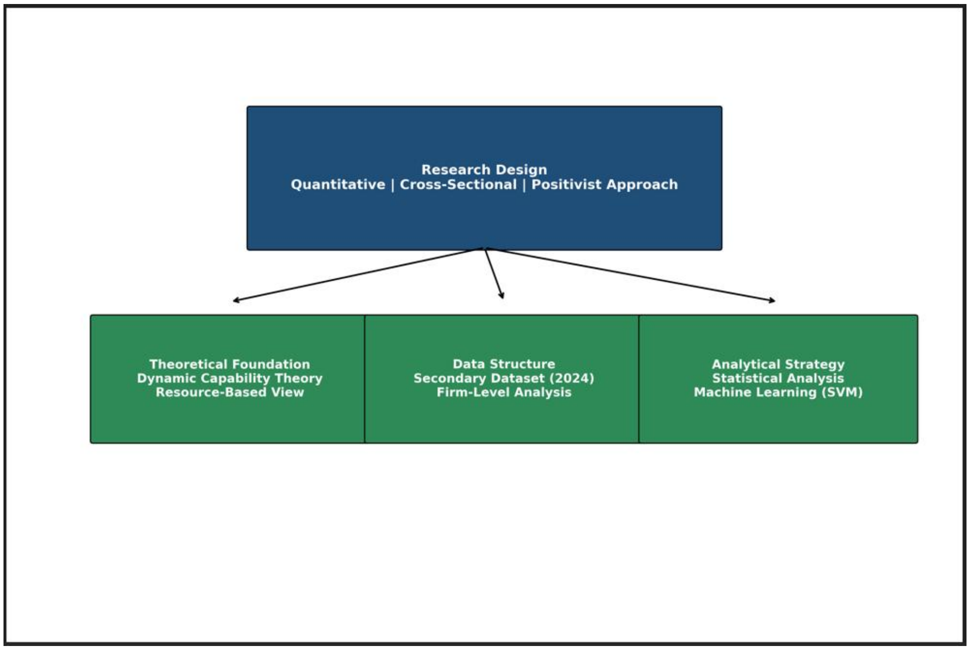


This flowchart shows the methodological process of systematic quantitative research

3.1 Research Design

The proposed research takes the form of a quantitative study that is cross-sectional in nature and aims at exploring the links between Artificial Intelligence (AI) capability and the long-term competitive advantage in world technological companies [36]. The study is based on the Dynamic Capability Theory and the Resource-Based View that imagines AI as an integrated organizational ability, and not an independent technological resource [37]. In this theoretical framework, AI is considered a strategic resource, which contributes to the firm gaining capacity to feel the changes in the environment, capture opportunities, and reform internal operations. The study is based on a positivist research philosophy, which focuses on objective measurement, statistical validation, and empirical testing of constructs of theory [38]. The cross-sectional approach allows performing systematic analysis of the year 2024 firm-level AI capability and financial performance indicators. Though such design does not make it possible to infer causality throughout time, it offers a solid observation of current AI-based competitive dynamics in industries [39]. The research design is a combination of explanatory and predictive elements. Explanatory analysis is done with correlation and distribution tests to establish structural relationship between AI capability measure and financial performance measures. To test whether

AI capability can be used to distinguish high-growth and low-growth firms, predictive analysis is carried out based on a machine learning classification model [40]. The research design guarantees both theoretical soundness and empirical topicality by taking a strategic theory and supplementing it with quantitative analytics . The method is appropriate in the analysis of a complicated, technology-based competitive landscape in which quantifiable innovation pointers and monetary measurements can be methodically reviewed to determine organizational performances.



This flowchart depicts the systematized quantitative research design
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This flow chart displays the research design framework followed in the study. The main research design, which is presented at the top, is quantitative, a cross-sectional study, and based on a positivist approach that focuses on objective measurement and empirical validation . There are three pillars underpinning the design. First, the theoretical framework is based on the Dynamic Capability Theory and the Resource-Based View that will offer the conceptual framework to investigate AI as a strategic resource. Second, the data structure denotes the usage of a secondary 2024 firm-level data. Third, the analytical strategy incorporates both statistical analysis and machine learning (SVM) to assess the relationship and prediction efficiency.

3.2 Model Specification

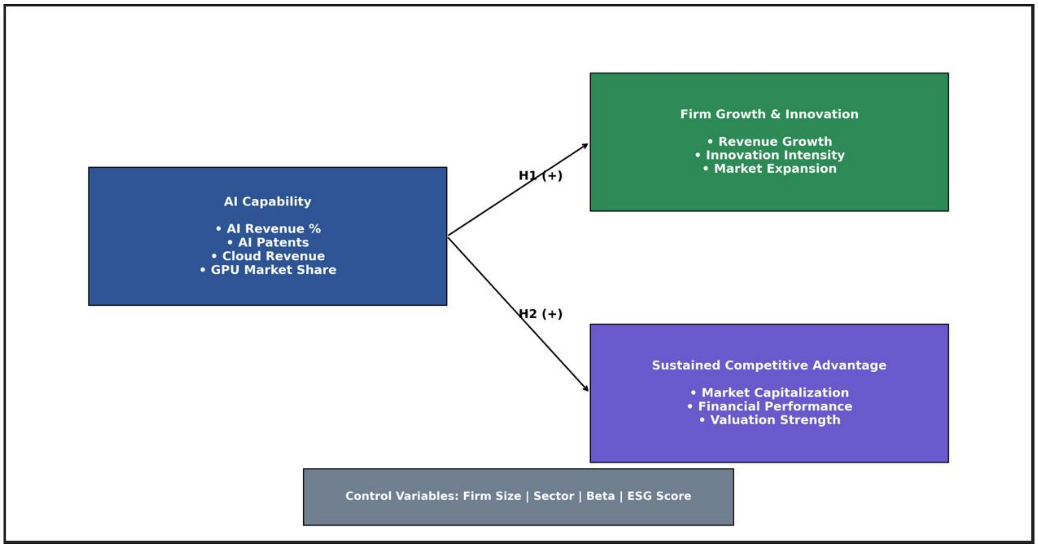
Firms with high-growth and low-growth were picked to investigate predictive relationships between AI capability and competitive outcomes, which is based on the median annual growth rate as the threshold. This dichotomous method of classifying allows us to determine whether AI-related indicators are able to differentiate between firms that have above-median growth and those that have below-median growth. The Support Vector Machine (SVM) classifier has been chosen because of its ability to deal with small to medium size data and its ability to express non-linear decision boundaries using kernel functions . The explanatory variables were AI Revenue Percentage, AI Patents Count, Cloud Revenue and GPU Market Share, which are dimensions of core AI capability. The feature of classification can be represented as follows:

$$Growth_{Class,i} = f(AIRevenue_i,\ AIPatents_i,\ CloudRevenue_i,\ GPUMarketShare_i)$$

The SVM model aims at identifying the best hyper plane, which maximizes the distance between high-growth and low-growth companies in the multidimensional feature space. The standardization of features was done before the estimation of the model to avoid the bias of the scale . To measure the performance of generalization, the dataset was split into training and testing subsets. The predictive results were measured on standard classification measures with which there was a thorough assessment of model capability . The specified criterion enables the analysis of the discriminative potential of AI capability in explaining the performance of firm growth in a competitive environment with technologies.

4.1 Conceptual Framework

The theoretical foundation of this study makes Artificial Intelligence (AI) capability a dynamic capability of higher order that affects the sustainable competitive advantage as an outcome of organizational performance . The framework is based on the Dynamic Capacity Theory and the Resource-Based View and is a conceptualization of AI as an integrated organizational capability that is integrated into innovation processes, digital infrastructure, and strategic decision-making systems rather than a technological asset . AI Capability, as the central independent construct of the framework, works as the core of the framework. It is operationalized by quantifiable measures such as AI revenue percentage, AI patent intensity, cloud-based AI revenue and GPU market share. All these dimensions represent the extent of AI integration, innovation power, and scaling potential of the firm. AI capability improves sensing capacity of a firm because it allows the firm to make decisions based on facts, seizing ability by enabling quick commercialization of solutions powered by AI and reconfiguration by ensuring that the operations of a firm are optimized. The market capitalization, revenue performance, and growth rate, and valuation indicators represent the dependent construct, the Sustained Competitive Advantage. These results are the financial magnitude as well as the investor trust, which is a proxy of long-term strategic location. The framework presupposes that companies that possess stronger AI have a greater potential to produce higher financial results and be competitive in comparison with rivals. Control variables such as firm size, sector type, market volatility, and ESG performance are added to control the contextual factors which might impact the AI-performance relationship.. Firm growth performance is viewed as a final performance and as an intermediate performance measure [1]. The conceptual framework suggests that the AI capability is positively related to competitive advantage based on the increased innovation, scalability, and organizational agility [2]. This framework offers a theory-based foundation of the empirical research of the strategic impact of AI in the modern digital markets.



This chart shows AI capacity as a source of expansion and benefit

The diagram below shows the study conceptual framework, that is, it demonstrates the structural relationships among AI capability, firm growth, and sustained competitive advantage. The primary independent construct is AI capability in terms of AI revenue percentage, AI patents, cloud revenue, and the market share of GPUs. The two positive relationships are described as H1 is between the AI capability and the growth and innovation of the firm, and H2 is the direct correlation between the AI capability and the sustained competitive advantage. Market capitalization, financial performance and strength in valuation are all forms of competitive advantage [3]. Control variables, such as firm size, industry, beta, and ESG score, are used to consider contextual effects on such relationships.

4.2 Dataset Overview

The data that has been utilized in this research is Tech and AI Companies Market Data 2024, which is a detailed, cross-sectional, view of 43 major companies worldwide that are currently working on the development, commercialization, and innovation of Artificial Intelligence (AI). The dataset incorporates both financial and operational metrics with AI-specific data and provides a multidimensional approach that can be used to analyze AI as a dynamic organisational capability [4]. The companies in the list represent various sectors that are technologically intensive hence covering semiconductors, software, cloud computing, internet services, consumer electronics, and e-commerce thus providing cross-industry coverage in AI-driven markets. Some of the main financial indicators present in the dataset include market capitalization (trillion USD), stock price (USD), 2024 revenue (billion USD), the price to earnings (P/E) ratio, the dividend yield, and 52-week high and low stock prices. These indicators reflect firm valuation, profit expectations, market volatility and financial health in general. Competitive positioning and organizational scale are major proxies represented by the market capitalization and revenue [5]. The dataset also includes the AI-specific performance indicators, in addition to the traditional financial variables. These will be AI revenue as a ratio of total revenue, AI patent counts, cloud revenue (billion USD), and GPU market share (as a ratio). These variables indicate the level of AI adoption, level of innovation, infrastructure potential and techno-power [6]. The percentage of AI revenue shows how important AI is in the business of any given firm, and the number of patents reflects the level of knowledge and innovation potential [7]. Cloud revenue and GPUs market share are indicators of scalability and computing architecture power which are critical elements of AI capability. There are also organizational and contextual variables included in the dataset, i.e., the total number of employees, the headquarters location, the sector classification, the ESG score, the growth rate (2024, %), and the beta value that indicates stock volatility [8]. These variables allow the control over the size of the firm, industry influences, sustainability orientation, and exposure to market risk. The dataset includes a close mix of both innovation measures and financial performance measures, which enables the strong empirical research of the relationship between AI capability and competitive advantage [9]. It is multidimensional in nature, allowing both descriptive statistical analysis and future projections in a strategic management context.

Company	Ticker	Market_Cap_Trillion_USD	Stock_Price_USD	Revenue_2024_Billion_USD	AI_Revenue_Percent	Employees	Headquarters	Sector	AI_Focus_Area	R&D_Spending_Billion_USD	Growth_Rate_2024_Percen	P_E_Ratio	Dividend_Yield_Percent	52_Week_High_USD	52_Week_Low_USD	Beta	ESG_Score	AI_Patents_Count	Cloud_Revenue_Billion_US	GPU_Market_Share_Percent
NVIDIA	NVDA	4.44	1150	242.5	85	29600	Santa Clar	Semicond	AI Chips	8.7	122.4	75.2	0.03	1200	108	1.65	B	3847	14.5	88
Microsoft	MSFT	3.18	429	245.1	35	228000	Redmond	Software	Cloud AI	29.5	16.5	35.8	0.68	468	362	0.89	A	2156	125	0
Apple	AAPL	3.15	201	383.3	8	164000	Cupertino	Consumer	AI Integration	31.9	2.1	31.2	0.44	237	164	1.24	A	1523	7.2	0
Alphabet	GOOGL	2.08	168	307.4	45	182000	Mountain	Internet S	AI Search	39.5	13.8	23.4	0	191	129	1.05	B	4521	33.1	0
Amazon	AMZN	1.89	181	574.8	15	1541000	Seattle W	E-commer	Cloud AI	85.9	11.2	45.6	0	201	118	1.33	C	1897	96.1	0
Meta	META	1.38	542	134.9	25	77805	Menlo Pa	Social Me	AI Content	38.5	37.6	25.8	0.37	542	274	1.18	C	2834	0	0
Tesla	TSLA	0.82	256	96.8	30	140473	Austin TX	Electric V	Autonomous AI	3.1	-15.2	89.4	0	414	142	2.09	B	1245	0	0
Broadcom	AVGO	0.72	166	51	45	26000	San Jose C	Semicond	AI Infrastructure	5.8	47.3	31.2	1.88	185	95	1.45	B	892	0	0
Oracle	ORCL	0.52	187	53.8	40	164000	Austin TX	Enterprise	Cloud AI	7.2	6.8	45.2	1.06	127	99	1.12	B	756	14.1	0
Taiwan Semic	TSM	0.87	168	75.9	60	76476	Hsinchu T	Semicond	AI Chip Manufac	4.8	31.2	21.4	1.79	212	84	1.02	A	1234	0	0
Salesforce	CRM	0.28	287	34.9	35	79390	San Franci	Cloud Sof	CRM AI	2.4	8.9	58.7	0	344	212	1.34	A	567	34.9	0
AMD	AMD	0.24	149	25.4	55	31000	Santa Clar	Semicond	AI Processors	6.8	9	198.4	0	227	93	1.97	B	1089	0	7
Snowflake	SNOW	0.05	159	3	70	7249	Bozeman	Cloud Ana	Data AI	1.2	32.8	-65.2	0	237	107	1.89	B	234	3	0
Palantir	PLTR	0.12	53	2.2	85	3838	Denver C	Data Anal	Government AI	0.6	27.2	312.5	0	45	15	2.45	C	178	0	0
CrowdStrike	CRWD	0.08	346	3.1	40	8123	Austin TX	Cybersecu	Security AI	0.7	35.2	91.7	0	398	200	1.43	B	145	3.1	0
DataDog	DDOG	0.04	135	2.1	30	5800	New York	Monitorin	Observability AI	0.4	25.6	67.8	0	199	66	1.52	B	89	2.1	0
ServiceNow	NOW	0.17	867	10.9	50	24000	Santa Clar	Workflow	Enterprise AI	1.8	23.1	58.4	0	1021	637	1.25	A	234	10.9	0
MongoDB	MDB	0.04	289	1.7	25	4500	New York	Database	Database AI	0.3	22.5	-48.9	0	509	212	1.68	B	67	1.7	0
UiPath	PATH	0.01	13.5	1.1	60	4180	New York	Automati	RPA AI	0.4	-8.2	-15.6	0	27	10	1.95	B	198	1.1	0
Splunk	SPLK	0.03	197	4.2	35	7500	San Franci	Data Anal	Security AI	0.8	12.4	67.3	0	178	105	1.34	B	156	4.2	0
Workday	WDAY	0.07	280	7.3	20	18000	Pleasanto	HR Softwa	HR AI	1.1	16.8	45.2	0	311	199	1.28	A	89	7.3	0
Zscaler	ZS	0.02	189	1.9	45	6800	San Jose C	Cloud Sec	Security AI	0.4	30.2	312.8	0	259	153	1.67	B	134	1.9	0
Autodesk	ADSK	0.05	267	5.5	25	13500	San Rafae	Design So	Design AI	1.2	8.7	58.9	0	296	195	1.45	A	234	5.5	0
Adobe	ADBE	0.22	487	21.5	40	29239	San Jose C	Creative S	Creative AI	3.1	11.2	45.3	0	638	433	1.23	A	1567	21.5	0
Intuit	INTU	0.18	647	16.3	30	19500	Mountain	Financial S	Financial AI	2.8	13.5	63.2	0.62	721	523	1.12	A	178	16.3	0
IBM	IBM	0.17	185	62.8	35	288300	Armonk N	Enterprise	Enterprise AI	6.2	0.4	24.1	4.63	199	157	1.15	A	8934	22.1	0
SAP	SAP	0.21	174	35.9	25	112000	Walldorf (	Enterprise	ERP AI	5.8	8.9	28.4	1.15	188	143	1.08	A	1234	35.9	0
ASML	ASML	0.32	789	28.3	20	42000	Veldhove	Semicond	Chip Manufactu	3.1	8.7	38.2	0.95	1110	597	1.34	A	567	0	95
Marvell Techn	MRVL	0.06	70	5.9	50	7000	Wilmingto	Semicond	Data Infrastructu	1.4	7.8	67.9	0.06	87	42	1.78	B	345	0	0
Micron Techno	MU	0.13	118	30.8	35	48000	Boise ID	Memory C	AI Memory	8.9	62.8	14.2	0.37	157	71	1.67	B	1234	0	0
Applied Mater	AMAT	0.15	153	26.5	40	36000	Santa Clar	Semicond	AI Manufacturin	3.4	5.2	17.8	0.78	197	114	1.45	B	2345	0	0
Lam Research	LRCX	0.09	632	15.9	45	17500	Fremont (	Semicond	Memory Manufa	2.1	20.1	23.4	0.96	1067	523	1.56	B	567	0	0
KLA Corporati	KLAC	0.06	429	10.1	40	14000	Milpitas C	Semicond	Process Control	1.8	28.3	24.7	1.05	587	297	1.67	B	234	0	0
Synopsys	SNPS	0.08	523	6.2	60	19336	Mountain	EDA Softw	AI Design Tools	1.2	12.8	58.9	0	629	472	1.23	A	445	6.2	0
Cadence Desig	CDNS	0.07	267	4.1	55	9800	San Jose C	EDA Softw	AI Chip Design	0.9	14.2	67.8	0	315	223	1.34	A	334	4.1	0
Arm Holdings	ARM	0.15	145	3.2	70	7500	Cambridg	Semicond	AI Processors	1.1	39.2	89.4	0	164	86	1.89	B	1567	0	0

Technology and AI Companies Mar

(Source Link: https://www.kaggle.com/datasets/imaadmahmood/tech-and-ai-companies-market-data-2024)

5. Results

The empirical evidence based on descriptive statistics, correlation analysis, and machine learning classification models on AI-intensive firm 2024 dataset. The findings measure how AI capability measures, including AI revenue, percentage, AI patent intensity, cloud revenue, and GPU market share, relate to the result performance of firms in terms of revenue, market cap, and growth rate [10]. Descriptive and correlation analyses will give preliminary findings on structural relationships among financial and innovation variables with the Support Vector machine (SVM) model evaluating predictive ability of AI metrics to classify high-growth firms [11]. Taken together, the results provide quantitative data on the level of AI as a dynamic capability in terms of competitive positioning and organizational performance.

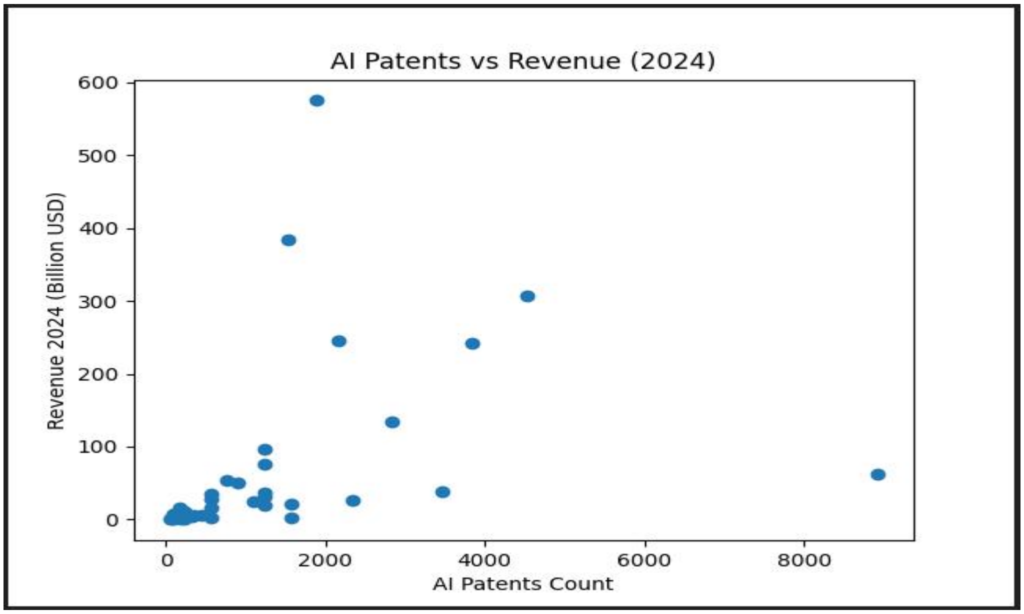


Figure 1: This image represents the AI patents versus revenue of firms

As shown in figure 1, AI patent count relates to the total revenue (2024) of the top global AI-driven companies. AI patent number is placed on the horizontal axis, and revenue (billion USD) on the vertical axis of the scatter plot, which allows observing the extent of innovation in relation to financial results [12]. The graphs of the data points suggest that there is an overall positive correlation between the patent activity and revenue generation of AI. Companies that have moderate and high numbers of patents have a higher level of revenue than those that have low patent portfolios [13]. There are a few high-revenue companies that are concentrated in the middle-to-high patent space (roughly, 1,500-4,500 patents), which means that the continuity of AI innovation activity can lead to better market performance [14]. The relation is not, however, seen to be linear. Some companies have very high rates of patents and relatively even average rates of revenue and other companies in this category have low rates of patents but large revenue rates [15]. This difference suggests that the quantity of patents in its own right is not a complete determinant of financial performance, but instead corrective assets, like commercialization potential, market positioning, and scale of operation, probably fish out the innovation-revenue relationship [16]. Also, the plot shows that most of the companies are clustering in the low range of patent (the range of less than 1,000 patents) and the range of less- than-mid to mid income, which creates imbalance in terms of AI innovation intensity in the industry [17]. The existence of the high-revenue outliers implies that companies that manage to implement AI in the scalable business models receive disproportionate financial returns. The hypothesis that AI innovation capability, which is represented by patent intensity, is correlated with firm-level revenue performance was empirically supported in Figure 1. The finding supports the idea of viewing AI as a strategic dynamic capability that adds to the competitive advantage.

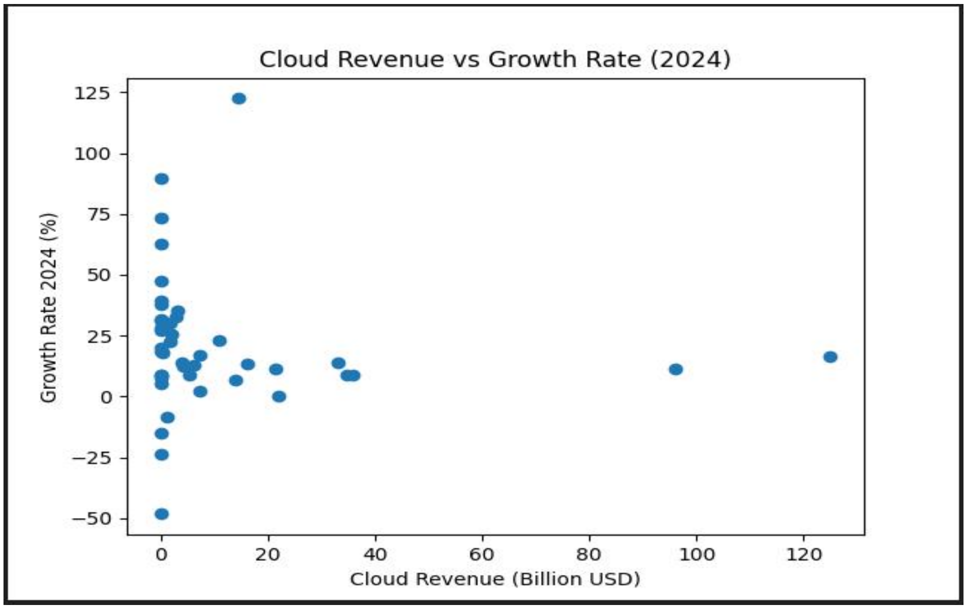


Figure 2: This image illustrates the cloud revenue and the growth rate of the firms

Figure 2 below shows the correlation between cloud revenue (billion USD) and the growth rate of the firm (percentage) in the year 2024. In the scatter plot, the cloud revenue is plotted on the horizontal axis, and the growth rate per year on the vertical axis, which allows evaluating the contribution of AI-driven cloud capabilities to the growth of the organization. The observation distribution gives support to a moderately positive but non-linear relationship existing between cloud revenue and growth performance. The companies that have low to moderate amounts of cloud revenue (less than about 20 billion USD) are characterized by very large ranges in their growth rates, including negative decline and unusually high growth rates over 100 percent. This dispersion suggests that the cloud AI early or mid-scale adoption can have unstable growth results, which might be caused by variations in the market penetration, business model maturity, and operational efficiency. Interestingly, companies that have extremely high cloud revenue (more than 80 billion USD) show positive but relatively steady rates of growth [18]. A benefit of these organizations seems to be that they enjoy the benefits of scalability, in which mature cloud ecosystems create a steady, sustainable growth, as opposed to extreme growth [19]. The high-growths observed over the firms with moderate revenues on cloud services cluster around the middle of these values, which implies that the scaling of AI-enabled cloud services might initially lead to increased performance and this will plateau as the firms age. The fact that some low-cloud-revenue firms have negative growth values also suggests that competitive agility may not be as flexible in dynamic markets when AI is limited in its integration with the cloud [20]. Companies that are more equipped with cloud-based AI seem to be at a better position to sustain favorable growth patterns. In general, Figure 2 confirms that cloud revenue, which is a proxy of scalable AI capability, facilitates the growth of the firms, but the impact of the latter depends on the technological integration stage [21]. These results support the role of AI-powered cloud infrastructure as a dynamic capability that improves the adaptability and the competitiveness of the organization.

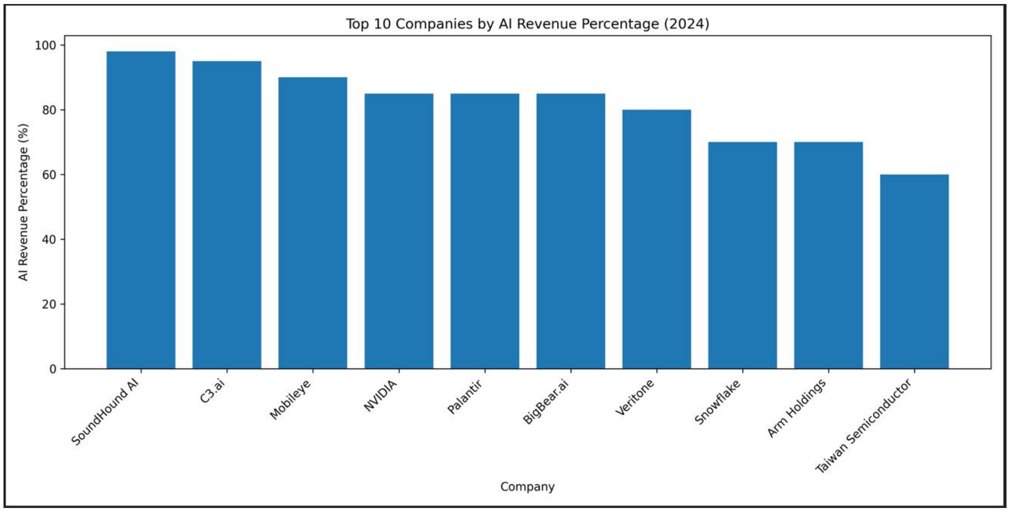


Figure 3: This image depicts the greatest firms in terms of AI revenue share

Figure 3 shows the bar chart with the top ten companies, in terms of their percentage of AI revenue as of 2024. The companies fall in the horizontal axis and the ratio of total revenue obtained through AI related activities are indicated in the vertical axis. This chart emphasizes how much the chosen companies rely on AI-based business models. The chart also shows that a large portion of AI revenue is concentrated in the specialized AI-focused companies. Sound Hound AI is the primary earner in the AI based operations closely followed by C3.ai and Mobil eye. Such companies can be characterized by business models that are expected to be largely driven by artificial intelligence technologies, which indicate high strategic ties between the core operations and the capabilities of artificial intelligence [22]. The shares of AI revenue are also significant in NVIDIA, Palantir, and BigBear.ai, which implies the strong involvement of AI in product development and services. Conversely, other companies, like Snowflake, Arm Holdings, and Taiwan Semiconductor, have relatively less -yet substantial- proportions of AI revenue. In these companies, AI is a significant source of expansion and not the only source of income. This range shows the distinction in strategic positioning: there are those firms which are AI-native businesses and those that use AI as an auxiliary feature in larger operational ecosystems [23]. There is a relationship between the conceptualizing AI capability intensity as the percentage of AI revenue and the distribution pattern [24]. AI revenue share firms will tend to have more dynamic capabilities to sense the technological trends, capture AI-affiliated opportunities, and amend resources in innovation [25]. As a result, concentration of AI revenue can be an indicator of strategic dedication and sustainability of rivalry in digital markets. Figure 3 illustrates the different levels of AI dependence by major technology companies, which supports the position that AI capacity level varies to a great extent within the industry context.

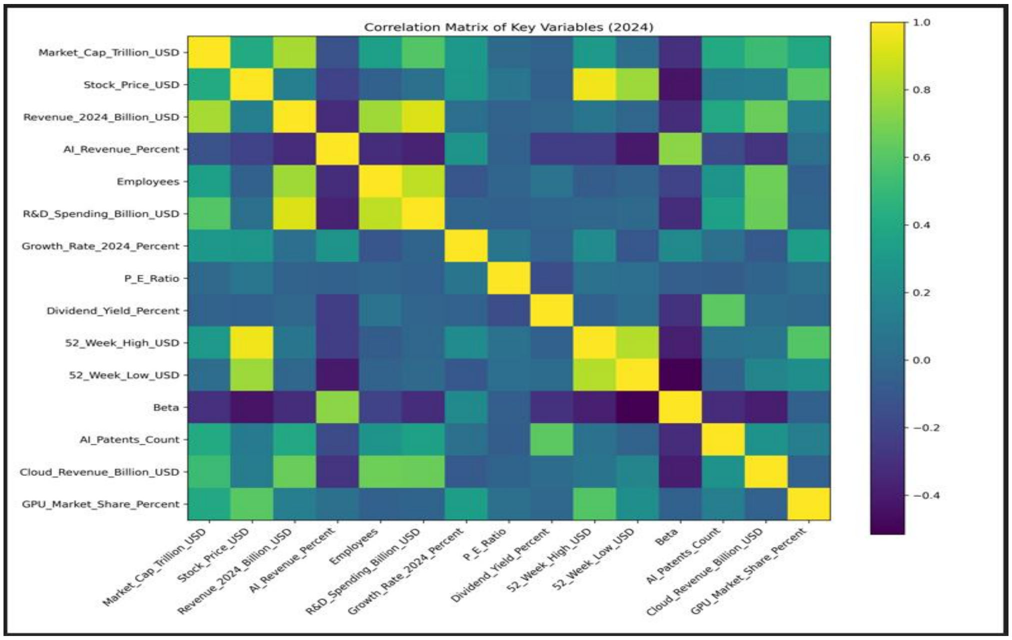


Figure 4: This image demonstrates the relationship between AI and financial variables

Figure 4 shows a correlation matrix with the key financial and innovation, and AI-specific variables in correlation with 2024. The heatmap is used in the form of a visual representation of the correlation coefficients between strong negative (dark purple) and strong positive (yellow) where important associations between firm-level indicators could be identified. The correlation analysis shows positive significant relationships between the market capitalization, stock price and revenue that are stronger, which implies that more profitable and bigger companies have a better command of their market values [26]. Another strong positive association of revenue and market capitalization can also be seen in the area of R&D expenditure, indicating that the investment in innovation can play a role in financial magnitude and competitive position [27]. The indicators AI-specific show significant trends. The correlation between AI patents and revenue and R&D expenditure is positive, which supports the relationship between the intensity of innovation and financial performance. Cloud revenue follows the same pattern of increasing with revenue and market capitalization, which sheds light on the strategic value of scalable AI-driven systems [28]. The results of the market share of GPUs show moderate positive correlations with revenue and stock price, which means that infrastructure dominance helps to maintain competitive advantage. Growth rate shows less impressive correlations with core financial measures, which implies that new trends of growth in the short term can be affected by other external variables than the firm size and AI intensity [29]. The beta exhibits moderate negative associations with valuation indicators that indicate the association between the volatility and stability of the market and the firm. Comprehensively, the matrix proves that proxies of AI capabilities, including patent number, cloud revenue, and market share of GPUs are positively related to key performance indicators. These interrelations give empirical grounds to the idea of conceptualizing AI as a dynamic capability, which is connected to wider innovation and financial frameworks. Most of the AI variables have no severe multicollinearity, which also indicates that it can be used later in regression analysis.

Figure 4 thus provides the overall picture of structural relationships between AI-based innovation and competitive results of firms in the 2024 technological world.

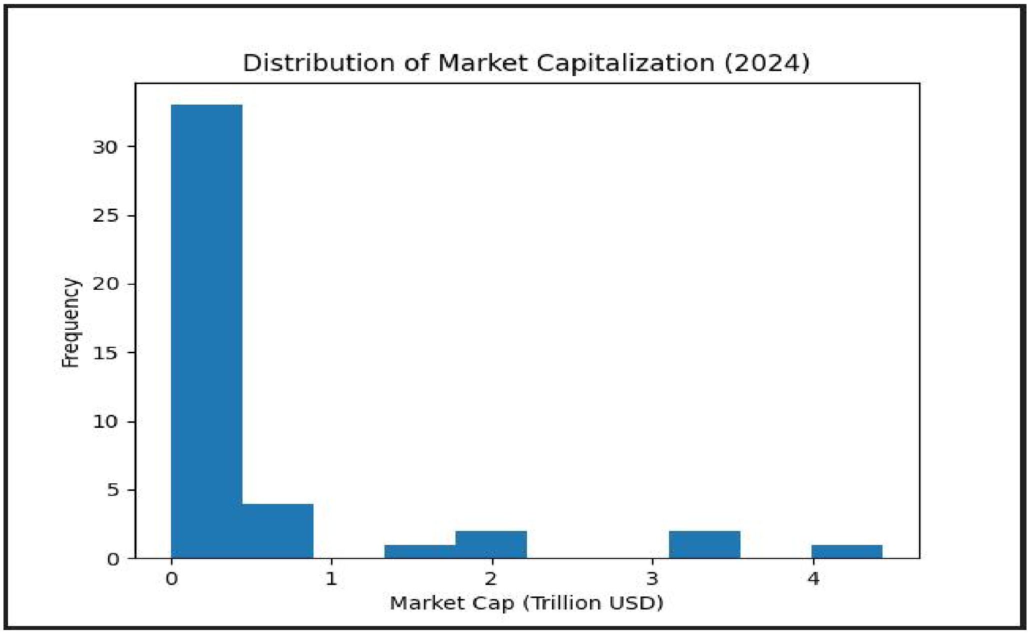


Figure 5: This image illustrate to the distribution of the firm market capitalization levels

The data shown in Figure 5 represent the distribution of market capitalization (in trillion USD) of AI-intensive firms in 2024. The histogram shows how many times the firms have been within the various ranges of market capitalization, which gives us an idea as to the structural make up of the industry. The capitalization of the market in the horizontal axis corresponds to the number of firms in each market range as indicated in the vertical axis. It is also very skewed to the right with most of the firms having their concentration on the lower end of the market capitalization range. The majority of companies do not exceed the one trillion USD level, which means that, although numerous companies are engaged in AI-based markets, a small number of companies are evaluated at mega-cap [30]. This concentration implies that the AI ecosystem comprises many medium-sized and start-up companies and a minor number of industry giants. There are a few outliers in the upper ranges which stretch to more than two and even four trillion USD. These companies will be technology giants with high financial size, diversified income, and large AI integration capacity. They present a long right tail in the distribution, which demonstrates a high level of valuation differences in the sector. The distorted trend demonstrates market power and concentration of capital inequality [31]. Those companies that have developed AI infrastructure, powerful innovation piping, and a viable cloud system are better placed to attain superior market valuations [32]. Smaller companies can be specialized in AI but not as large as to control similar capitalization. Figure 5 underlines that the distribution of competitive advantage in AI-driven industries is skewed. Dominating market leadership seems to be centered in a small number of players, whereas most of them present in the market have relatively average ranges of valuation. This distribution justifies the strategic value of dynamism in AI capabilities in attaining higher market positioning.

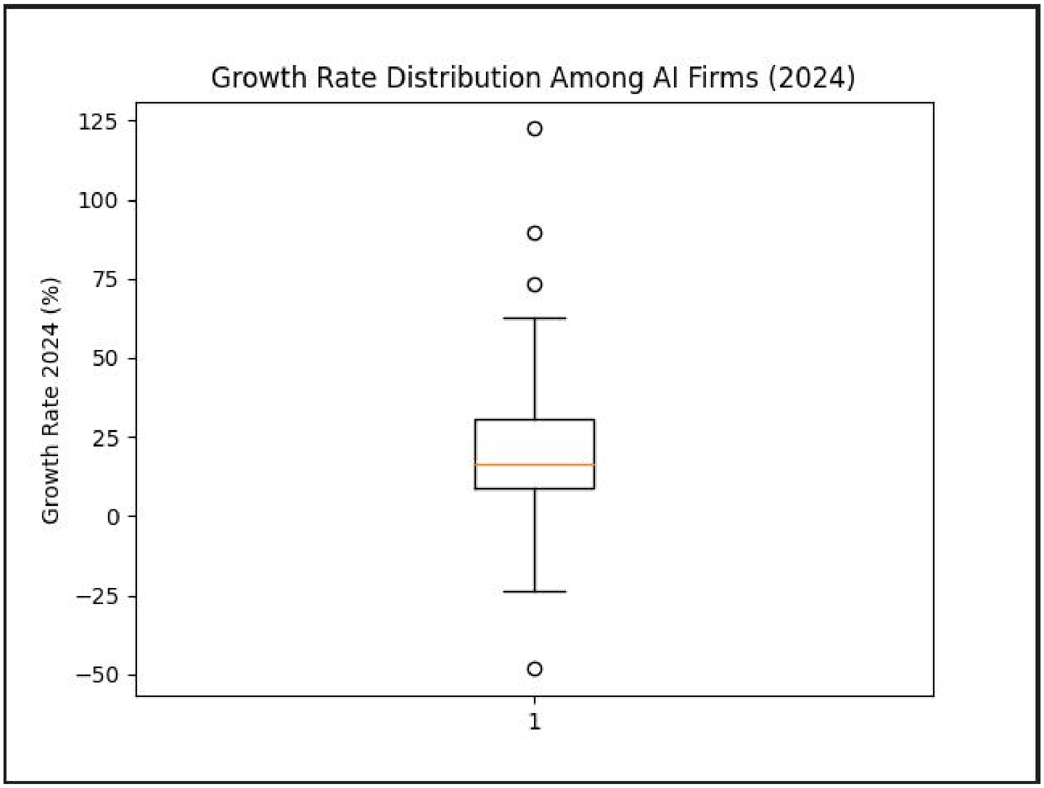


Figure 6: This image shows the growth rates distribution of AI firms

Figure 6 has a boxplot that shows the distribution of the growth rates (percent) of the AI-intensive firms in 2024. The vertical axis is the percentage growth rate per year and the boxplot gives an understanding of the central tendency, dispersion, and existence of outliers in the data. This chart gives a little understanding of variation in performance within firms within AI-driven markets [33]. The median growth rate is observed to be in the low-mid positive range which means that the majority of AI companies have had a moderate growth in 2024. The box is the interquartile range (IQR) that depicts that the median 50 percent growth of the firms was within the range of impressive single-digit growth and about 25-30. Such a concentration implies relatively stable positions of a considerable number of firms. The whiskers and outliers however show a lot of variability. A few companies show very high growth rates of over 70 and even over 120 which means that they are growing very fast and that is perhaps due to active adoption of AI, a breakthrough in innovation or good positioning. There is at least one company with such a high negative growth that is close to -50, and it demonstrates the vulnerability to market fluctuations or operational difficulties. The variances observed in the boxplot indicate that although AI capability has the potential to create significant growth opportunities, the results do not cut across firms. Some of the factors that could include growth performance are scalability, efficacy of commercialization, capital investment, and competitive dynamics [34]. The inclusion of the extreme positive and negative outliers strengthens the dynamic and risky character of AI-intensive industries [35]., Figure 6 shows that AI-driven markets are typified by heterogeneous growth patterns [36]. Although the median suggests successful growth, the high diversity of results highlights the role of proper strategic management and dynamic integration of the integration of the strategic capability in maintaining competitive advantage.

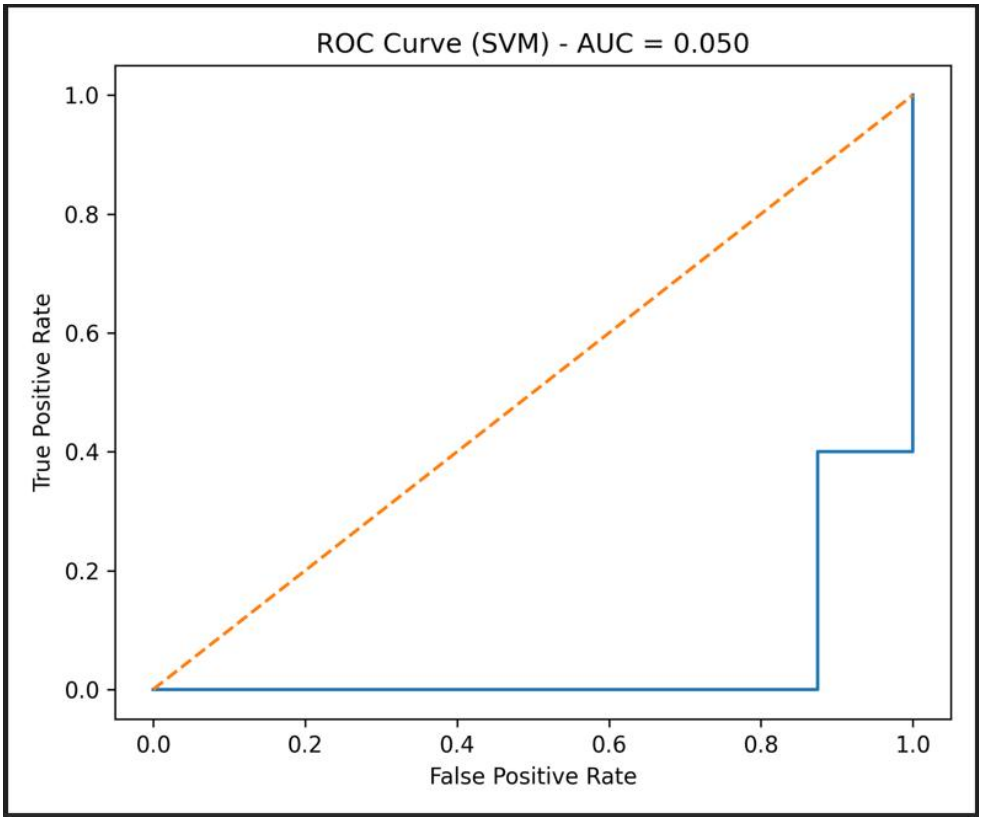


Figure 7:This image illustrates the ROC curve of SVM classification accuracy of growth prediction

Figure 7 shows the Receiver Operating Characteristic (ROC) curve of the Support Vector Machine (SVM) classifier that has been trained to predict the high-growth firms according to the indicators of AI capability. The ROC curve is a curve whose axes are True Positive Rate (sensitivity) vs. False Positive Rate (1 -specificity), which is a full spectrum of discriminative strength of the model, at different levels of classification. A random classifier is plotted in the dashed diagonal and it acts as a benchmark. The ROC curve observed is nearer to the diagonal and has Area under the Curve (AUC) of 0.050. The value of AUC near 0.5 is usually the random classification and near 1.0 shows a strong predictive ability. Here the very low AUC indicates that the present SVM model represents a poor discriminative model in high-growth and low-growth firms in samples. The shape of this curve shows that the model finds it difficult to obtain an excellent balance between sensitivity and specificity [37]. The sharp increase towards the far right of the curve means that the true positive detection is effective in the high false positive rates only, restricting the practical predictive reliability [38]. It is likely to be due to a rather low sample size, class imbalance, or insufficient explanation capacity of the chosen AI capability features. Analytically, Figure 7 indicates the difficulty of forecasting firm growth based on the cross sectional AI metrics [39]. Although the indicators of AI capability have the theoretical connection with competitive advantage, its predictive ability to grow in the short term might need other financial or macroeconomic factors. The findings underline the importance of the refinement of the model, feature engineering, or other algorithms to increase predictive validity.

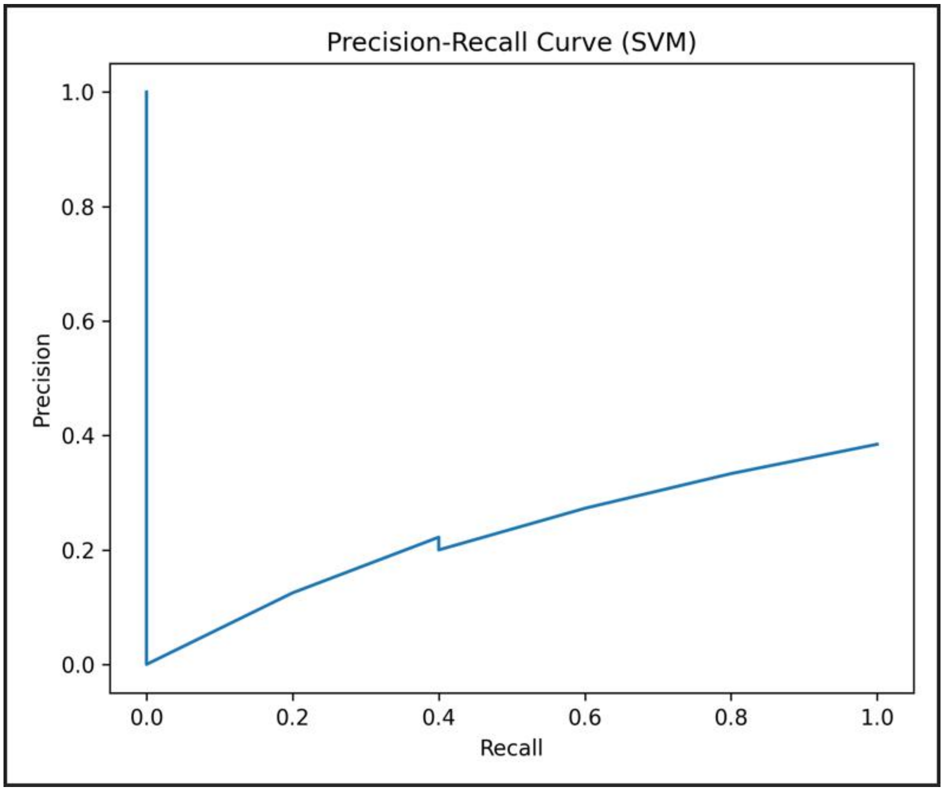


Figure 8: This image demonstrate on Precision recall curve used to estimate the performance of SVM classification model

The Precision Recall (PR) curve of the Support Vector Machine (SVM) model designed to categorize the firms into high growth and low growth is shown in Figure 8. The horizontal axis is the recall (sensitivity), a ratio of the number of actual high-growth firms that the model correctly identifies and the vertical axis is the precision, a ratio of the number of predicted high-growth firms that actually are high-growth firms. One application of the PR curve is to consider the classification performance when there is a possibility of class imbalance. The curve is relatively imprecise at the majority of recall levels. Whereas the recall is large, meaning that the model manages to recognize a significant percentage of high-growth firms, the precision is not enormous, being on average smaller than 0.40. This trend implies that the model is able to reflect a high-growth rate in a large number of actual high-growth cases, and it produces a significant number of false positives. Practically the high-growth category is over-predicted by the classifier. Precision peaks briefly at very low values of recall, and this is common when there are just a few predictions with high levels of confidence [39]. The higher the recall however, the lower is precision meaning that classification reliability decreases. The slow increase curve towards the high recall levels portrays medium improvement, yet the general performance is poor. Analytically, Figure 8 supports the results realized in the ROC analysis. The model has good sensitivity, but has limited predictive precision. This implies that the variables of AI capability might not possess adequate discriminatory power in predicting future growth with short term accuracy. Other remedies such as model tuning, additional explanation features or ensemble can enhance the classification strength. The PR curve, in general, demonstrates the exchange between the identification of high-growth firms and reduction in false alarms, which highlights the importance of increased predictive modeling strategies.

6. Future Research Directions

Although this research offers empirical evidence on the concept of Artificial Intelligence (AI) as a dynamic capability affecting competitive advantage, there are still a few research directions that can be developed in the future]. First, the existing analysis implies the use of cross-sectional data of 2024, which does not allow studying long-term causal relations. The future research could be done in the form of longitudinal or a panel data design to determine the changing effects of AI capability over time. A multi-year data set would enable the researcher to examine dynamic impact, path dependencies and lagged performance results of AI investments. Second, it would be better to increase the sample size, which is currently 43 firms, and increase the generalizability . The future studies can cover medium size companies, young AI startups, the non-technical industries that use AI. Such a broad area of focus would offer comparative information on the functioning of AI capability under various institutional and competitive conditions . The relationship between AI and performance could also be studied comparatively across countries, to understand how regulatory framework, digital infrastructure and national systems of innovation may moderate this relationship. Third, there are other variables that are needed to narrow down measurement of AI capability. The qualitative indicators that can be incorporated in future research are the intensity of an AI talent, the level of data governance, the capacity to learn, and the mechanisms of strategic alignment. The integration of managerial measurement as a survey would be an addition to the financial performance and serve to better understand the development of internal capabilities. Fourth, predictive modeling can be improved by methodological development . Other machine learning models like the Random Forest, Gradient Boosting or Neural Networks can potentially achieve a better result on classification and reveal nonlinear relationships among variables. SEM may also be used to show mediation effects including whether firm growth mediates the relationship between AI capability and sustained competitive advantage. Lastly, further studies might be conducted to understand the ethical and social aspects of AI-based competitive advantage. Research into the effect that responsible AI behaviors, ESG integration, and regulatory compliance would have on long-term valuation would be a significant contribution in the sustainability sense. Delving into theoretical, methodological, and contextual aspects will enhance the knowledge of AI as a strategic dynamic ability that can form competitive advantage in the digital economy.

7. Conclusion

This study has discussed Artificial Intelligence (AI) as a dynamic element of capabilities and the prospects of its relevance in the context of the long-term competitive advantage of global technology giants. The research was based on the Dynamic Capability Theory and the Resource based View, and the conceptualization of AI was that of a technological investment, but an intrinsic organizational ability that affects financial performance, market position, and growth results. The combination of AI-specific innovation indicators with financial and operational ones enabled the study to offer empirical data on the strategic role AI plays in the modern digital markets. The results show that AI capability, which is gauged by AI revenue intensity, patent activity, cloud revenue and GPU market share, has a positive relationship with firm valuation and financial scale. Companies that show greater integration of AI and intensity of innovation are more likely to have increased market capitalization and performance in revenues. These findings confirm the theoretical hypothesis that difficult-to-replicate and essential, systematic, and hidden technological capabilities are part of competitive differentiation. Nonetheless, the distributional and predictive studies indicate that the capacity to use AI does not alone with certainty lead to short-term growth. Although AI will be useful in structural competitive power, variability of growth across firms brings to light the relevance of complementary resources, strategic implementation and market circumstances. The results of the machine learning classification further indicate that even though AI indicators have explanatory relevance, they do not have explanatory predictive ability when alone in classifying annual growth. This further supports the thesis that AI would best serve as a strategic facilitator in the long term and not a short-term predictor of growth. An enduring competitive advantage is developed in the case of the use of AI ability that is combined with organizational learning, innovation governance, and scalable business models. the research contributes to the body of strategic management literature by demonstrating through empirical study that AI is a dynamic capability that has an impact on competitive positioning. It helps in the dichotomy between the theoretical conceptualization and the quantifiable firm level performance results. Digital transformation is gaining momentum and organizations need to go past AI adoption to integrate ability and be strategic to achieve sustainable value. The results offer scholarly and managerial implications of capitalizing on AI investments to gain a sustainable competitive advantage in the fast-paced changing technological landscapes.

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