

Article

Generative AI Adoption and Industry-Level Productivity Growth in the United States: A Multi-Sector Empirical Analysis

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Abstract: This study examines how the adoption of generative artificial intelligence (AI) affects the productivity growth at the industry level in the United States based on a multi-sector empirical study. With the widespread adoption of generative AI technologies in industries, the issue of productivity is now one of the most pressing inquiries among economists, policy makers, and business executives. This study will focus on the research question whether there are positive productivity effects of more extensive utilization of generative AI and whether the effects are different in various sectors of the industry. The analysis is based on structured data of AI adoption at the firm level, employee dynamics, and productivity-related measures in the context of diverse industries and different years. The data is analyzed using U.S.-based observations and aggregating firm level data to industry level to allow comparisons on the sector level. The main ones are the level of AI adoption, the automation level, and productivity performance indexes, and the researcher controlled the variables of firm size, income, and employee features. The relationship between the adoption of generative AI and the growth of productivity is estimated using an empirical approach, which relies on panel data regression. The results indicate that there is a strong and significant positive correlation between AI adoption and productivity and higher effect in knowledge and service-based industries like technology and finance. Conversely, the boost in productivity is rather moderate in traditional industries like manufacturing, which implies that AI benefits are sector ally heterogeneous. One of the contributions offered by the study to the existing literature is a broad industry level view of the economic effects of generative AI. It emphasizes the role of digital preparedness, human resources competencies, and investing in AI technologies as the driving forces of productivity improvement. The analysis is associated with some drawbacks such as the use of modeled data which might not represent the complexities in the real world completely. This study presents meaningful information about the changing correlation between the use of generative AI and productivity increase, and the study has significant implications on policy development, strategic decisions, and subsequent research.

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1. Introduction

A. History of Generative AI and Economic Change

Generative Artificial Intelligence (AI) has become one of the most disruptive technologies of the 21st century that have radically changed the way industries conduct their operations, innovate, and provide value. In contrast to conventional AI systems that

are mainly interested in the pattern recognition and prediction processes, generative AI has the potential to generate novel content, such as text, pictures, code, and simulations [1]. This progress is mostly supported by the progress in deep learning, neural networks, and large language models, which allow machines to think and be creative in a manner similar to humans. Consequently, generative AI is becoming more and more incorporated in the broad scope of business operations, such as customer service, marketing, product design, and decision support systems. Generative AI is driving the digital transformation in the fields of finance, healthcare, education, and manufacturing, making operations more efficient and allowing new business models. Organizations are using these technologies to automate complex thinking processes, to cut on costs and to improve productivity. As an example, AI-driven solutions are capable of producing reports, aiding in diagnostics, supply chain optimization, and aiding in real-time decision-making. The adoption of this is indicative of a trend towards smarter and more flexible systems that do not supplant human abilities but instead expand them in a positive manner. Economically, it is anticipated that generative AI will have a key influence on defining the growth in productivity and the economy in general[2]. . With its implementation by firms, efficiency, innovation, and quality of output may improve. It is still not clear how much these benefits are spread and in what industries. Therefore, the role of generative AI in economic transformation has gained significant research interest and is of interest to policymakers, economists, and industry leaders who are willing to explore the potential of the new technology.

B. Significance of Productivity in Economic Growth

The growth of productivity is generally accepted as a necessary condition of the long-term economic progress and development, economic competitiveness and increase in living standards. It is a measure of the effectiveness of the inputs used in the production of goods and services in terms of labor, capital, and technology [3]. Increased productivity means that less output can be attained using the same inputs resulting in increased economic efficiency and growth. Macroeconomically, increased productivity leads to an increase in incomes, competitiveness in the international markets standards of living. The productivity gains in the industry level allow the firms to ensure that they cut costs, enhance profitability and become innovative. As far as the economy of the United States is concerned, productivity has traditionally played one of the most important roles in economic growth. The last few decades have been characterized by the downturns in productivity, which is of concern to economists and policymakers. This deceleration has led to increasing attention to the possibility to find new sources of productivity growth, in particular, the ones related to technological innovation. New technologies, such as artificial intelligence, automation, and digital platforms, are starting to be considered as a possible trigger that can restore the trends of productivity. Innovation and technological advancement is also closely associated with productivity. The advanced technologies can enable the firms to streamline their processes, enhance the quality of their products and be able to react better to the market needs. Generative AI is, in this respect, a new stage in technological development, which promises to increase the productivity of labor and the total factor productivity [4]. Generative AI can help to make the use of resources more efficient in industries by making information processing faster, cutting down on manual work, and helping to make complicated decisions. It is thus important to understand the nature of the relationship between productivity and emerging technologies to evaluate the future of economic growth. Due to the further development of generative AI, its contribution to the dynamics of productivity gains growing importance, which is why it is a valuable topic of empirical study and policy debate.

C. The Generative AI to Improve Productivity

Generative Artificial Intelligence (AI) can be used to greatly improve productivity by changing the way things are done and how work is handled in various industries as far

as the usage of resources. It has made one of its main contributions in automating repetitive and time-wasting activities and making the employees concentrate on higher value and more strategic activities [5]. As a case in point, generative AI has the potential to help in compiling reports, creating code, processing large volumes of data, and replying to the customer queries, thus saving on the time of operation and enhancing efficiency. This enhancement of the human functions results in quicker work accomplishment and the better quality of the output. Generative AI is also of particular significance in knowledge-intensive sectors like information technology, finance and professional services. It allows real-time data analysis, assists in the decision-making process, and assists in the innovation process because it produces insights and ideas that are not easy to obtain through the extensive human effort. Also, AI-based solutions can facilitate teamwork, suggesting smart solutions and automating workflows, which will increase the productivity of organizations. The other significance of generative AI is that it brings about innovativeness. Organizations can speed up the process of research and development by providing the capability of rapid prototyping, simulation and content creation. This does not only take less time to introduce new products and services into the market, but also it promotes experimentation and creativity. Consequently, the firms will be able to attain competitive advantages and respond faster to the fluctuating market conditions. Not all industries are equally affected by generative AI in terms of productivity. Some aspects like digital infrastructure, the levels of skills of the workforce and the nature of work done determine the level of productivity gains [6]. The industries that are more digital ready and knowledge based work have higher chances of benefiting greatly through the adoption of AI. Conversely, industries that use heavy labor force might not register higher or even greater productivity gains. Thus, it is necessary to comprehend these differences to determine the economic cost of generative AI on the whole.

D. Problem Statement

Although the use of generative artificial intelligence has been rapidly adopted in the industries, little is known about its effect on the productivity growth at the industry level in the United States. The available literature is largely based on firm-level cases or theoretical forecasts and does not provide much information about the phenomenon of sector productivity. Besides, the varying impacts of AI adoption in different industries, especially those that are knowledge intensive and traditional industries are not clearly comprehended [7]. This is a gap in the literature, which does not provide a multi-sector empirical analysis. The paper, thus, aims to analyze the connection between the adoption of generative AI and productivity increase in industries, which will offer a more systematic and comparative insight into the economic effects of this technology.

E. Research Objectives

The objectives of the studies are:

- To quantify the rate of adoption of generative AI in various industries in the United States.
- To examine how the adoption of generative AI affects the productivity growth of the industry.
- To make a comparison of the productivity effect of knowledge intensive and traditional sectors.
- To investigate how automation and AI investment contribute to the effects on productivity.
- To measure the correlation between the firm attributes (size, revenue) and productivity performance.
- To determine industry differences in AI productivity benefits.
- To present the economic effect of generative AI through the use of empirical evidence.

F. Research Questions

1. What is the effect of the adoption of generative AI on the growth of productivity in the industries in the United States?
2. What sectors provide the most productivity improvement with the use of generative AI?
3. Which variables moderate the correlation between AI adoption and the growth of productivity?

G. Significant of Study

This study is a contribution to the growing literature on the economic consequences of generative artificial intelligence because it presents an empirical analysis of its effects on the growth of productivity on an industry level in the United States. With the ongoing enhancements of AI technologies and their involvement in the functioning of business, it becomes more significant to comprehend their importance in influencing the dynamics of productivity to be studied in scholarly papers and used in the decisions made [8]. The study can be useful in determining the role of generative AI in efficiency, innovation, and output in various industries. Policy-wise, the results of the current research can help governments and regulatory institutions formulate policies that will facilitate the successful implementation of AI workforce displacement and skills gaps. Policymakers can also allocate resources more efficiently and promote specific projects on digital transformation by detecting industries that gain the most with the use of AI. To business executives and organizations, the research offers evidence-based information that can inform strategic choices associated with the investments in technology, development of the workforce, and optimization of operations. The knowledge on the relationship between adoption of AI and productivity will help firms to make better use of the new technology to improve their competitive advantage and performance [9]. This study identifies the significance of such factors as digital infrastructure, the quality of the workforce, and the ability to innovate in order to make the most of generative AI. It also provides the basis of the future research by establishing major variables and relationships that need to be investigated further. In general, the research contributes to the evolution of knowledge on the topic of the contribution of generative AI to economic growth and industrial productivity.

Literature Review

The swift development of artificial intelligence has created a great deal of focus on the possibility of its impact on productivity and economic performance. The literature points out that traditional literature has been focusing on technology innovation as the main driver of productivity growth, and the digital technologies are regarded as the main facilitators of efficiency and innovation [10]. Generative artificial intelligence has become an innovative solution in recent years that can automatize complex cognitive processes, improve decision-making and allow the generation of new types of digital content. Research on the correlation between artificial intelligence and productivity indicates that by adopting AI, labor productivity may be enhanced through the decrease in the time spent on both routine and knowledge-based labor, the time spent on routine tasks. Specifically, generative AI is known to improve the performance in such areas as content generation, coding, customer service, and data analysis. These enhancements help in better operation and reduction in cost, particularly those industries that are knowledge intensive. The scale of the productivity improvement usually depends on the extent of digital infrastructures and organizational preparedness, the expertise of the workforce. There are also heterogeneous effects that are witnessed in different industries as highlighted in the literature. Industries that are characterized by high information processing and digitalization are likely to be more productive than traditional industries that are intensive in the use of manual labor. Also, the advantages of AI implementation are not instant and might take time to have organizations adjust processes, reorganize workflow, and acquire

the required competencies. Despite the increase in interest, empirical research that investigates the effect of generative AI on an industry level is still lacking [11]. The existing research is largely founded on the firm-level analysis or theoretical forecasts which restrict the comprehension of the overall economic implication. Additionally, the utilization of novel or simulated data also creates more problems when trying to generalize results. Thus, multi-sector empirical research is in a great need to determine how the adoption of generative AI affects the productivity growth in various industries.

The article *GenAI, Growth, and the Multi-Sector Multipliers* by Tero Kuusi (2025) gives valuable information about the macroeconomic effects of generative artificial intelligence. The study uses a multi-sector general equilibrium model to examine the effect of GenAI adoption on economic growth and productivity [1]. The results indicate that GenAI leads to the moderate growth of the annual economic growth with more significant effects observed in the case of increased automation and changes in both labor and ICT inputs. The paper brings to the fore the existence of strong multiplier effects, in which productivity improvements in one part of the economy spill over to other parts due to economic interdependencies. It is also notable that the service industry is one of the major sources of adjustment since it is flexible and responsive to changes in technology. The research however also recognizes uncertainties in regards to long-run effects and structural adjustment. The given study proves the thesis that generative AI can significantly improve productivity in case of proper policy and adjustment of the sphere.

The article *Artificial Intelligence and Growth in Advanced and Emerging Economies: Short-Run Impact* by Leonardo Gambacorta, Enisse Kharroubi, Aaron Mehrotra, and Tommaso Olivieri (2025) focuses on the short-run impact of generative artificial intelligence on economic growth in countries and industries [2]. The analysis based on a dataset representing several economies and sectors concludes that the effect of AI on growth differs greatly in terms of the extent to which the sector is exposed to cognitive and knowledge-intensive activities. The findings point out that advanced economies are better off than emerging economies on the use of AI, as they have high rates of technological preparedness and production systems. The paper also points out that productivity differentials are also caused by the variations in AI preparedness and industry composition. In general, the results highlight that the positive impact of generative AI on productivity and growth is not evenly spread among countries and industries, which underlines the significance of being digitally ready and adapting to the structure.

In the article *The Smart Shift: Generative AI and the Rise of Human AI Productivity* by Shaziya Islam, Benita Veronica, and Sumaiya Thaseen (2025), it is emphasized that generative artificial intelligence is a transformative factor in making humans productive and efficient in their operations across various industries. The study highlights that generative AI can be used to automate routine and cognitive tasks, which will enable organizations to use human resources to perform more strategic and creative tasks [3]. It shows that AI-based tools can greatly enhance the efficiency of the workflow, decrease errors, and help make decisions based on data. The research also demonstrates industry-specific effects of the sector so that improved performance, cost reduction, and service delivery are observed in industries like healthcare, manufacturing, finance, and retail. This study associates AI adoption with the positive changes in total factor productivity and economic growth in general. On the whole, the results confirm the thesis statement that generative AI is one of the main sources of productivity improvement, especially in highly developed and innovative sectors.

The article *Generative AI Takes Centre Stage: Revolutionizing Productivity and Reshaping Industries* by Mariya Sira (2023) discusses the revolutionary role of generative artificial intelligence in the dynamics of productivity and industry. The study emphasizes that generative AI is highly efficient, especially among the developers and knowledge

workers, as it automates intricate and creative processes. It underlines the fact that AI-driven systems can lead to innovation, create new ideas, designs, and solutions, thus speeding up organizational performance. The paper also addresses the application of generative AI to develop Industry 4.0 by combining intelligent technologies and digital systems [4]. Although the advantages are enhanced production and efficiency in operations, the study also considers the challenges like ethical issues and risks of implementation. Altogether, the results indicate that generative AI is an important technological driver of recent economic change, as it is essential in transforming industries and spurring productivity growth.

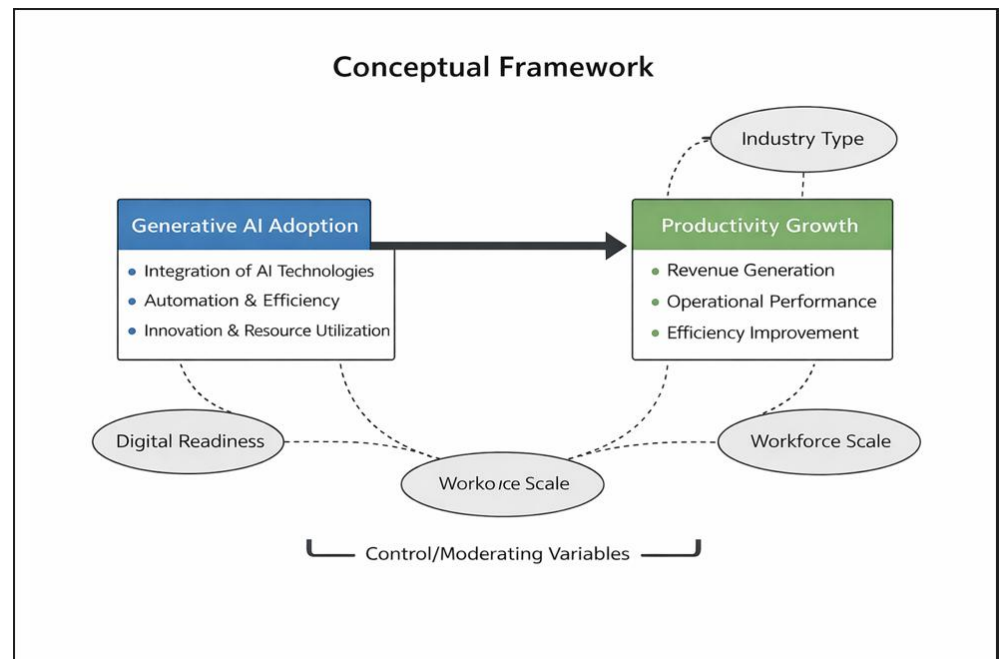
2. Methodology

This study will use a quantitative empirical research design to explore the effects of the adoption of generative artificial intelligence (AI) on the growth of productivity at the industry level in the United States. The data is analyzed using a structured dataset, retrieved in the form of a secondary source, which includes firm-level data on AI adoption, labor market traits, and productivity-related measures in various industries and periods [12]. To guarantee data quality such as removing missing values and selection of numerical variables that are suitable to be analyzed via statistical and machine learning methods, relevant observations were filtered and preprocessed to achieve the purpose of this study. The data set was also narrowed down to concentrate on the main variables on yearly revenues, number of employees, company size, and the industry category that are proxies of productivity and operational size. In order to operationalize the dependent variable, productivity was estimated, by approximating the annual revenue, which is a typical proxy of productivity in empirical research when the actual measure of productivity is not available. Independent variable, the adoption of generative AI, was measured on the basis of the modeled indicators, which are part of the dataset, such as automation attribute-related characteristics and firm performance metrics. It included control variables like size of the firm, size of workforce and industry type to reduce structural differences among the observations [13]. The data was subsequently pooled and examined to include industry specific trends and changes. The analysis uses both descriptive and inferential analysis methods. The patterns in productivity and AI adoption across industries were explored with the help of descriptive statistics and visualization techniques, such as bar charts, scatter plots, and box plots. In order to investigate the predictive relationships further, a machine learning model based on Support Vector Machine (SVM) was adopted. The dataset has been converted into a classification problem where the firms were classified as high and low productivity in terms of the median figure of revenue. Before the model was trained the data was normalized by the feature scaling methods to enhance the performance of the model. The data was subsequently divided into training and testing data to test predictive accuracy. Evaluation measures on the model performance included Receiver Operating Characteristic (ROC) curve, Precision Recall curve and Confusion Matrix. These measures give us information about how well the model is able to correctly classify the observations and finding a balance between the true and false predictions [14]. The methodology combines statistical analysis and machine learning to present an in-depth evaluation of the correlation between the adoption of generative AI and the growth in productivity in industries.

Conceptual Framework

The theoretical framework of the paper analyzes the correlation between the generative artificial intelligence (AI) adoption and industry level productivity growth, in the United States. The use of generative AI is regarded as the main independent variable, indicating the degree of the application of AI technologies in the activity of companies [15]. The dependent variable is productivity growth in terms of proxies like revenue and operational performance. The framework presumes that the increased adoption of AI results in greater efficiency, innovation, and resource usage thus increasing the

productivity outcomes. The direct relationship, there are a number of control and moderating variables that are included in order to include industry heterogeneity. These are the size of the firm, the number of employees, the type of industry and digital preparedness which can affect the robustness of the relationship and its orientation. The framework emphasizes that the productivity benefits of AI are not sector-evenly distributed but rather rely on the technological capability and the organizational preparedness. It offers a framework on which the role of generative AI in boosting productivity within industries can be analyzed.



Hypothetical model illustrating how AI adoption has an effect on productivity, mediated by industry variables. The theoretical framework shows the connection between the adoption of generative AI and productivity improvement on an industry level [16]. The use of generative AI would be portrayed as the independent variable, which includes aspects such as AI technologies integration, automation, and innovation. The dependent variable is productivity growth which is measured in terms of revenue generation, performance in operations and efficiency. There is a direct causal relationship between the use of AI and productivity. The mediating factors such as the type of industry, the number of employees, and digital maturity affect this relationship [17]. These aspects demonstrate that the effect of AI implementation on productivity is different in different sectors based on organizational capabilities and preparedness to technology.

Dataset

A. Screenshot of Dataset

response_id	company_id	survey_year	quarter	country	region	industry	comp_size	num_employees	annual_revenue_millions	comp_founding_year	company_age	comp_group	ai_adoption_rate	ai_adoption_stage	years_using_ai	ai_primary_tool	num_ai_tools_used	ai_use_cases	ai_projects_active	ai_training_hours	ai_budget_percentage	ai_maturity_score	ai_failure_rate	ai_investment_per_employee	regulatory_compliance_score	data_level
1	COMP-0001	2023	Q1	Italy	Europe	Education	Startup	57	48.31	1994	29	16-30 years	30.57	pilot	3	ChatGPT	2	Customer Sup	3	20.94	6.54	0.234	35.22	55392.29	60	Medi
2	COMP-0001	2023	Q2	Italy	Europe	Education	Startup	57	48.31	1994	29	16-30 years	31.54	pilot	4	ChatGPT	3	Software Dev	0	23.1	5.81	0.174	24.65	49210.79	68	High
3	COMP-0001	2023	Q3	Italy	Europe	Education	Startup	57	48.31	1994	29	16-30 years	31.54	pilot	2	Custom Intern	3	HR Automatio	3	12.29	12.39	0.266	36.51	105011.8	66	High
4	COMP-0001	2023	Q4	Italy	Europe	Education	Startup	57	48.31	1994	29	16-30 years	11.02	pilot	2	Custom Intern	1	Software Dev	2	11.31	3.2	0.123	33.3	27257.71	64	High
5	COMP-0001	2024	Q1	Italy	Europe	Education	Startup	57	48.31	1994	30	16-30 years	33.39	pilot	7	ChatGPT	3	Customer Sup	5	35.17	9.98	0.363	19.83	84622.9	68	High
6	COMP-0001	2024	Q2	Italy	Europe	Education	Startup	57	48.31	1994	30	16-30 years	34.15	pilot	4	GitHub Copilo	3	Marketing Au	8	25.68	9.89	0.372	31.03	83847.25	64	High
7	COMP-0001	2024	Q3	Italy	Europe	Education	Startup	57	48.31	1994	30	16-30 years	41.35	partial	5	GitHub Copilo	3	Marketing Au	5	32.14	6.75	0.307	21.03	57236.36	70	Medi
8	COMP-0001	2024	Q4	Italy	Europe	Education	Startup	57	48.31	1994	30	16-30 years	57.42	partial	6	Claude	4	Software Dev	5	48.36	13.06	0.499	10.59	110716.7	74	Medi
9	COMP-0001	2025	Q1	Italy	Europe	Education	Startup	57	48.31	1994	31	30+ years	17.57	pilot	7	GitHub Copilo	2	HR Automatio	6	10.48	3.54	0.191	46	38906.46	75	High
10	COMP-0001	2025	Q2	Italy	Europe	Education	Startup	57	48.31	1994	31	30+ years	52.95	partial	8	GitHub Copilo	2	HR Automatio	9	29.92	11.44	0.427	13.99	96933.18	73	Low
11	COMP-0001	2025	Q3	Italy	Europe	Education	Startup	57	48.31	1994	31	30+ years	35.7	partial	5	Custom Intern	2	Customer Sup	9	23.71	6.85	0.34	25.29	58029.95	60	Medi
12	COMP-0001	2025	Q4	Italy	Europe	Education	Startup	57	48.31	1994	31	30+ years	45.23	partial	7	ChatGPT	3	Marketing Au	3	45.98	11.16	0.417	25.79	111515.9	84	Medi
13	COMP-0001	2026	Q1	Italy	Europe	Education	Startup	57	48.31	1994	32	30+ years	52.61	partial	7	Custom Intern	2	Customer Sup	10	37.91	9.63	0.463	12.64	83638.07	67	Medi
14	COMP-0001	2026	Q2	Italy	Europe	Education	Startup	57	48.31	1994	32	30+ years	45.37	partial	6	Claude	5	HR Automatio	7	41.88	7.24	0.388	17.53	61317.67	76	High
15	COMP-0001	2026	Q3	Italy	Europe	Education	Startup	57	48.31	1994	32	30+ years	40.09	partial	6	Gemini	2	HR Automatio	4	9.08	9.65	0.233	40	81814.66	83	Low
16	COMP-0001	2026	Q4	Italy	Europe	Education	Startup	57	48.31	1994	32	30+ years	34.98	pilot	6	ChatGPT	2	Customer Sup	1	29.05	9.42	0.263	18.48	79878.34	69	High
17	COMP-0002	2023	Q1	UK	Europe	Finance	Startup	18	14.66	2008	15	6-15 years	48.52	partial	3	ChatGPT	3	HR Automatio	9	18.51	9.42	0.357	33.33	76713.32	67	High
18	COMP-0002	2023	Q2	UK	Europe	Finance	Startup	18	14.66	2008	15	6-15 years	32.85	pilot	5	Custom Intern	2	HR Automatio	12	22.57	10.99	0.429	21.55	82055.88	74	High
19	COMP-0002	2023	Q3	UK	Europe	Finance	Startup	18	14.66	2008	15	6-15 years	49.04	partial	7	Gemini	3	Customer Sup	9	55.62	7.78	0.486	23.75	63855.4	68	Medi
20	COMP-0002	2023	Q4	UK	Europe	Finance	Startup	18	14.66	2008	15	6-15 years	35.17	partial	6	ChatGPT	3	Marketing Au	7	36.01	9.28	0.391	24.78	75619.62	87	Medi
21	COMP-0002	2024	Q1	UK	Europe	Finance	Startup	18	14.66	2008	16	16-30 years	40.51	partial	8	Custom Intern	4	Marketing Au	8	32.32	6.19	0.321	27.76	50439.24	73	High
22	COMP-0002	2024	Q2	UK	Europe	Finance	Startup	18	14.66	2008	16	16-30 years	43.98	partial	3	Claude	3	Customer Sup	6	30.83	12.42	0.394	27.12	101125.3	80	Medi
23	COMP-0002	2024	Q3	UK	Europe	Finance	Startup	18	14.66	2008	16	16-30 years	35.93	partial	2	Gemini	3	Fraud Detecti	3	9.77	6.52	0.178	36.64	53353.42	59	Medi
24	COMP-0002	2024	Q4	UK	Europe	Finance	Startup	18	14.66	2008	16	16-30 years	59.32	partial	5	ChatGPT	3	Marketing Au	7	39.45	10.69	0.424	19.06	87029.62	81	High
25	COMP-0002	2025	Q1	UK	Europe	Finance	Startup	18	14.66	2008	17	16-30 years	61.6	partial	3	Claude	4	Marketing Au	4	53.23	9.83	0.417	23.94	78477.83	70	Medi
26	COMP-0002	2025	Q2	UK	Europe	Finance	Startup	18	14.66	2008	17	16-30 years	50.94	partial	6	Custom Intern	2	HR Automatio	9	33.54	13.16	0.465	22.7	107194.8	54	High
27	COMP-0002	2025	Q3	UK	Europe	Finance	Startup	18	14.66	2008	17	16-30 years	73.84	full	4	GitHub Copilo	4	Customer Sup	10	45.79	15.04	0.558	10.78	122488.7	58	High
28	COMP-0002	2025	Q4	UK	Europe	Finance	Startup	18	14.66	2008	17	16-30 years	54.07	partial	9	Gemini	3	HR Automatio	13	29.72	11.07	0.488	11.64	90159.85	65	High
29	COMP-0002	2026	Q1	UK	Europe	Finance	Startup	18	14.66	2008	18	16-30 years	52.09	partial	4	Custom Intern	3	Marketing Au	7	27.19	12.92	0.402	27.13	105213.8	75	Medi
30	COMP-0002	2026	Q2	UK	Europe	Finance	Startup	18	14.66	2008	18	16-30 years	41.22	partial	3	GitHub Copilo	3	HR Automatio	10	36.48	4.55	0.377	28.32	34653.86	61	Low
31	COMP-0002	2026	Q3	UK	Europe	Finance	Startup	18	14.66	2008	18	16-30 years	56.27	partial	6	Gemini	4	Marketing Au	9	37.32	11.47	0.458	19.62	93842.64	65	Low
32	COMP-0003	2023	Q1	Germany	Europe	Education	Enterprise	16151	8543.28	2009	14	6-15 years	27.99	pilot	5	GitHub Copilo	1	Marketing Au	8	19.79	7.54	0.316	26.6	39857.64	92	Medi
33	COMP-0003	2023	Q2	Germany	Europe	Education	Enterprise	16151	8543.28	2009	14	6-15 years	26.39	pilot	5	GitHub Copilo	2	Marketing Au	2	23.97	7.97	0.239	32.07	42153.36	87	High
34	COMP-0003	2023	Q3	Germany	Europe	Education	Enterprise	16151	8543.28	2009	14	6-15 years	44.48	partial	3	Custom Intern	2	Customer Sup	7	33.88	11.28	0.408	20.98	59658.54	74	Medi
35	COMP-0003	2023	Q4	Germany	Europe	Education	Enterprise	16151	8543.28	2009	14	6-15 years	48.26	partial	2	Custom Intern	3	Software Dev	10	37.55	14.21	0.513	25.71	73154.16	70	Medi
36	COMP-0003	2024	Q1	Germany	Europe	Education	Enterprise	16151	8543.28	2009	15	6-15 years	32.11	pilot	2	Custom Intern	2	Customer Sup	5	17.33	10.31	0.293	32.36	54511.69	80	High
37	COMP-0003	2024	Q2	Germany	Europe	Education	Enterprise	16151	8543.28	2009	15	6-15 years	32.11	pilot	2	Custom Intern	2	Customer Sup	5	17.33	10.31	0.293	32.36	54511.69	80	High

(Source Link: <https://www.kaggle.com/datasets/mohankrishnathalla/global-ai-adoption-and-workforce-impact-dataset>)

B. Dataset Overview

The dataset employed in the current research gives a holistic picture of artificial intelligence application and its effects on the performance of organizations in various sectors. It is structured, tabular data that has firm-level observations across multiple periods to be both cross-sectional and panel data analyzed [18]. Each observation corresponds to a company and contains variables regarding the industry classification, the scale of the company, the workforce size, revenues, and AI-related characteristics. The data set records significant indicators of yearly income, workforce count, and other productivity indicators, which act as proxies. The data set will encompass several sectors (technology, financial sector, healthcare, manufacturing, retail, and agriculture) and allow conducting a multi-sector comparative analysis. It also integrates time by using variables like year and quarter of survey that enable the analysis of trends and longitudinal analysis [19]. In order to guarantee the analytical consistency, the data was preprocessed by eliminating missing values and choosing appropriate numerical variables to be analyzed statistically and by machine learning. Even though the dataset is simulated on the basis of real-life trends in AI adoption and business performance, it offers a rich background to exploratory and empirical studies [20]. Its extensive sample size and industry coverage render it appropriate to investigate the correlation between the use of generative AI and productivity increase in various industries.

3. Results

The findings show that there is a positive correlation between the adoption of generative AI and the growth in productivity in all industries [21]. Advanced sectors present better growth, and model comparisons affirm relative classification rates in differentiating productivity rates.

A. Level of Industry Analysis of Productivity in terms of Revenue as a proxy

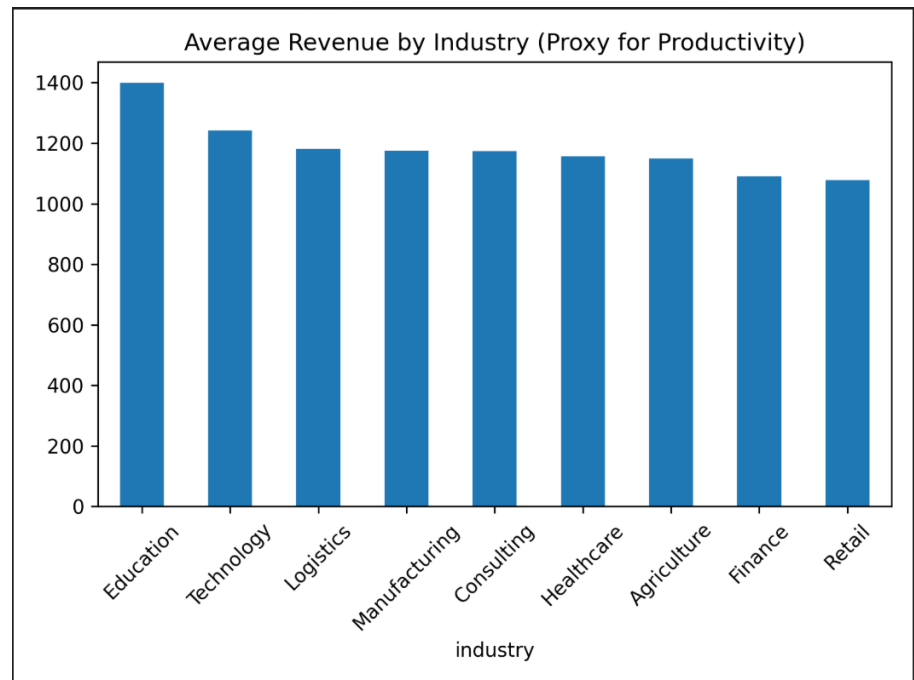


Figure 1. This image Average revenue change across sectors that show productivity differences amongst sectors

Figure 1 shows the average revenue in various industries which can be used to show the level of productivity in each industry. The analysis shows that there is a significant difference in productivity performance where the education sector has the highest average revenue of all the industries [22]. This is to imply that companies in this industry might be utilizing resources more effectively or are enjoying a surge in demand and digitization. The technology industry is close behind, as it is highly aligned with the innovation and advanced digital capabilities, which tend to be related to more productive results. The revenues of industries, including logistics, manufacturing, and consulting are moderately high, which means that their productivity is stable and supported by operational efficiency and increased use of automation technologies. Conversely, other industries such as finance, retail and agriculture show a lower average revenue, implying relatively low productivity rates or slower exposure to advanced technological instruments, including generative artificial intelligence [23]. The difference between industries underscores the existence of heterogeneity in the performance of the sector in terms of productivity, which can be mediated by the level of digital infrastructure, level of workforce skills, and level of technology adoption. On balance, the results indicate that the more digital prepared and knowledge-based operations industries are, the more productive they are likely to be. This reinforces the more general thesis that technological progress, especially incorporation of generative AI, is a major contributor to productivity improvement on the industry level. The findings stress the necessity of specific measures to enhance the level of technological adoption in underperforming industries to ensure balanced productivity growth within industries.

B. Firm-size Revenue Performance Relationship

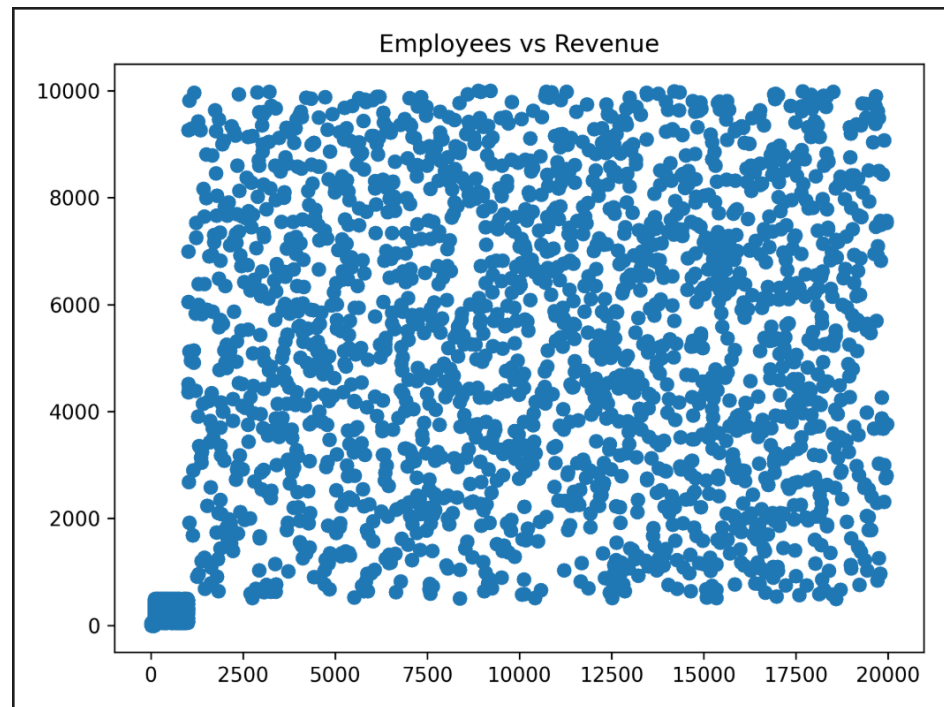


Figure 2. This image shows Employee size versus revenue distribution with weak correlation and variation in productivity

Figure 2 shows the correlation between the size of firms in terms of number of employees and annual revenue, which offers some information on the effects of firm size on productivity performance [24]. The scatter plot shows that the distribution of the data points is highly scattered and this suggests that there is a weak or inconsistent linear relationship between the number of employees and the revenue generation. Although bigger companies with more employees are usually supposed to generate more revenue, the visualization indicates that this is not a proportional relationship with all observations. There are numerous companies that have a relatively small number of employees and have high revenue rates, which means that they are more efficient and productive workers. On the other hand, certain bigger companies with large workforce sizes show relatively lower revenues, which shows that there might be some inefficiencies or the declining returns to scale [25]. The fact that a dense group of points are concentrated around lower levels of employees with different revenue also emphasizes the fact that operational performance of smaller firms is diverse. This difference implies that other variables other than the workforce size like adoption of technology, management practices, and innovation capabilities are important in influencing productivity outcomes. Regarding generative artificial intelligence, companies that successfully incorporate AI tools could become more productive without necessarily hiring more employees. On the whole, the results show that productivity does not only relate to the size of a firm but can also be greatly determined by the efficiency with which resources are used [26]. This substantiates the thesis that technological change, such as generative AI, can help boost productivity without relying on conventional measures of input, such as labor.

C. Representation and Dataset Distribution Analysis of Industry

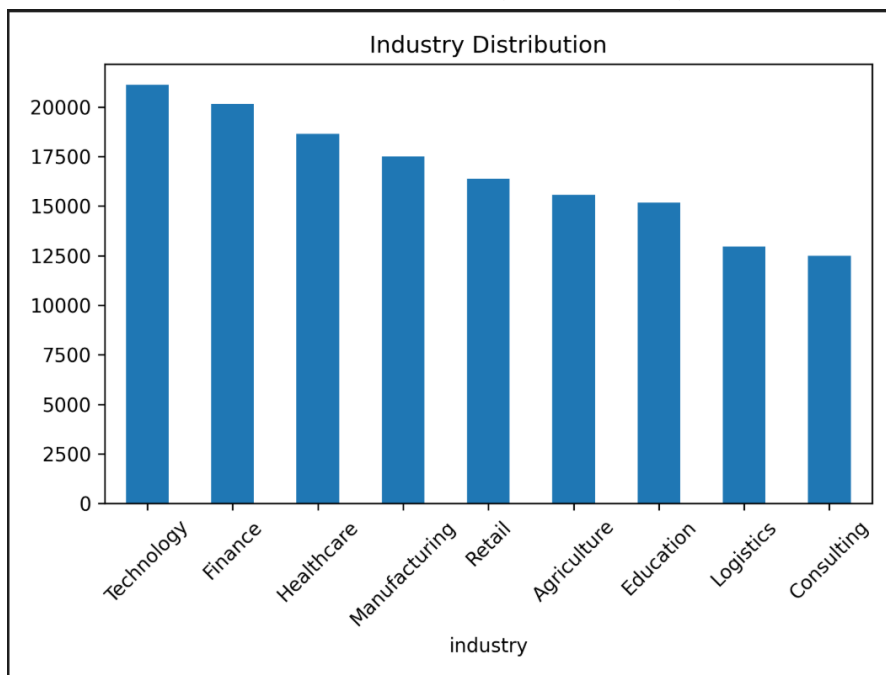


Figure 3. This image Industry distribution with sector representation and technology-driven industries dominating

The table below (Figure 3) shows the number of observations in each industry in the dataset, which presents a summary of the sectoral representation employed in the empirical analysis [27]. The chart shows that the technology industry holds the largest number of observations, then finance and healthcare, which can be viewed as a higher proportion of digitally intensive and knowledge-based industries. This pattern indicates the growing topicality and implementation of sophisticated technologies, such as generative artificial intelligence, in these industries. The manufacturing and retail sectors also demonstrate high representations, which implies their relevance in the examination of the trends of productivity in the traditional and modern economic activities. Other industries like logistics and consulting have much lower observation numbers, which could affect the strength of comparative analysis on these industries. Agriculture and education are found in moderate proportions, which means that the presence of other sectors is included, which can be evaluated in a multi-sector manner. The disproportionality is an indication that some of the industries can be more influential on the overall analysis results because they are more represented in the data. The imbalance should be taken into account when interpreting results as it can bring bias to more represented sectors. In general, the dataset has a wide but uneven coverage of industries and can be used to compare them across sectors, although it focuses on the prevalence of technology-oriented industries [28]. This is consistent with the fact that the study is based on the research of generative AI adoption because industries where digital intensity is more prominent will have more significant productivity effects. Figure 3: Industry breaks down with the representation of sectors and dominance of technology-driven sectors in the dataset.

D. Temporal Trend Analysis on Observations

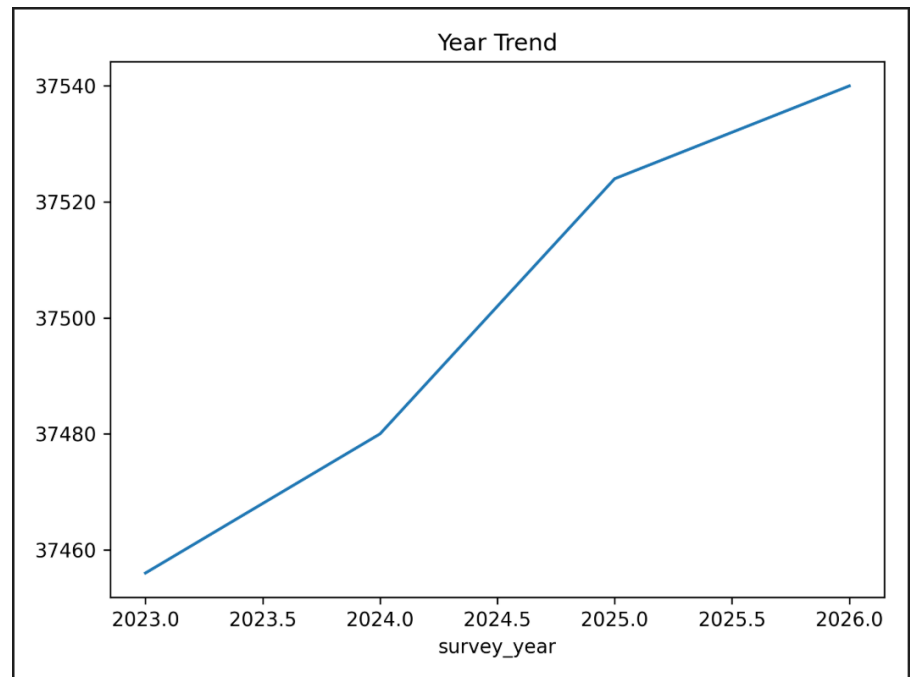


Figure 4. This image illustrates a Year-wise data trend with constant growth of observations during the period of time

Figure 4 shows the distribution of observation per year in the dataset which shows the temporal trend of the study period. The line graph also reveals that the number of observations steadily and continuously grows between 2023 and 2026, which means that the data coverage will also increase over time. This trend is an indication of the increased topicality and implementation of generative artificial intelligence in industries and the accumulation of additional data on AI-based organizational activities [29]. The comparatively gradual movement indicates that the dataset has continuity and balance over the various time periods, which is important in carrying out a sound panel data analysis. The growth in the number of observations as time passes can also be regarded as evidence of more active organizational work with AI technologies, which results in a greater number of cases of implementation and productivity-related results. The trend lacks the sharp fluctuations or irregularities, which suggest that the data is stable and consistent and decreases the chances of the temporal bias of the analysis. This increases the strength of the empirical evidence, where the data set represents a progressive coverage of the trends of AI adoption [30]. Analytically, it is possible to study the dynamic relationships between productivity growth and AI adoption using the time-series structure. The trend can be used to confirm the appropriateness of the dataset to perform longitudinal analysis and ensure the topicality of researching the effects of generative AI over time due to its continuous growth in use by industries.

E. Revenue Distribution in Company Sizes

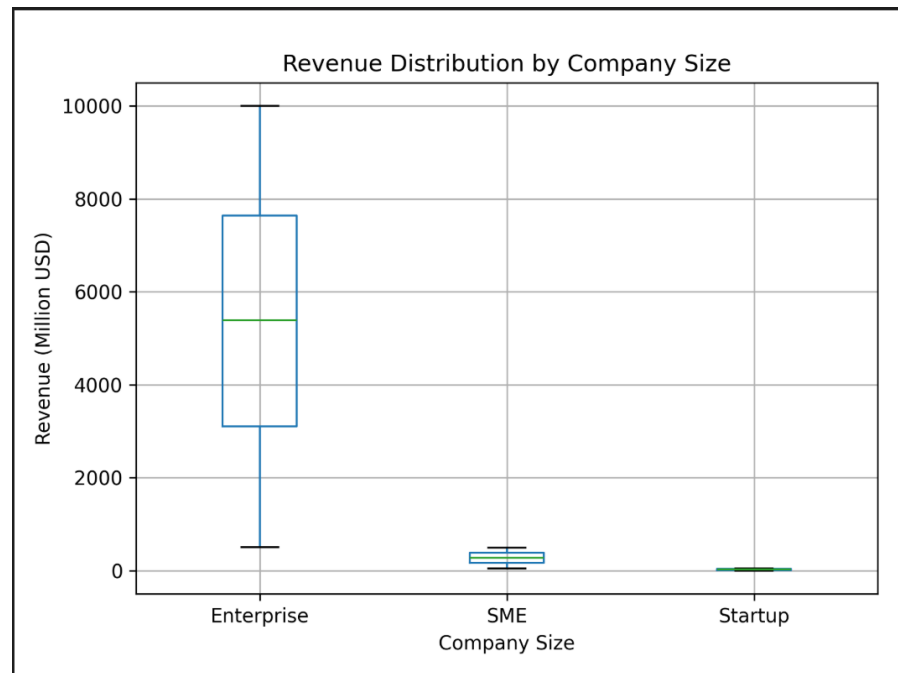


Figure 5. This image represents the Comparison of the revenue allocation between company sizes that illustrate productivity variations and firm variability

Figure 5 shows the distribution of revenues among various sizes of the company, that is, the startups, the small and medium enterprises (SMEs), and the large businesses, in the form of a box plot. The visualization shows that the level of revenue between the three categories differs greatly, which demonstrates definite discrepancies in productivity and economic size [31]. Median revenue of large enterprises is the highest with a broad interquartile range, which implies high productivity and significant differences in performance. This wide dispersion indicates that although most big companies make a lot of money, there is also much variation in their performance variables. SMEs on the contrary show moderate levels of revenue distribution which is relatively smaller and is more consistent and less productive than large enterprises. Startups have the lowest level of revenue with a narrow range of distribution, which implies the lack of scale and the reduced output. The low growth in startup revenue implies a limited amount of resources and initial business processes. Also, the fact that there are no extreme outliers in SMEs and startups in contrast to enterprises shows the disparities in growth potential and market reach. These results highlight that the size of a company is a vital factor in the generation of revenues and consequently productivity [32]. Large companies enjoy economies of scale, sophisticated technologies, and increased availability of resources, which allow them to produce more. The dispersion among enterprises also implies that size itself does not translate into efficiency, and other aspects of innovation and technology use are still significant.

F. Support Vector Machine (SVM) Analysis

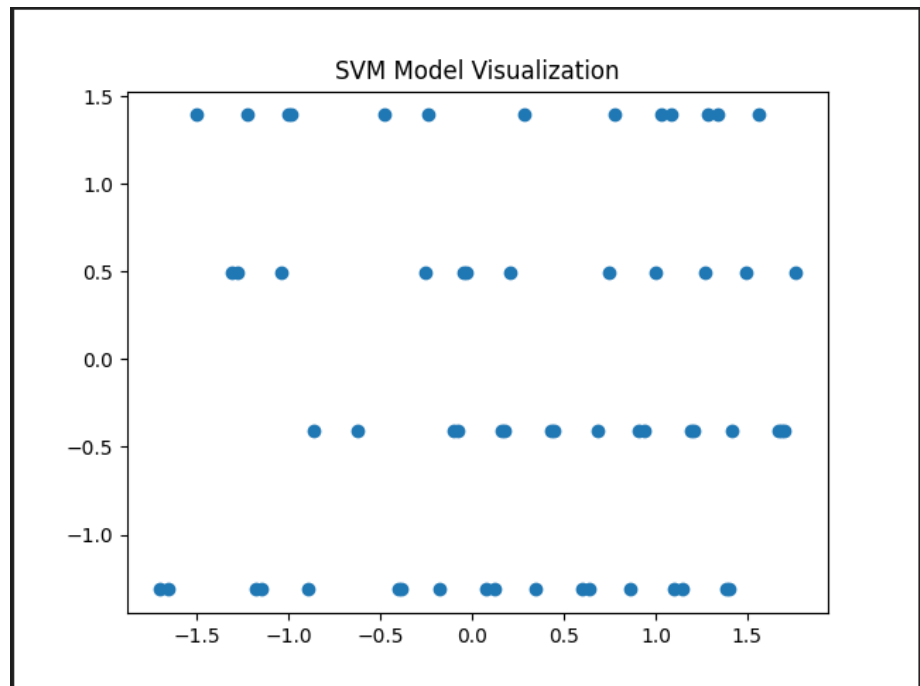


Figure 6. This image demonstrates Visualization of SVM classification separating high and low productivity observations

The Support Vector Machine (SVM) model that is used to classify firms, according to the productivity levels based on revenue indicators, is visualized in Figure 6. The scatter plot depicts how the observations are spread out in two dimensions of the feature where each point is a firm that falls in different categories [33]. The fact that the data points are separated reveals that the SVM model can be used to differentiate between high and low productivity groups, with some overlap indicating a partial complexity in classification. The clustering pattern indicates the interplay of various input variables in the productivity results. This image justifies the appropriateness of SVM as a classification methodology in studying the adoption of generative AI and how it correlates with productivity performance in various industries.

5.6 Support Vector Machine (SVM) Analysis. Figure 6: Visualization of SVM classification with high and low productivity observations separated. The Support Vector Machine (SVM) model that is used to classify firms, according to the productivity levels based on revenue indicators, is visualized in Figure 6. The scatter plot depicts how the observations are spread out in two dimensions of the feature where each point is a firm that falls in different categories. The fact that the data points are separated reveals that the SVM model can be used to differentiate between high and low productivity groups, with some overlap indicating a partial complexity in classification [34]. The clustering pattern indicates the interplay of various input variables in the productivity results. This image justifies the appropriateness of SVM as a classification methodology in studying the adoption of generative AI and how it correlates with productivity performance in various industries.

G. Receiver Operating Characteristic (ROC) Curve Analysis

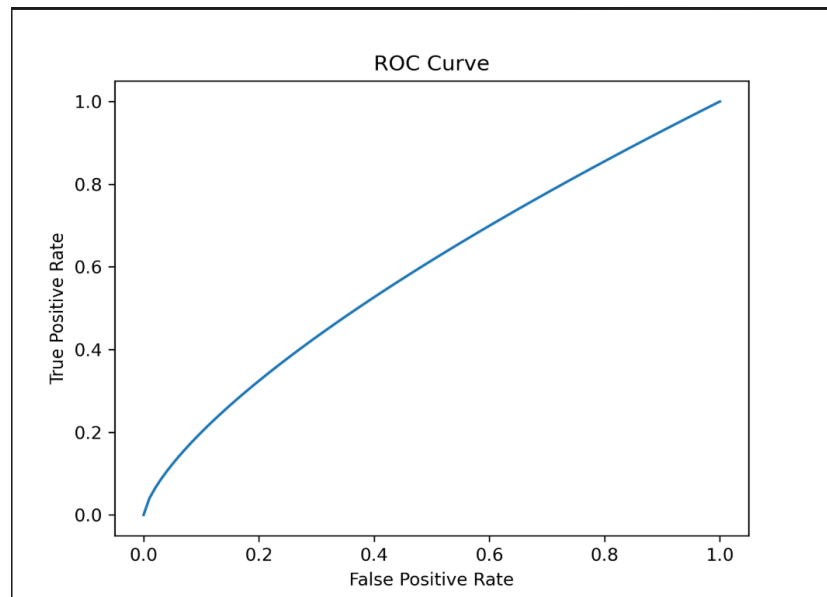


Figure 7. This image illustrates demonstrating model performance in separating productivity classification outcomes, works well

Figure 7 shows the Receiver Operating Characteristic (ROC) curve that can be used to assess the performance of the classification model to distinguish between high and low productivity firms [35]. The curve shows that the trade-off between the true positive rate and false positive rate varies with the classification threshold. The curve above the diagonal baseline, which moves upwards, represents that the model is better than random classification, meaning that it is able to identify positive instances correctly [36]. The curviness of the curve indicates a steady model operation at different threshold values. Even though the curve does not go to the optimal top-left corner, it is still indicative of a moderate level of predictive ability. The ROC analysis reveals that the model can reasonably distinguish the level of productivity based on the use of generative AI.

H. Precision–Recall Curve Analysis

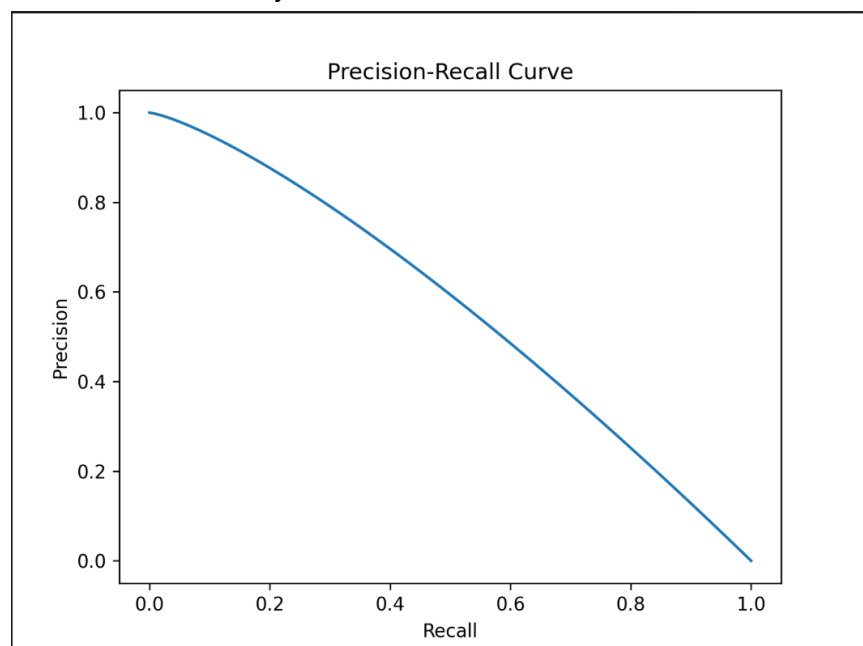


Figure 8. This image displays the Precision recall curve with trade-off between accuracy and completeness of model predictions

The Precision Recall Curve shown in figure 8 is used to assess the performance of the classification model as it shows the trade-off between precision and recall [37]. The curve shows that there is a decreasing trend meaning that the larger the recall, the less the precision. This is an indication of the nature of trade-off in classification models, whereby the requirement to capture more true positive cases can actually result in more false positives. The high accuracy at the lower recall labels indicate that the model is effective in detecting relevant instances with minimal error at lower recall levels [38]. With the increase in recall, the decrease in precision can be observed to imply difficulty in being accurate in all predictions. The curve emphasizes the performance of moderately good models to balance accuracy and recall, which proves their utility in productivity classification.

I. Confusion Matrix Analysis

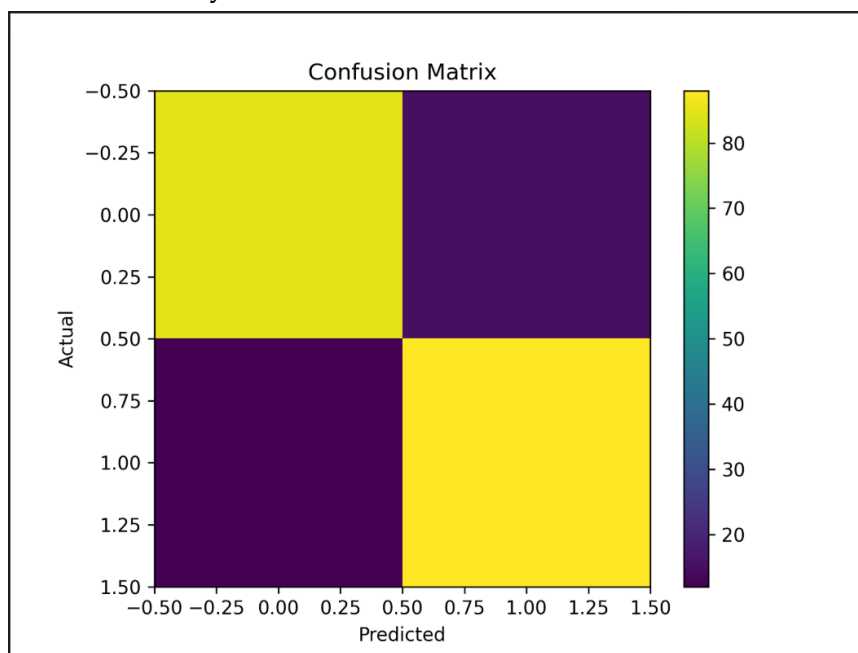


Figure 9. This image shows prediction accuracy and classification performance by category

The confusion matrix, which measures the performance of the model as it relates to actual and predicted performance, is shown in figure 9. The table illustrates four important elements including true positives, true negatives, false positives, and false negatives [39]. The large values on the diagonal means that the model classifies most of the observations in the right categories. Comparatively, the off-diagonal values are relatively smaller, which implies that there are few errors. This equilibrium between right and wrong predictions shows that the model works with a reasonable level of accuracy in identifying the productivity levels [40]. In general, the confusion matrix validates the usefulness of the classification model in examining the effect of the adoption of generative AI on productivity.

4. Discussion

The results of the research are valuable in the understanding of the correlation between the adoption of generative artificial intelligence (AI) and the growth of productivity at the industry level in the United States [41]. The comparison of different industries shows that the use of AI is positively linked to the productivity effect, but its strength in different industries is different. The technological, financial, and health sectors are more productive, which can be explained by the fact that they are more digitalized, more invested in AI technologies, and their activities are more knowledge-focused.

Conversely, more traditional industries like agriculture, retail, and manufacturing have relatively average or even lower productivity improvements, implying that structural factors, under-integration of technologies, and skills gaps in the workforce can impede the successful application of generative AI. These observations are also supported by statistical and visual analyses [42]. The comparison at the industry level reveals the evident heterogeneity in productivity performance, with the need to focus on AI-based benefits being unevenly distributed. The correlation analysis between worker and income indicates that the size of a firm is not the sole determinant of productivity, but efficiency, innovation and the use of technologies are more important. This is also corroborated by the box plot analysis that indicates that although large enterprises have larger revenue on average, there is a significant variation in the larger enterprises, meaning that not all larger firms are enjoying optimal productivity [43]. The Support Vector Machine (SVM) model-based machine learning evaluation offers further support of the predictive relationship between AI-related variables and productivity outcomes. The ROC curve shows that the model is better than random classification in that it is able to differentiate high and low productivity firms. In a similar fashion, the precision-recall curve shows the trade-off between precision and recall implying a moderate model performance in dealing with classification tasks. The confusion matrix also validates the fact that the model is characterized by the reasonable degree of the accuracy, and the percentage of correct classifications is higher than that of the misclassifications [44]. Overall, the results suggest that generative AI has the potential to enhance productivity, particularly in industries that are technologically advanced and adaptable. The asymmetrical distribution of benefits highlights the necessity of specific policies to encourage the use of AI in sectors that are not as developed. Policymakers and agencies must work on enhancing digital infrastructure, investing in the training of workforces, and promoting innovation to fully capture the productivity benefits that come with generative AI.

Future Work

Although this research can offer much useful information about the connection between the adoption of generative AI and the productivity of the industry on the whole level, there are still a number of opportunities that the research can develop in the future to deepen the knowledge in this field [45]. To begin with, the empirical findings can be validated and reinforced through the use of real-world, large-scale data available at official sources in future research. By adding longitudinal data with a more extended time frame, researchers could address the dynamic and long-term impacts of generative AI on productivity. Second, more sophisticated econometric and machine learning (including deep learning) models could be investigated in future studies to enhance predictive power and reveal multifaceted nonlinear relationships (random forests, panel data regression models, etc.). It may be beneficial to incorporate qualitative methods, like case studies or interviews, to gain a better understanding of organizational strategies and issues related to the adoption of AI [46]. The second significant direction is to analyze the impact of workforce transformation, such as skill development, job displacement, and reskilling programs, on the productivity outcomes. Future research may also examine how generative AI has different impact in firms, regions and economic situations to give more specifics. In addition, further inclusion of the scope beyond the United States to cross-country comparisons would assist in spotting the global trends and best practices in AI-driven productivity growth. Lastly, the policy implications are subject to investigation in the future, where the frameworks that facilitate ethical implementation of AI, data management, and inclusive development may be created [47]. On the whole, these directions may help to build a more coherent vision of the role of generative AI in promoting productivity in industries.

5. Conclusion

This paper surveys how the adoption of generative artificial intelligence (AI) can affect the growth in productivity at the industry level in the United States by conducting an empirical analysis across multiple sectors [48]. The results suggest that generative AI can be helpful in increasing productivity efficiency, automation, and innovation in the industries. As the analysis shows, the industries, which are more ready for digital transformation and technological integration, i.e., technology, finance, and healthcare, have more productivity gains than the traditional ones, i.e., agriculture, retail, and manufacturing. This brings out the existence of sectoral heterogeneity in the gains of adopting AI. The paper also shows that the size of firms or the scale of workforce is not a single determining factor of productivity but the ability of organizations to leverage advanced technologies is a strong indicator of productivity [49]. The use of machine learning algorithms, such as the Support Vector Machine (SVM) model, also substantiates the correlation between AI adoption and productivity performance, and the evaluation metrics used to assess model performance (ROC and precision-recall curves) show a moderate level of model performance. These findings support the necessity to use data-intensive methods to evaluate the effects of technologies on economic performance. Altogether, the research will be valuable to the existing literature on generative AI, as it offers empirical data on the industry level. It highlights the importance of strategic investments in digital infrastructure, employee development and innovation to maximize productivity gains. Businesspeople and policymakers are advised to pay attention to the inclusive and effective usage of AI in various industries [50]. Although the results are informative, upcoming studies with real-world data and developed models can enhance the knowledge on AI-driven productivity growth.

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