Evaluating the Impact of AI Research on Industry Productivity: A Dynamic Qualitative Comparative Analysis Approach

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Abstract

Within the digital age, the transformative potential of artificial intelligence (AI) on the global industrial and economic landscape is unprecedented, making exploring AI's impact on productivity critical and timely. This study leverages dynamic qualitative comparative analysis (QCA) to decode the intricate effects of AI research on industry productivity, utilizing a comprehensive dataset from the EU KLEMS database and per capita AI research publication counts across 30 countries. Our pioneering approach uncovers the synergistic configurations that catalyze productivity enhancements, offering a dynamic perspective on AI's evolving role. We highlight the indispensable role of trade openness, AI capital stock, labor cost, technological advancement, and AI research's strategic importance in driving productivity growth. This study emphasizes the criticality of international trade, technology transfer, and innovation as foundational to productivity improvements, revealing distinct pathways to high productivity through unique factor combinations, including the growing significance of AI research intensity. Providing a holistic understanding of AI's influence on productivity gains, this study delivers critical insights for policymakers and industry stakeholders, advocating for strategies to harness AI for economic and operational excellence. By elucidating the dynamic interplay between AI research, technological innovation, and productivity enhancement, this study significantly enriches the discourse on the role of AI in fostering industrial productivity growth, using a novel methodological approach that melds quantitative precision with qualitative insights to guide future strategic initiatives in the AI-driven economic landscape.

Keywords: *Industry Productivity, Artificial intelligence, Dynamic QCA, AI Research*

JEL Classification: C30, D24, O47

1 INTRODUCTION

In this rapidly advancing technological era, AI development and application are impacting the economy and people's lives by osmosis, and are playing an essential role in product innovation, stimulating consumer demand, and other areas (Piel & Seising, 2023). Damioli (2021) found that AI technology has experienced significant growth over the past five years, especially in China, Japan, South Korea, and the United States. In terms of industry, AI is being used to upgrade supply chain management in manufacturing, optimize extraction methods in mining, and identify fraudulent transactions in the financial industry, nearly all industries are gradually adopting AI to achieve innovative change (Wu et al., 2024; Corrigan & Ikonnikova, 2024; Aldoseri et al., 2024). As a measurement of production efficiency, productivity is a key driver of economic growth, and AI shows great potential for boosting productivity.

However, productivity improvement is a complex process that is affected by a combination of factors (Rosid et al., 2022), and the impact of AI technology is not static but develops and changes over time (Kumar, 2023). Current research lacks an in-depth understanding and comprehensive analysis of how AI technology affects productivity gains over time, under the influence of multiple intertwined factors. Therefore, this study chooses dynamic QCA as the research methodology to analyze and discuss different types of data and multiple causal pathways. By using dynamic QCA, this study not only identifies key influences but also reveals how these factors interact with each other, and tracking and analyzing changes in conditions forms a time dimension (Garcia-Castro & Ariño, 2016), resulting in a better understanding of how AI can improve productivity in the long run.

The contributions of this study are as follows. We provide an innovative perspective on how AI affects productivity gains over time by using dynamic QCA. This approach allows us to synthesize quantitative data and qualitative insights to gain a more comprehensive understanding of the mechanisms by which AI affects productivity gains. Secondly, this study identifies the factors and configurations that influence the generation of high productivity by analyzing data from 30 different countries, providing new insights into understanding the impact of AI on productivity enhancement globally. Furthermore, the findings and analyses of this study provide practical insights for policymakers and business stakeholders to better understand and utilize AI technologies to improve productivity and economic competitiveness.

The objective of this study is to apply the dynamic QCA approach to determine those factors and configurations that affect the generation of high productivity and to observe how the impact of AI evolves over time. The rest of the study is structured as follows. It begins with a literature review and hypothesis development, which presents a literature review of AI's impact and methods involved in the study and formulates the research hypotheses. Then we describe the data and the research methodology used. Next, the QCA results are presented. Finally, this study discusses and analyzes the results of the study, draws appropriate conclusions, and provides suggestions for future research.

2 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Overview of AI's impact on productivity

AI, as one of the major technologies used for change, has integrated with various industries, and not only ushered in a new era of productivity, but has also had a significant impact in several fields. For example, Wang et al. (2022) used a fixed effects model, mediated effects model, and difference-in-differences approach to explore the impact of AI on the total factor productivity of manufacturing firms in China. Their findings show that AI brings a significant improvement in TFP. At the same time, technological innovation and human capital optimization are the two main ways in which AI affects the TFP of Chinese manufacturing firms. Furthermore, Fang et al. (2022) analytically investigated AI applications using qualitative interpretive methods, single case study methods, and structural equation modeling methods and found that AI effectively improved office productivity for remote workers. Similarly, Yang and Liu (2024) found that industrial intelligence based on AI technology also positively improved green total factor productivity after incorporating environmental regulations into the analytical framework by applying GMM estimation, instrumental variable estimation, and a series of robustness tests.

In addition, Ying et al. (2023) explored that firms absorbing and unabsorbing idle resources positively moderated the positive impact of AI technology on firms' GTFP.

Based on a review of prior research, this study proposes the following hypotheses to identify the role of AI research intensity over time and the specific configurations that influence the generation of high productivity:

H1: AI research intensity over time has a positive effect on productivity.

H2: AI stock (or AI research) must be present, while AI research (or AI stock) must be absent in at least one configuration to achieve high productivity.

H3: Both AI stock and AI research must be present in at least one configuration to achieve high productivity.

H4: AI stock (or AI research) must be present, while AI research (or AI stock) must be an immaterial condition in at least one configuration to achieve high productivity.

2.2 Previous methodologies in assessing AI's impact

A review of the multiple methods used in previous studies to assess the impact of AI on productivity is presented. These studies look at the impact of AI on various industries from different perspectives, including TFP, labor productivity, and industry-specific applications. Most of the studies used quantitative methods such as fixed effects modeling and difference-in-differences modeling (Wang et al., 2022), structural equation modeling (Fang, 2022), GMM estimation, and IV estimation (Yang & Liu, 2024).

Meanwhile, apart from the impact on productivity, research on the impact of AI on other domains also provides scholars with a comprehensive view to help them understand the broad impact of AI from a macro perspective and segmentation. For instance, Li (2023) assessed the impact of AI on employees' on-the-job learning through an empirical research methodology, shifting the focus of the study to the impact of AI technology on individual development. In addition, Khogali and Mekid (2023) pointed out the far-reaching impact of AI technological development on social ethics and values through a combination of narrative literature review and thematic pattern analysis. Bulchand-Gidumal et al. (2023) utilized a grounded theory approach to assess the impact of AI from a hotel marketing perspective, focusing on the application and effects of AI in specific business strategies. Ding (2023) extended the study to the assessment of the impact of AI on the environment by using the SDM to measure the impact of AI development level on carbon emissions in China.

2.3 Introduction to dynamic qualitative comparative analysis

Dynamic qualitative comparative analysis as a research methodology is a development of the QCA approach, which was initially used to analyze cross-sectional data, and centers on the logical and configurational analysis of aggregates to reveal complex causal relationships between different cases (Ragin, 2014). Whereas dynamic QCA is used to analyze panel data, the difference is that it adds the consideration of the time dimension to QCA, emphasizing the interactions and influences between the variables at different points or stages in time (Garcia-Castro & Ariño, 2016). In fact, the authors did not provide a detailed explanation on how to apply Garcia-Castro and Ariño's (2016) analytical methodology in panel data QCA modeling, including the testing of the necessary and sufficient conditions and how to interpret the data analysis results. Still, reference can be made to Bhattacharya (2023), who conducted an applied study that explored in detail how to interpret the results of data analysis to fill this knowledge gap.

3 RESEARCH OBJECTIVE, METHODOLOGY AND DATA

The research objective is to identify the specific configurations that can influence high productivity generation and test the proposed hypotheses.

3.1 Data sources

This study focuses on the European Union, the United Kingdom, the United States, and Japan, which are in different geographic regions with different levels of industrialization and technologization. National data from 2000 to 2020 has been selected for the study, which helps to explore the factors influencing industrial productivity in different economic contexts and to understand from a longer-term perspective how AI research affects the dynamics of industrial productivity. In addition, the data sources for this study include the EU KLEMS database and the OECD AI Policy Observatory.

The EU KLEMS database is a comprehensive source of economic and productivity statistics for all sectors in E.U. countries and some non-E.U. (Japan, USA, UK), which provides a detailed breakdown of inputs and outputs for different sectors and countries, allowing for a nuanced understanding of the factors that drive E.U. economic performance (Bontadini et al., 2023). The EU KLEMS database was chosen as the primary data source for this study because of its wide coverage and high data granularity, which provides the study with complete data for 30 different countries for the period 2000-2020, which facilitates a detailed analysis of productivity trends. In addition, the database is regularly updated to ensure that the analysis is based on the latest available information. It is widely used among economic researchers, which facilitates comparisons with other studies and increases the credibility of the findings. AI research publications are collected by the OECD.AI (2024), the OECD's AI Policy Observatory for collating AI research and development data from various sources. Open Alex is the main repository of scholarly publications collated by the observatory. By accessing this data through the OECD interface, we can apply precise filters to segregate publications based on criteria such as country, year and institution.

3.2 Methodology

The dynamic QCA approach is based on the traditional QCA, which considers time and cross-section effects to evaluate the intrinsic panel data structure, while Garcia-Castro and Ariño (2016) proposed a new set of generalized descriptive indicators for assessing the pooling theory relationships of such panel data. From Bhattacharya's (2023) study, the steps of dynamic QCA assessment are as follows. Data calibration is the first step to be accomplished after data collection to determine the affiliation of the condition variables and the outcomes in the set they represent. This is followed by necessity analysis, then constructing and generating truth tables for sufficiency analysis checks, and finally, deriving causal configurations for analysis.

Garcia-Castro and Ariño (2016) proposed three alternative forms of consistency based on QCA: pooled consistency (POCONS), between consistency (BECONS), and within consistency

(WICONS). These can be used to assess the stability of consistency over time and cases. In addition, the adjustment distance is key to consider in dynamic QCA. The adjusted distance of BECONS and POCONS indicates the stability of consistency maintained over time. Hence, the smaller the adjusted distance, the more stable the consistency. If the adjustment distance is high, it is crucial to assess the temporal impact on the panel (Garcia-Castro & Ariño, 2016).

3.3 Variables and measurement

The definition and measurement of the outcome and condition variables for this study are shown in Table 1.

Tab. 1 – Variables and measurement. Source: own research

	Variables	Measurement
Outcome	Productivity	AI per worker
Condition	AI research	Number of AI research publications by institution
	AI stock	AI capital stock net
	Labor cost (Labor)	Real compensation per employee
	Technology (Tech)	Share of ICT capital compensation in nominal GDP
	Education (Edu)	Total enrollment rates by age group
	Trade openness (Trade)	The sum of exports and imports of goods and services measured as a share of gross domestic product
	Human capital (Hum)	Index of human capital per person

In this study, productivity is the outcome variable. Meanwhile, based on the review of factors affecting productivity in the literature review, seven causal conditions were measured: AI research, AI stock, labor cost, technology, education, trade openness, and human capital. The variables are measured as follows.

Productivity refers to the relationship between the number of products or services produced or created and the resources invested in each period. This study uses AI divided by the number of employees as a formula for measuring productivity, to compensate for the fact that traditional productivity measurement may not fully capture the contribution of technology to productivity gains, and dividing AI by the number of employees provides a more intuitive understanding of how much employee effectiveness has increased with the introduction of AI technology in the industry. AI research is the activity of conducting systematic research on AI techniques, methods, and theories. This study refers to Parteka and Kordalska (2022) using AI research publications as a measurement of AI research; AI stock refers to the sum or stock of money, technology, talent, and other resources that a country or industry has already accumulated in the field of AI. This study draws on Brynjolfsson et al. (2018) using AI capital stock net to measure it; Labor denotes the cost of labor, which is the sum of expenses paid by a firm to hire employees, including wages, salaries, benefits, bonuses, and other employee-related expenditures. This study refers to Qian and Wang's (2022) measurement using real compensation per employee; Technology refers to the technological capability and capacity of the country or industry in a particular technological field or category. This variable is measured with reference to the study of Li et al. (2022), using ICT capital compensation as a share of nominal GDP. Education usually refers to the extent and level of education in the country. This study refers to Chang et al. (2023) using the sum of enrollment rates for primary, secondary, post-secondary non-tertiary, and tertiary education by age, the number of years children of enrollment age are expected to spend at school or university, including the number of years of grade repetition. Trade indicates the degree of trade openness and the degree of openness or freedom of a country or region to engage in foreign trade activities. This study refers to Kumar's (2006) study that uses the sum of exports and imports of goods and services as a share of GDP for this measurement. Human denotes human capital, specifically the assets or resources in terms of human resources a country, organization, or individual possesses. Therefore, the study refers to Song and He (2023) to measure the human capital index per capita, which comprehensively reflects the quantity (years of schooling) and quality (returns to education) of the country's human capital.

3.4 Calibration of data

Since QCA is a case-oriented approach to studying theoretical sets, each research variable must be converted to a set measurement by data calibration before analyzing the data (Ragin, 2009). Garcia-Castro and Ariño (2016) used the direct calibration method to determine the data affiliation anchors by setting the quartiles of 0.75, 0.5, and 0.25 as the anchors of full affiliation, crossover, and full non-affiliation, respectively, to realize the calibration of the variables to the set of data within [0,1]. The specific calibration values are shown in Table A1.

4 DATA ANALYSIS

4.1 Necessity analysis

From the results of analyses in Table A1, the "trade" consistency score is greater than 0.9, and the coverage is greater than 0.5, which is a necessary condition to constitute "productivity" (Schneider & Wagemann, 2012). The conditions between consistency adjusted distance (BECONS Adj-distance) and within consistency adjusted distance (WICONS Adj-distance) were both less than 0.1, implying that the pooled consistency accuracy was high enough to be used as a basis for judgment, but when the BECONS Adj-distance was more than 0.2, the necessity of conditioned variable needed to be further analyzed (Garcia-Castro & Ariño, 2016).

Further observation of the variables with BECONS Adj-distance greater than 0.2 reveals that their consistency values for all years are less than 0.9, and there is no necessary relationship. But it is noteworthy that in the combination situation of the AI research variable and the productivity variable, although the AI research does not constitute a necessity for the outcome variable, the condition has shown a clear time effect. Starting in 2004, the level of necessity basically increases yearly (see Figure A1), and is expected to grow in importance. We refer to Zhao et al. (2021) to express the AI research intensity in terms of the ratio of the total number of publications, which is shown in Figure A1. The intensity of AI research increases year over year. Simultaneously, the consistency value of AI research shows a similar trend, gradually increasing over time.

4.2. Construction of truth tables

The process of determining the truth table involves setting the case frequency and raw consistency thresholds before dealing with contradictory groupings and making assumptions about the logical residuals. This study sets the consistency threshold at 0.8, the frequency threshold at 1, and the PRI (proportional reduction in inconsistency) value at 0.8 based on the QCA methodology research experts' recommendations (Benoît & Ragin, 2009; Ragin, 2006, 2009). This ultimately obtained four groupings. The detailed results are shown in Table 2. The notation in the table refers to the solution table notation introduced by Ragin and Fiss (2008).

Tab. 2 – Configuration analysis result. Source: own research

Configuration	1	2	3	4
AI research publications		⊗	⊗	●
AI_stock	●	●	●	
Labor	⊗	⊗	●	⊗
Tech	●	●		●
Edu	●		●	●
Trade	●	●	●	●
Hum	●	⊗	●	●
Consistency	0.910	0.904	0.920	0.901
PRI	0.879	0.856	0.885	0.857
Raw coverage	0.239	0.111	0.107	0.165
Unique coverage	0.056	0.068	0.035	0.008
BECONS Adj-distance	0.039	0.083	0.039	0.049
WICONS Adj-distance	0.316	0.368	0.259	0.322
Overall solution consistency	0.906			
Overall PRI	0.876			
Overall solution coverage	0.350			

Note: Black circles (●) represent the presence of a condition, and circles with an "x" (⊗) represent the condition absence. Large circles represent core conditions, and small ones, peripheral conditions. Blank spaces represent conditions that can be present or absent.

As shown in Table 2, the consistency values for all four configurations are greater than 0.9, with the overall solution consistency value of 0.906, which is higher than the minimum score of 0.75 for the consistency judgment criterion (Ragin, 2009), indicating that the consistency results have a better explanatory nature. These four configurations can be regarded as sufficient conditions for influencing the emergence of a high level of productivity. Additionally, the overall solution coverage value is 0.350, indicating a proportion of cases that could be described by at least one configuration in a solution set (Ragin, 2000). Configuration 3 shows the highest consistency value, with a between consistency adjusted distance of less than 0.1, and relatively high consistency for the outcome variable (Garcia-Castro & Ariño, 2016), which indicates that it is the key configuration for high productivity generation.

Specifically observing the four configurations, from the results of the necessity analyses, "trade" is a necessary condition for the outcome variable, which also appears in all four sufficient configurations. Therefore, according to the findings of Dul (2016), it can be further proven that "trade" is more likely to be a necessary condition for high productivity.

The BECONS Adj-distance for all four of the configurations was not greater than 0.1, suggesting no significant time effect (Garcia-Castro & Ariño, 2016). However, as shown in Figure A2, further observation of the temporal changes in the BECONS of the four configurations revealed that the consistency values of the three configurations, except for configuration 2, fluctuated above 0.75 from 2000-2017, but collectively showed a downward trend in 2018 and a collective upward trend in 2019. Among them, the consistency value of configuration 2 declined to 0.564, which is lower than the consistency judgment standard value of 0.75, and such fluctuations were concentrated in 2018, which is not randomly distributed and is not a benign bias (Garcia-Castro & Ariño, 2016). Overall, there is no impact on the overall explanatory strength, as the adjustment distance between groups is less than 0.1. Therefore, the results of the current study are still highly applicable for explaining high productivity.

5 DISCUSSION

5.1 Interpretation of findings

From the results of the necessity test, trade openness is a necessary condition for realizing high productivity, and trade openness appears in all configurations as a peripheral condition during the group analysis, thus providing further evidence that industries or firms can participate in global productivity through international trade to facilitate technology transfer and knowledge spillovers, leading to the generation of high productivity (Kumar, 2006; Hou et al., 2022).

Four configurations that can generate high productivity emerged from the sufficiency analysis process. Configuration 1 can be characterized by countries with high AI capital stock, technology level, and human capital (core condition), together with a high level of education and trade openness (peripheral condition), and lacking labor cost (peripheral condition), which is sufficient to generate high productivity regardless of the intensity of AI research. Configuration 1 supports Qian and Wang's (2022) conclusion that labor cost drives productivity through effects on technological advancement, with its impact diminishing at lower labor cost. In configuration 1, countries can maintain high levels of human capital to integrate the existing technology more efficiently (Suseno et al., 2020), and maintaining a certain degree of trade openness is conducive to absorbing and integrating technological innovations internationally (Hou et al., 2022), which compensates for the barrier that low labor cost generates to achieving high productivity. In addition, countries maintaining a high AI capital stock and technology level can further boost production efficiency and decision-making, thus achieving high productivity (Brynjolfsson, 2018; Li et al., 2022). Configuration 2 is characterized by having a high AI capital stock and technology level (core condition), trade openness (peripheral condition), missing AI research and labor cost (core condition), and human capital (peripheral condition). AI research publication is measured as technical knowledge output in existing studies (Onyancha & Maluleka, 2011). In configuration 2, the low AI research output indicates that the country not only needs to produce knowledge output through research but also needs to have the ability to absorb and apply knowledge and technology (Chang et al., 2023).

Maintaining a high level of AI capital stock and technology allows the country to have a strong internal knowledge base and technology base to effectively utilize technology. Moreover, a high level of technology reduces the dependence on high levels of human capital, as technology can substitute for human labor to a certain extent.

Configuration 3, as the key configuration that generates high productivity, is characterized by having a high AI capital stock and human capital (core condition), with a high labor cost, education level, trade openness (peripheral condition), and absence of AI research (core condition). This critical configuration explains 10.7% of the cases, of which 3.5% can be explained only by this configuration. Configuration 3 shows that a high AI capital stock implies that there are already enough AI technologies that can be used to improve production processes, thus contributing to productivity gains (Brynjolfsson, 2018; Wang et al., 2023). Meanwhile, high human capital ensures that there are sufficient levels of skills and knowledge to effectively apply these technologies (Suseno et al., 2020). Even if the output of new technological knowledge is not high, it means that the region's capacity for technological development and innovation is low (Hong et al., 2012). Hence, in this configuration, economies can still increase productivity through the efficient use of existing technological and human resources, thus compensating for the hindrance to productivity caused by constraints on the development of new technologies and innovation. In addition, there is a potential substitution relationship between configurations 1 and 3. For countries with high AI capital stock, education level, trade openness, and human capital, the configurations consisting of high technology level and absent labor cost can be substituted with configurations consisting of high labor cost and absent AI research. The last configuration has high AI research, technology level, human capital (core condition), education level and trade openness (peripheral condition), and absent labor capital (core condition), regardless of the AI capital stock. Configuration 4 involves high AI research publications, which usually implies countries have a strong research base and innovation capacity (Roper & Hewitt-Dundas, 2015; Hong et al., 2012). At the same time, the high level of technology also compensates for the barrier of low labor cost on technological progress, because countries' technology level is sufficient to increase productivity (Li et al., 2022). Additionally, based on the four configurations, it is also verified that H3 is not valid, while H2 and H4 are valid. AI capital stock or AI research alone can suffice, alongside other conditions, to drive high productivity configurations; simultaneous presence is not required.

As shown in Figure A1, as the intensity of AI research increases yearly, BECONS also grows yearly. The above results also prove the establishment of H1, implying an increasingly strong correlation between AI research intensity and productivity enhancement. The critical role of increasing AI research intensity over time in promoting high productivity can be seen in two ways. The first way is technological advancement and innovation-driven; as AI research intensity increases, more technological innovations and breakthroughs emerge, which can be applied to the production process (Gong et al., 2022), thus realizing productivity gains. In the second way, promoting the improvement of absorptive capacity, as the intensity of AI research increases, the absorptive capacity of firms and economies may be strengthened, as they need to adapt and integrate the new technological knowledge, which will increase the more skillful use of technology by firms and economies (Chang et al., 2023), to realize productivity gains. Lastly, the results of the BECONS analysis show that configuration 4, with the presence of AI research, has less time-varying consistency fluctuations than the other configurations and is more stable, indicating that the explanatory power of the high productivity achieved through this configuration is getting increasingly stronger (Fan et al., 2023). Regarding the change in consistency values of the four configurations in 2018, possible explanations are that the increased regulatory discussions on AI in the European Union, the United Kingdom, the United States, and elsewhere showed a pressing need for the development of appropriate AI laws, and that the divergence in the stances of well-known personalities on AI caused increased public attention to AI (Galanos, 2019). Consequently, this led to uncertainty about adopting and investing in AI technologies, affecting the speed and efficiency of AI adoption by industries and organizations, which has led to a diminution of the potential of AI technologies to improve productivity.

5.2 Comparison with other methodologies

Compared to previous research literature in the field of AI and productivity, this study adopts a new analytical research methodology. Previous studies have primarily used quantitative methods such as fixed effects modeling, double difference, and structural equation modeling (Wang et al., 2023; Fang et al., 2022) with a focus on numerical data analysis to quantify the impact of AI. In contrast, this study utilizes dynamic QCA, an approach that combines quantitative accuracy with qualitative insights to explore the complex causal configurations that drive productivity gains. Furthermore, many prior research efforts have been limited to assessing the impact of AI in specific industries or technology applications. However, this study provides a broader analysis that encompasses the entire field of AI, examining the synergistic effects of various factors, including the intensity of AI research, on productivity at the macro level. More importantly, the dynamic aspect of the methodology of this study sets it apart from earlier approaches that typically provide a static picture. By analyzing changes over time, this study captures the changing role of AI in productivity, providing insights into how the impact of AI on productivity varies across time and geography.

6 CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

This study utilizes dynamic QCA methodology to highlight how different factors contribute to productivity across various configurations. Necessity analysis results show that the consistency value of trade openness is 0.986 and coverage is 0.506, thus confirming trade openness as a necessary condition for generating high productivity. Also, the configuration analysis results show that trade openness exists in all configurations that generate high productivity, proving that trade openness can be a peripheral condition in configurations that generate high productivity, underscoring its importance in promoting international trade, resource allocation efficiency, and technology transfer and innovation. Observing further the BECONS value of the necessity analysis shows that the necessity of AI research has been increasing yearly, showing a time effect. The results highlight the multifaceted impact of AI on industrial productivity, suggesting that as AI research deepens, technological innovation and technology adoption are driven to increase productivity.

The configuration analysis reveals four key configurations leading to high productivity, each demonstrating the unique interplay of factors such as AI stock, technology level, and human capital in optimizing production and decision-making processes, reducing dependency on labor costs for technological advancement, and leveraging AI and human resources to boost productivity. Among the configurations, 3's consistency value is 0.920, which is the key configuration to generate high productivity. This key configuration is characterized by having a high AI capital stock and human capital (core condition), with a high labor cost, education level, and trade openness (peripheral condition), and the absence of AI research (core condition). Subsequently, the study found a potential substitution relationship between configurations 1 and 3, as evinced by the fact that configurations with a high level of technology and missing labor costs can substitute for configurations with high labor costs and missing AI research. Meanwhile, the study reveals that high AI stock and advanced technology levels enable countries and firms to enhance production efficiency and decision-making, independent of labor costs. Trade openness facilitates efficient resource allocation and technology innovation, while high human capital ensures effective technology use and integration. Furthermore, the study found that the four configurations of BECONS show a collective downward trend in 2018, possibly due to a less efficient use of AI in most countries during 2018, which leads to a weaker impact of AI on boosting productivity.

6.2 Implications for policymakers and industry stakeholders

Considering the necessity of trade openness to increase productivity, policymakers should advocate policies to enhance international trade, which include reducing trade barriers, negotiating trade agreements, and encouraging imports and exports to promote an efficient allocation of resources and incentivize technology transfer and innovation (Jongwanich & Kohpaiboon, 2020). Furthermore, the findings of this study also demonstrate the critical impact of AI and technological advances on high productivity. Therefore, the country should set up a specialized AI committee or department to bring expertise in AI and other advanced technologies into all departments and levels of the government, to aid in decision-making (Furman & Seamans, 2019), and to help the government understand these technologies' potential impacts and application scenarios. This will help the government better plan and formulate relevant policies to promote technological innovation and industrial development.

We suggest that industry stakeholders focus on building and maintaining a high AI capital stock and technology level to effectively utilize existing technological assets and human resources to improve productivity (Brynjolfsson, 2018; Zhao et al., 2021). Also, stakeholders should focus on investing in continuous learning and innovation, encouraging research activities, and keeping pace with technological advancements to remain competitive and productive (Yeh & Chang, 2019). Further, industry stakeholders should promptly adapt their strategies to implement AI since different factor configurations can lead to high productivity. Therefore, the strategy of specific companies should consider their particular context, resources, and objectives to determine the combination of factors that best suit their situation.

6.3 Research limitations and future prospects

Considering the limitations of this study, the results may not accurately reflect the impact on specific industries. In addition, apart from the variables considered in this study, there may be other potential factors that can generate conditional configurations of high productivity. Therefore, future research can explore the following two aspects in depth: on the one hand, researchers can select specific industries as samples and synthesize qualitative and quantitative methods for more in-depth analyses to obtain more targeted conclusions. On the other hand, researchers can replace or introduce other factors and explore their impact on productivity.

APPENDIX

Tab. A1 - Variable calibration. Source: own research

Variable	Calibration Anchors		
	Full membership	Crossover	Full non-membership
Productivity	0.022	0.01	0.005
AI research	0.164	0.062	0.018
AI stock	0.02	0.004	0
Labor	0.57275	0.521	0.478
Tech	0.43375	0.341	0.242
Edu	0.61075	0.5135	0.40025
Trade	0.335	0.2075	0.125
Hum	0.75475	0.604	0.484

Tab. A2 – Necessary conditions analysis. Source: own research

Condition	Productivity				~Productivity			
	CONS	COV	BECONS Adj-distance	WICONS Adj-distance	CONS	COV	BECONS Adj-distance	WICONS Adj-distance
AI research	0.651	0.657	0.236	0.483	0.400	0.425	0.231	0.707
~ AI research	0.43	0.405	0.398	0.679	0.677	0.672	0.152	0.500
AI stock	0.738	0.765	0.034	0.426	0.338	0.369	0.059	0.753
~AI stock	0.391	0.359	0.059	0.690	0.785	0.76	0.015	0.391
Labor	0.604	0.576	0.172	0.322	0.522	0.525	0.255	0.449
~Labor	0.502	0.499	0.172	0.397	0.579	0.607	0.206	0.391
Tech	0.652	0.631	0.118	0.535	0.442	0.451	0.216	0.610
~Tech	0.434	0.424	0.162	0.644	0.639	0.659	0.152	0.460
Edu	0.59	0.582	0.128	0.581	0.485	0.505	0.378	0.604
~Edu	0.498	0.478	0.147	0.581	0.598	0.606	0.290	0.512
Trade	0.986	0.506	0.029	0.035	0.944	0.511	0.083	0.104
~Trade	0.047	0.441	0.844	1.938	0.087	0.869	1.060	1.610
Hum	0.414	0.703	0.241	0.811	0.24	0.429	0.569	0.920
~Hum	0.663	0.453	0.142	0.397	0.834	0.600	0.152	0.265

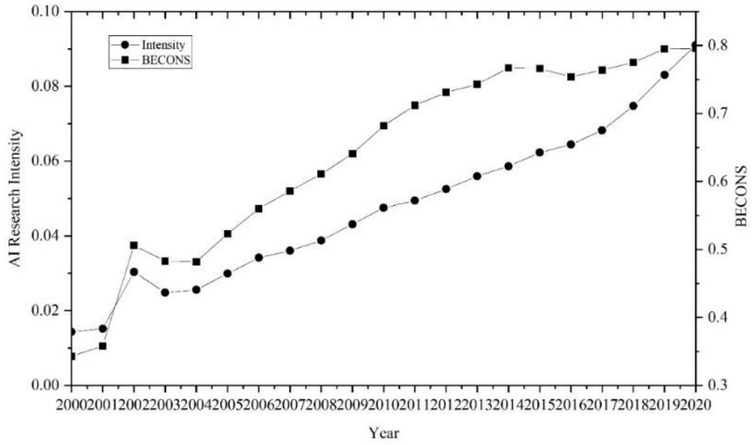

Fig. A1 – BECONS and AI research intensity. Source: own research

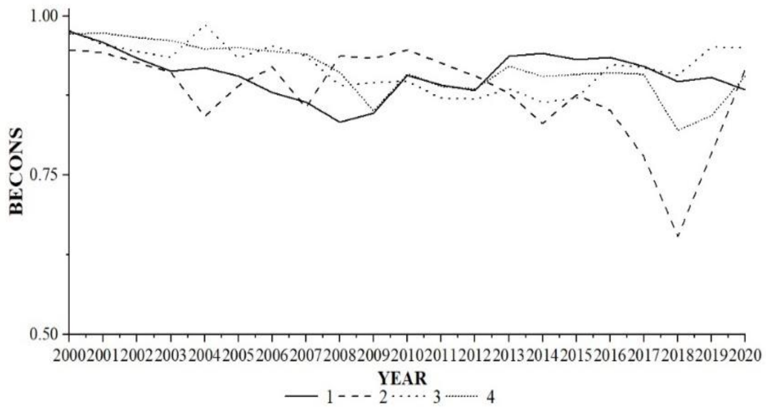

Fig. A2 – Change in between consistency. Source: own research

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