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Exploring complementary innovation of AI technology from a multidimensional knowledge network approach

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Graduate School of Seoul National University

Technology Management, Economics, and Policy Program

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Exploring complementary innovation of AI technology from a multidimensional knowledge network approach

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Abstract

Exploring complementary innovation of AI technology from a multidimensional knowledge network approach

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Innovation and diversification are fundamental drivers of long-term economic growth, evolving synergistically. This dissertation systematically examines the intricate interplay between a nation's innovation capabilities and its diversification into new technological and product domains, with a particular focus on evolutionary economic geography and economic complexity theory.

The first essay explores the relationship between scientific capability and technological diversification in the field of artificial intelligence (AI), seeking to elucidate how a nation's scientific capabilities may indicate its potential to venture into new AI technologies. The second essay explores the nexus between technological capability and product diversification, evaluating the extent to which technological capability fosters a diversified array of products.

This comprehensive analysis stratifies national capabilities into three interconnected categories: scientific research, technological innovation, and industrial production. These categories are situated within a complex, multidimensional knowledge network that illustrates their interconnections and synergies. Diversification in both technology and product dimensions is conceptualized as a conditional probability, assessing the likelihood of a nation achieving a comparative advantage in these new arenas. The empirical investigation utilizes a robust dataset spanning four decades, from 1980 to 2019, incorporating indicators such as scholarly publications, patent records, and export product data. A three-way fixed effects panel regression model serves as the analytical framework, revealing positive correlations between AI integration and a nation's diversification in technology and products, thereby underscoring AI's complementary role in enhancing innovative capabilities.

In the context of intensifying global competition for AI technological leadership, it is imperative for policymakers to swiftly integrate AI across diverse sectors while formulating R&D policies that promote diversification, which is crucial for long-term economic growth. As posited by evolutionary economic theory, while increased diversity without innovation may lead to some evolution, sustained long-term growth necessitates diversification grounded in innovation. Policies should leverage existing capabilities in scientific research, technological innovation, and industrial production, using these areas as foundations for expansion into related fields. This proactive and forward-looking strategy is essential for fostering innovation and ensuring a diversified and robust trajectory of economic development.

This dissertation provides several policy implications, synthesizing insights from endogenous growth theory and the concept of complementary innovation. From the perspective of endogenous growth theory, the explosive expansion of knowledge in the modern knowledge-based economy represents a significant opportunity for economic development. However, this expansion could also lead to a 'knowledge burden,' potentially hindering diversification into new fields for nations with limited capabilities. This research underscores the importance of complementary innovation in the knowledge economy, particularly highlighting the potential of general-purpose technologies (GPTs) such as AI, bioengineering, and quantum technologies. It reveals that the complementary function of AI is more pronounced for developing countries compared to developed ones when diversifying into new fields. Unlike developed countries, where technological capabilities accumulate in a virtuous cycle, developing countries struggle to amass these capabilities without complementary technologies. Consequently, nations lacking these capabilities should focus on integrating AI technologies into areas closely related to their existing strengths to secure a comparative advantage in economic development.

Moreover, a nation's scientific, technological, and productive capabilities evolve interdependently through multidimensional networks formed by mutual interactions. This finding suggests that nations aiming to diversify into new fields should enhance industry-academia-research collaborations and establish their R&D investment strategies to foster this evolution.

Keywords: Artificial intelligence, Economic diversification, Knowledge network, Multidimensional network analysis, Complementary innovation

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Chapter 1. Introduction

1.1 Research background

1.1.1 Research background and context of the study

The concept that diversification through innovative activities fosters national economic development has been a core tenet of evolutionary economic theory since the 1970s, gaining further refinement in the 1990s with the growing interest of economic geographers (Boschma & Lambooy, 1999; Nelson & Winter, 1982; Rigby & Essletzbichler, 1997). This evolution gave rise to the key concept of evolutionary economic geography (EEG), which defines and measures the diversity of economic activities at regional, urban, and national levels, and explores their linkage to economic development (Boschma & Frenken, 2006; Boschma & Martin, 2007). This topic has remained a focal point of academic debate, centered around EEG and economic complexity (EC) theories (Frenken et al., 2007; Hidalgo et al., 2007).

EEG emphasizes concepts such as path dependence, spatial dynamics, and the role of institutions and networks in regional economic development (Boschma & Lambooy, 1999; Frenken et al., 2007). In contrast, EC focuses on analyzing the diversity and ubiquity of products in a country's export portfolio to develop metrics like the Economic Complexity Index (ECI) (Hidalgo et al., 2007; Hidalgo and Hausmann, 2009).

Both EEG and EC share a foundational assumption: *the growth of knowledge drives* *economic growth*. This perspective aligns with the principles of endogenous growth theory (Romer, 1990; Weitzman, 1998), which posits that economic growth is primarily driven by internal factors like knowledge creation and technological advancement, rather than external influences. Endogenous growth theory emphasizes the continuous improvement of an economy through investments in human capital, innovation, and knowledge (Romer, 1990). It highlights the significance of research and development (R&D) investments and innovation activities in influencing market dynamics, particularly through the concept of creative destruction (Schumpeter, 1942). The theory also suggests that knowledge, sourced from diverse sectors, can be reconfigured in novel ways to spawn novel ideas (Weitzman, 1998).

However, not all knowledge holds equal value and influence. Some forms of knowledge are more universal, interdependent, and rapidly disseminated, possessing a complementary nature that enhances their value and significantly contributes to long-term economic development and national comparative advantages (Rosenberg, 1979). In contrast, other types of knowledge are more specialized, independent, and less disseminated, exhibiting characteristics that lead to their concentration within specific industries and regions. Particularly in today's knowledge-based economy, where there is a rapid quantitative increase in knowledge and a diverse specialization across research and industrial fields, the complementary knowledge is expected to grow further. This phenomenon can have widespread impacts across social, economic, institutional, and research and development policy domains. Firstly, the growth of knowledge does not directly translate into economic growth. According to endogenous growth theory, the increase in knowledge, one of the internal capabilities, should lead to sustained economic development. However, post the 20th century, despite the exponential increase in knowledge, there has been a declining trend in economic productivity (Bloom et al., 2020; Gordon, 2017). This discrepancy challenges the conventional understanding and suggests a complex relationship between knowledge accumulation and its economic impact. Secondly, the increase in the quantity and variety of knowledge has become a burden in knowledge production. The volume of knowledge has exceeded what a single individual can manage, complicating the generation of new ideas and innovative inventions. This growing 'knowledge burden' impedes disruptive discoveries and inventions as scientists and inventors struggle to keep abreast of expanding knowledge domains (Jones, 2009; Park et al., 2023). Such a burden leads to a decline in research productivity, posing a challenge to the conventional processes of innovation and discovery. Thirdly, knowledge is distributed unevenly and is becoming increasingly concentrated in specific countries or regions. This concentration is more severe for capabilities such as complex and specialized knowledge, technology, and skills. Complex technologies tend to develop in regions with a diverse array of other technologies (Balland et al., 2019; Hidalgo, 2015). Specialized knowledge production is often concentrated in a few key locations (Feldman et al., 2015). Activities that are inherently more complex, such as biotechnology, neurobiology, and semiconductor production, are more likely to occur in large urban agglomerations compared to less complex activities like apparel or paper manufacturing (Balland et al., 2020). Fourthly, businesses are increasingly limited in the breadth and diversity of knowledge they can manage internally. Consequently, there is a greater need for collaboration with more individuals. This trend is manifesting as an increase in the average size of teams within companies compared to the past (Neffke, 2019). Neffke (2019) argues that this phenomenon is due to the nature of complementarity, where the value of one capability is substantially enhanced in the presence of another. Teams composed of individuals with diverse but complementary skills can operate more efficiently and creatively, creating synergy that boosts overall team performance. As a result, the size of teams in businesses is growing.

Despite the increasing recognition of the importance of complementarity among internal and external capabilities like knowledge, technology, and skills, this aspect remains largely overlooked in much of the existing research. Some recent studies have begun to explore the potential for economic development through complementary innovation among these capabilities (Inoua, 2023; Van Dam & Frenken, 2022). These studies assert that capabilities frequently co-occurring in many production processes indicate a high level of complementarity, as the value of one capability significantly increases in the presence of another. This leads to an exponential increase in the variety of products, owing to the rapidly growing number of combinations of capabilities that translate into feasible products.

Our study aligns with the trajectory set by Neffke (2019) and recent research on the complementarity among endogenous capabilities (Inoua, 2023; Van Dam & Frenken, 2022). We propose the assumption that, analogous to individuals, nations with diverse but complementary capabilities are likely to be more efficient and creative in generating synergy. This perspective underpins our investigation into how the interplay of different national capabilities contributes to broader economic and technological advancements. The notion that complementary technologies hold substantial value and have the potential to transform economic growth and paradigms has been established for some time (Rosenberg, 1979). Rosenberg (1979) argues that technologies are interdependent and cumulative, emphasizing that the presence of complementary technologies is essential for technologies to function effectively and generate economic impacts. This is particularly apparent in the development of GPTs, which are comprehensive and pervasive complementary technologies. GPTs function as 'enabling technologies' that create new opportunities rather than providing complete, final solutions. The productivity of R&D in downstream sectors is enhanced due to innovations in GPT technology, a phenomenon referred to as 'Innovational Complementarities'. Bresnahan and Trajtenberg (1995) explore GPTs as 'enabling technologies' that not only open up new opportunities but also foster innovational complementarities. They propose that innovation in GPT technology leads to increased productivity of R&D in downstream sectors. Building on Rosenberg's ideas, Arora and Gambardella (1994) introduce the notion of generic technologies, aligning with the concept of highly pervasive complementary technologies. These studies collectively underscore the pivotal role of the complementarity of knowledge, technology, and skills in driving economic and innovation outcomes. They emphasize the significance of GPTs in technological development and economic growth, reinforcing Rosenberg's argument about the critical impact of complementary technologies (Helpman & Trajtenberg, 1996; Lipsey et al., 2005).

This study aims to explore significant theories currently under academic debate, with a focus on a commonly overlooked aspect: the complementarity among scientific research, technological innovation, and industrial production capabilities at the macro level, especially regarding diversification. This perspective aligns with evolutionary economic geography and economic complexity theory, which see economic development as a process of continuous diversification (Tacchella et al., 2012).

Our investigation seeks to highlight this critical dimension of national capabilities, which has not received sufficient attention in the rapidly changing technological landscape. Specifically, this research emphasizes the potential for complementary innovation in AI-related fields, driven by AI's transformative impact across various industries.

In the context of increasing international competition for AI technological leadership, our study examines the conditions necessary to fully realize AI's complementary capabilities. We hypothesize that national AI capabilities can be strengthened through the integration of relevant scientific, industrial, and technological capacities.

1.1.2 Statement of problem

Existing studies, including endogenous growth theory, have certain limitations. Endogenous growth theory underscores knowledge creation and diffusion as key drivers of economic growth. However, many of its models, including Romer (1990; 1994)'s contribution, perceive the economy as 'flat', overlooking explicit interactions across different disciplines, fields, and sectors. Such an oversimplification hinders these models' capability to accurately depict the complex, interdependent nature of real-world economic dynamics, where innovations in one area can significantly influence others. This limitation underscores the need for more nuanced models that better capture the intricacy of economic interactions and the ripple effects of innovations across various sectors.

Recent studies in EEG and EC, rooted in evolutionary economics, have significantly contributed to understanding economic development across various scales—regional, urban, and national (Boschma & Lambooy, 1999; Boschma, 2017; Boschma et al., 2013; Essletzbichler, 2015; Hausmann et al., 2007; Neffke et al., 2011; Tacchella et al., 2012; Zaccaria et al., 2014). This approach is rooted in capability-based theory, which emphasizes an economy's ability to integrate internal and external capabilities to adapt in rapidly changing environments (Klepper, 1996; Teece et al., 1997). It posits that capabilities serve as the foundational building blocks of a country's economy, shaping its competitiveness in the global market (Hidalgo & Hausmann, 2009). Successful nations demonstrate high diversification, akin to biosystems in dynamic competitive environments (Cristelli et al., 2013; Taccella et al., 2012). These economic models highlight the cumulative, path-dependent nature of evolutionary processes within the economic ecosystem (Jacobides et al., 2021). The existing knowledge base and competencies within a country dictate its future trajectories (Hidalgo & Hausmann, 2009).

However, apart from a few studies (Pugliese et al., 2019; Catalán et al., 2022; Castaldi and Drivas, 2023), there has been limited interest in exploring the complementary innovation among scientific, technological, and production capabilities. Most research has predominantly concentrated on path dependency of capabilities within single-dimensional frameworks, such as product space or technological space. This narrow focus overlooks the multidimensional and interconnected nature of capabilities and their crucial role in driving innovation and economic development. These limitations arise from the inherent invisibility of capabilities. The Hidden Capability Theory (Cristelli et al., 2013; Tacchella et al., 2012) proposes that capabilities, which are not directly observable, can be inferred from the bipartite network connecting countries to products. This network reflects the specific set of necessary capabilities a country must possess to produce and export a product (Cristelli et al., 2013). Consequently, empirical studies based on EC theory have been inherently constrained to focus solely on revealed outcomes, such as exported products.

The prevailing approaches in existing studies have limitations in adequately explaining the complementary relationships among scientific, technological, and production capabilities. This shortfall is largely attributable to the reliance on data that captures direct linkages, such as citations between patents and papers (van Eck & Waltman, 2009). Consequently, analyses are constrained in cases where there are no direct connections between scientific, technological, and product spaces. Even when connections, such as citations, are present, the analysis can face limitations due to issues like data omissions or biases towards certain papers. This restricts the ability to accurately measure the interrelations among different capabilities, underscoring the need for more comprehensive and nuanced analytical approaches.

1.1.3 Research questions and hypotheses

This study raises research questions about the relevance of economic diversification theories based on EEG and EC, which include path dependence, related diversification, and capability complementarity, in multidimensional spaces involving scientific research, technological innovation, and industrial production activities. It proposes hypotheses to validate this and seeks to explore whether these theories hold relevance across multidimensional spaces. The first research question is: *Do countries tend to diversify into new areas that are related to their existing scientific, technological, and productive capabilities?* In explaining the economic diversity of countries, we draw upon the central tenets of EEG and EC, particularly the concept of path dependence and related diversification (Boschma, 2017; Breschi et al., 2003; Hidalgo et al., 2007). We hypothesize that, even in a multidimensional space encompassing scientific research, technology, and products, 'new economic activities are dependent on existing scientific, technological, and productive capabilities of a country.' Therefore, this study includes a verification process for key concepts of EEG and EC, focusing on path dependence and related diversification. By integrating insights from EEG and EC, we can gain a comprehensive understanding of how path dependence and related diversification shape economic outcomes at various spatial scales (Boschma, 2017; Boschma et al., 2015; Hausmann & Klinger, 2007; Neffke et al., 2011) and different capability dimensions (Catalán et al., 2022; Puglies et al., 2019). This approach allows for a nuanced analysis of the interplay between historical contingencies, technological capabilities, and economic diversification processes (Boschma & Martin, 2007; Hidalgo et al., 2007).

The second research question is: *Do AI-related capabilities play a complementary role in the diversification process across different dimensions?* We posit that national competencies, comprising scientific, technological, and productive capabilities, gain a comparative advantage when complemented by a country's AI-related knowledge, skills, expertise, and techniques. This aspect, particularly focusing on the complementary role of AI-related capabilities, highlights a research gap previously overlooked. Specifically, our study assumes that the complementary roles of AI-related capabilities, characterized not only by their penetration into a wide range of industries but also by their intrinsic nature of continuous improvement and potential to foster future innovations, can be observed in AI-related knowledge and capabilities. These complementary effects of AI-related capabilities extend beyond their immediate applications, encompassing their penetration across industries, continuous improvement, and potential to foster future innovations. This multifaceted impact underscores the transformative potential of AI in driving economic growth and innovation (Agrawal et al., 2019; Brynjolfsson & McAfee, 2014).

This perspective builds upon prior studies and fundamental assumptions, leading to the establishment of the following hypotheses:

Hypothesis 1.1: (Related diversification) Countries are inclined to expand their AI technology into sectors closely linked to their current AI technological competencies.

Hypothesis 1.2: (Complementarity) The scientific research capabilities of a country, closely associated with its AI technological prowess, are more likely to impact technological diversification.

Hypothesis 2.1: (Related diversification) Countries tend to broaden their export product portfolio into sectors closely aligned with their existing production capabilities.

Hypothesis 2.2: (Complementarity) The production capabilities of a country, closely linked to its AI capabilities, are more likely to influence product diversification.

1.2 Research objectives

1.2.1 Purpose and significance of the study

Our research aims to deepen the understanding of the structure connecting a country's scientific, technological, and production capabilities with its economic diversification. Theoretically grounded in evolutionary economics, EEG, and EC, the study focuses on the field of AI. Guided by the proposed hypotheses, it explores the relationship between scientific research capabilities and technological diversification, as well as the link between technological capabilities and product diversification. Through this exploration, we seek to demonstrate that diversification in a multidimensional space adheres to the theory of path dependency and that AI-related national capabilities play a crucial role in promoting economic diversification. The importance of this study lies in its implications for a world where AI-related knowledge is increasing at an exponential rate. It underscores the need for individuals, corporations, and nations to overcome their inherent limitations by adopting policies that not only augment the diversity of their knowledge and capabilities but also ensure their complementarity. This research is poised to contribute significant insights into policy-making strategies, emphasizing the balance between diversification and complementarity in knowledge and capabilities. Such insights are crucial for effectively harnessing the potential of the rapid growth in AI-related knowledge and technology. This study aims to provide a comprehensive understanding of how policies can be structured to foster an environment where diverse and complementary capabilities synergize, leading to enhanced innovation and economic growth.

1.2.2 Contribution of the study

This thesis makes a substantial academic contribution across three key areas: theoretical, methodological, and empirical. The thesis offers a theoretical advancement by amalgamating insights from EEG and EC. It articulates the concept of ‘complementary innovation’ within the context of an era characterized by exponential knowledge growth. By synthesizing elements from EEG and EC, the study enriches endogenous growth theory, providing a more dynamic and nuanced understanding of economic growth and innovation. This theoretical integration facilitates a deeper comprehension of the interplay between technological advancements and economic development, particularly in the context of rapidly evolving knowledge economies.

Methodologically, the study introduces a novel probabilistic approach to assess relatedness or proximity within multidimensional spaces, especially those formed by cooccurring capabilities. This methodology signifies a substantial leap forward, addressing limitations inherent in prior studies that relied on co-citation or co-classification similarities within single-dimensional spaces. By harnessing cooccurrence data, our study provides a more sophisticated and realistic depiction of interdependencies and relationships across diverse knowledge and capability domains. This methodological approach substantially enhances the understanding of complex knowledge networks, offering valuable insights for strategic innovation and development in fast-changing scientific and technological landscapes. The approach marks a considerable advancement in the field, bringing new perspectives and methodologies to analyze dynamics within multidimensional knowledge and capability networks.

AI technology holds immense potential for enhancing the competitiveness of both traditional and emerging industries in advanced as well as emerging markets. However, developing countries are particularly susceptible to inadequately devised national AI strategies. These often prioritize superficial projects over more sophisticated investments that leverage AI specialization and foster diversification, neglecting core areas of economic expertise (Mishra et al., 2023). For nations with limited technological advancement, AI development and application strategies should prioritize knowledge creation and technology spillover effects to bolster national innovation levels (Liu et al., 2020). Moreover, resource-constrained countries may encounter challenges in making these investments, thereby exacerbating the "compute divide". Developing countries, for instance, may struggle to establish an AI ecosystem capable of uncovering new opportunities and maintaining the competitiveness of traditional industries (Ahmed & Wahed, 2020).

Empirically, this research yields crucial policy implications, especially for nations with constrained capabilities. It delineates strategic pathways for these countries to effectively integrate AI technology with their existing capabilities, thus enhancing their global competitive stance. By aligning AI adoption with their distinctive strengths and market demands, these nations can foster sustainable growth and resilience amidst evolving technological landscapes. This empirical contribution is significant as it not only showcases the practical application of theoretical and methodological advancements but also provides actionable insights for policymakers and stakeholders in nations aiming to bolster their technological and economic prowess.

1.3 Research outline

1.3.1 Overview of the methodology

The first step in our research methodology involves a thorough examination of the key concepts in evolutionary economics, EEG, and EC. This exploration aims to elucidate the relationship between diversification and economic development, as framed by these theoretical perspectives. Through this process, we intend to identify research gaps that have been overlooked in existing studies. Our goal is to bridge these gaps by formulating new hypotheses that more accurately reflect the complexities and dynamics of modern economies.

Once these hypotheses are defined, our research will conduct two critical empirical investigations. These investigations are designed to test the formulated hypotheses and explore the key linkages between the variables identified in our theoretical framework. By empirically examining these connections, our research seeks to offer novel insights into the processes and mechanisms through which diversification impacts economic development, particularly in the context of a rapidly evolving technological landscape. This methodological approach is aimed at providing a comprehensive understanding of the multifaceted relationships between scientific, technological, and production capabilities and their role in shaping economic trajectories.

Our study commences with a key empirical investigation examining the impact of scientific research capabilities in AI on a nation's technological diversification, especially pertinent in the backdrop of recent developments in export-oriented countries like South Korea. These countries have focused intensively on gaining a competitive edge in specific AI technologies, possibly at the expense of broader foundational scientific research. This aspect of our research seeks to evaluate the effectiveness of such strategic choices, positing that a narrow emphasis on applied technological specialization, without substantial investment in extensive scientific research capabilities, might not be adequate for comprehensive national AI competitiveness.

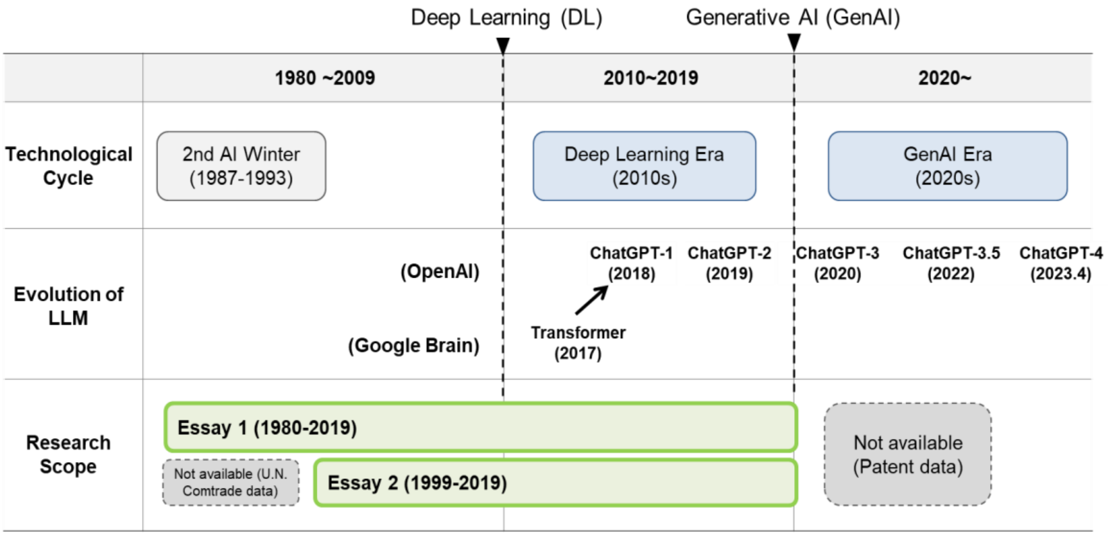
To capture the rapidly evolving characteristics of AI technology, our research compiled data on AI-related scholarly publications and patent records from various countries over four decades, from 1980 to 2019. This period is crucial as it encompasses the aftermath of AI's "second winter," a time marked by reduced enthusiasm and investment in AI research. Following this period was a resurgence of interest in the late 1990s, as evidenced by an increase in AI-related publications, often attributed to advancements in machine learning and neural networks (Crevier, 1993). The early 2000s witnessed a notable rise in AI-related patent filings, coinciding with a spike in commercial interest and major technological breakthroughs, notably the advent of deep learning techniques (Hinton & Salakhutdinov, 2006; Kirzhevsky et al., 2012). This phase, as Bianchini et al. (2022) suggest, has been pivotal in AI's evolution.

Additionally, our dataset includes scientific publications and patents related to Google Brain's Transformer, a seminal innovation instrumental in large language model (LLM) applications like ChatGPT. Introduced in the landmark paper “Attention Is All You Need” by Vaswani et al. (2017), the Transformer marked a significant milestone in natural language processing (NLP). This development laid the foundation for advanced language models, accelerating AI's rapid advancement and diverse applications. The incorporation of Transformer-related research and patents into our dataset is vital. It signifies a critical juncture in AI's trajectory, particularly in language model development. The subsequent surge in research and applications stemming from this LLM model (Devlin et al., 2018; Radford et al., 2019) underscores the influence of groundbreaking scientific discoveries in technological progress and specialization. By analyzing this rich dataset, our study aims to shed light on how the growing body of scientific knowledge has shaped technological specialization in AI at a national level, contextualizing both the historical and current AI landscapes. This approach provides a nuanced view of the interplay between scientific progress and technological innovation in AI's fast-paced field.

Our research is bifurcated into two segments to encapsulate AI's evolutionary dynamics: the early stage (1980–2009) and the growing stage, marked by the emergence of deep learning (2010–2019), as illustrated in Figure 1. Since 2020, the evolution of AI has been marked by the introduction of highly advanced systems and generative AI (GenAI) models, exemplified by the release of OpenAI's ChatGPT-3 in 2020 and ChatGPT-4 in 2023. These models have showcased remarkable abilities in generating human-like text and comprehending intricate prompts, representing a significant leap in AI capabilities. The OpenAI platform has simplified access to advanced GenAI programs, particularly large language models (LLMs), which have achieved new performance levels, driving research, development, and significant corporate investments in GenAI applications (WIPO, 2024).

However, research on this pivotal period is limited by the lack of recent data, which imposes constraints on this study. Considering the standard 18-month publication delay for patent applications (WIPO, 2019, p. 41), our analysis is constrained to data up until 2019. This limitation ensures the use of reliable data, accounting for delays in patent publication

(Figure 1).



Note: Patent applications are typically published 18 months after the priority date (WIPO, 2019).

Figure 1. Research scope

This study's exploration aims to contribute to the discourse on the equilibrium between scientific research and technological development, seeking to discern whether a robust foundation in scientific research is imperative for effective technological diversification, particularly in AI. This aspect is vital for understanding national competitiveness in technology and for guiding policy decisions on investing in scientific research versus applied technological development.

Our second empirical investigation focuses on whether the AI technological capabilities accrued by a nation significantly impact the product diversification of its export basket. This inquiry addresses a critical question: *Does technological capability in AI-related* *sectors enhance the diversification of the export product portfolio?* This aspect of our research is particularly significant as it provides insights into the potential synergies between AI technological capabilities and export diversification. Understanding whether AI-related capabilities can effectively enhance the variety and sophistication of a nation's export portfolio is crucial for informing strategic economic decisions and policies in today's technology-driven global market.

1.3.2 Structure of the dissertation

This structure is designed to systematically unfold our investigation, beginning with theoretical underpinnings, proceeding through methodological approaches, and culminating in the empirical studies that address our central research questions. Following is the overall structure of our research:

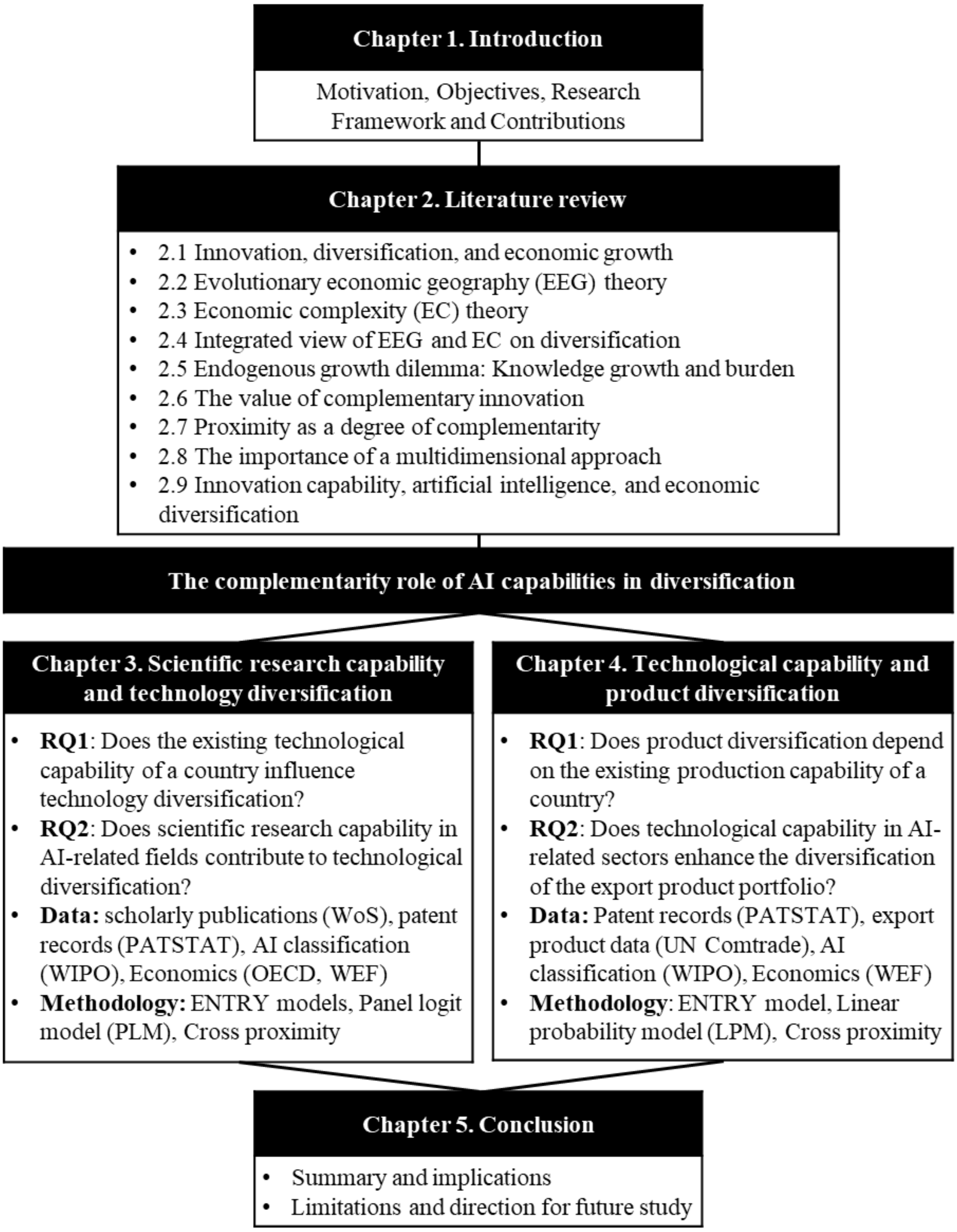


Figure 2. Research outline

Chapter 2. Literature Review

2.1 Innovation, diversification, and economic growth

Economic diversification within a national context represents a strategic decision aimed at broadening the scope of economic activities. This dynamic process involves the introduction of new sectors or activities, phasing out obsolete ones, and reshaping the significance and interactions among all economic endeavors (Saviotti & Pyka, 2004). This transformation is not merely peripheral but central to economic growth, as it stimulates the emergence of novel activities and revitalizes the economic system. Scholars advocating for economic complexity assert that an increase in diversity, reflecting enhanced complexity, correlates with economic growth (Hausmann et al., 2007; Hidalgo & Hausmann, 2009; Tacchella et al., 2012). Higher economic complexity, characterized by diverse and sophisticated productive capabilities, is linked to higher income levels, greater income equality, and accelerated economic growth (Hidalgo & Hausmann, 2009; Hausmann et al., 2014). Moreover, some evolutionary economic geographers argue that diversification is not solely about expansion but also resilience. As highlighted by Frenken et al. (2007), diversification enables countries to mitigate economic decline by branching into activities that complement their existing strengths. This plays a crucial role in dampening economic fluctuations, enhancing economic performance, and improving overall well-being.

However, this raises critical questions: Can economic growth be attained solely through economic diversification? Is diversification always beneficial? While economic diversification is acknowledged as a key driver of economic development (Freeman, 1974; Pasinetti, 1983; Saviotti & Pyka, 2004), the role of scientific and technological innovation in this process cannot be overlooked (Fritsch & Slavtchev, 2007). Some argue that variety alone can drive evolutionary processes, minimizing the need for innovation. This view is supported by the concept that evolutionary change is primarily driven by the selection of existing variations within a population rather than the continuous need for new innovations. The principle of self-organization, which explains how patterns emerge through interactions among entities, is also relevant here (Kauffman, 1993). Further, the relationship between variety and performance, as depicted by the inverted-U shaped curve or 'the hump', suggests that variety can boost performance up to a certain point, after which performance starts to decline (Imbs & Wacziarg, 2003). This pattern reflects the development process of countries, which typically first diversify by broadening their economic activities and then specialize again as they advance and focus on their strengths (Cadot et al., 2011). The optimal balance between diversification and specialization may vary across different contexts and stages of development, and it's necessary to consider the specific circumstances and characteristics of a country (Cadot et al., 2011; Imbs & Wacziarg, 2003).

A holistic perspective emphasizes the importance of both innovation and diversification for sustainable economic growth. In particular, technological innovation, crucial for long-term economic dynamism, introduces heterogeneity into economic systems. The complex relationship between technological innovation, industrial diversification, and economic growth is well-documented (Freeman, 1974; Lundvall, 1992; Patel & Pavitt, 1997). Diversification, particularly into related technological fields, allows countries to explore new avenues, avoiding stagnation and enhancing economic performance and well-being (Hidalgo et al., 2007; Hidalgo & Hausmann, 2009). Countries with high diversity tend to advance more easily beyond their existing research strengths, tapping into a broader range of capabilities and knowledge bases (Miao et al., 2022; Patelli et al., 2023). Countries with diversified scientific and technological portfolios are more likely to develop new areas of competence (Balland & Boschma, 2022; Barbieri et al., 2020; Perruchas et al., 2020; Petralia et al., 2017), evolving their innovation systems as they diversify further (Patelli et al., 2023). Diversification and innovation are not only linked but interdependent, creating a positive feedback loop where diversification drives further innovation (Arthur, 1989; Boschma, 2017; Rosenberg, 1979; Saviotti & Frenken, 2008). Moreover, the nexus of economic diversification and growth is multifaceted, influenced by factors such as a country's innovation capability and the relationship between new and existing industries (Xiao et al., 2018). For example, as noted by Saviotti and Frenken (2008), the variety in exports significantly impacts GDP per capita and labor productivity growth in OECD countries between 1964–2003. Additionally, diversification's impact extends beyond product exports to patents and research areas, with some nations finding it easier to advance in technology than in exports (Stojkoski et al., 2023).

This intricate relationship between a nation's innovation capabilities, encompassing scientific, technological, and production knowledge, and its diversification efforts forms a complex web of interdependencies. Despite significant scholarly attention, comprehensive explorations of these relationships are scarce. This study aims to fill this void by examining how various aspects of a nation's capabilities influence and shape its diversification efforts, exploring the complex interplay between these crucial economic factors.

2.2 Evolutionary economic geography theory

EEG is grounded in the principle that enhancing diversity through innovation is essential for the economic development of regions, cities, and countries (Boschma & Lambooy, 1999). This idea, emerging from the realm of evolutionary economics in the 1970s as proposed by Nelson and Winter (1982), has become a cornerstone of EEG. The impact of evolutionary metaphors and concepts on economic geography has been significant since the 1990s. Their power lies in explaining spatial and regional transformations, building upon the foundational work in evolutionary economics by David (1985) and Arthur (1989). These concepts explore regional development, emphasizing the importance of both maintaining and adapting traditional production modes. This perspective underlines the evolutionary dynamics at play in economic geography, crucial for understanding how regions develop and adapt over time (Boschma & Frenken, 2006).

EEG employs metaphors and models from evolutionary biology to interpret economic changes. It envisions the economic landscape as an ever-evolving ecosystem, consisting of technologies, firms, and industries that are in a constant state of adaptation through processes like innovation, competition, and selection (Boschma & Martin, 2007; Frenken et al., 2007). This dynamic interpretation highlights the fluidity and adaptability of economic systems. Moreover, EEG acknowledges the critical role of a region's innovative capability and economic development, dependent on its ability to enter new markets or technologies. This capability relies on the presence of related skills and knowledge, forming a foundation for economic progress. Studies by Boschma (2005), Frenken et al. (2007), and Klepper (1996) support this view, illustrating the intricate link between regional capabilities and innovation as key drivers of economic growth. This recognition underscores the importance of both internal and external factors in shaping regional economic landscapes.

While EEG has significantly advanced our understanding of the interplay between innovation, diversification, and economic development, it is not without its limitations. Martin & Sunley (2006) have criticized EEG for its tendency to oversimplify complex socio-economic systems into deterministic, path-dependent processes. They emphasized the importance of path creation in regional economic development. Furthermore, Bathelt et al. (2004) note that EEG often focuses excessively on relatedness and geographical proximity, at times neglecting the global interdependencies that are crucial in contexts like export product diversification and cross-country relationships. EEG's approach to local knowledge and capabilities has also been a point of contention. The field often treats these as homogenous entities, despite evidence suggesting that not all related activities contribute equally to regional development (Neffke et al., 2011). The degree of relatedness, for instance, can significantly influence the potential for knowledge spillovers (Breschi et al., 2003). Activities that are either too similar or too different may not effectively contribute to regional growth (Boschma & Iammarino, 2009). Additionally, the nature of relatedness—whether cognitive, organizational, social, or institutional—plays a critical role (Boschma, 2005). For example, while cognitive proximity can facilitate communication and learning, excessive similarity in this regard can lead to stagnation and a lack of innovation (Nooteboom, 2000). The quality and complexity of related activities also play a pivotal role, as industries that are more knowledge-intensive or complex tend to contribute more significantly to regional development (Hausmann et al., 2007; Hidalgo and Hausmann, 2009). Another area where EEG faces criticism is in its handling of entirely new innovations. The theory often concentrates on past industrial and technological phases and may not fully account for radical, disruptive innovations that create entirely new pathways—an essential element of economic evolution.

In conclusion, while the concept of relatedness is a fundamental aspect of EEG, the benefits of related activities for regional development are intricate and influenced by a variety of factors. Understanding these nuances is key to comprehensively grasping the dynamics of regional economic development within the framework of EEG.

2.3 Economic complexity theory

EC, developed by physicists Cesar A. Hidalgo and Ricardo Hausmann along with their colleagues at the Harvard Kennedy School and MIT Media Lab, represents a significant advancement in understanding economic development. The foundations of EC were laid in the paper "The Product Space Conditions the Development of Nations" (Hidalgo et al., 2007), which analyzed the network structure of related products in the global economy. This seminal work provided the initial empirical basis for the theory. The formal theorization and organization of EC were further refined in the 2009 paper "The Building Blocks of Economic Complexity" (Hidalgo & Hausmann, 2009). This paper not only advanced the theory but also introduced new measures of economic complexity. EC synthesizes insights from development economics, network science, and systems biology to offer a novel perspective on economic development, underscoring the critical role of knowledge and knowhow, encoded in extensive networks of individuals and organizations, in driving economic growth. At its core, EC posits that economic development is a process of accumulating productive capabilities, enabling a country to produce a more diverse and complex range of goods. The theory measures the complexity of an economy by assessing the diversity of its products and the ubiquity of these products globally.

Key to EC are the concepts of 'complexity' and 'relatedness', which are used to gauge the level of complexity in a nation's economic development and the interrelationships among products. These concepts are often examined using network analysis methods. Initial research on relatedness focused on locations specialized in clusters of related or unrelated activities, as explored in studies by Glaeser et al. (1992) and Frenken et al. (2007). This research utilized metrics of agglomeration (Ellison & Glaeser, 1997; Glaeser et al., 1992) or the hierarchy of administrative classifications (Frenken et al., 2007). It primarily investigated two types of spillover effects in economic activities: within-sector or

Marshall–Arrow–Romer (MAR) spillovers, and between-sector, or Jacobs spillovers (Ellison & Glaeser, 1997). MAR spillovers are typically associated with productivity and short-term growth, whereas Jacobs spillovers are linked to innovation and long-term growth (Saviotti & Frenken, 2008). This multifaceted approach to analyzing economic complexities and relationships highlights the depth and applicability of EC in contemporary economic analysis. The principle of relatedness is increasingly recognized as a crucial driver of national economic diversification and structural change (Boschma, 2017; Hidalgo et al., 2018; Kogler et al., 2017). This concept posits that the ability of a nation to diversify economically and undergo structural transformation is closely tied to the interconnections and synergies between various economic activities. The Economic Complexity Index (ECI) is a pivotal measure in assessing the complexity of a nation's economy, focusing on the diversity and sophistication of its economic activities, particularly in exports (Hidalgo & Hausmann, 2009). The ECI is founded on the idea that more complex economies can produce a broader range of products due to their diverse capabilities. This complexity is quantified by evaluating two main attributes: the diversity and ubiquity of the products. It is understood that a country's economic development is closely linked with product diversity, with the premise that an economy evolves by acquiring new capabilities that enable it to produce an increasingly varied array of complex products (Hidalgo, 2021).

Throughout history, there has been a trend of economies evolving towards greater diversity (Hausmann et al., 2014). As nations develop, they gain the ability to produce a wider variety of goods. These accumulated capabilities play a crucial role in facilitating the production of new, diverse products. Consequently, as product diversity increases, so does the potential for the emergence of new types of products. Capabilities are the essential inputs required for producing specific outputs (Hidalgo & Hausmann, 2009; Klepper, 1996; Neffke et al., 2011). The ECI also reflects a country's comparative advantage in the products it produces and exports. Products that hold a comparative advantage typically require a variety of knowledge for their production. This amalgamation of diverse knowledge culminates in the creation of a product. The complex knowledge involved, which is difficult to transfer and disseminate, remains localized, thereby preventing imitation and preserving a competitive edge for nations in the knowledge economy. A country's competitive advantage is linked to the ability to produce high-value, non-ubiquitous, sophisticated, and tacit knowledge products. Balland and Rigby (2017) demonstrate that as knowledge becomes more complex, it also tends to be less spatially mobile.

EC presents a distinctive perspective on the interplay between innovation, diversification, and economic development at the country level, setting it apart from EEG. Central to EC, as proposed by Hidalgo & Hausmann (2009), is the idea that a country's economic complexity, reflected in the diversity and ubiquity of its exports, is a crucial indicator of its innovation capability and future economic growth potential. The theory posits that economic growth is fueled by the accumulation of productive capabilities, which enables a nation to produce a wider and more complex array of goods (Hidalgo et al., 2007). In terms of diversification, EC argues that countries typically branch out into products that align with their existing capabilities. This alignment facilitates the production of new products and highlights the importance of product relatedness in guiding economic development and diversification paths (Hidalgo & Hausmann, 2009). The theory underscores the deep connection between a country's current capabilities and its future economic trajectory, emphasizing the strategic significance of leveraging existing strengths for growth.

However, the assumptions and methodological approaches of EC-related theories have faced challenges, particularly when compared to EEG in understanding innovation capability, diversification, and economic development. A primary limitation of EC is its reliance on export data, which may not fully represent a country's productive capabilities, especially for countries with significant domestic markets or those specializing in non-tradable sectors. Additionally, while EC's complexity measures effectively forecast economic growth, they may not fully capture the intricacies and dynamics of innovation and diversification processes (Pugliese et al., 2019), indicating a gap in the theory's ability to grasp nuanced economic evolution and change. Moreover, EC tends to overlook the roles of institutions, social factors, and power relations, which are emphasized in EEG and are crucial for understanding the conditions necessary for developing and utilizing capabilities. This omission highlights the need for a more integrated approach that considers broader socio-economic and institutional contexts. Lastly, EC's focus on a macro-level view of economic development may result in an underappreciation of micro-level processes and spatial dynamics, which are integral to EEG (Boschma & Martin, 2010). This underscores the importance of considering local and regional nuances that significantly shape economic landscapes.

The paramount concern lies in the challenges posed to economic complexity theories regarding their assumptions and methodologies. Contrary to EC's assumption, nations do not appear to actively pursue extreme diversity. Instead, countries endeavor to strike a balance between diversification and specialization efforts based on their existing capabilities, thereby fostering economic development (Cadot et al., 2011; Imbs & Wacziarg, 2003). This necessitates a more meticulous exploration of a nation's capabilities. Methodologically, EC originates from the capability-based theory (Teece et al., 1997), asserting that a nation's capabilities are not directly observable (Dosi et al., 2000). Consequently, EC infers economic complexity by gauging the observable diversity and ubiquity of products, thereby inferring the combination of capabilities. In essence, this poses a "hidden capability dilemma" (Cristelli et al., 2013; Tacchella et al., 2012), signifying a serious limitation in answering crucial questions about the optimal combination of capabilities. Policy makers thus cannot definitively determine the education, training, and investment policies required to enhance scientific, technological, and productive capabilities.

In summary, while EC provides valuable insights into economic complexity and development, it has limitations in fully capturing the complexities of innovation, diversification, and economic development, particularly in comparison to EEG. These limitations underscore the need for a more holistic and multi-faceted approach to economic analysis that incorporates diverse data sources and perspectives.

2.4 Integrated view of EEG and EC on diversification

Based on evolutionary economics, both EEG and EC acknowledge the importance of economic diversification as a crucial driver for sustaining long-term economic development. However, these theories fundamentally differ in their assumptions and the focus of their economic activity units. In particular, both theories encounter limitations when explaining economic diversification through the interactions among scientific, technological, and productive capabilities (Table 1).

Table 1. Comparison of EEG and EC theories

	Evolutionary Economic Geography (EEG)	Economic complexity (EC)
Theoretical Assumptions	Economic development is shaped by geographical and historical contexts, emphasizing path dependence and spatial distribution of economic activities (Almeida & Kogut, 1999; Ellison & Glaeser, 1997; Glaeser et al., 1992; Stuart & Sorenson, 2003).	- Economies evolve through processes enhancing the complexity of productive outputs, quantified by export diversity and sophistication. - Higher compositional and configurational complexity in a national economy leads to increased innovation, productivity, prosperity, and growth rates.
Mechanisms of Economic Diversification	Diversification stems from regional exploitation of local capabilities and adaptation to evolving conditions, underpinned by historical contingencies and institutional frameworks (Boschma, 2017).	Diversification is propelled by the accrual of capabilities, enabling production of increasingly complex products and market expansion (Hidalgo et al., 2007).
Theoretical Strengths	- Focuses on the role of geographic and institutional contexts in shaping economic development (Boschma, 2005).	- Uses quantitative methods to measure economic diversity based on export data, revealing hidden capabilities

	- Emphasizes path dependence, path creation, and the historical accumulation of capabilities (Martin & Sunley, 2006).	(Cristelli et al., 2013; Tacchella et al., 2012). - Provides a clear framework for understanding the complexity of products and the sophistication of economies (Hausmann & Hidalgo, 2009; Hausmann et al., 2014).
Limitations	- Less emphasis on quantifiable metrics, making it difficult to apply universally (Rodríguez-Pose, 2013). - May overlook the importance of technological innovation and sector-specific dynamics outside the geographic context (Storper, 1997). - Overemphasizing geographical proximity (Boschma, 2005).	- Oversimplifies the complexities of economic diversification by focusing mainly on export data, which may not capture the full scope of a country's economic activities (Kogler et al., 2023; Stojkoski et al., 2023). - Underestimates the role of institutions and non-economic factors that influence economic development.

EEG emphasizes geographic and historical path dependencies, suggesting that diversification is often influenced by existing industries and their interconnectedness (Boschma, 2017; Boschma & Frenken, 2006; Frenken et al., 2007; Neffke et al., 2011; Petralia et al., 2017). This approach underscores how pre-existing industrial structures shape the direction and nature of economic diversification. EEG also focuses on local-level processes, spatial dynamics, and the roles of institutions, social factors, and power relations in the economic landscape.

In contrast, EC centers on the role of new capability acquisition in driving economic diversification and growth. It posits that the development of an economy is linked to its ability to produce a diverse and complex range of products (Hidalgo & Hausmann, 2009). The 'complexity' of a product, determined by the required capabilities for its production, reflects the overall complexity of a national economy. This complexity increases as new capabilities are integrated into the economy’s production processes (Alshamsi et al., 2018; Hansmann et al., 2014; Hidalgo & Hausmann, 2009). EC also suggests that countries with higher levels of complexity are more likely to engage in unrelated diversification. This diversification trend grows with a country’s development and increasing economic complexity (Pinheiro et al., 2022). From an EEG standpoint, unrelated diversification offers the advantage of a diversified portfolio of unrelated sectors, serving as a buffer against external shocks (Frenken et al., 2007).

Integrating EEG and EC perspectives, it can be inferred that countries tend to diversify into areas closely related to their existing scientific, technological, and production areas. This diversification exhibits high path dependency, especially in less developed countries with limited capabilities, whereas more developed countries might engage in unrelated diversification to explore new developmental paths (Petralia et al., 2017; Pinheiro et al., 2022). Consequently, the trajectories of economic diversification within the domains of scientific research, technology, and production are shaped by a nation's pre-existing capabilities and its stage of economic development. These diversification pathways vary according to the economic development stage and are significantly shaped by the complexity and relatedness of scientific, technological, and production capabilities. This integrated view posits that economic development is not merely about accumulating capabilities but also strategically leveraging and expanding these capabilities in ways that align with a country's existing strengths and its developmental stage (Patelli et al., 2023).

According to this view, countries initially engage in a diversification of industries and activities, expanding the variety within their economies. This expansion allows them to explore various avenues for growth and innovation, drawing on a broad spectrum of capabilities (Hausmann et al., 2014).

As countries progress in their development, they often begin to specialize again, focusing on industries and activities where they have developed a competitive advantage (van Dam & Frenken, 2022). This process of "re-specialization" is crucial, as it enables economies to concentrate resources and efforts on areas with the highest potential for sustainable growth and returns (Frenken et al., 2007; Neffke et al., 2011). The dynamic of first increasing and then decreasing variety is reflective of an adaptive strategy in economic development, where the initial broad exploration of capabilities is followed by a more focused exploitation of competitive advantages (Boschma & Frenken, 2006; Hidalgo et al., 2007).

This approach underscores the importance of aligning economic strategies with a nation's specific developmental path and sectoral strengths. By doing so, countries can effectively transition through different stages of economic complexity, harnessing and refining their capabilities to optimize growth and competitiveness. Thus, the integrated EEG and EC view provides a nuanced understanding of how countries can manage their developmental trajectories by balancing diversification and specialization based on their evolving economic landscapes and capabilities. The holistic view is essential for crafting strategies that leverage both local conditions and global opportunities, facilitating a more balanced and sustainable developmental trajectory. This integration not only enriches the theoretical landscape but also enhances the practical applications of these theories in policy formulation, allowing for strategies that are responsive to both local nuances and global dynamics.

2.5 Endogenous growth dilemma: Knowledge growth and burden

The contemporary knowledge-based economy places a high premium on the production and dissemination of new and valuable knowledge. Endogenous growth theory posits that the growth of knowledge is a critical driver of economic growth, with the creation of economically valuable knowledge being key to economic prosperity and long-term regional development (Aghion & Howitt, 1990; Romer, 1990; Schumpeter, 1942). This theory emphasizes that economic growth is fundamentally linked to the growth of knowledge, which, as a non-rival good, plays a pivotal role in economic processes and development (Romer, 1990; 1994). In the realm of recombination innovation, invention is seen as a process of recombinant search across technology landscapes (Fleming & Sorenson, 2001). The expansion and diversification of knowledge increase the probability of generating new knowledge through recombination. Existing knowledge serves as a foundation for discovery and invention, suggesting that old ideas can be reconfigured in innovative ways to create new concepts (Fleming & Sorenson, 2001; Weitzman, 1998).

However, alongside the positive impacts of knowledge growth on innovation and economic development, there are also potential negative effects. The 'knowledge burden' phenomenon illustrates the paradoxical effects of knowledge growth on innovation and economic development (Jones, 2009). Despite the exponential increase in knowledge, the outcomes of innovation might diminish, largely because discovering new ideas is becoming increasingly challenging (Bloom et al., 2020; Gordon, 2017). This growing burden of knowledge can make it more difficult for scientists and inventors to make significant, disruptive discoveries, as they grapple with an ever-expanding body of knowledge (Park et al., 2023). Additionally, this escalating complexity in knowledge may alter the nature of innovation itself, potentially leading to negative implications for long-term economic growth (Jones, 2009). Such challenges could hinder the pace and scope of innovation, limiting the emergence of transformative discoveries and inventions (Bloom et al., 2020; Gordon, 2016; Park et al., 2023).

As the amount and diversity of knowledge continue to grow, especially with increasing specialization, the complexity of knowledge is also expected to rise. This escalating complexity poses several challenges to knowledge diffusion, potentially impeding economic growth. Knowledge complexity, which refers to the difficulty in understanding and applying knowledge, can limit its transferability. Complex knowledge typically requires more specialized skills and a deeper understanding for effective use. As a result, such knowledge is often less efficiently transferred, potentially slowing down innovation and economic growth processes (Cohen & Levinthal, 1990; Weitzman, 1998). The burgeoning of knowledge presents a complex dilemma for economic growth. As knowledge expands, it does so not just in volume but also in diversity, complexity, and interconnectedness. This multifaceted increase poses substantial challenges for individuals and corporations, making it increasingly difficult to master all realms of knowledge. This difficulty can hinder the discovery of new ideas and the development of innovative inventions. Consequently, there is a growing trend for individuals and corporations to specialize in increasingly narrow fields, heightening the awareness of the vast unknown areas of knowledge.

In the context of modern society, the expansion of knowledge is likely to have significant implications for decision-making by policymakers in countries seeking economic development through diversification and innovation activities such as education, academic research, corporate collaboration, and R&D investment in new facilities and technologies. A model of economic growth that focuses on innovation capabilities and diversification must consider the continuous expansion of knowledge. Also, it is worth noting that the implications of the knowledge burden are not universally negative. Park et al. (2023) discovered a positive effect of the growth of knowledge on disruptiveness for academic papers, although a negative effect was found for patents.

2.6 The value of complementary innovation

Complementary innovation, a concept rooted in endogenous growth theory and the idea of knowledge recombination, emphasizes that innovation is not an isolated phenomenon (Rosenberg, 1979). Within endogenous growth theory, the accumulation and recombination of existing knowledge are seen as crucial for generating new ideas and innovations (Fleming & Sorenson, 2001; Romer, 1990). This theory posits that economic growth is driven by technological changes that are endogenous to the system, often resulting from deliberate actions taken by individuals, such as engaging in innovative activities (Aghion & Howitt, 1990). The concept of complementary innovation highlights the interdependence of technological advancements, suggesting that the value of a specific innovation is often contingent on the existence of other complementary innovations or technologies (Rosenberg, 1979).

Firms tend to develop new, related products by leveraging their existing core capabilities because it is advantageous in terms of cost and risk of failure. As a result, a firm's product portfolio maintains coherence and sustainability over a long period (Teece et al., 1994). An illustrative example is the development and adoption of smartphones, which not only represented a significant innovation but also fostered a host of complementary innovations, such as mobile applications. This showcases the synergistic relationship between core technologies and subsequent innovations (Bresnahan & Trajtenberg, 1995).

When technological capabilities of a nation are viewed as the necessary inputs for producing specific outputs, two capabilities are considered complementary if they are jointly required to produce a range of products. The complementary nature of capabilities is assessed based on the number of products that necessitate the integration of both capabilities (Farinha et al., 2019; Frenken et al., 2023; Neffke, 2019; Pugliese et al., 2019). Innovation capabilities of a nation encompass scientific, technological, and productive dimensions (Catalán et al., 2022; Pugliese et al., 2019). Scientific research capabilities provide the foundational knowledge essential for innovation, while technological capabilities involve the skills required to transform scientific knowledge into practical technologies, including their development, adaptation, and integration into existing systems (Bell & Pavitt, 1992). Productive capabilities are vital for transforming technological innovations into tangible products and services, entailing effective resource management, processes, and systems for production and distribution (Lall, 2000).

The value of complementary innovation lies in its potential to trigger cascading innovations through the synergistic combination of these capabilities. Complementary configurations between different technological capabilities can spur cascade innovation, amplifying the impact of primary innovations and facilitating economic diversification (Pugliese et al., 2019). Such innovations can extend and apply primary innovations across various sectors, contributing significantly to economic diversification. The introduction of a primary innovation often necessitates additional innovations to fully exploit its potential. These subsequent innovations can lead to the emergence of new sectors and create new market opportunities, fostering a more diversified economy (Teece et al., 1994).

Complementary innovations not only stimulate further innovation but also promote the creation of new industries and diversify economic activities, contributing to broader economic growth (Bresnahan & Trajtenberg, 1995). The cascading effect of complementary innovations is vital in understanding their role in economic dynamics, acting as catalysts for transformative changes that extend beyond the initial scope of the primary innovation. This understanding highlights the importance of fostering an ecosystem where complementary innovations can thrive, ensuring that the full potential of primary innovations is realized and maximized.

2.7 Proximity as a degree of complementarity

Proximity serves as a crucial metric in assessing the relatedness or similarity between industries, products, or technologies, often employing various methods such as co-classification codes in patent documents, input-output tables for sector similarity, or conditional probabilities of co-exportation. In the context of economic complexity and innovation, proximity indicates the degree of complementarity between two entities. It can be measured using conditional probabilities based on outcomes like co-exports (Hidalgo et al., 2007). This implies that if two goods or industries are related, they are likely to be produced simultaneously. The proximity index, for instance, evaluates how frequently countries have a comparative advantage in two goods at the same period.

The application of proximity in knowledge networks is particularly significant for quantitatively measuring the complementary associations between various pieces of knowledge or capabilities. The study of relatedness has evolved with the introduction of proximity measures (Boschma, 2005) and co-agglomeration methods (Ellison & Glaeser, 1997), which link pairs of activities. Subsequent advancements included methodologies estimating the affinity or relatedness between a location and an activity, rather than solely between pairs of activities. Proximity, especially in economic complexity analysis, is used to measure the relatedness between two capabilities that occur simultaneously (Hidalgo et al., 2007). Various approaches to measuring proximity capture different aspects of relatedness, but their common goal is to quantify the degree of connection or similarity between two elements. Proximity often denotes cognitive closeness, particularly in the context of knowledge or technology (Boschma, 2005). It may reflect the frequency with which two elements co-occur or are used together, indicating a high degree of relatedness (Breschi et al., 2003; Nooteboom, 2000). Proximity measures offer an objective, outcomes-based approach to capturing the dynamic relatedness between industries (Neffke et al., 2011), products (Hidalgo et al., 2007), technologies (Boschma et al., 2015), knowledge (Boschma et al., 2014; Kogler et al., 2017), and skills (Neffke & Henning, 2013). These measures are advantageous because they effectively address the complexities of industry relatedness and adapt to changes over time due to technological developments (Hausmann et al., 2014). The ability to dynamically assess relatedness makes proximity measures essential for understanding the evolving nature of technologies and their interconnections, crucial for fostering innovation and economic growth. One key advantage of using proximity as a measure of complementarity is its probabilistic nature, offering a more robust framework than set-theoretic measures like cosine or Jaccard indexes (Van Eck & Waltman, 2009). This probabilistic approach accounts for the likelihood of co-occurrence, providing a dynamic and flexible understanding of relatedness. It captures the size effect in co-occurrence without being influenced by variations in volume (Boschma et al., 2014; Van Eck & Waltman, 2009). In contrast, traditional co-citation and co-classification measures are static and based on fixed classification codes, failing to adequately capture the cognitive dimension of proximity, which is crucial for knowledge transmission and interactive learning (Breschi et al., 2003). Several recent studies on relatedness in various dimensions are summarized in Table 2. In this context, "dimensions" refer to layers of activities within industries, products, technologies, sciences, know-how, knowledge, techniques, institutions, and social factors at the national, regional, or corporate levels. These dimensions interact in complex ways, shaping the economic landscape at each respective level.

Table 2. Studies on relatedness in various dimensions

Dimensions	Levels	Measures	Findings	References
Industry	Region	Technological relatedness between industries	Manufacturing regions predominantly diversify into industries that are technologically related to their current sectors.	Neffke et al., 2011
Product	Country	Core-periphery network structure of products (product space)	Countries move the product space by developing products similar to those they currently produce, but poorer nations struggle to reach the core due to the need to cross empirically rare distances.	Hidalgo et al., 2007
Technology	City	Technological relatedness at the city level	The probability of a new technology entering a city increases by 30% if the level of relatedness with existing technologies in the city increases by 10%.	Boschma et al., 2015
Science	City	Scientific relatedness between research topics	New scientific topics in biotech tend to systematically emerge in cities with existing scientifically related topics.	Boschma et al., 2014
Knowledge	Region	Patent co-classification	New patents are more prevalent in technology classes where individual knowledge subsets are more closely related than the average.	Kogler et al., 2017
Skills	Firm	The similarity of skills across different industries	Firms are more likely to diversify into industries related to their core activities by skill-relatedness than into industries linked by value chain or classification-based relatedness	Neffke & Henning, 2013

2.8 The importance of a multidimensional approach

A nation's economic system is a complex network encompassing various elements like scientific, technological, and productive activities. Adopting a multidimensional approach to analyze this system, particularly through the lens of a cross-proximity measure, enables the examination of not only direct relationships but also the broader network of related activities. This methodology is crucial for understanding the complex interactions at a national level. It provides a nuanced perspective on the dynamics and interdependencies characterizing a nation's knowledge space, offering insights into the multifaceted nature of national innovation ecosystems.

However, as illustrated in Table 2, most existing studies have focused on a single dimension, measuring the relatedness of activities within that dimension using proximity. This approach has led to insufficient attention to how social, economic, technological, and academic activities interact across different dimensions. Although the economic systems of firms, cities, regions, and nations are composed of multidimensional activities, our understanding of the interactions within these spaces remains limited.

To address this, Pugliese et al. (2019) proposed the concept of cross-proximity, which denotes the relationship or similarity between activities that co-occur across different dimensions. This concept extends Boschma's (2005) traditional notion of proximity to multidimensional spaces such as science-technology, technology-products, and science-technology-products. This framework is a valuable tool for understanding fundamental issues such as how a country's foundational scientific capabilities influence technological innovation and diversification into new industries (Balland & Boschma, 2022; Catalán et al., 2022).

In this framework, capabilities are envisioned as nodes within a network, with the degrees of proximity or relatedness among them represented as edges in multilayer networks (Boccaletti et al., 2014). This model highlights the interconnectivity of different human activities spanning scientific fields, technological sectors, and economic production (Pugliese et al., 2019). Entities in these networks are organized into distinct sets, interconnected through various types of relationships. This comprehensive approach allows for a deeper understanding of how scientific, technological, and economic domains are intertwined and how their interactions influence broader patterns of innovation and development. Figure 3 illustrates a multidimensional approach to national capabilities, showing how a nation's scientific capacities influence technological innovation over time, which then affects productive capacities. The diagram emphasizes the sequential progression from scientific to technological to productive capabilities and demonstrates how accumulated capabilities in new products drive technological innovation, which in turn promotes basic scientific research. This virtuous cycle of knowledge production within national innovation systems is further expanded by Catalán et al. (2022) with the concept of 'scientific and technological cross-density.' This metric, defined as the average proximity of new technology to a country's existing scientific and technological portfolio, evaluates how scientific research capabilities contribute to developing related technological specializations, highlighting the importance of integrating scientific and technological capabilities for diversification.

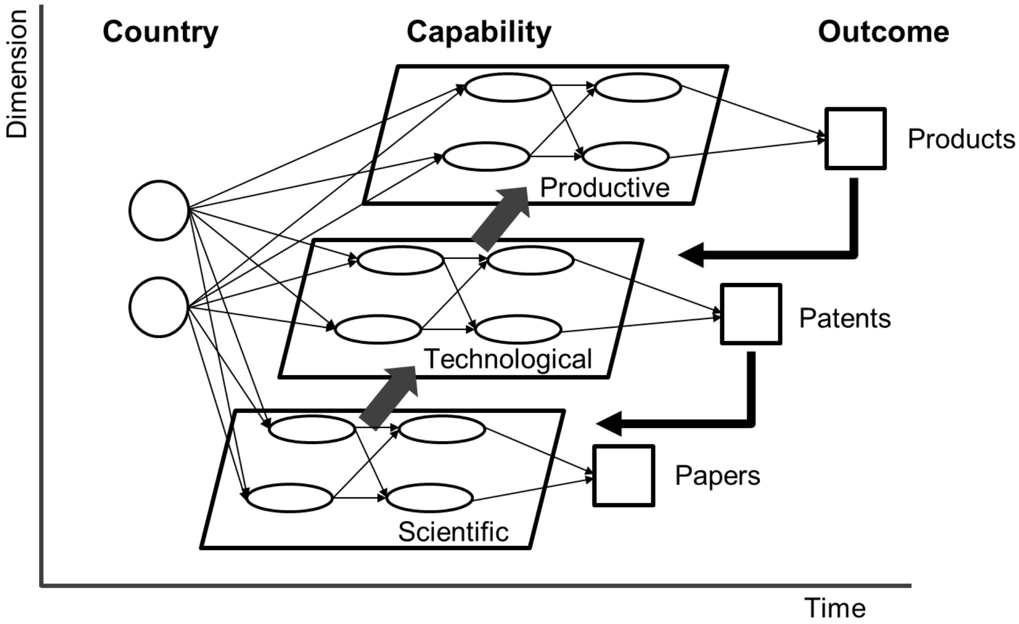


Figure 3. A multidimensional framework for national capabilities

While systematic studies on the complementary functions among diverse activities in multidimensional spaces are limited, consistent research has been conducted to measure knowledge externalities between different dimensions (Table 3). Knowledge externalities refer to the positive impacts that occur when knowledge created by an entity (such as a firm, research institution, or individual) spills over to others, leading to additional innovation and productivity gains without direct compensation to the original creator (Romer, 1994; Weitzman, 1998). These externalities are vital for the spread of technological advancements and contribute significantly to the growth of industries and economies (Bresnahan & Trajtenberg, 1995).

Table 3. Studies on knowledge externalities between different dimensions

Dimensions	Measures	Findings	References
Science-Technology	Patent citations to journal articles	Regions that leverage their scientific resources tend to produce inventions with greater impact, and the science-technology linkage is effective in advanced industrial areas.	Shin et al., (2023)
Science-Technology	Patent citations to journal articles	There are inherent time lags between scientific discoveries and technological advancements. In nanoscience, it typically takes 3-4 years for scientific findings to result in patents	Finardi (2011), Narin & Olivastro (1992)
Science-Technology	Cross-proximity	The closer a new technology is to a country's scientific portfolio, the higher its likelihood of successful entry.	Catalán et al. (2022)
Science-Technology	Relatedness between scientific domains and CPC classes	Regional scientific capabilities in a specific field significantly predicts the advancement of new technologies within that field.	Balland & Boschma (2022)
Technology-Product	Concordance matrix	Technological advancements and product production evolve along co-evolutionary paths with time lags.	Eum & Lee (2022)
Science-Technology-Product	Cross-proximity	Scientific, technological, and economic activities co-evolve through their interactions. Technological know-how significantly impacts economic wealth and scientific discoveries, albeit with time lags.	Puglies et al. (2019)
Technology-Design-Market	Cross-relatedness	There are interaction effects among the activities involved in developing patents, industrial designs, and trademarks, with patents exerting the most significant impact.	Castaldi et al. (2023)

To systemically understand the complementary function of AI, it is possible to extend Romer (1990) and Jones (1995)'s knowledge production function. Figure 4 presents a theoretical framework for knowledge production, drawing on the models proposed by Romer and Jones, as well as combinatorial-based knowledge production functions. This framework provides a deeper insight into how knowledge externalities and complementary functions interact within the context of AI.

The dashed line of the diagram depicts a combinatorial-based knowledge production function. In this model, potential combinations (Z) serve as the foundation for generating new knowledge. It incorporates two key elements: General-Purpose Technology (α) and Knowledge Relatedness (ω). General-Purpose Technology (α) encompasses versatile technologies applicable across various domains, thereby enhancing combinatorial potential. Knowledge Relatedness (ω) denotes the connectivity and compatibility between different knowledge domains, facilitating effective combinations.

The framework emphasizes the interaction between these elements in a structured process. Potential combinations (Z) are processed through General-Purpose Technology (α) and Knowledge Relatedness (ω), leading to the production of new knowledge (A'). This diagram underscores the importance of leveraging both existing knowledge and innovative combinations, facilitated by GPTs and domain relatedness, to drive continuous knowledge generation.

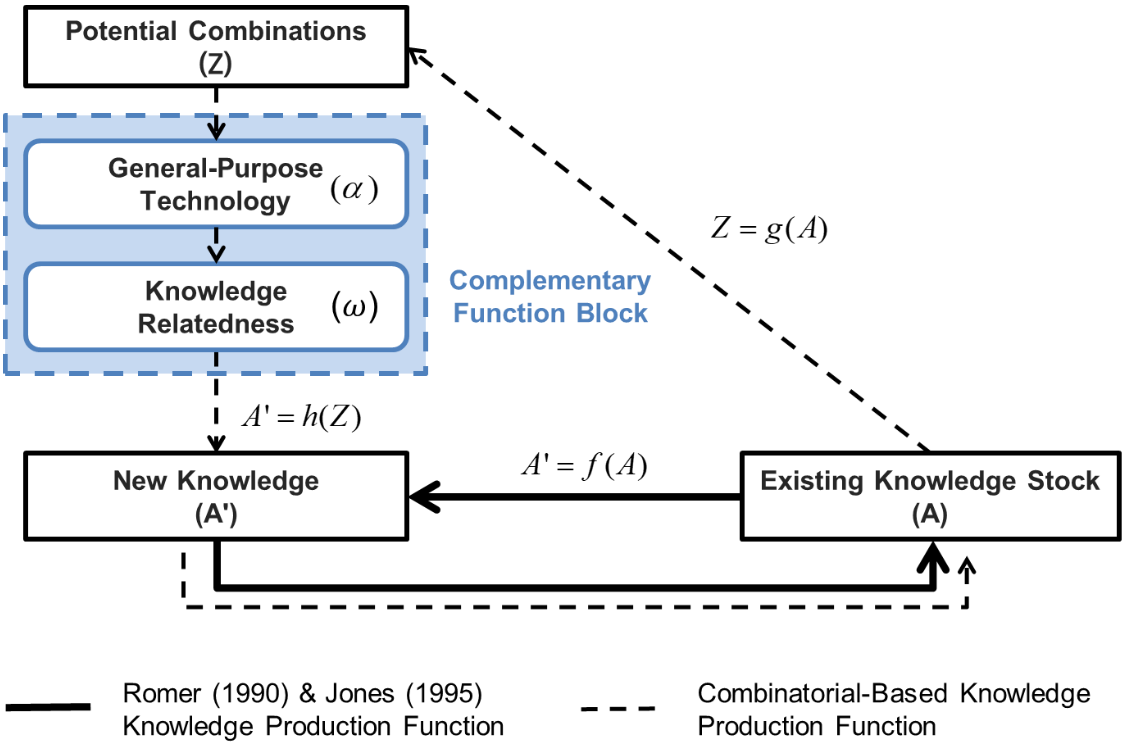


Figure 4. Knowledge production framework with complementary functions

2.9 Innovation capability, artificial intelligence, and economic diversification

The impact of knowledge-based innovation activities on economic diversification varies across countries, depending largely on each country's existing capabilities (Breschi et al., 2003; Frenken et al., 2007; Saviotti & Frenken 2008). Technologically advanced nations like the United States and China have used their sophisticated knowledge to not only develop AI-related technologies including but also to safeguard them (Delponte & Tamburrini, 2018). This indicates that their strong economic and technological foundations give them an edge in AI development. In contrast, countries with lower economic and technological development levels tend to follow a more path-dependent approach in their technology development (Antonietti & Montresor, 2021; EPRS, 2021). This indicates that their progress in AI is often limited by their historical events of development and current capabilities.

Crucially, to understand AI's role in fostering a country's economic diversification, it is essential to recognize its unique features. In addition, the country's heterogeneity must be considered, including its level of economic development, resource availability, innovation capability, geographical boundaries, institutional framework, and social acceptance. AI stands out from other technological advancements due to its versatility. This ability to be applied across a wide range of sectors highlights AI's unique potential in driving innovation and diversification, particularly in environments where it can be merged with existing knowledge and capabilities. Although the mechanism is not yet clearly understood, AI can complement or replace existing capabilities due to its innovative characteristics. To better understand the attributes of AI, we need to examine how AI has evolved, how it has transformed from early concepts to modern interpretations, and what its technical characteristics are.

AI technology has gone through cycles of booms and winters, marked by periods of rapid advancements and stagnation. These fluctuations have been driven by technological advancements in computing power, big data, and algorithms (Brynjolfsson & McAfee, 2014). Notably, deep learning, a subset of representation learning, has profoundly influenced AI's evolution, especially since the pivotal contributions of Geoffrey Hinton and his colleagues in 2012 (Hinton & Salakhutdinov, 2006; Kirzhevsky et al., 2012). Presently, AI is heralded as a universally relevant technology, significantly impacting diverse industries, with machine learning methods being particularly transformative (Borges et al. 2021). The progression of AI technologies is intimately connected to specific scientific breakthroughs, and deep learning is increasingly being incorporated into a wide range of computer science disciplines (Klinger et al., 2021). As AI continues to advance, it is anticipated that an increasing number of tasks will be automated or enhanced through machine-based solutions. The exponential growth and varied application of AI in different fields are evidenced by the surge in academic publications and patent registrations, a trend particularly noticeable since the early 21st century (Bianchini et al., 2022; Klinger et al., 2021). This increase is fueled by a sustained commitment to AI research, maintained even during periods of skepticism, and the continuous emergence of innovative ideas (Nilsson, 2009).

AI is poised to significantly influence technological changes and economic growth across various sectors. It has the potential to enhance productivity, drive innovation, and enable new business models (Brynjolfsson & McAfee, 2017). AI is transforming numerous sectors, including healthcare, transportation, and finance, by automating complex tasks, enhancing accuracy, and streamlining decision-making processes. For instance, AI technologies have applications in automating routine and non-routine tasks in both manufacturing and services (Albanesi et al., 2023). In finance, AI is reshaping international trade in goods and services, and significantly impacting economic growth (Goldfarb & Trefler, 2019; Goldfarb et al., 2023). Advanced generative AI tools, like ChatGPT, are designed to produce complex text that is virtually indistinguishable from human writing, making them applicable in a diverse array of contexts (Dwivedi et al., 2023).

However, despite significant advancements and investments in AI, its impact on economic growth is less evident than anticipated (Hestness et al., 2017; Kaplan et al., 2020; Zhai et al., 2022). The Solow Paradox, named after Nobel Prize-winning economist Robert Solow, refers to the gap between the broad adoption of information technology and the lack of corresponding growth in productivity statistics (Solow, 1956). This paradox is relevant to AI, suggesting that even though AI technologies are becoming more prevalent, their influence on measurable productivity gains remains ambiguous.

There are several potential explanations for this paradox. First, there may be a time lag between the adoption of AI and its tangible impacts on productivity, similar to what was observed with electricity in the early 20th century (Brynjolfsson & McAfee, 2014). Second, the benefits of AI may be concentrated among a small number of individuals or firms, thus not being reflected in aggregate statistics. Third, existing metrics may not fully capture the impact of AI and other digital technologies on productivity (Brynjolfsson et al., 2021). Although AI holds considerable potential benefits, the social, economic, and environmental implications of this technology are yet to be fully understood (Khakurel et al., 2018; Kopka & Grashof, 2022).

The concerns raised about the time lags between scientific discovery, technological innovation, and commercialization have been a subject of much debate (Narin & Olivastro, 1992; Narin et al., 1997). Historically, these time lags have been significant, reflecting the time needed to transform an idea into a marketable product (Mansfield, 1991). However, recent evidence suggests that these lags are shortening, attributed to faster technological progress, improved communication and collaboration tools, and more efficient regulatory processes (Jones, 2009). This trend indicates a dynamic shift in the innovation landscape, affecting the development and market introduction of new technologies and products. In relation to AI development, research confirms that knowledge spillovers in AI research are localized, which justifies sub-national and national policies to support AI development (Klinger et al., 2021). Key examples of this are DeepMind in London and the Vector Institute in Toronto, both of which were established in the cities where the lead researchers resided (Goldfarb & Trefler, 2019). This concentration of AI expertise in specific regions mirrors the global trend of AI innovation hubs, such as Silicon Valley, Berlin, Seattle, London, Boston, Shanghai, Toronto, and Montreal (Goldfarb & Trefler, 2019). Several factors contribute to this trend. The increasing velocity of scientific knowledge in the AI field is a key driver. Companies strive to internalize the latest scientific discoveries into their technologies as quickly as possible, which reduces the time lags for scientific knowledge to be transformed into technological inventions (Kopka & Grashof, 2022; Liu et al., 2020).

However, the narrowing of time lags between scientific knowledge and technological invention in the field of AI is a relatively recent phenomenon. Turing's 1950 concept of a "thinking machine" was a foundational influence in AI development (Turing, 1950), but it took considerable time for this idea to manifest in numerous technological inventions, due to a pattern of advancements and setbacks marked by the fluctuating prominence of various technologies (Nilsson, 2009). The progression of AI technologies is intimately connected to specific scientific breakthroughs, and deep learning is increasingly being incorporated into a wide range of computer science disciplines (Klinger et al., 2021). As AI continues to advance, it is anticipated that an increasing number of tasks will be automated or enhanced through machine-based solutions. The exponential growth and varied application of AI in different fields are evidenced by the surge in academic publications and patent registrations, a trend particularly noticeable since the early 21st century (Bianchini et al., 2022; Klinger et al., 2021). This increase is fueled by a sustained commitment to AI research, maintained even during periods of skepticism, and the continuous emergence of innovative ideas (Nilsson, 2009).

The perception that the impact of AI is limited to a few individuals or companies is increasingly being challenged. AI is expected to have far-reaching effects across many countries. Recognizing its potential, nations worldwide are developing policies to guide AI’s development and application (Russell & Norvig, 2016; Tegmark, 2018). Leading countries, including the United States, China, and several European nations, have formulated comprehensive AI strategies, highlighting AI's broad impact (Webster et al., 2017). AI is also poised to significantly influence societal aspects such as governance, education, and healthcare (Bostrom & Yudkowsky, 2018), indicating its transformative potential beyond technology and into wider social contexts.

Despite significant progress in AI, quantifying its impact remains challenging due to the expanding knowledge in each domain and the increasing number of domains (Bianchini et al., 2022). Adding to this complexity is AI's environmental footprint, encompassing electricity consumption, hardware manufacturing and disposal, and the water and land use of data centers (Bender et al., 2021; Kez et al., 2022; Memmel et al., 2022). These environmental aspects further complicate the assessment of AI’s impact. Consequently, while AI holds immense potential for innovation and economic development, accurately assessing its multifaceted impact is a complex task (Aghion et al., 2019; Annoni et al., 2018; Goldfarb & Trefler, 2019).

AI, including technologies like machine learning, deep learning, and natural language processing, is considered a GPT due to its ability to augment and complement existing products and processes across various industries (Brynjolfsson & Mitchell, 2017; Cockburn et al., 2019; Russell & Norvig, 2016). The impact of AI on technological innovation and productivity has been extensively studied, with researchers noting its role in enhancing knowledge creation, learning and absorption, and R&D investment (Liu et al., 2020; Rammer et al., 2022; Yang 2022). AI's function is evident in its capability to combine and recombine distant knowledge items, crucial for environmental technologies that rely on complex and interdisciplinary knowledge (Cicerone et al., 2023).

The significance of GPTs is anchored in their unique characteristics and profound impact on economies (Helpman & Trajtenberg, 1996; Lipsey et al., 2005). GPTs are notable for their technological dynamism, wide-ranging applicability across various sectors, and their capability to foster subsequent innovations, known as 'innovational complementarities' (Bresnahan & Trajtenberg, 1995). These technologies are deeply pervasive, infiltrating every aspect of the economy and playing a critical role in driving economic growth and industrial revolutions throughout history (Helpman & Trajtenberg, 1996; Foray et al., 2009; Montresor & Quatraro, 2017; Xiao & Boschma, 2022).

GPTs serve as enablers that unlock new possibilities rather than offering complete solutions themselves. They create a ripple effect of innovation within their domain, extending these effects across the economy. This ability to induce cascades of complementary innovations in various sectors, many of which may become broadly applicable themselves, is a defining feature of GPTs (Lipsey et al., 2005).

AI, categorized as a GPT, exemplifies this enabling capability. AI can integrate with existing systems and technologies to generate new functionalities, applications, and efficiencies (Bresnahan & Trajtenberg, 1995). The concept of 'innovational complementarities' is particularly relevant in the context of AI, as innovation in one part of a system can amplify the value and functionality of other parts (Bresnahan & Trajtenberg, 1995). Additionally, AI's potential for complementary innovation is emphasized in multidimensional knowledge network approaches. In these frameworks, AI technologies interact and combine with different knowledge domains, leading to diverse and enhanced innovations.

In summary, AI as a GPT is not just a standalone technology but a key driver of broader technological and economic transformations. Its ability to foster innovational complementarities and integrate into multidimensional knowledge networks makes it a pivotal technology in shaping the future of industries and economies. The ongoing exploration and utilization of AI's capabilities will likely continue to reveal new ways in which this technology can catalyze innovation and drive economic development.

Chapter 3. Scientific research capability and technology diversification in AI fields

3.1 Introduction

In recent years, the intensifying global competition among nations to achieve national competitiveness in AI technology has significantly increased interest in technological diversification (Delponte & Tamburrini, 2018; EPRS, 2021). Technological diversification is defined as a country's emphasis on producing and developing specific technologies in a new area where it holds a comparative advantage over others. This competitive environment has led to a significant expansion in both research fields and technological areas associated with AI. However, the production of scientific knowledge does not always result in new technologies; the transition from scientific discovery to technological innovation involves a much more complex mechanism than one might expect (Callaert et al., 2014; Narin & Olivastro, 1992; Narin et al., 1997). From 1960 to early 2018, approximately 340,000 AI-related patent families and over 1.6 million scientific papers were published, with the number of papers being around 4.7 times that of patents (WIPO, 2019). This disproportionate growth raises an essential question: Do increased scientific publications significantly impact a nation's technological specialization in emerging AI fields?

In the current knowledge-driven economy, characterized by intense competition among nations for technological supremacy, the development of new technologies through innovative scientific concepts has become increasingly vital. However, national-level exploration of this phenomenon has been limited, with a few significant exceptions like the study by Catalán et al. (2022). This research uniquely points out that previous studies have typically concentrated either on technologies or scientific areas in isolation, neglecting the exploration of their interconnections. Specifically, they investigate whether a nation's intrinsic scientific research capability can determine its potential for technological specialization. Traditionally, research has focused on the regional aspects of knowledge spillovers, examining the transformation of scientific knowledge into technological innovations (Almeida & Kogut, 1999; Breschi & Lissoni, 2009; Stuart & Sorenson, 2003). It is recognized that university research generally fosters innovation within its region, a trend largely due to knowledge spillovers confined by geographical boundaries (Jaffe et al., 1993).

This dissertation investigates the intersection of scientific knowledge and technological diversification in AI-related fields at the national level. We analyzed data on AI-related scholarly articles and patents from 170 countries over a span of four decades, from 1980 to 2019. This timeframe is particularly significant as it includes key historical events that have led to recent breakthroughs in the evolution of AI technology. For example, it covers the period following the 'AI winter'—a phase in the late 1980s and early 1990s characterized by reduced interest and investment in AI, coinciding with the market collapse of early AI technologies like expert systems and machine learning algorithms. The late 1990s witnessed a resurgence of optimism in AI, evidenced by a surge in related publications, often linked to advancements in machine learning and neural networks (Crevier, 1993). The early 2000s saw a significant increase in AI patent filings, reflecting increased commercial attention and major technological breakthroughs, especially in the realm of deep learning techniques (Hinton & Salakhutdinov, 2006), which were pivotal in AI's development (Bianchini et al., 2022).

Our dataset also includes pivotal research and patents related to Google Brain's Transformer, as introduced by Vaswani et al. (2017) in 'Attention Is All You Need.' This discovery marked a significant breakthrough in natural language processing and laid the groundwork for advanced language models, such as ChatGPT. This period is crucial in AI's evolution, especially in language models, as evidenced by the explosion of research and technological applications stemming from this model (Devlin et al., 2018; Radford et al., 2019). These developments have profoundly influenced the contemporary AI landscape, underscoring the importance of groundbreaking scientific discoveries in driving technological advancement and specialization.

This study, through the analysis of a comprehensive dataset, aims to shed light on how the expanding corpus of scientific knowledge has impacted the technological specialization of countries in AI-related fields. By considering both the historical and contemporary contexts of AI development, this approach seeks to unravel the intricate relationship between scientific progress and technological innovation in the rapidly evolving domain of AI. Such an analysis promises to offer a nuanced understanding of the dynamic interplay between these two critical elements, contributing significantly to our grasp of AI's development trajectory.

Our findings indicate that both scientific and technological capabilities significantly contribute to a country's AI specialization. Notably, scientific knowledge that aligns closely with a country's existing technological strengths tends to positively impact its technological comparative advantage, implying a beneficial knowledge spillover from scientific research to technology when there is a certain level of alignment between the two domains. Furthermore, the influence of scientific research capabilities on AI specialization appears to be more pronounced than that of technological complexity, even though complex technologies also positively contribute to AI specialization.

The insights derived from this study are particularly pertinent for policymakers in developing countries, where technological resources may be more constrained (Lall, 2000). This is because developing countries find it challenging to accumulate technological capabilities independently without complementary technologies (Bell & Pavitt, 1992). In these technologically and economically less developed nations, focusing on gaining a comparative advantage in sectors closely linked to the latest AI knowledge presents a more feasible strategy than attempting to emulate the approach of advanced countries, which often involves refining existing technologies to stay ahead of competitors (Lall, 2000). This underscores the critical need for integrating advanced scientific knowledge into industries that are strategically important for AI specialization. Adopting such a strategy is essential for countries striving to carve out or strengthen their niche in the fast-paced AI landscape. In this arena, where both scientific and technological breakthroughs are key to maintaining a competitive edge, a focused approach towards leveraging scientific advancements can offer significant strategic benefits.

Our study marks a significant advancement by transitioning from a unidimensional approach to a multidimensional perspective, intertwining scientific and technological knowledge spaces. We have utilized the multi-layer network approach (Pugliese et al., 2019), leveraging co-occurrence data to more effectively map out the interactions within the national innovation system. This method surpasses the boundaries of conventional approaches by accounting for the diverse and concurrent interactions between scientific research and technological economic activities (Catalán et al., 2022; Patelli et al., 2023). This comprehensive viewpoint equips policymakers with holistic insights, facilitating the development of integrated AI strategies that acknowledge the interdependent nature of research and innovation. In a fast-evolving technological landscape, adopting a strategy that leverages the latest knowledge to extend comparative advantage into new areas, rather than merely complicating existing technologies to deter competitors, becomes increasingly vital. The findings of our study provide valuable guidance for policymakers in crafting AI technology policies, underscoring the necessity of a multidimensional approach that addresses both scientific research and technology in tandem.

3.2 Literature review

In the realm of EEG, the concepts of diversification and economic growth are foundational. Diversification is recognized as a pivotal driver for regional economic development and growth (Breschi et al., 2003; Frenken et al., 2007; Jacobs, 1969). Similarly, the EC posits that the principle of relatedness and the Economic Complexity Index (ECI) are crucial in elucidating both diversification and growth (Hidalgo et al., 2007; Hidalgo & Hausmann, 2009; Hidalgo et al., 2018).

Relatedness pertains to the extent of similarity or proximity among various types of knowledge, technologies, or industries. This notion underscores that new knowledge, or technologies frequently evolve from existing ones through novel combinations. Companies often diversify into technological fields that share overlapping or complementary knowledge bases. The level of relatedness among activities influences innovation, productivity, and growth (Boschma 2005; Hidalgo et al., 2007). The ECI, meanwhile, quantifies a country's complexity based on exports, patent filings, and scholarly publications. It is commonly utilized alongside data on the geographical distribution of exports by product, patent categorizations by technology, and academic publications by research field. This multifaceted approach facilitates an understanding of variations in economic growth, income disparity, and greenhouse gas emissions (Stojkoski et al., 2023).

For tracking diversification paths in goods, technology, and knowledge that have a comparative advantage, the revealed comparative advantage (RCA) is often introduced. The RCA serves as a measure of relative specialization, indicating a country's proficiency in specific activities compared to others (Balassa, 1965). The RCA acts as an initial marker of a country's current strengths. The principle of relatedness then guides the direction of diversification, leading countries to branch into fields related to their established areas of expertise. This diversification, steered by relatedness and manifested in changes in RCA, contributes to an increase in economic complexity, as reflected by the ECI (Hidalgo & Hausmann, 2009).

3.2.1 RCA-based technology specialization

Technology diversification is a strategic process where countries expand into new technological areas, leveraging their comparative advantages (Saviotti & Frenken, 2008). This approach involves broadening a nation's technology portfolio to include specialized, novel technologies, essentially contributing to technological specialization. The economic success of nations is intricately connected to their ability to specialize in specific technologies, products, and skills. This concept has its roots in the early works of Marshall (1920) and Jacobs (1969) and has been further elaborated by Glaeser et al. (1992). This idea resonates with Jacobs' notion that a diverse knowledge base spurs more opportunities for new activities to emerge, thus contributing to economic dynamism (Jacobs, 1969). Such research highlights the pivotal role of specialization in propelling a country's economic growth and prosperity.

Balassa (1965) introduced the concept of comparative advantage, suggesting that a country excels in producing a specific product when its production surpasses the global average. This concept led to the development of the RCA index, a pivotal economic measure used to assess a country's competitive edge in various industries or trades. The RCA index calculates the proportion of a country's exports of a particular good or service relative to its share in global exports. An RCA greater than 1 indicates a comparative advantage, signifying greater proficiency in producing that good or service compared to other countries.

RCA is not only applicable to product specialization but also to technological specialization. Many recent studies have adopted it to measure technological competitiveness at regional, city, and national levels (Antonietti & Montresor, 2021; Balland & Rigby, 2017; Boschma et al., 2015; Patelli et al., 2023; Petralia et al., 2017). Balland and Boschma (2022) expanded the concept of RCA to measure the relative technological advantage of a technology across multiple regions that are inventing it. They discovered that the presence of scientific capabilities in a particular domain within a region strongly predicts the development of new technologies in that same domain. This phenomenon is a key aspect of technological diversification.

The process of technological diversification in a country is path-dependent, meaning that the existing capabilities determine the trajectory of technology diversification. A country's transition towards new technologies is heavily influenced by its existing technological and industrial capabilities (Bell & Pavitt, 1992; Patel & Pavitt, 1997). Therefore, countries tend to specialize in technologies related to their pre-existing capabilities. This is consistent with the principle of relatedness, which suggests that countries, regions, and cities tend to diversify into areas related to their current technological and industrial capabilities (Antonietti & Montresor, 2021; Balland & Rigby, 2017). Boschma et al. (2015) demonstrated the path-dependent nature of technology evolution, including emergence and decline, in U.S. cities. They expanded RCA's utility by introducing ENTRY and EXIT metrics, using patent class relatedness to predict technological shifts, suggesting regions often develop industries akin to their existing ones. They found a 10% increase in technological relatedness boosts the likelihood of adopting new technology (ENTRY) by 30%, while reducing the obsolescence (EXIT) of current technologies by 8%.

The factors influencing technological diversification extend beyond mere technological relatedness to include technology complexity. The significance of technology complexity in bolstering diversification is substantial. Profound and intricate knowledge in a specific field positively influences the introduction of novel technologies, thereby reinforcing diversification (Asheim & Gertler, 2005; Kogut & Zander, 1992). Additionally, this complexity is often correlated with enhanced economic value due to its geographic concentration and the difficulties it presents for widespread dissemination, posing challenges for other countries and regions in terms of replication or adaptation (Fleming & Sorenson, 2001; Jaffe et al., 1993). As such, nations tend to exhibit distinct patterns of diversification along their developmental trajectories, gravitating towards more complex and economically valuable technologies in efforts to rapidly monopolize economic benefits (Petralia et al., 2017). This aggregation of complex knowledge in specific countries leads to the emergence of more advanced and sophisticated export patterns. As countries progress, they refine and augment their distinctive technological capabilities, underlining the pivotal role of knowledge complexity in shaping and driving the trajectory of technological development and diversification (Balland & Boschma, 2022).

However, excessive dependence in a particular technology carries the risk of technological lock-in (Arthur, 1989). This occurs when an economy becomes excessively reliant on a specific technology, leading to significant transition costs or barriers to adopting new technologies. The risk of technological lock-in is heightened when the focus is on increasing the complexity of a specific technology, as this can lead to path dependence, where future technological developments are heavily influenced by past decisions (David, 1985). This scenario limits flexibility and adaptability, potentially hindering economic progress and innovation.

Indeed, while RCA-based diversification measures are not without limitations, they offer significant advantages in assessing technological emergence and decline in a specific sector. ENTRY and EXIT indicators, derived from RCA, do not provide direct measurements of entry or exit in a specific technological field. Instead, they indicate the level of comparative advantage in that area, thus enhancing robustness in minimizing the impact of external volatility (Hidalgo et al., 2021). When utilizing patent data to measure technology diversification, the application of RCA-based ENTRY indicators is more beneficial than merely counting the number of patents. This is primarily because patent data are subject to variability due to diverse factors such as changes in patent laws, differences in patenting behavior across countries, and technological shifts (Strumsky et al., 2012). The RCA-based diversification measure, as a relative indicator, effectively mitigates these volatilities by emphasizing comparative strengths rather than absolute patent counts.

Despite these limitations, the RCA-based ENTRY metric plays a crucial role in quantifying technological diversification (Colombelli et al., 2014). It is particularly effective because it evaluates diversification through relative comparisons between countries, rather than depending solely on the absolute count of specific technologies. This relative approach offers a more resilient and nuanced understanding of a nation's technological capabilities and limitations. It provides valuable insights that are less prone to external influences such as fluctuations in patenting activities or changes in global market trends, thereby offering a more reliable and insightful analysis of technological diversification.

3.2.2 A symbiotic relationship of scientific research and technological invention

Theories of scientific and technological change conceptualize discovery and invention as endogenous processes (Schumpeter 1942), positing that accumulated knowledge serves as a foundation for future progress by enabling researchers to leverage existing knowledge stocks. Research indicates that countries typically develop new knowledge aligned with their established knowledge bases (Boschma, 2017), and the spectrum of technological domains in which they can gain a comparative advantage is limited by their existing technological trajectories and scientific research capabilities.

From the perspectives of EEG and EC, the symbiotic relationship between scientific research and technological invention is underpinned by principles of relatedness, cognitive proximity, and diversification (Balland & Boschma, 2022). Technological advancements are often rooted in scientific research (Fritsch & Slavtchev, 2007), a relationship that has become increasingly interwoven with the advent of deep learning and other AI technologies, which are heavily reliant on scientific knowledge (Brynjolfsson et al., 2021; Cicerone et al., 2023; Cockburn et al., 2019).

Central to this interplay is the cognitive proximity between scientific and technological knowledge bases. The genesis of new technological innovations frequently originates from scientific fields with which they share cognitive proximity or relatedness, facilitating knowledge spillovers and fostering technological advancement (Balland & Boschma, 2022; Catalán et al., 2020). In this context, technological diversification emerges as a pivotal aspect of the scientific and technological nexus, with countries branching into technologies that dovetail with their existing competencies, effectively recombining existing knowledge into new applications (Frenken et al., 2023). Historically, significant time lags between scientific discovery and technological application have been noted, mirroring delays in translating scientific prowess into technological diversification (Mansfield, 1991). However, these time lags have been diminishing progressively (Finardi, 2011). For example, the gap between Faraday's discovery of electromagnetic induction and the realization of the first practical electrical generator spanned 51 years, while the development of semiconductor diodes took a mere 6 years. In the fields of nanoscience and nanotechnology, the typical time lag between the generation of scientific knowledge and its technological application is around 3–4 years (Finardi, 2011; Narin & Olivastro, 1992;

Narin et al., 1997).

The field of AI, particularly deep learning, exemplifies this trend, with the time lags between research and practical application narrowing, largely due to AI's nature as a GPT (Klinger et al., 2021). This convergence is propelled by a dynamic amalgam of technological advancement, augmented R&D investments, collaborative endeavors, and a global exchange of information. Strengthened collaboration between academia and industry has accelerated the transformation of research into market-applicable solutions, complemented by considerable increases in R&D funding from both public and private sectors, expediting scientific discoveries and their subsequent application in technological solutions.

3.2.3 AI specialization in the scientific and technological nexus

Exploring AI specialization through the scientific and technological nexus entails a deep dive into how scientific research underpins technological progress in AI. This relationship is reciprocal: AI technological breakthroughs often arise from foundational scientific research, and technological strides pave the way for new scientific inquiries. Understanding this interplay offers valuable insights into the dynamics driving AI specialization, the birth of novel AI technologies, and their sector-wide adoption.

In today's knowledge economy, marked by fierce global competition for technological leadership, the role of science in fostering new technologies with a comparative edge is crucial. However, this crucial aspect has been less explored at the country level, despite its significance in regional dynamics of knowledge spillovers and the transformation of scientific knowledge into technological innovations (Jaffe et al., 1993). These spillovers, often geographically bound to areas surrounding universities and research institutes, highlight the importance of local knowledge in innovation processes (Almeida & Kogut, 1999; Breschi & Lissoni, 2009; Stuart & Sorenson, 2003).

Regarding AI, research suggests that knowledge spillovers in this domain tend to be localized, supporting the need for targeted sub-national and national AI development policies (Klinger et al., 2021). Notable examples include AI powerhouses like DeepMind in London and the Vector Institute in Toronto, established where their leading researchers were based (Goldfarb & Trefler, 2019). This phenomenon of AI expertise clustering in certain regions is a global trend, with innovation hubs emerging in cities like Silicon Valley, Berlin, Seattle, London, Boston, Shanghai, Toronto, and Montreal. Several factors drive this trend, including the rapid pace of scientific advancement in AI. Companies aim to integrate the latest scientific findings into their technologies promptly, aiming to shorten the time it takes for scientific knowledge to be transformed into technological applications (Kopka & Grashof, 2022; Liu et al., 2020).

However, the transition from scientific theory to technological application in AI has not always been swift. Alan Turing's 1950 concept of a 'thinking machine' laid the groundwork for AI, yet it took decades for these ideas to materialize into practical technological advancements due to intermittent progress and setbacks marked by the varying prominence of different technologies (Nilsson, 2009). The advent of deep learning, especially after significant contributions by Geoffrey Hinton and his colleagues in 2012, marked a crucial turning point in AI's development. Today, AI is recognized as a critical technology across various industries, with machine learning methods proving particularly transformative (Brynjolfsson & McAfee, 2017).

The advancement of AI technologies is intricately linked to key scientific breakthroughs. For example, the incorporation of deep learning into various computer science disciplines has significantly propelled the progress of AI (Klinger et al., 2021). The widespread application and exponential growth of AI are evidenced by the sharp rise in academic publications and patent registrations, particularly since the early 21st century (Bianchini et al., 2022; Klinger et al., 2021). This increase is attributable to a persistent commitment to research and ongoing innovation, sustained even during periods of skepticism (Nilsson, 2009).

The global competition in AI specialization has intensified, with the United States and China holding a significant advantage due to their access to extensive datasets. In contrast, Europe's stringent data privacy laws may hinder its capacity to develop advanced AI systems (Klinger et al., 2021; Savage, 2020). China, alongside the USA, Canada, and Asian countries such as Singapore and South Korea, has emerged as a global leader in AI (Klinger et al., 2021). This international rivalry has driven an increase in both academic and patent publications related to AI. Between 1960 and early 2018, nearly 340,000 AI-related patent families and over 1.6 million scientific papers were published, with the number of scientific papers being approximately 4.7 times greater than that of patents (WIPO, 2019). The surge in AI-related scientific publications began about a decade before the rise in patents, with an average annual growth rate of 8 percent between 1996 and 2001 (WIPO, 2019).

While it may seem logical that an increase in scientific and technological knowledge would naturally lead to a nation's specialization in AI, the reality is more complex. For instance, AI patenting is primarily dominated by a few large firms, suggesting that simply increasing knowledge does not automatically result in widespread AI specialization (Igna & Venturini, 2023). Moreover, there has been a recent stagnation in the diversity of AI research, further complicating the relationship between knowledge accumulation and AI specialization (Igna & Venturini, 2023).

The situation is particularly challenging in less technologically and economically developed countries with limited AI technical capabilities. Despite the importance of understanding how these countries can specialize in AI, this area has not received sufficient attention. Liu et al. (2020) argue that for nations with lower levels of technological development, strategies should be formulated to foster AI development and application, promoting knowledge creation and technology spillover effects. Their evidence indicates that the impact of AI on technological innovation varies across sectors, with AI exerting a more significant influence on low-tech sectors in China. This suggests that even countries with limited technological advancement can harness AI to catalyze innovation, particularly in less complex sectors.

3.2.4 A multidimensional approach to science and technology

Adopting a multidimensional approach to comprehend the interaction between scientific research and technological development, various studies have utilized the analysis of publication-patent citations (Callaert et al., 2014; Narin & Olivastro, 1992; Narin et al., 1997). This method involves examining data on citations in patents by local inventors to scientific publications of researchers in the same region, offering insights into the scientific and technological relationship. Extensive exploration of this relationship has shown a positive influence of scientific publications on patenting, as evidenced in several studies (Fleming & Sorenson, 2001; Fritsch & Slavtchev, 2007).

However, this approach has limitations, particularly in understanding multidimensionality through paper-patent citation links or volume comparisons. A key challenge is the discrepancy in citation frequencies between patents and scientific publications, which hinders the accurate capture of knowledge flows (Engelsman & van Raan, 1994). This indicates that paper-patent citations may not fully capture the comparative advantage in the multidimensional knowledge space among countries (Guevara et al., 2016). Moreover, the rapid increase in scientific and technological knowledge does not always translate into significant advancements. Recent research suggests a stagnation in progress across various fields, with papers and patents becoming less impactful in guiding new directions in scientific research and technological invention (Park et al., 2023). Thus, comparing the quantity of patents and papers also falls short in understanding spatial spillovers.

Addressing these limitations, Pugliese et al. (2019) proposed a novel, multi-layered approach to connect scientific, technological, and productive capabilities. Expanding upon the conditional probability model, they devised a tri-layered network to capture interactions among scientific publications, patenting, and industrial production across sectors, incorporating time lags. This method is grounded in the concept of relatedness, the statistically significant co-occurrence of two activities within the same countries at specific times (Hidalgo et al., 2018). This framework establishes connections across different activity layers, including scientific fields, technological sectors, and economic production, offering insights into the capabilities and timelines needed to convert technological expertise into economic wealth and scientific innovation.

Furthering this multidimensional approach, Catalán et al. (2022) introduced the 'cross-proximity' concept, defining scientific and technological cross-density as the average proximity of potential new technologies to a country's existing scientific and technological portfolio, examining the influence of endogenous scientific research capabilities on technological diversification. Their two-stage method, applied to data from 182 countries over 1988–2014, started with constructing the 'scientific research and technological invention cross-space' network, linking knowledge and technologies based on co-occurrence values. They then assessed the impact of scientific-technological cross-density and technological density on technological diversification at the country level. Their results showed that the proximity of new technology to a country's scientific portfolio positively impacts its adoption probability. They also discovered that the effect of technological density on diversification surpasses that of the combined scientific and technological density.

Moreover, the optimal cognitive proximity theory to the multidimensional space of scientific research and technological invention, suggesting that knowledge transfer may be impeded if the cognitive proximity between two entities is either too low or, conversely, too similar (Nooteboom, 2000). This is because a great cognitive distance may impede effective communication, whereas a small cognitive distance may result in lock-in, preventing learning from external sources (Boschma, 2005).

Despite these advancements, these studies may not entirely address the diverse impacts of different knowledge characteristics. They align with traditional economic views that consider technologies as uniform drivers of economic growth (Abramovitz, 1956; Solow, 1957). Conversely, GPTs like AI demonstrate high self-productivity, boosting productivity and the innovation process, significantly contributing to economic growth (Aghion et al., 2019; Brynjolfsson et al., 2019; Cockburn et al., 2019; Goldfarb & Trefler, 2019). The diffusive potential of AI technologies enables them to permeate a broad and continuously expanding range of application sectors. Additionally, their complementary nature allows them to augment and enhance products and processes across various industries (Brynjolfsson & Mitchell, 2017; Cockburn et al., 2019). This highlights the need to investigate how GPTs like AI exhibit complementary effects in a multidimensional space.

3.3 Data and Methodology

3.3.1 Data

AI-related patents

Identification of AI technologies presents a challenge due to the dynamic nature of AI concepts and their broad application across various industries, including autonomous vehicles, drug discovery, and robotics (UKIPO, 2019; WIPO, 2019). Consequently, many researchers have proposed diverse methods for extracting information from patents and articles (Buarque et al., 2020; Cicerone et al., 2023; Cockburn et al., 2019; WIPO, 2019; Xiao & Boschma, 2022). Several strategies for classifying AI technologies have been suggested, such as keyword-based searches of titles and abstracts of documents like patents, proceedings, and studies (Cicerone et al., 2023; Hötte et al., 2022), categorizing AI patents using the Cooperative Patent Classification (CPC) system (Xiao & Boschma, 2022), and combining key phrases with CPC symbols (Buarque et al., 2020). These methods can be broadly grouped into key-phrase-based, CPC-based, and hybrid approaches, each with its own advantages and limitations. CPC-based methods are noted for their weak GPT features like growth, generality, and complementarity (Hötte et al., 2022), while hybrid approaches exhibit similar characteristics. In contrast, the keyword-exact matching method demonstrates robust growth and generality in the technology (Hötte et al., 2022). For this study, we employed the key-phrase-based method and assessed its robustness by comparing results with alternative approaches, including the CPC-only method, a combination of keywords and CPC codes, and keywords from titles only. In the appendix, a detailed overview of these methods is provided.

This research utilizes patents registered with the United States Patent and Trademark Office (USPTO), sourced from the European Patent Office (EPO)'s PATSTAT database (EPO, 2022). The focus on USPTO patents, excluding patent families from offices like the Japanese Patent Office (JPO), Korean Intellectual Property Office (KIPO), and China National Intellectual Property Administration (CNIPA), is due to the USPTO's unique advantages. Firstly, the USPTO adheres to the Cooperative Patent Classification (CPC) system, a continuously evolving framework that systematically categorizes emerging technologies, including AI, with over 260,000 categories (Kang & Tarasconi, 2016). Secondly, the lack of a unified classification system for AI-related patent applications across different jurisdictions means that each country's patent management system and standards could lead to data inconsistencies when integrating patents globally (UKIPO, 2019). Additionally, patent applicants often file in multiple jurisdictions, potentially causing duplicate records and overrepresentation of certain countries' patents (UKIPO, 2019). Therefore, the USPTO is widely used in research, though it does not encompass innovation activities from all countries (Catalán et al., 2022; Montresor & Quatraro, 2020).

AI-related papers

This study collected and refined USPTO patents from the PATSTAT 2022 Spring version, a globally recognized database for bibliographic patent information maintained by the EPO, following specific criteria (EPO, 2022). AI-related patent applications were initially gathered using AI-relevant keywords from the titles and abstracts in the patent bibliographic information. The approach for selecting AI-related keywords, as suggested by WIPO (2019), was adopted to ensure high relevance to AI (for details on AI-related keywords and CPCs, refer to Appendix).

In collecting patent applications, this study limited the documents to invention patents only. Utility models and other non-invention patents were excluded by filtering the PATSTAT 'ipr_type' field to 'PI'. Applicant and inventor names were sourced from the PATSTAT 'Standardized Name' field (psn_name), and the country information for applicants and inventors came from the 'person_ctry_code' field in PATSTAT, with additional processing due to incomplete data coverage. In cases where a patent inventor was affiliated with institutions in two countries, the patent application was counted separately for each country, without considering the inventor's proportional contribution. However, where country information was predominantly missing, no country was assigned. Notably, data for China is underrepresented due to inconsistencies in applicant and inventor information for Chinese patents in the PATSTAT database, as identified by the UKIPO (2019).

After excluding subclasses without registered patents, 654 subclasses and 407,386 patents were analyzed. To examine temporal patterns, we split the data into nine 5-year snapshots. The data were organized by country (204 countries), time period (eight 5-year intervals), and technology subclass (four-digit CPC codes), resulting in a (204 × 8 × 654) matrix for the invention patent matrix.

This study analyzed scientific publications from the Web of Science (WoS) Core Collection, covering the period from 1980 to 2019, to construct a scientific knowledge space. The WoS database includes three primary citation indices: The Science Citation Index Expanded (SCIE), the Social Sciences Citation Index (SSCI), and the Arts and Humanities Citation Index (AHCI). Our analysis was centered on the SCIE sections of the WoS Core Collection, which span five major disciplines: Arts & Humanities, Life Sciences & Biomedicine, Physical Sciences, Social Sciences, and Technology. In line with the methodology described by Catalán et al. (2022), we targeted articles within SCIE related directly to technological inventions in AI. As a result, this study excluded the SSCI and AHCI sections. Furthermore, we confined our dataset solely to journal articles, specifically excluding conference proceedings, reviews, and books. Publications lacking an institutional address were also omitted from our analysis.

The WoS bibliographic database enables the classification of papers based on the authors' institutional affiliations and the journals' research categories (WoS, 2020). In this system, publications are associated with countries using the institutional addresses provided by the authors, with each author's country considered to contribute equally to the publication. Our study did not distinguish between countries based on the order of authors, the first author, or the degree of co-authorship contributions, as fractional counting and corresponding authorship-based counting are alternative methods. This approach was influenced by WoS's notably inaccurate coverage of corresponding author information before 2008, which often defaulted to the first author/institution as the corresponding author.

Consequently, in cases where an author is affiliated with institutions in multiple countries, each country is equally attributed the journal publication. These methods show high correlation at a macro level (Catalán et al., 2022).

Overall, the WoS is a valuable tool for analyzing the global landscape of AI research, but potential biases in classifying countries based on author affiliations should be considered. Additionally, it is important to recognize that this method of bibliographic data collection may overestimate research outputs from Western countries and English-language publications, introducing potential bias in country classification.

Through these meticulous data preprocessing efforts, we were able to construct the following dataset: The AI-related papers we collected encompass 230 subcategories out of 252, totaling 468,104 scientific articles published between 1980 and 2019. To examine temporal patterns, we divided the data into eight 5-year intervals. The data were organized by country (170 countries), time period (eight 5-year intervals), and research area (230 disciplines), resulting in a (170 × 8 × 230) matrix of scientific publications.

3.3.2 **Dependent variable**

Balassa (1965) introduced RCA to determine a country’s relative advantage in specific products. This methodology can be suitably adapted for specific technologies using the following mathematical representation:

$$RCA_{c,j,t} = \frac{patent_{c,j,t} / \sum_{j} patent_{c,j,t}}{\sum_{c} patent_{c,j,t} / \sum_{c}\sum_{j} patent_{c,j,t}} \qquad \text{Eq.(1)}$$

where $c, j,$ and t denote the country, technology, and time, respectively. An RCA value greater than 1 signifies a comparative advantage in technology j for country c at time t. ENTRY refers to the introduction of new technologies or activities into a certain area such as a city, region, or country (Klepper, 1996). It represents the diversification and renewal in technological industries and is used to measure technological change (Boschma et al., 2015). In some contexts, ENTRY is used as a binary variable (0 or 1) to show the introduction of a new technology with comparative advantage in a country. The $ENTRY_{c,j,t}$ formula represents the probability of a country transitioning to a comparative advantage with a specific technology (technological specialization). This can be mathematically expressed as

$$ENTRY_{c,j,t} = P(RCA_{c,j,t} > 1 \mid RCA_{c,j,t-1} < 1) \qquad \text{Eq.(2)}$$

where $ENTRY_{c,j,t}$ calculates the probability that country c will gain a comparative advantage in technology j at time t, since it did not have a comparative advantage in the same technology at the previous time point ($t - 1$). This measure captures the likelihood of a country transitioning from a disadvantage to an advantage position in a particular technological domain over time. The $EXIT_{c,j,t}$ formula denotes the likelihood that a country will relinquish its comparative advantage in a specific technological domain. This is formally defined as

$$EXIT_{c,j,t} = P(RCA_{c,j,t} < 1 \mid RCA_{c,j,t-1} > 1) \qquad \text{Eq.(3)}$$

where $EXIT_{c,j,t}$ computes the probability that country *c* loses its comparative advantage in technology *j* at time *t*, since it possesses a comparative advantage in the same technology during the previous period ($t - 1$). This metric gauges the propensity of a country to shift from a position of strength to weakness within a specific technology field over a given period.

3.3.3 Independent variable

Technology relatedness density

Technology relatedness density measures how closely related technologies are clustered around a given technology within a country at a certain time (Balland & Rigby, 2017). This can be derived from the technological relatedness of a technology to all other technologies in which the country has a relative technological advantage. The measure is calculated dividing the sum of the technological relatedness of the technology to all the other technologies in a specific country by the sum of technological relatedness of the technology to all the other technologies in a reference country. The calculation process for technology relatedness and technology-relatedness density is as follows. First, the technological relatedness ($\varphi_{i,j,t}$) between technology i and technology j is calculated as follows:

$$\varphi_{i,j,t} = P(RCA_{c,j,t} > 1 \mid RCA_{c,i,t} > 1) \qquad \text{Eq.(4)}$$

This value denotes the conditional probability that technology j exhibits a comparative advantage (RCA > 1) given that technology i has an RCA. Second, the technology-relatedness density is determined as follows:

$$TECH\_DEN_{c,j,t} = \frac{\sum_{j \in c, j \neq i} \varphi_{i,j,t}}{\sum_{i \neq j} \varphi_{i,j,t}} \times 100 \qquad \text{Eq.(5)}$$

This metric measures the average degree of technological relatedness between technology *i* and all other technologies *j* in country *c* at time *t*, excluding *i*. The value of relatedness density lies between 0% and 100%. A value of 0% indicates that there is no technology related to technology i in the country, while a value of 100% indicates that all the technologies related to technology i belong to the country's technological portfolio.

Cross-proximity density

The cross-proximity density between scientific research and technological invention, also known as "sci-tech cross-density", is a measure of how the scientific development in a country is connected to the technology sectors in which it aims to grow (Pugliese et al., 2019). This measure indicates the average proximity of a technology class to the current scientific structure of a country during a specific time period. A high sci-tech cross-density value implies that a country has a high degree of scientific development in areas closely related to the technology field it aims to develop. The importance of this measure lies in its ability to reveal the potential for a country to successfully develop new technologies based on its existing scientific research capabilities (Catalán et al., 2022).

For the cross-density analysis, we first calculate the proximity between scientific fields and technological classes. This calculation reflects the extent of overlap or connection between scientific fields and technological classes within a specific context, such as a country. It is instrumental in revealing how a country's scientific research capabilities align with its technological classes. A high proximity value indicates a close relationship between the country's scientific research and the technological areas it is focusing on, potentially leading to more efficient technology development and innovation. This proximity is measured using the minimum conditional probability, a well-established method in the literature (Catalán et al., 2022; Pugliese et al., 2019). This approach selects pairs of scientific fields and technological domains where both exhibit an RCA greater than 1. For these pairs, the minimum conditional probability is determined, using the lower of the two calculated conditional probabilities as the cross-proximity measure. This conservative approach offers a more accurate estimate of the relatedness between the two entities. The formula for this measurement is as follows:

$$\varphi^{X}{}_{sci,tech,t} = \min\begin{Bmatrix} P(RCA_{sci,t} > 1 \mid RCA_{tech,t} > 1) \\ P(RCA_{tech,t} > 1 \mid RCA_{sci,t} > 1) \end{Bmatrix} \qquad \text{Eq.(6)}$$

where *sci* denotes scientific category, *tech* denotes technological field, and *t* indicates time period. Second, for measuring the cross-relatedness density, we compute the average sci-tech cross-proximity for a technology class relative to the country's existing scientific structure within a specified time period. This is achieved through the equation:

$$CROSS\_DENSITY = \omega^{X}{}_{c,tech,t} = \frac{\sum_{tech \in c, tech \neq sci} \varphi^{X}{}_{sci,tech,t}}{\sum_{sci \neq tech} \varphi^{X}{}_{sci,tech,t}} \times 100 \qquad \text{Eq.(7)}$$

In this equation, cross-density quantifies the average degree of cross-proximity between a specific technological class (for instance, as defined by a four-digit CPC code) and all other scientific fields in the country *c* at time *t*. This metric is essential as it reveals the interrelatedness and co-occurrence patterns between scientific and technological fields, providing insights into the dynamics within a country’s innovation ecosystem.

Technology complexity

The technology complexity index (TCI) quantifies the complexity of technologies by analyzing the structure of the bipartite network that links countries to the technologies they develop. We employ the 'Method of Reflections' technique, as proposed by Hidalgo and Hausmann (2009), to calculate technology complexity. This approach accounts for a country's diversity (the range of technological fields it produces) and the ubiquity of these technologies (how commonly they are found across different countries). Initially, a country's diversity is determined by the number of technologies it produces, and the ubiquity of a technology is indicated by the number of countries producing it. Diversity mesures the degree centrality of country c in bipartite network that links countries to the technologies:

$$DIVERSITY = \sum_{j} M_{c,j} \qquad \text{Eq.(8)}$$

The ubiquity represents the degree centrality of technological class j:

$$UBIQUITY = \sum_{c} M_{c,j} \qquad \text{Eq.(9)}$$

Here, $M_{c,j}$ refers the two-mode matrix involving country c and technology j. It is defined as:

$$M_{c,j}\ (j = 1\ \ if\ \ RCA \geq 1,\ otherwise\ 0) \qquad \text{Eq.(10)}$$

This matrix indicates whether or not country c has a comparative advantage (RCA) in the production of technology j. In this approach, the use of "$M_{c,j}$" effectively minimizes undue variation by focusing solely on a marked presence ($M_{c,j} = 1$) or absence ($M_{c,j} = 0$). In the second step, technology complexity is calculated by sequentially combining diversity and ubiquity using two equations over a series of n iterations:

$$ECI = \frac{1}{UBIQUITY} \sum M_{c,j} TCI \qquad \text{Eq.(11)}$$

$$TCI = \frac{1}{DIVERSITY} \sum M_{c,j} ECI \qquad \text{Eq.(12)}$$

where ECI represents the economic complexity index, TCI signifies the technology complexity index, c denotes a country, and j denotes a technology. With each subsequent iteration, this method yields increasingly precise estimates of complexity by integrating feedback effects and considering the complexity of the technologies produced by a country or the complexity of countries producing a particular technology. The iterations cease when the ranking of countries and technologies stabilizes from one step to the next. The variables are represented in the following Table 4.

Table 4. List of variables and definitions

Variables	Abbreviation	Description	Data source
Entry of Technology	ENTRY	Introduction of new technology with RCA in a country	PATSTAT
Exit of Technology	EXIT	Termination of existing technology with RCA in a country	PATSTAT
Technology Relatedness Density	TECH_DENSITY	Density of technologies related to a specific technology	PATSTAT
Technology Complexity	TECH_ COMPLEXITY	Average diversity of countries with RCA in a given technology	PATSTAT
Scientific and Technological Cross-Density	CROSS_DENSITY	Average proximity of new technology to a country's scientific & technological portfolio	WoS PATSTAT
Population	POP	Total population of a country	World Bank
GDP per Capita	GDP_CAPITA	Gross domestic product divided by midyear population	World Bank
Technological Knowledge Stock	TECH_STOCK	Number of patent applications produced by a country	PATSTAT
Technology Size	TECH_SIZE	Number of patents per Cooperative Patent Classification (CPC)	PATSTAT

3.3.4 **Regression model**

To examine the probability of binary dependent variables, namely the entry and exit of technology, this study employs a panel logit model incorporating three-way fixed effects (FEs) for country, technology, and time to account for unobserved, time-invariant heterogeneity across cross-sectional units in countries (Country FEs), technologies (CPC FEs), and periods (Period FEs). The specified model is as follows:

$$\begin{aligned} ENTRY_{c,j,t} = {} & \beta_1 \times TECH\_DENSITY_{c,j,t-1} + \beta_2 \times TECH\_COMPLEXITY_{j,t-1} \\ & + \beta_3 \times CROSS\_DENSITY_{c,j,t-3} + \beta_4 \times TECH\_DENSITY^{sq}_{c,j,t-1} \\ & + \beta_5 \times TECH\_COMPLEXITY^{sq}_{j,t-1} + \beta_6 \times CROSS\_DENSITY^{sq}_{c,j,t-3} \\ & + \beta_{7-10} \times CONTROL_{c,j,t-1} + \alpha_c + \gamma_j + \delta_t + \varepsilon_{c,j,t} \end{aligned} \qquad \text{Eq.(13)}$$

where *c*, *j*, and *t* represent country, technology, and time period, respectively. The dependent variables include ENTRY and EXIT, which represent the introduction and termination of technology, respectively (Klepper, 1996). In the ENTRY model, the dependent variable is assigned a value of 1 if country *c* adopts a new RCA technology at time *t*; otherwise, the value is 0. In the EXIT model, the dependent variable takes a value of 1 if country c discontinues a preexisting RCA technology at time *t*; otherwise, the value is 0. The independent variables technology relatedness density (TECH_DENSITY) and technology complexity (TECH_COMPLEXITY) are lagged by one year, whereas sci-tech cross-density (CROSS_DENSITY) is lagged by three years, given that scientific knowledge adoption may take three years in this context (Finardi, 2011). Although previous studies (Catalán et al., 2022) considered four-year lag periods, the adoption process in AI fields, particularly in computer science, may be faster (WIPO, 2019). We also test for robustness by changing the time lag from 0 to 4. Because complexity and density may have an inverted U-shaped relationship with the dependent variable, this study includes squared terms for the independent variables. The control variables (POP, GDP_CAPITA, TECH_STOCK, and TECH_SIZE) were logarithmically transformed to mitigate size effects and normalize their distribution. All control variables are lagged by one year. To account for FEs, this study includes α_c, γ_j, and δ_t, which represent the country, technology, and time, respectively. In the preceding model, $\varepsilon_{c,j,t}$ represents the error term that captures the unexplained variation in the dependent variable that is not accounted for by the included independent variables and FEs.

3.4 Results

3.4.1 Descriptive statistics

Table 5 presents the descriptive statistics and correlation coefficients of the variables. The key independent variables (TECH_DENSITY, TECH_COMPLEXITY, and CROSS_DENSITY) had values ranging from 0 to 100. Because of the requirement for simultaneous observations in the scientific and technological knowledge space, TECH_DENSITY and TECH_COMPLEXITY have 26,300 observations each, whereas CROSS_DENSITY has 19,035 observations.

Table 5. Descriptive statistics and correlations

Variables	1	2	3	4	5	6	7	Obs.	Min	Max	Mean	S.D
1 TECH_DENSITY	1.0							26,300	-6.08	93.91	-1.51e-07	11.29
2 TECH_COMPLEXITY	–0.243	1.0						26,300	-60.63	39.36	1.45e-06	30.89
3 CROSS_DENSITY	0.531	–0.044	1.0					19,035	-22.46	77.53	3.22e-07	18.16
4 POP	0.278	0.002	0.306	1.0				24,719	9.62	21.05	15.92	2.28
5 GDP_CAPITA	0.327	–0.025	0.501	–0.413	1.0			23,583	5.63	12.08	9.09	1.36
6 TECH_STOCK	0.582	0.007	0.609	0.322	0.518	1.0		25,754	0.69	14.77	7.47	2.77
7 TECH_SIZE	0.082	–0.334	0.116	–0.044	0.063	–0.067	1.0	26,300	2.39	12.82	9.61	1.35

Note: TECH_DENSITY, TECH_COMPLEXITY, and CROSS_DENSITY are mean-centered. Values that are only observed in the technology or scientific research space are removed. The number of observations for the control variables varies due to uneven data collection across countries for TECH_SIZE, which also has 26,300 observations representing patents per CPC. As a result, the correlation coefficients between variables were generally low.

Figure 5 presents the trends in AI research and patenting activities, represented by the annual number of AI-related patents and articles from 1980 to 2019 in global countries. This analytical overview delineates the expansion and progression of AI-related research and innovation over time. An uninterrupted augmentation in AI-centered innovation activities in both the scientific and the technological sectors has been discernible since the 1980s. Notably, during the 2010s, the proliferation of research publications outpaced that of patents, emphasizing an accelerating intrigue in AI research and development across diverse disciplines.

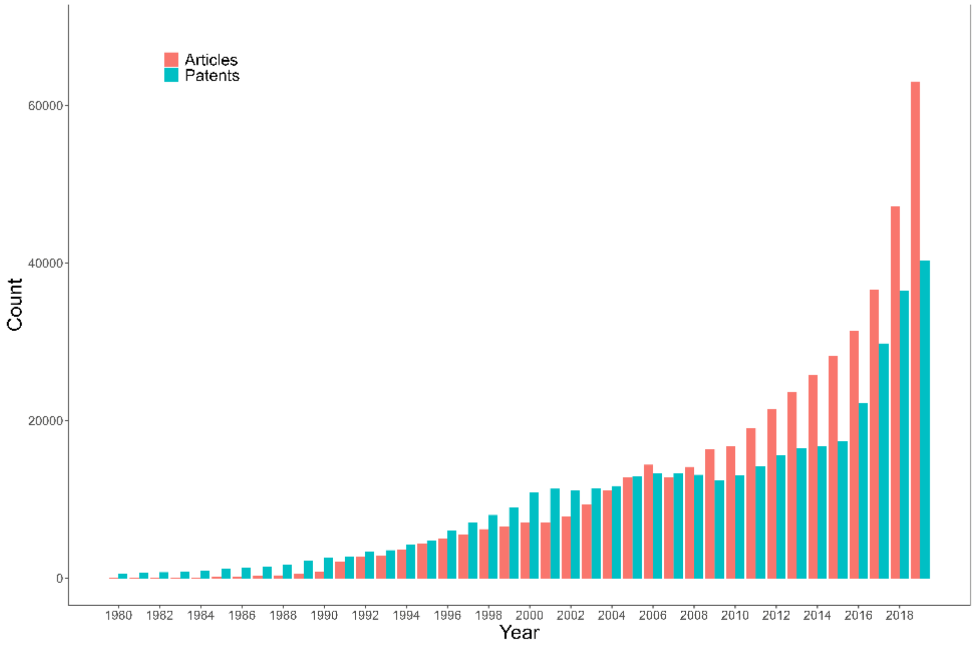


Figure 5. Number of AI articles and patents by year

Table 6 presents the top countries in AI knowledge production, which encompasses both technological and scientific knowledge, and the corresponding fields, from 1980 to 2019. In addition, the top 10 countries, CPC symbols, and disciplines were identified based on the greatest number of patents and articles. In terms of technological knowledge, the United States had 202,867 patents, followed by South Korea, Japan, Germany, and China. The most prevalent CPCs were G06F, G06N, H04L, G06Q, and G06V. The United States ranked first in scientific knowledge with 115,120 articles, followed closely by China, the United Kingdom, Germany, and Canada. The top disciplines in scientific knowledge production are computer science (AI), engineering (electrical & electronic), computer science (interdisciplinary), computer science (information systems), and neuroscience.

3.4.2 Scientific and technological space

In this study, we employ co-occurrence-based knowledge networks to probe the interaction between scientific and technological knowledge generation activities, emphasizing the period following the rapid AI advancements of the 2010s. The significant strides made in AI since 2012, underscored by the success of AlexNet (Kirzhevsky et al., 2012), provide the context for exploring the scientific and technological nexus from 2013 to 2017. Figure 6 depicts a knowledge space showing 161 scientific areas and 145 CPCs across 112 countries. This space, produced by the product of the matrix in Figure 7B and its transposed version in Figure 8B, illustrates the degree of interaction between scientific research and technological invention.

Table 6. Top AI knowledge production countries and fields

Technological Knowledge				Scientific Knowledge			
Country	Patents per Country	CPCs	Patents per CPC	Country	Articles per Country	Disciplines	Articles per Discipline
US	202,867	G06F	78,504	US	115,120	Computer Science (AI)	84,501
KR	48,915	G06N	71,052	CN	114,944	Engineering (Electrical & Electronics)	75,808
JP	36,548	H04L	38,946	UK	39,246	Computer Science (Interdisciplinary)	34,659
DE	35,995	G06Q	38,050	GE	26,235	Computer Science (Information Systems)	34,287
CN	32,102	G06V	31,098	CA	23,667	Neuroscience	33,175
FR	14,807	G06T	30,236	IN	21,776	Computer Science (Theory & Method)	28,257
CA	13,917	G06K	28,880	SE	19,836	Automation and Control Systems	20,353
UK	13,197	H04W	22,693	IT	19,817	Operations Research & Management Science	18,525
NL	9,542	H04N	20,235	IR	19,590	Environmental Sciences	17,066
IN	8,374	A61B	18,880	FR	19,035	Telecommunications	16,534

In Figure 6A, a network layout algorithm (Fruchterman & Reingold, 1991) situates undirected graph nodes based on their pairwise distances. The size of each node signifies the patent and article counts per CPC and discipline, with labels representing the initial three digits of each discipline and CPC category. These are subdivided into five scientific areas and eight technological fields. Figure 6B presents a cross-proximity matrix clustering scientific areas and technological fields with high co-occurrence probabilities. A limited number of these fields and areas, especially G06, H04, and A61, are significantly involved in the production of AI knowledge, including prolific disciplines such as computer science. Figure 7 illustrates the scientific research space encompassing 225 scientific areas in 160 countries during the same period. The WoS Core Collection (WoS, 2020), a widely used database for scholarly research, was used to categorize these scientific areas. This figure depicts the distribution of scientific areas and highlights the most active and visible research areas. Figure 8 shows the technology space, which includes 630 four-digit CPCs from 144 countries. The CPC scheme is divided into nine sections (A–H and Y) and subdivided further into classes, subclasses, groups, and subgroups. This figure offers a comprehensive view of technological fields, highlighting the most productive R&D areas. Collectively, these figures contribute to a broad understanding of the scientific and technological knowledge space, making it easier to identify potential academia–industry collaborations and future research opportunities.

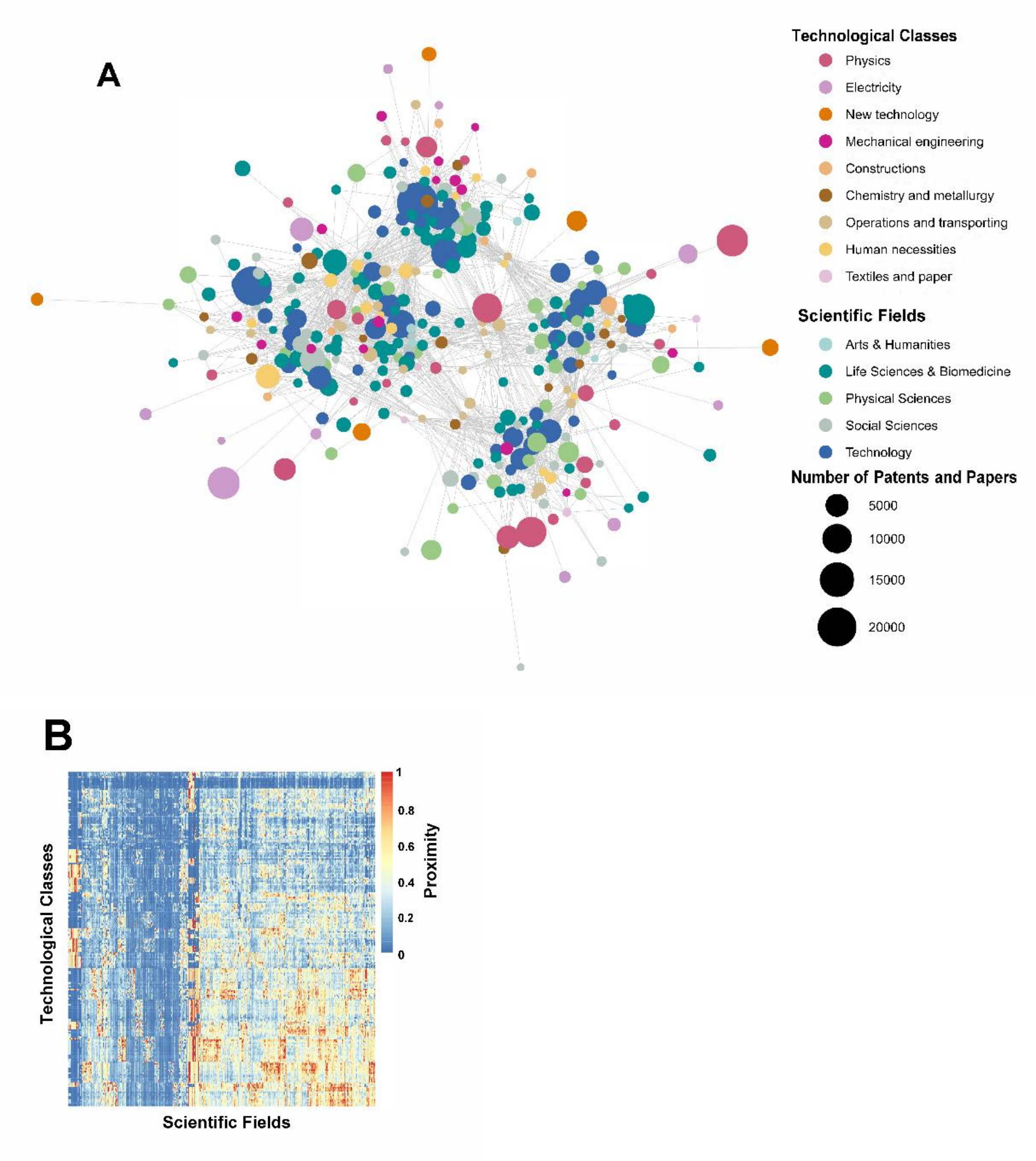


Figure 6. Scientific and technological knowledge space.

(A) Visualization of the scientific and technological knowledge space. (B) Representation of the hierarchically clustered proximity matrix.

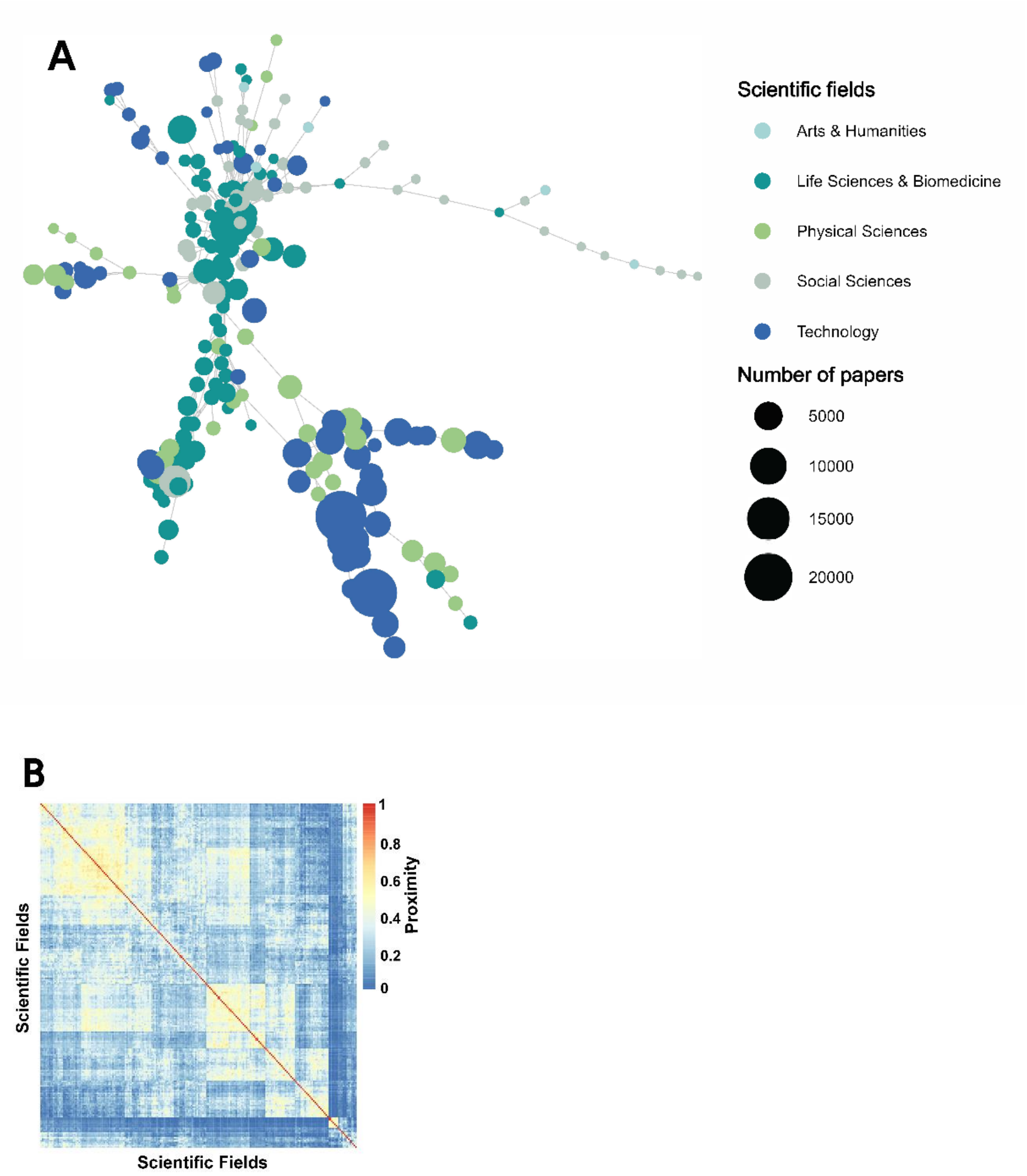


Figure 7. Scientific knowledge space.

(A) Graphic representation of the scientific research space. (B) Hierarchically clustered proximity matrix depiction.

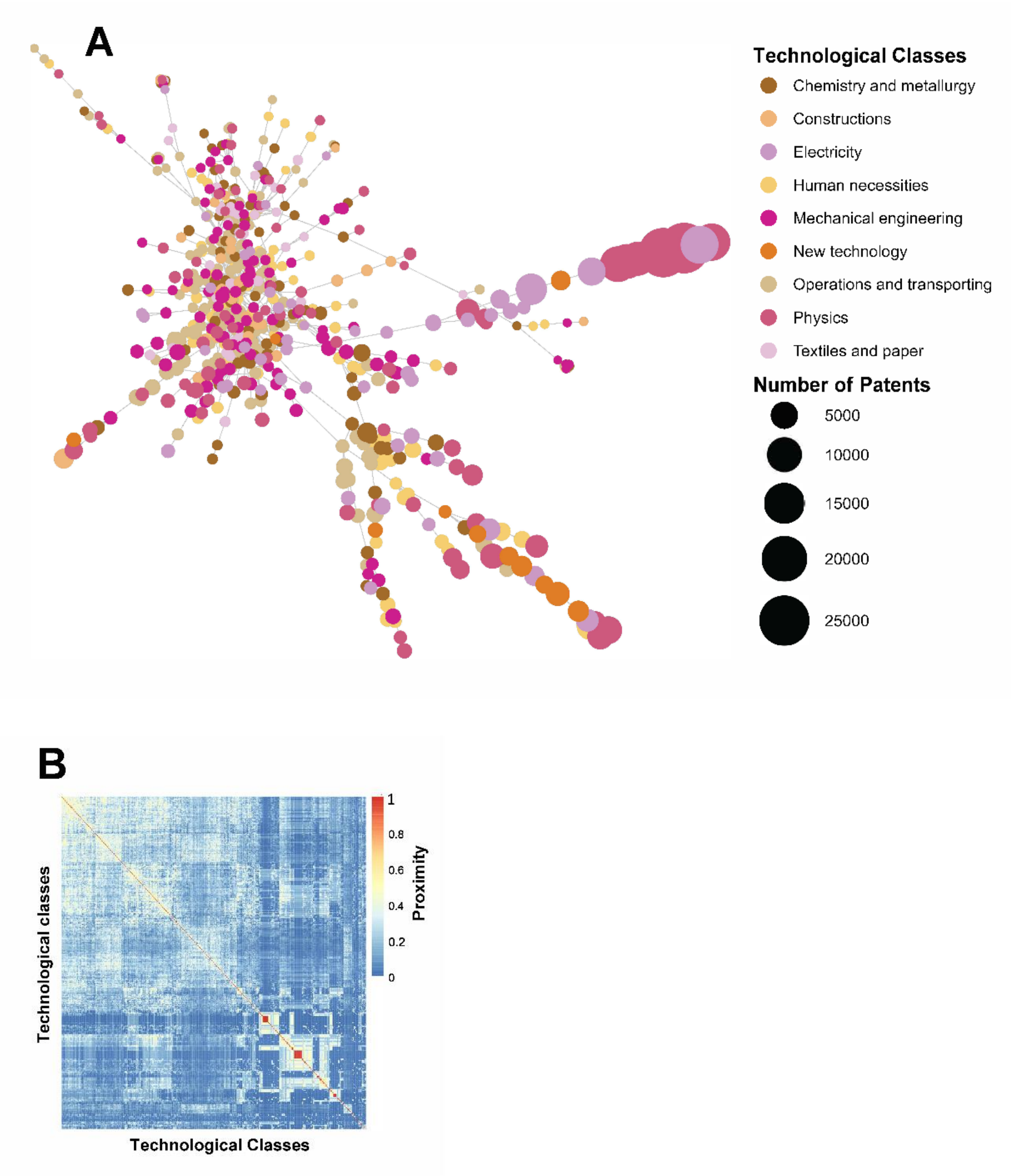


Figure 8. Technological knowledge space.

(A) Graphical illustration of the technology space. (B) Hierarchically clustered proximity matrix representation.

3.4.3 Panel logit regression results

Table 7 presents the panel logit regression results for ENTRY, examining three primary independent variables (TECH_COMPLEXITY, TECH_DENSITY, and CROSS_DENSITY) and control variables. In the panel logit model, the coefficients represent the estimated change in the log-odds of the outcome for a one-unit increase in the predictor variable. Therefore, these coefficients do not denote direct probabilities. Instead, they are associated with the odds, defined as the ratio of the event's probability (in this context, ENTRY) to the non-occurrence of the same event. The odds ratios are obtained by exponentiating the logistic regression coefficients. For example, the coefficient for TECH_DENSITY is 0.3206. The corresponding odds ratio, calculated as $e^{0.3206}$, equates to 1.378, suggesting a 37.8% increase in the odds of ENTRY for each unit increment in TECH_DENSITY. The findings reveal a statistically significant relationship between entry and both technology complexity and relatedness density at the 1% level. Specifically, increases in these variables are associated with a greater likelihood of entry into new technology with the other variables held constant.

Table 7. Panel logit regression main results

	Dependent variable: ENTRY				Dependent variable: EXIT			
	M1	M2	M3	M4	M1	M3	M2	M4
TECH_DENSITY	0.2137*** (0.0031)	0.3225*** (0.0047)	0.2137*** (0.0031)	0.3206*** (0.0047)	–0.1019*** (0.0031)	–0.1800*** (0.0067)	–0.1019*** (0.0031)	–0.1802*** (0.0068)
TECH_ COMPLEXITY	0.0073*** (0.0015)	0.0135*** (0.0015)	0.0066*** (0.0015)	0.0142*** (0.0016)	–0.0096*** (0.0031)	–0.0131*** (0.0031)	–0.0096*** (0.0031)	–0.0130*** (0.0032)
CROSS_DENSITY	0.0320*** (0.0016)	0.0286*** (0.0015)	0.0319*** (0.0016)	0.0431*** (0.0022)	0.0049** (0.0022)	0.0048** (0.0021)	0.0049** (0.0022)	0.0057 (0.0045)
DENSITY_sq		–0.0024*** (0.0001)		–0.0023*** (0.0001)		0.0011*** (0.0001)		0.0011*** (0.0001)
TECH_ COMPLEXITY_sq			–0.0001** (0.0001)	–0.0001** (0.0001)			0.0000 (0.0001)	0.0000 (0.0001)
CROSS_ DENSITY_sq				–0.0004*** (0.0001)				–0.0000 (0.0001)
POP	1.6318*** (0.1948)	1.5062*** (0.1980)	1.6182*** (0.1949)	1.3460*** (0.2012)	0.4190 (0.6125)	0.5112 (0.6204)	0.4204 (0.6129)	0.5152 (0.6208)
GDP_CAPITA	0.5374*** (0.0700)	0.5041*** (0.0713)	0.5289*** (0.0701)	0.4381*** (0.0719)	0.3316* (0.1742)	0.3216* (0.1825)	0.3318* (0.1743)	0.3240* (0.1826)

TECH_STOCK	–0.1529*** (0.0391)	–0.3956*** (0.0406)	–0.1492*** (0.0391)	–0.4172*** (0.0407)	0.4199*** (0.0985)	0.5690*** (0.1033)	0.4198*** (0.0985)	0.5682*** (0.1033)
TECH_SIZE	0.4954*** (0.0413)	0.4721*** (0.0417)	0.4951*** (0.0412)	0.4585*** (0.0418)	–0.3353*** (0.0858)	–0.3212*** (0.0867)	–0.3354*** (0.0858)	–0.3216*** (0.0868)
Country FEs	YES	YES	YES	YES	YES	YES	YES	YES
CPC FEs	YES	YES	YES	YES	YES	YES	YES	YES
Period FEs	YES	YES	YES	YES	YES	YES	YES	YES
N (group)	55,154 (11,403)	55,154 (11,403)	55,154 (11,403)	55,154 (11,403)	9,691 (3,059)	9,691 (3,059)	9,691 (3,059)	9,691 (3,059)
LR (χ^2)	17615***	17778***	17620***	18703***	2096***	2273***	2096***	2274***

Notes: Standard errors in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01

The dependent variable (ENTRY or EXIT) is binary (0 or 1). The independent and control variables are lagged by one year except for the CROSS_DENSITY, which is lagged by three years. The term 'sq' indicates a squared term.

The analysis reveals a robust, statistically significant correlation between scientific and technological cross-density and technology entry (ENTRY) at the 1% level. This suggests that a closer integration of a country's scientific and technological capabilities enhances the probability of technology entry, after adjusting for extraneous variables. The impact on the probability of ENTRY being 1 is notably most pronounced in the order of TECH_DENSITY, CROSS_DENSITY, and TECH_COMPLEXITY. Furthermore, the squared terms of these primary independent variables exhibit negative and statistically significant associations with ENTRY, indicating potential diminishing returns or intricate dynamics. This pattern suggests a nonlinear relationship, wherein initial increments in these variables may augment the likelihood of ENTRY. However, beyond a threshold, further increases could lead to reduced or even inverse effects on ENTRY.

Furthermore, as shown in Figure 9, the combined effect of technology complexity and scientific–technological relatedness density leads to a probability of ENTRY being 1. Thus, we can infer that the optimal combination of knowledge complexity and scientific–technological collaboration maximizes the effect of technological diversification within a given country.

In models where EXIT is the dependent variable, the coefficients represent the impact of the independent variables on the logarithmic odds of a technology's exit from a country. The analysis reveals that increases in technology complexity and technology-relatedness density are linked to a decreased likelihood of technology exit at a 1% significance level. The scientific and technological cross-density exhibits a positive association with EXIT at a 5% significance level in specific models; however, this relationship becomes statistically insignificant in subsequent models. The squared terms suggest a nonlinear relationship between technology-relatedness density and EXIT, whereas the relationships involving technology complexity and cross-density remain ambiguous. In conclusion, the results indicate distinct associations between the main independent variables and technology exit compared with technology entry. These findings have considerable implications for understanding the factors that influence the entry and exit, ultimately informing innovation policymaking.

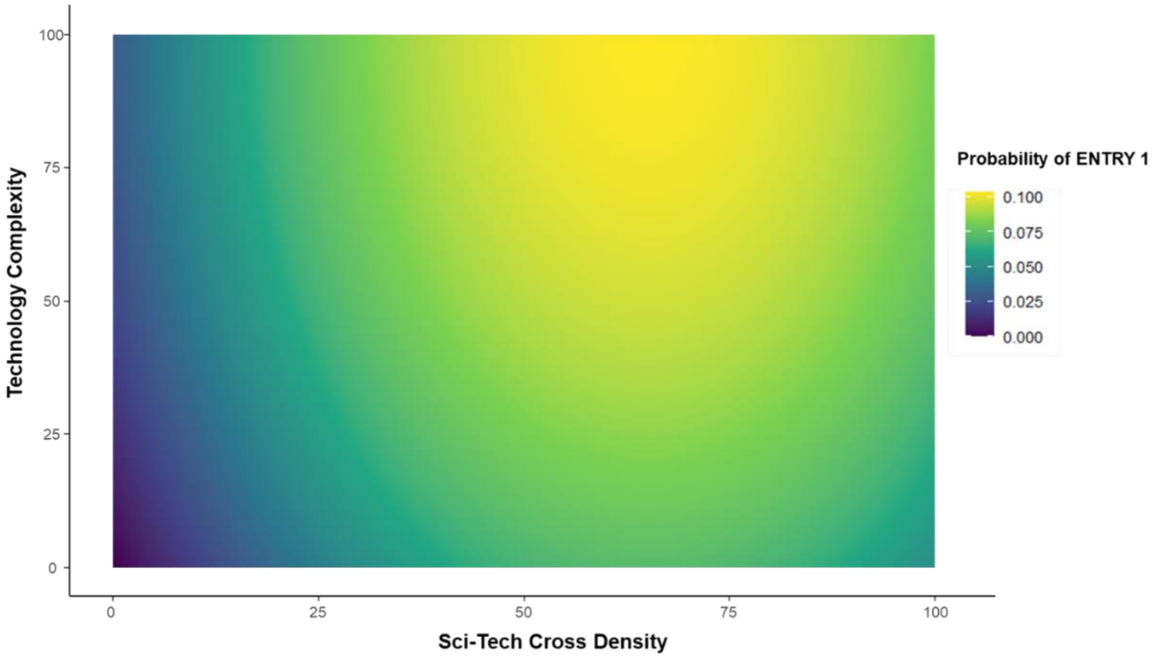


Figure 9. Combined marginal effects.

Notes: The brighter yellow shades indicate a stronger combined effect of technology complexity and scientific-technological relatedness density on the probability of ENTRY being 1. Second-degree terms were used to calculate the marginal effects of each variable. All variable coefficients are statistically significant at the 95% confidence level.

3.4.4 Robustness checks

Table 8 presents the robustness assessments of the main findings from Table 7 for ENTRY (Model 4) and EXIT (Model 4). The focus is on independent variables, segmented by income level and the top 10 AI knowledge producers. The analysis highlights key insights, notably the top 10 countries that effectively leverage complex knowledge for technology entry. These nations exhibit a higher impact of technology complexity on entry compared to others. However, the relationship between technology complexity and its effectiveness is characterized by an inverted-U shape, indicating that the benefits decrease when the complexity is either too high or too low.

In contrast, countries at lower stages of economic development appear less capable of utilizing complex technologies. In other words, the incremental increase followed by a decrease effect, as indicated by the squared terms, was not significant in these nations. This suggests that these countries may struggle to specialize in complex AI technologies due to a lack of foundational infrastructure, such as cloud services capable of training and managing large language models. The inability to utilize such advanced technologies for specialization highlights the challenges faced by less developed economies in harnessing the full potential of complex AI innovations.

Table 8. Panel logit regression results (outcome level)

	Dependent variable: ENTRY				Dependent variable: EXIT			
	High	Mid and Low	TOP10	Others	High	Mid and Low	TOP10	Others
TECH_DENSITY	0.3012***	0.3985***	0.1771***	0.4135***	–0.1715***	–0.2049***	–0.1236***	–0.2745***
	(0.0048)	(0.0130)	(0.0039)	(0.0073)	(0.0066)	(0.0458)	(0.0052)	(0.0166)
TECH_COMPLEXITY	0.0196***	0.0072*	0.0314***	0.0106***	–0.0148***	–0.0074	–0.0227***	–0.0046
	(0.0020)	(0.0031)	(0.0030)	(0.0021)	(0.0039)	(0.0105)	(0.0049)	(0.0064)
CROSS_DENSITY	0.0308***	0.0771***	0.0155***	0.0653***	0.0053	–0.0032	0.0039	0.0078
	(0.0022)	(0.0060)	(0.0023)	(0.0033)	(0.0040)	(0.0308)	(0.0037)	(0.0089)
DENSITY_sq	–0.0023***	–0.0032***	–0.0015***	–0.0033***	0.0011***	0.0004	0.0010***	0.0026***
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0009)	(0.0001)	(0.0003)
TECH_COMPLEXITY_sq	–0.0001***	–0.0001	–0.0001***	–0.0001**	0.0001	–0.0005	0.0001	0.0002*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
CROSS_DENSITY_sq	-0.0002***	-0.0010***	-0.0001	-0.0006***	-0.0001	0.0001	0.0001	-0.0002
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0008)	(0.0001)	(0.0001)
POP	1.0770***	0.5745	1.6070**	1.6911***	0.18055	–2.9284	0.4967	–0.6695
	(0.2502)	(0.4220)	(0.7042)	(0.2331)	(0.7088)	(1.9322)	(1.1141)	(0.8257)
GDP_CAPITA	0.7627***	0.2326*	–0.1816	0.9308***	0.4229	–0.1204	–0.0753	0.2992
	(0.1108)	(0.1333)	(0.1470)	(0.0932)	(0.2717)	(0.4091)	(0.2843)	(0.2766)

TECH_STOCK	–0.3366***	–0.5412***	–0.3277***	–0.4470***	0.6956***	0.2322	0.8476***	0.4627***
	(0.0575)	(0.0802)	(0.0853)	(0.0523)	(0.1294)	(0.2448)	(0.1676)	(0.1471)
TECH_SIZE	0.4049***	0.5592***	0.2531***	0.5349***	–0.3441***	–0.2729	–0.3343***	–0.3602***
	(0.0489)	(0.0861)	(0.0726)	(0.0529)	(0.0914)	(0.3124)	(0.1200)	(0.1354)
Country FEs	YES	YES	YES	YES	YES	YES	YES	YES
CPC FEs	YES	YES	YES	YES	YES	YES	YES	YES
Period FEs	YES	YES	YES	YES	YES	YES	YES	YES
N (group)	41,153	13,496	16,730	37,726	8,673	1,004	5,489	4,191
	(8,284)	(3,027)	(3,530)	(7,794)	(2,639)	(414)	(1,587)	(1,471)
LR (χ^2)	14482***	4388***	6331***	12903***	2107***	217***	1542***	849***

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The dependent variables (ENTRY and EXIT) are employed from Model 4 in the main results, respectively. High denotes a high-income country. Middle- and low-income countries encompass upper-middle-, lower-middle-, and low-income countries. TOP10 denotes the top 10 countries that are most productive in terms of patents, whereas “Other” denotes the remaining countries.

Building on this, the concept of technology-relatedness density reflects a country's dependency on existing technological capabilities. In the context of technological diversification, it signifies the extent to which past competencies influence current endeavors (Colombelli et al., 2014). This effect was observed uniformly across all countries, where on average, nations exhibited a strong reliance on their existing capabilities when diversifying into new technological areas. Notably, the relationship between technology-relatedness density and diversification follows an inverted-U shape, as indicated by the positive first-order term and the negative second-order term. This implies that an overreliance on existing capabilities or a low correlation with them can diminish the effectiveness of diversification efforts.

Crucially, this path dependence seems to have a more pronounced impact in countries at lower levels of economic development. This suggests that nations with limited AI technological capabilities are at risk of being 'locked-in', finding it challenging to gain a comparative advantage in new AI domains. Consequently, this could exacerbate the 'rich get richer and the poor get poorer' phenomenon in the field of AI. Countries already advanced in AI are likely to continue advancing, while those with limited capabilities might struggle to catch up, potentially widening the technology gap in AI between more and less developed nations.

The research conducted by Liu et al. (2020), which observed positive effects from the integration of AI in China's low-tech industries, further supports this notion. For less technologically advanced countries, strategic development and application of AI could be a catalyst for knowledge creation and technology spillover effects. This, in turn, could enhance their overall level of technological innovation. Specifically, AI's role in bolstering technological innovation within low-tech sectors has been significant, indicating that AI technology is not just beneficial for high-tech industries or advanced economies. Expanding upon the research conducted by Liu et al. (2020), AI can be seen as a GPT that can augment and complement existing products and processes, affecting a wide range of industries (Brynjolfsson and Mitchell, 2017; Cockburn et al., 2019).

The EXIT models demonstrate a negative correlation across all groups between technology complexity and EXIT, with the negative effects being more pronounced in technologically advanced countries. This indicates that increased technological complexity reduces the probability of industry exit in these countries. Similarly, the technological relatedness density negatively influences the EXIT across all groups, suggesting that an increased relatedness density decreases the odds of industry exit. Nonetheless, the effects of scientific and technological relatedness density on EXIT are not statistically significant, indicating that the interaction of scientific research and technological invention does not significantly contribute to a nation’s ability to maintain technological competitiveness. Despite differences in income levels and top AI knowledge producers when compared with the average, the relationships are statistically significant and consistent with expectations. Technologically advanced countries tend to capitalize on complex knowledge, lowering the likelihood of exit from a technologically complex industry.

Conversely, less advanced countries appear to rely more on preexisting knowledge bases, exhibiting distinct technology entry and exit dynamics when compared with the global norm. These findings add to our understanding of the determinants of technology entry and exit, and they may have implications for future innovation policy formulation while preserving the robustness of the findings. The notion that income-specific factors shape these relationships suggests that policymakers should investigate further.

To bolster the reliability and consistency of our findings, we conducted robustness checks on the panel logit models using various specifications, accounting for potential biases and confounding influences. This involved stratifying specifications through groupings and applying three-way FEs for countries, technologies, and periods. Initially, the countries were categorized by income level, which facilitated validating our results in different stages of development and exploring heterogeneity between income groups. Subsequently, the countries were divided into two groups: The top 10 countries that produce the most knowledge in terms of technological advancement and the rest. This allowed us to examine whether the level of technological development of a country influenced the regression model coefficients. Technologies were then classified according to specific schemes, addressing the potential effects of technology-specific characteristics on the relationship between the dependent and independent variables. This step helped ensure the robustness of our findings across various technologies. Finally, time lags were incorporated into the analysis to control for potential period-specific effects, recognizing that relationships between variables might evolve or display time-lagged effects, strengthening our results’ robustness and consistency across time frames.

In conclusion, when countries were divided into groups based on their economic and technological maturity, some deviation from the global average was observed. Nonetheless, the primary model's main findings retained statistical consistency and significance.

For additional validation, table 9 provides a robustness check using various AI classification schemes: 1) key phrases from patent document abstracts and titles, 2) key phrases from patent document titles, and 3) CPC symbols suggested by the World Intellectual Property Organization. Despite some differences between these schemes and the limitations of the CPC-only approach, the robustness of the relationships between the independent and control variables, as well as ENTRY and EXIT, is confirmed across the schemes, underscoring the validity and generalizability of the main results.

Table 9. Panel logit regression results (classification schemes)

	Dependent variable: ENTRY			EXIT		
	Key phrases (Title, Abs.)	Key phrases (Title)	CPC symbols	Key phrases (Title, Abs.)	Key phrases (Title)	CPC symbols
TECH_ COMPLEXITY	0.01426***	0.01267***	-0.00683**	-0.01304***	-0.01228***	0.01612*
	(0.00160)	(0.00188)	(0.00308)	(0.00321)	(0.00432)	(0.00832)
TECH_DENSITY	0.32061***	0.26685***	0.04666***	-0.18025***	-0.16474***	0.00545
	(0.00472)	(0.00475)	(0.00617)	(0.00685)	(0.00746)	(0.01404)
CROSS_DENSITY	0.04314***	0.03744***	0.03276***	0.00578	-0.00044	-0.00824
	(0.00220)	(0.00238)	(0.00626)	(0.00452)	(0.00554)	(0.01238)
TECH_ COMPLEXITY_sq	-0.00006**	-0.00006	-0.00042***	0.00001	-0.00003	0.00040**
	(0.00004)	(0.00004)	(0.00007)	(0.00007)	(0.00009)	(0.00016)
TECH_ DENSITY_sq	-0.00234***	-0.00178***	0.00027*	0.00113***	0.00106***	-0.00104***
	(0.00006)	(0.00006)	(0.00014)	(0.00008)	(0.00008)	(0.00031)
CROSS_ DENSITY_sq	-0.00042***	-0.00042***	-0.00050***	-0.00002	0.00006	0.00022
	(0.00004)	(0.00005)	(0.00016)	(0.00007)	(0.00009)	(0.00032)

POP	1.34602***	1.29161***	0.12742	0.51524	1.79639**	-0.60172
	(0.20128)	(0.26106)	(0.51051)	(0.62082)	(0.82830)	(1.42528)
GDP_CAPITA	0.43813***	0.17222**	0.12439	0.32404*	0.57281**	-0.28630
	(0.07199)	(0.08676)	(0.19999)	(0.18266)	(0.22582)	(0.42370)
TECH_STOCK	-0.41726***	-0.19816***	0.16544	0.56821***	0.46714***	0.37608
	(0.04072)	(0.04953)	(0.10354)	(0.10334)	(0.13429)	(0.23014)
TECH_SIZE	0.45857***	0.46403***	0.40700***	-0.32163***	-0.48436**8	-0.0776
	(0.04184)	(0.04630)	(0.08611)	(0.08680)	(0.09844)	(0.19172)
Country FEs	YES	YES	YES	YES	YES	YES
CPC FEs	YES	YES	YES	YES	YES	YES
Period FEs	YES	YES	YES	YES	YES	YES
N (group)	55,154	41,864	4,590	9,691	6,669	970
	(11,403)	(8,705)	(1,080)	(3,059)	(2,152)	(311)
LR (χ^2)	18703.03***	13884.53***	713.04***	2274.06***	1608.62***	89.79***

Notes: Standard errors in parentheses * p<0.1, ** p<0.05, *** p<0.01. The dependent variables ENTRY and EXIT in Model 6 from the main results are analyzed using different AI technology classification schemes. These schemes include key phrases from abstracts and titles of patent documents, key phrases from the titles of patent documents, and the CPC symbols suggested by the World Intellectual Property Organization (WIPO, 2019).

Table 10 evaluates the robustness of the main findings by varying the lagged years for ENTRY.

Table 10. Panel logit regression of ENTRY model (Lag 0–4)

	Dependent variable: ENTRY				
	M4 (Lag 0)	M4 (Lag 1)	M4 (Lag 2)	M4 (Lag 3)	M4 (Lag 4)
TECH_COMPLEXITY	0.01579***	0.01551***	0.01423***	0.01426***	0.00760***
	(0.00270)	(0.00159)	(0.00161)	(0.00160)	(0.00161)
TECH_DENSITY	0.55090***	0.29944***	0.30739***	0.32061***	0.22319***
	(0.00922)	(0.00455)	(0.00463)	(0.00472)	(0.00324)
CROSS_DENSITY	0.11203***	0.05855***	0.05210***	0.04314***	0.03554***

	(0.00314)	(0.00208)	(0.00217)	(0.00220)	(0.00216)
TECH_COMPLEXITY_sq	-0.00007	-0.00002	-0.00003	-0.00006*	-0.00007**
	(0.00005)	(0.00004)	(0.00004)	(0.00004)	(0.00004)
TECH_DENSITY_sq	-0.00318***	-0.00222***	-0.00225***	-0.00234***	-0.00234***
	(0.00016)	(0.00006)	(0.00006)	(0.00006)	(0.00006)
CROSS_DENSITY_sq	-0.00097***	-0.00033***	-0.00037***	-0.00042***	-0.00055***
	(0.00006)	(0.00004)	(0.00004)	(0.00004)	(0.00005)
POP	2.11210***	1.55846***	1.44574***	1.34602***	1.25800***
	(0.23975)	(0.19752)	(0.19888)	(0.20128)	(0.20377)
GDP_CAPITA	0.77203***	0.53743***	0.50835***	0.43813***	0.39546***
	(0.09342)	(0.07084)	(0.07103)	(0.07199)	(0.07234)
TECH_STOCK	-1.03117***	-0.36454***	-0.37079***	-0.41726***	-0.26026***
	(0.05196)	(0.03946)	(0.03995)	(0.04072)	(0.04119)
TECH_SIZE	0.42554***	0.46919***	0.44697***	0.445857***	0.46360***
	(0.05766)	(0.04123)	(0.04161)	(0.04184)	(0.04186)
Country FEs	YES	YES	YES	YES	YES
CPC FEs	YES	YES	YES	YES	YES
Period FEs	YES	YES	YES	YES	YES
N (group)	60,689	58,746	56,503	55,154	53,229
	(11,898)	(11,731)	(11,533)	(11,403)	(11,220)
LR (χ^2)	31429.38***	20365.80***	19325.38***	18703.03***	16946.67***

Notes: Standard errors in parentheses * p<0.1, ** p<0.05, *** p<0.01
The dependent variable ENTRY in Model 4 from the main results is analyzed by varying lagged years. In Model 4 (Lag 0–1), independent and control variables are lagged by zero or one year. In contrast, Model 4 (Lag 2-4) has most variables lagged by one year, while the CROSS_DENSITY is lagged from two to four years.

Table 11 presents a similar robustness test for EXIT.

Table 11. Panel logit regression of EXIT model (Lag 0–4)

	Dependent variable: EXIT				
	M6 (Lag 0)	M6 (Lag 1)	M6 (Lag 2)	M6 (Lag 3)	M6 (Lag 4)
TECH_	-0.03335***	-0.01256***	-0.01307***	-0.01304***	-0.01398***

COMPLEXITY	(0.00999)	(0.00319)	(0.00319)	(0.00321)	(0.00321)
TECH_DENSITY	-0.56658***	-0.17376***	-0.17689***	-0.18025***	-0.18109***
	(0.03558)	(0.00698)	(0.00691)	(0.00685)	(0.00683)
CROSS_DENSITY	-0.04674***	-0.01045**	-0.00123	0.00578	0.00890**
	(0.01218)	(0.00483)	(0.00464)	(0.00452)	(0.00445)
TECH_COMPLEXITY_sq	-0.00025*	-0.00001	-0.00000	0.00001	0.00000
	(0.00015)	(0.00007)	(0.00007)	(0.00007)	(0.00007)
TECH_DENSITY_sq	-0.00068	0.00114***	0.00113***	0.00113***	0.00115***
	(0.00074)	(0.00008)	(0.00008)	(0.0008)	(0.00008)
CROSS_DENSITY_sq	-0.00038	-0.00000	-0.00002	-0.00002	-0.00008
	(0.00025)	(0.00008)	(0.00007)	(0.00007)	(0.00007)
POP	-4.43734***	0.14604	0.26026	0.51524	0.43236
	(1.19452)	(0.61811)	(0.61913)	(0.62082)	(0.62903)
GDP_CAPITA	-0.28694	0.28401	0.30337*	0.32404*	0.34537*
	(0.38664)	(0.18155)	(0.18177)	(0.18266)	(0.18389)
TECH_STOCK	2.04376***	0.55428***	0.55978***	0.56821***	0.58182***
	(0.22589)	(0.10150)	(0.10269)	(0.10334)	(0.10367)
TECH_SIZE	-0.28930	-0.31566***	-0.31389***	-0.32163***	-0.32716***
	(0.19897)	(0.08701)	(0.08700)	(0.08680)	(0.08701)
Country FEs	YES	YES	YES	YES	YES
CPC FEs	YES	YES	YES	YES	YES
Period FEs	YES	YES	YES	YES	YES
N (group)	9,854	9,746	9,746	9,746	9,746
	(3,102)	(3,076)	(3,076)	(3,076)	(3,076)
LR (χ^2)	6301.2-***	2286.73***	2246.39***	2274.06***	2287.30***

Notes: Standard errors in parentheses * $p<0.1$, ** $p<0.05$, *** $p<0.01$
The dependent variable EXIT in Model 6 from the main results is analyzed by varying lagged years from zero to four years.

3.4.5 Marginal and net effect analysis

To elucidate the relationship between AI technology dynamics and influential factors, we present the estimated average marginal effects of these factors on the probability of AI technology entry and exit (Table 12).

Table 12. Average marginal effects and net effects

	Dependent variable: ENTRY				Dependent variable: EXIT			
	M1	M2	M3	M4	M1	M2	M3	M4
TECH_DENSITY	0.0066***	0.0104***	0.0066***	0.0103***	–0.0119***	–0.0218***	–0.0119***	–0.0219***
	(0.00008)	(0.00010)	(0.00001)	(0.00010)	(0.00026)	(0.00060)	(0.00026)	(0.00060)
TECH_COMPLEXITY	0.0002***	0.0004***	0.0006***	0.0007***	–0.0012***	–0.0016***	–0.0012	–0.0016**
	(0.00004)	(0.00000)	(0.00011)	(0.00011)	(0.00029)	(0.00028)	(0.00080)	(0.0032)
CROSS_DENSITY	0.0009***	0.0008***	0.0009***	0.0017***	0.0006***	0.0005***	0.0006***	0.0012**
	(0.00004)	(0.00004)	(0.00004)	(0.00010)	(0.00023)	(0.00021)	(0.00023)	(0.00073)
DENSITY_sq		–0.0001***		–0.0001***		0.0001***		0.0001***
		(0.00000)		(0.00000)		(0.00000)		(0.00001)
TECH_COMPLEXITY_sq			–0.0000***	–0.0000***			–0.0000	0.0000
			(0.00000)	(0.00000)			(0.00001)	(0.00001)
CROSS_DENSITY_sq				–0.0001***				–0.0001
				(0.00000)				(0.00001)
POP	0.0491***	0.0419***	0.0486***	0.0394***	0.0124	0.0237	0.0124	0.0252
	(0.00509)	(0.00517)	(0.00510)	(0.00525)	(0.05729)	(0.05517)	(0.05739)	(0.05538)
GDP_CAPITA	0.0161***	0.0137***	0.0158***	0.0120***	0.0418**	0.0425**	0.0418**	0.0430**
	(0.00188)	(0.00517)	(0.00188)	(0.00191)	(0.05729)	(0.01647)	(0.01554)	(0.01645)
TECH_STOCK	–0.0043***	–0.0102***	–0.004***	–0.0011***	0.0472***	0.0605***	0.0472***	0.0603***
	(0.00101)	(0.00517)	(0.00101)	(0.00105)	(0.00823)	(0.00883)	(0.00823)	(0.00881)
TECH_SIZE	0.0140***	0.0129***	0.0141***	0.0120***	–0.0400***	–0.0364***	–0.0400***	–0.0365***
	(0.00117)	(0.00115)	(0.00116)	(0.00115)	(0.00781)	(0.00758)	(0.00780)	(0.00759)
Net effects†		0.01045	0.00061	0.00173		-0.02186		
Country FEs	YES	YES	YES	YES	YES	YES	YES	YES
CPC FEs	YES	YES	YES	YES	YES	YES	YES	YES
Period FEs	YES	YES	YES	YES	YES	YES	YES	YES

N (group)	41,153 (8,284)	13,496 (3,027)	16,730 (3,530)	37,726 (7,794)	8,673 (2,639)	1,004 (414)	5,489 (1,587)	4,191 (1,471)
Log Likelihood	-17322.89	-16591.83	-17317.15	-16524.15	-4491.97	-4347.49	-4491.97	-4346.94

Notes: Standard errors in parentheses * $p<0.1$, ** $p<0.05$, *** $p<0.01$

† The net effects were calculated only for quadratic terms that have statistically significant marginal effects at the 95% level or higher.

This study estimated the average partial effects for binary regression models with FEs and identified significant coefficient values at the 95% level or higher. As demonstrated in Figure 10, the average marginal effect of cross-density on ENTRY exceeds that of technology complexity. Concurrently, these factors positively correlate with a country’s AI technology specialization. Figure 11 delineates the average marginal effects of technology complexity and scientific and technological cross-relatedness density on the probability of AI technology exit. Both factors attenuate the potential of AI technology to exit from a country up to a certain threshold, beyond which they impart divergent impacts. With the escalation of technology complexity, the probability of AI technology exit correspondingly diminishes. However, cross-density, surpassing a certain threshold, fails to safeguard against the exit of AI technologies. Further, the net effects were calculated for quadratic terms that have statistically significant marginal effects at the 95% level or higher. For instance, the net influence on entry from technological relatedness is 0.01045, derived from $2 \times [-0.00007 \times -0.000000151] + [0.0104588]$ with an average value of -0.000000151, a marginal impact of -0.00007, an unconditional effect of 0.0104588, and a factor of 2 from quadratic derivation. The directionality and statistical significance of these coefficients were corroborated within the framework of the linear probability model.

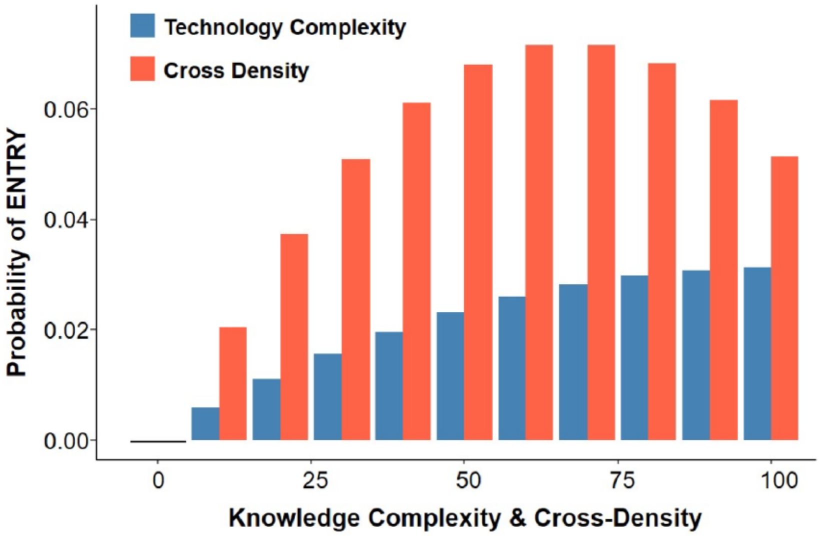


Figure 10. Marginal effects of ENTRY.

Note: Marginal effects of technology complexity and cross-density on the probability of ENTRY.

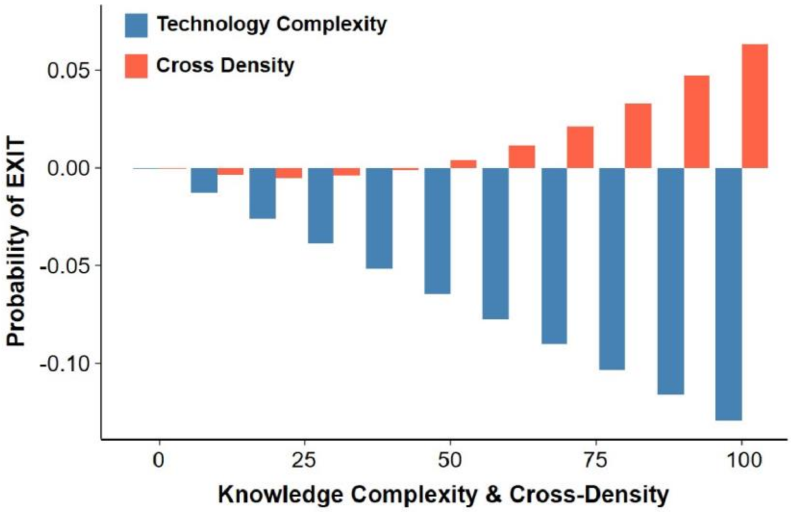


Figure 11. Marginal effects of EXIT.

Note: Marginal effects of technology complexity and cross-density on the probability of EXIT.

Hence, the results indicate that while the synergistic effects of scientific knowledge and technology significantly contribute to the creation of new knowledge for competitive advantage, complex technologies exert a weaker influence on new knowledge creation. However, they maintain a strong relationship with retaining competitiveness in existing technologies.

3.5 Discussion and conclusions

3.5.1 Discussion

This study explores the determinants influencing AI technology specialization, a key element for national competitiveness. We evaluate technological specialization at the country level using an RCA-based method, quantifying the relative advantage of technologies across multiple countries. Particularly, our research introduces the concept of cross-proximity density to explore how scientific research underpins technological progress in AI. Employing a three-way fixed-effect panel logit model, we analyze data from 170 countries spanning from 1980 to 2019.

Building on this framework, we discover that AI specialization is path dependent. This means that a country's transition towards new AI technologies is heavily influenced by its existing technological capabilities. Countries tend to specialize in AI technologies that are related to their pre-existing technological portfolios, supporting the principle of relatedness in economic complexity theory (Antonietti & Montresor, 2021; Balland & Rigby, 2017; Hidalgo et al., 2018). This principle posits that countries are inclined to branch out into areas akin to their existing technological and industrial capabilities.

Our findings also reveal that scientific research is a crucial underpinning for technological progress in AI, enhancing the comparative advantage of a country in these areas. This suggests that AI technological breakthroughs often originate from foundational scientific research. The scientific and technological cross-proximity density, reflecting the closeness between a country's scientific research and its focused technological fields, shows a positive and statistically significant relationship with the development of new AI technologies, pointing towards more efficient technological development and innovation. This finding aligns with recent empirical studies showing that scientific research capabilities can significantly influence the likelihood of countries developing technologies related to their scientific fields (Catalán et al., 2022; Guevara et al., 2016).

However, we note an intriguing pattern: the relationship between cross-proximity density and AI specialization takes an inverted-U shape. This extends the optimal cognitive proximity theory to the multidimensional space of scientific research and technological invention, suggesting that knowledge transfer may be impeded if the cognitive proximity between two entities is either too low or, conversely, too similar (Nooteboom, 2000). This highlights the importance of maintaining a balanced cognitive proximity for fostering innovation.

The study also identifies the influence of complex technologies on AI specialization.

While complex technologies do positively influence AI specialization, their impact is less pronounced than that of scientific knowledge. This suggests that in rapidly advancing fields like AI, incorporating new scientific knowledge into related industries may be more advantageous than simply advancing existing technologies to outpace competitors. These findings challenge the traditional view that increasing technological complexity is the primary pathway to gaining a competitive edge in AI (Petralia et al., 2017). On the other hand, it appears that increasing technological complexity is more effective in maintaining existing technological competitiveness than acquiring new scientific knowledge.

These insights offer valuable guidance for policymakers, especially in less developed nations. They underscore that these countries might lack the infrastructure for fostering AI specialization through technical complexity. However, in a rapidly evolving technological landscape, integrating AI into relevant sectors using novel scientific knowledge, even if less technically complex, could be more beneficial than emulating the approach of more advanced nations. This indicates a strategic pivot from prioritizing technological complexity to adopting a balanced strategy that capitalizes on fresh scientific discoveries.

Our study is not without limitations. The publication records used in this research do not fully represent all activities in the field of AI, particularly in the humanities, social sciences, and arts, due to our reliance on data from SCI journals. Nonetheless, by using paper and patent data that predominantly represent the academic and inventive activities in AI's computer science domain, this research contributes to connecting these two dimensions.

Looking ahead, we anticipate that future research could more comprehensively explore how technological breakthroughs in AI, such as those in recent large language models like ChatGPT, impact national technological competitiveness. This could be achieved using the multidimensional space model proposed in our study.

3.5.2 Conclusions

In conclusion, while enhanced scientific and technological knowledge acts as a catalyst for AI specialization in nations, the contemporary landscape presents a more complex picture. Merely expanding knowledge does not guarantee extensive AI specialization; its success depends on its relevant application. The interaction between scientific research and technological innovation is crucial for the emergence of new technologies, especially in settings characterized by optimal cognitive proximity. Moreover, the transition from scientific knowledge to technological specialization involves time lags, which are steadily shortening in rapidly evolving areas like AI. For nations seeking technological comparative advantage, integrating the latest scientific discoveries into related sectors is more effective than merely increasing the complexity of existing technologies to outstrip competitors. These insights are particularly valuable for policymakers in less technologically and economically developed countries, indicating that even with limited technological resources, strategically incorporating relevant AI technologies into closely aligned fields can provide a comparative edge.

3.5.3 Acknowledgments

This paper greatly benefited from comments and discussions by participants in the special session *"Data and network science methods in economic geography"* of the GEOINNO2022 conference (4–6 July 2022) at Bocconi University in Milan, Italy.

3.5.4 Data availability statements

The classification criteria for keyword searches of AI-related papers and patents were based on the WIPO's PATENTSCOPE Artificial Intelligence Index, accessible at https://www.wipo.int/tech_trends/en/artificial_intelligence/patentscope.html. Bibliometric data for this study were sourced from the Web of Science (WoS) Core Collection databases, owned by Clarivate Analytics. These bibliometric datasets can be obtained via keyword searches at https://www.webofscience.com/wos/woscc/basic-search. Patent bibliographic data can be accessed through the European Patent Office's PATSTAT online service, available at https://www.epo.org/searching-for-patents/business/patstat.html. Additionally, for economic data, including the classification of countries by income levels, the World Bank database is a viable resource (World Bank, 2023).

Chapter 4. National AI capabilities and product diversification

4.1 Introduction

Economic growth is driven by an evolutionary process of technological change and economic diversification, where technological change not only contributes to economic development but also necessitates the creation of new economic activities to sustain growth (Dosi, 1982; Freeman, 1974; Jacobs, 1969; Nelson & Winter, 1982; Pasinetti, 1983). As the economy evolves, diversification acts as a branching mechanism—spurring new economic ventures, bolstering resilience against disruptions (Frenken et al., 2007), and leveraging local competencies to give rise to fresh technologies, products, and industries, which in turn, fuel sustained growth (Saviotti & Pyka, 2004).

The genesis of these economic activities is intricately linked to the nation's existing capabilities, creating a path-dependent trajectory that influences the export of new products (Hidalgo et al., 2007; Tacchella et al., 2012; Zaccaria et al., 2014), the nurturing of emergent industries (Neffke et al., 2011), the exploration of novel scientific ideas (Boschma et al., 2014; Guevara et al., 2016), and the development of new technologies (Boschma et al., 2015). In particular, technological change and economic diversification enter a coevolutionary dance, each reinforcing the other to drive continuous economic progress (Eum & Lee, 2022).

Pugliese et al. (2019) conceptualize the national innovation system as a multi-layered network, elucidating the synergistic interaction between economic activities. They contend that a nation's product portfolio derives comparative advantages from not only its production capabilities but also the integration with technological competencies, a perspective echoed by Hausmann et al. (2014), who assert that economic complexity is intrinsically tied to a diverse knowledge base and is manifested in the country's array of complex product outputs.

The impact of technological capabilities on product diversification varies across countries. Traditional economic models often view technology as a homogeneous factor within production functions (Abramovitz, 1956; Solow, 1957), potentially overlooking the diverse evolutionary trajectories of product diversification across countries. Recent empirical studies reinforce the concept of co-evolution between technological innovation and product diversification in various sectors (Eum & Lee, 2022). However, these studies often treat technological capabilities as uniform contributors to economic growth, overlooking the heterogeneity and varying impacts of technological advancements. Most research has given insufficient attention to how the economic effects can differ based on the attributes of the technology.

In contrast, some economic historians emphasize the transformative impact of GPTs, such as steam engines, electricity, and semiconductors, historically catalysts for economic growth (Helpman & Trajtenberg, 1996; Rosenberg, 1979). GPTs, with their broad applicability and potential for stimulating complementary innovations, serve as enabling technologies that enhance downstream sector R&D productivity (Helpman & Trajtenberg, 1996; Bresnahan & Trajtenberg, 1995; Lipsey et al., 2005). Building on the role of GPTs in economic transformation, we focus on AI-related technologies, recently recognized as a next-generation GPT (Agrawal et al., 2019; Brynjolfsson et al., 2021; Cockburn et al., 2019). AI's capability to augment and integrate across sectors is profound, from automating tasks to transforming production methods and product features (Brynjolfsson & Mitchell, 2017; Cockburn et al., 2019). Its impact on R&D productivity is especially notable in fields like drug discovery, where its predictive abilities and management of large combinatorial spaces accelerate innovation (Agrawal et al., 2023; Liu et al., 2020).

However, the adoption of AI varies across industries and nations, influenced by disparities in technological progress and economic development (Mishra et al., 2023). Developed countries, with complex knowledge bases, integrate AI more effectively in product innovation, partly due to network externalities (Goldfarb & Trefler, 2019). In contrast, developing nations often follow a path-dependent approach, relying on existing knowledge and technologies (Hidalgo et al., 2007). This divergence not only illustrates varying AI adoption rates but also highlights economic growth disparities, underscoring the need for AI integration strategies tailored to each nation's unique context.

AI's transformative potential suggests a paradigm shift, introducing new economic activities and phasing out obsolete ones, contingent on a nation's existing capabilities (Hidalgo, 2021). The nexus between AI specialization and broader economic diversification remains underexplored (Mishra et al., 2023), leaving a gap in understanding AI's role in export product diversification.

This study addresses the underexplored area of AI's complementary effects on export product diversification. To assess the impact of AI on this diversification, we adopt the concept of 'cross-proximity density', initially proposed by Pugliese et al. (2019), building upon the fundamental principle of RCA from traditional trade theory (Balassa, 1965). We explore the relationship between national technological capabilities and product diversification through an analysis of international export data covering 145 countries over two decades (1999–2019). Our hypothesis is that products and AI technologies, which secure a comparative advantage for a nation, can act as catalysts for future product innovations. Considering AI's broad applicability, its potential for widespread integration, and its capability to augment diverse industries, we anticipate a significant impact, particularly in countries with diverse export portfolios. Countries with a broad range of capabilities are more likely to diversify into new industries and products, especially ones related to their existing strengths (Frenken & Boschma, 2007; Hidalgo et al., 2007). AI technologies can contribute to this process by boosting the competitiveness of products and enabling countries to diversify into new areas related to their current strengths (Mishra et al., 2023; Petralia et al., 2017).

Our findings demonstrate a complementary relationship between AI technology and a nation's export product diversification. Specifically, products closely associated with AI technologies are more likely to successfully enter new markets. However, this effect appears more pronounced in nations that have attained a certain level of technological and economic maturity. We observed that in countries at lower stages of economic development, the impact of AI on product diversification was less discernible. Additionally, our results suggest that path dependency, a concept central to evolutionary economic geography (Frenken & Boschma, 2007) and economic complexity theory (Hidalgo et al., 2007), influences the relationship between multidimensional spaces of technology and products. This implies that for a country to expand its export product portfolio and capitalize on the synergies between existing export strengths and AI competencies, it must maintain a comparative advantage in its existing export products while also developing competitive AI technologies.

The structure of this paper is as follows: Section 2 provides a review of pertinent literature, establishing the foundation for our core research questions. Section 3 describes the data, variables, and analytical models utilized in our study. Section 4 discusses our findings, while Section 5 concludes the paper with a thorough summary of our results, accompanied by an in-depth exploration of the implications and insights derived from our research.

4.2 Literature review

4.2.1 Technological change and economic diversification

Economic expansion is propelled by an evolutionary mechanism of technological innovation and economic diversification (Dosi, 1982; Freeman, 1974; Jacobs, 1969; Nelson and Winter, 1982; Pasinetti, 1983). This mechanism underscores that technological progress not only fosters economic development but also necessitates the genesis of novel economic activities to sustain long-term growth. Economic diversification functions as a branching mechanism within economies, stimulating new entrepreneurial ventures and enhancing resilience against disruptions (Frenken et al., 2007). It capitalizes on local competencies, thereby nurturing the development of new technologies, products, and industries, which, in turn, perpetuate economic growth (Saviotti & Pyka, 2004).

The emergence of these economic activities is intricately connected to a nation's extant capabilities, establishing a path-dependent trajectory that affects the export of new products (Hidalgo et al., 2007; Tacchella et al., 2012), the cultivation of nascent industries (Neffke et al., 2011), the exploration of innovative scientific concepts (Guevara et al., 2016), and the development of groundbreaking technologies (Kogler et al., 2013; Petralia et al., 2017; Rigby, 2015). Technological change and economic diversification engage in a coevolutionary interplay, mutually reinforcing each other to drive continuous economic advancement.

The principle of relatedness, as posited by Hidalgo et al. (2018), contends that the diversification and development of economic activities within a country are path-dependent, building upon and constrained by the existing capabilities of the country (Hidalgo et al., 2007). This principle is predicated on the notion that the array of products a country can develop is circumscribed by its current capabilities. Consequently, it is more probable for countries to develop activities that are akin to those they have previously undertaken (Petralia et al., 2017). In terms of diversification, it is observed that regions tend to diversify into new industries related to pre-existing local industries (Neffke et al., 2011). Similarly, nations and cities are inclined to engage in related technologies, and the new publications of countries, universities, and researchers tend to be in cognate research domains (Guevara et al., 2016).

Path dependence, molded by the accumulation of specific industry or technological knowledge and capabilities, constitutes the bedrock for future developments, thus creating a trajectory profoundly influenced by historical patterns (Arthur, 1989; David, 1985; Dosi, 1982). This dynamic poses a formidable challenge for less developed countries striving to transcend established economic paradigms and explore new domains. These countries, constrained by limited resources and capabilities, often find themselves reliant on extant industries and technologies, which impedes their capacity for innovation and growth (Boschma, 2017; Hidalgo et al., 2007; Neffke et al., 2011).

This dependency on existing capabilities and the ensuing path dependence not only underscores the interconnected and co-evolutionary nature of technological and product diversification but also accentuates the challenges that less developed countries encounter in leveraging new technologies for diversification. Path dependence can significantly constrain these countries' abilities to effectively adopt and integrate new technologies for broader economic diversification (Petralia et al., 2017).

4.2.2 The impact of artificial intelligence on product diversification

Traditional economic models, which often view technology as a uniform factor in production (Abramovitz, 1956; Solow, 1957), miss the diverse evolutionary trajectories of economic development due to their generalization of technological change. In contrast, some economic historians emphasize the transformative impact of GPTs, such as steam engines, electricity, and semiconductors, highlighting their role as catalysts for economic growth (Bresnahan & Trajtenberg, 1995; Rosenberg, 1979). These GPTs, characterized by broad applicability, potential for stimulating complementary innovations, and inherent capability for technical improvements, have historically acted as enabling technologies enhancing downstream sector R&D productivity, leading to increasing returns-to-scale and unlocking complementary innovation opportunities (Lipsey et al., 2005).

AI, spurred by the growth of big data, advancements in computing power, and algorithmic innovations, is increasingly recognized as a next-generation GPT. AI's capability to enhance productivity and foster continual development across various domains positions it as a significant influencer across industries (Brynjolfsson & Mitchell, 2017). Its role in augmenting existing products and processes, especially in sectors like drug discovery, underlines its crucial position in enhancing R&D productivity and as a cornerstone of the Fourth Industrial Revolution (Liu et al., 2020).

Beyond its role as a GPT, AI uniquely emerges as an invention in the method of invention itself, particularly in deep learning, redefining productivity paradigms in both idea generation and practical applications (Cockburn et al., 2019). Agrawal et al. (2019) highlight deep learning's transformative impact on knowledge production, especially in combinatorial research, by revolutionizing 'search' and 'discovery' dimensions. This aspect of AI in influencing regional diversification has drawn attention from policymakers, with regions harboring key enabling technologies like deep learning often diversifying into a broader array of unrelated technologies (Montresor & Quatraro, 2017; Klinger et al., 2021). AI's facilitation of knowledge creation and spillover, and enhancement of learning and absorptive capabilities, especially in low-tech industries, has been recognized (Liu et al., 2020), and studies show a positive correlation between AI knowledge and regional specialization in green technologies (Cicerone et al., 2023).

Despite AI's crucial role in economic growth and enhancing national competitiveness, research into its geographic dynamics is limited. The effective adoption of AI for economic diversification requires consideration of existing capabilities, industrial portfolios, and economic development levels, with disparities in AI adoption and integration varying across nations and industries, influenced by technological progress and economic development levels (Goldfarb & Trefler, 2019; Mishra et al., 2023). This disparity highlights the varying rates of economic growth and the need for customized AI integration strategies.

However, AI technology may not uniformly impact all industries and countries positively, as some scholars point out potential drawbacks, including a negative correlation between neural network methods and recombinatorial novelty (Bianchini et al., 2022). The proliferation of knowledge in the AI era, while beneficial, may also impose a 'knowledge burden (Jones, 2009)' on scientists and engineers, complicating new idea discovery and innovative breakthroughs (Park et al., 2023).

In conclusion, AI's transformative potential marks a significant paradigm shift in economic activities, influenced by a nation's existing capabilities. This shift underscores the urgency for governments to integrate AI into national strategies as a critical element in reshaping industrial strategies and opening strategic diversification opportunities, especially for developing countries. However, the dynamics of AI specialization and its strategic harnessing for diversification, particularly in nations with specific existing endowments, remain under-explored. Addressing how less developed countries might use AI to maintain competitiveness in traditional industries and discover new growth avenues (Mishra et al., 2023) highlights the complex interplay between AI specialization and broader economic diversification, presenting both challenges and opportunities for further research and policy development.

4.2.3 A multi-layered network approach on economic complexity

The concept of economic complexity, as introduced by Hidalgo and Hausmann (2009), provides a nuanced perspective on the diversification and growth of regional economies in evolutionary economic geography. This approach analyzes a system by identifying distinct components and their interactions, offering insights beyond traditional economic measures like GDP. It focuses on the diversity and sophistication of a country's productive output, emphasizing the variety and intricacy of production capabilities. This perspective is particularly significant in evolutionary economic geography, aiming to understand the dynamic evolution and diversification of economic landscapes. Economic complexity sheds light on a country's economy by assessing not just the output but also the complexity and diversity of its production capabilities, thereby highlighting its potential for future growth and innovation.

Hausmann et al. (2014) posit that an economy's complexity is intricately tied to its repertoire of useful knowledge. This idea stems from the premise that producing more complex products necessitates a broader array of knowledge. Consequently, an economy's complexity can only increase through the acquisition and innovative recombination of both existing and new capabilities into economically valuable configurations (Hidalgo & Hausmann, 2009; Van Dam & Frenken, 2022). The existence and sustainability of a complex society hinge on the collaborative integration of diverse knowledge domains—design, marketing, finance, technology, human resource management, operations, and trade law, to create products. Societies lacking in any part of this comprehensive capability set are unable to manufacture these complex products. Therefore, economic complexity is reflected in a country's productive output, signifying the underlying structures that facilitate the amalgamation and application of knowledge (Hidalgo, 2021).

However, the ongoing interaction and evolution of innovation activities across various dimensions like scientific, technological, and production capabilities, scholarly exploration into their co-evolutionary dynamics is relatively nascent. The body of research specifically examining the interconnected and co-evolutionary relationships among these disparate dimensions is sparse, with only a handful of recent empirical studies beginning to address this complex interplay.

Recently, Pugliese et al. (2019) propose a framework conceptualizing the national innovation system as a multi-layered network. This network integrates activities across scientific, technological, and economic domains. It operates on the principle that if two activities frequently co-occur in the same countries, it indicates overlapping capabilities necessary for proficiency in both, suggesting competitive advantages. The framework positions technology as a key predictor for future industrial and scientific production, offering insights into the reciprocal impacts between various activity pairs. They also determine the essential capabilities and timeframes required to convert technological know-how into scientific and productive advancements. This approach provides a nuanced understanding of the synergistic relationship between technological and economic activities, highlighting that a nation’s product portfolio gains comparative advantages not only from its production capabilities but also through technological synergies (Hausmann et al., 2014).

Catalán et al. (2022) enhanced the multi-layer network model (Boccaletti et al., 2014), with the introduction of 'scientific and technological cross-density.' This concept assesses how closely new technologies align with a country's existing scientific and technological portfolio. Analyzing data from 182 countries over the period 1988–2014, their two-stage approach first constructed a network linking knowledge and technologies based on co-occurrence. They then examined the influence of scientific-technological cross-density on technological diversification at the national level. The study found that a new technology's alignment with a nation's scientific portfolio significantly increases its adoption probability. It also highlighted that the impact of technological density on diversification is more substantial than that of scientific and technological density combined, thereby advancing the understanding of how existing scientific foundations influence a country's technological advancement and diversification.

Overall, the product output of a nation is an outcome of its innovation activities, representing the structure of its innovation system. Each product is an integration of various innovation activities, encompassing the exploration of new ideas, invention, design, production, marketing, sales, and operations, thereby bringing together diverse knowledge domains. By categorizing these innovation activities into specific dimensions, like technological and production innovations, and conceptualizing the necessary capabilities as nodes linked through relationships of relatedness, a multi-layer network perspective profoundly enhances our comprehension of a nation's innovation system. This method effectively maps how different capabilities and knowledge areas interact, contributing significantly to the nation's overall capability for innovation and its resultant product offerings.

4.3 Data and methodology

4.3.1 Data

In this study, we meticulously compiled an expansive dataset by integrating patent and trade data over two decades (1990–2019), to investigate the intricate relationship between technological evolution, as represented by patents, and international trade dynamics, as indicated by the introduction of new products through RCA (Balassa, 1956). The patent dataset provides a detailed examination of AI patents, encompassing significant variables, such as application count, application year, country of origin, and CPC codes. To distinguish between AI and non-artificial intelligence (non-AI) patents, we employed a keyword-exact matching method based on guidelines provided by the World Intellectual Property Organization (WIPO, 2019). This approach leverages bibliometric information extracted from patent documents obtained from the European Patent Office's PATSTAT database (EPO, 2022). The AI patent keywords used in this study are listed in Appendix 1. Grounded in keyword analysis, this strategy effectively delineates the characteristics of AI as a GPTs, circumventing the constraints inherent in CPC classification-based methods (Hötte et al., 2022). Hötte et al. (2022) examine the co-occurrence of technology classes of AI patents to understand how strongly technology classes complement existing or novel products and processes. They assume that If AI can be combined with many other fields of technology, we would expect to observe that AI patents are classified across a diverse pool of technological classes. They find that the keyword approach produces the patent pool with the highest growth rates, generality and second highest level of complementarity.

Figure 12 provides a nuanced illustration through a stacked bar graph, showcasing the growing significance of AI technologies. This growth is measured by the proportion of AI-related patents in comparison to the overall patents filed in both AI and non-AI domains from 1980 to 2019. The analysis reveals that AI patents constitute a relatively small portion of the total, with an average of 3.4%. However, this small share should not be understated; it reflects a steady increase in AI innovations within the broader spectrum of technological advancements. Despite AI's minor representation in overall patenting, its impact on diversification is considerable, as inferred from its three general characteristics: pervasiveness in the economy, consistent growth, and its complementary nature to other technologies (Agrawal et al., 2019; Brynjolfsson et al., 2021; Cockburn et al., 2019). Particularly, our study encompasses the transformative phases of the 2000s and the 2010s, a period distinctly characterized by the pervasive influence of AI on product development. This era signifies the maturation of AI as a key driver in technological evolution, reinforcing its strategic role in shaping future innovations.

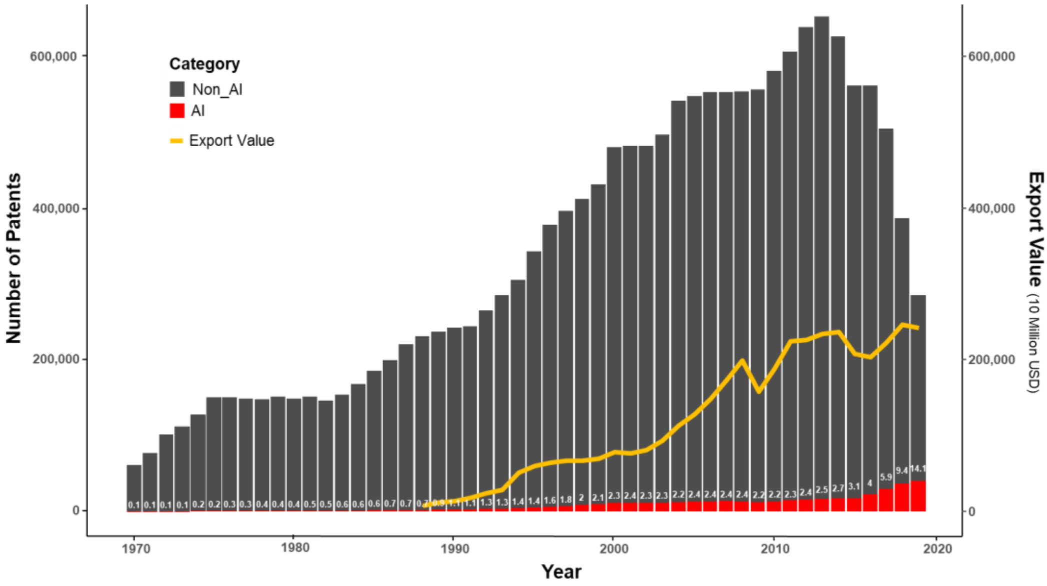


Figure 12. AI and non-AI patents and export products by year

The trade data, obtained from The Growth Lab at Harvard University (2019) and organized according to the 1992 Harmonized System (HS), was augmented with details from the United Nations Commodity Trade Statistics Database (U.N. Comtrade, 2022). The raw data on trade in goods provided by U.N. Comtrade was refined by The Growth Lab researchers using the Bustos-Yildirim Method. This algorithm utilizes bilateral trade flows to correct for inconsistent reporting (The Growth Lab at Harvard University, 2019). Our study employed a subset of The Growth Lab's data, excluding categories that were unclassified or grouped under headings like ICT, financial services, and travel. This exclusion was necessary to avoid bias in the frequency of certain industries, which could skew the path dependence effects on individual industries. The annual export volumes from this dataset enhance our patent graph, leading to the dual-axis representation in Figure 12, which indicates export values in tens of millions of dollars. This setup enables a comparative analysis of patenting patterns and global trade trends across the last fifty years. However, this analysis is limited by the unavailability of pre-1988 product export data due to the absence of the U.N. Comtrade (2022) database.

Given the limited availability of product export data before 1988 and the imperative to faithfully mirror current AI technology trends, we leveraged patent and export data from 1999 to 2019. These data, partitioned into seven three-year intervals (i.e., 1999–2001, 2002–2004, 2005–2007, 2008–2010, 2011–2013, 2014–2016, and 2017–2019), serve to mitigate fluctuations provoked by external perturbations, thereby effectively dampening the potential volatility resulting from commodity price variations, shifts in seasonal employment, and exchange rate fluctuations (Hidalgo, 2021). Our analysis focused on economies with a minimum export volume of one billion USD and a population exceeding 1 million. Abiding by established norms, we systematically excluded products with global exports below the 1 billion USD threshold at the four-digit level, which is a pivotal step in ensuring the validity of the comparisons (Hidalgo, 2021). As shown in Table 13, the United States led globally in total (3,463,686) and AI-specific (149,457) patent applications during this period, demonstrating its robust innovative prowess. Conversely, China's commanding trade value (USD 298,072 in tens of millions) attests to its predominance in global trade, hinting at a complex nexus between innovation and economic productivity.

Table 13. Top innovative and productive countries (1999–2019)

Innovative country				Productive country	
Country	Patents	Country	AI patents	Country	Trade value
Global	11,080,773 (100%)	Global	353,047 (100%)	Global	2,684,179 (100%)
US	3,463,686 (31.3%)	US	149,457 (42.3%)	CH	298,072 (11.1%)
KR	1,709,162 (15.4%)	KR	45,963 (13.0%)	US	233,941 (8.7%)
JP	1,655,529 (14.9%)	CN	27,508 (7.8%)	DE	231,476 (8.6%)
DE	981,583 (8.9%)	JP	26,841 (7.6%)	JP	129,008 (4.8%)
FR	519,409 (4.7%)	DE	23,666 (6.7%)	FR	96,641 (3.6%)
TW	336,541 (3.0%)	FR	9,214 (2.6%)	IT	86,806 (3.2%)
CN	318,860 (2.9%)	CA	9,002 (2.5%)	KR	82,660 (3.1%)
UK	282,572 (2.5%)	UK	7,614 (2.2%)	NL	82,524 (3.1%)
CA	184,979 (1.7%)	NL	5,849 (1.7%)	UK	81,276 (3.0%)
CH	180,604 (1.6%)	TW	5,346 (1.5%)	CA	74,294 (2.8%)

Note: Trade values are presented in units of hundreds of millions of US dollars. The percentages for each country are calculated based on their respective share of global totals for all patents, AI patents, and trade value. The following abbreviations are used in the table: "US" for United States, "KR" for South Korea, "JP" for Japan, "DE" for Germany, "FR" for France, "TW" for Taiwan, "CN" for China, "UK" for United Kingdom, "CA" for Canada, "NL" for Netherlands, "CH" for Switzerland, and "IT" for Italy.

4.3.2 Variables

Our study employed the dependent variable ENTRY, which indicates the likelihood of product introductions within a specified country and period. The independent variables include AI_REL, denoting the density of AI technology cross-relatedness, and PRO_REL, representing the product relatedness density. The control variables comprise the logarithm of the average population (POP), per capita GDP (GDP_CAPITA), patent count (TECH_STOCK), and the ECI. A comprehensive catalogue of these variables is provided in the Table 14.

Table 14. List of variables

Variable	Abbreviation	Description	Data source
Entry of product	ENTRY	Inception of new product with RCA within a nation.	UN Comtrade
Product Relatedness Density	PRO_REL	Interconnectedness or proximity of products in relation to s specific product.	UN Comtrade
AI and Product Cross-Density	AI_REL	Cross-relatedness density between AI technology and specific products.	PATSTAT
Technological Knowledge Stock	TECH_STOCK	Number of patent applications produced by a country	PATSTAT
Economic Complexity Index	ECI	An economy's complexity by considering the diversity and sophistication of its export product	UN Comtrade

		portfolio.	
Population	POP	Total population of a country	World Bank
GDP per Capita	GDP_CAPITA	Gross domestic product divided by midyear population	World Bank

Our model integrates two mean-centered interaction terms: the intersection of AI technology and economic complexity (INT_ECI_AI) and that of AI technology and product relatedness (INT_PRODUCT_AI). A stepwise approach is used to assess the effects of each variable. We employed the Z-transform standardization method to contend with invariant elements in terms of economic and product complexity. Within this framework, ECI values exceeding zero signify locations with above-average complexity.

Overall, this approach elucidates the dynamics between AI technology relatedness, product relatedness, and the emergence of specialized products while controlling for country-level economic and technological factors.

4.3.2.1 Dependent variable

Drawing on Balassa (1965) articulation of the RCA index, our study invokes a similar analytical approach to identify the relative advantages in specific product categories, adapting the work of Hidalgo et al. (2007). The RCA, specified for a particular product in a given country and time, is calculated as

$$RCA_{c,p,t} = \frac{patent_{c,p,t} / \sum_{p} patent_{c,p,t}}{\sum_{c} patent_{c,p,t} / \sum_{c} \sum_{p} patent_{c,p,t}} \qquad \text{Eq.(14)}$$

where *c, p,* and *t* denote country, product, and time, respectively. An RCA value exceeding 1 signifies that the country under consideration has a comparative advantage in the specified product at that time. Notably, RCA indicates that a country has a comparative advantage in producing a specific product when its production level surpasses average global production.

To measure a country's likelihood of transitioning toward a comparative advantage in a specific product, we introduced the variable $ENTRY_{c,p,t}$, computed as

$$ENTRY_{c,p,t} = P(RCA_{c,p,t} > 1 \mid RCA_{c,p,t-1} < 1) \qquad \text{Eq.(15)}$$

This formulation calculates the conditional probability that country *c* will gain a comparative advantage in product *p* at time *t*, as it lacked a comparative advantage in the same product at the previous timepoint (*t−1*). This variable measures a country's potential to shift from a relative disadvantage to an advantage in the product space.

4.3.2.2 Independent variable

As an independent variable, product relatedness density (PRO_DEN), following Hidalgo et al. (2018), PRO_DEN signifies the mean product relatedness between products *p* and *q* within country *c* at time *t*. It measures the co-occurrence likelihood of products with an RCA > 1. The steps to calculate product relatedness and product relatedness density are outlined as follows:

Product relatedness ($\emptyset_{p,q,t}$) computes the conditional probability of product *p* holding a comparative advantage (RCA > 1), as product *q* does as well. This can be mathematically represented as follows:

$$\varphi_{p,q,t} = P(RCA_{c,p,t} > 1 \mid RCA_{c,q,t} > 1) \qquad \text{Eq.(16)}$$

Subsequently, the product-relatedness density (PRO_REL) was formulated by computing the average degree of relatedness among products while disregarding self-relations:

$$PRO\_DEN_{c,p,t} = \frac{\sum_{p \in c, p \neq q} \varphi_{q,p,t}}{\sum_{p \neq q} \varphi_{p,q,t}} * 100 \qquad \text{Eq.(17)}$$

This measure conveys the interconnectivity and co-occurrence patterns within a nation's export portfolio.

We also introduced the cross-relatedness density between a product and the AI technology (AI_REL), an adaptation of the cross-proximity measure proposed by Catalán et al. (2022). This metric estimates the interconnectedness between AI technological fields (four-digit CPC codes) and product classifications (four-digit HS codes). The cross-relatedness between the AI technology *j* and product *p* is calculated as follows:

$$\varphi^{X}{}_{j,p,t} = \min\left\{ \begin{array}{l} P(RCA_{c,j,t} > 1 \mid RCA_{c,p,t} > 1) \\ P(RCA_{c,p,t} > 1 \mid RCA_{c,j,t} > 1) \end{array} \right\} \qquad \text{Eq.(18)}$$

This equation denotes the minimum conditional probability between two scenarios: the likelihood that AI technology *j* possesses a comparative advantage (RCA > 1) as product category *p* also does, and vice versa. Subsequently, the cross-relatedness density (AI_REL) is computed as follows:

$$AI\_REL_{c,p,t} = \omega^{X}{}_{c,p,t} = \frac{\sum_{p \in c, p \neq j} \varphi^{X}{}_{j,p,t}}{\sum_{p \neq j} \varphi^{X}{}_{j,p,t}} \times 100 \qquad \text{Eq.(19)}$$

This measure signifies the average degree of cross-proximity between product category *p* and all other AI technologies *j* in country *c* at time *t*, excluding *p*. This highlights the patterns of interrelations and co-occurrence between products and AI technologies within the national innovation system (Pugliese et al., 2019).

Utilizing the economic complexity framework of Hidalgo et al. (2007), our study employs ECI as an indicator of a country's economic sophistication. The procedure for computing the ECI comprised the following steps:

We defined the incidence matrix $M_{c,p}$ as follows:

$$M_{c,p,t} = \begin{Bmatrix} 1 \ if \ RCA_{c,p,t} \geq 1 \\ 0 \ if \ RCA_{c,p,t} < 1 \end{Bmatrix} (c = 1, ..., n; \ j = 1, ..., k) \quad \text{Eq.(20)}$$

This matrix determines whether country c has a comparative advantage for product *p* at time *t*. The $M_{c,p}$ matrix limits unnecessary variation by focusing solely on the conspicuous presence ($M_{c,p} = 1$) or absence ($M_{c,p} = 0$) of a product. We adopt the 'Method of Reflections' technique proposed by Hidalgo and Hausmann (2009) to calculate economic complexity. This method yields a symmetric set of variables for the two types of nodes present in the bipartite network, namely countries and products. The calculation involves the utilization of the incidence matrix ($M_{c,p}$) and its transpose ($M^T_{c,p}$). By multiplying these matrices, we derive the product matrix (C = $M_{c,p} * M^T_{c,p}$). This matrix serves as an adjacency matrix for the corresponding product codes, which in this study are represented by a harmonized system (HS) four-digit codes. Each country's economic complexity (ECI_c) is derived from the elements of the second eigenvector (Q) of the product matrix (C): These elements underwent Z-transformation to ensure comparability, resulting in a mean of zero and a standard deviation of one.

$$ECI_{c,t} = \frac{\vec{Q} - \langle \vec{Q} \rangle}{stdev(Q)} \qquad Eq.(21)$$

This indicator quantifies the economic complexity of country *c* at a given time *t*. The EC suggests that an economy's ability to sustain a diverse array of products is instrumental in its development and growth (Hidalgo et al., 2007). Accordingly, economies that produce and export unique and diverse sets of products are perceived to be more complex.

4.3.1 LPM regression model

To assess the correlation between specialized product entries and corresponding AI technologies, this study employed a linear probability model (LPM) with three-way fixed effects (FEs) for country, product, and time (in three-year intervals). LPMs, with a dichotomous dependent variable (assuming values of 0 or 1) and with independent variables maintaining a linear relationship with the probability of the outcome being 1, are favored for their consistency (Balland et al., 2019; Boschma et al., 2015; Colombelli et al., 2014). These are preferable to logit models, which may be inconsistent with excessive zeros in the dependent variable (King & Zeng, 2001), which is applicable to this study. The consistent use of the LPM as a robustness check for three-way FE panel logit models yields similar results, validating its credibility (Balland et al., 2019; Uhlbach et al., 2022).

The model is defined as follows:

$$\begin{aligned} & ENTRY_{c,p,t} = \beta_1 \times PRO\_REL_{c,p,t-3} + \beta_2 \times AI\_REL_{c,p,t-3} \\ & +\beta_3 \times INT\_AI\_ECI_{c,p,t-3} + \beta_4 \times INT\_AI\_PRO_{c,p,t-3} \\ & +\beta_{5-8} CONTROL_{c,p,t-3} + \alpha_c + \gamma_p + \delta_t + \varepsilon_{c,p,t} \qquad Eq.(22) \end{aligned}$$

Here, *c*, *p*, and *t* represent the country, product, and time, respectively. The dependent variable is ENTRY, which denotes the introduction of a new specialized product (an RCA product) in a country within a specific timeframe. The dependent variable in the ENTRY model is assigned a value of 1 if country *c* adopts a new RCA product at time *t*, and 0 otherwise.

Considering the time-lag effect of AI innovation on product diversification, all independent and control variables in our analysis were adjusted with a three-year lag. The impact of this delay varies significantly across different fields, potentially ranging from a few years to centuries (Catalán et al., 2022; Pugliese et al., 2019). Furthermore, the complexity within a country's innovation system, encompassing scientific research, technology development, and industrial production, contributes to these time-lag effects. This often leads to a state of nestedness in various sectors, indicative of growing diversification and specialization in scientific research and technological invention (Patelli et al., 2023).

However, this effect is not uniform across all domains. In some areas, such as certain energy products, the time-lag might be notably shorter due to quicker market adoption (Lund, 2006; Gross et al., 2018). Given the rapid advancements in computer science and AI, coupled with data limitations, a three-year lag was deemed appropriate for our study (Pugliese et al., 2019). It's crucial to recognize that these time-lag effects are influenced not just by the scientific and technological fields themselves. External factors, including geography, language, and institutional resources, also play a significant role (Catalán et al., 2022). Consequently, our study incorporates controls for both time-varying and static characteristics pertinent to countries, products, and AI technologies. This methodology allows us to delve deeper into the relationship between product diversification and the interplay between products and AI at a national level.

To effectively manage the unobserved heterogeneity arising from these external factors, we employed a three-way fixed effects panel regression model encompassing country, product, and time variables. This model selection is pivotal in isolating and examining the relationship between AI technology and diversification. Although the fixed effects model, as affirmed by the Hausman test, may sacrifice some efficiency compared to random effects models, it offers enhanced control over confounding variables, ensuring a more accurate analysis.

The following provides a detailed explanation of how we controlled for time-varying and time-invariant characteristics relevant to countries, products, and AI technologies to examine the relationship between product diversification and product-AI interrelatedness at the national level.

First, GDP_CAPITA, POP, and ECI encapsulate the observable dynamic economic traits of a nation as vector control variables. These markers represent factors such as the economic development level (GDP per capita) and economic activity scale (population size), which could potentially influence product diversification. Existing studies suggest that the ECI, which reflects a nation's productive diversity and sophistication inferred from its export range and ubiquity (Hidalgo et al., 2007), largely accounts for disparities in product diversification at the national level. Hence, the ECI is anticipated to subsume the predictive power of traditional economic indicators, such as GDP per capita.

Second, TECH_STOCK signifies a nation's observable dynamic technological characteristics. Patents, which are frequently used as technology or knowledge stock proxies, embody a country's innovation potential and output (Griliches, 1998; Jaffe & Trajtenberg, 2002)). Incorporating TECH_STOCK into the product diversification analysis captures a nation's capability to diversify into technologically advanced goods production. Diversification is a process that leads to new activities and innovations within countries. The more technological capabilities a country possesses, the greater its potential for diversification. This potential increases exponentially with each new capability, due to the larger number of combinations possible with existing ones (Hausmann & Hidalgo, 2009). Therefore, to effectively evaluate the specific and significant impact of AI technologies on general product diversification, controlling for technology stock is crucial.

Finally, this study includes α_c, γ_j, and δ_t, representing the country, product, and time, respectively, to account for time-invariant characteristics. These are FEs, with α_c as a country FEs, γ_j as a product FEs, and δ_t as a time FEs. Further, $\varepsilon_{c,p,t}$ in the model captures any unexplained variation in the dependent variable not accounted for by the independent variables and FEs. We initially considered the product complexity index and non-AI cross-relatedness density as controls. However, owing to their lack of statistical significance and redundancy with the technology stock, we excluded them from our model.

4.4 Results

4.4.1 Descriptive statistics

Table 15 presents the summary statistics and correlation matrices of the principal variables. The outcome variable ENTRY was encapsulated within 738,445 observations, with an average incidence rate of 4%. This rate signifies the relative scarcity of new market entrants to RCA.

Table 15. Descriptive statistics and correlations

	Summary statistics						**Correlation matrix**					
	Variables	**Obs.**	**Mean**	**S.D**	**Min**	**Max**	1	2	3	4	5	6
1	ENTRY	738,445	0.04	0.18	0	1						
2	POP	879,174	16.02	2.18	9.90	21.06	0.011					
3	GDP_CAPITA	852,642	9.15	1.36	5.10	11.67	–0.002	–0.354				
4	ECI	897,264	0.00	1	-3.43	2.26	0.042	–0.005	0.599			
5	PRO_REL	897,264	17.61	12.22	0	91.32	0.107	0.410	0.185	0.538		
6	TECH_STOCK	736,866	5.99	2.59	0	14.07	0.026	0.628	0.247	0.525	0.526	
7	AI_REL	897,264	14.29	13.04	0	70.28	0.019	0.345	0.477	0.578	0.491	0.675

Note: The ECI variable is Z-transformed to negate constant factors, a standard practice for economic complexity metrics not adhering to heavy-tailed distributions (Hidalgo, 2021).

Among the salient independent variables, PRO_REL and AI_REL exhibit considerable variance. PRO_REL, which embodies path dependency as reflected by product-relatedness density, exhibits an average value of 17.61, coupled with a relatively substantial standard deviation of 12.22. This indicates a considerable spread in product-relatedness density across various instances. AI_REL, indicative of a product's proximity to AI technologies, has an average value of 14.29 and a standard deviation of 13.04. These figures imply a significant disparity in AI integration across different products.

Examining the correlations, PRO_REL and AI_REL displayed positive associations with ENTRY, substantiating our conjectured relationship orientation. Moreover, these variables show robust positive correlations with ECI and TECH_STOCK. This is suggestive of the potential common influences that shape market-entry decisions. Notably, the range of the observed correlations was relatively low to moderate. This indicates that multicollinearity is unlikely to substantially impede subsequent analyses, although it will be stringently monitored and controlled.

We discerned the interrelationships among the variables through correlation analyses and summary statistics. Notably, AI_REL demonstrated potent positive correlations with TECH_STOCK (0.675) and exhibited positive associations with ECI (0.578) and PRO_REL (0.491). Descriptive statistics revealed wide dispersion in the key variables, specifically AI_REL, ECI, PRO_REL, and TECH_STOCK.

4.4.2 **LPM regression model**

Table 16 presents the outcomes of a series of rigorous linear probability regression models that examine the influence of key predictors, specifically PRO_REL and AI_REL, on the entry of products exhibiting RCA into export markets. PRO_REL signifies the density of product relatedness, reflecting path dependency theory, whereas AI_REL quantifies the affinity between certain products and AI technologies. The binary dependent variable “ENTRY” denotes export market entry, and independent and control variables are integrated with a three-year lag.

Table 16. Linear probability model regression main results

	Dependent variable: ENTRY				
	M1	M2	M3	M4	M5
POP	–0.04871*** (0.00422)	–0.03928*** (0.00423)	–0.03871*** (0.00423)	–0.03485*** (0.00428)	–0.03393*** (0.00429)
GDP_CAPITA	–0.00270** (0.00107)	–0.00028 (0.00108)	–0.00034 (0.00108)	0.00009 (0.00108)	0.00059 (0.00109)
TECH_STOCK	0.00351*** (0.00053)	0.00239*** (0.00053)	0.00215*** (0.00053)	0.00211*** (0.00053)	0.00204*** (0.00053)
ECI	0.01223*** (0.00102)	0.00488*** (0.00107)	0.00485*** (0.00107)	0.00524*** (0.00107)	0.00590*** (0.00108)
PRO_REL		0.00245*** (0.00010)	0.00246*** (0.00010)	0.00235*** (0.00010)	0.00238*** (0.00010)
AI_REL			0.00020*** (0.00005)	0.00021*** (0.00005)	0.00018*** (0.00005)
INT_AI_ECI				0.00003*** (0.00000)	0.00002*** (0.00000)
INT_AI_PRO					0.00020*** (0.00004)
Constant	0.81853*** (0.06999)	0.60853*** (0.07050)	0.59856*** (0.07076)	0.52859*** (0.07161)	0.50794*** (0.07176)
Country FEs	YES	YES	YES	YES	YES
Product FEs	YES	YES	YES	YES	YES
Period FEs	YES	YES	YES	YES	YES
N (group)	588,071 (129,299)	588,071 (129,299)	588,071 (129,299)	588,071 (129,299)	588,071 (129,299)
R^2	0.01027	0.01084	0.01084	0.01086	0.01106
Adjusted R^2	0.00854	0.00880	0.00881	0.00883	0.00902

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable (ENTRY) was binary (0 or 1). The independent and control variables are lagged by three years. The term "INT" indicates an interaction term.

The consistent positive relationship between PRO_REL and ENTRY across models M2–M5 signifies its substantial influence on market-entry decisions. Coefficients ranging from 0.00235 to 0.00246 imply that each incremental unit in PRO_REL amplifies the likelihood of entry by 0.235%–0.246%. The statistical significance at the 1% level across these models corroborated the applicability of the path dependency theory in this context. Similarly, AI_REL, which indicates the affinity of products for AI technologies, showed a positive association with ENTRY across models M3-M5. The coefficients, ranging from 0.00018 to 0.00021, suggest that, for every unit increase in AI_REL, the propensity for market entry increases by 0.018%–0.021%. Statistical significance at the 1% level reinforces the premise that products integrated with AI technologies have a greater likelihood of market entry.

The models (M1–M5) reveal a persistent negative influence of population (POP) on market entry, significant at the 1% level, suggesting that larger populations may inhibit market entry. Conversely, the GDP per capita (GDP_CAPITA) does not yield significant or consistent results, playing a role in market-entry decisions. However, the ECI consistently boosts the likelihood of market entry, thereby accounting for the majority of economic effects on market entry. Moreover, the interaction variables INT_AI_PRO and INT_AI_ECI enhance the likelihood of product entry, highlighting the complex dynamics of AI’s influence on market entry decisions.

Although the R-squared and adjusted R-squared values may seem relatively modest, they contribute significantly to a deeper understanding of the dynamics driving RCA product entry. This emphasizes the crucial roles PRO_REL and AI_REL play in this process.

Table 16 accommodates potential heteroscedasticity and group-level clustering. Standard errors are estimated using heteroscedasticity-consistent (HC) estimators, enhancing the robustness of the results and maintaining the validity of the estimated coefficients and hypothesis tests, even amid heteroscedasticity or intra-group correlations. Consequently, the analysis provides comprehensive insights into the determinants of RCA product entry, emphasizing the importance of PRO_REL and AI_REL while considering potential heterogeneity in error terms.

4.4.3 Robustness checks

4.4.3.1 Stratified sub-sample verification

Table 17 presents robustness checks for the primary findings. We conducted a stratified panel regression analysis, partitioning the data according to the economic status of the countries, product type, and period. This stratification allowed us to control for potential confounding variables and discern patterns and relationships within the data more intricately.

Table 17. Results of stratified panel regression (ENTRY)

	Country		Product		Time period	
	High	Mid and Low	ICT	Non-ICT	P1 and P4	P4 and P7
POP	–0.02720***	–0.03430***	–0.02832*	–0.02874***	–0.10393***	–0.04760***

	(0.00706)	(0.00590)	(0.01540)	(0.00227)	(0.01158)	(0.00755)
GDP_CAPITA	0.00321	–0.00053	–0.00054	0.00075	–0.00353	–0.01352***
	(0.00224)	(0.00154)	(0.00397)	(0.00057)	(0.00216)	(0.00221)
TECH_STOCK	0.00263***	0.00171***	0.00030	0.00128***	0.00078	0.00088
	(0.00067)	(0.00065)	(0.00194)	(0.00028)	(0.00112)	(0.00083)
ECI	0.00661***	0.00369***	0.00977**	0.00401***	0.01441***	0.01214***
	(0.00164)	(0.00126)	(0.00409)	(0.00058)	(0.00168)	(0.00215)
PRO_REL	0.00247***	0.00221***	0.00222***	0.000317***	0.00279***	0.00089***
	(0.00014)	(0.00016)	(0.00041)	(0.00006)	(0.00018)	(0.00016)
AI_REL	0.00015***	0.0025***	0.00035***	0.00018***	0.00026***	0.00016***
	(0.00008)	(0.00007)	(0.00017)	(0.00003)	(0.00008)	(0.00007)
INT_AI_PRO	0.00001***	0.00007**	0.00001	0.00001***	0.00005***	0.00003***
	(0.00001)	(0.00001)	(0.00002)	(0.00000)	(0.00001)	(0.00001)
Constant	0.48735***	0.46702***	0.45200***	0.42946***	1.6983***	0.90567***
	(0.09261)	(0.15485)	(0.25684)	(0.03777)	(0.19784)	(0.12642)
Country FEs	YES	YES	YES	YES	YES	YES
CPC FEs	YES	YES	YES	YES	YES	YES
Period FEs	YES	YES	YES	YES	YES	YES
N (group)	458,448	122,640	43,684	2,242,838	199,064	365,468
	(92,701)	(35,403)	(9,696)	(493,139)	(98,330)	(124,429)
R^2	0.00584	0.00441	0.01158	0.01721	0.00581	0.00684
Adjusted R^2	0.00421	0.00320	0.00995	0.01002	0.00460	0.00533

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We stratified the models based on various factors: the stages of economic development (M1–M2), sector classification (M3–M4), and time frames (M5–M6). “High and Mid” denote high- and upper-middle-income countries, respectively, whereas “Mid and Low” encapsulate lower-middle and low-income countries, respectively (World Bank, 2023). The abbreviation “ICT” represents the “communication technology” sector, whereas non-

ICT includes all other sectors (OECD, 2023). Models 3 and 4 utilize a six-digit HS to distinguish between ICT and non-ICT sectors. “P1 to P4” refers to four periods from the initial stage (1999–2001) to the final stage (2008–2010), whereas “P4 to P7” spans four periods from the initial stage (2008–2010) to the final stage (2017–2019).

The robustness checks detailed in Table 17 validate our primary findings, emphasizing the significant positive impact of the key variables, PRO_REL and AI_REL, on export market entry across all subgroups. This finding demonstrates the integral role of product relatedness (PRO_REL) and AI product proximity (AI_REL) in influencing a product’s competitive advantage in export markets.

Product relatedness (PRO_REL) has a significant role across all contexts. Regardless of a country’s income level, sector type, or timeframe, an increase in product relatedness consistently increases the likelihood of market entry. This finding corroborates the principle of path dependency in product development and export composition, suggesting a higher likelihood of the successful entry of products related to those already present in the market.

Similarly, AI product proximity (AI_REL) positively influenced export market entry across all subgroups. This finding underscores the escalating significance of AI technologies for enhancing product competitiveness and guiding market-entry decisions. The ECI also plays a crucial role across most subgroups, except in lower-middle- and low-income countries, where it has a negative effect. This variation highlights the ECI’s nuanced and context-dependent role in influencing market entry decisions. The interaction terms INT_AI_ECI and INT_AI_PRO retained their significance across all subgroups, emphasizing the synergistic benefits of integrating AI technologies with economic complexity (ECI) and product relatedness.

In summary, the robustness checks confirm our initial findings and underscore the pivotal role of PRO_REL and AI_REL in shaping a product’s competitive advantage in export markets across diverse contexts. These insights emphasize the importance of product relatedness and proximity to AI in strategic decisions related to product development and market entry.

4.4.3.2 Classification and regression validation

To validate our primary findings rigorously, we performed robustness checks using alternative product classification schemas and regression models. Detailed analyses are provided in the Supplementary Information. The main purpose of these checks is to confirm the robustness and reproducibility of our primary results.

For a more in-depth evaluation, we employed a six-digit HS classification (Table 18) to examine the sensitivity of our results to changes in product granularity. The statistical significance and alignment of this analysis with our primary findings affirm the robustness of our results, even with a more granular product classification.

Table 18. LPM regression results (HS 6 digits)

	Dependent variable: ENTRY				
	M1	M2	M3	M4	M5

POP	–0.04580*** (0.00217)	–0.03074*** (0.00219)	–0.03005*** (0.00219)	–0.02871*** (0.00219)	–0.02843*** (0.00220)
GDP_CAPITA	–0.00258*** (.00056)	0.00017 (0.00056)	0.00020 (0.00056)	0.00055 (0.00056)	0.00059 (0.00056)
TECH_STOCK	0.00423*** (0.00026)	0.00196*** (0.00027)	0.00171*** (0.00027)	0.00147*** (0.0027)	0.00148*** (00027)
ECI	0.00468*** (0.00045)	0.00119*** (0.00045)	0.00118*** (0.00045)	0.00284*** (0.00048)	0.00280*** (0.00048)
PRO_REL		0.00320*** (0.00006)	0.00322*** (0.00006)	0.00322*** (0.00006)	0.00321*** (0.00006)
AI_REL			0.00021*** (0.00003)	0.00017*** (0.00003)	0.00017*** (0.00002)
INT_AI_ECI				0.00020*** (0.00002)	0.00019*** (0.00002)
INT_AI_PRO					0.00001*** (0.00000)
Constant	0.77107*** (0.03605)	0.46814*** (0.03645)	0.45569*** (0.03648)	0.43124*** (0.03655)	0.42636*** (0.03670)
Country FEs	YES	YES	YES	YES	YES
Product FEs	YES	YES	YES	YES	YES
Period FEs	YES	YES	YES	YES	YES
N (group)	2,442,475 (547,717)	2,442,475 (547,717)	2,442,475 (547,717)	2,442,475 (547,717)	2,442,475 (547,717)
R^2	0.01049	0.01402	0.01508	0.01708	0.01829
Adjusted R^2	0.00867	0.00898	0.00946	0.00995	0.01048

Notes: Standard errors in parentheses * p<0.1, ** p<0.05, *** p<0.01

HS signifies the Harmonized System of product categorization. In these models, we utilize six-digit HS codes, a more granular level of classification than their higher-level counterparts.

We used CPC codes for AI patent data collection, aligned with the AI patent classification presented by the WIPO (2019). This approach tests the robustness of our findings against changes in the patent classification system. The outcomes were congruent with our primary results, reinforcing the robustness of our findings against variations in patent classification methodology (Table 19).

Table 19. LPM regression results (CPC 12 digits)

	Dependent variable: ENTRY				
	M1	M2	M3	M4	M5
POP	–0.05019*** (0.00421	–0.04026*** (0.00422)	–0.03935*** (0.00422)	–0.03926*** (0.00423)	–0.03689*** (0.00425)
GDP_CAPITA	–0.00327*** (0.00109)	–0.00058 (0.00109)	–0.00015 (0.00109)	–0.00012 (0.00109)	–0.00037 (0.00110)
TECH_STOCK	0.00517*** (0.00050)	0.00308*** (0.0.00051)	0.00264*** (0.00051)	0.00261*** (0.00051)	0.00247*** (0.00052)
ECI	0.00462*** (0.00074)	0.00230*** (0.00075)	0.00229*** (0.00075)	0.00253*** (0.00080)	0.00238*** (0.00081)
PRO_REL		0.00248*** (0.00010)	0.00251*** (0.00010)	0.00250*** (0.00010)	0.00247*** (0.00010)
AI_REL			0.00058*** (0.00008)	0.00055*** (0.00009)	0.00053*** (0.00009)
INT_AI_ECI				0.00005 (0.00006)	0.00001 (0.00007)
INT_AI_PRO					0.00003*** (0.00001)
Constant	0.83786*** (0.06998)	0.62350*** (0.07044)	0.60545*** (0.07049)	0.60383*** (0.07051)	0.05813*** (0.00167)
Country FEs	YES	YES	YES	YES	YES
Product FEs	YES	YES	YES	YES	YES
Period FEs	YES	YES	YES	YES	YES
N (group)	603,366 (133,097)	603,366 (133,097)	603,366 (133,097)	603,366 (133,097)	603,366 (133,097)

R^2	0.00764	0.00891	0.00909	0.00919	0.01002
Adjusted R^2	0.00560	0.00673	0.00689	0.00722	0.00847

Notes: Standard errors in parentheses * $p<0.1$, ** $p<0.05$, *** $p<0.01$

For the robustness testing, this study utilizes the CPC (Cooperative Patent Classification) system, specifically the 12-digit classification, to categorize patents.

Finally, rather than adopting LPM regression, we utilize a three-way FEs panel logit model (Table 20). This step was undertaken to assess whether our findings remained robust in alternative regression models. The consistency of these results with our primary findings further substantiates the robustness of our results as an alternative methodological choice.

Table 20. Three-way fixed effects panel logit results

	Dependent variable: ENTRY				
	M1	M2	M3	M4	M5
POP	–1.12024*** (0.16463)	–0.82034*** (0.16647)	–0.80109*** (0.16648)	–0.73498*** (0.16705)	–0.74039*** (0.16745)
GDP_CAPITA	–0.14646*** (0.04571)	–0.08195* (0.04601)	–0.08446* (0.04601)	–0.06507 (0.04619)	–0.06594 (0.04623)
TECH_STOCK	0.14693*** (0.02291)	0.11728*** (0.02307)	0.11131*** (0.02315)	0.10293*** (0.02320)	0.10331*** (0.02322)
ECI	0.39350*** (0.04563)	0.17478*** (0.04711)	0.17479*** (0.04714)	0.21315*** (0.04776)	0.21376*** (0.04777)
PRO_REL		0.06532*** (0.00367)	0.06545*** (0.00367)	0.06516*** (0.00368)	0.06594*** (0.00374)
AI_REL			0.00626*** (0.00199)	0.00387*** (0.00205)	0.00412*** (0.00211)
INT_AI_ECI				0.00924*** (0.00179)	0.00956*** (0.00190)
INT_AI_PRO					0.00008 (0.00017)

Country FEs	YES	YES	YES	YES	YES
Product FEs	YES	YES	YES	YES	YES
Period FEs	YES	YES	YES	YES	YES
N (group)	70,462 (16,057)	70,462 (16,057)	70,462 (16,057)	70,462 (16,057)	70,462 (16,057)
LR (χ^2)	1558.14***	1877.03***	1866.91***	1913.79***	1914.04***

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable (ENTRY) is binary (0 or 1). The independent and control variables are lagged by three years. The term 'INT' indicates an interaction term.

Our findings indicate that when the variable of national patent counts (TECH_STOCK) is held constant, non-AI mechanisms are insufficient to account for the observed levels of product diversification (Table 21). In contrast, AI contributes explanatory power to the diversification phenomenon beyond what is attributable to the technology stock.

Table 21. AI & non-AI models

	Dependent variable: ENTRY				
	M1	M2	M3	M4	M5
Non_AI_REL			0.00019*** (0.00006)	–0.00002 (0.00006)	0.00001 (0.00006)
AI_REL			0.00015*** (0.00005)	0.00016*** (0.00005)	0.00014*** (0.00005)
TECH_STOCK				0.00357*** (0.00053)	0.00330*** (0.00054)
ECI		0.00013*** (0.00003)	0.00012*** (0.00003)	0.00011*** (0.00004)	0.00021*** (0.00004)
PCI		0.00001 (0.00003)	0.00001 (0.00003)	–0.00002 (0.00003)	–0.00002 (0.00003)
PRO_REL		0.00256*** (0.00010)	0.00255*** (0.00010)	0.00248*** (0.00010)	0.00248*** (0.00010)

INT_AI_ECI					0.00001***
					(0.0000)
POP	–0.01850***	–0.02152***	–0.02213***	–0.03929***	–0.03855***
	(0.00283)	(0.00296)	(0.00297)	(0.00440)	(0.00440)
GDP_CAPITA	0.00159*	0.00124	0.00077	–0.00048	–0.00025
	(0.00096)	(0.00102)	(0.00103)	(0.00114)	(0.00114)
Country FEs	YES	YES	YES	YES	YES
Product FEs	YES	YES	YES	YES	YES
Period FEs	YES	YES	YES	YES	YES
Obs.	716,624	668,775	667,704	563,051	563,051

Notes: Standard errors in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01

The dependent variable, ENTRY, is binary, taking values of 0 or 1. Independent and control variables are lagged by three years. The abbreviation 'INT' denotes an interaction term. The models are analyzed using a linear probability model.

Collectively, these robustness checks amplify the credibility and generalizability of the primary findings. They provide further evidence of the robustness of our conclusion that AI technology significantly impacts the introduction of new products regardless of the product and patent classification systems or regression model applied. The details of these robustness checks are provided in the Tables 18–21. These tables enhance the overall argument of the manuscript by validating the consistency of our findings across various classifications and methodological alternatives.

In summary, the robustness checks performed in our study strengthen the empirical foundation of our research. These checks demonstrate the stability and reliability of our findings under various plausible scenarios, reaffirming the rigor and credibility of our high-level academic research.

4.5 Discussion and Conclusion

This study investigates the role of AI technology in enhancing export product diversification, specifically how national AI capabilities contribute to developing new products with comparative advantages. Using a three-way FE panel regression model, we analyzed data from 145 countries over two decades (1999–2019). Our findings confirm that a nation's AI proficiency is positively correlated with its ability to diversify into new, competitive products. These findings align with current research highlighting AI as a GPT, potentially revolutionizing international trade in goods and services and reshaping global trade dynamics (Goldfarb & Trefler, 2019). Moreover, this trend significantly accelerates new product development, contributing to rapid innovation.

Our research shows that the impact of AI on product diversification depends on a nation's economic complexity. More complex economies tend to have more diverse product portfolios than less complex ones (Hidalgo & Hausmann, 2009). In such environments, AI technologies can markedly improve products and processes across industries, boosting productivity and efficiency (Brynjolfsson & Mitchell, 2017; Cockburn et al., 2019). More complex economies are thus more likely to experience substantial benefits from AI implementation. This is supported by our stratified panel regression analysis. When categorizing countries by income levels, the impact of AI integration on product diversification was not significant in middle- and low-income countries, indicating that less developed countries might struggle to gain competitive advantages by integrating complex AI technologies.

In terms of AI, global competition is intensifying, led by the United States and China. Their advantage comes not just from having access to large data sets but also from supportive government policies and substantial corporate investments (Savage, 2020). This highlights the importance of national strategies and resources in advancing AI development and competitiveness.

Our study also reveals that AI's impact on diversification is noteworthy even when considering a country's existing technology stock. Despite AI's small scale in our dataset (an average of 3.4% over 20 years), it significantly influences diversification. On the other hand, Non-AI technologies (an average of 96.6 %) do not significantly contribute to explaining diversification, underscoring AI's unique role in transforming a wide array of sectors (Agrawal et al. 2019; Brynjolfsson et al. 2019; Cockburn et al. 2019; Trajtenberg 2019).

However, it is difficult to say that AI's impact is limited to advanced products like ICT. Our findings indicate significant positive effects of AI on both ICT goods (like digital computers, data storage, communication equipment, and electronic components) and Non-ICT goods. This corroborates recent research showing AI's significant impact on low-tech sectors (Liu et al., 2020).

These findings have important implications for countries with lower economic and technological levels. Often having smaller product portfolios and exporting simpler goods, these countries could still enhance their comparative advantages in exports by integrating AI technologies associated with low-tech products. This provides actionable insights for policymakers in these countries, suggesting strategic AI integration as a viable means to improve their competitive edge in the global market.

An important caveat in our study is our failure to find evidence supporting the hypothesis that recent advancements in AI technology, especially post-2010, have a more positive impact on product diversification. This might be due to our dataset only extending to 2019, not fully capturing recent AI advancements. This is a limitation of our study. Future research should include data post-2020 to assess how AI influences export product competitiveness over time, considering recent technological developments. Despite this limitation, our methodological approach expands the theoretical foundations of evolutionary economic geography and economic complexity from regional to national levels. Our study highlights AI as a complementary innovation in export products, contributing significantly to the field.

Chapter 5. Conclusion

5.1 Overall summary

This thesis presents an integrated approach combining EEG and EC to explore the interplay between national capabilities and diversification, with a specific focus on the complementary role of AI's scientific and technological capabilities in this process. Addressing the emerging challenges posed by the 'knowledge burden' and declining R&D productivity in the face of rapidly expanding scientific and technological knowledge (Jones, 2009; Neffke, 2019; Park et al., 2023), this study redefines the concept of complementary innovation (Rosenberg, 1979). It builds upon the theoretical foundations of EEG and EC to provide a nuanced understanding of how complementary innovations can propel scientific and technological progress amidst increasing knowledge complexity.

The thesis posits that complementary innovation is the process through which a nation's existing scientific, technological, and productive capabilities are leveraged and integrated with GPTs like AI, catalyzing new areas of diversification. AI, as a next GPT, operates within a multidimensional space that includes scientific, technological, and production capabilities, playing a crucial role in driving innovation and diversification.

The first essay of the thesis demonstrates that integrating a nation's scientific research capabilities with its existing technological capabilities can lead to a comparative advantage in diversifying into new AI domains. The second essay reveals that when a country's innovation capabilities in AI technology are related to its export products, it positions the nation to gain a comparative advantage in producing new export goods. These findings highlight the strategic importance of utilizing AI and complementary innovations for achieving a national competitive edge and diversification in the global economy.

The central tenet of this study is that nations develop through innovation and diversification, a concept that is fundamental to endogenous growth theory, EEG, and EC. However, this theoretical framework needs refinement to address the challenges posed by the recent knowledge explosion characteristic of a knowledge-based industrial society. The proposition that exponential increases in exploration costs and time for new inventions may ensue from an infinitely expanding knowledge space challenges the fundamental recombination process central to established endogenous growth theories (Fleming & Sorenson, 2001; Romer, 1990; 1994). This study explores AI technology's potential as a tool for complementary innovation, examining its capability to contribute to national development in an era marked by rapidly expanding knowledge. The findings of this thesis offer crucial insights for understanding the role of AI in national innovation ecosystems and provide valuable implications for policymakers and stakeholders in leveraging AI for economic development and diversification.

In conclusion, while AI, particularly deep learning, is argued to be not only a GPT but also a method of invention (Cockburn et al., 2019; Brynjolfsson & McAfee, 2017), it does not independently create new inventions. The domain of new discoveries and inventions remains a distinctly human endeavor. The research aligns with the view that AI plays a complementary role, augmenting and integrating with relevant capabilities (Borges et al., 2021). AI's role is seen as augmentative and integrative, enriching and extending national innovation capabilities, contributing significantly to the innovation ecosystem. This thesis offers critical insights into AI's role in national innovation ecosystems and provides valuable implications for leveraging AI in economic development and diversification strategies.

5.2 Policy implications and contributions

Integrating EEG and EC, this thesis offers a theoretical foundation for research on national economic diversification with an emphasis on the importance of 'relatedness' in knowledge or innovation capabilities. The empirical analysis of 40 years of panel data solidifies the understanding of how interconnected capabilities impact a nation’s diversification, underscoring the significance of related capabilities in national economic development and innovation. This insight is crucial for countries looking to utilize AI and other emerging technologies for economic growth.

Methodologically, the thesis connects scientific, technological, and productive capabilities through a conditional probability-based knowledge network. This novel approach offers policymakers a multifaceted framework to explore AI’s potential complementary role, distinguishing the study from previous research and enabling a deeper examination of the interactions and synergies of various capabilities in AI integration.

The thesis provides critical policy implications for nations aspiring to harness emerging technologies for economic advancement. It highlights the strategic use of AI for nations with limited innovation capabilities, suggesting a focus on diversifying into areas closely related to their existing capabilities. This approach, rooted in the insights of evolutionary economic geographers, leverages path dependencies in strategic decision-making, particularly in adopting and integrating AI technologies.

The research demonstrates that a nation's AI research capabilities are instrumental in technological diversification. This finding highlights the necessity of fostering collaboration among industry, academia, and government to develop a skilled workforce capable of transforming complex knowledge into practical applications. The development of GPTs like deep learning benefits from co-location and collaboration within dense research and industrial ecosystems, as these environments facilitate the generation of new ideas and their application across sectors.

Additionally, the study explores the role of AI in enabling nations to diversify into new, competitively advantageous export products, emphasizing the need for policies that align AI technology development with the country's existing product portfolio. This approach ensures strategic resource allocation and strengthens industrial capabilities.

Furthermore, the thesis acknowledges AI's significant role as an 'invention in the method of inventing,' vital for generating knowledge in the face of the escalating complexity that characterizes modern innovation (Jones, 2009; Cockburn et al., 2019; Brynjolfsson et al., 2021). National strategies incorporating AI are crucial for managing this complexity, facilitating knowledge recombination, and fostering economic growth.

In conclusion, this research makes a significant contribution to policy development by providing a comprehensive framework for leveraging AI in economic diversification. It offers actionable insights for policymakers, especially in less developed contexts, highlighting AI's potential in reshaping national economic trajectories. The findings underscore AI's transformative role in enhancing national competitiveness and driving sustainable economic development.

5.3 Limitations and future research

This research acknowledges several limitations that merit attention in future investigations. Conventional proxies—specifically academic papers, patents, and products—for measuring activities in scientific, technological, and production capabilities do not fully capture the breadth of these activities and thus have a limited scope. To date, the study of these latent capabilities has been constrained by measurement challenges. However, the adoption of machine learning techniques, such as natural language processing, offers the potential to quantify these capabilities more effectively. For example, a skills space can be generated from the text of job postings. Utilizing the multidimensional approach presented in this thesis, future research can explore the relationships among the broader dimensions that constitute national capabilities, including skills, knowledge, and know-how.

Furthermore, it is imperative to rigorously investigate the time lags among these indicators due to their critical relationship with the pace of innovation. When a scientific discovery requires considerable time to be actualized through technological inventions, the reverse influence—where technological advancements impact scientific discoveries—may also experience significant delays. Consequently, this results in a slower rate of innovation. Conversely, in cases where the temporal lags are short, the speed of innovation can escalate exponentially due to positive feedback mechanisms. The complexity arises from the fact that these time lags can vary across different industries, potentially influencing their respective innovation rates. Future research should undertake a more granular examination of these industrial differences. By doing so, future studies can better understand the innovation mechanisms of AI by exploring how complementary effects manifest differently in industries such as healthcare, finance, manufacturing, and transportation. Nonetheless, it is important to emphasize that this does not diminish the implications of the present study, which investigates the impact of artificial intelligence on the entire industrial landscape at the national level.

Another critical point is that AI is not the only GPT; it is one among several GPTs. Future research should address emerging technologies that possess the characteristics of GPTs. The development of AI, for instance, has been driven by a combination of factors such as increased computing power, advances in algorithms, and the growth of trainable data. Similarly, quantum technologies, including quantum computing, quantum sensing, and quantum networks, are poised to become significant drivers of AI advancement. These technologies are expected to serve as complementary innovations across various industries due to their GPT nature. Future research should apply our proposed methodologies to these emerging technologies to validate and extend our approach. By integrating these considerations, future investigations can build upon our findings, offering a more comprehensive understanding of the dynamic interplay between various national capabilities and the evolving landscape of general-purpose technologies.

Finally, this research acknowledges the limitations of the data used. In the first essay, while we tracked 40 years of paper publication records and patenting activities, this data does not comprehensively capture all national innovation activities. Notably, this research was limited to publications from the Science Citation Index (SCI) within the Web of

Science's core collections, representing STEM fields. Future research should expand to include publications from social sciences, arts, and humanities to explore how diversity evolves in these areas. It is anticipated that the humanities, unlike engineering fields, may exhibit higher path dependency.

In the second study, we explored the impact of a nation's technological capabilities and product diversification by utilizing patent information from EPO’s PATSTAT and export product records from UN Comtrade, covering the period from 1999 to 2019. This analysis focused on how AI technology influenced diversification. However, similar to the first study, AI technology is still in a developmental phase, and there is a need to examine the national impacts of AI technology, particularly post-deep learning, using more recent data. One limitation of patent data is the delay in record availability, which typically ranges from 1.5 to 2 years. Future research could benefit from analyzing the most recent patent data to provide a more detailed examination of these dynamics.

Additionally, such detailed data can enable research at the regional and city levels. This is particularly relevant in the case of the European Union, where technology and economic policies are often implemented at the regional level. Consequently, it becomes feasible to examine how digital transition occurs through diversification in more granular geographic entities like regions and cities, rather than just at the national level.

In summary, this thesis expands the multidimensional knowledge space of science, technology, and products to lay a foundational understanding of AI's complementary role. However, future research can extend the methodologies proposed in this study to a broader range of capabilities. By doing so, we can gain a better understanding of the complementary functions among national capabilities and provide valuable policy implications.

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Appendix 1: List of AI keywords and CPC codes

List of AI patent keywords[†]

artificial intelligen, computational, intelligen, neural network, neural_network, bayes network, bayesian network, bayesian-network, bayesian_network, chatbot, learning, learning model, learning algorithm, learning sys, intelligen, classification model, optimiz, training data, training method, convolutional network, anomaly detection, feature ext, prediction model, data mining, decision model, deep learning, deep-earning, deep_learning, genetic algorithm, inductive logic, machine learning, machine_learning, machine-learning, natural language, image recogni, reinforcement learning, supervised learning, supervised training, supervised-learning

supervised_learning, swarm intelligen, swarm-intelligen, unsupervised learning, unsupervised training, unsupervised-learning, unsupervised_learning, semi-supervised learning, semi-supervised training, semi_supervised_learning, semi-supervised, connections, expert system, fuzzy logic, transfer learning, transfer-learning, transfer_learning, learning algorithm, learning model, support vector machine, random forest, decision tree, gradient tree boosting, xgboost, adaboost, rank boost, logistic regression, stochastic gradient descent, multilayer perceptron, semantic analysis, dirichlet allocation, multi-agent system, hidden markov model, pattern recogni

List of AI patent CPCs[†]

A61B 5/7264, A61B 5/7267, A63F 13/67, B23K 31/006, B25J 9/161, B29C 66/965, B29C 2945/76979, B60G 2600 /1876, B60G 2600/1878, B60G 2600/1879, B60W 30/06, B60W 30/10, B60W 30/14, B62D 15/0285, B64G 2001/247, E21B 2041/0028, F02D 41/1405, F03D 7/046, F05B 2270/707, F05B 2270/709, F05D 2270/709, F16H 2061/0081, F16H 2061/0084, G01N 29/4481, G01N 33/0034, G01N 2201/1296, G01R 31/2846, G01R 31/3651, G01S 7/417, G05B 13/027, G05B 13/0275, G05B 13/028, G05B 13/0285, G05B 13/029, G05B 13/0295, G05B 2219/33002, G05D 1/00, G05D 1/0088, G06F 11/1476, G06F 11/2257, G06F 17/3069, G06F 17/30702, G06F 17/30705, G06F 17/30731, G06F 17/30743, G06F 17/30784, G06F 19/24, G06F 19/707, G06F 2207/4824, G06K 7/1482, G06K 9/0, G06N 3/0, G06N 3/004, G06N 7/005, G06N 7/006, G06N 7/046, G06N 99/005, G06T 3/404, G06T 9/00, G06T 2207/2008, G06T 2207/20084, G06T 2207/30236, G06T 2207/30248, G08B 29/186, G10H 2250/151, G10H 2250/311, G10K 2210/3024, G10K 2210/3038, G10L 15, G10L 17, G10L 25/30, G11B 20/10518, H01J 2237/30427, H01M 8/04992, H02H 1/0092, H02P 21/0014, H02P 23/0018, H03H 2017/0208, H03H 2222/04, H04L 25/0254, H04L 25/03165, H04L 41/16, H04L 45/08, H04L 2025/03464,

<table>
<tr><td>G06F 15/18, G06F 17/2282, G06F 17/27, G06F 17/28, G06F 17/30029, G06F 17/30247, G06F 17/30401, G06F 17/3043, G06F 17/30522, G06F 17/30654, G06F 17/30663, G06F 17/30666, G06F 17/30669, G06F 17/30672 G06F 17/30684, G06F 17/30687,</td><td>H04L 2025/03554, H04N 21/4665, H04Q 2213/054, H04Q 2213/13343, H04Q 2213/343, H04R 25/507, Y10S 128/924, Y10S 128/925, Y10S 706</td></tr>
<tr><td colspan="2">List of AI article key phrases††</td></tr>
<tr><td colspan="2">artificial intelligen* OR computational intelligen* OR neural network* OR neural_network* OR bayes network* OR bayesian network* OR bayesian-network* OR bayesian_network* OR chatbot* OR learning* OR learning model* OR learning algorithm* OR learning sys* OR intelligen* OR classification model* OR optimiz* OR training data* OR training method* OR convolutional network* OR anomaly detection* OR feature ext* OR feature ext* OR prediction model* OR data mining* OR decision model* OR deep learning* OR deep-learning* OR deep_learning* OR genetic algorithm* OR inductive logic* OR machine learning* OR machine_learning* OR machine-learning* OR natural language* OR image recogni* OR reinforcement learning* OR supervised learning* OR supervised training* OR supervised-learning* OR supervised_learning* OR swarm intelligen* OR swarm-intelligen* OR unsupervised learning* OR unsupervised training* OR unsupervised-learning* OR unsupervised_learning* OR semi-supervised learning* OR semi-supervised training* OR semi_supervise.</td></tr>
</table>

Notes: † Employing a "wildcard search" or "pattern matching search" is applied to retrieve the bibliometric information with patents from the PATSTAT database (EPO, 2022). In this case, the percentage sign (%) is used. Source: WIPO (2019).

†† A wildcard search, the asterisk symbol (*) is employed to obtain bibliographic information from the WoS Core Collection.

Appendix 2: Income levels of countries

Income level	Country (145)
High income (64)	Andorra, United Arab Emirates, Antigua and Barbuda, Australia, Austria, Belgium, Bahamas, Bermuda, Barbados, Brunei, Canada, Switzerland, Chile, Curaçao, Cayman Islands, Cyprus, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, United Kingdom, Gibraltar, Greece, Greenland, Hong Kong China, Croatia, Hungary, Ireland, Iceland, Israel, Italy, Japan, St. Kitts and Nevis, South Korea, Kuwait, Lithuania, Luxembourg, Latvia, Macao, Malta, Netherlands, Norway, New Zealand, Oman, Panama, Poland, Portugal, Qatar, Romania, Saudi Arabia, Singapore, Slovak Republic, Slovenia, Sweden, Seychelles, Turks and Caicos Isle, Trinidad and Tobago, Taiwan, Uruguay, United States, British Virgin Islands
Upper-middle income (36)	Albania, Argentina, Armenia, Azerbaijan, Bulgaria, Bosnia and Herzegovina, Belarus, Belize, Brazil, China, Colombia, Costa Rica, Cuba, Dominica, Dominican Republic, Ecuador, Georgia, Grenada, Guatemala, Indonesia, Kazakhstan, Libya, Moldova, Mexico, Macedonia, Mauritius, Malaysia, Namibia, Peru, Paraguay, Russian Federation, El Salvador, Serbia, Thailand, Turkey, South Africa
Lower-middle income (33)	Anguilla, Benin, Bangladesh, Bolivia, Cote d'Ivoire, Cameroon, Algeria, Egypt, Ghana, Honduras, India, Iran, Jordan, Kenya, Kyrgyz Republic, Lebanon, Sri Lanka, Morocco, Myanmar, Mongolia, Mauritania, Nigeria, Nicaragua, Nepal, Pakistan, Philippines, Swaziland, Tunisia, Ukraine, Uzbekistan, Venezuela, Vietnam, Samoa
Low income (12)	Burkina Faso, Bouvet Island, Eritrea, Ethiopia, Madagascar, Niger, North Korea, Sudan, Sierra Leone, Syrian, Tokelau, Uganda

Note: The income levels of each country adhere to the World Bank's standards (World Bank, 2023). Please note that these income levels can vary over time. In our analysis, we used the income level applicable to the year when the data was collected. For data aggregated over three years, the income level of the final year is considered. Notably, we have reclassified data for Taiwan, which was not previously differentiated in the UN Comtrade, in accordance with the standards set by The Growth Lab at Harvard University (2019).

Abstract (Korean)

기술혁신 역량과 경제 다각화는 국가가 장기적인 경제 성장을 이루기 위한 핵심 동력이다. 이 연구는 경제 복잡성과 진화 경제 지리학의 이론적 관점에서 국가의 인공지능 역량과 경제 다각화 간의 상호 연관성을 탐색하는 것을 목적으로 한다.

첫 번째 논문은 국가의 인공지능에 대한 과학적 연구 역량이 산업 기술 다각화에 미치는 영향을 탐구한다. 국가가 인공지능에 대한 과학적 연구 역량을 향상시키는 정책을 수립하고 촉진하는 것이 인공지능관련 산업에서 글로벌 기술경쟁력을 확보하는 데 어떻게 기여하는지를 실증적으로 검증한다. 특히, 이 논문은 인공지능의 기초 과학분야에 대한 투자를 소홀히 하면서 글로벌 기술패권을 추구하려는 국가와 기업들에게 중요한 시사점을 제공한다.

두 번째 논문은 국가가 인공지능관련 기술혁신 역량을 축적하는 것이 글로벌 수출 상품 시장에서 경쟁력을 향상시킬 수 있다는 가설을 실증적으로 검증한다. 이는 인공지능이 국가 차원에서 새로운 수출 상품으로 다각화하는 데 기여할 수 있음을 의미한다. 이 연구는 특히 한국, 대만, 중국과 같은 수출 주도 국가들에게 인공지능에 대한 투자가 장기적으로 글로벌 산업 경쟁에서 경쟁 우위를 선점하는데 기여할 수 있다는 시사점을 제공한다.

이 연구는 실증적 분석을 위해 국가의 혁신 역량을 기초과학 연구역량, 응용기술 혁신역량, 그리고 수출상품 생산역량이라는 세 가지 차원으로 구분한다. 그리고 각 역량들을 연결할 수 있도록 다차원 지식 네트워크를

구축한다. 특히, 이 연구는 국가-역량의 이분 그래프(Bipartite graph)에 대한 행렬 곱을 통해 서로 다른 차원을 연결하는 방법론을 채택하여 특정 시기에 국가들 간에 동시 출현하는 역량들 사이의 상관성 또는 연관성을 확률적으로 추정한다.

다차원 지식 네트워크 사이의 연관성을 분석하기 위해 학술 논문 출판물, 특허 출원 정보, 수출입 상품 데이터와 같은 다양한 지표를 포함하는 패널 데이터를 구축하고, 고정 효과 패널 회귀 모델을 사용하여 인공지능 역량과 국가의 경제 다각화 간의 상관관계를 밝힌다. 이 연구의 결과는 인공지능 역량을 국가가 지속적으로 축적하는 것이 글로벌 경쟁 환경에서 비교 우위를 확보하는 데 기여한다는 것을 보여주었다. 특히, 인공지능 역량의 효과가 선진국보다 개발도상국에서 더 크게 나타났으며, 개발도상국들이 자국의 산업에 직접적인 연관성이 있는 인공지능 기술을 도입했을 때 더욱 유의미한 결과를 보였다.

이 연구의 결과는 선진국 또는 OpenAI, 구글, 마이크로소프트와 같은 빅테크 기업들이 추구하는 기술 트렌드를 단순히 따라가는 것보다, 각 국가가 보유한 산업과 연관성 있는 인공지능 역량을 집중하는 정책이 더 효과적임을 시사한다. 이는 국가별 고유한 산업 강점을 활용하여 인공지능 기술을 접목시키는 전략이 경제 성장과 글로벌 경쟁력 강화에 더욱 유리하다는 점을 강조한다. 따라서, 정책 입안자들은 각국의 특수한 산업 환경과 역량을 고려한 맞춤형 인공지능 연구개발 정책을 수립하여 보다 효과적인 경제 다각화와 지속 가능한 성장 경로를 확보하는 데 주력해야 한다.

최근 인공지능은 국가 기술 주권의 하나로 간주되고 있어 국가 간 협력과 경쟁이 치열해지고 있다. 이런 경쟁 환경에서 살아남기 위해 국가는 인공지능 역량을 기존에 확보한 과학적, 기술적, 생산적 역량에 통합하는 노력과 함께 부족한 역량은 협력을 통해 보완하는 정책이 요구된다. 여기서 과학적, 기술적 역량의 통합이란 인공지능을 학문적으로 연구하고 새로운 지식을 생산하는 학계와 학술적 지식을 도입하여 기술혁신을 추구하는 산업계의 협력과 상호 교류를 의미한다. 우리는 이것을 상호 이질적인 지식을 가진 주체들 사이의 보완적 혁신이라고 정의한다.

마지막으로, 이 연구는 과학, 기술, 상품 공간을 연결하는 다차원 분석 프레임워크를 제안하고 실증적으로 검증함으로써 진화 경제 지리학과 경제 복잡성 이론 분야에서 방법론적으로 기여한다.

주요어 : 인공지능, 경제 다각화, 지식 네트워크, 다차원 네트워크 분석, 보완적 혁신
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