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MEASURING NATIONAL ARTIFICIAL INTELLIGENCE CAPACITY: A HOLISTIC APPROACH BASED ON HUMAN CAPITAL SPECIALIZATION

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Abstract

The transformative impact of artificial intelligence has made the acquisition of skills necessary for technology adoption and adaptation increasingly critical. This has brought to the forefront the need to develop criteria, metrics, and methods to measure progress in the field of artificial intelligence. The purpose of this study is to determine the extent to which countries are specialized in artificial intelligence. The research was conducted in three stages. In the first stage, the fundamental components of human capital in the field of artificial intelligence were identified. In the second stage, a hybrid model based on the AHP–Gauss method was employed to evaluate these components within an integrated framework. In the final stage, this model was used to quantitatively measure the human capital specialization levels of selected countries in the field of artificial intelligence. The results reveal the current status and relative specialization levels of countries within a comparable framework. According to the findings, the United States, the United Kingdom, India, Germany, and Canada are leading countries in terms of human capital specialization in artificial intelligence. These nations possess knowledge capacity, skilled human resources, and sectoral experience sufficient to support advancements in artificial intelligence. The findings of the study underscore the need to clarify a strategic approach to developing human capital in the field of artificial intelligence. In this regard, they provide insightful guidance on the priority areas that require focused attention.

Keywords: Artificial intelligence management, Management of technological change, human capital, specialization, AHP-Gaussian
JEL Classification: J21, O32, O33

ULUSAL YAPAY ZEKA KAPASİTESİNİN ÖLÇÜMÜ: BEŞERİ SERMAYE UZMANLAŞMASINA DAYALI BÜTÜNSEL BİR YAKLAŞIM

Öz

Yapay zekânın dönüştürücü etkisi, teknolojiyi benimseme ve uyum sağlama sürecinde gerekli becerilerin kazanılmasını daha da kritik hâle getirmiştir. Bu durum, yapay zekâ alanındaki ilerlemeleri ölçmek için kriterler, metrikler ve yöntemler geliştirme ihtiyacını ön plana çıkarmıştır. Bu araştırmanın amacı, ülkelerin yapay zekâ alanında ne ölçüde uzmanlaştığını belirlemektir. Çalışma üç aşamada yürütülmüştür. İlk aşamada, yapay zekâ alanındaki beşerî sermaye yapısı ile ilgili temel unsurlar belirlenmiştir. İkinci aşamada, belirlenen unsurları bütünleşik bir çerçevede değerlendirmek üzere AHP–Gauss yöntemine dayalı hibrit bir model kullanılmıştır. Son aşamada ise bu model aracılığıyla seçilen ülkelerin yapay zekâ alanındaki beşerî sermaye uzmanlaşma düzeyleri nicel olarak ölçülmüştür. Elde edilen sonuçlar, ülkelerin mevcut durumlarını ve göreli uzmanlaşma düzeylerini karşılaştırılabilir bir çerçevede ortaya koymuştur. Araştırma bulgularına göre, ABD, Birleşik Krallık, Hindistan, Almanya ve Kanada'nın yapay zekâ alanında beşerî sermaye uzmanlaşma düzeyi açısından öncü konumdadır. Bu ülkelerde bilgi birikimi, yetenekli insan kaynağı ve sektörel deneyim, yapay zekâ alanındaki gelişimi destekleyecek düzeydedir. Çalışmanın sonuçları, yapay zekâ alanında beşerî sermayenin geliştirilmesi için stratejik yaklaşımın netleştirilmesi gerektiğini vurgulamakta ve bu bağlamda odaklanılması gereken alanlara yönelik ışık iç görüler sunmaktadır.

Anahtar kelimeler: Yapay zeka yönetimi, Teknolojik değişimin yönetimi, Beşeri sermaye, Uzmanlaşma, AHP-Gauss
JEL Sınıflaması: J21, O32, O33

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1. Introduction

The world is undergoing a rapid process of change with new technological developments. In the 21st century, the main driving force behind this change is artificial intelligence technology. The rate of development in artificial intelligence provides clues that it will take over many tasks currently performed by humans. Artificial intelligence refers to technologies that possess human-like thinking and interpretation skills, enabling the conscious and adaptive transformation of data into knowledge. The term artificial intelligence was first used by Alan Turing in 1950. In his article titled "Computing Machinery and Intelligence" he put forward some ideas about the intellectual activities of machines. Until the 1990s, artificial intelligence research had not achieved the desired momentum. At the end of the 1990s, a different perspective on artificial intelligence research was developed. After this date, studies related to artificial intelligence began to be addressed by dividing them into sub-components. Another important development in this period was the use of artificial intelligence technology for practical applications. Applications such as computers winning against human opponents in chess games have led to significant conclusions that artificial intelligence could surpass human intellectual abilities. Again in this period, successes in computer and autonomous vehicle applications stood out as promising advancements for artificial intelligence research. From 2010 onwards, the generation and use of big data, along with the development of machine learning and computers with high computational power, have taken progress in this field to another dimension (Aslan, 2024). These advancements have shown that artificial intelligence's ability to solve complex problems could surpass human capacity and therefore could assume a transformative role (National Science and Technology Council, 2016).

Artificial intelligence, with its revolutionary transformative potential, can have large-scale consequences for individuals, organizations, and countries (Albrecht & Aliaga, 2023). Even in its current state of development, artificial intelligence has numerous application areas due to the support it provides to human capabilities in production, education, and service industries. The wide range of applications for artificial intelligence also offers opportunities for economic development (Rao & Verweij, 2017). These opportunities encourage the increasing use of artificial intelligence by public and private sectors, non-profit organizations, and individuals. Actors who prioritize efficiency, productivity, effectiveness, and economy are particularly willing to adapt to the solutions brought by artificial intelligence technology (Grievson et al., 2022). Despite this willingness, industries and firms may face significant challenges due to operating in a complex and dynamic environment (Aslan & Uzun, 2021). However, for

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countries with human capital that shows strong adaptation to artificial intelligence technology, this change can yield positive results. Therefore, countries need to make the necessary preparations now to avoid negative situations or minimize their effects (National Science and Technology Council, 2016).

For technology to create economic value, it is not sufficient for it to be adopted merely as a product or service. Human capital must also be developed (Vandeweyer et al., 2020). Specialization is the fundamental variable of human capital. Therefore, in the process of adopting and spreading new technologies, skill specialization is of critical importance (Frigenti & Stiles, 2019). Human capital facilitates adaptation to technological change through skill specialization and contributes to the development of effective practices (UNCTAD, 2019). However, adaptation to new technologies may not always occur at the same level for individuals, institutions, and countries. Uncertainty regarding new technologies and resource constraints can make it difficult for human capital to adapt (Grievson et al., 2022).

The development of the ability to perform human-like tasks, in particular, may lead to a reduction in the need for workforce in certain professional groups (Albrecht & Aliaga, 2023). Moreover, in industries where technological progress has a greater impact on productivity, the importance of experience gradually diminishes. The decreasing importance of experience results in a reduction in the importance of human capital. Failure to acquire adequate skills, skill shortages, and skill mismatches may lead to future problems such as skills gaps in the labor market, income inequality, reduced innovation and creativity, and decreased competitiveness of institutions (OECD, 2011b; Orkestra, 2020).

Countries with strong human capital are developing more rapidly (OECD, 2011b). To increase the skill capacity of countries, it is first necessary to identify practices and gaps (Rodrigues et al., 2021). Additionally, studies need to be conducted at both national and international levels. This issue was addressed at a summit held in 2010 by the leaders of the world's 20 most developed economies. At this summit, it was emphasized that a comprehensive framework is needed for the development of human capital at global and local levels. For the applicability and effectiveness of this framework, it was stated that there is a need to determine common standards or criteria that will make skill levels comparable through international cooperation. Similarly, specific policies and plans should be developed at the national level to address skill shortages and needs in the labor market (Keese & Tan, 2013).

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Policy instruments are designed for objectives related to knowledge generation, dissemination, or exploitation. Knowledge generation includes measures aimed at generating scientific and technological knowledge. Knowledge dissemination involves measures related to attracting and retaining talents, establishing relationships between workforce demand and supply, cooperation, mobility, establishing innovation infrastructure, and access to capital. Knowledge exploitation includes measures for education and vocational training programs, access to research and development activities, supportive measures for developing innovative skills and abilities, and measures for entrepreneurship and innovation ecosystems (OECD, 2011b).

A critical component of this preparation is the continuous development of human capital capacity to achieve success in artificial intelligence technology (Brandt et al., 2022). In this context, the study aims to determine in which areas and to what extent human capital makes progress (level of specialization) in relation to artificial intelligence. Countries' advancements in the field of artificial intelligence are considered in terms of knowledge generation, diffusion, and exploitation. The strengths and weaknesses of the specialization level of human capital are evaluated from an inclusive perspective.

The fundamental assumption underlying the determination of this research's scope is that the development and diffusion of AI technologies will exert a decisive influence on nations' knowledge production, dissemination, and utilization processes. This impact will fundamentally reshape the existing structure of their human capital. However, an important point here is that the interaction between the processes of knowledge production, dissemination, and utilization, and their reciprocal impact on human capital, is crucial. In other words, advancements in the processes of knowledge production, dissemination, and utilization will serve to enhance the qualities and capabilities of human capital, while at the same time, improvements in human capital will further nurture and sustain these knowledge-related processes. In line with this fundamental assumption, the data used in this study is drawn from the OECD Artificial Intelligence Policy Observatory database, which aggregates data from a wide range of platforms from social media to academic databases, and from code-sharing platforms to employment portals. This diverse data pool captures various facets of the AI ecosystem. Accordingly, the countries selected for this study are limited to those with the most comprehensive data sets in the OECD database. This situation has resulted in the exclusion of some OECD countries from the scope of the study. To enhance the representativeness of the research, it would be important to include as many countries as possible. However, in cases where data quality and breadth are uneven, a more selective approach may be necessary to

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maintain the credibility of the findings. This approach was adopted to ensure the findings of the research are more reliable and representative. However, this has resulted in the exclusion of some OECD countries from the scope of the study.

2. Literature Review

Previous studies have made significant contributions to the literature on measuring the skill level of human capital. This is especially true for research conducted by international institutions, organizations, and other relevant entities. In this context, the World Indicators of Skills for Employment (WISE), developed by the Organization for Economic Co-operation and Development (OECD), aimed to measure skill development in 214 countries. The study examined how digital skill demand and supply are shaped in the process of digital transformation. Within the framework of world employment skills indicators, it used 5 indicators and 64 components, including contextual factors, skill acquisition, skill requirements, skill mismatch, and economic and social outcomes (OECD, 2015). Another study developed by the International Development Research Centre (IDRC) used an artificial intelligence readiness ranking index. This study examined the relationship between the AI readiness levels of Latin American and Caribbean countries and several factors. These factors included unemployment rate, gross domestic product per capita, purchasing power parity, the cost of hiring an AI researcher and nationwide education level (Montoya & Rivas, 2019). Additionally, a study conducted by the European Commission used the Digital Economy and Society Index (DESI). DESI is an index framework covering specific policy areas and indicators, which is used to monitor and evaluate the digital transformation processes of EU member states. This index measured the digital progress of EU member states by considering important elements such as human capital, connectivity infrastructure, integration of digital technologies and digital public services (Europe Comission, 2021). In their study, Lanvin & Monteiro (2023) developed the Global Talent Competitiveness Index framework to measure countries' talent competitiveness. They used an input-output model in the index to compare national-level progress in the generation, development, and acquisition of human capital. The input dimension of the index consists of four indicators and ten components, namely enable, attract, grow, and retain. The output dimension comprises two indicators and four key components, specifically global knowledge skills and vocational-technical skills. In a related study, Baguma vd. (2023) developed a comprehensive set of indicators to assess the progress of African countries in the field of artificial intelligence. These indicators encompassed vision, governance and ethics, digital capacity, technology sector size, research and development,

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education, infrastructure, and data accessibility. They also included measures of overall employment, employment in data science and AI roles, and purchasing power parity per GDP, providing a comprehensive framework to evaluate AI progress in African countries.

Studies in the literature have examined global developments related to digitalization and artificial intelligence skills across a wide geography, ranging from Latin America and the Caribbean to Africa. These studies have also addressed the impacts of this technology on countries from different perspectives. This clearly demonstrates that the relationship between information and communication technologies such as digitalization and artificial intelligence and human capital is a significant focus of interest in scientific circles across countries. Another conclusion drawn from the examination of the literature reveals that although there are various indicators for evaluations related to artificial intelligence, specialized assessments focusing on specific areas are still limited. This situation may make it difficult to conduct conceptual models, descriptive variables, and empirically supported evaluations aimed at examining the level of specialization of human capital in the field of artificial intelligence.

3. Contextual Framework

A clear and robust contextual framework is needed for the logical validation of the proposed model. When bringing together different indicators, it is necessary to define what each variable represents and how it is measured. This ensures correct interpretation of the phenomenon. When each variable is evaluated separately, it provides information about its own scope, measured characteristic, and the phenomenon it represents. Conversely, by combining different complementary variables, a complex or multidimensional phenomenon becomes more understandable and measurable. While a single variable offers a narrow insight, combining different variables yields more comprehensive insights (Hardeman et al., 2013).

Considering the transformative effect of artificial intelligence in many areas, individual indicators alone may not be sufficient to evaluate progress in the field of human capital (Brandt et al., 2022; Fatima et al., 2020). Therefore, to understand and improve the economic success of individuals and society, skill and human capital factors should be evaluated together (Rodrigues et al., 2021).

Human capital is defined as the qualitative and quantitative elements possessed by individuals responsible for generating value through the generation, diffusion, and exploitation of knowledge in an organization, society, or economy (OECD, 2013). The generation, diffusion, and exploitation of knowledge are carried out through human capital (OECD, 2011a).

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Endogenous growth theory posits that human capital is the main determining factor of technological advancement. This theory emphasizes that the research and diffusion effects of human capital have a critical impact on technological progress. The research effect captures the processes through which new ideas are generated and technological innovation emerges. The diffusion effect, in turn, represents the mechanisms that enable these innovations to be adopted, implemented, and enhanced through the skills and competencies of a highly qualified workforce (De Grip, 2006).

Skill specialization is the theoretical and practical knowledge required to perform a job, find employment, and maintain it (ILO, 2012). The level of specialization refers to the internalization of knowledge gained through research, education, practice, and experience by means of individual cognitive processes. It also encompasses the ability to adapt this knowledge to changing conditions and to apply it effectively in successfully carrying out tasks. The skills and competencies acquired and developed through the work practices, personal experiences, intuitions, and conceptual understandings of individuals, groups, or institutions enhance job performance. When complemented by professional, technical, and scientific knowledge, these abilities enable more effective execution of specific tasks. The adaptation and specialization level of human capital is directly linked to the acquisition and application of such knowledge and skills (Bozeman & Youtie, 2017). Factors such as individuals' academic achievements, literacy levels, and vocational or workforce training play a critical role in determining the level of specialization. Together, these elements provide a foundation for assessing the workforce’s knowledge and skills, offering essential insights for evaluating human capital specialization in the field of artificial intelligence (Frigenti & Stiles, 2019).

The specialization level of human capital in the field of artificial intelligence encompasses gains obtained in a value chain extending from researchers' discoveries to application developers and end-users. These gains are the values obtained in the process from the generation of knowledge in the field of artificial intelligence to the use of this knowledge in business and services (National Science and Technology Council, 2016).

In accordance with the context given above, the criteria in Table 1 have been selected to measure the level of specialization of human capital in the field of artificial intelligence. A wide range of data and resources that enable comprehensive research contributes significantly to scientific and technological progress (Aslan, 2023). However, using too many criteria in studies can increase complexity and make it difficult to understand the relationships between criteria and accurately determine weights resulting from correlation (Tuccio, 2019). Conversely, selecting

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too few criteria can narrow the scope of the decision-making process and risk overlooking some important factors. Therefore, to conduct an inclusive analysis, a reasonable number of criteria has been preferred, appropriate to the decision-making context.

Table 1. Decision criteria and directions

Code	Criteria	Direction
C1	Scientific research publications	Max
C2	International collaboration in artificial intelligence research publications	Max
C3	Artificial intelligence courses	Max
C4	Interest in artificial intelligence courses	Max
C5	Questions and answers in the field of artificial intelligence	Max
C6	Accepted answers to questions in the field of artificial intelligence	Max
C7	Contribution to open-source artificial intelligence software development projects	Max
C8	Artificial intelligence skill penetration	Max
C9	Artificial intelligence hiring index	Max
C10	Size of venture capital investments	Max
C11	Venture capital investments	Max

2.1. Scientific Research Publications

The driving force behind technological advancement is scientific research and development activities (Brandt et al., 2022). In the process of developing a new technology, scientific research plays a decisive role in creating knowledge, methods, and applications. Scientific research supports the feasibility of technology with solid evidence. This evidence demonstrates that the developed technology has the ability to meet the needs of industry and society. Evidence that the technology is feasible and usable facilitates acceptance and adoption processes. Scientific research encourages the acquisition of new skills. It supports new ventures based on scientific discoveries. Additionally, it enables individuals to receive new training and acquire explicit and tacit knowledge. It develops the scientific and technical capabilities of human capital for the generation, diffusion, and use of knowledge (Beck et al., 2019).

Techniques, concepts, and knowledge related to technology are discovered through scientific research conducted by universities, institutes, public research institutions, and industry (OECD, 2011a). Scientific research imparts skills to a wide range of individuals from students to educators in universities and research institutions (Grievson et al., 2022). Research activities carried out in these institutions enable the generation and diffusion of knowledge through outputs such as scientific publications and intellectual property rights (National Science and Technology Council, 2016). The obtained outputs are transformed into technology-based economic value with industry expertise (Grievson et al., 2022). Additionally, through these institutions, the training of potential and existing workforce and the transfer of knowledge are realized. The use of knowledge is achieved by supporting ventures through consultancy or joint projects in research and development processes (OECD, 2011a). It enables the acquisition of knowledge related to fundamental skills and the development of a culture of innovation (Grievson et al., 2022).

Widely used measurable skill indicators in the field of science and technology are scientific publications and patents. Information on which scientific publications are produced in which countries provides insights into the research skills of those countries (National Science Board, 2022). The countries showing high performance in the scientific research publication criterion categorized in the field of artificial intelligence are, in order, the USA, India, the United Kingdom, Germany, and Italy. The countries showing low performance in this field are Hungary, Croatia, Bulgaria, Slovenia, and Estonia (OECD.AI, 2024).

2.2. International Collaboration in Artificial Intelligence Research Publications

International cooperation is a fundamental mechanism encompassing the systematic collaboration of individuals, groups, and institutions from different nations toward common goals. This process facilitates the sharing of knowledge, expertise, and critical resources, thereby deepening mutual understanding and trust among participants (Bozeman & Youtie, 2017). The core objective of cooperation is to achieve shared goals by generating synergistic value that surpasses the mere sum of individual capabilities. Consequently, the diffusion of competencies accelerates, and the likelihood of achieving large scale positive outcomes significantly increases (National Science and Technology Council, 2016).

Moreover, the level of cooperation skills stands out as a determinant factor in gaining a competitive advantage, particularly in pioneering technologies (Brandt et al., 2022). This strategic importance translates into a range of tangible benefits for researchers and institutions. For instance, cooperation contributes to human resource processes such as recruitment, promotion, and increased prestige; it optimizes infrastructure utilization; and it facilitates the commercialization of research and the promotion of interdisciplinary studies. All these advantages simultaneously foster cost effectiveness (Bozeman & Youtie, 2017; Liu et al., 2020). At the structural level, international cooperation plays a vital role in establishing widely accepted standards and common frameworks (National Science and Technology Council, 2016).

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A significant portion of current advancements in the field of artificial intelligence is achieved through international dialogue, collaboration, and shared efforts among researchers and experts from different countries. Researchers working on artificial intelligence tend to collaborate more in scientific publications. These collaborative studies are recognized as an effective method to address the complexity of the field, combine knowledge from different areas of expertise, and obtain more comprehensive results (Bozeman & Youtie, 2017; Liu et al., 2020). The international collaboration criterion used in the study refers to collaborations consisting of co-authorships between institutions in different countries (OECD.AI, 2024). The United States ranks first in the field of international collaboration. The UK, Australia, Germany, and India follow the USA. The countries ranking last in this field are Hungary, Slovenia, Croatia, Estonia, and Bulgaria.

2.3. Artificial Intelligence Courses

New skills required to adapt to technological developments are supported through on the job training or various courses (De Grip, 2006). Courses are delivered either online or in physical classroom settings. A wide user base accesses online courses for skill acquisition. Online courses are generally less costly and are therefore becoming increasingly prevalent (UNCTAD, 2019). These courses offer participants the opportunity to receive education without encountering geographical, economic, or physical barriers. Additionally, they use tools such as text, audio, video, and visuals to provide content suitable for various learning styles. They provide an interactive learning environment that allows participants to communicate, exchange ideas, and collaborate (Diaz-Infante et al., 2022).

Courses related to applications in the field of artificial intelligence make significant contributions to the acquisition of necessary skills by the existing workforce (National Science and Technology Council, 2016). The criterion for the number of artificial intelligence courses is measured by the number of English courses offered through online education platforms worldwide. The USA ranks first in the number of artificial intelligence courses. The UK, Australia, Canada, and Germany follow the USA. The countries ranking last in this field are Estonia, Slovenia, Croatia, Israel, and Bulgaria. The level of interest in artificial intelligence courses is measured by the number of page views of English AI courses. These courses are offered on a platform that provides information about online education programs worldwide. (OECD.AI, 2024). Germany ranks first in the criterion of interest in artificial intelligence courses. Other countries that stand out in this field are the UK, USA, Canada, and Italy. The countries ranking last in this field are Estonia, Croatia, Bulgaria, Slovenia, and Israel.

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2.4. Knowledge Flow

Knowledge finds more opportunities for interaction and use as it is shared and made accessible in society. Sharing knowledge increases access to information, collaboration, and interaction while preventing unnecessary repetitions. Technological developments progress and spread more rapidly thanks to different perspectives offered by complementary information. In the process of knowledge sharing, criticisms, contributions, and questions asked encourage the knowledge holder to continuously review, develop, and renew their knowledge (European Investment Bank, 2014). The knowledge produced is shared through scientific and technological outputs, making it available for use by others. In addition to knowledge generation, the diffusion and effective use of knowledge are necessary. The more widely knowledge is disseminated, the greater its adoption and impact. Knowledge gains value when it is disseminated through various formal tools such as articles, papers, books, patents, and educational notes.

There may be situations where formal tools are insufficient for the diffusion of knowledge. It may not always be possible to disseminate knowledge gained from experiences, learned lessons, and practices to large audiences due to geographical constraints, cost, and time limitations (European Investment Bank, 2014). The development of online technologies facilitates making this information accessible. Knowledge sharing in online communities takes place on various platforms such as social media channels, forums, blogs, video sharing sites, and online communities. These platforms support knowledge sharing and allow participants who come together for different purposes to share their research, experience, and expertise. Connecting diverse pieces of knowledge accelerates collective knowledge generation and learning. Additionally, as participants learn from each other, they increase knowledge exchange through question-and-answer interactions. As a result, access to knowledge increases for individuals outside scientific communities, and social interaction is encouraged. A global relationship is established based on common interests, independent of geographical boundaries (Beck et al., 2019; Parameswaran & Whinston, 2007).

Online technologies are used for knowledge generation and diffusion by individuals as well as businesses (Chai et al., 2011). When these technologies are used effectively and efficiently, employees' access to information is facilitated, and work productivity increases (Ammirato et al., 2019). Artificial intelligence knowledge flow measures how individuals and communities discussing various AI topics share specialized AI knowledge of countries through online platforms. It also captures changes in interest in AI topics (OECD.AI, 2024). In terms of the

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number of questions and answers transmitted through the online platform, the USA ranks first. The USA is followed by India, Germany, the United Kingdom, and France. By contrast, countries showing low performance in this area are Hungary, South Africa, Slovenia, Bulgaria, and Estonia. According to the criterion of accepted answers to questions in the field of artificial intelligence, the USA ranks first. Other prominent countries in this field are Germany, India, the United Kingdom, and France. Portugal, Bulgaria, Slovenia, South Africa, and Estonia are the countries ranking last in this area.

2.5. Contribution to Open Source Artificial Intelligence Software Development Projects

A wide variety of metrics are employed for assessing national performance in the field of artificial intelligence. Nevertheless, the impact of open-source software is often neglected in these comprehensive evaluations. AI policies that fail to account for open-source solutions risk overlooking a critical component in the technology's development and widespread diffusion. This omission consequently prevents the full realization of potential opportunities and expected contributions, leading to an incomplete assessment of national performance (Engler, 2021).

Open-source software offers a broad spectrum of benefits, including the capacity for flexible customization and modification tailored to user requirements. In addition to providing cost-free access, these programs possess a continuous development potential thanks to uninterrupted updates and community support. Furthermore, this software provides the advantage of leveraging a large user and developer ecosystem, enabling the creation of rapid solutions (Hauge et al., 2010). Open-source software projects, due to their dynamic nature, often allow community members with diverse skills and interests to actively take on various roles (Ducheneaut, 2005). These roles may include code development, review, and evaluation. Members can also contribute by translating software or content into different languages, facilitating usage and dissemination, or simply showing interest (Engler, 2021). The contributions offered by these comprehensive communities provide diversity, increasing the likelihood of the project's success and adoption (Ducheneaut, 2005; Young et al., 2021). For example, Linux, developed as an open-source software project, has a wide user base in cloud computing, server operating systems, smartphones, tablets, personal computers, embedded systems, supercomputers, and many other areas. Especially in the last 15 years, more than 400 companies have contributed to the project's development. This has been effective in Linux's widespread acceptance and use (Korkmaz et al., 2024).

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Contribution to open artificial intelligence software development projects is measured by the number of times AI projects are replicated by others / number of followers (OECD.AI, 2024). The countries showing high performance in contributing to open artificial intelligence software development projects are, in order, India, USA, United Kingdom, Canada, and Germany. Hungary, Croatia, Slovenia, Bulgaria, and Estonia are the countries showing low performance in this area.

2.6. Artificial Intelligence Skill Penetration

New technologies like artificial intelligence have the potential to increase job opportunities while also eliminating existing jobs. These technologies also enable the transformation of individuals' knowledge and skills by enhancing existing competencies (Foray et al., 2012). Existing knowledge, experiences and business models can facilitate the transition to and adaptation of a new technology. However, transition and adaptation may not always be easy and may require retraining of human capital (Grievson et al., 2022). Education and skill acquisition methods should be prioritized to address the likely emerging skill gap (LaPrade et al., 2020).

Technological advancements such as artificial intelligence, big data and blockchain have led to an increasing need for specialized workforce in the industrial field (UNCTAD, 2019). However, the labor market may not always be able to immediately provide the required skills. Therefore, the increase in demand may enhance the potential for individuals in the labor market to transition from existing jobs to new and growing sectors. People who want to seize these opportunities achieve career transformation by acquiring new skills (World Economic Forum, 2022).

The rapid advancement of technology is causing a quick decline in the functionality of skills. Generally, the validity period of skills decreases significantly within five years. For technical skills, this period has shrunk to as little as three years. In light of breakthrough developments in artificial intelligence and information technologies, this trend is expected to become even more pronounced in the next few years. In contrast, current data shows that the time required to acquire new skills has extended from 3 days to up to 36 days (LaPrade et al., 2020). This situation increases the need for continuous learning, rendering traditional education models inadequate. This brings about significant issues such as the widening gap between the obsolescence of skills and the acquisition of new ones. Therefore, efforts need to be made towards continuously updating skills and adapting to different sectors (De Grip, 2006).

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Artificial intelligence skill penetration indicates the extent to which individuals within a workforce or professional group have acquired AI skills or how frequently they use these skills in their jobs (OECD.AI, 2024). For the penetration of AI skills, the prevalence of employees with AI skills compared to the OECD/G20 average is taken into account. India ranks first in AI skill penetration, followed by the USA, Germany, Israel, and Canada respectively. Estonia, New Zealand, Slovenia, Czech Republic, and Portugal are the countries showing low performance in this area.

2.7. Artificial Intelligence Hiring Index

Due to its potential for use in every field, the demand for specialized talent in the field of artificial intelligence is continuously increasing (Aiken et al., 2020). Achieving the necessary progress in the field of artificial intelligence can only be possible with a workforce of sufficient number and expertise (Babina et al., 2024).

Regions where investments in artificial intelligence are increasing tend to become centers for a workforce with more AI skills. In these regions, there is a greater tendency for skill concentration in job areas based on AI technologies. As a result of the concentrated workforce, knowledge, and experience, innovation and entrepreneurship develop (Mou, 2019). This pattern is also reflected in workforce employment trends. According to a study, in the United States, more than half of the individuals with doctoral degrees in artificial intelligence are concentrated in academia, while more than one-third are in industry. The same study determined that three out of every four doctoral graduates in the field of artificial intelligence tend to work in academia or large companies (Aiken et al., 2020).

The artificial intelligence hiring rate is based on the approach of comparing the increase in general employment levels with the employment rate of individuals possessing AI skills. The value obtained from this comparison determines the hiring rates of individuals with AI skills. For example, in the United Kingdom, where the hiring index is 1.23, the AI employment rate is 23 percent higher than the general employment rate. This indicates that hiring in the AI field is occurring faster than the general hiring increase (OECD.AI, 2024). According to the hiring rate criterion in the field of AI, the United Kingdom, Australia, Estonia, Canada, and Croatia are the most successful countries in rapidly hiring new talent in this field. On the other hand, India, Belgium, Austria, Korea, and Romania are the countries with the lowest hiring rates.

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2.8.Artificial Intelligence Investments

Real progress cannot be discussed if entrepreneurial skills for applying technology are absent or not at the same level as basic research. Basic research conducted in universities and various research centers provides understanding about new knowledge and technology rather than obtaining value. The widespread diffusion of scientific research and its acceptance in society are supported by the insights gained from research findings. Public support is maintained when these findings provide solutions to real-world problems. Thus, research gains value not only in academic circles but among all stakeholders (National Science Board, 2020). Therefore, entrepreneurs have important roles in ensuring that a new technology provides new discoveries that create value. Entrepreneurs contribute to the development of skills related to the discovered technology by synthesizing scattered and fragmented knowledge. They conduct various experimental studies and applications related to a new technology. Through the results obtained, whether successful or not, they can generate new knowledge and skills for different areas of technology (Foray et al., 2012).

Startups play a crucial role in bringing new ideas to life in the technology field. For example, a study conducted in the Euro zone determined that a significant portion of employment growth was provided by startups (Bello et al., 2022). Similarly, venture capital investments in the USA have played a decisive role in developing breakthrough technologies (Brandt et al., 2022). The role of startups in technology development is also leading to the emergence of innovative solutions and applications in the field of artificial intelligence (Liu et al., 2020; Mou, 2019). A study analyzing startups with the potential to provide innovative solutions in the field of artificial intelligence across multiple industries revealed that, on average, each startup engaged in 3.67 deals. Each of these deals secured an investment of approximately $1.17 billion, underscoring the substantial investor interest in this sector. These findings are important in terms of indicating the high potential of investor interest in the field of artificial intelligence (Mou, 2019).

In terms of the criterion of venture capital investment size for research, product, and service development activities in the field of artificial intelligence, the USA, United Kingdom, Sweden, India, and Israel are high-performing countries. The countries showing low performance in this area are, in order, New Zealand, Romania, Slovenia, Bulgaria, and Croatia. In terms of the criterion of the number of venture capital investments in research, product, and service development activities, the USA, South Korea, United Kingdom, India, and Japan have the

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highest number of investments. The countries showing low performance in this area are, in order, Romania, Bulgaria, Hungary, Slovenia, and Croatia.

3. Method

A successful decision-making process requires selecting the most suitable alternative for the intended outcome. This process often unfolds under high levels of uncertainty and complexity (Pereira et al., 2023). In situations involving numerous interdependent factors, it becomes essential to use methods capable of evaluating all alternatives simultaneously. Bringing together different factors makes complex or multidimensional phenomena more understandable and measurableb (Hardeman et al., 2013).

One of the most commonly used approaches for such complex evaluations is multi-criteria decision-making (MCDM). This method supports decision-makers by incorporating mathematical and computational techniques into a structured decision process. Among MCDM techniques, the Analytic Hierarchy Process (AHP) is particularly widespread. It enables decision-makers to compare criteria and alternatives systematically and to identify the most appropriate option. However, AHP has limitations because it relies heavily on subjective judgments. These subjective inputs can be influenced by various factors and may introduce uncertainty into the final decision. To mitigate this issue, the Gaussian Analytic Hierarchy Process (AHP-G) was developed (Da Silva et al., 2021). This approach incorporates measurable data and objective weighting procedures into the evaluation process. In AHP-G, the performance of each alternative is assessed relative to the performance of other alternatives under the same criterion (Pereira et al., 2023). Criterion weights are then determined based on the coefficient of variation. The coefficient of variation reflects how the data behave within the decision matrix. It captures differences in criterion performance across alternatives and therefore indicates how important each criterion is relative to the others (Dos Santos et al., 2023).

The AHP-G method consists of the following steps:

1. In the first step of the method, a decision matrix is created.
2. After the decision matrix is created, the normalization process is carried out. In this process, normalization is performed using the formulas given in Equation (1) for maximum-oriented criteria and Equation (2) for minimum-oriented criteria.

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$$\text{Normalize (N)} = \frac{a_{ij}}{\sum a_{ij}} \tag{1}$$

$$N = \frac{\left(\frac{1}{a_{ij}}\right)}{\left(\frac{a_{ij}}{\sum a_{ij}}\right)} \tag{2}$$

3. The mean and the standard deviation for each criterion are calculated using Equation (3) and Equation (4).

$$\text{Mean}(\mu) = \frac{1}{n}\sum N \tag{3}$$

$$\text{Standard deviation } (\sigma) = \sqrt{\frac{\sum(a_{ij}-\mu)^2}{n}} \tag{4}$$

4. Using the standard deviation and mean values, the Gaussian factor and normalized Gaussian factors are calculated using Equation (5).

$$\text{Gauss factor } (k) = \frac{\sigma}{\mu} \tag{5}$$

5. In the final stage, for each alternative, the weighted decision matrix values are calculated by multiplying the normalized decision matrix with the normalized Gaussian values (Pereira et al., 2023).

2. Findings and Discussion

The normalized decision matrix obtained as a result of creating the decision matrix, which is the first step of the AHP-G method, is presented in Table 2. While the rows in the table represent alternatives, the columns represent normalized values for specific criteria. The values are normalized values showing the performance of each country in each criterion. Cells with high values in the matrix indicate that the relevant country performs well in that criterion, while cells with low values represent low performance.

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Table 2. Normalized decision matrix

Criteria / Countries	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
Australia	0,041	0,065	0,048	0,020	0,023	0,026	0,014	0,030	0,036	0,018	0,019
Austria	0,011	0,019	0,007	0,024	0,008	0,006	0,003	0,019	0,031	0,032	0,005
Belgium	0,012	0,022	0,007	0,022	0,011	0,012	0,004	0,021	0,031	0,028	0,005
Bulgaria	0,002	0,002	0,000	0,001	0,001	0,002	0,001	0,018	0,032	0,006	0,000
Canada	0,047	0,055	0,031	0,078	0,043	0,039	0,051	0,053	0,036	0,028	0,035
Croatia	0,003	0,003	0,001	0,001	0,004	0,004	0,001	0,018	0,036	0,005	0,000
Denmark	0,011	0,019	0,005	0,010	0,007	0,007	0,005	0,018	0,034	0,018	0,004
Estonia	0,001	0,003	0,001	0,001	0,001	0,000	0,001	0,018	0,036	0,025	0,004
Finland	0,010	0,016	0,006	0,016	0,004	0,004	0,004	0,022	0,034	0,015	0,004
France	0,046	0,046	0,024	0,045	0,053	0,060	0,035	0,039	0,035	0,041	0,027
Germany	0,070	0,062	0,028	0,249	0,104	0,119	0,051	0,059	0,034	0,038	0,039
Hungary	0,005	0,006	0,003	0,002	0,003	0,003	0,002	0,020	0,033	0,091	0,000
India	0,127	0,061	0,015	0,004	0,167	0,093	0,369	0,111	0,032	0,023	0,073
Ireland	0,006	0,012	0,015	0,015	0,007	0,005	0,007	0,024	0,032	0,015	0,006
Israel	0,008	0,012	0,001	0,000	0,028	0,038	0,004	0,057	0,033	0,041	0,039
Italy	0,048	0,043	0,016	0,050	0,043	0,050	0,026	0,032	0,032	0,036	0,005
Japan	0,047	0,027	0,002	0,004	0,016	0,014	0,019	0,043	0,033	0,011	0,065
South Korea	0,041	0,033	0,002	0,005	0,021	0,013	0,029	0,049	0,030	0,015	0,121
New Zealand	0,006	0,010	0,008	0,003	0,009	0,014	0,003	0,015	0,033	0,006	0,002
Norway	0,012	0,023	0,004	0,020	0,008	0,010	0,005	0,022	0,034	0,032	0,004
Poland	0,016	0,017	0,007	0,024	0,029	0,046	0,013	0,028	0,034	0,019	0,003
Portugal	0,012	0,015	0,005	0,011	0,006	0,003	0,006	0,014	0,032	0,038	0,003
Romania	0,007	0,007	0,003	0,003	0,006	0,009	0,003	0,018	0,030	0,009	0,001
Slovenia	0,002	0,004	0,001	0,001	0,002	0,001	0,001	0,015	0,033	0,016	0,000
South Africa	0,009	0,013	0,007	0,003	0,003	0,001	0,008	0,022	0,034	0,017	0,002
Spain	0,033	0,045	0,016	0,017	0,023	0,019	0,024	0,034	0,033	0,028	0,021
Sweden	0,016	0,026	0,010	0,017	0,011	0,009	0,008	0,023	0,034	0,234	0,009
Switzerland	0,018	0,043	0,005	0,013	0,014	0,018	0,010	0,031	0,032	0,032	0,015
UK	0,084	0,117	0,270	0,209	0,078	0,087	0,064	0,053	0,037	0,034	0,078
USA	0,247	0,177	0,451	0,130	0,265	0,288	0,229	0,076	0,035	0,051	0,412

UK: United Kingdom, USA: United States of America

In the next step, standard deviation and mean values were calculated for each criterion using the values obtained from the normalized decision matrix. Following these calculations, the Gauss factor and normalized Gauss factor were calculated for each criterion. The values obtained from these calculations are presented in Table 3.

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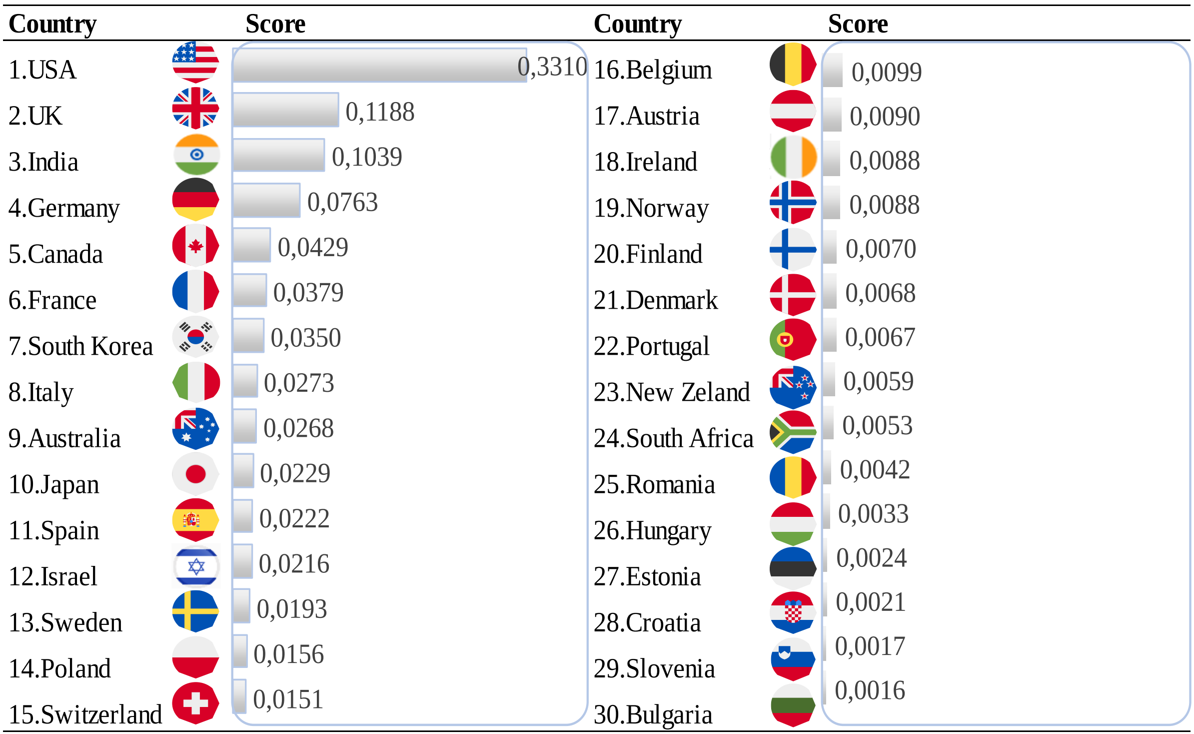
Table 3. Standard deviation- Mean- Gauss factor- Normalized Gauss factor

Parameters	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
Standard Deviation	0,049	0,036	0,091	0,059	0,056	0,056	0,075	0,021	0,002	0,101	0,076
Mean	0,033	0,033	0,033	0,033	0,033	0,033	0,033	0,033	0,033	0,033	0,033
Gauss Factor	1,458	1,091	2,735	1,769	1,669	1,675	2,253	0,638	0,053	3,038	2,279
Normalized Gauss Factor	0,078	0,058	0,147	0,095	0,089	0,090	0,121	0,034	0,003	0,163	0,122

In the final stage, the AHP-Gauss factor was calculated using the normalized Gauss factor and the normalized weight matrix. The AHP-Gauss factor is a measure that indicates how close or similar each alternative's performance is to the ideal situation. High AHP-Gauss values indicate the proximity of the ranked alternatives to the ideal situation.

The overall scores of each country are presented in Figure 1.

Figure 1. Performances and rankings of countries



A notable high standard deviation in the countries' scores (AHP-G factor) suggests a marked disparity between nations with low and high levels of specialization. The most influential criterion on the AHP-G factor is the magnitude of venture capital investments directed towards research, product, and service development activities in artificial intelligence. Additional significant criteria include the number of artificial intelligence courses and the number of venture capital investments. The diverse behaviors of individual criteria have had a significant

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impact on the countries' AHP-G factor and subsequent rankings. Nonetheless, nations with average and low AHP-G factors exhibited subpar performance across all criteria. The US led in 7 criteria, India in 2, and both the UK and Germany in one criterion. The superior performance of the US, the UK, India, Germany, Canada, France, and South Korea in these criteria has elevated their overall standings. While numerous countries have contributed to the development of metrics for assessing artificial intelligence specialization, many have fallen short in meeting these standards. This is especially evident in countries such as South Africa, Romania, Hungary, Estonia, Croatia, Slovenia, and Bulgaria.

The findings suggest that these underperforming nations encounter various obstacles in the generation, diffusion, and application of knowledge. Furthermore, if current trends persist, countries including the United States, the United Kingdom, India, Germany, and Canada are poised to secure substantial advantages in terms of the specialization level of their AI human capital.

3. Results

This study provides a valuable framework for comparing and analyzing countries' progress in order to assess the degree of human capital specialization in response to advancements in artificial intelligence technologies. The study proposes a model for how to comprehensively address the progress necessary in determining the level of specialization of human capital. Interrelated factors have been brought together on the basis of the generation, diffusion, and use of knowledge. The factors that need to be considered for determining the level of specialization and the importance levels of these factors have been examined. In this direction, prominent countries and areas of specialization have been identified to adapt more successfully to developments in the field of artificial intelligence. Thus, an effort has been made to create a clear perspective on the priorities that countries should focus on.

To develop policies and strategies or to make changes to existing policies by monitoring global developments, it is necessary to track advancements in the field of artificial intelligence. Countries with a strong scientific research and development foundation may be advantageously positioned in developing new technologies. These countries can also develop robust strategies and policies for new technologies (Brandt et al., 2022). By examining the level of specialization of these high-performing countries, growth in the field of artificial intelligence, revealing economic potential, and allocating funding to the right areas can be achieved (National Science and Technology Council, 2016).

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Global competition in artificial intelligence is increasing while many countries are making efforts across various indicators. However, only a limited number of nations have achieved consistent progress. These successful countries share a common characteristic in that they demonstrate balanced performance across all factors while developing long-term strategies. It is critically important for the sustainability of success that countries focus on their relatively weak areas. At the same time, they must consider their distinctive conditions and circumstances when formulating these strategies. Within this framework, the primary step in developing human capital is to enhance scientific research and publication activities. Achieving this requires increased funding and resource support allocated to researchers. Alongside strengthening the scientific infrastructure, the development of educational and training infrastructure serves as a crucial catalyst in elevating the quality of human capital. To this end, artificial intelligence-focused online courses should be expanded and their quality improved. These courses should also be translated into local languages and made accessible to everyone. Such measures serve as a vital tool for developing the competencies of the existing workforce. In addition to strengthening the educational infrastructure, supporting online question-and-answer platforms accelerates knowledge sharing and learning. Encouraging participation in open-source software projects and facilitating integration into international knowledge networks further reinforces this process. As a result, employees' knowledge and skills develop more rapidly, enhancing the capacity of human capital.

In translating this theoretical and practical knowledge into the business sphere, the effective implementation of employment and skill development strategies is essential. Equally important is the creation of programs that accelerate the integration of artificial intelligence capabilities into the workforce. Additionally, establishing standards to evaluate AI competencies during recruitment is critical to ensure the success of these initiatives.

To ensure the sustainable development of the artificial intelligence ecosystem, a financial foundation should be established through the simultaneous implementation of multiple strategies. In this context, direct government support, including grants, low-interest loans, and tax incentives, plays a critical role, particularly for early-stage technologies and start-ups. Venture capital and private sector investments strengthen the financing of innovative projects through risk-sharing, while government-backed incentives make these investments more attractive. Furthermore, public-private partnerships enhance resource efficiency through joint projects involving universities, research institutions, and industry. Risk mitigation strategies and co-investment models enable the financing of high-potential yet risky projects. This multi-

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dimensional approach can increase the participation of all actors in the ecosystem, supporting the acceleration of knowledge generation, skill development, and innovation processes.

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