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RESEARCH ARTICLE

A Monitoring Framework for Progress in Artificial Intelligence Technology: A Research Based on Scientific and Technological Indicators

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ABSTRACT

In the past century, the key technologies that shaped societal and economic transformation were mechanical, electrical, and automation technologies. In the current century, there are strong trends indicating the prominence of artificial intelligence technology. Therefore, artificial intelligence technology has become more important for all countries. The success of countries in artificial intelligence technology is only possible with well-designed artificial intelligence policy tools. It is important to measure the level of technological advancement for the formulation of policies. However, efforts to measure the scientific and technological advancement of artificial intelligence technology are insufficient. Therefore, this study aims to develop a framework to measure the scientific and technological progress of AI technology. The developed framework includes the number of publications and citations, the number of high-impact scientific journals, the number of patent applications, the number of universities ranked in the top thousand in the field of computer science, the number of international high-impact conferences, and the total number of researchers in higher education. Through these criteria, the level of scientific and technological progress of the countries has been analysed in detail. The findings clearly revealed the leading position of the USA in this field. China followed the USA. These two countries are clearly and positively differentiated from the other countries. Other countries with good performance are the UK, the Netherlands and Germany.

Keywords: Artificial intelligence, Technology management, Scientific and technological progress, Entropy, Grey system theory
JEL Clasification: O31, O32, O33

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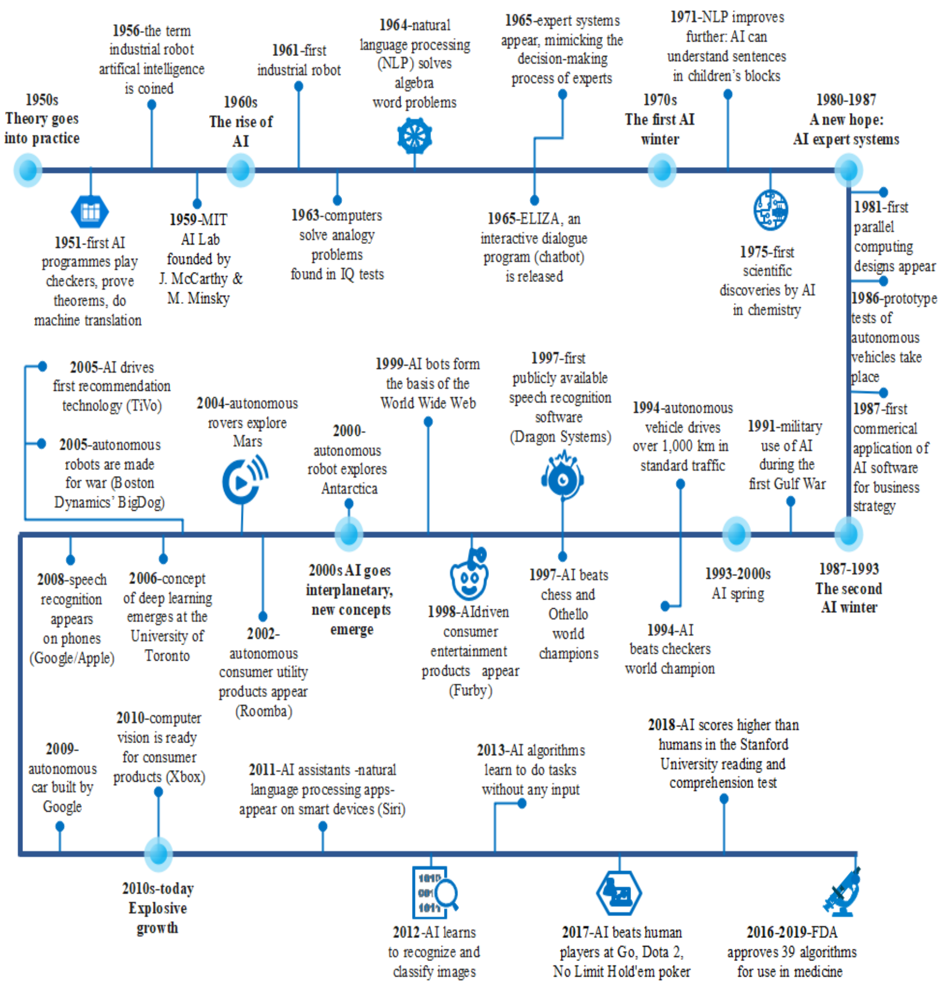
1. Introduction

Disruptive technologies have created significant economic and social impacts. Leading and influential roles in these technologies by countries, industries, and individuals promote positive progress in economic and social effectiveness. According to economic theory, in countries that stand out in terms of technological progress, both positive and negative outcomes can occur simultaneously, and these can balance each other out. However, countries that cannot adapt to technological advancement suffer from its negative consequences (Korinek, Schindler and Stiglitz, 2021, p. 4). Artificial intelligence (AI) is the technology that influences today's world and will create the most significant change in the future. Artificial intelligence has a significant impact on various aspects of life, including healthcare, food, automotive, security, aviation, and pharmaceuticals. Therefore, progress in artificial intelligence technology will place countries in an advantageous position in various ways compared to their competitors. According to predictions, artificial intelligence will contribute approximately 15.7 trillion dollars to the world's GDP by 2030 (World Economic Forum, 2022).

Artificial intelligence refers to information processing-based systems with the ability to learn, interpret, and make decisions based on acquired data. Built upon the foundation of the mathematical sciences, logic, computation, and knowledge constitute the disciplines. The progress in the field of artificial intelligence is depicted in figure 1. As shown in the figure, the origin of artificial intelligence technology is considered to have begun with its conceptual expression at a conference held in the United Kingdom in 1956. In the 1960s, research and studies were conducted in the fields of industrial robots, chatbots, and expert systems. By the 1970s, the first scientific discoveries in natural language processing and artificial intelligence had taken place. However, during the 1960s and 1970s, the desired progress in artificial intelligence could not be achieved. In the 1980s, expert systems emerged as the prominent focus, leading to a decline in interest in artificial intelligence. The 1990s marked the beginning of a period of revolutionary developments in artificial intelligence technology. During this period, an approach based on learning rather than programming artificial intelligence was adopted. The increase in computing power and data volume over the internet were prominent factors in the development of artificial intelligence in the 2000s. The most significant step in the development of artificial intelligence after 2010 has been the deep learning method, which has high prediction capabilities by developing nonlinear models using very large datasets (World Economic Forum, 2022).

Figure 1: Artificial intelligence timeline (World Economic Forum, 2022)



Research and development activities play a decisive role in enabling countries to achieve sustainable growth. These activities also serve as determinants of competition, growth, and industrial progress (Campbell et al., 2015). Global scientific and technological advancement can yield significant benefits on a global scale in terms of goods and services, employment, skill acquisition, and productivity (Bernanke, 2011). Science and technology drove more than half of economic growth in the 20th century (Evans et al., 2021).

Akçiğit & Tok, (2020), emphasised the positive relationship between scientific and technological progress and economic development. Scientific and technological progress encompasses research, development, and technical education activities that span from the creation of scientific and technical knowledge to its use (OECD, 1994). The direction of scientific progress varies. Topics that are popular in certain periods may lose their impact over an extended period. Conversely, areas without progress or obvious potential can evolve and become prominent. Hence, it is essential to determine the direction of scientific progress correctly. Countries can be successful to the extent that they adapt to scientific and technological progress.

Scientific and technological progress refers to the research, development, and technical education activities that occur from the generation of scientific and technical knowledge to its use (OECD, 1994). The direction of scientific progress varies. Popular topics at certain periods can lose their impact over an extended period of time. However, areas where no progress has been made and have no potential can still develop and come to the forefront. Therefore, it is essential to determine the direction of scientific progress correctly. Countries can be successful to the extent that they adapt to scientific and technological progress. Some measurable factors and methods need to be developed to determine the relative positions of countries in this progress. The semantic forms of these factors should be easily understandable and accessible to everyone. Thus, the acquired information can yield meaningful results. The initial studies on measuring progress in scientific and technological research date back to the early 20th century. Hulme conducted one of the earliest studies in this field in 1923. Hulme measured social progress using patent and scientific literature indicators (Okubo, 1997). Throughout the historical process, studies aimed at measuring scientific and technological progress have consistently maintained their importance. The numerical evaluation of scientific and technological indicators assists in the correct formulation of policies in science, technology, economics, society, and the environment (Okubo, 1997). Scientific and technological progress inherently may require a long period and entail high costs. A well-made foresight provides accurate guidance for funding providers, policymakers, and researchers. Efforts aimed at determining the direction of scientific progress can lead to time and cost savings, increase the likelihood of making correct decisions, and establish a balance between effort and impact and results (National Research Council, 2007). In particular, in OECD countries, evaluation activities have become mandatory to ensure the efficient and effective utilisation of resources and to direct research activities towards current developments in science and technology (Moed, 2005).

The aim of this study is to develop a data-driven framework for international comparisons and performance monitoring in order to analyse the levels of scientific and technological expertise in the field of artificial intelligence. The fundamental questions motivating this study are as follows: Which criteria can be used to measure scientific and technological progress in the field of artificial intelligence? Is it possible to create a common framework for measuring the national-level scientific and technological progress in the field of artificial intelligence and for comparing countries? What is the level of scientific and technological progress in the field of artificial intelligence for countries?

2. Literature review

Artificial intelligence is a new technology with significant potential across various industries and disciplines. Therefore, there are limited approaches available for measuring progress in this field. Reviewing previous approaches provides significant contributions to how scientific and technological progress in the field of artificial intelligence should be approached.

One of the first studies aimed at measuring progress in the field of artificial intelligence was conducted by the European Commission's Joint Research Centre

(EC-JRC) in 2018. In this study, patent and scientific publication data were utilised to track developments and contributions in the field of artificial intelligence (Baruffaldi et al., 2020). On the other hand, in another study in the field of artificial intelligence, IBM developed an index methodology to measure the adoption of artificial intelligence in organisations. On the other hand, in another study in the field of artificial intelligence, IBM developed an index methodology to measure the adoption of artificial intelligence in organisations. Similarly, in the study conducted by Baruffaldi et al. (2020), scientific publications, open-source software, and patent data were utilised to measure the progress of AI in the fields of science, technology, and software. This scale was applied to 7,502 businesses worldwide. The evidence obtained indicates that 44% of organisations have undertaken activities to integrate AI into existing applications and processes. The issue of continued bias against artificial intelligence is another significant finding in the study (IBM Corporation, 2022). In another study by Rogerson et al., (2022), an index was developed to measure the level of AI implementation in public services across 182 countries. This index was calculated using criteria such as capacity, frameworks, skills, resources, and infrastructure requirements. The findings have indicated that the United States, Singapore, and the United Kingdom are the countries that use artificial intelligence applications in public services the most. On the other hand, in the study conducted by Nestor et al. (2023), countries have measured their progress in artificial intelligence using factors including research, development, technical advancement, artificial intelligence ethics, economics, education, public administration, policy, diversity, and social participation. Cesareo and White's (2023) study measured countries' capabilities in using artificial intelligence. For this purpose, they used three main factors: the primary factor for AI applications, the innovation factor for measuring progress in technology and methodologies, and the investment factor for financial and procedural commitments to AI. Under these main factors, 111 sub-factors were defined.

3. The conceptual framework for selecting criteria

The comprehensive definition of issues in specific fields and the formulation of appropriate policies rely significantly on the selection of suitable criteria.

Defining the conceptual framework associated with these criteria facilitates the identification of the right criteria. In this context, the criteria employed in the study have been developed on the basis of the definitions of science and technology provided here.

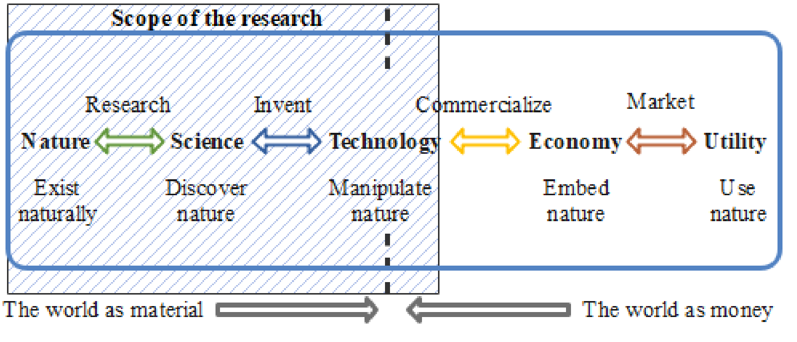
Science is the intellectual activity conducted to explore, verify, and apply the principles and rules of knowledge found in natüre. It is used in the development of technology (National Research Council, 1986). Technology, on the other hand, is defined as tangible outputs that provide both indirect and direct contributions to the production of goods and services from the knowledge found in nature. The transformation of science into technology is achieved through invention. Inventions generate economic benefits, but in some cases, they only gain value as scientific knowledge. The common belief is that technology develops on the basis of science (Eto, 2003).

The criteria used to measure scientific and technological progress can include the number of articles and citations, academic awards, research activities conducted through collaboration, the number of researchers, data related to the research infrastructure of universities, government, and industry, and the financial resources allocated for research (Ministry Of Education, Culture, Sports, Science And Technology Japanese Government, 2005). Furthermore, criteria such as the increase in scientists' efforts in the field, the creation of new courses and programmes and the rise in the number of participants, the expansion of research scope to encompass other scientific domains, the frequency of publication of studies in leading journals, and the growth in academic activities related to scientific events like conferences and symposia, as well as the increase in collaboration across different fields, can be used in measuring scientific and technological progress (National Research Council, 2007).

Measuring the scientific and technological progress in artificial intelligence technology within an international comparative framework is a complex process. One of the most significant reasons for this is the constraints related to data acquisition. There are generally accepted frameworks for data acquisition.

However, countries may be insufficient in implementing fundamental standards for data collection, dissemination, and similar processes (Everaers, 2022). In very few countries, there are studies aimed at monitoring long-term scientific and technical subjects (OECD, 1995). This situation poses a significant challenge in the selection of common criteria and the acquisition of data. Furthermore, the proliferation of artificial intelligence technology across various disciplines, ranging from the arts and social sciences to veterinary medicine, agriculture, engineering, and medical research, brings another significant challenge. The multidisciplinary nature of artificial intelligence makes the determination of boundary complex. This uncertainty complicates the identification of the data needed to develop a common measurement model. Additionally, it is possible to access the data used in the study from different databases. However, in Okubo's (1997) study, it is emphasised that the data to be used in the data collection process should be obtained from databases that best meet the analysis requirements.

Figure 2: Relationship between science, technology, and innovation (Betz, 2011)



Time is a determining factor in measuring the output, results, and impact on scientific and technological progress. Measuring the output factors may require a shorter time, while measuring the result and impact factors may require longer periods. One of the good examples that explains this situation is the studies conducted in the field of magnetism. The knowledge obtained from previous studies in magnetism eventually turned into tangible benefits with the invention of the telegraph after a considerable amount of time (Aslan, 2023, p. 29). The innovation model presented in Figure 2 comprehensively explains the relationship between science, technology, and innovation. This model was used as a reference for criteria selection in the study

Table 1 shows the evaluation framework consisting of the number of citable publications, number of citations, number of high-impact scientific journals, number of patent applications, number of universities, number of top conferences, and number of higher education researchers.

Table 1: Criteria used in the study

Abbreviation	Criteria	Date	Database
C1	Number of citable publications	2022	SJR
C2	Number of citations	2022	SJR
C3	Number of high-impact scientific journals	2022	SJR
C4	Number of patent applications	2022	OECD (USPTO)
C5	Number of top universities	2022	THE
C6	Number of top conferences	2022	Research.com
C7	Number of higher education researchers	2021	OECD

Note: SJR: Scimago Journal & Country Rank, OECD: Organisation for Economic Co-operation and Development, USPTO: United States Patent and Trademark Office, THE: Times Higher Eduction

3.1. Publications and citations

Scientific publications are produced as a result of scientific studies. Scientific publications and citations enable the quantitative monitoring of the outputs of scientific studies. The number of scientific publications refers to the number of research results published in articles, books, journals, etc. produced by individuals, countries or institutions. Number of publications refers to the number of citable research results, such as articles, books, journals, etc., produced by individuals, countries or institutions (Okubo, 1997). Scientific publication and citation counts are used to assess the state of science by linking individuals, research groups, organisational structures and countries (National Research Council, 2007; Okubo, 1997). Scientific publications demonstrate the extent to which researchers contribute to their field of study. These publications also reveal the importance of the relevant field at both national and international levels. Additionally, they reflect the collaboration between individuals and institutions that contribute to scientific developments. (National Research Council, 2007). Technology development activities that are not based on scientific foundations can often lead to higher costs and lengthen the development time (Mansfield, 1991). The connection between R&D activities and scientific publications is stronger in scientifically productive countries (OECD and SCImago Research Group, 2016). The number of scientific publications per capita and per capita gross domestic product (GDP) exhibit a positive and exponential relationship (Akçiğit and Tok, 2020). Especially in the United States and the United Kingdom, most patents in the fields of clinical medicine and biomedicine have been developed significantly based on scientific articles. Additionally, scientific publications play a significant role in patent studies in the fields of chemistry, physics, and engineering (Narin, Hamilton and Olivastro, 1997). The data related to citable scientific publications and citation numbers were obtained from the SCImago database and are presented in figure 3.

Figure 3: Distribution of citable publications among countries

Country	No. Publications	Country	No. Publication
China	42293	Spain	1842
United States	13101	Türkiye	1734
United Kingdom	4816	Netherlands	1276
Germany	4001	Singapore	1209
Japan	3964	Switzerland	951
Italy	2943	Poland	910
Canada	2844	Greece	895
South Korea	2546	Belgium	607
France	2520	Czechia	496
Russia	1914	Slovenia	160
Taiwan	1883		

Note: No: Number of

When new and important topics are addressed in scientific studies, several publications and citations are usually obtained to advance knowledge in this field (Schreiber, 2007). Citation is the act of incorporating information, text or other content used in previous works, while referencing the source, to create new knowledge or present information in a different form. Citation is a determining factor in measuring the significance and impact of information within the research context in a study. Citations provide a supporting foundation for the information presented in the current study (Hellsten, Lambiotte, Scharnhorst, & Ausloos, 2007). It is increasingly important to gain recognition in the academic field, to increase visibility, to emphasise the quality and importance of work, as well as to build wider academic relationships and strengthen collaboration. The level of citation is an indicator of the level of adoption of the study (Hyland, 2003). The relationship between citation analysis and science and technology is shown in Table 2.

However, the contribution of self-citation to the assessment of scholarly impact, creating scientific influence, and measuring ubiquity is a controversial topic. For this reason, self-citations are sometimes not considered in the calculation (Costas, Van Leeuwen and Bordons, 2010). The use of self-citation as a scientific indicator can weaken the proposed argument, especially when self-citation accounts for 20% to 35% of all citations (Aksens, 2003).

Table 2: Relationship between citation and science and technology

Influencing/cited	**Influencing/citing**	
	Science	**Technology**
Science	Contribution of science groups to scientific progress Citations in science papers to other science papers	The science base of technology Citations in patents to scientific literature
Technology	The influence of technology upon scientific development Citation gap	Contribution of technologies to technological progress Citations in patents to other patents

Source: (Moed, 2005)

Figure 4 shows the distribution of citations related to artificial intelligence studies by country.

Figure 4: Distribution of citations among countries

Country	No.Citations	Country	No.Citations
China	7909	Japan	1286
United States	7823	France	1156
United Kingdom	4917	Taiwan	1055
Canada	2299	Netherlands	847
South Korea	2087	Poland	562
Singapore	1937	Belgium	516
Germany	1883	Greece	476
Italy	1857	Russia	404
Spain	1850	Czechia	234
Türkiye	1451	Slovenia	112
Switzerland	1301		

3.2. High-impact scientific journals

Scientific publishing, while determining the scope of knowledge and facilitating its dissemination, also has economic implications (OECD and SCImago Research Group, 2016). Criteria for assessing the quality of scientific publications play a crucial role in measuring the contributions of scientific studies (Moed, 2005). The impact and quality of scientific studies is as important as the impact and quality of the journals in which these studies are published. Each scientific study is not of the same characteristics and quality, just as every scientific journal does not possess the same characteristics and quality. Not every scientific study has the same characteristics and quality, and not every scientific journal has the same characteristics and quality. Therefore, both scientific studies and journals should be evaluated according to objective evaluation criteria (Guerrero-Bote and Moya-Anegón, 2012).

Different performance criteria are used to measure the impact and quality of the journals. The assessment of research quality and impact is typically done using the journal impact factor. This factor is based on the citation impact of scientific studies (Moed, 2005). One of the latest approaches used in measuring journal impact factor is the SJR (Scientific Journal Rankings) indicator. SJR is an assessment framework based on data obtained from the Scopus database, measuring the scientific value of journals (Guerrero-Bote and Moya-Anegón, 2012). The SJR indicator takes into account the number of citations and the impact of the journal in which the cited publication was published. In addition, citations within the journal itself are included in this calculation at a lower rate. A high SJR indicator means that the influence or prestige of the journal is higher than the influence or prestige of the publication (González-Pereira, Guerrero-Bote and Moya-Anegón, 2010).

The distribution of the number of high-impact journals by country is shown in figure 5.

Figure 5: Distribution of the number of high- impact scientific journals by country

Country	No. high-impact scientific journals	Country	No. high-impact scientific journals
United States	50	South Korea	3
Netherlands	48	Spain	3
United Kingdom	44	Canada	2
Switzerland	21	France	2
China	15	Greece	2
Germany	13	Italy	2
Singapore	13	Taiwan	2
Poland	6	Belgium	1
Japan	5	Slovenia	1
Czechia	4	Türkiye	1
Russia	4		

3.3. Patents

Patents are an indicator of the acquisition of a new and applicable technique because of scientific and technological activities. Patents are the result of the technology development process. However, all technologies obtained at the end of the development process can't always be patented (Isaka, 2013).

Patent statistics provide both quantitative and qualitative data about the concrete applications of the developed technology. Patents provide information on the coefficient of inventiveness, technology penetration, the size of the technology market, and the diffusion of technology. Inventive capacity reflects the technological development efforts of inventors within a country, while penetration refers to patent applications originating from foreign sources. The size of the technology market is determined by the total number of patent applications, both domestic and international. Technology diffusion, on the other hand, refers to the efforts to protect domestically developed patents in foreign markets (Okubo, 1997).

Patents and scientific publications are frequently used indicators for analysing technological progress (WIPO, 2019). The relationship between patent data and scientific publications and citation numbers is used as a criterion for investing in the relevant research field (National Research Council, 2007). The success of scientific studies in transitioning into technology is directly proportional to the rate at which publications result in patents. The increased production of scientific publications may result in more patents (Akçiğit and Tok, 2020).

The field of artificial intelligence patents can encompass various areas such as algorithms, robotics, autonomous vehicles, and software. In 2017, the OECD categorised AI-related technologies, such as natural language processing, human interface and cognitive processes, in the information and communication technologies (ICT) patent category (Baruffaldi et al., 2020).

Within this classification framework, the distribution of patents by country occurred as depicted in figure 6.

Figure 6: Distribution of patent applications by country

Country	No. Patent Applications	Country	No. Patent Applications
United States	52361	Singapore	524
Japan	15762	Netherlands	487
China	14886	Belgium	379
South Korea	11834	Russia	371
Taiwan	6401	Spain	214
Germany	3495	Poland	130
United Kingdom	2489	Czechia	87
Canada	2331	Türkiye	56
France	1692	Greece	42
Switzerland	611	Slovenia	15
Italy	573		

3.4. Top-performing universities

The labour market offers better opportunities to individuals with higher education and high skill levels (Samuelson and Sarrico, 2017). Universities play a decisive role in the development of knowledge-based capital. Successful universities produce highly skilled individuals with high-quality research experiences and further research investments (Kaloudis et al., 2019). University rankings are becoming increasingly important as they provide benefits such as improving the functioning of universities, attracting qualified students and staff, developing more research and cooperation, and obtaining more resources (Sobral, 2021). According to Akçiğit and Tok, (2020), countries with the highest number of universities in the top 1000 are also in a leading position in terms of economic development.

Universities around the world are evaluated and ranked by different institutions for different purposes. Different university ranking and evaluation criteria such as The World University Rankings, QS World University Rankings, Academic Ranking of World Universities, and US News Education Rankings are used (Samuelson and Sarrico, 2017). The information related to university rankings in the field of artificial intelligence used in the study is based on the performance data provided by the "Times Higher Education World University Rankings." In this ranking, universities are comprehensively evaluated in terms of teaching, research, and reputation factors. The assessment delves into 5 main factors and 13 sub-factors, including teaching, research, research impact, international outlook, and knowledge transfer (Pavel, 2015; Times Higher Education, 2022).

In the context of these factors, Figure 7 presents the distribution of successful universities in the field of computer science within the top thousand by country.

Figure 7: Distribution of universities in the top 1000 in the field of computer science by country

Country	No. Universities	Country	No. Universities
United States	163	Greece	11
United Kingdom	86	Netherlands	11
China	64	Switzerland	11
Germany	48	Türkiye	11
Italy	47	Belgium	9
Spain	32	Taiwan	9
Canada	31	Czechia	4
France	29	Poland	2
Japan	20	Singapore	2
South Korea	19	Slovenia	1
Russia	18		

3.5. High-impact conferences

Scientific meetings are platforms serving various purposes for scientific studies. It makes important contributions to the advancement of science in many ways, such as access to new ideas and information, sharing research results and findings, transferring experience, funding research, and realising the objectives of improving cooperation and interaction (Parsons, 2015). One of the criteria considered in the evaluation of artificial intelligence research activities is academic conferences (Tsinghua University, 2018).

A study of researchers attending International Marine Conservation Congresses has provided considerable evidence in favour of this view. Participants in the study indicated that 58% supported their research with new ideas, 56% learned new techniques, and 64% gained new skills. Additionally, 91% of participants mentioned communicating with new individuals in their field, while 39% communicated with those providing funding (Oester et al., 2017).

Considering the contributions of scientific meetings, data from high impact international conferences in the field of artificial intelligence can be regarded as a significant criterion in measuring scientific and technological progress. In this context, the Number of high impact conferences in the field of computer science in a country has been used as a measure of scientific and technological progress. The ranking of the high impact conferences in computer science is determined based on the impact score provided in equation (1). The impact score was calculated by considering factors such as the predicted h-index in scientific articles of leading computer scientists and the number of contributing scientists to the study. The index value was calculated using data from the last four years in the Microsoft Academic database.

$$\text{Impact Score} = \frac{\text{H}_{\text{index}}\ \text{Value} * \text{Number of Top Scientists}}{2 * \text{Number of Years}} \tag{1}$$

Accordingly, the distribution of the number of international high-impact conferences by country is given in figure 8.

Figure 8: Distribution of the number of high-impact conferences by country

Country	No. Conferences	Country	No. Conferences
United States	54	Switzerland	5
Italy	31	Taiwan	4
Spain	21	Belgium	3
China	19	Czechia	3
France	16	Netherlands	3
Germany	14	South Korea	3
United Kingdom	13	Poland	1
Greece	12	Russia	1
Canada	7	Slovenia	1
Singapore	7	Türkiye	1
Japan	5		

3.6. Researchers in higher education

A researcher is defined as a professionalprofessionals responsible for designing or creating new knowledge in a specific field. Data related to researchers are essential indicators used to measure the performance of research and development activities (OECD, 2017).

Social and economic development is possible through the creation of knowledge-based capital. The driving force behind knowledge-based capital is individuals with scientific and engineering skills (Bernanke, 2011). The most effective way to acquire these skills is through higher education. The higher education system can achieve this in two ways. The first of these is the cultivation of human resources, while the second is the utilisation of research conducted at universities as a source of innovation (Samuelson and Sarrico, 2017).The development of technical and vocational knowledge through higher education enables the enhancement of human resources. Higher education contributes to the development of human resources by increasing technical and vocational knowledge. At the same time, it provides the opportunity to elevate the level of education while enhancing skills. In a specific field, institutions and industries that achieve a certain level of success can contribute to a country's better performance in that area (OECD and SCImago Research Group, 2016). Countries and institutions with a greater number of academic human resources tend to be more successful in R&D activities. This tendency promotes innovation and allows for the improvement of products, processes and services. Furthermore, it provides an opportunity for elevating the education level and the enhancement of skills (Samuelson and Sarrico, 2017). Technological progress is closely related to making long-term R&D investments and accumulating experience. Research conducted at universities serves as a source of innovation (Le et al., 2022).

The distribution of the total number of researchers in higher education by country is illustrated in figure 9.

Figure 9: Distribution of the total number of researchers in higher education by country

Country	No. Researchers	Country	No. Researchers
China	599515	Türkiye	49649
United States[-1]	175941	South Korea	43772
United Kingdom[-2]	172489	Taiwan	29022
Japan	137303	Netherlands	26732
Germany	120901	Switzerland	26133
France	91582	Greece	23082
Russia[-1]	78864	Belgium	22175
Spain	69984	Singapore[-1]	16848
Canada[-1]	65340	Czechia	13963
Poland	59457	Slovenia	2431
Italy	57204		

Note: Interpolation has not been applied-[1,-2]

4. Research methodology

In this section, the entropy and grey relational analysis methods used to determine the weights of the criteria, the relationships between the criteria, and the ranking of alternatives based on the criteria are explained in detail.

4.1. Entropy method

The entropy method was developed by Claude Shannon in 1948. This method is an information weight method that allows for an objective evaluation using probability theory. It produces effective and reliable results in the weighting criteria (Dwivedi and Sharma, 2022; Zhu, Tian, and Yan, 2020).

The entropy method begins with the creation of the decision matrix consisting of x_{ij} values. Here, x_{ij} represents the score obtained from the ith alternative for the jth evaluation criterion (Dwivedi and Sharma, 2022).

$$DM = [x_{ij}]_{mn} = \begin{bmatrix} x_1(1) & x_1(2) & \cdots & x_1(n) \\ x_2(1) & x_2(1) & \cdots & x_2(n) \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ x_m(1) & x_m(2) & \cdots & x_m(n) \end{bmatrix} \tag{2}$$

Normalisation process, denoted by $\acute{x}_{ij}$, is carried out to represent data from different scales and intervals on the same scale. It is calculated using the following equation.

$$\acute{x}_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{3}$$

Following the normalisation process, the internal entropy values of the criteria (e_j) are calculated according to equation (4).

$$e_j = -\frac{1}{lnt} \cdot \sum_{j=1}^{n} \acute{x}ij \cdot ln(\acute{x}_{ij}) \tag{4}$$

The differentiation degrees shown in equation (5) are calculated using the obtained entropy (e_j) values.

$$d_j = 1 - e_j \tag{5}$$

In the final step, the weight of each criterion is calculated using equation 6. (Uludağ and Doğan, 2021).

$$w_j = \frac{d}{\sum_{j=1}^{n} d_j} \tag{6}$$

4.2. Grey relational analysis

The grey system theory, which forms the basis of grey relational analysis, was proposed by Julong Deng (Tan, 2005). In real-world applications, there are situations that involve insufficient information and small samples. Many systems such as social, environmental, economic, and human systems can be cited as examples of these situations (Ng, 1994). These systems are often expected to generate useful information by effectively using the existing conditions (Liu et al. , 2020). However, the information generated is unreliable due to the weakness in the current state (Ng, 1994).

Grey relational analysis method, which is one of the important analysis methods of grey system theory, uses the basic principles of grey system theory. Real systems are inherently complex and uncertain. Grey relational analysis aims to reduce uncertainty by focusing on determining the degree of relationship between subsystems and causality. The existence of the relationship is evaluated based on the similarity level of the geometric curves of the data (Peng et al., 2021).

The grey relational analysis method begins by determining the decision alternatives and criteria that will form the decision matrix.

Equation (7) is used to define the values of decision alternatives and criteria. The value of the series to be created is denoted by m.

$$\mathrm{x_i} = \left(\mathrm{x_i(j)}, \dots, \mathrm{x_i(n)}\right)\ \mathrm{i} = 1,2, \dots, \mathrm{m}\ ;\ \mathrm{j} = 1,2, \dots, \mathrm{n} \tag{7}$$

The m series consisting of decision alternatives and criteria is represented by Equation (8).

$$x_{\mathrm{i}} = \begin{bmatrix} x_1(1) & x_1(2) & \cdots & x_1(\mathrm{n}) \\ x_2(1) & x_2(1) & \cdots & \mathrm{x}_2(\mathrm{n}) \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ x_{\mathrm{m}}(1) & x_{\mathrm{m}}(2) & \cdots & x_{\mathrm{m}}(\mathrm{n}) \end{bmatrix} \tag{8}$$

After creating the decision matrix, a reference series is established. The reference series determines the ideal or best value for the criteria in decision alternatives. Thus, a decision matrix can be created to facilitate the comparison of decision alternatives. The value $x_0(j)$ in equation (9) represents the reference series.

$$x_0 = \left(x_0(\mathrm{j})\right) \ \ \mathrm{j} = 1,2, \dots, \mathrm{n} \tag{9}$$

In the next step, a normalisation and absolute value matrix is created. The normalisation process enables the comparison of criteria that do not have the same value and unit through the same scale. It can be defined as taking the values of the criteria between 0 and 1. The normalised decision matrix is calculated in three ways as benefit, optimal and cost oriented. In cases where all criteria are benefit-oriented, calculations are made according to equation (10).

$$x_i^* = \frac{x_{\mathrm{i}}\,(\mathrm{j}) - \underset{j}{min}\, x_{\mathrm{i}}\,(\mathrm{j})}{\underset{j}{max}\, x_{\mathrm{i}}\,(\mathrm{j}) - \underset{j}{min}\, x_{\mathrm{i}}\,(\mathrm{j})} \tag{10}$$

The absolute value matrix is formed by taking the difference in the value in the normalised decision matrix from its normalised value in the reference series.

$$\Delta_{0i} = x_0^*(j) - x_i^*(j) \tag{11}$$

In the next stage, the grey relational coefficient matrix is created. To form the grey relational matrix, the coefficients of each matrix element are calculated using equations (12), (13), (14).

$$\Upsilon_{0i}(j) = \frac{\Delta_{\min} - \zeta \cdot \Delta_{\max}}{\Delta_{0i}(j) - \zeta \cdot \Delta_{\max}} \tag{12}$$

$$\Delta_{\max} = \max_{i} \max_{j} \Delta_{0i}(j) \tag{13}$$

$$\Delta_{\min} = \min_{i} \min_{i} \Delta_{0i}(j) \tag{14}$$

Grey relational degrees are calculated according to the importance level of the criteria. The grey relational degree is associated with the closeness of a criterion of an alternative to the reference series. In the decision problem, equation (15) is used when the importance levels of the criteria are different. In this equation, $w_i(j)$ is the weight of the j-th criterion.

$$\Gamma_{0i} = \sum_{J=1}^{n} [w_i(j) \cdot \Upsilon_{0i}(j)] \tag{15}$$

5. Findings

To calculate the weight of each criterion using the entropy method, the normalised decision matrix, internal entropy values, and values related to the weights of the criteria are presented in Table 3. The rows in the table represent the alternatives, and the columns represent the normalised values for the specific criteria.

Table 3: Normalised decision matrix, entropy values, and criteria weights

Country	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Belgium	0,0065	0,0123	0,0041	0,0033	0,0143	0,0134	0,0118
Canada	0,0306	0,0548	0,0083	0,0203	0,0494	0,0313	0,0347
China	0,4552	0,1885	0,0620	0,1297	0,1019	0,0848	0,3185
Czech Republic	0,0053	0,0056	0,0165	0,0008	0,0064	0,0134	0,0074
France	0,0271	0,0275	0,0083	0,0147	0,0462	0,0714	0,0487
Germany	0,0431	0,0449	0,0537	0,0305	0,0764	0,0625	0,0642
Greece	0,0096	0,0113	0,0083	0,0004	0,0175	0,0536	0,0123
Italy	0,0317	0,0443	0,0083	0,0050	0,0748	0,1384	0,0304
Japan	0,0427	0,0306	0,0207	0,1374	0,0318	0,0223	0,0729
Netherlands	0,0137	0,0202	0,1983	0,0042	0,0175	0,0134	0,0142
Poland	0,0098	0,0134	0,0248	0,0011	0,0032	0,0045	0,0316

Table 3: Continued

Country	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Russian	0,0206	0,0096	0,0165	0,0032	0,0287	0,0045	0,0419
Singapore	0,0130	0,0462	0,0537	0,0046	0,0032	0,0313	0,0090
Slovenia	0,0017	0,0027	0,0041	0,0001	0,0016	0,0045	0,0013
South Korea	0,0274	0,0497	0,0124	0,1031	0,0303	0,0134	0,0233
Spain	0,0198	0,0441	0,0124	0,0019	0,0510	0,0938	0,0372
Switzerland	0,0102	0,0310	0,0868	0,0053	0,0175	0,0223	0,0139
Taiwan	0,0203	0,0251	0,0083	0,0558	0,0143	0,0179	0,0154
Türkiye	0,0187	0,0346	0,0041	0,0005	0,0175	0,0045	0,0264
United Kingdom	0,0518	0,1172	0,1818	0,0217	0,1369	0,0580	0,0916
United States	0,1410	0,1864	0,2066	0,4563	0,2596	0,2411	0,0935
e_j	0,3084	0,1468	0,2321	0,4108	0,1823	0,1731	0,1895
w_j	0,1877	0,0894	0,1413	0,2500	0,1110	0,1053	0,1153

When the criteria weights (wj) in table 3 are analysed, it is seen that the weights of criteria C_2, C_3, C_5, C_6 and C_7 are low. This indicates that the criteria are largely homogenously distributed. In other words, it can be said that there is a similar performance among countries in these criteria. For the criteria of number of publications (C_1) and number of patent applications (C_4), the criterion weight is higher. This can be interpreted as a more differentiated and varied performance among countries in terms of (C_1) and C_4 criterion.

The results of the grey relational coefficient matrix are presented in table 4. Based on this matrix and the criterion weights obtained from the entropy method, the Grey relational degrees in figure 9 and country rankings were determined. If a country has high coefficients in many criteria in the Grey relational coefficient matrix, it can generally be interpreted as having a high potential for scientific and technological advancement.

Table 4: Grey relational coefficient matrix

Country	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Belgium	0,3357	0,3453	0,3333	0,3349	0,3447	0,3419	0,3408
Canada	0,3481	0,4100	0,3379	0,3435	0,3803	0,3605	0,3585
China	1,0000	1,0000	0,4118	0,4112	0,4500	0,4309	1,0000
Czech Republic	0,3351	0,3368	0,3475	0,3336	0,3375	0,3419	0,3377
France	0,3463	0,3660	0,3379	0,3406	0,3767	0,4109	0,3702

Table 4: Continued

Country	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Germany	0,3549	0,3928	0,3984	0,3488	0,4133	0,3985	0,3841
Greece	0,3373	0,3440	0,3379	0,3334	0,3476	0,3869	0,3412
Italy	0,3487	0,3918	0,3379	0,3357	0,4112	0,5354	0,3550
Japan	0,3547	0,3705	0,3525	0,4170	0,3616	0,3510	0,3924
Netherlands	0,3393	0,3557	0,9245	0,3353	0,3476	0,3419	0,3426
Poland	0,3373	0,3467	0,3577	0,3338	0,3347	0,3333	0,3560
Russian	0,3428	0,3419	0,3475	0,3349	0,3584	0,3333	0,3644
Singapore	0,3390	0,3950	0,3984	0,3355	0,3347	0,3605	0,3388
Slovenia	0,3333	0,3333	0,3333	0,3333	0,3333	0,3333	0,3333
South Korea	0,3464	0,4011	0,3427	0,3924	0,3600	0,3419	0,3495
Spain	0,3424	0,3915	0,3427	0,3342	0,3821	0,4454	0,3605
Switzerland	0,3376	0,3711	0,4579	0,3359	0,3476	0,3510	0,3424
Taiwan	0,3427	0,3626	0,3379	0,3628	0,3447	0,3464	0,3435
Turkey	0,3418	0,3764	0,3333	0,3335	0,3476	0,3333	0,3519
United Kingdom	0,3598	0,5658	0,8033	0,3442	0,5127	0,3926	0,4115
United States	0,4192	0,9784	1,0000	1,0000	1,0000	1,0000	0,4134

In figure 9, the Grey relational degrees provide an indication of the closeness or similarity of each country's performance to the ideal performance. Higher grey relational degrees suggest a closer resemblance to the ideal state, reflecting stronger scientific and technological capabilities.

Figure 10: Grey relational degree and country rankings

Ranking	Country	Γ_{0i}	Ranking	Country	Γ_{0i}
1	United States	0,8214	12	Canada	0,3571
2	China	0,6487	13	Singapore	0,3533
3	United Kingdom	0,4633	14	Taiwan	0,3495
4	Netherlands	0,4240	15	Russian	0,3446
5	Germany	0,3773	16	Greece	0,3438
6	Japan	0,3761	17	Türkiye	0,3426
7	Italy	0,3751	18	Poland	0,3416
8	South Korea	0,3636	19	Belgium	0,3383
9	Spain	0,3621	20	Czechia	0,3379
10	Switzerland	0,3602	21	Slovenia	0,3333
11	France	0,3584			

The country rankings derived from these analyses can be considered an overall evaluation of each country's scientific and technological progress. Countries with higher rankings are deemed to have a more favourable performance across the evaluated criteria. Each indicator has a distinct impact on the scientific and technological progress of each country. Therefore, evaluating these indicators collectively helps us gain a more comprehensive understanding of a country's overall performance in the field of artificial intelligence. The USA is the leader in 4 of the 7 criteria used in the evaluation, while China is the leader in 3 of them. The USA is in a leading position in terms of the number of patents, the number of high-impact scientific journals, conference participation, and the number of universities within the top 1000 in the field of computer science. China is in a leading position in terms of criteria such as scientific publications, citations, and the total number of researchers. China is the leader in terms of scientific publications, citations, and the total number of researchers. Superiority in more criteria and the high weights of these criteria have generally ensured that the United States has a high performance level in scientific and technological progress in the field of artificial intelligence. The US and China have shown a markedly positive divergence from other countries in terms of scientific and technological progress in the field of artificial intelligence. The UK ranks third. The UK has shown a consistent performance in terms of the number of publications, number of citations, number of universities in the computer sciences, number of researchers in higher education, and number of effective scientific journals. This situation suggests that the implemented policies and strategies are consistent and coherent with each other. However, despite ranking in the top three in all these criteria, the discrepancy in performance concerning the number of patents may necessitate a reassessment of the relevant policies and strategies. The Netherlands ranks fourth. It is particularly successful in terms of the criterion of high-impact scientific journals. However, it does not appear within the top 10 in other indicators. In this context, specific research is needed to understand the factors influencing this positive situation in the number of high-impact journals. Germany and Japan are ranked fifth and sixth, respectively. The criterion in which Germany performs best is the number of publications, whereas the criterion in which it shows inadequate performance is the number of citations. Japan, on the other hand, demonstrates its best performance in the criterion of patent applications. This situation supports the notion that in Japan, there is a higher likelihood of scientific studies transforming into innovation. Japan has shown low performance in the number of high-impact conference publications. Japan should put more effort into organising international conferences. Italy ranks second after the USA in terms of the number of high-impact conferences. However, it ranked seventeenth in terms of the number of high-impact journals, showing a poor performance. South Korea, Spain and Switzerland performed similarly, ranking eighth, ninth and tenth. South Korea's best performance in terms of scientific and technological progress criteria is patent applications, and it is ranked 4th in this field. This situation strengthens the idea that scientific studies will increase the possibility of turning into innovation for South Korea. South Korea should take measures to improve its performance in the high-impact conference and journal criteria. Spain performed very well in terms of the number of high-impact conferences. However, it did not perform at the same level in terms of the number of publications and patent applications. Switzerland ranks fourth in terms of the number of high-impact journal publications. However, more effort is needed in terms of the number of scientific publications. The number of citations criterion of South Korea, Spain and Switzerland performed better than the number of scientific publications criterion. This situation can be evaluated by the fact that the scientific studies conducted by researchers in these countries in the field of artificial intelligence are of high quality, effective and citable. France, Canada and Singapore ranked eleven, twelve and thirteenth. France is in a very good position in terms of the number of high-impact conferences and the number of researchers. In addition, France and Canada showed similar performance in terms of scientific publications and patenting activities. The similar performance of both countries in terms of scientific publications and patenting criteria, when other factors are excluded, supports the notion that scientific publications and patenting activities complement each other. Singapore performed well in the criteria of number of high-impact journals and number of citations. The number of citations criteria performed better than the number of scientific publications criteria. Although Singapore performed better in both the number of high-impact journals and the number of citations criteria, the reasons for its second-to-last position in the ranking of universities in the field of computer science should be investigated. Taiwan, Russia, Greece, Turkey, Greece, Turkey and

Poland performed quite close to each other. Taiwan has shown a very high performance in patenting studies like other Asian countries such as China, Japan and South Korea. However, further efforts should be made to improve its performance in terms of the number of high-impact journals and university ranking criteria in the field of computer science. Russia performed very poorly in the criteria of the number of high-impact conferences and the number of citations. However, it ranked among the top 10 countries in terms of the number of publications. When these two situations are evaluated together, it can be thought that the main reason for the insufficient performance in terms of the number of citations is due to language and alphabetic factors. Greece is in a good position in terms of the number of high-impact conference publications. However, it has a low performance in other criteria. Therefore, more policies and strategies should be developed. Turkey is better in terms of the number of scientific publications and citations compared to other factors. However, it ranks last in terms of high-impact conference and journal rankings. Poland is in a better position in terms of the total number of researchers and the number of high-impact journal publications. However, these factors are not sufficient for Poland to make progress in artificial intelligence technology and create economic value. Belgium, Czechia and Slovenia are in the last three places. Although Belgium does not perform well in terms of the number of scientific publications, citations and researchers, it performs better in terms of patenting activities. This situation reinforces the idea that scientific and technological studies are mostly conducted through experimental and applied research. Czechia should develop policies and programmes for criteria other than the number of high-impact conferences and journals, while Slovenia should develop policies and programmes for all criteria.

6. Conclusion

The need to establish a consensus framework for assessing the status and applications of scientific and technological progress in the field of artificial intelligence is the main motivation for this research. This study provides a framework for comparing advances in AI technology at the global level and across countries. The field of artificial intelligence research has a complex and comprehensive nature. There are significant shortcomings in the generation and presentation of the data. Drawing a framework agreed upon by all parties is only possible through the generation and publication of more comprehensive data. There are studies in the grey literature on measuring progress in the field of artificial intelligence. However, there are almost no scientific studies contributing to the research. In this context, the study has provided significant contributions to gathering, understanding, developing the necessary evidence and contemplating potential pathways for measuring scientific and technological progress in the field of AI.

Almost every country provides support for research and development activities. Choosing the right policy tools is crucial for determining how support should be allocated. Therefore, it is crucial to carefully examine the information provided in the findings section regarding the identification of factors that countries need to consider in achieving strategic goals in the field of AI and taking the necessary steps to accomplish these objectives. Strategic issues and policies should be revised based on the findings on which factors countries perform poorly and which factors they perform well in the field of AI. The information obtained allows for making objective and data-driven decisions on which areas of scientific and technological progress require more resource allocation and focus.

According to the obtained data, the driving force in measuring scientific and technological progress is the criteria of scientific publications and patents. Countries with a successful performance in scientific and technological progress in the field of artificial intelligence are generally developed countries. In particular, the efforts of the US to transform its scientific and technological leadership in this field into economic benefits should be carefully monitored. Some countries, despite demonstrating a particularly strong performance in terms of scientific publications, should be closely examined for their weak performance in terms of the number of patents. Some strategic priorities need to be reassessed in these countries, such as the level of cooperation between industry and the scientific community, resource allocation for translating scientific work into applied and experimental research, and the creation of stronger incentives for patenting.

Finally, efforts to measure progress in AI technology are still at a very nascent stage. In particular, the representation of AI by computer science data limits the use of comparable situation-specific data. Moreover, the wide range of AI fields makes data collection and classification difficult. Additional studies on methodological approaches and the presentation of data can obtain better analysis results.

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