

EXPLORING OECD COUNTRIES IN TERMS OF GOVERNMENT ARTIFICIAL INTELLIGENCE READINESS WITH MULTIDIMENSIONAL SCALING

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ABSTRACT

Artificial intelligence (AI), impacting all sectors today, is employed to enhance production processes and increase business efficiency through advanced algorithms and big data analysis. AI-powered decision support systems and autonomous devices transform healthcare, finance, education, and production. AI also helps governments serve citizens faster, better, and more efficiently. Big data analytics and automation can cut public service costs, speed up bureaucracy, and improve quality. Citizens can get instant answers from AI-powered chatbots and automated response systems. Countries are competing to advance the use of AI and become leaders in its benefits. The 2024 Government AI Readiness Index (GAIRI) investigates the AI readiness of countries by analyzing forty indicators across ten dimensions, which make up three fundamental pillars (government, technology sector, and data and infrastructure). This study visualizes the thirty-eight member countries of the Organisation for Economic Co-operation and Development (OECD) according to their similarities in terms of AI readiness using the three pillar scores of the 2024 GAIRI with multidimensional scaling. Thus, OECD countries that are similar to each other in terms of AI readiness are identified.

Keywords: *Artificial Intelligence, OECD, Government Artificial Intelligence Readiness Index, Multidimensional Scaling*

*Research Article, Received: 07.08.2025, Accepted: 17.10.2025.
In this article, Ethical Committee Approval is not needed.

DEVLET YÖNETİMİNDE YAPAY ZEKÂYA HAZIR OLMA AÇISINDAN OECD ÜLKELERİNİN ÇOK BOYUTLU ÖLÇEKLEME İLE İNCELENMESİ

ÖZ

Günümüzde tüm sektörleri etkileyen yapay zekâ, gelişmiş algoritmalar ve büyük veri analizi sayesinde üretim süreçlerini geliştirmek ve iş verimliliğini artırmak için kullanılmaktadır. Yapay zekâ destekli karar destek sistemleri ve otonom cihazlar sağlık, finans, eğitim ve üretimi dönüştürmektedir. Yapay zekâ ayrıca hükümetlerin vatandaşlara daha hızlı, daha iyi ve daha verimli hizmet vermesine yardımcı olmaktadır. Büyük veri analitiği ve otomasyon, kamu hizmeti maliyetlerini azaltabilir, bürokrasiyi hızlandırabilir ve kaliteyi artırabilir. Vatandaşlar, yapay zekâ destekli sohbet robotlarından ve otomatik yanıt sistemlerinden anında yanıt alabilirler. Ülkeler yapay zekâ kullanımını ilerletmek ve onun sağlayacağı faydalarda lider olmak için yarışmaktadır. 2024 Devletlerin Yapay Zekâya Hazır Olma Endeksi, üç temel sütunu (hükümet, teknoloji sektörü ve veri ve altyapı) oluşturan on boyutta kırk göstergeyi analiz ederek ülkelerin yapay zekâya hazır olup olmadığını araştırmaktadır. Bu çalışma, 2024 Devletlerin Yapay Zekâya Hazır Olma Endeksinin üç sütun puanını kullanarak çok boyutlu ölçekleme ile otuz sekiz OECD üye ülkesini yapay zekâya hazır olma açısından benzerliklerine göre görselleştirmektedir. Böylece, yapay zekâya hazır olma açısından birbirine benzer OECD ülkeleri belirlenmiştir.

Anahtar Kelimeler: *Yapay Zekâ, OECD, Devletlerin Yapay Zekâya Hazır Olma Endeksi, Çok Boyutlu Ölçekleme*

INTRODUCTION

Intelligence can be compactly defined as the aggregate of perception, analysis, and response (Chowdhary, 2020). However, a universally accepted definition of AI does not exist (OECD, 2019). One reason might be that AI tools possess the ability to perform a diverse array of tasks and generate various outputs (NASA, 2024). Nevertheless, it generally denotes the capacity of machines to replicate the intelligence of higher organisms (Bhardwaj et al., 2022). It primarily focuses on the automation of intelligent behavior, examined in all domains, including the human, animal, and vegetative worlds (Chowdhary, 2020). In November 2018, a subgroup was established by the AI Group of Experts at the OECD to create a description of an AI system. The description is intended to be technically accurate, technology-neutral, and applicable to both short- and long-term time horizons. It is also intended to be comprehensible. Afterwards, a definition of an AI system was established in 2019 (OECD, 2019). However, this definition was revised in 2023, and the revised definition is as follows: “An AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment” (OECD, 2024).

John McCarthy credited the origin of modern AI research, coining the term at a conference at Dartmouth College in 1956. This signified the inception of the AI scientific domain (Xu et al., 2021). Herbert Simon, Arthur Samuel, Alan Newell, and Marvin Minsky also participated in this conference (OECD, 2019). Nonetheless, the potential for machines to replicate human behavior and possess cognitive abilities was previously proposed by Alan Turing (Mintz & Brodie, 2019), who formulated the Turing test to distinguish between humans and machines. A machine that passes the test is deemed qualified to be designated as AI (Mintz & Brodie, 2019). Although AI research has advanced consistently over the last sixty years, the expectations set by early AI proponents have been excessively optimistic. This resulted in an "AI winter" characterized by diminished funding and interest in AI research throughout the 1970s. The AI winter concluded in the 1990s as advancements in computational power and data storage rendered complex tasks achievable (OECD, 2019).

Humans have been the main determinant concept in solving many management problems, such as how to proceed, how to work the most

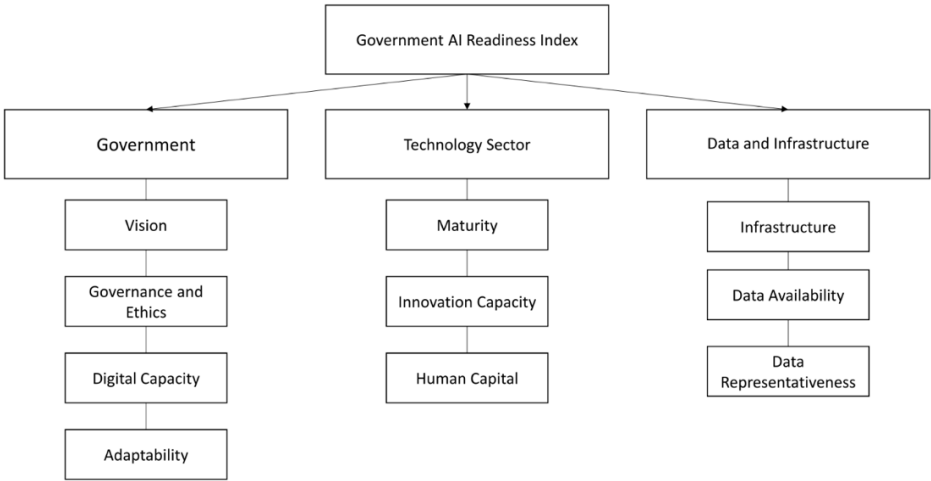
effective and efficient way, and how to achieve results. Scientists have constantly searched and studied to find better solutions, which has led to different periods. The digital age is the last stage of this development. It refers to the period when humans create technological infrastructure and data, service delivery is time- and labor-saving and efficient, and customers interact with software and applications instead of service providers (Ölmez & Bayrak, 2025). Currently, AI is revolutionizing the digital age. Since its rapid rise in recent years, AI has impacted almost all sectors. Thanks to advanced algorithms and big data analysis, AI has been implemented in a wide range of areas, including the optimization of production processes and the enhancement of business efficiency. AI offers innovative solutions in decision support systems and autonomous devices, revolutionizing healthcare, finance, education, and production. This rapid growth is transforming business and daily life. AI also helps governments provide faster, more efficient, and effective services to citizens. Big data analytics and automation can reduce public service operational costs, speed up bureaucratic processes, and improve service quality (Turkish Informatics Association, 2024). AI-powered chatbots and automated response systems can instantly answer questions from the public. In health, security, and transportation, smart systems can improve safety and reliability. AI-powered data analysis tools can improve public policy planning and resource efficiency. Thus, a more socially conscious and solution-focused public administration can be created (Turkish Informatics Association, 2024; Kayacı, 2025). In his study, Kayacı (2025: 413-422) lists the opportunities that AI offers to public administration at the individual and organizational levels. The opportunities offered by AI at the individual level include standardization of public service behavior, reduction of making different decisions, more effective decision-making processes and outcomes, increased information analysis capacity, insensitivity to incentives associated with decisions/tasks, prevention of corruption, and reduction of workload. Opportunities at organizational level include effective planning and allocation of necessary resources, increasing organizational efficiency through process automation, ensuring organizational flexibility, facilitating inter-organizational communication and cooperation, and strengthening transparency (Kayacı, 2025).

Countries are presently vying to establish leadership in AI development and to maximize the advantages of this technology previously outlined (Angın & Doğmazer, 2023). For this reason, they are engaging in research

and development endeavors to leverage AI. Dominant global economies, notably the United States of America, Russia, and China, anticipate the emergence of an ecosystem centered on AI in the future (Öztürk, 2022). The use of AI in the public sector is rapidly spreading in many different countries as a consequence of this (Busuioc, 2021).

Government AI Readiness Index (henceforth, GAIRI) (Nettel et al., 2024) evaluates the AI readiness of one hundred eighty-eight countries. While the global discourse predominantly centers on the governance of AI technology, a crucial inquiry pertains to how governments can utilize AI to enhance their performance. The effective and responsible adoption of AI can enable governments to improve service delivery, optimize operations, and tackle public challenges with increased precision and impact. The 2024 GAIRI investigates this readiness by analyzing forty indicators across ten dimensions which make up three fundamental pillars as shown in Figure 1 (Nettel et al., 2024).

Figure 1. Three pillars and ten dimensions of the GAIRI



Source: Nettel et al., 2024

A government must possess a strategic vision for the governance and development of AI, underpinned by suitable regulation and consideration of ethical risks (governance and ethics). Furthermore, it must possess robust internal digital capabilities, encompassing the skills and practices that facilitate its adaptability to emerging technologies (Nettel et al., 2024). Public entities depend on a robust provision of AI tools from the national

technology sector, that must be sufficiently developed to meet governmental demands. The sector must possess substantial innovation capacity, supported by a business environment conducive to entrepreneurship and a robust flow of research and development investment. Equally significant are robust levels of human capital, which propel the advancement of sophisticated AI solutions and guarantee the sector's responsiveness to the changing demands of governments (Nettel et al., 2024).

AI tools require substantial high-quality data (data availability) that must also be representative of the citizens within a specific country to mitigate bias and error (data representativeness). Ultimately, the potential of these data cannot be actualized without the requisite infrastructure to support AI tools and provide access to citizens (Nettel et al., 2024).

The GAIRI is calculated as follows: All indicator scores are normalized to a range of 0 to 100. The dimension score is derived by calculating the arithmetic mean of the indicator scores. The arithmetic mean of dimension scores within a pillar gives the pillar score. The GAIRI is the arithmetic mean of the three pillar scores. All indicators, dimensions, and pillars are assigned equal weight (Nettel et al., 2024).

This study seeks to address the research question: How similar are the thirty-eight OECD countries in terms of government AI readiness? OECD countries have set common goals, such as sustainable economic development, contributing to the development of global trade, and improving living standards in general (Eurostat, 2025). It is interesting to reveal how much similarity or difference there is among countries that share common goals. To that end, this study used the three pillar scores of the 2024 GAIRI for the thirty-eight OECD countries and employed multidimensional scaling to visualize these countries based on their similarities in AI readiness. To the best of the author's knowledge, multidimensional scaling has not been used to visually compare countries' readiness for AI in that sense. The resulting figure is subsequently analyzed to detect similar countries.

LITERATURE REVIEW

Montoya and Rivas (2019) examine factors affecting AI readiness in Latin America and the Caribbean (LAC) countries. They compare a ranking by the International Development Research Center (IDRC) on AI technology use in public services, governance, skills, and infrastructure to economic metrics such as unemployment rate, GDP-PPP, AI researcher cost, and

education levels. The study examines non-economic factors that affect AI readiness and its impact on citizens, such as data privacy policies and automation potential. It investigates current evaluation criteria for AI readiness and highlights key factors for LAC countries to consider during the AI revolution.

Nzobonimpa and Savard (2023) conduct a qualitative comparative analysis to assess governmental readiness for the responsible implementation of AI technologies. The authors contend that although numerous governments demonstrate readiness via policies and frameworks for AI integration, the actual execution frequently neglects ethical considerations and accountability measures, thereby posing substantial risks to trust and public interest. They utilized a fuzzy set qualitative comparative analysis method, establishing a stringent consistency threshold of 0.80 to guarantee the robustness of their findings concerning the configurations of conditions that promote responsible AI practices. The study emphasizes that readiness encompasses more than technical infrastructure; it necessitates a comprehensive grasp of ethical ramifications and governance frameworks, thereby providing significant insights for both policymakers and academics in AI governance and responsible execution.

Nasution et al. (2024) critically examine the weighting criteria analyzed in the GAIRI to enhance assessment accuracy. Instead of using traditional averaging methods, the authors use geometric and arithmetic non-linear functions to analyze and evaluate the ranking of countries. They classify countries into three distinct groups through cluster analysis based on observed criteria. This classification provides a more nuanced view of how ready governments are for AI. The clustering method improves the way countries are grouped by their AI readiness and shows the similarities and differences within each cluster. This gives a better understanding of regional trends and allows for the formulation of targeted improvement strategies for each cluster.

Socol and Iuga (2024) utilize a dynamic panel data model with the System Generalized Method of Moments to examine the relationship between government AI readiness and brain drain from 2018 to 2022. They include multiple control variables, including government expenditure growth, GDP per capita growth, the number of employed ICT specialists, and various governance indicators. The findings demonstrate that brain drain adversely impacts governmental readiness for AI. The presence of ICT

specialists, strong governance frameworks, and favorable macroeconomic indicators, including government expenditure growth and GDP per capita growth, positively impact AI readiness.

Shonhe et al. (2024) examine the Eastern and Southern African Regional Branch of the International Council on Archives (ESARBICA) governments' readiness to use AI to improve public services. They used desktop research to analyze the 2022 GAIRI quantitative data. The findings showed that South Africa, Botswana, and Kenya are committed to using AI to advance. In the Data and Infrastructure pillar, ESARBICA countries excel, especially in data representativeness. The region is not ready to adopt AI due to several factors, including an immature technology sector for AI implementation, insufficient human capital, a deficit in innovation and digital capabilities, and the absence of a governmental AI strategy.

Tun et al. (2025) evaluate the GAIRI from 2020 to 2023 to measure the readiness of ASEAN (Association of Southeast Asian Nations) for AI implementation in healthcare. The study shows that AI governance for healthcare readiness in the ASEAN region is very different from one country to the next. Some member states are making a lot of progress, while others are falling behind, which could make the digital divide even bigger. Enhancing regulatory frameworks for comprehensive AI strategies, developing human capital, improving digital infrastructure, facilitating knowledge transfer, and guaranteeing access to high-quality Internet across the region will be crucial for the governance of AI in healthcare.

METHODOLOGY

Multidimensional scaling is a method employed to visualize the distances or dissimilarities among collections of objects. In a multidimensional scaling plot, similar objects are positioned in proximity to one another, while dissimilar objects are situated at greater distances apart. This method comprises various statistical techniques that spatially depict data structure, facilitating visualization and interpretation. It is especially effective for elucidating complex relationships and is frequently linked to mapping techniques (Manjunatha et al., 2024).

This method does not make any assumptions about the distribution of the data, whereas for factor analysis, there are assumptions such as multivariate normality and linear relationships (Alpar, 2013). Clustering analysis, a method comparable to multidimensional scaling, serves to group objects

without addressing their geometric representation in a low-dimensional space (Timm, 2002).

Multidimensional scaling comprises two types in general: metric and non-metric (Alpar, 2013). This study employs metric multidimensional scaling, and the steps are listed below. Let $\mathbf{D}$ be an $n \times n$ matrix with the observed distances (original dissimilarities) $|\delta_{ij}|$ obtained from n objects and p variables. The following steps are then used to determine the coordinates of the objects in the plot. (Cox & Cox, 2001; Wickelmaier, 2003; Bulut, 2018):

- 1) By using Eq. (1), the matrix $\mathbf{A}$ is calculated from $\mathbf{D}$ by

$$\mathbf{A} = \left[-\frac{1}{2} \delta_{ij}^2 \right] \quad (1)$$

- 2) Eq. (2) is used to compute the matrix $\mathbf{B}$

$$\mathbf{B} = \left(\mathbf{I} - \frac{1}{n} \mathbf{J} \right) \mathbf{A} \left(\mathbf{I} - \frac{1}{n} \mathbf{J} \right) \quad (2)$$

where $\mathbf{I}$ is an $n \times n$ identity matrix and $\mathbf{J}$ is an $n \times n$ matrix of ones.

- 3) $\mathbf{B}$ is a symmetrical matrix and, with Eq. (3) it can be written as

$$\mathbf{B} = \mathbf{L} \mathbf{\Lambda} \mathbf{L}' = \mathbf{L} \mathbf{\Lambda}^{1/2} \mathbf{\Lambda}^{1/2} \mathbf{L}' \quad (3)$$

by using spectral decomposition where $\mathbf{\Lambda} = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_n)$, the diagonal matrix of eigenvalues of $\mathbf{B}$, and $\mathbf{L} = [\mathbf{v}_1 \ \mathbf{v}_2 \ \dots \ \mathbf{v}_n]$, the matrix of corresponding normalized eigenvectors.

If, for instance, $\mathbf{B}$ is a positive semidefinite matrix of rank q it has q positive eigenvalues and $n - q$ zero eigenvalues. By using Eq. (4), the matrix $\mathbf{B}$ can be rewritten as

$$\mathbf{B} = \mathbf{L}_1 \mathbf{\Lambda}_1 \mathbf{L}_1' = \mathbf{L}_1 \mathbf{\Lambda}_1^{1/2} \mathbf{\Lambda}_1^{1/2} \mathbf{L}_1' \quad (4)$$

where $\mathbf{\Lambda}_1 = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_q)$ and $\mathbf{L}_1 = [\mathbf{v}_1 \ \mathbf{v}_2 \ \dots \ \mathbf{v}_q]$.

- 4) By extracting the largest k ($k < p$) from q positive eigenvalues and corresponding eigenvectors, the coordinate matrix $\mathbf{X}$ can be calculated by using Eq. (5)

$$\mathbf{X} = \mathbf{L}_2 \mathbf{\Lambda}_2^{1/2} \quad (5)$$

where $\mathbf{\Lambda}_2^{1/2} = \text{diag}(\sqrt{\lambda_1}, \sqrt{\lambda_2}, \dots, \sqrt{\lambda_k})$ and $\mathbf{L}_2 = [\mathbf{v}_1 \ \mathbf{v}_2 \ \dots \ \mathbf{v}_k]$. k is usually chosen as 2.

FINDINGS

First, it should be noted that the three pillars have different numbers of indicators and dimensions, and as explained in the introduction, the GAIRI is calculated by taking the arithmetic mean of the three pillar scores. Therefore, each of the three pillar scores has equal weight in the GAIRI.

This study used only the three pillar scores that make up the GAIRI in multidimensional scaling to visually compare countries regarding government AI readiness, as the comparison focused on the specified pillars with equal weight and averages.

The data were sourced from the report by Nettel et al. (2024), and the analysis was conducted utilizing R, resulting in Figure 2. The figure demonstrates how some countries stand out from the dominant group. In this context, the United States of America is prominent at first glance. The result is not surprising, as the United States of America possesses the highest score in all three pillars, ranking first among all OECD countries in terms of government AI readiness. Figure 2 indicates that Canada is also in close proximity to the United States of America.

At this point, it should be noted that North America leads the GAIRI in performance, a trend that is likely to persist. In terms of overall AI readiness, the United States of America and Canada are ranked first and sixth, respectively, on the global scale (Nettel et al., 2024).

In Figure 2, numerous Western European countries are also seen to be adjacent to the United States of America and Canada since Western Europe remains a robust contender in the GAIRI. France tops the regional ranking in 2024, closely followed by the United Kingdom. This region commands a prominent position within the global top ten, with the Netherlands, Germany, and Finland alongside France and the United Kingdom, establishing Western Europe as the most prominent region in the upper echelon (Nettel et al., 2024).

East Asia is positioned as the third highest-performing region in the 2024 GAIRI, and this region significantly exceeds the global average in all three pillars (Nettel et al., 2024). This explains the proximity of the Republic of Korea and Japan to the North American and Western European countries in Figure 2. The Government pillar is this region's primary strength, while the Data and Infrastructure pillar is also notable; however, as noted in the study by Tun et al. (2025), the Technology Sector pillar is underperforming, indicating a necessity for increased investment (Nettel et al., 2024).

Figure 2 also shows that Australia, which is from the Pacific region and ranks first in this region, and Israel, which is from the Middle East and North Africa region and ranks second in this region (Nettel et al., 2024),

are also situated close to the countries from the North America region, Western Europe region, and East Asia region mentioned before.

The upper section of Figure 2 shows that countries from the Eastern Europe region are close to each other. Eastern Europe is positioned 4th in the 2024 GAIRI, with the region exceeding the global average in all three pillars. Nonetheless, the Technology Sector presents a challenge, indicating the necessity for increased investment in technological capacity and innovation to realize the region's complete AI readiness potential (Nettel et al., 2024). It is important to acknowledge that Luxembourg, located in Western Europe, is close to these countries due to its low score in the Technology Sector pillar.

The Eastern Europe region perceives Türkiye, included in the South and Central Asia region, and Chile, Colombia, and Costa Rica, from the Latin America and the Caribbean region, as closely aligned. The Government pillar is a relative strength for the former region, reflecting efforts to advance AI strategies and governance frameworks. The latter region continues to face a challenge with the Technology Sector pillar, underscoring the necessity of additional investment in technological advancements (Nettel et al., 2024).

It can be noted that Switzerland, New Zealand, Greece, and Mexico, are distant from the other countries. Switzerland scored well in both the Data and Infrastructure pillar and the Technology Sector pillar, ranking among the top ten OECD countries in both pillars, but scored very low in the Government pillar. New Zealand, Greece, and Mexico occupy the lowest three positions in the Government pillar, indicating their proximity in Figure 2. Mexico ranks last among the thirty-eight OECD countries regarding average score.

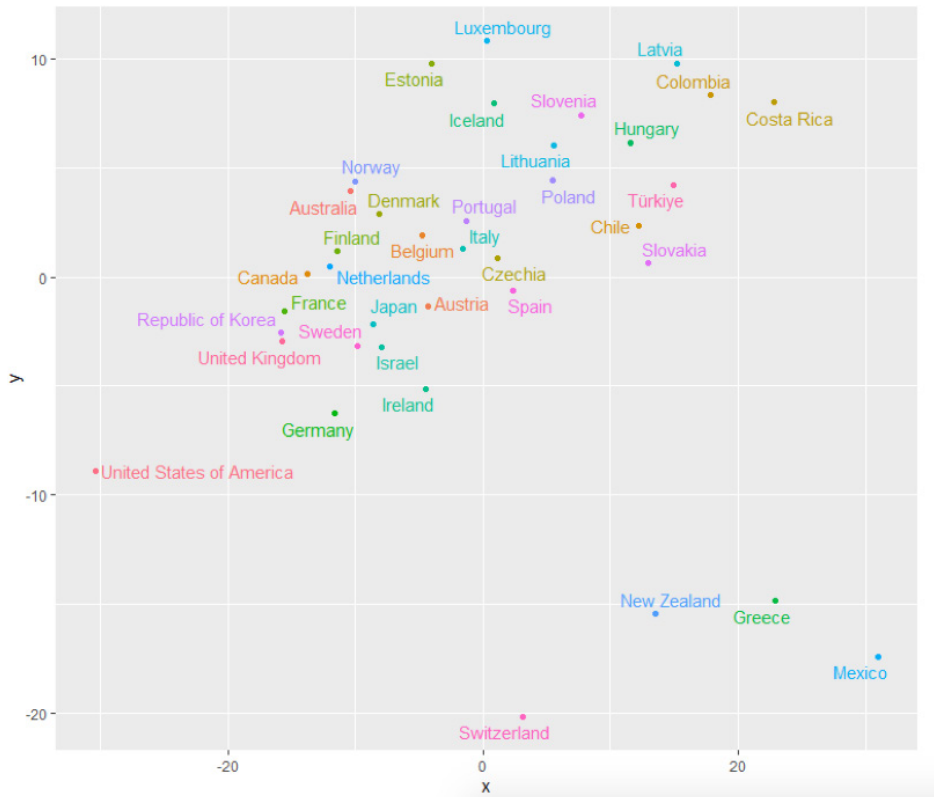
In R, there are two measures for goodness of fit calculated by Eqs. (6) and (7):

$$GOF_1 = \frac{\sum_{i=1}^k \lambda_i}{\sum_{i=1}^n |\lambda_i|} \quad (6)$$

$$GOF_2 = \frac{\sum_{i=1}^k \lambda_i}{\sum_{i=1}^n \max\{0, \lambda_i\}} \quad (7)$$

(Bulut, 2018). The proportion of variance elucidated by the initial two dimensions is 0.947381 for both GOF_1 and GOF_2 . The closeness of these values to 1 signifies an excellent fit.

Figure 2. Visualization of OECD countries with regard to government AI readiness



CONCLUSION

AI has become an integral part of everyday life. AI is employed not only in the corporate sector but also in governmental administration, facilitating the delivery of swifter, more efficient, and superior services to citizens. The primary advantages of employing AI in governmental administration include the reduction of public service expenditures, the acceleration of bureaucratic processes, the enhancement of quality, and the facilitation of equitable access to public services for all societal segments, thereby promoting greater equality within society. Consequently, countries are making substantial investments and competing to enhance the utilization of AI.

Alongside these advantages, several concerns must be addressed regarding the broader implementation of AI. The accountability in the event of an issue remains ambiguous. The reliability of data and the utilization of precise information are of paramount significance. Moreover, not all societal segments may possess equitable access to technology, a phenomenon referred to as the digital divide. The overutilization of AI may lead to a bigger digital divide. Consequently, the pursuit of equality may inadvertently result in the contrary outcome.

The OECD consists of countries that come together to achieve common goals. The increased utilization of AI has the potential to substantially assist in attaining these goals. Nonetheless, disparities have been identified among countries regarding their government AI readiness.

This study sought to visually emphasize the similarities and differences and consequently employed multidimensional scaling, a method commonly utilized in the literature. This study utilized data from only thirty-eight OECD countries. Future studies could expand the number of countries analyzed to elucidate the disparities among countries worldwide that exhibit significant variation in economic development. Subsequent research may employ alternative methodologies to perform a comparative analysis with the findings of this study. Moreover, this study utilized data from only one year. Analyzing data over multiple years may elucidate variations in countries' readiness and alterations in the grouping of analogous countries.

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