The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/0368-492X.htm

Kybernetes

Addressing brain drain and strengthening governance for advancing government readiness in artificial intelligence (AI)

Adela Socol and Iulia Cristina Iuga
Department of Finance-Accounting, 1 Decembrie 1918 University of Alba Iulia, Alba Iulia, Romania

Received 8 March 2024
Revised 30 June 2024
Accepted 29 July 2024

Abstract

Purpose – This study aims to investigate the impact of brain drain on government AI readiness in EU member countries, considering the distinctive governance characteristics, macroeconomic conditions and varying levels of ICT specialists.

Design/methodology/approach – The research employs a dynamic panel data model using the System Generalized Method of Moments (GMM) to analyze the relationship between brain drain and government AI readiness from 2018 to 2022. The study incorporates various control variables such as GDP per capita growth, government expenditure growth, employed ICT specialists and several governance indicators.

Findings – The results indicate that brain drain negatively affects government AI readiness. Additionally, the presence of ICT specialists, robust governance structures and positive macroeconomic indicators such as GDP per capita growth and government expenditure growth positively influence AI readiness.

Research limitations/implications – Major limitations include the focus on a specific region of countries and the relatively short period analyzed. Future research could extend the analysis with more comprehensive datasets and consider additional variables that might influence AI readiness, such as the integration of AI with emerging quantum computing technologies and the impact of governance reforms and international collaborations on AI readiness.

Practical implications – The theoretical value of this study lies in providing a nuanced understanding of how brain drain impacts government AI readiness, emphasizing the critical roles of skilled human capital, effective governance and macroeconomic factors in enhancing AI capabilities, thereby filling a significant gap in the existing literature.

Originality/value – This research fills a significant gap in the existing literature by providing a comprehensive analysis of the interaction between brain drain and government AI readiness. It uses control variables such as ICT specialists, governance structures and macroeconomic factors within the context of the European Union. It offers novel insights for policymakers to enhance AI readiness through targeted interventions addressing brain drain and fostering a supportive environment for AI innovation.

Keywords Artificial intelligence (AI), Brain drain, Governance, ICT specialists, EU member countries, Macroeconomic indicators

Paper type Research paper

1. Introduction

Artificial Intelligence (AI) simulates human intelligence in machines, enabling them to learn, understand complex content, engage in conversations, and perform tasks like visual perception, speech recognition, decision-making, and language translation (Russell and Norvig, 2016). As AI technologies advance, AI readiness—referring to the preparedness of countries, organizations, or governments to implement and leverage AI—has become crucial. It involves having technological infrastructure, a skilled workforce, regulatory frameworks, and innovation ecosystems (Oxford Insights, 2023). Public AI, a key aspect of AI readiness, uses AI technologies to enhance public services and government operations, improving areas like healthcare, education, transportation, and public safety (Margetts and Dorobantu, 2019).

In our rapidly evolving tech world, AI is a pivotal force redefining global society (Lv *et al.*, 2023). Its implications are vast, particularly for governments eager to tap into its multifaceted benefits (Valle-Cruz *et al.*, 2022). For the EU, AI's promise extends beyond commerce to revolutionizing governance and public services. As AI offers transformative possibilities for public services, it can lead to advanced efficiency, effectiveness, and innovation. Predictive healthcare tailored to one's genetics, real-time data-driven urban planning, or public transport systems must respond to citizen requirements (Todisco *et al.*, 2023). These changes demand governments to be nimble, forward-thinking, and AI-ready. Ignoring AI's influence on effective governance is not an option (Dwivedi *et al.*, 2019). EU countries have much to gain by fully leveraging AI.

An important consideration is the "brain drain" phenomenon. The migration of skilled professionals seeking better prospects elsewhere can weaken a nation's AI potential. Within the interconnected EU, understanding this trend is crucial (Gasser, 2023). Decisions in EU nations about retaining talent directly influence their AI prospects.

The relationship between brain drain and government AI readiness is particularly relevant due to its significant implications for national innovation capacities and the effective implementation of AI technologies. Despite its importance, this relationship is underexplored in the literature, which presents a critical gap that this study aims to address. Brain drain involves the emigration of skilled professionals seeking better opportunities abroad, resulting in a loss of human capital for their home countries (Jovcheska, 2024). This loss directly affects the capacity for innovation and technological advancements, including AI, as these professionals often possess essential skills and expertise needed for such developments.

However, AI readiness extends beyond talent and human capital, even though the presence of skilled ICT specialists is fundamental for AI innovation (He *et al.*, 2023). Governance, specifically how decisions are made, significantly impacts AI adoption. Effective governance not only fosters AI integration but also formulates policies that ensure the technology aligns with national values (Margetts, 2022). Moreover, macroeconomic factors play a crucial role in this process. Economic growth indicates the availability of resources for AI research and infrastructure, while government spending patterns highlight national priorities (Nguyen and Bui, 2022). These elements collectively shape the environment in which AI can thrive, illustrating the interconnectedness of governance, economic conditions, and technological advancement.

Focusing on the EU offers a unique perspective. With its shared values and goals (Pirozzi and Bonomi, 2022a), the EU is committed to a digital single market and has set global standards in data protection and tech governance (European Council, 2023). However, there's variability in AI readiness across EU nations. While some countries lead in AI, others are behind (Foffano *et al.*, 2023). Factors like policy, infrastructure, and human resources influence this disparity. Several EU countries, especially from the east and south, face brain drain, with professionals moving to wealthier EU nations (Pollacci *et al.*, 2022). This not only affects the country they leave but enriches the recipient country's talent base.

Considering this, we estate the research question: ***How does the phenomenon of brain drain, as measured by the Human Flight and Brain Drain Index, impact government AI readiness, as measured by the Government Artificial***

Intelligence Readiness Index, in EU member countries, and what role do governance structures and macroeconomic factors play in this relationship?

The aim of this study is to examine the impact of human flight and brain drain on government AI readiness, as well as the roles of economic, governance, and institutional factors.

The primary objective of this paper is to investigate the relationship between brain drain and government AI readiness, taking into consideration the distinctive governance characteristics, macroeconomic conditions, and varying levels of ICT specialists in EU member countries.

This study's originality is rooted in its exhaustive examination of the interplay between brain drain and governmental AI readiness, with a particular focus on the unique governance frameworks, macroeconomic conditions, and the diverse levels of ICT specialist expertise across EU member states. By integrating these elements, the study offers a novel perspective on how the loss of skilled professionals affects a government's ability to implement and benefit from AI technologies, an area that has been underexplored in existing literature. This approach not only addresses a significant research gap but also provides actionable insights for policymakers to enhance AI readiness through targeted interventions.

The theoretical value of this study lies in providing a nuanced understanding of how brain drain impacts government AI readiness, emphasizing the critical roles of skilled human capital, effective governance, and macroeconomic factors in enhancing AI capabilities, thereby filling a significant gap in the existing literature.

The remainder of this paper is organized as follows. Section 2 presents the actual stage of the knowledge in the field and the research hypothesis; Section 3 describes the data and method; Section 4 refers to results and discussion; Section 5 provides some aspects regarding Management Decision-making and EU-Level Policies, and Section 6 concludes the paper.

2. Literature review

While specialized literature has separately addressed the phenomena of "brain drain" (Fu *et al.*, 2023; Miller and Collins, 2023; Böttger *et al.*, 2023) and governmental readiness in the realm of AI (Ojo and Millard, 2017; Bullock, 2019; Sousa *et al.*, 2019), there remains a notable research gap in exploring the nexus between these two variables. Specifically, no studies have delved into how the migration of skilled labor might influence the ability of EU governments to adapt to and implement AI technologies.

2.1 Brain drain and government AI nexus

The theory of brain drain (Bhagwati and Hamada, 1974) primarily addresses the emigration of skilled and educated individuals from one country to another, leading to a loss of human capital in the originating country. According to Docquier and Rapoport (2012), brain drain occurs when professionals such as scientists, engineers, and healthcare workers move to countries with better opportunities, often driven by higher wages, advanced research facilities, and improved living standards. This migration can lead to significant economic and social challenges for the countries losing their talent, as it depletes their pool of educated individuals who are crucial for innovation and development. Beine *et al.* (2008) elaborated on how brain drain can negatively impact a nation's ability to develop and implement advanced technologies, including AI, due to the loss of essential skills and expertise. This theoretical framework underscores the necessity of addressing brain drain to maintain and enhance government AI readiness, as the retention of skilled professionals is pivotal for fostering an environment conducive to technological innovation and growth.

The rapid advancement of technology, particularly artificial intelligence (AI), presents transformative prospects for societies. However, the challenge of "brain drain" complicates this landscape, especially within EU member states. Brain drain refers to the emigration of talented professionals seeking better opportunities elsewhere (Chen *et al.*, 2022). Driven by factors like higher wages, cutting-edge research facilities, or improved living standards, this exodus deprives nations of essential human capital needed for innovation, including AI. The effects are multifaceted: countries experience economic setbacks as key sectors like research and health are impacted (Massaro, 2023), societal challenges like population aging arise, and knowledge gaps emerge (Gomes de Sousa *et al.*, 2019). Conversely, recipient countries benefit from an influx of expertise, enhancing their innovation capacity. Brain drain thus presents a global dilemma. Departing talent hinders origin countries from fostering a dynamic AI environment, while recipient nations gain an advantage, potentially exacerbating the global AI disparity.

However, this global phenomenon takes on unique nuances when viewed through the lens of the EU, a consortium of 27 nations, which is characterized by its open borders, shared market, and collective policies. In theory, this setup should facilitate a balanced distribution of talent. In practice, however, certain EU countries, primarily due to economic disparities, are more susceptible to brain drain, especially to non-EU nations offering lucrative opportunities (World Bank, 2023).

In Europe, "brain drain" pertains to the migration of skilled professionals from eastern or southern nations to wealthier European or global destinations in search of improved opportunities, wages, and living standards. Countries like Poland, Romania, and Bulgaria often see their top talents move westward (Omar *et al.*, 2017), potentially stifling their AI advancements. Meanwhile, nations like Germany, France, and the Netherlands benefit from this talent influx, enhancing their AI sectors (Foffano *et al.*, 2023). The EU's ambition to establish a Digital Single Market (European Council, 2023) and unify AI strategies emphasizes the need to retain talent within the region and avoid losing it to external competitors.

Previous research (Agrawal *et al.*, 2019; Gesk and Leyer, 2022; Villani *et al.*, 2018) highlights those countries losing top-tier tech talent face hurdles in AI innovations and policy implementation. This "brain drain" doesn't just hinder immediate advancements but also impacts long-term AI strategy. Such nations often rely on external consultancies, leading to misaligned AI approaches. The resulting challenges encompass reduced innovation in state-led AI projects and inefficiencies in utilizing AI for public services.

The historical evolution of the scientific thought on brain drain and government AI readiness provides essential context for understanding current research trends. Early studies by Harris and Todaro (1970) laid the groundwork by exploring migration patterns and their economic impacts. Subsequent research by Beine *et al.* (2008) extended this understanding by examining how brain drain affects a nation's capacity to innovate and develop advanced technologies.

Recent literature has built on these foundational theories to explore the practical implications of brain drain in the context of AI readiness. For instance, Agrawal *et al.* (2019) highlight the dual impact of skilled emigration, where brain drain can both hinder domestic innovation and facilitate global knowledge exchange. This underscores the importance of strategic policies to mitigate negative impacts while leveraging potential benefits. Moreover, Nwaka (2021) discusses how African nations can harness their diaspora to foster innovation, providing valuable insights into policy frameworks that can be adapted to the EU context.

Studies such as Docquier and Rapoport (2012), demonstrate the adverse effects of brain drain on national innovation capacities. Can (2022), emphasize that brain drain severely limits a country's capacity to develop and implement AI technologies by depleting its skilled workforce. Similarly, the Government AI Readiness Index 2023 by Oxford Insights (2023) highlights how countries with higher brain drain rates struggle with lower AI readiness scores, underscoring the need for retaining skilled professionals to maintain competitive advantage in AI development.

Taking these factors into account, we can posit the main research hypothesis for this study:

H1. Brain Drain adversely impacts AI governmental readiness in the European Union Member States.

2.2 Interplay between governance and government AI readiness

Effective governance in the EU sets a strategic direction for AI, harmonizing it with both national and European objectives. Governance, by creating comprehensive AI policies, addresses AI's ethical, societal, and legal aspects, facilitating its responsible deployment (Kuziemski and Misuraca, 2020). Adequate resource allocation ensures collaboration between academia, industry, and government, enhancing AI innovation. Rigorous regulatory frameworks ensure AI transparency and fairness, building public trust (Carbonaro, 2022). Furthermore, emphasis on education equips nations with a workforce ready to exploit AI's benefits, while governance proactively manages AI-related risks (Smuha, 2021).

In delivering public services to citizens, contemporary governments face unmanageable challenges in developing AI and machine learning-based tools to detect fake news and disinformation, whose potential to circulate through online platforms and social networks is huge today. Cutting-edge approach to the field presents scenarios in which governments should create AI-based tools through which fake news can be detected and make such tools freely available to civil society, which will help decrease disruption and change perceptions of decision-making processes (Akhtar *et al.*, 2023).

In the EU, governance reflects decision-making across multiple tiers. It encompasses a range of stakeholders, from national entities to central EU institutions like the European Commission and the European Parliament (European Union, 2023). The EU, due to its collective nature, aims for unified AI policies (Pirozzi and Bonomi, 2022b). While EU institutions outline broad directives, national governments adapt them to their contexts. Such governance structures ensure AI decisions resonate with the EU's shared values and goals (Gasser, 2023).

In response to the challenges posed by AI and the talent exodus, the EU has launched several initiatives and policies. One of these is the creation of a *Digital Single Market*, aimed at facilitating the free flow of data and promoting AI research collaboration across the EU (EU4Digital, 2023). This could help counteract the talent exodus by offering attractive opportunities throughout the region. The EU unveiled the *European Strategy for AI*, targeting enhanced AI research, education investment, and clear AI ethical guidelines. This strategy is bolstered by *Horizon Europe*, a funding scheme supporting AI and tech-centric research and innovation (European Commission, 2023).

Some studies (Taeihagh, 2021; Ariansyah *et al.*, 2024; Margetts, 2022) have demonstrated the positive impact of governance on government AI readiness, leading to the idea that effective governance structures can facilitate the adoption and integration of AI technologies. Governance that emphasizes transparency, accountability, and inclusivity allows governments to align technological advancements with societal values and legal standards. Furthermore, strategic governance fosters collaboration between public and private sectors, promoting innovation and enhancing the overall AI ecosystem within the country. This comprehensive approach not only accelerates AI adoption but also ensures its sustainable and responsible use.

2.3 Linking specialist skills to government AI readiness

AI expertise in EU is gauged by specialized talent depth (Rodriguez-Hevía *et al.*, 2020). As AI evolves, member states recognize the need for a workforce adept in AI's technical, ethical, and societal dimensions. This aligns the EU's AI approach with its core values and legal standards. Universities and research institutions across the EU play a crucial role, offering advanced AI courses and promoting interdisciplinary research merging AI with humanities and law (Konopik *et al.*, 2022). EU-wide initiatives strive to bridge academia with the tech industry (Konys, 2020), translating academic findings into real-world benefits for citizens. A persistent challenge, however, is retaining top AI talent amidst global tech hubs' allure, prompting the EU to devise strategies to keep its innovators close (Grigorescu *et al.*, 2021). Ultimately, the EU's AI stance is linked to its specialist capabilities. Despite its academic reputation (Burinskienė and Seržantė, 2022), the balance between education, industry, and policy will shape its global AI leadership. Retaining talent is pivotal for the EU's AI success.

Regarding the connection between specialists' skills and government AI readiness, there are studies in the literature (Alhosani and Alhashmi, 2024; Sousa and Rocha, 2019) that demonstrate the positive impact of ICT specialists on government AI readiness. These studies suggest that the presence of skilled ICT experts is essential for the effective development and implementation of AI technologies. ICT specialists significantly enhance government capabilities to adopt and integrate AI solutions by promoting innovation and fostering collaboration between the public and private sectors, thereby improving the overall AI ecosystem.

2.4 Interrelation of macroeconomic indicators with government AI readiness

Economic growth, reflected by a nation's Gross Domestic Product (GDP), indicates its financial health. EU countries experience varied growth rates. Nations like Germany and the Netherlands, with steady economic expansion, often possess greater financial agility. This allows them to invest in innovative areas, notably AI research (Corrado *et al.*, 2021). Conversely, countries with erratic growth may find it challenging to prioritize AI due to economic constraints. While growth rate matters, the overall economic size is crucial too (Fan and Liu, 2021). Bigger economies can potentially channel more resources into AI, even with moderate growth rates.

Government expenditure reveals a nation's strategic focus. The proportion of funds directed towards AI, from the total budget, signifies its dedication to this game-changing tech. AI readiness necessitates massive investment in infrastructure and education. Countries allocating substantial budgets to these areas inherently indicate a proactive AI stance (Wang and Cui, 2022). In the EU, nations prioritizing AI in their budgets not only strengthen domestic capabilities but also inspire global competition (Bobanović, 2022), showcasing their commitment to AI's transformative potential (Ciftci and Durusu-Ciftci, 2022).

Studies have shown a positive impact of GDP and government expenditure on government AI readiness. A high GDP indicates a robust economy capable of investing in the technology and infrastructure necessary for AI. Effective government spending, particularly in education, research, and development, also plays a crucial role in building a solid foundation for AI implementation. For example, the Government AI Readiness Index reports consistently highlight how economic strength and strategic expenditure contribute to higher AI readiness scores among nations (European Commision, 2020).

Furthermore, empirical studies support these findings. A study by Gonzales (2023) examined the relationship between AI innovation and economic growth, finding that countries with higher GDP and strategic government expenditure are better positioned to leverage AI technologies. Other studies (Tuan *et al.*, 2020; Iuga and Socol, 2024; Bredt, 2019) have also demonstrated a positive impact of GDP and government expenditure on government AI readiness.

Finally, from the qualitative and quantitative perspective, recent works (Lu *et al.*, 2024; Wang *et al.*, 2024) demonstrate the potential of AI models in optimizing complex data structures. There have been increasingly sophisticated studies that underscore the importance of collaborative and integrative AI methods in medical imaging, offering improved diagnostic accuracy and efficiency, which can be parallelly applied to optimize other digitalized healthcare systems. He *et al.* (2024) propose a methodology that could be instrumental in refining AI-driven optimization processes across diverse applications, from healthcare to finance, by ensuring more coherent and reliable data interpretations.

3. Data and research methodology

Based on the current stage of knowledge, the novelty of the theme that addresses AI in government and the lack of the literature in the field, this study examines the relationship between brain drain and the AI government readiness in the EU between 2018–2022. The choice of this research period is based on the low availability of data in the field, caused in particular by researchers' recent interest in creating tools and indicators to measure the impact of artificial intelligence in different areas of economic, social life or governance of nation states. Available statistical data on governments' readiness to implement AI is scarce and spans only a small recent number of years. To the best of our knowledge, indices of governments' readiness to deploy AI were not published until 2017 at the earliest, and there are extremely few organizations issuing data series (e.g. McKinsey Global Institute, Stanford University, Oxford Insights and International Development Research Center). We chose the Oxford Insights and International Development Research Center Index regarding the government AI to implement AI as a dependent variable because it considers complex dimensions of governance, technology, human capital and infrastructure. The Government Artificial Intelligence Readiness Index scales governments' readiness to implement AI in public service delivery by including 39 indicators from 10 dimensions, developed on 3 pillars: the government pillar (vision, governance and ethics, digital capacity, adaptability), the technology sector pillar (human capital, innovation capacity, maturity) and the data and the infrastructure pillar (data representativeness, data availability, infrastructure), (Oxford Insights and International Development Research Centre, 2022).

The choice of studying EU states is based on the unique characteristics of such a grouping of states, governed by a communitarian set of rules and influenced in internal governance by common policies, which makes them challenging for the present analysis, given the national specificities in the transposition of Community legislation in the Member States, as well as their different historical evolution in different context and particularities of economic, social and political development.

For an analysis of the relationship between AI in government and human capital, this study considers the Government Artificial Intelligence Readiness Index (AI_GOV) as the main dependent indicator, while the Human Flight and Brain Drain Index (BRAIN_DRAIN) is considered the core explanatory variable.

The study's variables selection is based on their direct relevance and impact on understanding the relationship between brain drain and government AI readiness. The Government Artificial Intelligence Readiness Index is chosen as the dependent variable because it measures a government's capability to implement AI technologies in public services, covering infrastructure, governance, and innovation capabilities. The Human Flight and Brain Drain Index is the core explanatory variable, capturing the economic impact of skilled labor migration, which affects human capital crucial for innovation and AI development. Control variables include the number of employed ICT specialists, reflecting the technical human resources necessary for AI, and economic factors like GDP per capita growth and government expenditure growth, indicating financial health and public investment levels. Governance-related variables such as regulatory quality, political stability and absence of violence or terrorism, control of corruption, rule of law, and government integrity capture the institutional and political environment that supports or hinders AI development. This comprehensive approach addresses both the direct effects of brain drain and broader socio-economic and political factors influencing government AI readiness.

Table 1 describes the variables and data sources from which the information was gathered. Several ICT skills of workforce, macroeconomic and country-specific governance indicators were considered as control variables, based on the results of previous studies. To control the quality of workers from the entire economy, this study uses the number of Employed ICT specialists (ICT_SPEC), while to control the macroeconomic conditions, GDP per capita growth (GDPPPG) and Government expenditure growth (GOVEXPG) are employed. To render the characteristics of each country's governance system, we alternatively use the Worldwide Governance Indicators (Kaufmann and Kraay, 2023) and the Government integrity (GOV_INTEGRITY), last issued by the Heritage Foundation.

To unearth the causal nexus between the Brain drain and AI government readiness in the European Union (2018–2022), we employ the following dynamic panel data model:

$$AI\_GOV_{i,t} = \propto_0 + \propto_1 AI\_GOV_{i,t-1} + \propto_2 BRAIN\_DRAIN_{i,t} + \propto_3 ICT\_SPEC_{i,t} + \propto_4 GDPPPG_{i,t} + \propto_5 GOVEXPG_{i,t} + \propto_6 GOVERNANCE_{i,t} + u_{i,t}$$

where i represents the country, t is the period (years), $_{i,t-1}$ represents 1-year lag of variables as they are set in Table 1, α_0 is constant (intercept), $\alpha_{1,2,3,4,5,6}$ are the coefficients of the estimated parameters and $u_{i,t}$ is the error term.

The paper gradually approaches several static and dynamic panel methods, with the aim of identifying the most appropriate and robust methodologies for identifying the relationships and causal links between the analyzed variables. To ensure the accuracy and validity of the developed models and to select the most appropriate to the studied data, we initially verify the classical assumptions of linear regression models, by resorting to statistical techniques for studying multicollinearity between variables, stationarity, heteroscedasticity, cointegration, serial correlation and normal distribution (Maladjian and Khoury, 2014). Violation of these assumptions and subsequently choosing an analysis method that would not handle possible problems that arose could lead to insufficiently substantiated or even spurious results. Specifically, the multicollinearity between variables was studied using the correlation matrix and the VIF test (Koengkan *et al.*, 2019) and stationarity through the Augmented Dickey-Fuller test, which takes care of short-term dynamics in a parametric way (Lanne and Lutkepohl, 2002). Heteroscedasticity has been studied with the modified Wald test and the Breusch-Pagan test (Breusch and Pagan, 1979). To analyze whether there are prerequisites for long-term cointegration between variables, the cointegration Kao test was applied (Kao, 1999), while the Wooldridge test was applied to serial correlation analysis (Wooldridge, 2002). The normality of variables was studied by Skewness and Kurtosis tests (Kim, 2015).

We also checked the cross-sectional independence between the analyzed countries, given that the studied sample, European Union states, could be susceptible to interstates effects, which occurs because of the existence of common factors or common features (Burdisso and Sangiacomo, 2016). In the presence of cross-sectional dependence, studied by us through the Pesaran test (2004), the type of model appropriate to the data must be determined in such a way as to be able to efficiently manage such a characteristic of the observations used in the sample.

The endogeneity of variables leads to unreliable and biased parameters and is a property of data difficult to scale because endogeneity can be generated either by unobservable factors, by mutual influence between variables, or by dynamic endogeneity between variables, or by the impact of the past value of a variable on its present value (Chatterjee and Nag, 2023; Labras and Torrecillas, 2018). In addition to the theoretic reasoning and previous literature underlying the establishment of factors influencing governments' readiness to

Variables/Symbol	Description/Unit	Data source
Dependent		
Government Artificial Intelligence Readiness Index/AI_GOV	The measure of governments readiness to implement AI in the delivery of public services Score: 0 (low) - 100 (high)	Oxford Insights and International Development Research Center, https://www.oxfordinsights.com/government-ai-readiness-index
Core explanatory		
Human Flight and Brain Drain Index/BRAIN_DRAIN	The measure of the economic impact of human displacement (for economic or political reasons) and the consequences this may have on a country's development Score: 0 (low) – 10 (high)	The Global Economy, via Fund for Peace, https://fragilestatesindex.org/indicators/e3/
Control variables		
ICT_SPEC	Employed ICT specialists represent workers who have the ability to develop, operate and maintain ICT systems, and for whom ICT constitute the main part of their job (Thousand persons) The variable is used in logarithm form in analysis	Eurostat, https://ec.europa.eu/eurostat/databrowser/view/ISOC_SKS_ITSPT/default/table
Gross Domestic Product per capita Growth/GDPPPG	Annual percentage growth rate of GDP per capita based on constant local currency. GDP per capita is gross domestic product divided by midyear population (%)	The World Bank, https://databank.worldbank.org/source/world-development-indicators
Government Expenditure Growth/GOVEXPG	Annual percentage growth rate of general government final consumption expenditure (general government consumption) (%)	
Regulatory Quality/REG_QUAL	The ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development Score: −2.5 (low) – +2.5 (high)	The Worldwide Governance Indicators (WGI), https://www.govindicators.org/
Political Stability and Absence of Violence or Terrorism/POL_STAB	The perceptions of the likelihood of political instability and/or politically motivated violence, including terrorism Score: −2.5 (low) – +2.5 (high)	
Control of corruption/CTRL_CORRUPTION	The perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests Score: −2.5 (low) – +2.5 (high)	
Rule of law/RULE_LAW	The perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence Score: −2.5 (low) – +2.5 (high)	
Governance/GOVERNANCE	Indicator obtained by Principal Component Analysis from Worldwide Governance Indicators: Voice and accountability, Political stability and absence of violence/terrorism, Government effectiveness, Regulatory quality, Rule of law and Control of corruption	
Government Integrity/GOV_INTEGRITY	The integrity of government is based on measuring the perceptions of corruption, bribery risk and control of corruption that could affect the government institutions and decision-making by practices as bribery, extorsion, nepotism, cronyism, patronage, embezzlement and graft Score: 0 (low) – 100 (high)	The Heritage Foundation https://www.heritage.org/index

Table 1.
Variables and data sources

implement AI, our strategy for managing endogeneity between variables technically involved determining whether there are causal relationships between the chosen variables, based on the Granger causality test (Granger, 1969; Lopez and Weber, 2017).

After preliminary data analysis, an initial test of the link between several variables was performed by several static panel models (Ordinary Least Squares, the Robust Regression, the Fixed Effects, the Random Effects and the Prais Winsten Regression), whose results were statistically significant, but which do not take in consideration of dynamics of time-varying and of endogeneity of the variables, that is often ignored in economic research, but which is very important because it leads to uncertain and biased estimates of parameters (Chatterjee and Nag, 2023).

Once demonstrating the endogeneity of variables by the Granger causality technique, it turned out that a dynamic panel method, system Generalized Method of Moments (GMM) (Roodman, 2009; Blundell and Bond, 1998; Arellano and Bond, 1991) would be suitable for the data we tested, because it manages reverse causality problems, as well as the serial correlation, cross-sectional dependence and unobserved heterogeneity (Forgione and Migliardo, 2020; Sarafidis and Wansbeek, 2012). The econometric data processing was carried out using STATA.

4. Findings and discussion

The basic summary statistics of the variables are presented in the Table 2, which reveals significant differences between countries in all analyzed variables, in terms of recording a wide range of values, average dispersion of data, arising from different degrees of governmental development in the field of AI of the studied countries, as well as in terms of the rest of the variables considered. The study period includes the years affected by the COVID-19 pandemic, in which macroeconomic conditions and governance of states have been severely put to the test and further emphasized the heterogeneity of the analyzed states and their different degrees of AI training in government, as well as levels of governance.

We start with the preliminary investigation of the multicollinearity of several variables grouped in a basic model, named model 1 (AI_GOV, BRAIN_DRAIN, ICT_SPEC, GDPPPG and REG_QUAL), for which multicollinearity analysis denotes that the variables are not correlated (Table 3), while the studying of cross-sectional dependence reveals that data are cross-sectionally dependent (except for BRAIN_DRAIN), as follows from the Table 4.

The study of the stationarity (Table 4) shows that the variable is stationary at the level.

The data are cointegrated, there is no heteroscedasticity in the residuals, the serial correlation is present (Table 5) and the variables are normally distributed (except for AI_GOV and ICT_SPEC), (Table 6).

Variables	Obs	Mean	Std. Dev	Minimum	Maximum
AI_GOV	129	65.562	9.391	42.397	88.102
BRAIN_DRAIN	135	3.105	1.323	0.600	5.800
ICT_SPEC	135	312.203	421.462	11.200	2114.000
GDPPPG	135	2.316	4.637	−11.757	17.989
REG_QUAL	135	1.121	0.478	0.292	2.013
GOVEXPG	135	2.751	3.252	−4.282	15.791
POL_STAB	135	0.680	0.279	0.013	1.347
CTRL_CORRUPTION	135	0.940	0.767	−0.322	2.402
RULE_LAW	135	1.035	0.577	−0.127	2.034
GOVERNANCE	135	3.19e−09	2.241	−4.511	3.776
GOV_INTEGRITY	135	65.618	18.299	35.100	99.500

Source(s): Authors' processing

Table 2.
Descriptive statistics

In determining endogeneity, in addition to the theoretical reasoning of choosing variables, we considered that there are unobservable factors that are not identified in our research and that can generate endogeneity, by correlating these relevant unidentified variables with dependent variable, one or more independent factors. Our strategy for determining possible endogeneity was based on PVAR Granger causality methods, because methods of studying endogeneity in small data series are difficult, as second and third generation causality tests of variables cannot be explored on such series. Causality between variables (Table 7), based on Granger PVAR tests (Lopez and Weber, 2017), illustrates that the overall Granger causality between the variables rejects the null hypothesis that all the lags of the independent variables have no effect on the AI_GOV (f-stat. 10.840*) and suggests that independent variables cause AI_GOV. Statistical significance was also obtained for the general causality of all model variables on independent variables BRAIN_DRAIN, GDPPPG and GOVEXPG. Punctually,

	AI_ GOV	BRAIN_ DRAIN	ICT_ SPEC	GDP PPG	GOV EXPG	REG_ QUAL	VIF
AI_GOV	1.000						
BRAIN_ DRAIN	−0.627	1.000					1.91
ICT_SPEC	0.481	−0.447	1.000				1.45
GDPPPG	−0.063	0.240	−0.093	1.000			1.06
GOVEXPG	−0.108	0.127	−0.366	0.066	1.000		1.15
REG_QUAL	0.702	−0.561	0.102	−0.161	0.025	1.000	1.51

Source(s): Authors' processing

Table 3. Matrix correlation of the variables and VIF factor (model 1)

Variables	Stationarity ADF test	Cross-sectional dependence Pesaran CD test
AI_GOV	332.823***	11.26***
BRAIN_DRAIN	208.446***	1.40
ICT_SPEC	105.854***	34.19***
GDPPPG	77.680**	35.30***
GOVEXPG	180.811***	9.32***
REG_QUAL	161.720***	5.42***

Note(s): ***, ** and * denote significance at 1, 5 and 10 percent level respectively
Source(s): Authors' processing

Table 4. Results of stationarity and cross-sectional dependence (model 1)

Cointegration (Kao test)		Homoscedasticity		Serial correlation	
Modif. Dickey-Fuller t	1.979**	Breusch-Pagan test	1.25	Wooldridge test	11.486***
Dickey-Fuller t	−5.039***	White test	17.54		
Augmented Dickey-Fuller t	0.379	Cameron and Trivedi test	17.54		
Unadj. modif. Dickey-Fuller t	−0.348				
Unadj.Dickey-Fuller t	−7.173***				

Note(s): ***, ** and * denote significance at 1, 5 and 10 percent level respectively
Source(s): Authors' processing

Table 5. Results of cointegration, homoscedasticity and serial correlations tests (model 1)

the GOVEXPG variable contains predictive information about the future values of the independent AI-GOV variable (even after controlling the effects of past AI_GOV values on AI_GOV itself). Also, we found that AI_GOV causes GDPPPG, which in turn is also influenced by ICT_SPEC and influences GOVEXPG. For the remaining variables analyzed, no statistically significant causal relationships were obtained.

In the early stages of research, several static panel data methods were employed (the Ordinary Least Squares, the Robust Regression, the Fixed Effects, the Random Effects and the Prais Winsten Regression), whose results were statistically significant (Table 8), but which do not take in consideration of dynamics of time-varying and of endogeneity of the variables. The role of these initial methods of analysis was to identify the relationships between variables in a static approach and understand the meaning of interactions between variables. Despite most statistically significant results obtained in static panel models, given that there are endogeneity issues, dynamic panel methods have the potential to lead to more reliable results.

Based on mentioned above results of the classical assumption, we perform several system GMM models, that are presented in Table 9. We progressively applied the sets of country's governance control variables in distinct phases, to check the robustness of our baseline

Table 6.
Results of normality tests (model 1)

Variables	Skewness	Kurtosis	Jarque-Bera test
AI_GOV	0.868	0.902	0.04
BRAIN_DRAIN	0.527	0.000	21.96***
ICT_SPEC	0.752	0.043	4.24
GDPPPG	0.017	0.014	10.11***
GOVEXPG	0.000	0.000	25.63***
REG_QUAL	0.955	0.000	47.65***

Note(s): ***, ** and * denote significance at 1, 5 and 10 percent level respectively
Source(s): Authors' processing

Table 7.
PVAR Granger causality between variables (model 1)

Null hypothesis of no causality		F-stat	Null hypothesis of no causality		F-stat
AI_GOV	L. BRAIN_DRAIN	1.500	GDPPPG	L.AI_GOV	8.998***
AI_GOV	L.ICT_SPEC	0.060	GDPPPG	L. BRAIN_DRAIN	0.976
AI_GOV	L.GDPPPG	0.104	GDPPPG	L. ICT_SPEC	9.216***
AI_GOV	L.GOVEXPG	6.899***	GDPPPG	L.GOVEXPG	0.500
AI_GOV	L.REG_QUAL	1.353	GDPPPG	L.REG_QUAL	0.592
AI_GOV	all	10.840*	GDPPPG	all	38.138***
BRAIN_DRAIN	L.AI_GOV	1.104	GOVEXPG	L.AI_GOV	0.027
BRAIN_DRAIN	L.ICT_SPEC	1.907	GOVEXPG	L. BRAIN_DRAIN	0.443
BRAIN_DRAIN	L.GDPPPG	0.102	GOVEXPG	L. ICT_SPEC	2.512
BRAIN_DRAIN	L.GOVEXPG	0.865	GOVEXPG	L. GDPPPG	6.771***
BRAIN_DRAIN	L.REG_QUAL	0.215	GOVEXPG	L.REG_QUAL	0.644
BRAIN_DRAIN	all	12.035**	GOVEXPG	all	14.351**
ICT_SPEC	L.AI_GOV	1.087	REG_QUAL	L.AI_GOV	1.994
ICT_SPEC	L. BRAIN_DRAIN	0.029	REG_QUAL	L. BRAIN_DRAIN	0.495
ICT_SPEC	L.GDPPPG	0.712	REG_QUAL	L. ICT_SPEC	0.543
ICT_SPEC	L.GOVEXPG	0.011	REG_QUAL	L. GDPPPG	0.249
ICT_SPEC	L.REG_QUAL	0.082	REG_QUAL	L. GOVEXPG	0.025
ICT_SPEC	all	2.739	REG_QUAL	all	2.938

Note(s): ***, ** and * denote significance at 1, 5 and 10 percent level respectively
Source(s): Authors' processing

Table 8. Static panel results (model 1)

AI_GOV	Ordinary least squares	Robust regression	Fixed effects	Random effects	Prais Winsten regression
BRAIN_DRAIN	−1.125** (0.491)	−1.452*** (0.411)	2.720 (1.686)	−0.796 (0.626)	−1.090** (0.529)
ICT_SPEC	2.648*** (0.441)	2.088*** (0.369)	11.971*** (4.414)	2.829*** (0.571)	2.710*** (0.474)
GDPPPG	0.178* (0.103)	0.179** (0.087)	0.159 (0.098)	0.192** (0.097)	0.195* (0.100)
GOVEXPG	0.053 (0.158)	0.029 (0.133)	0.067 (0.186)	0.051 (0.162)	0.080 (0.161)
REG_QUAL	11.565*** (1.220)	10.941*** (1.021)	11.703** (4.909)	11.881*** (1.585)	11.459*** (1.314)
Constant	42.004*** (4.041)	46.903*** (3.383)	−16.801 (23.565)	39.731*** (5.132)	41.507*** (4.331)
R-squared	0.683	–	0.362	0.682	0.620
Hausman test	–	–	0.02	–	–

Note(s): Standard errors in parentheses; ***, ** and * denote significance at 1, 5 and 10 percent level respectively
Source(s): Authors' processing

Table 9.
The effect of Brain drain on AI government readiness (system GMM models)

AI_GOV	System GMM (model 1)	System GMM (Model 2)	System GMM (Model 3)	System GMM (Model 4)	System GMM (Model 5)	System GMM (model 6)
L.AI_GOV	0.496*** (0.114)	0.624*** (0.100)	0.367** (0.144)	0.420*** (0.127)	0.468*** (0.136)	0.522*** (0.110)
BRAIN_DRAIN	−1.028*** (0.349)	−1.129** (0.451)	−0.828** (0.402)	−0.799** (0.402)	−0.677* (0.386)	−0.943** (0.429)
ICT_SPEC	0.745*** (0.217)	0.612** (0.282)	0.733** (0.293)	0.944*** (0.305)	0.930*** (0.318)	0.460** (0.216)
GDPPPG	0.344*** (0.077)	0.373*** (0.075)	0.294*** (0.074)	0.315*** (0.074)	0.324*** (0.077)	0.328*** (0.078)
GOVEXPG	0.258* (0.146)	0.320** (0.140)	0.245* (0.147)	0.277** (0.123)	0.268** (0.132)	0.286** (0.143)
REG_QUAL	4.504*** (1.599)	–	–	–	–	–
POL_STAB	–	4.115** (1.712)	–	–	–	–
CTRL_ CORRUPTION	–	–	4.447*** (1.459)	–	–	–
RULE_LAW	–	–	–	5.134*** (1.659)	–	–
GOVERNANCE	–	–	–	–	1.194** (0.468)	–
GOV_INTEGRITY	–	–	–	–	–	0.115** (0.054)
Constant	25.784*** (6.726)	20.214*** (6.883)	34.576*** (8.447)	28.732*** (6.791)	30.583*** (8.319)	21.978*** (5.655)
AR(1) test (p-value)	0.015	0.011	0.011	0.017	0.007	0.005
AR(2) test (p-value)	0.153	0.234	0.164	0.175	0.170	0.164
Hansen test (p-value)	0.373	0.084	0.229	0.162	0.475	0.146

Note(s): Standard errors in parentheses; ***, ** and * denote significance at 1, 5 and 10 percent level respectively. This table reports results of system GMM (each column represents a separate regression model), based on xtabond2 Stata command, with orthogonal (to use the forward orthogonal deviations transform instead of first differencing), collapse (to create one instrument for each variable and lag distance, rather than one for each period, variable and lag distance) and robust (with Windmeijer's finite-sample correction for two-step covariance matrix) options. The instruments are the independent variables and their lag1 and/or lag2
Source(s): Authors' processing

results, obtained in model 1. To verify whether the main outcomes are sensitive to alternative estimation, we re-estimate the models alternatively using the Worldwide Governance Indicators (Kaufmann and Kraay, 2023) and the Government integrity (GOV_INTEGRITY), issued by the Heritage Foundation.

Table 9 presents the results of the System Generalized Method of Moments (GMM) estimation for six different models, examining the factors influencing Government AI Readiness (AI_GOV). The lagged dependent variable (L.AI_GOV) is significant across all models, indicating persistence in government AI readiness. The coefficients range from 0.367 to 0.624, suggesting that past AI readiness strongly predicts current readiness.

The variable BRAIN_DRAIN exhibits a significant negative association with AI_GOV across all models, with coefficients ranging from −0.677 to −1.129. This suggests that higher levels of brain drain adversely impact government AI readiness, aligning with the concept that the loss of skilled professionals hinders AI development and implementation. Conversely, ICT_SPEC is consistently positively significant across all models, with coefficients between 0.460 and 0.944, demonstrating that a higher number of ICT specialists significantly enhances AI readiness, underscoring the critical role of a skilled workforce in AI innovation. Additionally, GDPPPG is positively significant in all models, with coefficients ranging from 0.294 to 0.373, indicating that economic growth, measured by GDP per capita growth, provides essential resources for AI development and implementation. Lastly, GOVEXPG is significantly and positively related to AI_GOV in all models, with coefficients between 0.245 and 0.320, indicating that increased government expenditure supports AI readiness, likely through investments in technology and infrastructure.

REG_QUAL is only included in Model 1 and is highly significant with a coefficient of 4.504, implying that better regulatory quality strongly enhances AI readiness. POL_STAB is included in Model 2 and is significant with a coefficient of 4.115. This indicates that political stability positively influences AI readiness, as stable political environments are conducive to technological advancements. CTRL_CORRUPTION is included in Model 3 and is highly significant with a coefficient of 4.447, suggesting that lower levels of corruption significantly enhance AI readiness by fostering a more reliable and efficient public sector. RULE_LAW is included in Model 4 and is significant with a coefficient of 5.134, indicating that stronger adherence to the rule of law promotes AI readiness by ensuring a predictable and stable legal environment. GOVERNANCE is included in Model 5 and is significant with a coefficient of 1.194. This aggregate measure of governance quality positively affects AI readiness. GOV_INTEGRITY is included in Model 6 and is significant with a coefficient of 0.115, indicating that higher government integrity positively influences AI readiness by reducing corruption and improving trust in public institutions.

The post-estimation analysis of the system GMM models indicates that the *p*-values of the Hansen tests accept the null hypothesis of overidentifying restrictions (because values do not exceed 0.8). Thus, the instruments are adequate and all the restrictions of overidentification are valid, based on prior literature (Labras and Torrecillas, 2018). Additionally, the second-order no-autocorrelation hypothesis is not rejected by the Arellano and Bond tests for autocorrelation AR(2), whereas AR(1) is significant, confirming the serial autocorrelation in the errors.

We obtained the dynamic persistence of AI_GOV and confirmed the dynamic specification of the models with statistically significant lag1, which specifies a positive correlation between AI_GOV_{it-1} and AI_GOV itself (the coefficients of the models presented in Table 9 are: 0.496, 0.624, 0.367, 0.420, 0.468 and 0.522).

4.1 The negative influence of the brain drain on government AI readiness

For the H1 assumption, the results indicate a negative correlation between BRAIN_DRAIN and AI_GOV (the coefficients of the models presented in Table 9 are: −1.208, −1.129, −0.828,

−0.799, −0.677 and −0.943) so H1 can be accepted. *We emphasize that there is no specific previous literature addressing this particular relationship*. Brain drain poses a significant challenge to government AI readiness by depleting countries of their crucial human capital. When top-tier professionals migrate, especially from economically weaker nations to more affluent ones, the departing country faces a loss of specialized expertise crucial for AI growth (Chen *et al.*, 2022). The exodus of these experts impedes the creation of a domestic knowledge-sharing ecosystem, essential for AI innovation. The loss means fewer mentorship opportunities and collaboration for budding talents, slowing AI research and development (Foffano *et al.*, 2023).

Moreover, governments require in-house expertise for informed AI decision-making. Brain drain results in a dearth of knowledgeable leaders, complicating AI strategy formulation. Over time, the continuous talent outflow can deter foreign investments, as businesses and investors prioritize regions rich in talent (Gesk and Leyer, 2022).

Professionals skilled in AI are instrumental in innovation and academic research (Agrawal *et al.*, 2019). Their migration can delay AI technology adoption, reduce innovation, and diminish global competitiveness (Gomes de Sousa *et al.*, 2019). The talent vacuum can force governments to over-rely on external consultancies, which may misalign with the nation's objectives.

Several factors influence this talent migration in the EU. Economic disparities, marked by wage differences and career opportunities, drive professionals from Eastern or Southern European nations to wealthier regions (Omar *et al.*, 2017). Countries with advanced AI research hubs attract talent from those lacking such facilities (Foffano *et al.*, 2023). The allure of better living standards, education, and stable political environments further magnifies this trend, compelling professionals to migrate to nations offering superior AI resources, education, and a thriving tech community.

4.2 The positive influence of the governess on government AI readiness

Governance positively affects the readiness of governments to implement AI, a result consistent with recent previous studies (Kuziemski and Misuraca, 2020; Margetts, 2022). Positive governance acts as the bedrock upon which government AI readiness can be effectively built, ensuring that AI advancements are harnessed responsibly, ethically, and in alignment with a nation's broader vision and objectives. For all six models developed in Table 9, positive coefficients (4.504, 4.115, 4.447, 5.134, 1.193, 0.115) were obtained for the variables that captures the institutional governance of the analyzed countries, both for the separately analyzed variables and for the governance determined by the method Principal Component Analysis (from the following Worldwide Governance Indicators - Voice and accountability, Political stability and absence of violence/terrorism, Government effectiveness, Regulatory quality, Rule of law and Control of corruption), as well as government integrity variable.

Governance, when effectively exercised, provides the foundational framework that can be instrumental in advancing government AI readiness. At its core, governance encompasses structured decision-making processes, regulatory mechanisms, and the orchestration of policies and initiatives that address the complex challenges and opportunities presented by AI (Kuziemski and Misuraca, 2020).

The clarity and consistency that good governance brings ensures that AI strategies are coherent, future-focused, and adaptable to evolving technological landscapes. It enables the streamlining of AI-related policies, ensuring that they are not only in tune with the current state of technology but also anticipate future advancements (Margetts, 2022).

Furthermore, robust governance structures enable transparent oversight of AI projects, ensuring ethical and responsible AI development and deployment. This not only boosts public trust in AI but also ensures that AI solutions are equitable, unbiased, and don't perpetuate societal disparities.

Another key aspect is the facilitation of multi-stakeholder collaboration. Effective governance actively engages academia, the private sector, civil society, and other relevant entities in the AI conversation. Such inclusivity ensures a holistic approach to AI readiness, drawing from diverse expertise and perspectives, ultimately enriching the quality and applicability of AI solutions.

Additionally, governance helps in resource allocation and prioritization. AI projects require significant investment, and good governance ensures that funds are channeled into projects that align with a nation's broader developmental goals, ensuring sustainability and maximum impact.

Lastly, governance plays a pivotal role in capacity-building. Recognizing the importance of human capital in AI readiness, governance mechanisms can drive initiatives for education, training, and upskilling, ensuring a steady pipeline of talent that can harness the potential of AI for the betterment of society.

4.3 The positive influence of the specialist skills on government AI readiness

Table 9 indicates that ICT_SPEC contributes to an increase in AI_GOV (the model coefficients presented in Table 9 are 0.745, 0.612, 0.733, 0.944, 0.930, and 0.460), a result consistent with the study by Burinskienė and Seržantė (2022) and Grigorescu *et al.* (2021). AI systems rest on advanced computing, necessitating foundational ICT expertise. Professionals armed with such skills can adeptly manage and refine AI systems, ensuring effective integration into government operations (Burinskienė and Seržantė, 2022). With solid ICT knowledge, government entities can evaluate AI applications' efficacy, ensuring a more strategic AI transition without over-relying on external parties.

Additionally, in-house ICT capabilities spur innovation. Public officials, equipped with these skills, can devise and execute groundbreaking AI solutions, transforming policy-making and service delivery (Grigorescu *et al.*, 2021). ICT proficiency is also central to data management, a cornerstone of AI. Mastery in ICT facilitates optimal data collection, preprocessing, and analysis (Rodriguez-Hevía *et al.*, 2020), setting the stage for efficient AI algorithm deployment.

4.4 The positive influence of the macroeconomic indicators on government AI readiness

GDPPPG and GOVEXPG positively influence the capacity of EU governments to implement AI (AI_GOV). The results of our study are in line with those of Wang and Cui (2022) and Fan and Liu (2021).

Economic growth and government spending are central to a nation's AI readiness. Steady economic expansion provides fiscal flexibility, allowing countries to invest in sectors like AI research. Such growth often attracts global investments, enhancing AI capacities (Corrado *et al.*, 2021). Even countries with large economies, despite modest growth, can channel considerable resources into AI. As economies thrive, a culture of innovation emerges, pushing governments to stay updated (Fan and Liu, 2021). This progression sees AI as a primary focus, with the necessary investments becoming increasingly feasible. In such settings, the private sector's AI initiatives often complement government efforts, promoting swift AI adoption.

Government expenditure reflects national priorities. A significant budget allocation to technology signifies a modernization drive. Investing heavily in AI not only elevates AI preparedness but also signals the state's commitment to the private sector and academia. Such investments can foster partnerships and collaborations, advancing AI readiness (Wang and Cui, 2022). Moreover, prioritizing AI in government budgets can enable training for officials, establish AI departments, and acquire essential technologies. Committing funds to AI also drives demand in the wider economy. Public AI contracts stimulate the tech sector to innovate (Ciftci and Durusu-Ciftci, 2022), cultivating a thriving AI industry.

5. Management Decision-making and EU-Level Policies

The very structure of the EU offers potential solutions. Leveraging collective resources, shared research initiatives, and pan-European educational programs can help in retaining talent. For instance, programs that offer research grants, innovation hubs, or collaborative AI projects spanning multiple EU countries can make staying within the EU an attractive proposition for professionals (EU4Digital, 2023).

Furthermore, there's an opportunity to reframe the narrative around brain drain. Instead of viewing it solely as a loss, it can be perceived as creating a diaspora of ambassadors equipped with global experiences. If governments, particularly in the EU, can create channels for collaboration and knowledge transfer with their diaspora, it can foster a two-way exchange of ideas and innovations, enriching the home country's AI landscape.

5.1 Strategies and solutions adopted by different EU member states to respond to brain drain challenges and to improve AI training

Different EU member countries have approached the challenges of brain drain and the need to better prepare for the AI era in various ways, tailored to their national contexts and available resources.

Firstly, to eliminate and/or reduce the exodus of talent, many countries have increased their investments in higher education and research, offering competitive scholarships and grants to retain and attract domestic and international talent (Shneiderman, 2020).

Secondly, some nations have established partnerships between academia, industry, and government to create innovation hubs or tech clusters. These collaborative spaces facilitate the exchange of ideas, provide training, and often lead to startup creation and commercialization of research, making them attractive prospects for young professionals and innovators (Jarrahi *et al.*, 2023).

In terms of AI readiness, many member states have launched national AI strategies focusing on areas such as AI research, ethical guidelines, public sector application, and workforce training. These strategies often come with dedicated funding, ensuring that the initiatives are actionable and not just aspirational.

5.2 Best practices observed in EU member countries

EU member states employ adaptive strategies, tailored to their unique challenges and assets, while also engaging in collaborative European initiatives to address brain drain and boost AI readiness. Finland, following its 2017 national AI strategy, launched the AI 4.0 Program, establishing itself as an EU AI frontrunner. This program merges AI with diverse digital innovations, including the Internet of Things and augmented reality (Ministry of Economic Affairs and Employment of Finland, 2023). In parallel, Estonia, renowned for its digital governance, has long incorporated AI in public services, setting a benchmark for AI in governance (Ministry of Economic Affairs and Communications, Republic of Estonia, 2023). Illustrating the strength of collaboration, the European Laboratory for Learning and Intelligent Systems (ELLIS) brings multiple countries together, highlighting the collective push for AI research (ELLIS Society, 2023).

5.3 The implications and impact of strategic decisions on the competitive positioning of EU member countries on the global AI scene

The strategic decisions of EU member countries could cement the EU countries positions as global AI leaders.

Strategic decisions play a pivotal role in determining the competitive positioning of EU member countries on the global AI stage. Firstly, the strategic choices made by a country influence its capability to attract talent and investments, both vital to AI development and innovation. Countries with forward-thinking AI policies and infrastructure investments tend to become magnets for leading AI researchers and companies (Foffano *et al.*, 2023).

Secondly, the synergy between AI strategies and other technological and economic policies can drive holistic growth.

Furthermore, countries that effectively collaborate on AI, both within the EU and internationally, can harness shared resources, knowledge, and market access, amplifying their collective strength. Conversely, those not aligning their AI strategies with global trends risk being left behind, missing out on the numerous economic, social, and technological benefits AI promises.

Lastly, the regulatory environment sculpted by strategic decisions also holds significant sway. Clear, flexible, and forward-looking regulations can accelerate AI adoption, instilling confidence in entrepreneurs and investors, while stringent or ambiguous regulations can stifle innovation.

5.4 Recommendations for the future: actions that could be taken to maximize the potential of AI in EU countries

To maximize the potential of AI in EU countries, it is essential to address the issue of brain drain. Firstly, mitigating brain drain by creating competitive career opportunities within the EU is crucial. Retaining skilled professionals will enhance the AI talent pool, ensuring that countries can effectively develop and implement AI technologies.

Secondly, increasing investments in ICT specialists is vital. Enhancing AI education and training programs will build a robust workforce capable of driving AI innovation, further strengthening the AI talent pool initially boosted by retaining skilled professionals.

Thirdly, harmonizing governance structures across EU member states will foster a conducive environment for AI. Creating unified regulations and ethical guidelines ensures transparent and accountable AI deployment, which is essential for sustainable AI integration and utilization in public services, supported by the skilled workforce and retained talent.

Lastly, leveraging macroeconomic factors by increasing GDP per capita and government expenditure on AI research and infrastructure will provide the necessary resources for AI advancement. Strategic government spending will support technology development, infrastructure enhancement, and innovation hubs, driving AI readiness and competitiveness.

By addressing these interconnected areas—brain drain, ICT specialist investment, governance harmonization, and macroeconomic support—EU countries can enhance their AI readiness, ensuring they remain at the forefront of AI innovation and application.

6. Conclusion

This study investigates the impact of brain drain on government AI readiness in European Union countries (2018–2022), considering distinctive governance characteristics, macroeconomic determinants, and ICT skills.

The findings of this study underscore the multifaceted nature of government AI readiness, particularly highlighting the significant impact of brain drain and the essential roles of ICT specialists, macroeconomic indicators, and governance structures. Our results reveal that brain drain negatively affects AI readiness, suggesting that the loss of skilled professionals undermines a country's capacity to develop and implement AI technologies effectively. This finding is consistent with previous studies that emphasize the critical role of human capital in technological advancements (Docquier and Rapoport, 2012).

Furthermore, the presence of ICT specialists within a country is a strong positive predictor of AI readiness. This aligns with the understanding that ICT professionals are integral to the development, maintenance, and innovation of AI systems (Burinskienė and Seržantė, 2022).

Our study also demonstrates that macroeconomic indicators such as GDP per capita growth (GDPPPG) and government expenditure growth (GOVEXPG) positively influence government AI readiness. Economic growth provides the necessary financial resources for investment in AI infrastructure and research, while increased government spending reflects a commitment to technological advancement and innovation. These findings are consistent with previous research that links economic prosperity to greater capacity for technological adoption (Fan and Liu, 2021; Wang and Cui, 2022).

Governance factors, including regulatory quality, political stability, control of corruption, rule of law, and overall governance quality, also play crucial roles in enhancing AI readiness. Effective governance ensures that policies and regulations create a conducive environment for AI development, fostering public trust and ethical use of AI technologies. This comprehensive approach to governance supports sustainable AI integration and utilization in the public sector (Margetts, 2022; Gasser and Almeida, 2017).

These results directly address the research question posed in the introduction, providing a comprehensive analysis of the factors influencing government AI readiness in EU member countries. By examining the impact of brain drain on government AI readiness, using ICT specialists, macroeconomic indicators, and governance as control variables, this study provides valuable insights into the dynamics that enable AI adoption in the public sector.

The major limitations of the study include its focus on a specific region of countries (EU countries) and the relatively short period analyzed. Future research could extend the analysis with more comprehensive datasets and consider additional variables that might influence AI readiness, such as the integration of AI with emerging quantum computing technologies and the impact of governance reforms and international collaborations on AI readiness.

Considering significant studies, such as Awan *et al.* (2022), our future research aims to explore the integration of AI with emerging quantum computing technologies, utilizing quantum algorithms to improve the optimization of digitalized systems. By leveraging the superior problem-solving capabilities of quantum computing, AI can significantly enhance the efficiency of governance, financial portfolio management, energy distribution, and other critical areas of digitalization.

Another future research direction is studying how different socio-economic and political contexts influence AI readiness across the globe. Future research could explore how different governance reforms within the EU impact AI readiness, as well as the role of international collaboration and partnerships in tackling brain drain and leveraging global talent for AI advancement.

References

Agrawal, A., Gans, J. and Goldfarb, A. (2019), *The Economics of Artificial Intelligence: an Agenda*, University of Chicago Press, doi: 10.7208/chicago/9780226613475.001.0001.

Akhtar, P., Ghouri, A.M., Khan, H.U.R., Amin ul Haq, M., Awan, U., Zahoor, N., Khan, Z. and Ashrat, A. (2023), "Detecting fake news and disinformation using artificial intelligence and machine learning to avoid supply chain disruptions", *Annals of Operations Research*, Vol. 327 No. 2, pp. 633-657, doi: 10.1007/s10479-022-05015-5.

Alhosani, K. and Alhashmi, S.M. (2024), "„Opportunities, challenges, and benefits of AI innovation in government services: a review", *Discover Artificial Intelligence*, Vol. 4 No. 18, 18, doi: 10.1007/s44163-024-00111-w.

Arellano, M. and Bond, S. (1991), "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations", *Review of Economic Studies*, Vol. 58 No. 2, pp. 277-297, doi: 10.2307/2297968.

Ariansyah, K., Setiawan, A.B., Hikmaturokhman, A., Ardison, A. and Walujo, D. (2024), "Big data readiness in the public sector: an assessment model and insights from Indonesian local governments", *Journal of Science and Technology Policy Management*, Vol. ahead-of-print No. ahead-of-print, doi: 10.1108/JSTPM-01-2023-0010.

Awan, U., Lea, H., Luukela-Tandon, A., Goyal, R.K. and Dhir, A. (2022), "Quantum computing challenges in the software industry. A fuzzy AHP-based approach", *Information and Software Technology*, Vol. 147, doi: 10.1016/j.infsof.2022.106896.

Beine, M., Docquier, F. and Rapoport, H. (2008), "„Brain drain and human capital formation in developing countries: winners and losers", *The Economic Journal*, Vol. 118 No. 528, pp. 631-652, doi: 10.1111/j.1468-0297.2008.02135.x.

Bhagwati, J. and Hamada, K. (1974), "The brain drain, international integration of markets for professionals and unemployment: a theoretical analysis", *Journal of Development Economics*, Vol. 1 No. 1, pp. 19-42, doi: 10.1016/0304-3878(74)90020-0.

Blundell, R. and Bond, S. (1998), "Initial conditions and moment restrictions in dynamic panel data models", *Journal of Econometrics*, Vol. 87 No. 1, pp. 115-143, doi: 10.1016/S0304-4076(98)00009-8.

Bobanović, M. (2022), "The shadows of economic growth: AI automation and globalisation", *Economic Research-Ekonomska Istraživanja*, Vol. 35 No. 1, pp. 4149-4158, doi: 10.1080/1331677X.2021.2012217.

Böttger, T., Poschik, M. and Zierer, K. (2023), "Does the brain drain effect really exist? A meta-analysis", *Behavioral Sciences*, Vol. 13 No. 9, p. 751, doi: 10.3390/bs13090751.

Bredt, S. (2019), "„Artificial Intelligence (AI) in the financial sector – potential and public strategies", *Frontiers in Artifical Intelligence*, Vol. 2, 16, doi: 10.3389/frai.2019.00016.

Breusch, T.S. and Pagan, A.R. (1979), "A simple test for heteroscedasticity and random coefficient variation", *Econometrica*, Vol. 47 No. 5, pp. 1287-1294, doi: 10.2307/1911963.

Bullock, J.B. (2019), "Artificial intelligence, discretion, and bureaucracy", *The American Review of Public Administration*, Vol. 49 No. 7, pp. 751-761, doi: 10.1177/0275074019856123.

Burdisso, T. and Sangiacomo, M. (2016), "Panel time series: review of the methodological evolution", *The Stata Journal*, Vol. 16 No. 2, pp. 424-442, doi: 10.1177/1536867X1601600210.

Burinskienė, A. and Seržantė, M. (2022), "Digitalisation as the indicator of the evidence of sustainability in the European union", *Sustainability*, Vol. 14 No. 14, p. 8371, doi: 10.3390/su14148371.

Can, M. (2022), "Under the leadership of our president: 'Potemkin AI' and the Turkish approach to artificial intelligence", *Third World Quarterly*, Vol. 44 No. 2, pp. 356-376, doi: 10.1080/01436597.2022.2147059.

Carbonaro, A. (2022), "Interpretability of AI systems in electronic governance", in Ortiz-Rodríguez, F., Tiwari, S., Sicilia, M.A. and Nikiforova, A. (Eds), *Electronic Governance with Emerging Technologies. EGETC 2022*, Communications in Computer and Information Science, Springer, Cham, Vol. 1666, pp. 109-116, doi: 10.1007/978-3-031-22950-3_9.

Chatterjee, C. and Nag, T. (2023), "Do women boards enhance firm performance? Evidence from top Indian companies", *International Journal of Disclosure and Governance*, Vol. 20 No. 2, pp. 155-167, doi: 10.1057/s41310-022-00153-5.

Chen, C., Bernard, A., Rylee, R. and Abel, G. (2022), "Brain circulation: the educational profile of return migrants", *Population Research and Policy Review*, Vol. 41 No. 1, pp. 387-399, doi: 10.1007/s11113-021-09655-6.

Ciftci, C. and Durusu-Ciftci, D. (2022), "Economic freedom, foreign direct investment, and economic growth: the role of sub-components of freedom", *The Journal of International Trade and Economic Development*, Vol. 31 No. 2, pp. 233-254, doi: 10.1080/09638199.2021.1962392.

Corrado, C., Haskel, J. and Jona-Lasinio, C. (2021), "Artificial intelligence and productivity: an intangible assets approach", *Oxford Review of Economic Policy*, Vol. 37 No. 3, pp. 435-458, doi: 10.1093/oxrep/grab018.

Docquier, F. and Rapoport, H. (2012), "„Globalization, brain drain, and development", *Journal of Economic Literature*, Vol. 50 No. 3, pp. 681-730, doi: 10.1257/jel.50.3.681.

Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C.R., Ilavarasan, V., Janssen, M., Crick, T., Duan, Y., Dwivedi, R., Edwards, J.S., Eirug, A., Galanos, V., Raman, R., Rana, N.P., Spencer, J., Walton, P., Jones, P., Kar, A.K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., Medaglia, R., Le Meunier-FitzHugh, K., Le Meunier-FitzHugh, L., Misra, S., Mogaji, E., Sharma, S.K., Singh, J.B., Raghavan, V., Samothrakis, S., Tamilmani, K., Tubadji, A. and Williams, M.D. (2019), "Artificial Intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy", *International Journal of Information Management*, Vol. 57 No. 7, 101994, doi: 10.1016/j.ijinfomgt.2019.08.002.

ELLIS Society (2023), "European laboratory for learning and intelligent systems", available at: https://ellis.eu/

EU4Digital (2023), "EU digital strategy", available at: https://eufordigital.eu/discover-eu/eu-digital-strategy/

European Commision (2020), "Government AI readiness Index 2020", available at: https://ec.europa.eu/newsroom/rtd/items/700847/en

European Commission (2023), "Horizon Europe", available at: https://research-and-innovation.ec.europa.eu/funding/funding-opportunities/funding-programmes-and-open-calls/horizon-europe_en

European Council (2023), "Digital single market for Europe", available at: https://www.consilium.europa.eu/en/policies/digital-single-market/

European Union (2023), "Types of institutions and bodies", available at: https://european-union.europa.eu/institutions-law-budget/institutions-and-bodies/types-institutions-and-bodies_en

Fan, D. and Liu, K. (2021), "The relationship between artificial intelligence and China's sustainable economic growth: focused on the mediating effects of industrial structural change", *Sustainability*, Vol. 13 No. 20, p. 11542, doi: 10.3390/su132011542.

Foffano, F., Scantamburlo, T. and Cortés, A. (2023), "Investing in AI for social good: an analysis of European national strategies", *AI and Society*, Vol. 38 No. 2, pp. 479-500, doi: 10.1007/s00146-022-01445-8.

Forgione, A.F. and Migliardo, C. (2020), "CSR engagement and market structure: evidence from listed banks", *Finance Research Letters*, Vol. 35, 101592, doi: 10.1016/j.frl.2020.101592.

Fu, Y.C., Vásquez, J.J.M., Macasaet, B.T., Chi Hou, A.Y. and Powell, J.W. (2023), "Game of brains: examining researcher brain gain and brain drain and research university policy", *Higher Education Policy*, Vol. 37 No. 2, pp. 237-258, doi: 10.1057/s41307-023-00303-6.

Gasser, U. (2023), "An EU landmark for AI governance", *Science*, Vol. 380 No. 6651, p. 1203, doi: 10.1126/science.adj1627.

Gasser, U. and Almeida, V.A.F. (2017), "A layered model for AI governance", *IEEE Internet Computing*, Vol. 21 No. 6, pp. 58-62, doi: 10.1109/mic.2017.4180835.

Gesk, T.S. and Leyer, M. (2022), "Artificial intelligence in public services: when and why citizens accept its usage", *Government Information Quarterly*, Vol. 39 No. 3, 101704, doi: 10.1016/j.giq.2022.101704.

Gomes de Sousa, W., Pereira de Melo, E.R., De Souza Bermejo, P.H., Sousa Farias, R.A. and Oliveira Gomes, A. (2019), "How and where is artificial intelligence in the public sector going? A literature review and research agenda", *Government Information Quarterly*, Vol. 36 No. 4, 101392, doi: 10.1016/j.giq.2019.07.004.

Gonzales, J.T. (2023), "„Implications of AI innovation on economic growth: a panel data study", *Economic Structures*, Vol. 12 No. 13, 13, doi: 10.1186/s40008-023-00307-w.

Granger, C.W.J. (1969), "„Investigating causal relations by econometric models and cross-spectral methods", *Econometrica*, Vol. 37 No. 3, pp. 424-438, doi: 10.2307/1912791.

Grigorescu, A., Pelinescu, E., Ion, A.E. and Dutcas, M.F. (2021), "Human capital in digital economy: an empirical analysis of Central and Eastern European countries from the European union", *Sustainability*, Vol. 13 No. 4, p. 2020, doi: 10.3390/su13042020.

Harris, J.R. and Todaro, M.P. (1970), "Migration, unemployment and development: a two-sector analysis", *The American Economic Review*, Vol. 60 No. 1, pp. 126-142, available at: http://www.jstor.org/stable/1807860

He, G., Liu, P., Zheng, X., Zheng, L., Hewlin, P.F. and Yuan, L. (2023), "Being proactive in the age of AI: exploring the effectiveness of leaders' AI symbolization in stimulating employee job crafting", *Management Decision*, Vol. 61 No. 10, pp. 2896-2919, doi: 10.1108/MD-10-2022-1390.

He, Z., Wan, S., Zappatore, M. and Lu, H. (2024), "A similarity matrix low-rank approximation and inconsistency separation fusion approach for multiview clustering", *IEEE Transactions on Artificial Intelligence*, Vol. 5 No. 2, pp. 868-881, doi: 10.1109/TAI.2023.3271964.

Iuga, I.C. and Socol, A. (2024), "„Government Artificial Intelligence readiness and brain drain: influencing factors and spatial effects in the European Union member states", *Journal of Business Economics and Management*, Vol. 25 No. 2, pp. 268-296, doi: 10.3846/jbem.2024.21136.

Jarrahi, M.H., Askay, D., Eshraghi, A. and Smith, P. (2023), "Artificial intelligence and knowledge management: a partnership between human and AI", *Business Horizons*, Vol. 66 No. 1, pp. 87-99, doi: 10.1016/j.bushor.2022.03.002.

Jovcheska, S. (2024), "„Exploring corruption in higher education: a case study of brain drain in North Macedonia", *International Journal of Educational Development*, Vol. 107, 103025, doi: 10.1016/j.ijedudev.2024.103025.

Kao, C. (1999), "„Spurious regression and residual-based tests for cointegration in panel data", *Journal of Econometrics*, Vol. 90 No. 1, pp. 1-44, doi: 10.1016/s0304-4076(98)00023-2.

Kaufmann, D. and Kraay, A. (2023), "Worldwide governance indicators, 2023 update", available at: www.govindicators.org

Kim, N. (2015), "„Tests based on skewness and Kurtosis for multivariate normality", *Communications and Statistical Applications and Methods*, Vol. 22 No. 4, pp. 361-375, doi: 10.5351/CSAM.2015.22.4.361.

Koengkan, M., Fuinhas, J.A. and Marques, A.C. (2019), "The relationship between financial openness, renewable and nonrenewable energy consumption, CO2 emissions, and economic growth in the Latin American countries: an approach with a panel vector auto regression model", in *The Extended Energy-Growth Nexus: Theory and Empirical Applications*, Academic Press, pp. 199-229, doi: 10.1016/B978-0-12-815719-0.00007-3.

Konopik, J., Jahn, C., Schuster, T., Hoßbach, N. and Pflaum, A. (2022), "Mastering the digital transformation through organizational capabilities: a conceptual framework", *Digital Business*, Vol. 2 No. 2, 100019, doi: 10.1016/j.digbus.2021.100019.

Konys, A. (2020), "How to support digital sustainability assessment? An attempt to knowledge systematization", *Procedia Computer Science*, Vol. 176, pp. 2297-2311, doi: 10.1016/j.procs.2020.09.288.

Kuziemski, M. and Misuraca, G. (2020), "AI governance in the public sector: three tales from the frontiers of automated decision-making in democratic settings", *Telecommunications Policy*, Vol. 44 No. 6, 101976, doi: 10.1016/j.telpol.2020.101976.

Labras, R. and Torrecillas, C. (2018), "Estimating dynamic Panel data. A practical approach to perform long panels", *Revista Colombiana de Estadistica*, Vol. 41 No. 1, pp. 31-52, doi: 10.15446/rce.v41n1.61885.

Lanne, M. and Lutkepohl, H. (2002), "Unit root tests for time series with level shifts: a comparison of different proposals", *Economic Letters*, Vol. 75 No. 1, pp. 109-114, doi: 10.1016/S0165-1765(01)00593-6.

Lopez, L. and Weber, S. (2017), "Testing for granger causality in panel data", *The Stata Journal*, Vol. 17 No. 4, pp. 972-984, doi: 10.1177/1536867X1801700412.

Lu, H., Jin, T.T., Wei, H., Nappi, M., Li, H. and Wan, S. (2024), "Soft-orthogonal constrained dual-stream encoder with self-supervised clustering network for brain functional connectivity data", *Expert Systems with Applications*, Vol. 244, 122898, doi: 10.1016/j.eswa.2023.122898.

Lv, B., Deng, Y., Meng, W., Wang, Z. and Tang, T. (2023), "Research on digital intelligence business model based on artificial intelligence in post-epidemic era", *Management Decision*, Vol. ahead-of-print No. ahead-of-print, doi: 10.1108/MD-11-2022-1548.

Maladjian, C. and Khoury, R.E. (2014), "Determinants of the dividend policy: an empirical study on the Lebanese listed banks", *International Journal of Economics and Finance*, Vol. 6 No. 4, pp. 240-256, doi: 10.5539/ijef.v6n4p240.

Margetts, H. (2022), "„Rethinking AI for good governance", *Daedalus*, Vol. 151 No. 2, pp. 360-371, doi: 10.1162/daed_a_01922.

Margetts, H. and Dorobantu, C. (2019), "„Rethinking public policy in the age of AI: learning from experience", *Journal of European Public Policy*, Vol. 26 No. 4, pp. 1-20, doi: 10.1080/13501763.2019.1567573.

Massaro, M. (2023), "Digital transformation in the healthcare sector through blockchain technology. Insights from academic research and business developments", *Technovation*, Vol. 120, 102386, doi: 10.1016/j.technovation.2021.102386.

Miller, J.C. and Collins, S. (2023), "What is the economic impact of "brain drain" in Mississippi?", *Community Development*, Vol. 55 No. 2, pp. 211-223, doi: 10.1080/15575330.2023.2186455.

Ministry of Economic Affairs and Communications, Republic of Estonia (2023), "E-state and connectivity", available at: https://www.mkm.ee/en/e-state-and-connectivity/digital-skills/digital-state-academy

Ministry of Economic Affairs and Employment of Finland (2023), "Artificial intelligence 4.0 programme", available at: https://tem.fi/en/artificial-intelligence-4.0-programme

Nguyen, M.L.T. and Bui, N.T. (2022), "Government expenditure and economic growth: does the role of corruption control matter?", *Heliyon*, Vol. 8 No. 10, e10822, doi: 10.1016/j.heliyon.2022.e10822.

Nwaka, S. (2021), "„Brain drain, the African diaspora and innovation in Africa", in *Social and Technological Innovation in Africa*, Palgrave Macmillan, Singapore, doi: 10.1007/978-981-16-0155-2_10.

Ojo, A. and Millard, J. (2017), *Government 3.0 Next Generation Government Technology Infrastructure and Services*, Springer International Publishing, Cham, doi: 10.1007/978-3-319-63743-3.

Omar, A., Arrieta, D., Pammolli, F. and Petersen, A. (2017), "Quantifying the negative impact of brain drain on the integration of European science", *Science Advances*, Vol. 3 No. 4, e1602232, doi: 10.1126/sciadv.1602232.

Oxford Insights (2023), "Government AI readiness Index 2023", available at: https://www.oxfordinsights.com/government-ai-readiness-index

Oxford Insights and International Development Research Centre (2022), "Government AI readiness Index", available at: https://oxfordinsights.com/wp-content/uploads/2023/11/Government_AI_Readiness_2022_FV.pdf

Pesaran, M.H. (2004), "General diagnostic tests for cross section dependence in panels", CESifo Working Paper Series, 1229; IZA Discussion Paper, 1240, available at: http://ssrn.com/abstract=572504

Pirozzi, N. and Bonomi, M. (2022a), "„Differentiation and EU governance: key elements and impact", *The International Spectator*, Vol. 57 No. 1, pp. 160-178, doi: 10.1080/03932729.2022.2034361.

Pirozzi, N. and Bonomi, M. (2022b), "Governing differentiation and integration in the European union: patterns, effectiveness and legitimacy", *The International Spectator*, Vol. 57 No. 1, pp. 1-17, doi: 10.1080/03932729.2022.2038424.

Pollacci, L., Sîrbu, A., Magos, P.M. and Rossetti, G. (2022), "Deliverable 5.4", Report on the developed indicators for estimating brain drain in Europe (Part 2), available at: https://hummingbird-h2020.eu/images/projectoutput/d5-4-eind.pdf

Rodriguez-Hevía, L.F., Navío-Marco, J. and Ruiz-Gómez, L.M. (2020), "Citizens' involvement in E-government in the European union: the rising importance of the digital skills", *Sustainability*, Vol. 12 No. 17, p. 6807, doi: 10.3390/su12176807.

Roodman, D. (2009), "How to do Xtabond2: an introduction to difference and system GMM in Stata", *The Stata Journal: Promoting Communications on Statistics and Stata*, Vol. 9 No. 1, pp. 86-136, doi: 10.1177/1536867X0900900106.

Russell, S. and Norvig, P. (2016), *Artificial Intelligence: A Modern Approach*, Pearson Education Limited.

Sarafidis, V. and Wansbeek, T. (2012), "Cross- sectional dependence in panel data analysis", *Econometric Reviews*, Vol. 31 No. 5, pp. 483-531, doi: 10.1080/07474938.2011.611458.

Shneiderman, B. (2020), "Human-centered artificial intelligence: reliable, safe and trustworthy", *International Journal of Human–Computer Interaction*, Vol. 36 No. 6, pp. 495-504, doi: 10.1080/10447318.2020.1741118.

Smuha, N.A. (2021), "From a 'race to AI' to a 'race to AI regulation': regulatory competition for artificial intelligence", *Law, Innovation and Technology*, Vol. 13 No. 1, pp. 57-84, doi: 10.1080/17579961.2021.1898300.

Sousa, M.J. and Rocha, Á. (2019), "„Skills for disruptive digital business", *Journal of Business Research*, Vol. 94, pp. 257-263, doi: 10.1016/j.jbusres.2017.12.051.

Sousa, W.G., Melo, E.R.P., Bermejo, P.H.D.S., Farias, R.A.S. and Gomes, A.O. (2019), "How and where is artificial intelligence in the public sector going? A literature review and Research Agenda", *Government Information Quarterly*, Vol. 36 No. 4, 101392, doi: 10.1016/j.giq.2019.07.004.

Taeihagh, A. (2021), "„Governance of artificial intelligence", *Policy and Society*, Vol. 40 No. 2, pp. 137-157, doi: 10.1080/14494035.2021.1928377.

Todisco, L., Tomo, A., Canonico, P. and Mangia, G. (2023), "The bright and dark side of smart working in the public sector: employees' experiences before and during COVID-19", *Management Decision*, Vol. 61 No. 13, pp. 85-102, doi: 10.1108/MD-02-2022-0164.

Tuan, T.A., Long, H.V., Son, L.H., Kumar, R., Priyadarshini, I. and Nguyen, T.K.S. (2020), "Performance evaluation of Botnet DDoS attack detection using machine learning", *Evolutionary Intelligence*, Vol. 13, pp. 283-294, doi: 10.1007/s12065-019-00310-w.

Valle-Cruz, D., Fernandez-Cortez, V. and Gil-Garcia, J.R. (2022), "From E-budgeting to smart budgeting: exploring the potential of artificial intelligence in government decision-making for resource allocation", *Government Information Quarterly*, Vol. 39 No. 2, 101644, doi: 10.1016/j.giq.2021.101644.

Villani, C., Schoenauer, M., Bonnet, Y., Berthet, C., Cornut, A., Levin, F. and Rondepierre, B. (2018), "AI for humanity: French strategy for artificial intelligence", available at: https://stip.oecd.org/stip/interactive-dashboards/policy-initiatives/2021%2Fdata%2FpolicyInitiatives%2F24070

Wang, X. and Cui, X. (2022), "PPP financing model in the infrastructure construction of the park integrating artificial intelligence technology", *Computational Intelligence and Neuroscience*, Vol. 2022, 6154885, doi: 10.1155/2022/6154885.

Wang, H., Dandan, Z., Jun, F., Lucia, C., Michele, N. and Wan, S. (2024), "„A multi-objective segmentation method for chest X-rays based on collaborative learning from multiple partially annotated datasets", *Information Fusion*, Vol. 102, 102016, doi: 10.1016/j.inffus.2023.102016.

Wooldridge, J.M. (2002), *Econometric Analysis of Cross Section and Panel Data*, MIT Press, Cambridge, MA.

World Bank (2023), "Migrants, refugees and societes", available at: https://www.worldbank.org/en/publication/wdr2023

Corresponding author
Iulia Cristina Iuga can be contacted at: iuga_iulia@yahoo.com