ISSN 1611-1699/eISSN 2029-4433

VILNIUS TECH
Vilnius Gediminas Technical University

JOURNAL of BUSINESS ECONOMICS & MANAGEMENT

2024
Volume 25
Issue 2
Pages 268–296
https://doi.org/10.3846/jbem.2024.21136

GOVERNMENT ARTIFICIAL INTELLIGENCE READINESS AND BRAIN DRAIN: INFLUENCING FACTORS AND SPATIAL EFFECTS IN THE EUROPEAN UNION MEMBER STATES

Iulia Cristina IUGA ✉, Adela SOCOL

Department of Finance-Accounting, Faculty of Economic Sciences, "1 Decembrie 1918" University of Alba Iulia, Alba Iulia, Romania

Article History:
- received 29 May 2023
- accepted 1 February 2024

Abstract. In the swiftly advancing field of Artificial Intelligence (AI), a field where every country aims to keep pace, significant disparities are observed in how different nations adopt AI. This study explores the deep, yet insufficiently studied, effects of AI on societal, economic, and environmental aspects. It particularly examines how brain drain influences governmental AI implementation capabilities, addressing a gap in existing literature. The study investigates the interplay between government AI implementation and brain drain, factoring in macroeconomic conditions, governance quality, educational levels, and R&D efforts. Utilizing 2022 data from European Union countries, the research employs instrumental-variables regressions (2SLS and LIML) to counteract endogeneity and uses clustering methods for categorizing countries based on their government AI levels, alongside spatial analysis to detect cross-national spillovers and interactions. The findings reveal brain drain's detrimental effect on governmental AI preparedness, highlight clustering tendencies, and identify spatial interdependencies. This paper underscores the need for strategic policy-making and institutional reforms to bolster government AI capabilities. It advocates for a paradigm shift in government frameworks post-New Public Management era, tailored to the new challenges posed by AI. The research, however, is limited to a single year and region, with constraints on data availability and indicator breadth.

Keywords: government AI readiness, brain drain, government expenditure, spatial effects, spillover effects, human capital.

JEL Classification: O15, H52, O38.

✉Corresponding author. E-mail: *iuga_iulia@yahoo.com*

1. Introduction

The concept of Artificial Intelligence (AI), often utilized in specialized studies and increasingly prevalent in recent language, encompasses technically complex and computer-oriented ideas that are difficult to succinctly express. From a governmental standpoint, AI represents a multifaceted blend of technology, policy, and social impact, necessitating a multidisciplinary approach for its successful integration and application.

In citizen services, AI's applications range from handling inquiries and processing documents to directing requests, aiding translations, and drafting documents (Mehr, 2017). Three primary AI applications in government stand out: Robotic and cognitive automation, enabling the reallocation of human labor to more value-added tasks through technologies like Robotic

Process Automation; Cognitive insights generation, improving predictive capacities; and Cognitive engagement, addressing citizen queries (Eggers et al., 2017).

Government entities are increasingly adopting AI, expected to fundamentally transform their operations, from policy-making to the execution of daily public services. AI provides tools for predictive analytics, decision-making, and problem-solving, particularly valuable in contexts of significant uncertainty. Utilizing AI capabilities allows public sector organizations to enhance agility, anticipate citizen needs, optimize resource allocation, and improve service delivery quality (Mikhaylov et al., 2018).

AI presents countries with a vital opportunity to advance their economic landscapes, especially in public services. It enables enhanced, personalized service delivery (Robles & Mallinson, 2023). Its powerful data analytics capacity helps governments derive insights from large data sets, supporting evidence-based policymaking. AI equips governments with powerful tools for automating bureaucratic tasks, extracting insights from vast data, and customizing public services to meet individual needs, thus symbolizing a beacon for improved governance, informed policymaking, and heightened citizen engagement (Frățilă et al., 2023).

The European Union, a unique assembly of countries with varied economic and technological paths, offers a key study area for examining government AI readiness and brain drain within its unified political and economic structure. Understanding each member state's AI preparedness is crucial, as disparities could significantly impact the EU's collective policy and strategic direction.

The EU's principle of free movement (Article 45, Treaty on the Functioning of the EU (European Union, 2012)) highlights its unique brain drain issues, with high-skilled workers easily relocating between states, differing from global patterns. Member states face similar problems like aging populations (Walker & Maltby, 2012) and upskilling needs (Jacobs, 2023). Examining AI readiness in this context reveals opportunities for collective strategies and cooperation.

Given the EU's acknowledgment of AI as an instrumental force shaping future socio-economic contours (European Parliament, 2023), gauging the AI readiness of its governments is indispensable. "The Government AI Readiness Index provides an overall estimate for how prepared each country's national government is for implementing AI in public service delivery" (Oxford Insights, 2022).

The EU's policy harmonization, alongside its member nations' varied economic and technological stages (Calderaro & Blumfelde, 2022), poses challenges and opportunities in tackling brain drain and enhancing AI readiness. The EU's Coordinated Plan on Artificial Intelligence (European Commission, 2018) encouraged nations to develop or integrate AI strategies. By 2023, all 27 EU countries had AI strategies (OECD, 2023; European Commission, 2020; Cath et al., 2017). Studying the EU offers a comprehensive view on AI readiness and brain drain dynamics, yielding relevant insights into AI integration and labor mobility trends in the EU.

Prior research reveals new emerging paradigms in public administration (post-New Public Management Paradigms) have been identified that focus on the importance of technological innovation and artificial intelligence to improve the delivery of services to citizens and the policies implemented by the government (Ojo et al., 2019). These new paradigms focus on tangible benefits and creating public value through investment in disruptive technologies.

Integrating AI into governance introduces innovation but also challenges. Studies indicate that governments struggle to keep pace with AI advancements, showing a noticeable gap in public sector AI governance (Wirtz et al., 2020). Challenges often arise from skill shortages

(Dwivedi et al., 2021), evident in employees' limited AI and machine learning knowledge (Ojo et al., 2019) and a lack of local AI experts (Gupta, 2019). The scarcity of AI professionals (Al-Mushayt, 2019) and insufficient advanced technology education (Montoya & Rivas, 2019) add to these difficulties. Simultaneously, many countries, especially developing ones, face a significant "Brain drain" – skilled workers migrating to developed countries for better opportunities. The Fragile States Index highlights the economic and developmental impacts of such human displacement (Fund for Peace, 2022).

In the context of the European Union (EU), spatial interactions and spillovers between member states are crucial for understanding phenomena like brain drain and AI readiness. In the EU, countries are interdependent; developments in one can influence others. This interconnectedness, inherent to the EU's structure, necessitates a comprehensive view of these dynamics, considering the collective impact rather than isolated national trends.

The EU's principle of free movement for workers fosters a unified labor market, enabling professionals to pursue opportunities across borders with fewer migration barriers. This mobility carries significant consequences: professionals transfer their skills, experiences, and insights as they move (Frankowska & Pawlik, 2022), encouraging cross-border collaborations in research and innovation.

The interconnectedness of the EU means that member states are continually observing, learning from, and adapting policies from their neighbors (Altuzarra et al., 2019). A successful policy or initiative in one country can serve as a blueprint for others.

To our knowledge, there has been no research exploring within the EU member states how the national context influences government readiness to adopt AI in neighboring states.

The aim of the study is to analyze whether governments' readiness for artificial intelligence AI in the European Union countries depends on "brain drain", using Government Artificial Intelligence Readiness Index as dependent variable and the Human Flight and brain drain as the major independent proxy. Also, given the specifics of the EU labour market and the freedom of movement of workers, we were interested in discovering possible spatial interactions and spillover effects between countries.

The objective of the paper is threefold:

1. Examines the influence of brain drain on government AI readiness in EU countries;
2. Studies the existence of spatial effects and spillover effects between neighboring EU countries;
3. Highlight the policies that can be adopted to reduce the government AI discrepancy between the EU member states.

This study addresses the following research questions:

- RQ1: Does the European Union experience a negative effect of brain drain on AI government readiness?
- RQ2: Are there positive effects of EU-funded projects for R&D, economic freedom, and government spending on AI government readiness in the European Union countries?
- RQ3: Does the brain drain (along with control variables) in a country influences the government's readiness to adopt AI in the neighboring states?

While there is indirect literature exploring the individual phenomena of brain drain and government AI readiness, there remains a paucity of research specifically examining the interplay between these two dimensions, especially within the unique context of the European Union. The existing body of work often treats brain drain and AI readiness as distinct entities, with limited exploration of how they might influence each other. Moreover, the spatial interactions and spillover effects within the EU, shaped by its singular policies such as the freedom of movement, present a nuanced backdrop that hasn't been adequately addressed in current studies. This lacuna in understanding becomes particularly significant given the rapid technological advancements and shifting labor dynamics within the EU. As such, there is a pressing need for an integrative analysis that holistically examines how brain drain might impact AI readiness across governments and vice versa, and how these dynamics manifest in the EU's interconnected landscape. This study endeavors to bridge this gap, offering insights that can inform both policy-making and future academic pursuits.

The present study bridges gaps in the prevailing literature on AI in government and the phenomenon of brain drain. Historically, AI's role in public sector augmentation has been discussed in isolation, with emphasis on its potential to streamline operations and elevate citizen engagement. This study illuminates the intricate interplay between brain drain and government AI readiness, a dimension underexplored in earlier works. Echoing findings from Oxford Insights (2019) we underscore the criticality of human capital in the AI realm. This aligns with Docquier and Rapoport (2012), who highlighted the repercussions of high-skilled labor emigration on a country's technical prowess. Our research deviates from merely acknowledging brain drain as a challenge, extending into its direct and indirect impacts on AI adoption, especially in the European context. Furthermore, while past literature like Brynjolfsson and McAfee (2014) touched upon potential delays in AI development due to expertise shortage, our findings delve deeper into the cascading effects of such delays on public service quality and national security. By juxtaposing economic freedom, EU-funded R&D projects, and government readiness for AI, we offer a comprehensive narrative that not only augments existing literature but also charts out potential trajectories for future research in the domain.

The innovation of this paper is that we incorporate five major groups of factors (human, macroeconomic, governance, education and research & development) into the model and study both panel effects for European Union states, as well as spatial effects and data clustering.

The research's originality lies in its unique combination of geographical focus, methodological robustness, emphasis on spatial interactions, exploration of the brain drain phenomenon, and its bridge between theoretical findings and policy implications.

The remainder of this paper is organized as follows: Section 2 outlines the current state of knowledge in the field and the research hypothesis; Section 3 details the data and methodology; Section 4 focuses on the results and discussion; and the paper concludes with the conclusions.

2. Literature review

2.1. Interaction between government AI and brain drain

Government AI signifies the use of AI technologies in the public sector, enhancing efficiency, effectiveness, and decision-making. It possesses the potential to transform government operations by improving citizen services, reducing costs, and optimizing resource use. AI involves computational techniques that enable machines to learn, reason, and solve problems, akin to human cognition. Worldwide, governments are increasingly interested in embedding AI into their operational fabric.

AI's application in government spans various domains: in *Public Services*, it could automate tasks like application processing and inquiry handling; in *Policy and Decision-making*, it could analyze extensive datasets for policy shaping; in *Law Enforcement and Public Safety*, technologies like facial recognition and predictive analytics could augment safety efforts; in *Infrastructure and Resource Management*, AI could assist in resource management and infrastructure planning (Wang & Cui, 2022); and in *Healthcare*, AI could improve public health outcomes by analyzing medical data for disease detection and treatment optimization (Gomes de Sousa et al., 2019).

Countries' readiness for AI technology varies, as revealed by an Oxford Insights (2019) review, which identified challenges in adopting AI for the common good, including policy, capacity, and resources, with human capital as a key resource. The Human flight and brain drain indicator focuses on the economic effects of skilled labor migration and its impact on a nation's advancement. Brain drain, a complex phenomenon, particularly affects developing countries, with skilled workers emigrating to more developed regions (Docquier & Rapoport, 2012). This migration impacts a nation's capacity to maintain and grow its expertise in critical areas like AI. In the context of globalization and international competition, brain drain affects a country's ability to maintain and develop its expertise in key areas such as AI and attract foreign direct investment (Czaika & de Haas, 2015; Siar, 2013).

In the European Union, there's a notable migration of experts from Central and South-Eastern Europe to Western countries (Bălan & Olteanu, 2017). This movement, driven by personal and socio-economic factors, began after the fall of communist regimes in the 1990s. The impact of brain drain on government AI is multi-dimensional: It restricts access to needed expertise for AI development (Brynjolfsson & McAfee, 2014), potentially causing delays in AI adoption and risks to data protection (Dignum, 2019). It also leads to a loss of AI talent to the private sector, slowing public sector innovation. Additionally, governments might become over-reliant on private AI solutions (Gesk & Leyer, 2022), posing national security risks and loss of control over data and algorithms (Offer, 2022). The public-private pay gap (Agrawal et al., 2019) and the lack of public sector investment in AI R&D (Johnson, 1965) further fuel brain drain.

Overall, while AI holds transformative potential for government operations, its effective integration faces hurdles due to brain drain, resource limitations, and evolving AI development and policy landscapes. This interplay requires a multifaceted approach to enhance AI readiness in the public sector, considering the dynamics of economic disparities and global talent mobility.

Considering these, we can formulate the main research hypothesis of this study:

H1: There is a negative effect of brain drain on AI government readiness in the European Union countries.

2.2. Interaction between macroeconomic, governance, education and research & development variables on AI government readiness

Brain drain, government spending, economic freedom and EU-funded research and development projects for artificial intelligence are fundamental themes for the contemporary debate on sustainable development and national or European competitiveness.

The introduction of artificial intelligence into government operations has the potential to transform the mode the public sector operates, optimizing efficiency, effectiveness and decision-making. Government spending can have a positive impact on government readiness for AI, ensuring that public institutions can reap the benefits of this innovative technology (Bredt, 2019).

Investing in infrastructure, health, education and research can help increase a country's competitiveness and improve citizens' quality of life (Bose et al., 2007), while the development of the telecommunication infrastructure has a significant positive impact on the efficiency of government (Doran et al., 2023). Thus, governments can also help prepare the workforce for the integration of AI in the public sector. By investing in training and reskilling programs, governments can ensure that public sector employees are prepared to work with AI technologies and manage the changes associated with the automation of certain tasks (Duan et al., 2019). This can lead to a better adaptation of the workforce to technological developments and to a smoother transition into the digital age. With the development of advanced language models using Artificial Intelligence (AI), the issue of AI readiness becomes critical, and the quality of the human factor involved in AI depends largely on the use of AI for purposes truly useful to humanity and without associated risks, especially those related to unpredictability and ethical concerns.

Another important aspect of government spending is investment in the infrastructure needed to support AI implementation (Wang & Cui, 2022). This may include the development of high-speed communication networks, data centers and other technological resources that enable the efficient use of AI in public services and decision-making processes. On the other hand, investments in infrastructure, education and research and development can help increase a country's AI competitiveness. Studies show that governments investing in AI can benefit from economic growth and improved quality of life for citizens (Arntz et al., 2019).

Government investment in AI can also foster international cooperation (Millard, 2017) and partnerships between different governments and organizations, promoting a global and harmonized approach to AI regulations and standards. This can lead to greater interoperability between AI systems used in different countries and to strengthen collaboration to address common challenges such as cybersecurity and data protection (Pan & Zhang, 2021).

Government spending on R&D in AI is another key issue for sustainable economic development. The European Commission has made significant investments in the projects of Artificial Intelligence (AI) research and development firms. This is done with the intention of enhancing the preparedness of governments to adopt AI technologies.

Given the premise that governmental expenditures are directed towards enhancing the capability of governments to deploy artificial intelligence, it is hypothesized that:

H2: There is a positive effect of government spending on AI government readiness in the European Union countries.

The Economic Freedom Index by The Heritage Foundation assesses economic liberty worldwide, often used to examine the economic conditions favorable for Artificial Intelligence (AI) growth. Nations scoring higher on this index typically present a conducive environment for AI adoption, characterized by lower taxes, fewer regulations, and better property rights protection.

Economic freedom is instrumental for governments in AI readiness, mainly by attracting investment and fostering innovation. Countries with high scores in the Index of Economic Freedom attract investors, thanks to stable economic conditions and growth potential. This environment helps governments gather necessary capital and expertise for AI development and implementation (World Economic Forum, 2023).

Moreover, countries with greater economic freedom usually have dynamic, competitive markets, sparking innovation and advanced AI technologies. In such markets, companies invest more in research and development, striving to create and market top-tier AI products (Ciftci & Durusu-Ciftci, 2022).

Another benefit of economic freedom for government AI readiness is the promotion of entrepreneurial spirit and risk-taking. High-scoring countries on the Index of Economic Freedom offer favorable conditions for entrepreneurship, like easier credit access and strong property rights. These factors encourage individuals and businesses to pursue innovative ideas, including AI-related ventures. As a result, governments in these countries have access to a continuous stream of innovative AI technologies and applications (Le & Kim, 2020).

Economic freedom also facilitates the integration of AI technologies within governments. High-ranking countries on the Index of Economic Freedom typically have efficient, streamlined bureaucratic systems that can easily adapt to AI-driven changes. These nations face fewer bureaucratic hurdles to innovation, allowing government entities to experiment with new AI applications and technologies more freely (Okulich-Kazarin et al., 2020).

In summary, economic freedom significantly influences government AI readiness. It draws investment, stimulates innovation, fosters entrepreneurship, and eases AI technology integration within government. Countries prioritizing economic liberty are better positioned to leverage AI's benefits, thus reaping the rewards of this transformative technology.

Considering these, we can estate:

H3: There is a positive effect of economic freedom on AI government readiness in the European Union countries.

EU-funded projects for R&D in AI are another key element in supporting technological development and innovation. The European Union has invested massively in programs such as Horizon 2020 and the new Horizon Europe program (2021–2027) to boost AI research and development (European Commission, 2021a). These initiatives offer financial support and collaborative prospects among researchers, universities, and companies across various European countries, thereby advancing the sharing of knowledge and the creation of innovative solutions (Spence, 2021). A pertinent example is the AI4EU project, funded by the EU under Horizon 2020. It strives to establish a European platform for the advancement and utilization of AI, contributing positively to both the economy and society (AIoD Platform, 2019).

The substantial investment by the European Commission in projects related to AI research and development firms has notably enhanced government readiness for AI. These initiatives have contributed to better government efficiency, increased citizen engagement and satisfaction, and augmented accountability and transparency. As AI technology continues to evolve, these advantages are expected to become even more distinctive, positioning AI as an increasingly vital instrument for governments globally. These projects have produced considerable positive effects, furnishing governments with the essential tools to leverage the potential of AI and revolutionize their operations.

A key advantage of the European Commission's funding in AI research and development firms' projects lies in the improvement of government operations' efficiency and efficacy. Utilizing AI-powered instruments, governments can automate mundane tasks and procedures, consequently cutting operational expenses, enhancing accuracy, and boosting speed. For example, AI can assist governments in swiftly and precisely processing enormous quantities of data, facilitating superior decision-making and more efficient resource allocation (European Parliament, 2021a).

Another significant benefit of these projects is improved citizen engagement and satisfaction. AI-driven chatbots and virtual assistants can facilitate citizens in accessing government services with greater speed and efficiency, leading to reduced waiting times and an enhanced overall experience. Additionally, AI-enabled tools can assist governments in more comprehensively comprehending the needs and preferences of their citizens (Ojo, 2019), thereby allowing for the delivery of more tailored services (European Parliament, 2021b).

The investments made by the European Commission in AI research and development firms' projects have additionally contributed to enhancing government accountability and transparency. AI-enabled tools can aid governments in overseeing and assessing their performance, simplifying the process of pinpointing areas that need improvement and tracking progress over time. Moreover, AI can assist governments in identifying and averting fraud and corruption, thereby guaranteeing that public funds are utilized properly (European Commission, 2021b).

Considering the abovementioned, we can formulate the last hypothesis:

H4: There is a positive effect of EU-funded projects for R&D on AI government readiness in the European Union countries.

3. Data and methodology

Our study analyzes whether governments' readiness for artificial intelligence AI in the European Union (EU) countries depends on "brain drain", using Government Artificial Intelligence Readiness Index as dependent variable and the Human flight and brain drain as the major independent proxy. Several economic, research and development and governance factors are considered control variables, based on the results identified in the previous studied literature. To control the macroeconomic conditions, the study use Government Expenditure, Gross Domestic Product and Economic Freedom, while to control governance and education in AI field, two proxies are employed: Government Pillar of AI Index and AI in University Bachelor's Programs (proportion of programs with AI content in the total number of programs). Also, the study considers the variable represented by AI R&D Firms' Projects founded by European Commission (percentage of the total number of AI R&D players financed) as a proxy to capture Research and Development activities in AI.

The panel comprises the European Union countries, except for Cyprus, Malta and Ireland, which are excluded from the studied sample, given their geographical status without EU neighboring countries (bases on spatial analysis methods that do not allow the analysis of those states that do not have common borders with the rest of the states in the chosen sample).

Table 1 presents the description of the variables and data sources from which the information was gathered.

To best to our knowledge, at regional or global level, the scarcity of indicators to capture the preparation of governments in the implementation of artificial intelligence is obvious, because there are limited initiatives to develop such indicators. We are interested in capturing the situation of AI implementation in government in the period as close to the present as possible, so we use a year window which refers to the year 2022, and for the rest of the variables we rely on the most recent data collection available, published in 2022 and related to the previous year or years, depending on the collection criteria of those variables.

The issue of preparing governments for AI deployment is rarely studied in the literature, much less its connection to brain drain, given the novelty of the subject and the incipient concerns of scientific communities to analyze unconventional perspectives of AI implementation by governments. As far as the author's knowledge is concerned, no study has explored such a topic from the perspective of the European Union and the variables chosen by us.

Table 1. Variables and data sources

Category	Variable / Symbol / Source	Definition / Measurement
Explained – Governance	AI IN GOVERNMENT. Government Artificial Intelligence Readiness Index (Oxford Insights, 2022)	The measure of governments readiness to implement AI in the delivery of public services. Score: 0 (low) – 100 (high).
Core explanatory – Human	BRAIN DRAIN. Human Flight and Brain Drain Index (Fund for Peace, 2022)	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).
Control variable – Macroeconomic	GOVERNMENT EXPENDITURE. Government Expenditure (World Bank, 2022a)	General government final consumption expenditure includes all government current expenditures for purchases of goods and services (including compensation of employees). Billion current U.S. dollars.
Control variable – Macroeconomic	ECONOMIC FREEDOM. Economic Freedom Index (Heritage Foundation, 2022)	The measure of fundamental right of every human to control own labor and property. The mix of 12 quantitative and qualitative factors, grouped into four broad categories: rule of law, government size, regulatory efficiency and open markets. Score: 0 (low) – 100 (high).
Control variable – R&D / Governance	AI R&D FIRMS EC FUNDED PROJECTS. AI R&D Firms' Projects founded by European Commission (European Commission, 2022)	Proportion of AI R&D Firms in the total number of AI R&D players financed by European Commission. Percentage.
Instrumental (only in 2SLS and LIML instrumental-variables regressions)		
Macroeconomic	GDP. Gross Domestic Product (World Bank, 2022b)	Gross Domestic Product is a basic measure of the value added created through the production of goods and services in a country. Billion current U.S. dollars.
Governance	GOVERNANCE Government Pillar of AI Index (Oxford Insights, 2022)	The assessment of vision, governance & ethics, digital capacity, and adaptability of governments in AI implementation. Score: 0 (low) – 100 (high).
Education / Governance	AI BACHELOR. AI in University Bachelor's Programs (European Commission, 2022)	Proportion of bachelor programs with AI content in the total number of bachelor programs. Percentage.

The theoretical previous identified literature mentions demographic shift, namely brain drain, which is composed of well-educated masses as a challenge for implementing the AI strategy in Turkey's case (Can, 2023).

The motivation for choosing brain drain as core explanatory variable is based on the essential role that the highly qualified human factor plays both in creating AI tools, AI implementing and assisting AI users. International mobility and the exodus of highly skilled workforce generate labor market distortions and shortages of specific skills needed by governments in AI implementation. The migration of highly skilled labor force from the former communist countries of the European Union has been sizeable for last three decades, amid socio-economic difficulties, political instability, social insecurity, corruption, unemployment, inflation, low wage levels, inefficient health and education systems etc. Based on the analyzed data, in the traditional countries of the European Union there are lower levels of labor migration with high knowledge and skills and are usually preferred as destination countries for skilled emigrants, attracted by job quality and career prospects.

A particularity of our analysis is given by the incorporation of a wide range of control variables belonging to macroeconomics (GDP), governance (Government pillar of AI Index), R&D (AI R&D Firms' Projects founded by European Commission) and education in AI (AI in University Bachelor's Programs).

The choice of economic freedom as a control variable is based on the fact that it is directly related to the fundamental right of individuals to work and property, and that it characterizes an environment conducive to growth and innovation. Economic freedom is organically linked to government, whose decisions influence individual autonomy, as well as personal and national prosperity.

Another control variable used in modelling the effect of brain drain on AI government readiness is proportion of AI R&D Firms in the total number of AI R&D players financed by European Commission. Its choice was based on the major role of AI companies in developing the AI-specific technology and software ecosystem, based on research, innovation and entrepreneurship, given that a country's AI advancement depends on grants and patent applications in AI-related technologies (Thomas & Murdick, 2020).

Government expenditure is a major macroeconomic determinant considered the explanatory control variable in our study. Governments' ability to implement AI depends significantly on their willingness to incur government spending, both to provide AI infrastructure and software, as well as to provide the necessary trained and sufficient human resources to operate the technical facilities of government AI.

Endogeneity represents an essential aspect to be studied in econometric analysis of economic data, whose potential for endogeneity is considerable compared to other areas and which, if ignored, increases the risk of including not only very few explanatory variables, but also irrelevant ones in the model, leading to the so-called omitted variable bias (Ibrahim & Arundina, 2022). Endogeneity can result from the omission of unobserved factors from the model, which could affect the relationships between the studied variables and also endogeneity can be understood as a consequence of the past on the present, both on the model (dependent variable) and on independent variables, or as a causal relationship between regressors and the variable explained over time (Labra & Torrecillas, 2018).

Based on these considerations, and in line with prior research, our approach is to identify the risk of endogeneity initially through theoretical judgement, followed by statistical Durbin-Wu-Hausman tests, which confirm endogeneity (Ullah et al., 2018). A detailed analysis of the significance of government spending shows that it is intrinsically linked to diverse specific factors, among which the following are relevant in the context of this analysis: economic growth, a composite indicator showing vision, governance & ethics, digital capacity, and adaptability of governments in AI implementation, and a specific factor related to the undergraduate degree program that addresses specific AI content.

We will detail in turn each of the three variables mentioned as influencing factors of government expenditure. First, the influence of government expenditure on economic growth is extensively studied in the literature, while the inverse relationship is less analyzed. The numerous competing theories that analyze the link between government spending and economic growth (Keynesian macroeconomic theory, Wagner's law, Peacock and Wiseman displacement effect hypothesis, etc.), although antagonistic, show consistent results of the determining role that economic growth has on government spending (Szarowska, 2022; Voda et al., 2022). From the perspective of our study, we want to find out to what extent economic growth influences government expenditure and we chose GDP as a reference, given its high degree of complexity, standardized methodology of determination and ability to reflect the fundamental aspects of the country's economic development (Trishch et al., 2023).

Second, governance is critical for government spending and institutional efficiency contributes to the efficacy of public expenditure (Thanh et al., 2020). We are interested in a particular form of governance (Government pillar of AI Index) aimed at openness, vision and digital capacity of states in implementing AI. Such a complex composite indicator of governance in AI implementation captures in a comprehensive manner the degree of governance of the analyzed state from the perspective of AI implementation: vision (by answering the question of whether governments have a vision for implementing AI and a specific strategy), governance and ethics (whether governments have set up specific legislation and an ethical framework for implementing AI in a manner that builds trust and legitimacy) digital capacity (whether governments have the digital capacity to implement AI – online services, IT infrastructure, government investment in emerging technologies) and adaptability (whether governments are indeed change and innovate effectively in AI field). A high degree of institutional governance contributes significantly to the digitalization of businesses and public services for citizens (Ionescu et al., 2022).

Third, although unconventional and previously unexplored by the literature studied to our knowledge, the link between government spending and AI content addressed in university studies represents an avant-garde approach that encompasses a specific education variable directly connected to the topic of AI. We believe that in studying the relationship between governments' AI readiness and brain drain and human flights, it is necessary to create an expanded perspective, by calling for an education variable, reflecting how much governments invest in education and familiarization of tertiary education graduates in AI. The AI contents of the undergraduate studies that have been considered refer to all types of studies, not only the technical ones, but also to AI-specific social, psychological, ethical, legislative, etc. contents. Countries in the European Union have integrated specific AI aspects into their university curricula, and as higher education systems in the European Union are mainly funded by the state (Lepori et al., 2018; European Tertiary Education Register, 2019), we consider that governments' motivation to invest in AI content is a strong marker of government spending. Government awareness of AI's staggering expansion has also led to the creation of educational mechanisms for AI to become part of university training. The generalized desideratum to recognize and learn about AI from various perspectives – technical, social, psychological, legislative, etc. – is obvious and can contribute over time to obtaining expected positive effects in terms of managing AI within appropriate moral, social and economic parameters.

The paper gradually approaches three econometric methods. First, given the conceptual links presented between the analyzed variables and the presence of endogeneity, the model suitable to address endogeneity proves to be instrumental-variables regression with regressors endogenously determined, namely two-stage least-squares 2SLS, and for robustness testing the LIML model (limited-information maximum likelihood). The choice of these methods is based on the systems of simultaneous equations, whose premises are built on the use of instrumental variables, correlated with the identified endogenous variable and unrelated with the error term and which allow to predict the links between the investigated variables.

Second, to find the similarities between countries in the government's readiness for artificial intelligence, we apply cluster analysis as a descriptive and explanatory technique for data analysis, whose principle is to place countries in homogeneous groups.

Third, founded on the spatial data of the countries, we set out to discover patterns of spatial dependence, global spatial autocorrelation, and spatial relationship. Europe shapefile (.shp) that store geographical characteristics of countries is used in GeoDa software and then import into Stata, which allowed the spatial analysis of the mentioned states from the perspective of the determinants of the government's readiness in the implementation of AI.

Instrumental-variables 2SLS and LIML regressions are developed based on the following model (equations 1 and 2), in which the endogenous regressor is considered GOVERNMENT EXPENDITURE, while BRAIN DRAIN, ECONOMIC FREEDOM and AI R&D FIRMS EC FUNDED PROJECTS are included in the model as exogenous regressors. The excluded exogenous regressors are lnGDP, GOVERNANCE and AI BACHELOR, which are instruments for endogenous variable GOVERNMENT EXPENDITURE. Government spending is considered endogenous starting from the endogenous growth model valences, according to which the role of government expenditure in allocating resources in the economy is very important and the lever of government spending improves the quality of public services (Nguyen & Bui, 2022).

$$AI\,IN\,GOVERNMENT_{it} = \alpha_1 + BRAIN\,DRAIN_{it}\beta_1 + GOVERNMENT\,EXPENDITURE_{it}\beta_2 + \\ ECONOMIC\,FREEDOM_{it}\beta_3 + AI\,R\,\&\,D\,FIRMS\,EC\,FUNDED\,PROJECTS_{it}\beta_4 + u_i; \quad (1)$$

$$GOVERNMENT\,EXPENDITURE_{it} = \alpha_2 + \ln GDP_{it}\Pi_1 + GOVERNANCE_{it}\Pi_2 + AI\,BACHELOR_{it}\Pi_3 + \\ BRAIN\,DRAIN_{it}\Pi_4 + ECONOMIC\,FREEDOM_{it}\Pi_5 + AI\,R\,\&\,D\,FIRMS\,EC\,FUNDED\,PROJECTS_{it}\Pi_6 + v_i, \quad (2)$$

where i represents country; t is time; α_1 and α_2 represent intercepts; u_i and v_i are zero-mean error terms, and the correlation between u_i and the elements of v_i are presumably nonzero.

Cluster analyses is performed through the hierarchical clustering methods, based on them main premise that the geographically close countries exhibit similar behaviors compared to the more distant states (Noja, 2018). The analyzed countries are grouped into clusters formed based on complete link method and Ward's method. In the hierarchical clustering methods, the distance or dissimilarity between a group k and a group (ij), which consists of the fusion between two groups (i and j), based on the Lance-Williams formula is the following (Everitt et al., 2011):

$$d_{k(ij)} = \alpha_i d_{ki} + \alpha_j d_{kj} + \beta d_{ij} + \gamma \left| d_{ki} - d_{kj} \right|, \quad (3)$$

where i, j and k represent group i, j or k; d_{ij} is the distance between groups i and j; d_{ki} is the distance between groups k and i; d_{kj} is the distance between groups k and j; α_i, α_j, β and γ are parameters; n_i, n_j and n_k are the number of observations in group i, j and k, respectively.

In the third phase of the study, spatial analysis is conducted to find out whether the data collected from the European Union countries are spatially correlated, specifically whether the observations of closer countries tend to be more similar than further ones and the spatial spillovers decrease as the distance between countries increases (Belotti et al., 2017).

In developing the spatial dependency model, we started from the general equation (Equation (4)) of the Spatial Error Model (Belotti et al., 2017; Pisati, 2001):

$$Y = X\beta + \lambda W\xi + \in, \quad (4)$$

where Y denotes an $Nx1$ vector of observations on the dependent variable; X denotes Nxj matrix of observations on the explanatory variables; β is a $jx1$ vector of regressions coefficients; λ denotes the spatial autoregressive parameter; ξ is an $Nx1$ vector of spatial errors; and $\dot{o}$ represents an $Nx1$ vector of normally distributed, homoscedastic, and uncorrelated errors. The testing of the spatial autocorrelation is performed using the Moran test. The expected values of the Moran coefficient could vary between –1 and +1 (perfect dispersion or perfect correlation) and show how much close countries are in comparison with other close countries (Noja, 2018).

$$Moran's\, I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(Y_i - \bar{Y}\right)\left(Y_j - \bar{Y}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i=1}^{n}\left(Y_i - \bar{Y}\right)^2}, \quad (5)$$

where i and j are countries; Y represents the variable of interest; $\bar{Y}$ is the average value of Y; W_{ij} is an element of a matrix of spatial weights and is generally a binary value.

The preliminary statistic descriptive analysis of the variables is stated in Table 2 and Table 3.

Table 2. Descriptive statistics (part 1)

Characteristics	AI in government	Brain drain	Government expenditure	Economic freedom
Mean	65.810	3.204	154.275	71.041
Std. Dev.	7.911	1.552	235.461	4.813
Minimum	48.590	0.700	7.360	61.000
Maximum	77.590	5.700	947.78	78.000

Table 3. Descriptive statistics (part 2)

Characteristics	AI R&D firms EC funded projects	GDP	Governance	AI bachelor
Mean	0.675	692.810	70.788	5.309
Std. Dev.	0.097	1041.030	10.378	4.307
Minimum	0.461	37.190	48.700	0.000
Maximum	0.809	4259.930	88.450	14.070

Regarding the dependent variable, AI IN GOVERNMENT, it varies between 48.590 and 77.590 values, with a mean of 65.810 and the standard deviation of 7.911, which suggests the significant differences between countries. Also, the interval in which BRAIN DRAIN varies between 0.700 and 5.700, as well as the other disclosed statistic values, outline for the human flight and brain drain a character of increased heterogeneity in the studied countries. The lowest degree of dispersion from the average is found for the variable ECONOMIC FREEDOM, whose mean is 71.041, with a standard deviation of 4.813 between the analyzed states. At the opposite pole, with the highest values of disparity from the mean, it stands out GOVERNMENT EXPENDITURE, GDP and AI BACHELOR, which denotes a higher degree of diversity between countries, in terms of the evolution of indicators especially regarding macroeconomic conditions and AI implementation in curricula for bachelor's studies. The rest of the examined variables (AI R&D FIRMS EC

FUNDED PROJECTS and GOVERNANCE) display medium significant values of the dispersions compared to the average.

4. Results and discussion

4.1. Instrumental-variables regressions

The influence of brain drain on AI in government is estimated for the analyzed EU countries through the instrumental-variables 2SLS and LIML regressions models, whose outcomes are presented in Table 4.

Table 4. Indicators' impact on AI IN GOVERNMENT: instrumental-variables 2SLS and LIML approaches

AI IN GOVERNMENT	2SLS	LIML
BRAIN DRAIN	–1.661** (0.821)	–1.520* (0.853)
GOVERNMENT EXPENDITURE	0.012*** (0.004)	0.013*** (0.004)
ECONOMIC FREEDOM	0.710*** (0.158)	0.728*** (0.163)
AI R&D FIRMS EC FUNDED PROJECTS	19.661* (11.502)	20.076* (16.575)
Constant	5.485 (16.020)	3.228 (16.575)
R-squared	0.816	0.807
Durbin test	2.753*	na
Sargan test	5.060*	na
Basman test	4.542	2.211
Anderson-Rubin test	na	6.243**
Instrumented: GOVERNMENT EXPENDITURE *Instruments*: BRAIN DRAIN, ECONOMIC FREEDOM, AI R&D FIRMS EC FUNDED PROJECTS, lnGDP, GOVERNANCE, AI BACHELOR		

Note: * Significant at 10%; ** Significant at 5%; *** Significant at 1%; na – not applicable. Standard errors are in round brackets.

To confirm the reliability of the results, several robustness checks are employed. First, we perform endogeneity test to determine whether GOVERNMENT EXPENDITURE as endogenous regressor are in fact exogenous and for that, the performed Durbin test shows that null hypothesis which considers variable as exogenous can be reject (at 10% significance level in the SLS model). Therefore, the variable GOVERNMENT EXPENDITURE considered initially endogenous based on the theory of economic growth models, it really proves in the econometric robustness test to be endogenous to the government's readiness for artificial intelligence. Second, in both models, we test whether the instruments are uncorrelated with the error term, through Sargan and Basman tests in 2SLS approach, whose results show that the null hypothesis that instruments are valid cannot be rejected (not significant at 1% and 5% levels for Sargan test and not significant for the Basman test). In the case of the LIML model, the tests obtained, Anderson-Rubin and Basman, illustrate the validity of the instruments (not significant at the level of 1%

for Anderson-Rubin and not significant for the Basman test). Also, in the 2SLS model, we perform tests to study the explanatory power of the instruments, whose outcomes confirm that additional instruments (lnGDP, GOVERNANCE and AI BACHELOR) have significant explanatory power for AI IN GOVERNANCE after control for the effect of the rest of the independent variables of the model (F statistic significant at 1% level). The minimum eigenvalue statistic as a test of weak instruments compared with critical values of 2SLS relative bias denotes that our instruments are not weak (the F statistic exceeds the critical value if we were willing tolerate a 10% relative bias).

As far human proxy is concerned, BRAIN DRAIN has a significant negative influence on AI IN GOVERNMENT, which shows that the increase in the flows of human flight and brain drain from a country that is losing human capital we are witnessing a reduction in the government's ability to implement and manage artificial intelligence in public services for citizens. There are only circumstantial indications within the cited literature suggesting a negative effect of brain drain on government AI readiness. Our findings are consistent with this body of literature (Czaika & de Haas, 2015; Siar, 2013; Brynjolfsson & McAfee, 2014; Dignum, 2019) and validate the main research hypothesis H1 that brain drain negatively affects AI in government.

The brain drain phenomenon can have a negative impact on a country's government's AI readiness, for several reasons:

1. Shortage of AI-skilled human resources can slow down or even stop the development and implementation of AI-based solutions in the public sector (Vicsek, 2021);
2. Brain drain can negatively affect the level of innovation in a country (Spence, 2021) (when AI experts leave the country, they take their knowledge and experience with them, which can lead to a decrease in scientific and technological advances in AI);
3. Brain drain can lead to a loss of investment in education and training: governments invest in the education and training of AI specialists, with the hope that they will contribute to the country's economic development and growth. When these specialists choose to work abroad, the government loses the benefits of its investments, while the host countries benefit from these talents;
4. Brain drain can create major difficulties in international collaboration: experts who leave their home country may be less interested in working with the government and institutions in their country of origin, which can make it difficult to access international knowledge and resource networks;
5. Brain drain can weaken ability to compete globally: as other countries attract talent into AI, they can become more technologically and economically competitive. At the same time, the country of origin could be left behind in the global AI race.

Adopting strategies can help governments counter the negative effects of brain drain on government AI training and develop an environment conducive to growing AI expertise and skills in the country. From the multitude of strategies that can be applied by governments, we present the most important ones:

1. Enhancing education systems: Investing in academic and research institutions to deliver superior AI programs, developing AI training and research initiatives, and fostering partnerships between universities, businesses, and governmental entities. Promoting STEM education: Encouraging interest in AI from an early school level through emphasis on science, technology, engineering, and mathematics.
2. Providing financial incentives and support: Allocating government funds for AI research and development and establishing a tax-friendly environment for companies developing and applying AI technologies.

3. Creating a conducive environment for innovation: Encouraging collaboration between public and private sectors to tackle societal and governmental issues via AI, and facilitating access to essential infrastructure and resources for AI solution development and implementation (Bredt, 2019).
4. Attracting and retaining of AI talent: implementing favorable migration policies to attract and retain foreign AI talent; providing competitive and advantageous career opportunities in the public sector for AI specialists. Even more, the policy of increasing wages and benefits can also be applied (governments can increase wages and benefits for public sector AI professionals to encourage retaining and attracting talent. This strategy could also include the development of bonus schemes and other benefits that would attract and retain AI professionals in the country) (Agrawal et al., 2019).
5. International cooperation and knowledge exchange: participation in international AI alliances, partnerships and projects to benefit from the expertise and resources of other countries; promoting academic and professional exchanges in the field of AI to facilitate the transfer of knowledge and good practice; supporting cooperation between research and innovation institutions in different countries to work together in the development of AI solutions.
6. AI infrastructure development: governments can develop the infrastructure needed to support AI development, such as data centers, communication networks, and cloud computing infrastructure (Duan et al., 2019). This strategy could also include investments in the country's digital infrastructure, including connectivity and the development of advanced digital technologies.

Regarding the control variables of the models, the contribution of GOVERNMENT EXPENDITURE in strengthening the capacity of governments to implement artificial intelligence is confirmed and demonstrates a positive relationship with dependent variable: the higher the volume of government spending, the higher the government's readiness in artificial intelligence. The results confirm the general assumptions from previous literature (Wang & Cui, 2022; Bredt, 2019; Duan et al., 2019; Bose et al., 2007) and the resorts of such an interdependence are related to the innovative and relatively expensive technical character of the state's investments in the artificial intelligence infrastructure and software for the public services. Also, the personnel needed to develop and manage informatic applications and infrastructure based on artificial intelligence leads to significant government spending. Given the premise that governmental expenditures are directed towards enhancing the capability of governments to deploy artificial intelligence, the outcomes of the study empirically validate and substantiate Research Hypothesis H2, which posits a positive effect of such spending on AI government readiness in the European Union countries.

ECONOMIC FREEDOM is positively significantly associated with the government's ability to implement artificial intelligence (Ciftci & Durusu-Ciftci, 2022; Le & Kim, 2020; Okulich-Kazarin et al., 2020). The more economic freedom is experienced in EU countries, the more it creates premises for governments to adopt artificial intelligence. Drawing from the empirical findings of the study, Research Hypothesis H3, which posits that there is a positive effect of economic freedom on AI government readiness in the European Union countries, has been validated.

The financing by the European Commission of research & development firms for artificial intelligence projects is also found to be a significant determinant of increasing artificial intelligence in public administration (Spence, 2021). The higher the percentage of research & development companies that benefit from financing artificial intelligence projects, the more national governments benefit from scientific research results in artificial intelligence, which can be developed and implemented at government level. Upon rigorous examination of the data, Research Hypothesis H4, which postulates a positive effect of EU-funded projects for R&D on AI government readiness in the European Union countries, has been validated.

In the instrumental-variables regressions, GOVERNMENT EXPENDITURE is considered the instrumented variable, whose configurated instruments are lnGDP, GOVERNANCE and AI BACHELOR. Employing GDP as an indicator to assess the influence of AI on the economy has been beneficial for gauging governmental AI readiness. GDP, a prevalent metric of economic activity, when used to measure AI's impact, underscores the technology's significance for economic expansion. By monitoring AI's contribution to GDP, governments can achieve a more profound comprehension of AI's economic benefits and identify the sectors where AI can make the most substantial impact (Piasecki et al., 2021).

The development of Government Pillar of AI Index has been a positive development for government AI readiness. The index is a tool for assessing the readiness of governments for AI adoption, and it includes a range of metrics related to AI policies, regulations, and infrastructure. It provides the assessment of vision, governance and ethics, digital capacity, and adaptability of governments in AI implementation.

By using the index to benchmark their AI readiness, governments can identify areas for improvement and develop strategies to support the growth of AI in their countries.

The Government Pillar of AI Index also provides a platform for international comparison, allowing governments to assess their AI readiness in relation to other countries. This can help to promote competition and encourage governments to adopt policies and strategies that support the growth of AI in their countries.

As AI's role in shaping the future of work expands, its integration into University Bachelor's Programmes has gained importance. Governments globally acknowledge the significance of AI readiness and developing AI strategies for sustainable economic growth. The use of GDP and AI in University Bachelor's Programmes, as well as the development of Government Pillar of AI Index, have both had a positive impact on government AI readiness.

The drive to integrate AI into University Bachelor's Programmes stems from the increasing demand for AI skills in the job market. The application of AI tools is quickly becoming an integral part of numerous industries, including finance, healthcare, and manufacturing. Universities, by incorporating AI in their programmes, equip students with vital skills for the future workplace (Vicsek, 2021).

Moreover, this integration fuels innovation and economic growth. AI is a potent innovation tool, and the emergence of new AI technologies could stimulate new industries and jobs. Universities, by teaching students the skills needed to create and apply AI solutions, spur economic growth and pave the way for new opportunities for graduates.

In summary, the use of GDP as an AI impact measure, the creation of the Government Pillar of the AI Index, and the integration of AI into University Bachelor's Programmes have positively influenced government AI readiness. By tracing AI's economic benefits, providing a gauge for government AI readiness, and preparing students with essential skills for the future workplace, these initiatives bolster global governments' capacity to leverage the opportunities AI offers.

4.2. Cluster analysis

To establish groups of EU countries and discover their mutual similarities based on the set of independent variables associated with the government artificial intelligence readiness, we carried out the cluster analysis for the year 2022. EU countries are characterized by disparities in socio-economic development and unequal national evolution, especially as the states that joined the European Union in 2004 and 2007 (Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia) experienced centralized communist economies until the early 1990s, have since passed through difficult periods of transition to the market economy and have had to overcome structural differences and gaps in their economies compared to those of the developed countries of the European Union. In addition, traditionally, national inequalities also derive from the different size of states, discrepancies in equipment and public technological infrastructure. The determination of homogeneous clusters of states in terms of AI implementation in government is quite challenging given the obvious conditions of heterogeneity exposed.

The clusters associated with the government artificial intelligence readiness index were developed through two categories of hierarchical clustering algorithm (complete linkage that produces spatially compact clusters and Ward's linkage where groups were joined to maximize an error-sum-of-squares objective function), which were applied to establish the groups of homogeneous states and which creates a hierarchy of clusters, based on dissimilarity measure in comparing two observations. The suitable number of clusters was established based on cluster stopping rules (Duda-Hart pseudo-T-squared small values and Calinski-Harabasz pseudo-F large values, which both indicated four clusters), as well as from the study of the dendrogram and graphic representation.

By applying the complete linkage and Ward's methods for year 2022, four countries clusters based on their similarities are obtained (Table 5). The synthetic description of the characteristics of the countries in each cluster, according to the studied variables, confirms that the degree of implementation of artificial intelligence in public services is inversely proportionally with the brain drain phenomenon. Also, the positive associations of the dependent variable with spending expenses, economic freedom and research and development projects funded by the European Commission for AI companies are confirmed.

Table 5. Clusters by AI IN GOVERNMENT – complete linkage and Ward's methods

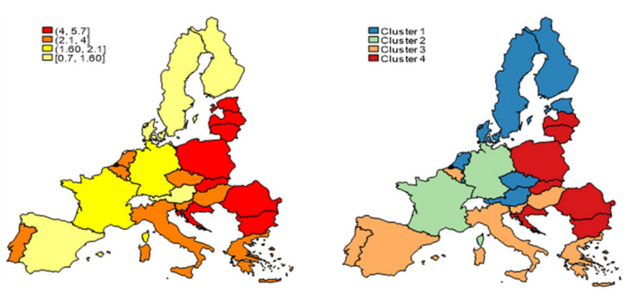
Group of country	AI IN GOVERNMENT dimension	Number of cluster – complete linkage method	Number of cluster – Ward's method
Countries with the average highest degree of government artificial intelligence			
Czechia, Finland, Netherlands, Luxembourg, Austria, Denmark, Estonia, Sweeden	High to medium (in terms of AI IN GOVERNMENT) Medium to low (in terms of BRAIN DRAIN) High (in terms of ECONOMIC FREEDOM and AI R&D FIRMS EC FUNDED PROJECTS) High to medium and low (in terms of GOVERNMENT EXPENDITURES)	Cluster 1	Cluster 1
Countries with high level of government artificial intelligence			
France, Germany	High to medium (in terms of AI IN GOVERNMENT) Medium (in terms of BRAIN DRAIN, ECONOMIC FREEDOM and AI R&D FIRMS EC FUNDED PROJECTS) High (in terms of GOVERNMENT EXPENDITURES)	Cluster 2	Cluster 3

End of Table 5

Group of country	AI IN GOVERNMENT dimension	Number of cluster – complete linkage method	Number of clus-ter – Ward's method
Countries with moderate level of government artificial intelligence			
Belgium, Hungary, Italy, Greece, Portugal, Slovenia, Spain	Medium (in terms of AI IN GOVERNMENT) Medium to low (in terms of BRAIN DRAIN) High to medium (in terms of AI R&D FIRMS EC FUNDED PROJECTS) High to medium and low (in terms of GOVERNMENT EXPENDITURES) Medium to low (in terms of ECONOMIC FREEDOM)	Cluster 3	Cluster 2
Countries with low degree of government artificial intelligence			
Romania, Slovakia, Croatia, Latvia, Poland, Bulgaria, Lithuania	High to medium (in terms of AI IN GOVERNMENT) High (in terms of BRAIN DRAIN) Medium to low (in terms of GOVERNMENT EXPENDITURES, ECONOMIC FREEDOM) Low (in terms of AI R&D FIRMS EC FUNDED PROJECTS)	Cluster 4	Cluster 4

The geographical representation of the countries based on the main proxy BRAIN DRAIN compared with the cluster's representation in complete linkage methods are illustrated in Figure 1.

The lowest values of core explanatory variable (BRAIN DRAIN) are in Romania, Bulgaria, Croatia, Slovakia, Poland, Latvia, Lithuania and Estonia. This group of states overlaps (with the exception of Estonia) with the last cluster obtained, cluster 4, determined on the basis of cluster analysis and containing states with low degree of government artificial intelligence. The similar type of correspondence between the two maps (Figure 1) is found for the first three clusters, in the sense that the countries in categories 2, 3 and 4 after the decreasing volume of the brain drain are in distinct clusters and for the entire set of data analysis by the cluster method, in which all variables were considered in the AI government estimation (Figure 1b and Table 6). For example, the countries with the lowest brain drain values (Finland,



a) b)

Figure 1. Geographical representation of the EU (24) countries based on: a – brain drain; b – Clusters in complete linkage method

Netherlands, Luxembourg, Denmark, and Sweden) are included in cluster 1 with the average highest degree of government artificial intelligence. States such as Czechia and Austria, placed in cluster 1 and having medium brain drain values are in the first part of the states studied from the perspective of adopting AI in government. Estonia's case is a special one, in the sense that although it presents high values of brain drain migration flows, it has developed and consolidated AI in government, through targeted and successful national measures. Germany and France (cluster 2 in complete linkage method) present medium values in terms of brain drain and high level of government artificial intelligence, while the rest of countries (cluster 3 – Belgium, Hungary, Italy, Greece, Portugal, Slovenia, Spain) shows average to low brain drain values, as well as average values of AI in government. The analyzed geographical distribution reveals situations in which immediately neighboring states have the same type of behavior from the perspective of the clusters of belonging and the variation of the variables studied by the cluster analysis, which adds preliminary signals of influences between states, as we will study in the following through spatial analysis.

To determine if the selected independent variables have the potential to explain the evolution of the degree of implementation of the government artificial intelligence, we estimate a cluster multivariate regression model (Table 6). The results display high rates of explanation of the chosen model for each independent variable (R-squared), as well as statistically significant outcomes of the F statistic, which indicates that the model has predictive capability.

Table 6. Clusters analysis for AI IN GOVERNMENT (source: author's calculations using STATA)

AI IN GOVERNMENT	F	R-squared
BRAIN DRAIN	13.596***	0.671
GOVERNMENT EXPENDITURE	29.465***	0.815
ECONOMIC FREEDOM	10.468***	0.610
AI R&D FIRMS EC FUNDED PROJECTS	21.356***	0.762

Note: * Significant at 10%; ** Significant at 5%; *** Significant at 1%.

4.3. Spatial analysis

After identifying the relationship between the variables studied by the instrumental-variables regression method and cluster countries analysis, another aim of the study is to find the spatial pattern of the data, more precisely whether AI IN GOVERNMENT and its determinants display agglomeration of high values with high values between countries, low values with low values or high values is grouped next to low values.

To perform the spatial analysis, we initially design a spatial weight matrix in the GeoDa software (Anselin et al., 2006), which defines the neighborhoods between states, in a binary format, in which if there is a common border between countries the value is 1 and otherwise 0. As the weight matrix cannot reflect the specific relationships between countries (human, economic or governance in our case), we develop the nested spatial weight matrix obtained by multiplying the adjacent matrix with the weight matrix for human, economic or governance distance from our data. We use the nested standardized matrix, which can reflect the spatial characteristics of neighboring countries, as well as the degree of interdependence between countries (Elhorst, 2017; Wang et al., 2023).

Based on nested matrix, we estimate the global Moran index *I* and obtain positive values of it and quite close to 1 for the explained and core explanatory variables (AI IN GOVERNMENT and BRAIN DRAIN) which indicates that these variables have a substantial positive spatial autocorrelation, and the data is grouped on the principle high-high or low-low (Table 7). Values are also positive, but closer to 0 are obtained for control variables and show a lower degree of spatial grouping of observations. Overall, data presents significant spatial correlation and is suitable for their use in spatial models.

Table 7. Global Moran's I spatial correlation for the selected variable, year 2022

Variable(s)	Moran's I	p-value	z-value
AI IN GOVERNMENT	0.479	0.002	2.818
BRAIN DRAIN	0.699	0.000	3.930
GOVERNMENT EXPENDITURE	0.193	0.071	1.469
ECONOMIC FREEDOM	0.258	0.054	1.612
AI R&D FIRMS EC FUNDED PROJECTS	0.267	0.048	1.666

Note: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. Standard errors are in round brackets.

Following the confirmation of the existence of spatial correlations, the spatial error regression model is examined. The robustness check of the model shows that the lambda parameter is significant (as are the Wald and Lagrange multiplier tests), and the values of variance ratio and squared correlation ensure a considerable predict of dependent variable through explanatory indicators.

From the empirical results (Table 8) we can find that both core explanatory variable and control variables present statistically significant values of spatial correlation coefficients and explain government AI from spatial perspective between countries. The increasing BRAIN

Table 8. Spatial Error Model regression results (source: authors' calculations using STATA)

AI IN GOVERNMENT	SEM
BRAIN DRAIN	–1.826*** (0.633)
GOVERNMENT EXPENDITURE	0.008** (0.003)
ECONOMIC FREEDOM	0.703*** (0.108)
AI R&D FIRMS EC FUNDED PROJECTS	22.039* (11.850)
Constant	5.595 (14.669)
Variance ratio	0.843
Squared correlation	0.825
Lambda	–0.466*** (0.127)
Wald test	13.378***
Lagrange multiplier LM test	4.594**

Note: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. Robust standard errors are in round brackets.

DRAIN in neighboring countries has a spatial spillover effects or negative externality on the home country's AI IN GOVERNMENT. Also, the improvement of macroeconomic conditions (GOVERNMENT EXPENDITURE and ECONOMIC FREEDOM), as well as those for financing AI R&D (AI R&D FIRMS EC FUNDED PROJECTS) in neighboring countries are responsible for increasing the capacity of governments to manage AI adoption.

Spatial analysis of the influence of brain drain on AI in government highlights regional and global inequalities in the development and deployment of AI technologies in the public sector. Addressing these inequalities requires concerted efforts by governments, academia and the private sector to develop a strong talent base in AI, encourage international collaboration and support the development of local AI solutions tailored to the specific needs of different governments.

Spatial analysis of the influence of the brain drain on AI in government highlights regional and global disparities in the development and implementation of artificial intelligence in the public sector. Brain drain refers to the migration of highly qualified specialists, including AI experts, from countries of origin to destinations with better opportunities, such as developed countries (Kapur & McHale, 2005). This talent migration can have a negative impact on governments' ability to develop and deploy AI solutions.

Regional imbalances in AI development can critically affect government efficiency in public service delivery and policy formation (Wirtz et al., 2020). Governments with AI talent access and the resources to realize AI solutions are better equipped to tackle complex social and economic problems, meeting citizen needs (Mikhaylov et al., 2018). Conversely, governments failing to attract and retain AI specialists could see their public service and policy management efficiency decline (Zajko, 2022).

The brain drain can exacerbate inequalities between countries in access to innovations and advanced technologies in AI. Countries that manage to attract and retain talent in AI can benefit from investment in R&D and accelerated economic growth (Singh & Krishna, 2018). The concentration of talent in AI in certain regions or countries can amplify differences in AI development and adoption in governments around the world. Developed countries, especially Western European countries, have managed to attract many AI specialists, strengthening their AI positions. In contrast, developing countries and local governments may face difficulties in attracting and retaining AI talent (Banerjee & Duflo, 2019).

At the same time, countries affected by the brain drain may lag behind in the technological race, which may limit their ability to address social and economic problems and respond to citizens' needs (Sabry, 2021).

To address these spatial inequalities and encourage a more equitable development of AI in the public sector, governments need to consider several strategies. First, investment in education and research in AI should be encouraged and supported at local and regional level (Basri & Box, 2010). This can help develop a solid talent base in AI and create employment opportunities in the public sector (Yamashita et al., 2021). Second, international AI collaboration can be crucial to combat the brain drain and ensure that former communist EU countries have access to cutting-edge knowledge and technologies (Berger, 2022). Partnerships between countries and institutions can facilitate the transfer of technology and knowledge and contribute to the development of AI solutions tailored to the specific needs of different governments (Qin et al., 2023). Third, governments can encourage the development of local AI solutions and support small and medium-sized enterprises (SMEs) specializing in AI. Creating an innovative AI ecosystem can attract local and international talent and help build governments' capacities to implement AI in the public sector (Djeffal et al., 2022).

The findings lead to various inferences and recommendations. For public administrations, AI extends beyond being merely instrumental; it's a transformative catalyst with potential to reshape governance, policy formation, and public service provision. AI can help governments generate accurate predictions and simulate complex systems to experiment with different policy options (Margetts & Dorobantu, 2019). Hence, it's crucial for public servants to keep pace with AI advancements and comprehend its applicability for societal welfare (Reis et al., 2019).

Moreover, AI's role in government underscores the necessity for robust collaborations amongst public institutions, private enterprises, academic bodies, and civil society organizations. Such partnerships encourage knowledge exchange, resource sharing, and expertise pooling, which are vital for crafting AI systems tailored to governmental needs and goals.

It is important to note that brain drain impedes government AI development, as the emigration of AI professionals slows AI progress in public services, reducing expertise and innovation. This results in economic losses for governments, especially in resource-limited nations, and hampers international AI collaboration due to less cooperation from relocated experts. Such nations risk falling behind in the global AI race, while those retaining talent could advance technologically and economically. Government spending is key to AI readiness, and stable economic policies favor AI adoption. The European Commission's AI R&D investment underscores the need for ongoing financial support in this field.

Finally, addressing brain drain is vital for a nation's AI future, economic growth, and innovation. Governments must tackle these challenges with proactive strategies, fostering an environment conducive to AI progress for the benefit of all citizens.

5. Conclusions

Given the intersection between Artificial Intelligence (AI) and brain drain, this study garners broad public interest by providing valuable insights, enhancing understanding of AI's impact on society, economy, and environment and highlighting the need for governments to regulate and implement AI across various sectors.

This study offers nuanced understandings of the factors influencing AI government readiness within the European Union. Specifically, it delves into the potential negative repercussions of Brain Drain (RQ1) and the potential positive implications of EU-funded projects for R&D, economic freedom, and government spending (RQ2) on AI preparedness. Moreover, the research provides crucial insights into the interplay between brain drain and a country's influence on its neighboring states' AI adoption readiness (RQ3). These findings elucidate the significance of understanding both internal and external dynamics to enhance AI readiness and integration at the governmental level in the European region.

Our findings unequivocally indicate a negative correlation between brain drain and AI readiness in EU governments in 2022. This suggests that as brain drain intensifies, governments' preparedness to integrate AI diminishes. This correlation, coupled with the insights garnered from the spillover effects and the potential policy interventions, offers a comprehensive roadmap for EU nations to strategically address the challenges posed by brain drain in the realm of AI readiness.

Several implications arise from our findings:

Detrimental Effects of Brain Drain: Brain drain significantly undermines government AI readiness. Skilled AI professionals migrating abroad impede the progress and application of advanced AI in public services, confirming Hypothesis H1 and supporting existing research findings.

Innovation Lag: The migration of AI talent leads not only to a loss of expertise but also diminishes the potential for technological innovation within their home countries.

Economic Implications: When AI experts leave, their home countries lose the investments made in their education and training. This exacerbates economic difficulties, especially in resource-constrained nations.

Challenges in International Collaboration: The brain drain phenomenon can adversely affect international AI collaborations. Experts relocating abroad might become less willing to engage with their home countries, resulting in lost opportunities in international AI projects.

Global AI Race: Countries severely affected by brain drain risk falling behind in the international competition for AI advancement. In contrast, those retaining or attracting AI talent could see significant technological and economic growth.

Prominence of Government Expenditure: There is a notable correlation between government investment and AI readiness. Adequate government funding can substantially improve the public sector's AI capabilities.

The Role of Economic Freedom: An enabling economic environment is crucial for the adoption of AI in government. Countries with greater economic freedom typically have an easier path to AI integration, emphasizing the importance of stable and supportive economic policies.

European Commission's AI R&D Investment: The European Commission's funding in AI research and development has been pivotal. This investment is essential for advancing AI readiness, highlighting the importance of ongoing financial support in this field.

Addressing brain drain is crucial for a nation's future in the AI arena, ensuring economic growth and innovation. Governments need strategies to retain talent and create AI-friendly environments, benefiting citizens. However, *our study* faces *limitations*, including data availability constraints. Despite using reliable sources, data gaps and discrepancies may exist due to AI's dynamic nature and fluctuating socio-political factors influencing brain drain. Additionally, incorporating diverse qualitative insights, like AI professionals' or policymakers' experiences, could have enriched our methodology.

Future research could delve deeper into the following areas: *Global Perspective* (while our study focused on the EU, understanding this dynamic in other regions or on a global scale could provide more comprehensive insights); *sectoral Analysis* (AI's integration varies across sectors. Future studies could examine how brain drain affects AI readiness in specific government sectors, such as health or defense).

Author contributions

The authors (ICI and AS) contributed equally to the elaboration of this research.

Disclosure statement

Authors have no competing financial, professional, or personal interests from other parties.

References

Agrawal, A., Gans, J., & Goldfarb, A. (2019). *The economics of artificial intelligence: An agenda*. University of Chicago Press. https://doi.org/10.7208/chicago/9780226613475.001.0001

AIoD Platform. (2019). *About the AI-on-Demand Platform*. https://aiod.eu/about

Al-Mushayt, O. S. (2019). Automating E-government services with artificial intelligence. *IEEE Access*, *7*, 146821–146829. https://doi.org/10.1109/ACCESS.2019.2946204

Anselin, L., Syabri, I., & Kho, Y. (2006). GeoDa: An introduction to spatial data analysis. *Geographical Analysis*, *38*(1), 5–22. https://doi.org/10.1111/j.0016-7363.2005.00671.x

Altuzarra, A., Gálvez-Gálvez, C., & González-Flores, A. (2019). Economic development and female labour force participation: The case of European Union countries. *Sustainability*, *11*(7), Article 1962. https://doi.org/10.3390/su11071962

Arntz, M., Gregory, T., & Zierahn, U. (2019). *Digitalization and the future of work: Macroeconomic consequences* (IZA Discussion Paper No. 12428). SSRN. https://doi.org/10.2139/ssrn.3411981

Bălan, M., & Olteanu, C. (2017). Brain drain in the globalization era: The case of Romania. *Annals of the "Constantin Brâncuşi" University of Târgu Jiu, Economy Series*, *3*. https://www.utgjiu.ro/revista/ec/pdf/2017-03/03_MARIANA%20BALAN,%20COSMIN%20OLTEANU.pdf

Banerjee, A.V., & Duflo, E. (2019). *Good economics for hard times* (1st ed.). Public Affairs.

Basri, E., & Box, S. (2010). International mobility of the highly skilled: Impact and policy approaches. In *The innovation for development report* 2009–2010 (pp. 109–135). Palgrave Macmillan. https://doi.org/10.1057/9780230285477_5

Belotti, F., Hughes, G., & Mortari, A. P. (2017). Spatial panel-data models using Stata. *The Stata Journal, 17*(1)*,* 139–180. https://doi.org/10.1177/1536867X1701700109

Berger, S. (2022, November). *Brain drain, brain gain and its net effect*. (Knomad Paper 46). Knomad. https://www.knomad.org/sites/default/files/2022-11/knomad_paper_46_brain_drain_brain_gain_and_its_net_effect_sandra_berger_november_2022.pdf

Bose, N., Haque, M. E., & Osborn, D. R. (2007). Public expenditure and economic growth: A disaggregated analysis for developing countries. *The Manchester School*, *75*(5), 533–556. https://doi.org/10.1111/j.1467-9957.2007.01028.x

Bredt, S. (2019). Artificial Intelligence (AI) in the financial sector – Potential and public strategies. *Frontiers in Artifical Intelligence*, *2*, Article 16. https://doi.org/10.3389/frai.2019.00016

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.

Calderaro, A., & Blumfelde, S. (2022). Artificial intelligence and EU security: The false promise of digital sovereignty. *European Security*, *31*(3), 415–434. https://doi.org/10.1080/09662839.2022.2101885

Can, M. (2023). Under the leadership of our president: 'Potemkin AI' and the Turkish approach to artificial intelligence. *Third World Quarterly*, *44*(2), 356–376. https://doi.org/10.1080/01436597.2022.2147059

Cath, C., Wachter, S., Mittelstadt, B., Taddeo, M., & Floridi, L. (2017). Artificial intelligence and the 'good society': The US, EU, and UK approach. *Science and Engineering Ethics*, *24*, 505–528. https://doi.org/10.1007/s11948-017-9901-7

Ciftci, C., & Durusu-Ciftci, D. (2022). Economic freedom, foreign direct investment, and economic growth: The role of sub-components of freedom. *The Journal of International Trade & Economic Development*, *31*(2), 233–254. https://doi.org/10.1080/09638199.2021.1962392

Czaika, M., & de Haas, H. (2015). The globalization of migration: Has the world become more migratory? *International Migration Review*, *48*(2), 283–323. https://doi.org/10.1111/imre.12095

Dignum, V. (2019). *Responsible artificial intelligence: How to develop and use AI in a responsible way*. Springer. https://doi.org/10.1007/978-3-030-30371-6

Djeffal, C., Siewert, M. B., & Wurster, S. (2022). Role of the state and responsibility in governing artificial intelligence: A comparative analysis of AI strategies. *Journal of European Public Policy*, *29*(11), 1799–1821. https://doi.org/10.1080/13501763.2022.2094987

Docquier, F., & Rapoport, H. (2012). Globalization, brain drain, and development. *Journal of Economic Literature*, *50*(3), 681–730. https://doi.org/10.1257/jel.50.3.681

Doran, N. M., Puiu, S., Bădîrcea, R. M., Pirtea, M. G., Doran, M. D., Ciobanu, G., & Mihit, L. D. (2023). E-government development – A key factor in government administration effectiveness in the European Union. *Electronics*, *12*(3), Article 641. https://doi.org/10.3390/electronics12030641

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. *International Journal of Information Management*, *48*, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan. Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, Article 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Eggers, W. D., Schatsky, D., & Viechnicki, P. (2017). *AI-augmented government*. Deloitte University Press. https://www2.deloitte.com/us/en/insights/focus/cognitive-technologies/artificial-intelligence-government.html

Elhorst, J. P. (2017). Spatial panel data analysis. In S. Shekhar, H. Xiong, & X. Zhou (Eds.), *Encyclopedia of GIS* (pp. 2050–2058). Springer. https://doi.org/10.1007/978-3-319-17885-1_1641

European Commission. (2018). *Coordinated plan on artificial intelligence*. https://digital-strategy.ec.europa.eu/en/library/coordinated-plan-artificial-intelligence

European Commission. (2020). *White paper on artificial intelligence: A European approach to excellence and trust*. https://commission.europa.eu/publications/white-paper-artificial-intelligence-european-approach-excellence-and-trust_en

European Commission. (2021a). *Horizon Europe*. https://research-and-innovation.ec.europa.eu/funding/funding-opportunities/funding-programmes-and-open-calls/horizon-europe_en

European Commission. (2021b). *New rules for Artificial Intelligence – Questions and answers*. https://www.eumonitor.eu/9353000/1/j9vvik7m1c3gyxp/vli5fy8jickv?ctx=vg9pjpw5wsz1&v=1

European Commission. (2022). *Joint research Centre data catalogue. AI Watch Index 2021*. https://data.jrc.ec.europa.eu/dataset/e3757f41-fe54-4330-946d-ae897686164f

European Parliament. (2021a). *AI for public services*. https://www.europarl.europa.eu/RegData/etudes/BRIE/2021/662936/IPOL_BRI(2021)662936_EN.pdf

European Parliament. (2021b). *Challenges and limits of an open source approach to Artificial Intelligence*. https://www.europarl.europa.eu/RegData/etudes/STUD/2021/662908/IPOL_STU(2021)662908_EN.pdf

European Parliament. (2023). *EU AI Act: First regulation on artificial intelligence*. https://www.europarl.europa.eu/news/en/headlines/society/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence

European Tertiary Education Register. (2019). *How are European higher education institutions funded? New evidence from ETER microdata*. https://www.eter-project.com/uploads/analytical-reports/ETER_AnalyticalReport_02_final.pdf

European Union. (2012). *Consolidated version of the Treaty on the Functioning of the European Union*. Article 45. Official Journal of the European Union C 326/288 (26.10.2012). https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=CELEX:12012E/TXT:en:PDF

Everitt, B. S., Landau, S., Leese, M., & Stahl, D. (2011). *Cluster Analysis* (5th ed.). Wiley. https://doi.org/10.1002/9780470977811

Fund for Peace. (2022). *Fragile States Index*. https://fragilestatesindex.org/indicators/e3/

Frankowska, A., & Pawlik, B. (2022). A decade of artificial intelligence research in the European Union: A bibliometric analysis. In C. Biele, J. Kacprzyk, W. Kopeć, J. W. Owsiński, A. Romanowski, & M. Sikorski (Eds.), *Lecture notes in networks and systems: Vol. 440. Digital interaction and machine intelligence. MIDI 2021* (pp. 52–62). Springer. https://doi.org/10.1007/978-3-031-11432-8_5

Frățilă, A., Păunescu, M., Nichita, E.-M., & Lazăr, P. (2023). Digitalization of Romanian public administration: A panel data analysis at regional level. *Journal of Business Economics and Management, 24*(1), 74–92. https://doi.org/10.3846/jbem.2023.18574

Gesk, T. S., & Leyer, M. (2022). Artificial intelligence in public services: When and why citizens accept its usage. *Government Information Quarterly*, *39*(3), Article 101704. https://doi.org/10.1016/j.giq.2022.101704

Gomes de Sousa, W., Pereira de Melo, E. R., De Souza Bermejo, P. H., Sousa Farias, R. A., & Oliveira Gomes, A. (2019). How and where is artificial intelligence in the public sector going? A literature review and research agenda. *Government Information Quarterly*, *36*(4), Article 101392. https://doi.org/10.1016/j.giq.2019.07.004

Gupta, K. P. (2019). Artificial intelligence for governance in India: Prioritizing the challenges using analytic hierarchy process (AHP). *International Journal of Recent Technology and Engineering*, *8*(2), 3756–3762. https://doi.org/10.35940/ijrte.B3392.078219

Heritage Foundation. (2022). *Index of Economic Freedom*. https://www.heritage.org/index/

Ibrahim, M., & Arundina, T. (2022). *Practical panel modelling*. KNEKS. https://kneks.go.id/storage/upload/1675248927-[FINAL]%20Practional%20Panel%20Modeling%20-%20Applications%20in%20Islamic%20Banking%20and%20Finance_PDF.pdf

Ionescu, A. M., Clipa, A. M., Turnea, E. S., Clipa, C. I., Bedrule-Grigoruta, M. V., & Roth, S. (2022). The impact of innovation framework conditions on corporate digital technology integration: Institutions as facilitators for sustainable digital transformation. *Journal of Business Economics and Management*, *23*(5), 1037–1059. https://doi.org/10.3846/jbem.2022.17039

Jacobs, K. (2023). Future of work: Upskilling. *Work*, *74*(1). https://doi.org/10.3233/WOR-236000

Johnson, H. G. (1965). The economics of the "brain-drain": The Canadian case. *Minerva*, *3*, 299–311. https://doi.org/10.1007/BF01099956

Kapur, D., & McHale, J. (2005). *Give us your best and brightest: The global hunt for talent and its impact on the developing world*. Center for Global Development. https://www.cgdev.org/sites/default/files/9781933286037-Kapur-Hale-best-and-brightest.pdf

Labra, R., & Torrecillas, C. (2018). Estimating dynamic panel data. A practical approach to perform long panels. *Revista Colombiana de Estadistica*, *41*(1), 31–52. https://doi.org/10.15446/rce.v41n1.61885

Le, A. H., & Kim, T. (2020). The effects of economic freedom on firm investment in Vietnam. *Journal of Asian Finance, Economics and Business*, *7*(3), 9–15. https://doi.org/10.13106/jafeb.2020.vol7.no3.9

Lepori, B., Reale, E., & Spinello, A. O. (2018). Conceptualizing and measuring performance orientation of research funding systems. *Research Evaluation, 27*(3), 171–183. https://doi.org/10.1093/reseval/rvy007

Margetts, H., & Dorobantu, C. (2019). Rethink government with AI. *Nature*, *568*, 163–165. https://doi.org/10.1038/d41586-019-01099-5

Mehr, H. (2017). *Artificial intelligence for citizen services and government*. https://ash.harvard.edu/files/ash/files/artificial_intelligence_for_citizen_services.pdf

Mikhaylov, S. J., Esteve, M., & Campion, A. (2018). Artificial intelligence for the public sector: Opportunities and challenges of cross-sector collaboration. *Philosophical Transactions of the Royal Society A*, *376*(2128), 1–26. https://doi.org/10.1098/rsta.2017.0357

Millard, J. (2017). European strategies for e-Governance to 2020 and beyond. In A. Ojo & J. Millard (Eds.), *Public administration and information technology: Vol. 32*. *Government 3.0 – next generation government technology infrastructure and services* (pp. 1–25). Springer. https://doi.org/10.1007/978-3-319-63743-3_1

Montoya, L., & Rivas, P. (2019, November 15-16). Government AI readiness meta-analysis for Latin America and The Caribbean. In *Proceedings of 2019 IEEE international symposium on technology and society (ISTAS)*. Medford. https://doi.org/10.1109/ISTAS48451.2019.8937869

Nguyen, M. L. T., & Bui, N. T. (2022). Government expenditure and economic growth: Does the role of corruption control matter? *Heliyon*, *8*(10), Article e10822. https://doi.org/10.1016/j.heliyon.2022.e10822

Noja, G. G. (2018). Flexicurity models and productivity interference in C.E.E. countries: A new approach based on cluster and spatial analysis. *Economic Research-Ekonomska Istraživanja, 31*(1), 1111–1136. https://doi.org/10.1080/1331677X.2018.1456356

OECD. (2023). *OECD AI Policy Observatory*. https://oecd.ai/en/

Offer, A. (2022). *Understanding the private–public divide. Markets, governments, and time horizons*. Cambridge University Press. https://doi.org/10.1017/9781108866415

Ojo, A. (2019). Next generation government – hyperconnected, smart and augmented. In L. M. Camarinha-Matos, H. Afsarmanesh, & D. Antonelli (Eds.), *IFIP advances in information and communication technology*: *Vol. 568*. *collaborative networks and digital transformation*. *PRO-VE 2019* (pp. 285–294). Springer. https://doi.org/10.1007/978-3-030-28464-0_25

Ojo, A., Mellouli, S., & Zeleti, F. A. (2019, June 18–20). A realist perspective on AI – era public management. An analysis of mechanisms, outcomes and challenges of AI solutions in the public sector. In

Proceedings of the 20th Annual International Conference on Digital Government Research (pp. 159–170). Dubai. https://doi.org/10.1145/3325112.3325261

Okulich-Kazarin, V., Goloborodko, A., & Kravets, O. (2020). What is the priority of the political rhetoric of the Russian presidents: Growth of bureaucracy or economic freedom? In M. J. Lomott, K. Łyskawa, P. Polychronidou, & A. Karasavvoglou (Eds.), *Springer proceedings in business and economics. Economic and financial challenges for Balkan and Eastern European countries* (pp. 315–327). Springer. https://doi.org/10.1007/978-3-030-39927-6_20

Oxford Insights. (2019). *Government Artificial Intelligence. Readiness Index 2019*. https://oxfordinsights.com/wp-content/uploads/2023/12/ai-gov-readiness-report_v08.pdf

Oxford Insights. (2022). *Government AI Readiness Index 2022*. https://oxfordinsights.com/wp-content/uploads/2023/11/Government_AI_Readiness_2022_FV.pdf

Pan, Y., & Zhang, L. (2021). Roles of artificial intelligence in construction engineering and management: A critical review and future trends. *Automation in Construction*, *122*, Article 103517. https://doi.org/10.1016/j.autcon.2020.103517

Piasecki, R., Wolnicki, M., & Betancourt, E. W. (2021). Artificial Intelligence in the context of global resource mobility. What can be expected from it? *Comparative Economic Research-Central and Eastern Europe*, *24*(3), 93–107. https://doi.org/10.18778/1508-2008.24.23

Pisati, M. (2001). Tools for spatial data analysis. *Stata Technical Bulletin*, *60*, 21–37.

Qin, Y., Xu, Z., Wang, X., & Skare, M. (2023). Artificial intelligence and economic development: An evolutionary investigation and systematic review. *Journal of the Knowledge Economy*. https://doi.org/10.1007/s13132-023-01183-2

Reis, J., Santo, P. E., & Melão, N. (2019). Artificial intelligence in government services: A systematic literature review. In Á. Rocha, H. Adeli, L. P. Reis, & S. Costanzo (Eds.), *Advances in intelligent systems and computing. Vol. 930. New knowledge in information systems and technologies. WorldCIST'19 2019* (pp. 241–252). Springer. https://doi.org/10.1007/978-3-030-16181-1_23

Robles, P., & Mallinson, D. J. (2023). Artificial intelligence technology, public trust, and effective governance. *Review of Policy Research*. https://doi.org/10.1111/ropr.12555

Sabry, R. A. W. O. (2021). Artificial intelligence role for advertising campaigns development. *International Journal of Artificial Intelligence and Emerging Technology*, *4*(1), 1–16. https://doi.org/10.21608/ijaiet.2021.187258

Siar, S. V. (2013). *From highly skilled to low skilled: Revisiting the deskilling of migrant labor* (PIDS Discussion Paper Series, No. 2013-30). Philippine Institute for Development Studies (PIDS). http://hdl.handle.net/10419/126949

Singh, J., & Krishna, V. V. (2018). Trends in brain drain, gain and circulation: Indian experience of knowledge workers. *Science, Technology and Society*, *20*(3), 300–321. https://doi.org/10.1177/0971721815597132

Spence, M. (2021). Government and economics in the digital economy. *Journal of Government and Economics*, *3*, Article 1000020. https://doi.org/10.1016/j.jge.2021.100020

Szarowska, I., (2022). Relationship between government expenditure and economic growth in Visegrad Group. *Financial Internet Quaterly*, *18*(4), 12–22. https://doi.org/10.2478/fiqf-2022-0024

Thanh, S. D., Hart, N., & Canh, N. P. (2020). Public spending, public governance and economic growth at the Vietnamese provincial level: A disaggregate analysis. *Economic Systems*, *44*(4), Article 100780. https://doi.org/10.1016/j.ecosys.2020.100780

Thomas, P., & Murdick, D. (2020). *Patents and artificial intelligence: A primer. CSET data brief.* Center for Security and Emerging Technology. https://doi.org/10.51593/20200038

Trishch, R. M., Sichinava, A., Bartos, V., Stasiukynas, A., & Schieg, M. (2023). Comparative assessment of economic development in the countries of the European Union. *Journal of Business Economics and Management*, *24*(1), 20–36. https://doi.org/10.3846/jbem.2023.18320

Ullah, S., Akhtar, P., & Zaefarian, G. (2018). Dealing with endogeneity bias: The generalized method of moments (GMM) for panel data. *Industrial Marketing Management*, *71*, 69–78. https://doi.org/10.1016/j.indmarman.2017.11.010

Vicsek, L. (2021). Artificial intelligence and the future of work – lessons from the sociology of expectations. *International Journal of Sociology and Social Policy*, *41*(7/8), 842–861. https://doi.org/10.1108/IJSSP-05-2020-0174

Voda, A. D., Dobrota, G., Dobrota, D., & Dumitrascu, D. D. (2022). Error correction model for analysis of influence of fiscal policy on economic growth in EU. *Journal of Business Economics and Management*, *23*(3), 586–605. https://doi.org/10.3846/jbem.2022.16242

Walker, A., & Maltby, T. (2012). Active ageing: A strategic policy solution to demographic ageing in the European Union. *International Journal of Social Welfare*, *21*(s1), S117–S130. https://doi.org/10.1111/j.1468-2397.2012.00871.x

Wang, Z., Ma, D., Zhang, J., Wang, Y., & Sun, D. (2023). Does urbanization have spatial spillover effects on poverty reduction: Empirical evidence from rural China. *Economic Research-Ekonomska Istraživanja*, *36*, Article 2167730. https://doi.org/10.1080/1331677X.2023.2167730

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

Wirtz, B. W., Weyerer, J. C., & Sturm, B. J. (2020). The dark sides of artificial intelligence: An integrated AI governance framework for public administration. *International Journal of Public Administration*, *43*(9), 818–829. https://doi.org/10.1080/01900692.2020.1749851

World Bank. (2022a). *General government final consumption expenditure (current US$).* https://data.worldbank.org/indicator/NE.CON.GOVT.CD

World Bank. (2022b). *GDP (current US$)*. https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?view=chart

World Economic Forum. (2023). *For inclusive growth, leaders must embrace a global and open economic future*. https://www.weforum.org/agenda/2023/01/finance-inclusive-growth-wef23/

Yamashita, I., Murakami, A., Cairns, S., & Galindo-Rueda, F. (2021). *Measuring the AI content of government-funded R&D projects: A proof of concept for the OECD Fundstat initiative.* (OECD Science, Technology and Industry Working Papers, No. 2021/09). OECD. https://doi.org/10.1787/7b43b038-en

Zajko, M. (2022). Artificial intelligence, algorithms, and social inequality: Sociological contributions to contemporary debates. *Sociology Compass*, *16*(3), Article e12962. https://doi.org/10.1111/soc4.12962