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**SOCIOECONOMIC AND CULTURAL DETERMINANTS
OF THE DEVELOPMENT OF ARTIFICIAL INTELLIGENCE**

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Abstract

This study assesses the impact of socioeconomic and cultural factors that are likely to have effects on the development of artificial intelligence at the national level. This technology is evaluated both globally and in terms of its components: qualified users, technical capabilities, regulations, societal support, academic support, algorithms and platforms, support from public authorities, and private economic initiatives. Socioeconomic determinants include economic development and the speed of economic growth, funding for education and research and development, high-tech exports, urbanisation, population, and workforce. Cultural determinants are represented by national aggregate Hofstede's cultural indicators. The available data cover 60 countries from all continents and the period from 2012 to 2022. The research methodology employs hierarchical clustering and robust cross-sectional regression models to avoid heteroscedasticity. The main results indicate highly significant effects of GDP per capita, its growth rate, research and development funding, and the degree of urbanisation. Among cultural factors, only uncertainty avoidance is statistically significant. The multidimensional hierarchical clustering identified six groups corresponding to different national behaviours regarding preferences for the development of certain artificial intelligence technologies and activities.

Keywords: artificial intelligence, socioeconomic determinants, Hofstede cultural values, robust cross-sectional regressions, hierarchical clustering

JEL Classification: O33, O32, C21, C38

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Introduction

In the contemporary era, artificial intelligence (AI) has emerged as a distinct field, revolutionising society and the economy. The rapid development is attributed to the growth of computing power and the availability of vast amounts of data, making AI a catalyst for transformations in various sectors. In the economic domain, AI is a significant determinant of operational efficiency and process optimisation. AI-incorporated systems analyse and interpret data swiftly, leading to cost reduction, improved service quality, and increased market competitiveness. In innovation, AI plays a decisive role, particularly in medicine, automotive, and energy, contributing to the development of novel technologies that foster sustainable economic growth. AI's impact on labour markets is evident through the automation of routine processes, freeing resources for higher-value activities. However, it also raises the issues of workforce adaptability and the equitable distribution of technological progress benefits. While there are substantial benefits to AI use in the economy and society, its uneven global development is influenced by complex economic, social, institutional, and cultural factors. Assessing AI development involves considering various aspects, such as the presence of qualified users, technical capabilities, legal regulatory frameworks, academic support, funding, and private initiatives. The complexity necessitates addressing determinants to understand national levels and relationships between components. Motivations to study influencing factors include cultural diversity, adaptation to local needs, national economic context, resource availability, public policies, legislation, ethics, education, innovation, knowledge exchange, and regional risks. Cultural and social diversity affects AI adaptation to local markets, considering the heterogeneous values across countries. Examining these values aids in implementing AI through context-specific methods. Economic contexts influence development, with higher economic levels facilitating AI growth through technical accessibility and research funding. Regulations and public policies can catalyse new technologies, varying across nations in acceptance and support for AI. Considering ethical and social aspects is crucial to maximising global AI implementation efficiency. Establishing global ethical standards can avoid controversies and negative consequences, ensuring the well-being of the community. Human and technical resources availability, especially in education, influences AI skill development. Studying territorial differences helps to create initiatives to reduce disparities and ensure equitable development. Knowledge exchange and international collaboration are vital for innovative technologies like AI, expediting innovation processes and addressing common challenges. Regions may face specific risks related to AI security, emphasising the need for global standards and appropriate security measures. In summary, the multifaceted nature of AI development requires addressing influencing factors to comprehend national levels and ensure equitable progress across regions.

As a result, the development of AI within a national economy and society is not merely a matter of will, but a much more complex issue. In the literature, various causal relationships between different possible factors and AI development are explained. However, these are studied at the micro-level of human behaviours or at the national levels. Our study aims to fill this gap through a different approach, investigating international connections for a sample of countries with available data. Consequently, we set two main research objectives for this study: (1) Identifying and analysing behavioural patterns of countries worldwide regarding the level of development and the structure of AI activities. (2) Highlighting the key determinants of AI development at the national level.

The article is structured as follows: the literature review investigates current issues in AI, particularly from the perspective of its possible determinants; the data and methodology section describes the database, consisting of countries from all continents, variables related to AI development, and potential socioeconomic and cultural factors, as well as details about the regression equations and hierarchical clustering analysis used in this research; results and discussions highlight some main trends derived from the conducted statistical analyses, attempting to compare the obtained results with those of more or less similar studies; conclusions summarise the main ideas from the conducted research and refer to some limitations, future perspectives, and policy recommendations that could be grounded in this study.

1. Literature review

The literature on AI technologies used in the economy and society is quite extensive. We do not aim to conduct an exhaustive investigation of the main topics. Instead, we focus our attention on those that converge or are associated with the objectives of our study. Therefore, the literature review is structured into four parts: advantages of AI in contemporary society and the economy, challenges of AI in contemporary society, socioeconomic determinants of AI development, and cultural determinants of AI development.

1.1. Advantages of AI in contemporary society and the economy

Innovative technologies, particularly artificial intelligence, play a pivotal role in significantly contributing to both the economy and society. AI's primary benefit lies in its ability to take over repetitive tasks, increasing productivity and enabling individuals to engage in activities with higher creative value. Automation and algorithmic creativity in AI enhance operational efficiency in industrial processes, optimising resources, and execution time (Waltersmann et al., 2021). AI is a driving force behind innovation and technological development, solving complex problems and creating innovative applications and services (Verganti et al., 2020). These advancements yield substantial benefits in various fields. In the economic domain, AI addresses highly complex issues that exceed human capabilities, particularly in analysing large-scale data, simulations, scenarios, and predictions based on intricate models (Lu, 2019). AI systems provide rapid analyses and crucial information for decision-making in diverse areas such as business, finance, and governance (Duan et al., 2019). Beyond economic advantages, AI enhances user experiences by personalising recommendations and providing virtual assistance in e-commerce, online services, and entertainment, contributing to improved user satisfaction (Ameer et al., 2021). In medicine and healthcare, AI contributes to early identification, accurate diagnosis, and personalised treatments, potentially saving lives through the swift recognition of anatomical or physiological anomalies (Topol, 2019).

1.2. Challenges of AI in contemporary society

While AI presents numerous advantages, it introduces specific challenges that require diligent management to ensure that the benefits outweigh the drawbacks. One concern is technological unemployment, where the automation of AI-driven processes can lead to job losses, particularly in repetitive or routine sectors, necessitating workforce retraining (Frank et al., 2019). Economic disparities within the population can widen due to unequal adoptions of AI technologies, exacerbating economic and social divisions (Korinek and Stiglitz, 2019). Developed countries and large economic entities may disproportionately benefit from AI, intensifying global and corporate inequalities. The widespread use of AI raises issues of data

security and privacy, as massive data collection and analysis can occur without human intervention, potentially resulting in privacy violations and misuse of personal data (Villegas and García-Ortiz, 2023). Additionally, the educational process faces significant challenges, requiring rapid adaptation to equip the workforce with the necessary skills and knowledge for the AI era (Chen et al., 2020). These highlighted problems emphasise the importance of a careful and balanced approach to the implementation and management of AI to maximise benefits while minimising associated risks.

1.3. Socioeconomic determinants of AI development

The potential impacts of determinants on the progress and adoption of artificial intelligence (AI) are intricate and interconnected, influencing technological advancements and utilisation in the economy and society. Essential to cutting-edge technology development is substantial financial investment, often facilitated by high-level economic development measured through indicators like GDP (Makridis and Mishra, 2022). Economic growth not only creates larger markets for AI products, but also provides additional funding for vital research and development (R&D) in the AI field. A highly educated workforce is crucial for advanced technology creation. Educational resources in computer science, mathematics, and engineering contribute significantly to the formation of a skilled workforce aligned with technological development (Hwang and Tu, 2021). Beyond education, a country's economic orientation matters; nations focused on primary resource exploitation are less likely to engage in extensive AI development. In contrast, countries emphasising technology creation and export foster knowledge exchange and international collaborations, expediting AI progress (Smart et al., 2023). Such collaborations set the stage for developing international or global standards in AI. The orientation toward innovative technologies requires considerable and systematic efforts to secure continuous funding for R&D, stimulating innovation and furthering AI technology development. Consistency in legislative, administrative, and financial support for R&D accelerates progress, leading to more advanced AI solutions. Beyond economic factors, social organisation plays a crucial role. Urbanisation attracts human talents and technological resources, creating dynamic technological ecosystems with innovative capabilities (Lambert et al., 2015). The technical infrastructures in urban areas facilitate the local implementation of smart and connected technologies, expanding territorially. Demographic aspects also influence AI development, with consistent differences among countries in the proportion of citizens active in the labour market. Prioritising science, technology, engineering, and mathematics fields is desirable to establish the foundations for the practical adoption of AI technologies. In managing the rapid changes in innovative technologies, training and retraining the existing workforce becomes crucial for transitioning to a technology-based economy. These determinants interact and reciprocally influence each other. A highly skilled and correctly oriented workforce can attract R&D investments, contributing to economic growth and technology export. Viewing these factors independently is incorrect; an integrated approach with effective legislative and administrative actions is necessary to maximise the benefits of AI development in society.

1.4. Cultural determinants of AI development

Economic and social factors form the foundation for AI development, but understanding this phenomenon requires considering societal readiness to embrace these technologies. Cultural concepts guiding a country's citizens, particularly through Hofstede's cultural dimensions (1980), play a crucial role. While not all dimensions impact AI, some correlations can be observed. For instance, a community with a high power distance may prefer clear hierarchies

and respect for authority, reflecting a potential preference for AI systems adhering to norms and rules (Hossain and Lee, 2023). Additionally, in AI development, collectivism or individualism can influence preferences for personalised systems or those serving entire communities (Chi et al., 2022). Perception of risks and uncertainty can impact preferences for AI systems providing predictability and clarity in operation (Kim and Kim, 2021). Technological innovations emerge rapidly, but their societal effects are long-term. A long-term orientation can influence strategic planning for AI solutions, emphasising adaptation and continuous innovation (Jakšič and Marinč, 2019). These characteristics are interconnected, creating a complex combination within a community. Considering cultural diversity is crucial in the development and adoption of AI products and services, allowing technologies to respect and reflect the values and cultural preferences of each nation or society.

Summarising the ideas derived from the literature review, we find that there are concerns regarding the identification of determinants of AI development. However, these focus either on theoretically explaining the mechanisms of action of factors or on evaluating situations at the national level. Our approach is different, global, and in line with the stated objectives of the study, we formulate research hypotheses.

H1: There are different behavioural patterns among countries concerning the development and structure of AI activities and technologies. Even for a similar level of AI development, different proportions of associated activities may be manifested from one country to another. We aim to identify and analyse these patterns.

H2: Socioeconomic factors significantly influence the development of AI. As mentioned in the literature review, there are identifiable factors, and we intend to highlight them through regression models.

H3: Cultural factors significantly influence the development of AI. Individual cultural behaviours have been explained as mechanisms of interaction influencing the adoption of AI technologies. Our study aims to validate the influence of these potential determinants.

2. Research methodology

In order to achieve the objectives proposed in this study, we use linear econometrics on cross-section data, hierarchical clustering, standardisation of variables, and the creation of a composite variable. To estimate the coefficients from the regressions, we resort to cross-sectional econometric models, estimated by OLS (Ordinary Least Squares), with the following structure:

$$AI_INTENS_i = \alpha_0 + \alpha_1 ECONOMIC_i + \alpha_2 CULTURAL_i + \varepsilon_i \tag{1}$$

where $i = \overline{1, N}$ indexes the 60 countries in the sample for which there are data available in relation to all the variables in the study.

ECONOMIC is the vector of socioeconomic variables (GDPCAP, GDP_GROWTH, EDUC_GDP, HIGH_TECH, R&D_GDP, URBAN, POPULATION, LABOUR).

CULTURAL is the vector of Hofstede's five (out of six) national cultural variables for which there is theoretical or logical reasoning of interaction with AI development (PWR_DIST, INDIVID, MOTIVATION, UNCERT_AV, LNGTOR). The description of the variables,

with their abbreviated names, explanations, and some descriptive statistics, can be found in table no. 1.

Regressions are tested for heteroscedasticity. Heteroscedastic models are corrected by the robust estimator of the variance, respectively, the correction of White (1980), who proposes an HCE estimator (heteroscedasticity-consistent estimator):

$$v_{HCE}(\hat{\beta}_{OLS}) = (X'X)^{-1} X' \text{diag}(\hat{\varepsilon}_1^2, \dots, \hat{\varepsilon}_n^2) X (X'X)^{-1} \tag{2}$$

The statistical analysis also includes hierarchical clustering. We preferred Ward's linkage and Euclidean distance as clustering methods to measure proximities between countries and between groups. There are theoretical studies, through simulations, that indicate under what conditions certain grouping methods and certain distances are preferable; in our case the ones mentioned are appropriate (see, for example, Ferreira and Hitchcock (2009), which shows by comparison and simulations the performances of different versions possible hierarchical classification).

To avoid possible multicollinearity problems, we also use a composite variable, SOCIO_ECON as an average of four variables (GDPCAP, GDP_GROWTH, R&D_GDP, URBAN) in the regressions. Since they have very different units of measure and orders of magnitude, we first standardise them. For those that present an asymmetric, strongly positive distribution, we first logarithmise them, then they are all centered and reduced (subtracting the mean and dividing by the standard deviation (they become variables of zero mean and one variance). Then the normal distribution is applied and multiplied by 100. In this way, variables with a continuous uniform distribution are obtained, calibrated between 0 and 100, thus comparable to each other, and which can be combined by addition. Since for all four initial variables, the favourable situation corresponds to large values, the standardisation is carried out by the same formula:

$$X_{iST} = 100 \int_{-\infty}^{\frac{x_i - m}{\sigma}} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt \tag{3}$$

Through these transformations, the variables GDPCAP, GDP_GROWTH, R&D_GDP, URBAN become standardised. Their average defines the SOCIO_ECON variable. In the standardisation formula, *i* indexes the countries in the sample, *m* and *σ* denote the mean and standard deviation of the *X_i* values related to the variable *X*. The result, *X_{iST}*, is the standardised value of the *X_i* values, which have possible values only between 0 and 100, with large values signifying the favourable case of the considered socioeconomic aspect.

Table no. 1. Variables used and descriptive statistics

Variable	Explanations	Media	Std. Dev. ^s	Min	Max
TALENT	The component that refers to the existence of skilled users in the use of AI.	27.9	16.9	3.5	100
INFRASTR	Technical capabilities to use AI: high-speed Internet, adequate computers, etc.	57.5	16.5	5	100
OPR_ENVIR	Operating environment: regulatory and societal support for AI.	81.0	11.2	53.8	100
RESEARCH	Theoretical support from the academic environment, scientific publications.	15.7	16.3	0.2	100

Variable	Explanations	Media	Std. Dev. \$	Min	Max
DEVELOP	Algorithms and platforms that enable the use of AI projects and applications.	9.7	18.1	0	100
GOV_STR	The support of the authorities through funding and support programs for AI.	58.6	29.6	0	100
COMMER	Private initiatives in AI: enterprises, investments, business ideas.	8.8	14.5	0.7	100
AI_INTENS	Global intensity on all AI items. It considers the population of the country.	35.3	17.5	9.4	100
GDPCAP	GDP per capita, in thousands of USD.	31.0	25.6	1.4	117
GDP_GROWTH	Annual growth (%) of GDP per inhabitant.	1.8	1.6	-1.2	7.2
EDUC_GDP	Education financing, percentage of GDP.	4.7	1.2	1.9	7.7
HIGH_TECH	High-tech exports, percentage of manufactured goods exports.	15.1	11.4	0.7	51.7
R&D_GDP	R&D expenditure, percentage of GDP.	1.5	1.1	0.1	4.5
URBAN	The percentage of the urban population.	73.6	18.8	18.5	100
POPULATION	The country's population, in millions of inhabitants.	93.6	247	0.35	1390
LABOR	Labour force, % of the total population.	49.1	8.1	29.8	74.6
PWR_DIST	Power distancing. Dimension of acceptance of power inequality in society.	57.5	21.4	11	100
INDIVID	Individualism vs. Collectivism. Prevalence of personal goals.	51.4	23.9	4	100
MOTIVATION	Individual motivation for professional, material achievement, and success.	49.2	20.2	5	100
UNCERT_AV	Uncertainty avoidance. The tolerance in the face of the unpredictable.	64.5	22.3	8	100
LNGTOR	Long/short-term orientation. High values indicate pragmatism, and good education.	49.5	20.5	6	100

Note: \$Std.dev. = standard deviation

The data in this study comes entirely from international sources of the World Bank (2023), the Hofstede Institute (2022), and The Global AI Index – Tortoise Media (2023). The 60 countries in the sample (period 2012-2022) were not selected according to a particular algorithm, but they are those for which there is nationally aggregated data on artificial intelligence. A better representation of the world’s states would have been desirable, but it will only be possible when the databases are more complete. The calculations were performed in Excel and STATA, and the maps (figure no. 2 and figure no. 3) are represented in the Tableau software.

3. Results and discussion

As revealed by the study of literature and the table defining variables (Table no. 1), there are several aspects that can characterise the development of AI at the national level: legislation, available workforce, technical means, private investments, etc. These components can be found in very different proportions from one country to another, even if the overall level of AI development is comparable. For example, two neighbouring countries in the global AI development ranking (Spain, with an average of 43.4, and India with an average of 42.4) have very different profiles in terms of the levels of various components (Figure no. 1). The

existing structural differences deserve a more detailed study. It is therefore interesting to identify if there are certain groupings of countries based on AI development typologies. Consequently, we resort to hierarchical cluster analysis.

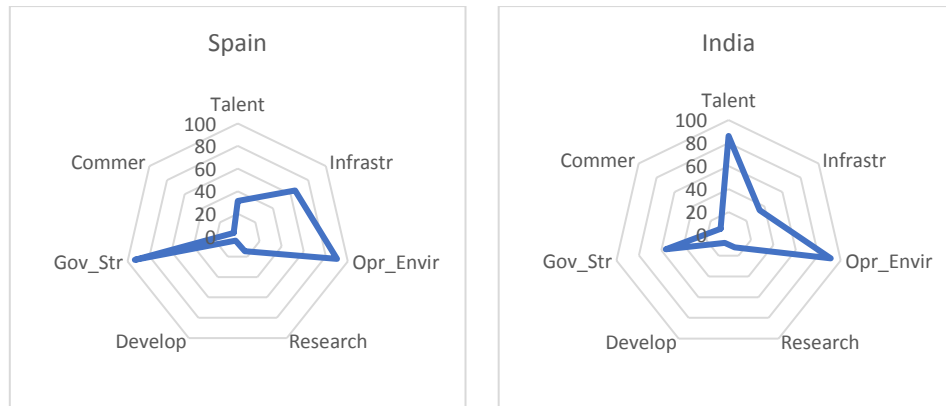


Figure no. 1. Structural differences in AI development between Spain and India

The clustering performed is based on the variables that constitute the components of AI development (TALENT, INFRASTR, OPR_ENVIR, RESEARCH, DEVELOP, GOV_STR, COMMER). Using the Ward linkage and Euclidean distance, five groups resulted (Table no. 2 and figure no. 2). The validation of groups, based on the principle of maximum homogeneity in groups and heterogeneity between groups, was carried out by ANOVA. For each group, the most representative countries, the closest (in terms of Euclidean distance) to the center of the cluster, were noted.

Table no. 2. Grouping of countries according to AI activities

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
TALENT	17.1	21.5	44.7	38.4	100	16.8
INFRASTR	54.8	58.4	70.8	63.7	100	39.9
OPR_ENVIR	79.1	81.7	84.8	90.2	82.8	68.6
RESEARCH	6.1	8.6	37.7	21.9	100	5.9
DEVELOP	0.9	2.8	33.7	13.0	100	0.9
GOV_STR	49.7	80.2	89.6	61.1	90.3	11.0
COMMER	2.2	4.3	19.1	10.9	100	4.2
Representative countries	Argentina Slovakia Hungary	Czechia Slovenia Brazil	the UK Canada Germany	the Netherlands Austria Norvegia	the US	Tunisia Armenia Greece

Firstly, it is observed that there are significant differences between countries regarding the strategy or opportunities to prioritise one component over another. The behaviour of the United States is entirely atypical, standing alone in a group, and exhibiting very high values across all indicators. Although there is no clear ordinal relationship between the groups, the third group demonstrates a stronger development of AI, with values almost universally higher than those of the other groups (except the USA). In Group 4, the behaviour is similar to that in Group 3, with relatively high values for all components and even excelling in the component related to the operating environment. Group 6 has the lowest values for all aspects of AI. Somewhat unexpectedly, there is considerable economic development heterogeneity within this cluster, ranging from New Zealand or Iceland to Nigeria, Kenya, or Sri Lanka. Groups 1 and 2

predominantly consist of countries with a medium to high level of economic development. From an AI perspective, these states exhibit imbalanced developments, excelling in some components (INFRASTR, OPR_ENVIR) while having poorly developed components (DEVELOP, COMMER). The major difference between the two groups lies in governmental support (GOV_STR), which is much more effective in the second group. The differences between the groups are substantial, indicating distinct behaviours and confirming hypothesis H1.

Although there is no ordinal relationship between the resulting groups, we have visually separated them. Countries marked in blue (Figure no. 2) have higher values for the average AI indicators. More developed areas can be identified from this perspective, encompassing countries with both a large population and strong economic development capable of financially supporting innovations. Notable examples include the US, the United Kingdom, Germany, China, Australia, or Canada. In Africa and Latin America, there are no states with high values for AI-related indicators. The results should be considered as prospective. There are no comparable results in the literature, only concerns about the use of AI in clustering methods (Kalinová, 2021), not about grouping countries based on AI structure. AI development is still in its early stages, and there are few clear outlines of public policies in this field, which is currently more of a niche. The behavioural patterns of each country are not yet stable, making it difficult to address causality at this point: what determines a country to adopt a specific AI component structure? When data becomes available for more countries and over a sequence of time periods, panel data econometrics could be employed. This would allow for the identification of both cross-sectional effects (from one country to another) and time effects. The existence of more consistent databases would also enable the study of determinants of AI structure at the national level. To make the situation even more complex, strong AI development is challenging in small countries, even if they are economically well-developed (Iceland, New Zealand). A critical mass of users is needed (easier to achieve in countries that are both economically developed but also have a larger population) for AI to develop.

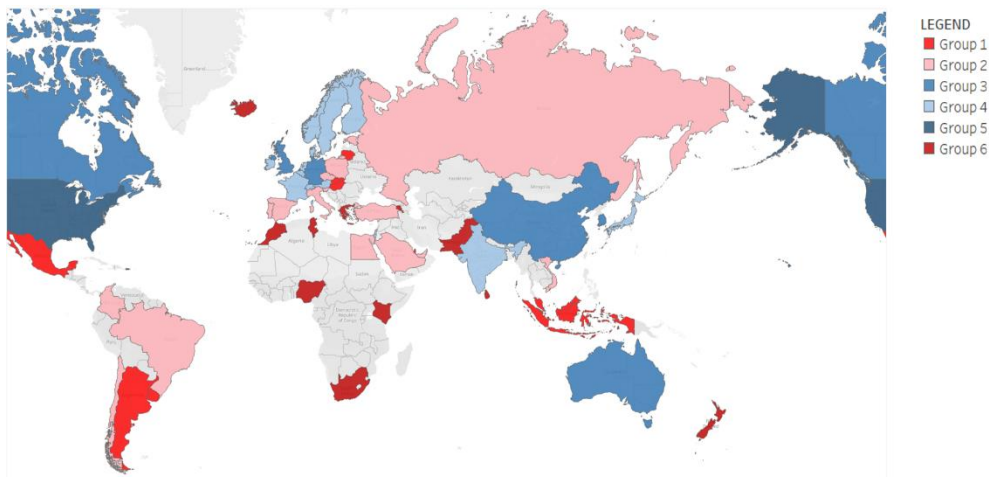


Figure no. 2. Distribution of the clusters in relation to the components of AI development

The items to which we referred in the cluster analysis were volume indices, so obviously, the highest values are possible in states that are both highly populated and economically

developed. However, an evaluation of the intensity of the phenomenon, namely the intensity of AI (variable IA_INTENS), which also takes into account the country’s population, is of interest. In this indicator, the ranking is dominated by less populated but developed countries, which generally move quickly and efficiently in adopting innovative technologies (Singapore, Israel, Switzerland, and Finland). The geographic distribution of countries for which data is available is shown in figure no. 3. The countries were divided into four groups in relation to quartile values, with the colour intensity associated with high values of the indicator (IA_INTENS). If we no longer talk about the volume of AI-related activities but focus on intensity, which considers the country's population, we observe that smaller-population countries (though all economically developed) appear at the top of the rankings. These countries manage to overcome the drawback of a critical mass of users through flexibility and adaptability to innovative technologies. Notable in this regard are Singapore, Ireland, Switzerland, Sweden, Finland, and South Korea. The strong correlation between economic development and AI is not a significant surprise (Pearson correlation coefficient of 0.77 between IA_INTENS and LnGDPCAP). The result is, of course, explainable by the fact that both appropriate technical means (computers, the high-speed Internet) and a highly skilled workforce are required. Moreover, in many cases, developed countries also have stable and efficient governance, making policies related to AI well-managed. In the literature, there are some studies (Makridis and Mishra, 2022; Smart et al., 2023) that assess the development of AI in certain countries, but without proposing classifications or behavioural groupings.

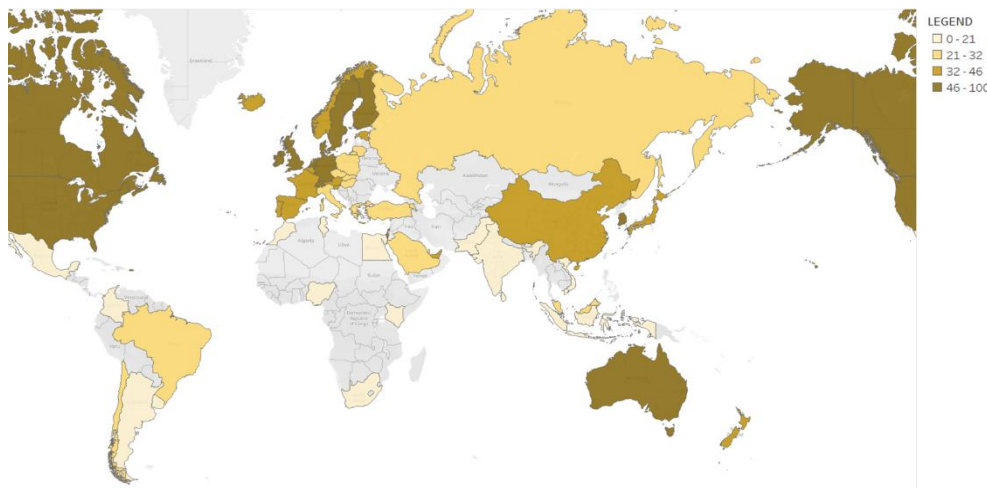


Figure no. 3. Geographical distribution of the intensity of AI activities

It is interesting to observe associations between national cultural behaviours and the adoption of AI. Beyond governmental policies, the use of AI must align with the behaviour of individuals within a society. At the macro-cultural level, there can be significant differences even among countries with the same level of economic development, similar historical backgrounds, and geographical proximity. The simple observation of cultural values can only lead to some hypotheses of a behavioural nature. Cultural factors may be correlated with economic development, and their visualisation effect from clustering can be misleading. Therefore, we can estimate the effect of culture on AI adoption only through regressions, in the presence of economic variables as control factors. Some variables used in our study

exhibit strong positive asymmetries, generating nonlinear connections with other variables. To eliminate this inconvenience, some variables will be used in their logarithmic form.

In table no. 3, the results of the OLS regressions (Models 1-5) are presented, including only the economic determinants of AI usage intensity. The models are constructed successively using backward stepwise regression. The purpose of this method is to gradually eliminate independent variables with the smallest impact or those that are not significant for the regression model. This technique can help simplify the model and eliminate redundant or insignificant variables. Ultimately, in Model 5, four socioeconomic determinants (GDPCAP, GDP_GROWTH, R&D_GDP, and URBAN) remain, which are significant both when introduced individually into regressions and collectively with others. Some variables (POPULATION, LABOUR) have no impact on AI development, while others have a redundant effect. When introduced individually, they may appear statistically significant, but not in the presence of others. For example, education funding (EDUC_GDP) and high-tech product exports (HIGH_TECH) are influenced by the country's economic development, already captured as an effect by other variables. The redundant effect is supported by the evolution of R², which changes insignificantly with the successive elimination of four explanatory variables. The statistically positive effects of both per capita GDP (GDPCAP) and the average percentage growth over the last 10 years (GDP_GROWTH) align with empirical observations (or theoretical arguments, not highlighted econometrically; see Makridis and Mishra (2022)). Countries with high values for both variables (for example, Ireland, with \$72,816 per capita and an average growth of 7.23%) are driven to develop AI. Conversely, countries excelling in only one of the two indicators (for example, Vietnam, with an average growth of 5.02% but a per capita GDP of only \$3,066, or Qatar, with \$73,632 per capita but a negative average growth of -1.23%) do not perform well in AI usage intensity. A similar pattern can be observed for research and development expenditures. For instance, Switzerland (with \$86,288 and 3.05% of GDP for R&D) tops the ranking in AI technologies. On the other hand, countries with high economic development but little focus on funding such activities (Qatar with \$73,632 and 0.55% of GDP for R&D) tend to have economic structures that do not favour AI development, occupying mediocre positions. At the bottom of the ranking are countries with poor performance in both indicators (Pakistan with \$1,383 and 0.22%, or Kenya with \$1,710 and 0.20%). It is noteworthy that some countries manage to achieve median positions in AI intensity, despite having a modest per capita GDP but investing more generously in research and development (China with \$9,244 and 2.11% for R&D). The results are consistent with the literature that theoretically investigates the positive connection between R&D funding and AI development (Smart et al., 2023).

Specific examples can also be cited to support the identified econometric effects of urbanisation. The top of AI intensity is dominated by countries with high values for both per capita GDP and urbanisation rates (Singapore with \$63,499 and 100% urbanisation, Luxembourg with \$11,874 and 90.7%, or Denmark with \$60,443 and 87.8%). Conversely, AI development is lower when economic development is accompanied by lower urbanisation (Austria, with \$49,466 and 58.1%). Clearly, urbanisation alone cannot drive AI if not accompanied by a consistent economic capacity, with such countries ranking lower in AI intensity (Uruguay, with \$17,876, despite having 95.2% urbanisation). Obviously, the weakest positions are held by states that are both economically less developed and have a very substantial rural component (Kenya with \$1,710 and 26.6%, or Sri Lanka with \$3,919 and 18.5%). The effects of urbanisation have been studied by Lambert et al. (2015) but without econometric validation.

Overall, to achieve high positions in AI, several socioeconomic conditions must be accumulated. Economic development alone is not sufficient if it is not accompanied by a consistent upward trend. Additionally, motivation is needed for economic opportunities to manifest in AI development: support for research and development through significant proportions of GDP funding. Moreover, it seems that the achievement of a critical mass, as in the case of other innovative technologies, is given serious impetus by the high urbanisation. We have identified some very significant socioeconomic determinants of AI development, validating hypothesis H2.

Table no. 3. The effects of socioeconomic factors on the intensity of the use of artificial intelligence (dependent variable: AI_INTENS)

	Model 1	Model 2	Model 3	Model 4	Model 5
(ln) GDPCAP	***0.248 (4.76)	***0.250 (5.23)	***0.237 (6.15)	***0.235 (6.08)	***0.245 (6.40)
(ln) GDP_GROWTH	***0.283 (3.49)	***0.283 (3.06)	***0.271 (3.08)	***0.323 (4.14)	***0.346 (4.54)
EDUC_GDP	-0.026 (-1.06)	-0.027 (-1.12)	-0.301 (-1.37)	-0.029 (-1.29)	
(ln) HIGH_TECH	0.044 (1.10)	0.045 (1.17)	0.047 (1.25)		
(ln) R&D_GDP	***0.485 (4.62)	***0.484 (4.70)	***0.505 (5.57)	***0.542 (6.27)	***0.495 (6.28)
URBAN	*0.003 (1.63)	*0.003 (1.66)	*0.003 (1.69)	**0.004 (2.20)	**0.004 (2.03)
(ln) POPULATION	0.008 (0.46)	0.008 (0.46)			
LABOUR	0.0004 (0.10)				
Constant	-0.209 (-0.31)	-0.206 (-0.30)	0.061 (0.18)	0.021 (0.06)	-0.162 (-0.53)
R ²	0.901	0.901	0.900	0.897	0.894

Notes: ***, **, * : significant at 1%, 5% and 10%. Coefficients and t-stat in parentheses.

The results of regressions that include socioeconomic factors are consistent, explaining a very large proportion (R2 around 0.9) of AI intensity. However, the question arises as to whether national cultural characteristics also contribute to explaining this phenomenon. In table no. 4, we have added simultaneously and successively five out of the six macro-cultural indicators of Hofstede (those for which there is theoretical support or logical explanations of connections with AI) in regressions (Models 6-11). We have also retained in the regressions, as control variables, the socio-demographic variables previously identified as statistically significant. The results are interesting, with only the uncertainty avoidance indicator being statistically significant. Although theoretically, the other variables have a logic of interaction with AI development, their significance cannot be demonstrated. There are several possible explanations for this. Firstly, there is a limitation imposed by the relatively small database, with 60 countries, which significantly reduces statistical significance. Secondly, cultural indicators may be correlated with socioeconomic ones, and the latter being highly significant greatly reduces the demonstrable effect of the former. Thirdly, AI development is still in its early stages. Its prevalence in the general population is extremely low in most countries. In practice, a small portion of the population is in contact with these technologies. Moreover, these relatively few individuals may, for example, be employees of large multinational

corporations. They may have diverse citizenships, so they do not necessarily fit into national cultural patterns. However, in the future, when the spread of AI technologies is more widespread in the population (as was the case with the use of computers or the Internet), the effects of cultural factors could be much more significant.

Table no. 4. The effects of cultural factors on the intensity of AI use under the control of socioeconomic factors (dependent variable: AI_INTENS)

	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
(ln) GDPCAP	***0.252 (5.48)	***0.241 (6.05)	***0.272 (6.13)	***0.244 (6.34)	***0.229 (6.07)	***0.244 (6.26)
(ln) GDP_GROWTH	***0.306 (3.65)	***0.347 (4.51)	***0.338 (4.27)	***0.345 (4.48)	***0.321 (4.28)	***0.340 (4.14)
(ln) R&D_GDP	***0.508 (5.25)	***0.488 (5.84)	***0.526 (6.42)	***0.495 (6.23)	***0.494 (6.46)	***0.508 (5.25)
URBAN	**0.004 (2.13)	**0.004 (1.98)	*0.003 (1.73)	*0.004 (1.90)	**0.005 (2.13)	*0.004 (1.91)
PWR_DIST	-0.001 (-0.52)	-0.0004 (-0.30)				
INDIVID	-0.002 (-1.32)		-0.002 (-1.37)			
MOTIVATION	-0.001 (-0.45)			-0.0004 (-0.41)		
UNCERT_AV	** -0.002 (-1.96)				** -0.003 (-2.12)	
LNGTOR	0.0002 (0.13)					0.0003 (0.21)
Constant	-0.075 (0.19)	-0.108 (-0.30)	-0.310 (-0.88)	-0.131 (-0.41)	0.099 (0.31)	-0.149 (-0.47)
R ²	0.899	0.894	0.889	0.897	0.992	0.894

Notes: ***, **, * : significant at 1%, 5% and 10%. Coefficients and t-stat in parentheses.

To ensure greater confidence in the lack of significance of the impact of cultural factors on AI, we examine, for the robustness of the results, whether the reduction in effect is not due to multicollinearity with socioeconomic variables. Instead of the four significant socioeconomic variables (GDPCAP, GDP_GROWTH, R&D_GDP, and URBAN), we constructed a single variable named SOCIO_ECON. This is an average of the four initial variables, each calibrated previously for possible values from 0 to 100. The regression results with cultural factors under the control of the SOCIO_ECON variable are presented in Table no. 5. The results of the new regressions are not significantly different from the previous ones. The SOCIO_ECON factor is highly significant (with a t-statistic higher than for the individual factors), as expected, as it encompasses development and economic growth, the orientation of the economy towards R&D funding, and urbanisation. Among the cultural factors, only uncertainty avoidance (UNCERT_AV) remains a significant factor. The econometric results obtained are consistent with the reasoning provided by (Kim and Kim, 2021). However, arguments linking AI development to power distance (Hossain and Lee, 2023), individualism (Chi et al., 2022), or long-term orientation (Jakšič and Marinč, 2019) could not be validated. Overall, across cultural factors, they are not statistically significant, invalidating hypothesis H3. These cultural factors may possibly manifest more significantly when AI technologies become more widely spread within the population.

Table no. 5. The effects of cultural factors on the intensity of AI use under the control of the SOCIO_ECON variable (dependent variable: AI_INTENS)

	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17
SOCIO_ECON	***0.023 (8.92)	***0.024 (14.1)	***0.025 (11.1)	***0.026 (17.4)	***0.026 (17.6)	***0.025 (12.7)
PWR_DIST	-0.002 (-1.17)	-0.002 (-1.58)				
INDIVID	0.001 (0.47)		0.001 (0.92)			
MOTIVATION	0.001 (0.74)			0.001 (0.48)		
UNCERT_AV	-0.002 (-1.22)				** -0.002 (-1.99)	
LNGTOR	0.001 (0.73)					0.001 (0.86)
Constant	***2.340 (11.89)	***2.328 (15.1)	***2.110 (24.7)	***2.083 (19.0)	***2.240 (19.5)	***2.108 (26.1)
R ²	0.846	0.849	0.832	0.843	0.848	0.845

Noets: ***, **, * : significant at 1%, 5% and 10%. Coefficients and t-stat in parentheses.

Conclusion

The issue of AI is more recent in the specialised literature, but it has experienced explosive growth in recent years, and the addressed topics are highly diverse. While most focus on the technical aspects of these technologies, economic considerations are becoming increasingly prevalent. Among these, the most common pertain to the economic, financial, and labour market consequences associated with the use of these innovative technologies. However, our study takes a different perspective, approaching AI as an outcome rather than a factor.

In this study, we have identified four socioeconomic determinants that significantly influence the development of AI: per capita gross domestic product (GDP), its growth rate, R&D funding, and the degree of urbanisation. Of the cultural variables, only uncertainty avoidance has emerged as statistically significant. We approach this result with caution, as causal relationships may change in the future. Currently, small proportions of each country's population operate with AI-associated technologies. Over time, these proportions will increase, bringing about a greater impact of cultural determinants, both on the level and structure of AI activities. Our research has identified six distinct national behaviours regarding the prioritisation of certain aspects of AI: skilled users, technical capabilities, regulations, societal support, academic endorsement, algorithms, and platforms, and support from public authorities and private economic initiatives.

The primary limitation of this study is the insufficient data, available for only 60 countries worldwide. We anticipate that this issue will be addressed in the future, given the increasing importance of these technologies. The nature of the data also prevents us from dynamically assessing the effects of cultural factors, since they are available only as static national values, not as time series.

Future research prospects could expand significantly with a wider range of available data. Panel data could allow the study of the effects of all determinants not only cross-sectionally, from one country to another, but also temporally, examining dynamic evolution. It would

also be worthwhile to consistently track existing differentiations between factors that influence different AI activities.

Identifying the economic and cultural determinants of AI development can have major effects on regulatory policies. Particularly, understanding the economic factors influencing AI development helps public authorities create policies that stimulate innovation in these new technologies, thereby contributing to economic growth and global competitiveness. Awareness of cultural factors is useful in crafting policies aimed at ensuring fairness in access to and benefits provided by AI. An awareness of the entire complex of factors can guide the regulation of AI by addressing risks and social impact, prioritising responsible development and ethical principles. Policies should also support the development of necessary human skills by incorporating technological education and adaptability into educational programs, ensuring a workforce prepared for the inherent changes brought about by the adoption of these technologies. From a broader perspective, the identification of determinants facilitates international collaboration, promoting common standards, and avoiding insurmountable inequalities in the adoption and development of AI technologies. As a corollary, analysing determinants contributes to the formulation of appropriate policies, encouraging equitable innovation, responsible regulation, and sustainable development in this technological field.

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