

Iamandi, Irina-Eugenia; Constantin, Laura-Gabriela; Munteanu, Sebastian Mădălin;
Cernat-Gruici, Bogdan

Article

Insights on the relationship between artificial intelligence skills and national culture

Amfiteatru Economic

Provided in Cooperation with:

The Bucharest University of Economic Studies

Suggested Citation: Iamandi, Irina-Eugenia; Constantin, Laura-Gabriela; Munteanu, Sebastian Mădălin; Cernat-Gruici, Bogdan (2024) : Insights on the relationship between artificial intelligence skills and national culture, Amfiteatru Economic, ISSN 2247-9104, The Bucharest University of Economic Studies, Bucharest, Vol. 26, Iss. 67, pp. 741-761,
<https://doi.org/10.24818/EA/2024/67/741>

This Version is available at:

<https://hdl.handle.net/10419/306181>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by/4.0/>

INSIGHTS ON THE RELATIONSHIP BETWEEN ARTIFICIAL INTELLIGENCE SKILLS AND NATIONAL CULTURE

Irina-Eugenia Iamandi^{1*}, Laura-Gabriela Constantin²,
Sebastian Mădălin Munteanu³ and Bogdan Cernat-Gruici⁴
¹⁾²⁾³⁾⁴⁾ Bucharest University of Economic Studies, Romania

Please cite this article as:	Article History
Iamandi, I.E., Constantin, L.G., Munteanu, S.M. and Cernat-Gruici, B., 2024. Insights on the Relationship Between Artificial Intelligence Skills and National Culture. <i>Amfiteatru Economic</i> , 26(67), pp. 741-761.	Received: 30 March 2024 Revised: 20 May 2024 Accepted: 19 June 2024
DOI: https://doi.org/10.24818/EA/2024/67/741	

Abstract

In order to fully benefit from the advantages induced by artificial intelligence (AI) at the corporate level, business organisations should be well aware of the factors contributing to the proper AI specialisation of their employees. In this context, the present paper aims to examine the role of national culture in supporting the distribution of AI skills and jobs across countries, starting from the theoretical and applied need of carrying out such a study. The investigation is developed by using Hofstede's model of the six dimensions of national culture and it focusses on a global sample of 44 leading countries regarding their AI talent concentration. For the fulfilment of the assumed objective, multiple linear regression models, accompanied by robust regression and enhanced by beta regression with novel robust estimators, were employed. The achieved results reflect the existence of a connection between national culture and AI skills development across the explored countries. More specifically, the outcomes exhibit the prevalence of a negative, statistically significant, relationship between individualism and AI talent concentration, and a positive, significant connection between long-term orientation and AI skills and jobs concentration. The results are relevant for organisations and managers aiming to support the development of AI skills of their employees by nurturing free communication, group collaboration, teamwork, peer learning, and forward-looking strategic education programmes for adjustment to AI.

Keywords: artificial intelligence (AI), AI skills, national culture, Hofstede, organisational competitiveness, OLS multiple regression, robust regression models

JEL Classification: J24, M50, M10, O33

* Corresponding author, Irina-Eugenia Iamandi – e-mail: irina.iamandi@rei.ase.ro



This is an Open Access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. © 2024 The Author(s).

Introduction

In recent years, the exponential growth of Artificial Intelligence (AI) and its thorough penetration in all spheres of human life generates profound socioeconomic shifts. Since the COVID-19 pandemic accelerated the pace of digitalisation (Wiley, 2021; CEDEFOP, 2023), individuals and organisations all over the world are aware of the importance to be prepared for the AI transformation. AI is deeply changing the way organisations operate.

The generally recognised benefits of AI implementation in organisations refer to: faster, efficient and more comprehensive decision-making process, increased efficiency and better use of resources, cost savings, higher labour productivity, improved customer experience, higher opportunities to innovate, supporting ESG initiatives, etc. (Artificial Intelligence Skills Alliance (ARISA), 2023; Dickens, Krenz and O'Reilly, 2023). At the national level, economic growth, improved efficiency, and competitiveness may be emphasised. Ethical, responsible, trustworthy, and transparent use of AI are some of the key demands stated in programmatic documents and scientific literature (ARISA, 2023; Dickens, Krenz and O'Reilly, 2023). Furthermore, the risks related to new technologies, in general, and AI, in particular, raise global concerns (Tortoise Media, 2023a).

One of the most significant challenges related to AI in organisations occurs in the human resources area and it refers to AI two-fold debated potential: on the one hand, to reduce jobs by replacing the human factor and, on the other hand, to create jobs and/or increase the efficiency of the human factor and the labour productivity (Dickens, Krenz and O'Reilly, 2023; WEF, 2023) if AI-based solutions and technologies are properly used by skilled staff. The World Economic Forum (WEF, 2023) found a net positive impact of AI on job creation in the near future, CEDEFOP (2023) mentions an organic complementarity between the human factor and AI, and Giraud et al. (2023) show that most of the managerial skills are expected to be enhanced by AI. As a result, the organisational performances are altered by staff abilities to quickly adapt to the new technological context and to reskill for economic adjustment. The current competitiveness of business organisations in an AI-driven economy highly depends on the skills and competencies of the personnel that should be able to use and integrate AI solutions and technologies in their present and future activities, no matter the business sector or division they are working in. At regional and country level, citing an IBM study from 2022, ARISA (2023) highlights that AI deployment rate in Europe and the USA is lower than in China or India, where almost 60% of the organisations have already succeeded in employing AI in an active manner in their current activities.

Today, it is widely accepted that having employees with AI skills is among top interests of business organisations worldwide when it comes to talent attraction and development. Furthermore, intuitively, skills, in general, and AI skills, in particular, are built and progress in human behaviour. It is the human behaviour that channels, through intricate capillaries, the general mindset of the national culture into the staff's professional development choices, and, eventually, into companies' structures and processes. Therefore, companies, in general, and especially those that act in a multinational and multicultural setting, should be deeply aware that AI talent varies across national cultures and adjust their human resources (HR) policies accordingly. Thus, the importance of national culture for shaping the AI competence profiles becomes a topic of interest in theoretical and practical terms, which can support organisational and national competitiveness.

However, as far as the authors know, there is a gap in a literature regarding the thorough investigation of the role that different cultural perspectives have on the distribution of AI

skills and competencies at a global level. Therefore, the present research contributes to filling this gap by examining the impact of Hofstede's cultural dimensions (Hofstede Insights. The Culture Factor Group, 2024a) on the concentration of AI talent at the international level.

Different arguments underline both the originality and the pragmatism of this research. First, the analysis is innovative, because this is the first study that fills a gap by exploring in detail the relationship between national culture and AI talent, as far as the authors are acquainted with; the AI talent is analysed in a cross-cultural context through the widely used lenses of Hofstede's national culture scores (Hofstede Insights. The Culture Factor Group, 2024b) that stands for a top method of studying international business-related facets. Secondly, the developed econometric research is among the first studies to extend the purely descriptive line of reasoning and employ quantified information to econometrically model the very novel phenomena of AI skills. Third, the analysis is business oriented, being innovative from the perspective of studying national concentration of AI skills and jobs across countries, but pertaining to the robust, long-standing mainstream literature that thoroughly approaches business and organisational phenomena with direct impact on the sustainable competitiveness of the companies. Fourth, the high representativeness of the study at the international level is based on highlighting how cultural differences influence the national concentration of AI talent for a select sample of countries, situated among the leaders for this specific metric. Finally, the pragmatic approach of this research derives from the added value of the achieved results and goes beyond the merely identification of the relationships between variables, as they can support (international) managers to adapt to the various challenges posed by the current quest for AI talent in a multicultural context.

The structure of the paper is briefly highlighted below. Section 1 presents the review of the scientific literature by focussing on the search of business organisations to have employees with AI skills and competencies, the role that national culture plays among other factors in supporting the achievement of these skills, and the development of hypotheses regarding the influence of culture on AI skills and competencies. Section 2 is dedicated to the research methodology and it outlines the sample, the variables, and the models that were developed in order to achieve the assumed research objective. Section 3 deals with the results of the identified relationships between national culture and AI skills, as well as their interpretation. Finally, the paper ends with a set of conclusions that pragmatically reflect the main findings of the research and their applicability.

1. Review of the scientific literature

1.1. Need for employees with AI skills and competencies

In order to benefit from the opportunities induced by AI at the organisational and national level and mainly related to higher productivity, efficiency, and competitiveness (CEDEFOP, 2023), the public and private actors – especially business organisations – should be aware of the necessity to have properly AI trained staff and, as a consequence, to invest in AI skills (Dalla Benetta, Sobolewski and Nepelski, 2021). The adequate acquiring of AI skills and competencies of the workforce entails a strategic vision on the long run, equally considering the specific requirements of the various economic sectors as well as the evolutive adaptation of the AI skills to a highly dynamic market (ARISA, 2023). In line with the digital skills gap previously identified (e.g., Wiley, 2021; CEDEFOP, 2023), the skills gap between the AI skills supply of the workforce and the AI skills demand of the organisations is considered to be the main obstacle

hindering the appropriate implementation of AI (ARISA, 2023) and obstructing its advantages at organisational level. The organisational change induced by AI should also be accompanied by the human skills related to context understanding (Sanders and Wood, 2023).

The European Commission (EC-DG Connect, 2020) identified the internal obstacles in enterprises and, more specifically, the AI skills needs as the most critical barrier that organisations face when it comes about the AI adoption in Europe. The AI skills barrier is reflected in the lack of AI skills of the current staff or difficulties in hiring new staff that already possesses the desired AI skills (EC-DG Connect, 2020). Moreover, the EC-DG Connect (2020) finds the AI skills barrier as highly severe, because all enterprises in one country are affected by the skills shortages in that national labour market.

In the context of acknowledging the importance of developing and deploying AI skills and competencies of the workforce that are in line with current and future needs, the Artificial Intelligence Skills Alliance (ARISA, 2023) proposes a detailed “Strategic Planning for Developing AI Skills in Europe”. The objectives of the strategy generally envisage the identification of AI skills requirements, the design of educational and training contexts for AI skills learning, and the consolidation of an all-inclusive environment for AI skills development, while engaging policymakers, public institutions, educational institutions, business organisations, and stakeholders altogether (ARISA, 2023).

1.2. Main types of AI skills and competencies

Generally, the AI-related skills and competencies of staff reflect both the technical perspective (e.g., data science, programming languages, neural networks, machine learning, mathematics, statistics, project management), as well as the soft component (e.g., communication, teamwork, conflict resolution, time management, critical thinking) and the transversal requisites (e.g., ethical reasoning, security, laws, and regulations).

According to a broad investigation developed by OECD.AI (2024a) at global level based on self-reported information provided by LinkedIn members in their profiles, the top 20 most frequent AI skills from 2015 to 2022 are depicted in the following order: Machine Learning (ML); Artificial Intelligence (AI); Data Structures; Deep Learning; Pandas; Natural Language Processing (NLP); Computer Vision; TensorFlow; Image Processing; Scikit-Learn; PyTorch; Neural Networks; Keras; OpenCV; Artificial Neural Networks (ANN); Pattern Recognition; Convolutional Neural Networks (CNN); Reinforcement Learning; MS Azure ML; Information Retrieval. The main AI skills subcategories emphasised by OECD.AI (2024a) on the labour demand side are AI software development, AI research and methodology, ML tools, AI data management, and AI web development.

1.3. Factors influencing the acquisition of AI skills and competencies

A series of factors may influence the acquisition of AI skills and competencies of the staff, and they could be divided into two groups: AI directly related factors and auxiliary factors for supporting AI at country level. The general development of AI at national level, investments in AI and/or forms of digitalisation, support for AI academic education and training programmes, AI strategy and awareness, visible and accessible AI initiatives for the general public, mitigating the risk of losing jobs due to AI emergence, etc. (Dalla Benetta, Sobolewski and Nepelski, 2021; ARISA, 2023; Dickens, Krenz and O'Reilly, 2023; Tortoise

Media, 2023b; WEF, 2023) are listed in the first category. The second class comprises support factors at country-level that may be seen as a prerequisite of acquiring AI skills: traditional IT graduates and ICT skills, digital skills, technological development, research and development (R&D) expenditures, strengthening of Science, Technology, Engineering and Mathematics (STEM) education and research, social and cultural contexts, etc. (Wiley, 2021; ARISA, 2023; Dickens, Krenz and O'Reilly, 2023; Giraud et al., 2023; Tortoise Media, 2023b; WEF, 2023).

An international comparison between countries in terms of their endowment with AI skills or talent becomes relevant in the context of existing differences between countries. For example, considering the information provided by LinkedIn members on their profiles regarding the AI skills they have and/or the AI jobs they hold (summing up the AI talent), OECD.AI (2024b) reveals the AI talent concentration for 45 countries, with the top 10 countries for 2022 listed in the following order: India, South Korea, Israel, Japan, Germany, Switzerland, Greece, Bulgaria, Türkiye, and Canada. Tortoise Media (2023a, b) develops its Global AI Index (GAI) that comprehensively measures the AI development in 62 countries and it also encompasses the AI Talent component. The ranking of countries according to AI Talent 2023 is led by the USA, India, Germany, Singapore, UK, Canada, Israel, Netherlands, Switzerland, and France (in this order) (Tortoise Media, 2023a, b).

As previously stated, the AI skills gap between staff demand and supply leads to a higher appreciation of AI-skilled employees and a competitive and sustainable advantage for their employers. Business organisations around the world try to identify the main factors that contribute to attraction and development of AI talent and, in this respect, national culture is an important driver to be considered.

1.4. Role of culture in supporting the achievement of AI skills and competencies

The various dimensions of national culture act as predictors or moderators for different perspectives of technology acceptance (Jan, Alshare and Lane, 2022). Nowadays, when technologies are changing and staff skills should be updated at a rate never seen before, the importance of the complex role that culture plays in influencing technology-related issues should be explored and understood in detail in order to be able to identify socially acceptable and economic efficient solutions for individuals across countries.

Considering the previous background, the influence of national culture in shaping different facets of AI development and deployment begins to receive attention in the literature (Eitle and Buxmann, 2020; Zolduoarrati, Licorish and Stanger, 2022; Giraud et al., 2023; Lerma, Kwarteng and Pílik, 2023). Both quantitative and qualitative studies were conducted to study the link between culture and AI. For instance, the individualism vs. collectivism cultural dimension influences the behaviour of software developers (Zolduoarrati, Licorish and Stanger, 2022), the risk aversion of national or regional cultures affects the successful implementation of AI by managers (Giraud et al., 2023), the personal cultural orientations influence the adoption of AI in SMEs (Lerma, Kwarteng and Pílik, 2023), and the cultural characteristics impact the machine learning adoption (Eitle and Buxmann, 2020).

Nevertheless, a comprehensive investigation regarding the impact of different cultural perspectives on the distribution of AI skills and competences at the global level is missing. Hence, as already asserted, the assumed research objective of the present study is to

investigate the role of national culture in developing AI talent across countries. This goal is considered from a pragmatic perspective in order to highlight a set of desired behaviours for managers and organisations that aim to support the growth of AI skills for their staff.

One of the most famous definitions and research of culture belongs to Geert Hofstede. Hofstede, Hofstede and Minkov (2010, p. 6) define culture as “the collective programming of the mind” specific to a society/nation. They identified six dimensions of national culture that were extensively used in several economic and social studies during the years: power distance, individualism vs. collectivism, masculinity vs. femininity, uncertainty avoidance, long-term orientation vs. short-term orientation, and indulgence vs. restraint (Hofstede, Hofstede and Minkov, 2010; Hofstede Insights. The Culture Factor Group, 2024a).

1.5. Development of hypotheses regarding the influence of culture on AI skills

In the formulation of the following research hypotheses on the influence of culture on AI skills, two relevant premises related to these skills were considered: a) similar research was not conducted in the literature; b) although related to technology/ICT (ICT skills) and digitalisation (digital skills), the AI skills are more than an extrapolation of these concepts and present their particular features.

Power distance (PDI) reflects the society’s way of dealing with inequalities between individuals and accepting authority, and it can be high power distance or low power distance. Focus on hierarchical order, centralisation, dependence of subordinates on superiors, and emotional relations are specific to high-power distance cultures. In contrast, focus on equalisation of power, decentralisation, interdependence-consultation between superiors and subordinates, and pragmatic relations are characteristics of low-power distance cultures (Hofstede, Hofstede and Minkov, 2010; Hofstede Insights. The Culture Factor Group, 2024a). A negative association between PDI and ICT adoption was found by Erumban and de Jong (2006) in a cross-country study, in support of earlier findings showing that a high level of PDI inhibits new ideas and innovation, while the autonomy given to employees in low PDI countries supports innovation.

When it comes to the endowment with AI skills of the workforce in a country, the question of preferential or equal access to this type of skills is of interest. In this regard, derived from the information presented in Hofstede, Hofstede and Minkov (2010), the low PDI countries put emphasis on the need for minimising the inequalities between individuals, the tendency to adapt to the new technological requirements of the society, and the focus on expertise and peer-learning. As a result, it may be assumed that there is a higher concern for AI skills in lower PDI countries due to their aim of having a broad distribution of AI talent in the society, with a large number of employees having AI skills. Individuals from low PDI cultures easily collaborate and share knowledge, which is an essential prerequisite of acquiring and improving AI skills. Therefore, the following hypothesis is formulated:

H1. Countries with a lower PDI culture have a higher level of AI skills than countries with a higher PDI.

Individualism (IDV) refers to the type of connections between individuals within the society, and the two poles of this dimension are individualism and collectivism. Weak ties between people, personal interest, individual freedom, individual work, and performance are some of the particularities of individualistic cultures. On the contrary, strong ties between individuals,

group loyalty, equality, teamwork, and group performance describe the core of collectivistic cultures (Hofstede, Hofstede and Minkov, 2010; Hofstede Insights. The Culture Factor Group, 2024a). In an investigation developed for the EU countries, contrary to their initial expectations and various results in the previous literature (for instance, Erumban and de Jong, 2006), Rubino et al. (2020) found a negative relationship between IDV and the country level of firms' digitalisation, stressing the potential of collectivism in supporting technological change. Lai et al. (2016) identified a positive connection between collectivism and the use of technology, justified as a group pressure consequence and not due to individual inclinations to innovation. Acquiring new skills – like AI skills – is indeed part of the technological transformation at the individual, corporate, and national level.

Another issue that is relevant for an investigation of AI skills at country-level refers to individual or in-group acquisition of this type of skills. Some of the characteristics of collectivistic cultures presented by Hofstede, Hofstede and Minkov (2010) and highly relevant for the investigated topic are the following: the collective interests prevail over individual interests, the training opportunities are highly necessary for improving existing skills or acquiring new ones, the proper performance of the job implies the full use of work skills, and collaboration between individuals is essential. As a consequence, it could be expected that these collectivistic societies put a higher focus on the development of AI skills, reflecting their joint contribution to technological change, an assumption that is in accordance with the findings of Rubino et al. (2020). Furthermore, collectivism supports teamwork, which is fundamental to software development (Zolduoarrati, Licorish and Stanger, 2022), and the power of social networks (Hofstede, Hofstede and Minkov, 2010), making it more feasible for AI skills and competencies to be 'copied'/replicated and distributed in societies where individuals are very accustomed to collaborating and working together. For the purpose of the present research, the collaboration and positive communication or interaction (Zolduoarrati, Licorish and Stanger, 2022) between members of collectivistic societies are oriented towards the enhancement of group performances through training and use of AI skills. Therefore, the following hypothesis is formulated:

H2. Countries with a lower IDV culture have a higher level of AI skills than countries with a higher IDV.

Masculinity (MAS) – currently, Motivation towards Achievement and Success (MAS) – is defined based on the values associated with different roles, with masculinity or femininity guiding the emotional status of a society. The emphasis on assertiveness and material success, achievement and competition, equity rewards, and performance society briefly describe masculine cultures. On the opposite side, accent on tenderness and quality of life, relations and moderation, equality rewards, and welfare society illustrate the *feminine cultures* (Hofstede, Hofstede and Minkov, 2010; Hofstede Insights. The Culture Factor Group, 2024a). In this paper, "Masculinity vs. femininity" is used when referring to previous research in the literature, while "Motivation towards Achievement and Success" is employed when mentioning the outcomes of the current study. However, the interpretation and acronym (MAS) of the dimension remain the same, as stated by Hofstede Insights. The Culture Factor Group (2024a). When exploring machine learning adoption in two different cultural contexts (Germany and USA), Eitle and Buxmann (2020) found the contribution of MAS in supporting competitive advantages and talent acquisition in organisations.

From a cultural perspective, the analysis of AI skills at the national level should also reflect the emotional reasons involved in the process of skill acquisition. According to Hofstede, Hofstede and Minkov (2010), the masculine societies focus on achieving high earnings and recognition on the jobs, look for advancement or promotion opportunities, and work-related challenges in order to nurture personal accomplishment or satisfaction, while engineers and scientists are among the most masculine analysed jobs. All these attributes could indicate a higher predisposition of masculine cultures towards acquiring AI skills for ensuring innovation and competitiveness at work. Therefore, the following hypothesis is formulated:

H3. Countries with a higher MAS culture have a higher level of AI skills than countries with a lower MAS.

Uncertainty avoidance (UAI) considers the aversion to ambiguity and unfamiliar situations of a society, and it distinguishes between high uncertainty avoidance and low uncertainty avoidance. Uncertainty seen as a threat, the need for predictability, strict rules and regulations, and fewer job switches are some of the most relevant traits of high uncertainty avoidance cultures. Alternatively, uncertainty perceived as a normal fact, tolerance, relaxed attitude rather based on practice, and more job switches are particular to low uncertainty avoidance cultures (Hofstede, Hofstede and Minkov, 2010; Hofstede Insights. The Culture Factor Group, 2024a). The tendency towards digital capability of people and technology adoption are frequently associated in the literature with low UAI cultures (Erumban and de Jong, 2006; Eitle and Buxmann, 2020; Rubino et al., 2020; Li, Zhang and Limniou, 2023) that are more likely to accept new challenges and innovation in their everyday life, compared to high UAI cultures that are more reluctant to change and supplementary effort to adopt new skills and technologies (Li, Zhang and Limniou, 2023).

The analysis of AI skills at country-level should equally address the reluctance to change or risk aversion of the societies. Although initially resistant to change, the higher UAI cultures may be more eager to secure their jobs and learn new skills in a formalised way when they realise that possessing AI skills becomes compulsory for reducing the risk of losing jobs due to lack of proper technological abilities. The behaviour of adopting AI skills of nations with higher levels of UAI may be supported by the following characteristics emphasised by Hofstede, Hofstede and Minkov (2010): individuals feel uncomfortable with unknown risks; formal education, structured learning situations, experts, and technical solutions are praised; there is the emotional need to stay busy and work hard. As a result, individuals from high UAI cultures could try to minimise the technological risks associated with AI by acquiring new skills in structured learning environments, while constantly struggling to secure their skills profile. Therefore, the following hypothesis is formulated:

H4. Countries with a higher UAI culture have a higher level of AI skills than countries with a lower UAI.

Long-term orientation (LTO) deals with the nurturing of virtues from a time perspective, opposing long-term orientation to short-term orientation. Future rewards, perseverance, moderation, pragmatism, support for skills, and modern education are specific to long-term oriented cultures. Conversely, present rewards, respect for traditions and norms, social duties, and personal stability define the short-term oriented cultures (Hofstede, Hofstede and Minkov, 2010; Hofstede Insights. The Culture Factor Group, 2024a). Lai et al. (2016) examined the influence of cultural values on technology adoption and brought evidence on the positive effect of LTO and collectivism on the use of technology for self-directed learning

of languages outside the classroom. Their findings underline that LTO could generally have a major impact on informal learning through technology use, especially considering its tacit outcomes that could be higher valued by forward-thinking individuals.

The time reference for AI skills is an issue that should be examined across countries from a strategic point of view. Some of the features of long-term oriented cultures depicted by Hofstede, Hofstede and Minkov (2010) reflect the investment in modern education and knowledge (these societies have talents and better results in mathematics and applied sciences) as a solution to persistently prepare for the future, learning from others, and patiently striving for personal adaptation in order to reduce wide economic and social differences. Considering the previous arguments, the long-term oriented cultures could show more interest in acquiring AI skills for the broad population in the long run. The association between LTO and the adoption of AI skills reflects the inner need of these societies to be well-prepared and trained for the coming technological future. These postulations are in line with the outcomes of Eitle and Buxmann (2020) that identified a pragmatic and strategic approach of a long-term oriented culture when using ML applications in organisations. Therefore, the following hypothesis is formulated:

H5. Countries with a higher LTO culture have a higher level of AI skills than countries with a lower LTO.

Indulgence (IVR) emphasises the way of satisfying human needs, with indulgence and restraint situated at two opposite poles of the continuum. Free satisfaction of needs, control of personal life, permissive society, and positive emotions are representative of indulgent cultures. In opposition, repressed gratification of needs, lack of control, restrictive society, and negative emotions are specific for restrained cultures (Hofstede, Hofstede and Minkov, 2010; Hofstede Insights. The Culture Factor Group, 2024a). Rubino et al. (2020) proved that a higher level of IVR – related to creativity and innovation – positively influences the digitalisation of companies in the EU countries.

Concerning the AI skills at country level from the perspective of gratifying needs, it may be assumed that the individuals pertaining to indulgent societies put a higher focus on acquiring AI skills, by following their desires to have a good life under their control and without risking the present benefits (for example, the good jobs they currently hold). Individuals in indulgent societies can also invest in AI skills for career promotion or innovation fostering. Therefore, the following hypothesis is formulated:

H6. Countries with a higher IVR culture have a higher level of AI skills than countries with a lower IVR.

2. Research methodology

2.1. The overview of the methodological aspects

This research investigates the connection between national culture and AI talent concentration through multiple regression models within a cross-sectional national setting. Therefore, the purpose of the analysis is to determine the influence of Hofstede's six national cultural dimensions on a national AI talent concentration metric retrieved from OECD.AI (2024b). For the purpose of this research and according to the explanations of the data

provider (OECD.AI, 2024c), the AI talent refers to individuals reporting to have AI skills and/or jobs, while the AI talent concentration is reflected by the share of AI talent in the total number of members with LinkedIn accounts (OECD.AI, 2024c). Taking into account the available data, the present analysis includes countries with the highest values of AI skills and jobs concentration worldwide.

The choice of multiple regressions is based on two arguments: (1) the use of regression analysis in the literature to study the relationship between national culture and a variety of indicators reflecting socioeconomic phenomena (e.g., Vitolla et al., 2021); and (2) the nature of the variables used (the national culture does not change for relatively long periods of time, having predominantly the quality of an independent variable, while the AI skills are in the early stage of measurement, being treated like a dependent variable). The analysis considers the nature of the response variable (AI talent concentration) – a series of continuous data limited in the unit interval, and thus the following regression models are employed, which either include the dependent variable with a logit transformation (Model 1 and Model 2) or directly account for the nature of the dependent variable (Model 3).

Model 1 is a traditional OLS multiple regression model with the logit transformed dependent variable. The regression assumptions and challenging aspects were investigated through various procedures and tests, as specified in literature and established resources (Chen et al., 2003; Hair et al., 2009; Mooi, Sarstedt and Mooi-Reci, 2018), as follows: 1. presence of influential observations; 2. multicollinearity of independent variables; 3. model linearity; 4. model specification; 5. normality of residuals; 6. homogeneity of variance.

Model 2 is a robust regression model with iteratively reweighted least squares to account for the behaviour of the observations in terms of influence. This model also employs the logit transformed response variable.

Model 3 is a robust beta regression with logit link-function model using novel robust estimators (LMDPDE – logit minimum density power divergence estimator and LSMLE – logit surrogate maximum likelihood estimator), proposed by Maluf, Ferrari and Queiroz (2024). This model directly considers the nature of the response variable (Ferrari and Cribari-Neto, 2004; Cribari-Neto and Zeileis, 2010; Maluf, Ferrari and Queiroz, 2024), while accounting for outliers, performing well both in their presence and absence (Maluf, Ferrari and Queiroz, 2024). In detail, the model works by using a tuning constant α , which can be fixed or selected by a data-driven algorithm. The model with new estimators is also suitable for small samples, although in the presence of outliers and in favour of robustness gain, a slight rise in variability may appear, according to Maluf, Ferrari and Queiroz (2024).

The last two models are implemented to confirm the associations between national culture and AI skills and jobs that were previously revealed in the OLS regression model. The data investigation, the OLS multiple regression analysis, and the robust regression are performed in STATA, while the robust beta regression analysis is performed in R (R Core Team, 2023) following the novel approach proposed by Maluf, Ferrari and Queiroz (2022, 2024) and implemented also in Queiroz, Maluf and Ferrari (2022).

2.2. The sample

The initial sample consisted of the 45 countries for which AI talent concentration values were available on the OECD.AI database. The OECD.AI sample is a select one as only includes

countries fulfilling the following two conditions on the LinkedIn platform, according to the OECD.AI (2024c) criteria: at least 40% labour force coverage and at least 10 AI hires per month. These countries are Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Saudi Arabia, Slovakia, Slovenia, South Africa, Spain, Sweden, Switzerland, Turkey, United Kingdom, and United States of America.

While screening the dataset for outliers, leverage points and potential influential points (Field, 2018), the initial sample of 45 countries was diminished to 44 by excluding India. The incidence of the value for India as an outlier was also confirmed by conducting robust beta regression with the LMDPDE and LSMLE estimators, presented in Maluf, Ferrari and Queiroz (2024). For this full dataset, the algorithm selects a tuning constant (α) of 0.08 for both estimators, indicating that the analysis required a robust adjustment. After removing the outliers, the algorithm returned an $\alpha = 0$ (maximum likelihood estimator – MLE) for both robust estimators. This evidence was not surprising, given that a disclaimer exists on the website of the data provider about potentially biased AI talent coverage for India on the LinkedIn platform (OECD.AI, 2024c).

2.3. The variables

The dependent variable is the latest available value (2022) of the Artificial Intelligence Talent Concentration (AI talent) and was collected from the OECD.AI dedicated website (OECD.AI, 2024b). AI talent refers to any LinkedIn member that either self-reported AI skills or an AI job within their profile (OECD.AI, 2024c) and, therefore, reflects a broader spectrum of the AI talent at the national level. The national AI talent concentration metric is determined as a ratio between the counts of AI talent at the level of a certain country and the counts of LinkedIn members for that specific country (OECD.AI, 2024c). Besides its inherent shortages, mainly the self-reported character and the limitation to only one provider, this metric is nowadays a staple measure for quantifying national AI skills. For example, it is used in the Global AI Index from Tortoise Media (Tortoise Media, 2023b) or in the AI Index Annual Report by Stanford University (Maslej et al., 2023). AI talent enters the OLS regression and the robust regression as a logit transformed variable, and in the robust beta regression as concentrations (proportions).

The independent variables represent the national culture, and they are the scores reflecting the cultural dimensions of the Hofstede's model: Power Distance (PDI), Individualism vs. Collectivism (IDV), Motivation toward Achievement and Success / Masculinity vs. Femininity (MAS), Uncertainty Avoidance (UAI), Long-Term Orientation vs. Short-Term Orientation (LTO), and Indulgence vs. Restraint (IVR). The national scores were collected through the Country Comparison Tool from The Culture Factor Group (Hofstede Insights Ltd.). The most recent update of this data was performed in 2023 for the LTO and IVR (Hofstede Insights. The Culture Factor Group, 2024b). Considering the relatively immutable nature of the national culture and according to the research practice, the most recent available values of cultural dimensions were included in the analysis. As the value of the IVR for Israel is not available on Hofstede's website, it was determined and included in the analysis as an

average of the other scores for this dimension in the sample. The national culture variables enter the entire analysis scaled on the 0-1 interval.

The control variables reflect three national facets that, besides the cultural setting, are to be considered stimulants for AI skills development. The economic facet is represented by Research and Development (R&D) expenditure as percent of GDP (RD_GDP), and it was collected from The World Bank (2024) database. The social-educational driver is mirrored by the Percentage of graduates from Science, Technology, Engineering, and Mathematics (STEM) programmes in tertiary education (STEM) and it was collected from The UNESCO Institute for Statistics (UIS, 2024). The third control variable, the AI Enablers score (AIE), shows the governmental and public initiatives aimed at advancing the national AI environment, in general, and AI talent, in particular. The values for the AI Enablers score were specifically computed by the authors using qualitative information provided by OECD.AI (2021, updated until 2022), in order to reflect a variate perspective on different AI incentives for each investigated country. The control variables R&D as percent of GDP and STEM graduates are % and they were logit transformed for a potentially more accurate prediction and to account for a probably more linear relationship between the logit transformations of the dependent variable and these two control variables (Moore et al., 2007). The AI Enablers score enters the models as scaled on the 0-1 interval. The three control variables are expected to exhibit a positive relationship with the response variable.

The correlations and descriptive statistics of the variables are presented below (Table no. 1).

Table no. 1. Correlations, descriptive statistics, and VIFs

Variables	Altalent (logit)	PDI	IDV	MAS	UAI	LTO	IVR	RD_GDP (logit)	STEM (logit)	AIE
Altalent (logit)	1									
PDI	-0.29	1								
IDV	0.25	-0.55*	1							
MAS	0.15	0.16	-0.26	1						
UAI	0.14	0.52*	-0.26	0.16	1					
LTO	0.59*	-0.32*	0.57*	-0.05	-0.10	1				
IVR	-0.13	-0.40*	0.24	0.04	-0.38*	-0.14	1			
RD_GDP (logit)	0.65*	-0.56*	0.70*	-0.02	-0.13	0.66*	0.16	1		
STEM (logit)	0.41*	-0.13	0.22	-0.09	0.01	0.14	-0.18	0.28	1	
AIE	0.34*	-0.17	0.26	0.21	0.01	0.23	0.12	0.42*	-0.05	1
Mean	-4.14	0.50	0.62	0.48	0.68	0.50	0.49	-4.17	-1.19	0.28
SD	0.54	0.20	0.18	0.23	0.20	0.17	0.21	0.76	0.26	0.24
Max	-2.66	1.00	1.00	1.00	1.00	1.00	0.97	-2.83	-0.61	1.00
Min	-5.03	0.11	0.05	0.05	0.23	0.12	0.13	-5.88	-1.73	0.00
Skew.	0.90	0.18	-0.66	0.04	-0.35	0.28	-0.09	-0.56	-0.05	1.31
Kurt.	4.07	2.52	3.91	2.58	2.13	4.12	2.21	2.67	2.27	4.28
VIF	-	2.31	2.65	1.25	1.57	2.29	1.65	3.53	1.24	1.35

Notes: $n = 44$; † For the pairwise correlations * = significant at the 5% level.

The correlation analysis (Table no. 1) indicates that the dependent variable (AI talent) is significantly and positively correlated with LTO and the three control variables (RD_GDP, STEM and AIE). The AI Enablers score (AIE) is one of the main originality elements of the present study, and it mainly reflects the national AI actions directed toward the support of AI skills and education, labour market policies, public awareness and civic participation, access

to information and knowledge sharing, etc. (OECD.AI, 2021). The descriptive statistics expose that, on average, the 44 countries in the sample score higher on IDV and UAI in comparison with the other four national cultural dimensions. The variance inflation factor test confirms that there is no multicollinearity as the VIF values are lower than 5.

2.4. The models

The OLS regression model and the robust regression model follow the equation:

$$AI_{talent_logit_i} = \beta_0 + \beta_1 PDI_i + \beta_2 IDV_i + \beta_3 MAS_i + \beta_4 UAI_i + \beta_5 LTO_i + \beta_6 IVR_i + \beta_7 RD_GDP_logit_i + \beta_8 STEM_logit_i + \beta_9 AIE_i + \varepsilon_i \quad (1)$$

where:

AI_{talent_logit} – the logit transformation of the AI talent metric;

PDI , IDV , MAS , UAI , LTO , IVR – the Hofstede’s national culture scores;

RD_GDP_logit – the logit transformation of the R&D expenditure as percent of GDP;

$STEM_logit$ – the logit transformation of the percentage of graduates from STEM programmes in tertiary education;

AIE – the Artificial Intelligence Enablers score.

The beta regression model, also called a “double index regression model”, encompasses two elements of regression – for the mean and for the precision (Grün, Kosmidis and Zeileis, 2012). The robust beta regression model is a beta regression that uses robust estimators when the sample is potentially contaminated with outliers. For the current analysis, the robust beta regression model with the logit transformation consists of the mean equation of the beta regression, assumes constant precision, and employs LMDPDE and LSMLE estimators. These two new robust estimators, which perform well in the presence of outliers even for small samples, were developed by Maluf, Ferrari and Queiroz (2002, 2004). As stated, a constant precision sub-model was used for the robust beta regression model, and the following equation was employed for the mean sub-model:

$$\log(\mu_i/(1-\mu_i)) = \beta_0 + \beta_1 PDI_i + \beta_2 IDV_i + \beta_3 MAS_i + \beta_4 UAI_i + \beta_5 LTO_i + \beta_6 IVR_i + \beta_7 RD_GDP_logit_i + \beta_8 STEM_logit_i + \beta_9 AIE_i + \varepsilon_i \quad (2)$$

where:

μ – the mean of the beta probability distribution of the AI talent indicator.

The other variables have the same meaning as above (Equation no. 1).

3. Results and interpretation

3.1. The results of the regression models

The results of the OLS regression, robust regression and robust beta regression – that are reflected by Models 1, 2, and 3 (Table no. 2) – confirm the existence of a relationship between some facets of the national culture and AI talent concentration for countries with high AI skills and jobs profiles. Model 3 provides similar results with both LSMLE (presented below) and LMDPDE. The three control variables and the independent variables explain about 71%

of the variance of the response variable in the OLS multiple model, while in the beta robust regression model the pseudo R-squared is about 70%.

Table no. 2. Results of the regression models

Variables	Model 1 (M1) OLS Multiple Regression	Model 2 (M2) Robust Regression	Model 3 (M3) Robust Beta Regression
			<i>Mean model with logit link</i>
PDI	-0.555 (0.371)	-0.473 (0.424)	-0.753** (0.316)
IDV	-1.424*** (0.445)	-1.389*** (0.508)	-1.885*** (0.366)
MAS	0.123 (0.240)	0.130 (0.274)	0.064 (0.206)
UAI	0.583* (0.312)	0.570 (0.356)	0.722** (0.289)
LTO	1.428*** (0.454)	1.531*** (0.519)	1.466*** (0.322)
IVR	0.0215 (0.313)	0.135 (0.357)	0.072 (0.302)
RD_GDP_logit	0.333** (0.123)	0.311** (0.141)	0.416*** (0.106)
STEM_logit	0.650*** (0.215)	0.657** (0.246)	0.604*** (0.184)
AIE	0.302 (0.238)	0.317 (0.271)	0.289 (0.194)
Constant	-2.067** (0.825)	-2.326** (0.942)	-1.467** (0.656)
			<i>Precision model with identity link</i>
(Phi)			734*** (157.6)
Observations	44	44	44
R-squared for M1 and M2 Pseudo R-squared for M3	0.712	0.650	0.703
Adj R-squared	0.6364		
Root MSE	0.3274		

Notes: Standard errors in parentheses; For OLS and robust regressions: p-value corresponding to t-value; For robust beta regression: p-value corresponding to z-value; *** p<0.01, ** p<0.05, * p<0.1.

The achieved results reflect the following findings:

- PDI has a negative coefficient that is statistically significant at the 5% level only in the third model;
- IDV has a negative coefficient that is statistically significant at the 1% levels on all three models;
- MAS is not statistically significant in any model;

- UAI has a positive coefficient that is statistically significant in the first model (at the 10% level) and in the third model (at the 5% level);
- LTO has a positive coefficient that is statistically significant at the 1% level in all three models;
- IVR is not statistically significant in any model;
- RD_GDP_logit has a positive, statistically significant coefficient (at the 5% level) in all three models;
- STEM_logit has a positive, statistically significant coefficient in the first and third models (at the 1% level), as well as in the second model (at the 5% level);
- AIE is not statistically significant in any model.

In conclusion, two of the research hypotheses (H2 and H5) were confirmed in all models through statistically significant relationships: IDV has a negative relationship with the dependent variable (AI talent), and LTO shows a positive relationship with the dependent variable (AI talent). In addition, the relationships between the dependent variable and the control variables RD_GDP and STEM were confirmed.

3.2. Interpretation of the identified relationships between national culture and AI skills

For the investigated sample, as assumed in the H2 research hypothesis, countries that score lower in terms of individualism seem to have a higher level of AI skills and jobs than countries that expose a higher level of individualism. This outcome may be due to the nature of AI skills and the increasing focus at organisational and national level in having strong staff communities endowed with specific abilities and competencies for dealing with the technological advances and related challenges posed by AI. Since collectivistic cultures are based on fruitful collaboration between persons, teamwork, networking, and peer-learning – critical for constantly acquiring and refining AI skills – they seem to concentrate a higher number of employees that are interested in proving their AI talents. A relevant aspect for the attainment of AI skills is precisely the possibility of individuals to comfortably communicate and collaborate with their colleagues that possess superior AI knowledge and that can serve as learning examples, without feeling the threat of competition.

Taking into account the novelty of the investigated topic, the present study confirms, in an original way, the prevalence of collective efforts regarding the assimilation of AI skills and not of individual actions, which have been highlighted in certain analyses on various aspects associated with technology adoption (e.g., Erumban and de Jong, 2006). At the same time, by identifying a positive relationship between collectivism and AI skills, the study confirms the findings of previous research exploring the links between national culture and the use of technology or the digitalisation of companies (Lai et al., 2016; Rubino et al., 2020). More specifically, supporting the argumentation line in the cited literature, the individualism-related relationship may be explained by considering the specific character of acquiring AI skills nowadays, the development of these competencies reflecting the group pressure, especially for the alignment with the requirements about the performance of the individual, organisation, and society as a whole. Moreover, the acquisition of AI skills is backed up by

prior accumulation of a relatively solid base of technological skills, that are not induced, at this level of development, by the individual inclination towards innovation, but, rather, by the constraints of the community.

The achieved results also support the H5 research hypothesis, indicating that countries that are rather long-term oriented show a higher concentration of AI skills for their people than countries that are rather short-term oriented of a cultural perspective. The explanation could reside in the increased interest of long-term oriented societies in investing in (modern and technological) education in order to be well-prepared for the unknown future. In this case, as AI is exponentially gaining ground, individuals, in general, and employees, in particular, may be more and more willing to have AI skills and competencies for securing their positions and achieving stability in the long run. The employees from these societies do not necessarily expect immediate outcomes from their learning efforts, but they are investing in the future. Learning from others, as in collectivistic societies, is a feature of long-term oriented cultures that supports their search for AI skills by dedicating their time, effort, and building relationships. The results regarding the positive influence of both collectivism and long-term orientation on AI skills of the individuals across countries correspond with the ones of Lai et al. (2016), while the strategic approach of long-term oriented cultures regarding the acquisition of these skills is similar to the findings of Eitle and Buxmann (2020) for applying ML at organisational level.

Some may argue that short-termism would be a very suitable piece in the AI skills development conundrum when reflecting upon the immediacy of the need of adopting new technologies, as assumed in some studies (e.g., Rubino et al., 2020). However, following a different line of argumentation regarding the relationship between culture and technology/innovation, also found in other studies (e.g., Lai et al., 2016), the present analysis confirms – for the first time for AI skills development – the assumed hypothesis that AI talent growth aligns more to a long-term results philosophy. This evidence is supported especially because the sophisticated AI skills are more likely to be attached to long-term investment in the learning processes. Additionally, informal, voluntary learning is able to contribute greatly to achieving AI skills, at least in the early stages of the phenomenon. Therefore, the long-term orientation emerging as a positive driver of AI talent could reflect the intrinsic process of learning and developing AI skills, on the one hand, and the attached value to long-term expected achievements and benefits, on the other.

The results also indicated that power distance, motivation towards achievement and success (masculinity vs. femininity), uncertainty avoidance, and indulgence did not generate statistically significant associations for all regression models. The non-statistically significant results that were registered for motivation towards achievement and success are also supported by previous studies. In a comprehensive investigation regarding the role of cultural dimensions in technology acceptance models, Jan, Alshare and Lane (2022) found no robust direct effect of masculinity on the technology acceptance models.

As assumed, there are a series of factors that influence the development of AI skills at national level in addition to cultural dimensions. From an economic perspective, the R&D expenditure of countries differentiates between the possibilities of the individuals to have access to funds for their scientific and technological development, including AI skills. From a social and educational insight, the graduates in the STEM field may be considered a relevant base for the development of AI-related talents. Finally, although not statistically significant for the studied sample, the AI governmental and public incentives (like training and

educational programs, labour markets policies, public awareness and participation actions, knowledge transfers, scientific networking, etc.) could make a positive distinction between countries more or less staff supportive in terms of AI skills and competencies.

The achieved results present a special importance at the organisational and managerial levels. Business organisations all over the world are aware of the importance of having AI well-trained staff in order to maintain or to gain a competitive position on the market. In this context, understanding the influence of different factors on the ability of the employees to upskill or reskill according to the technological context is crucial for the managers in the organisations. As cultural factors play an essential role in the development of AI skills of employees across countries, managers and organisations should learn from the best practice experience and take into account the cultural profile of the staff when designing AI training programmes. The behaviours that could be encouraged by managers regarding the attainment of AI skills and competences for the employees reflect the corporate support for long-term strategically intensive training and educational programmes, teamwork and peer-learning, as well as collaboration and networking between individuals within the organisations.

The achieved results are also valuable from a theoretical perspective, and they are in line with the mainstream literature, highlighting the impact that certain sociocultural factors may have on staff predilection to acquire technical skills related to AI, which contributes to increasing employee productivity and organisational competitiveness.

Conclusions

The main contributions of the paper are two-folded, bringing valuable insights both for researchers in the human resource management field, as well as for business professionals and decision-makers that focus nowadays on the challenges posed by AI. Specifically, the investigation validates the postulation that national culture has an influencing role in shaping the assimilation and development of AI skills of individuals across countries. Thus, the importance of the work resides mainly in conveying further light on the central part that national culture has when companies decide upon their human resources policies, in general, and their strategic approaches within the (AI) talent race, in particular.

Using a series of quantitative methods (OLS multiple regression, robust regression, and a novel approach of the robust beta regression), the present paper studied the connections between Hofstede's cultural dimensions and AI talent concentration at international level, across a select sample of 44 countries. The main results confirmed the initially assumed connections between two of the six cultural dimensions and AI talent concentration. More specifically, positive relationships were found between collectivism and AI skills and jobs, on the one hand, and between long-term orientation and AI skills and jobs, on the other hand. The findings are in line with recent insights in the mainstream literature that situate long-term orientation, along other national culture pillars, as a definite driver of various social and economic phenomena related to learning and innovation, as the case of AI skills is. Consistent with various sources, the positive effect of collectivism on AI talent has several possible explanations. Some are related to the fineness of the learning processes in AI skills absorption, while others explain the influence of collectivism on employee's behaviour.

This work has great applicability for business organisations. The study distils through a quantitative approach the importance of national culture by using the cultural diversity of the employees as a vector for business competitive advantage at global level. Future studies could accommodate more countries for alleviating one of the limitations of this research, namely the one referring to the size and composition of the sample (only countries with a relatively high level of AI skills) as a direct result of current data availability and selection criteria of the sample. Additionally, when more data becomes available, more drivers of AI talent could be studied. New research directions could be developed by using other multivariate analyses (e.g., cluster analysis), and other extensions of the investigation could materialise in inquiries of AI talent across industries or gender to call upon more granular, profound, and sensitive aspects that will be of interest in the near future.

References

- Artificial Intelligence Skills Alliance (ARISA), 2023. *AI skills strategy for Europe. Strategic planning for developing AI skills in Europe*. [online] Available at: <<https://aiskills.eu/wp-content/uploads/2024/01/AI-Skills-Strategy-for-Europe.pdf>> [Accessed 21 January 2024].
- CEDEFOP, 2023. *Going digital means skilling for digital: Using big data to track emerging digital skill needs*. [online] Luxembourg: Publications Office of the EU. Available at: <<http://data.europa.eu/doi/10.2801/772175>> [Accessed 4 February 2024].
- Chen, X., Ender, P., Mitchell, M. and Wells, C., 2003. *Regression with Stata*. [online] Available at: <<https://stats.oarc.ucla.edu/stata/webbooks/reg/>> [Accessed 25 February 2024].
- Cribari-Neto, F. and Zeileis, A., 2010. Beta regression in R. *Journal of Statistical Software*, [e-journal] 34(2), pp.1-24. <https://doi.org/10.18637/jss.v034.i02>.
- Dalla Benetta, A., Sobolewski, M. and Nepelski, D., 2021. *AI Watch: 2020 EU AI investments*. [online] Luxembourg: Publications Office of the EU. Available at: <<https://doi.org/10.2760/017514>> [Accessed 1 March 2024].
- Dickens, R., Krenz, A. and O'Reilly, J., 2023. *Comparing new measures of tech talent: Global AI, digital infrastructure, and innovation*. [online] Available at: <<https://www.researchgate.net/publication/359636228>> [Accessed 5 February 2024].
- Eitle, V. and Buxmann, P., 2020, Cultural differences in machine learning adoption: An international comparison between Germany and the United States. In: s.n., *The 28th European Conference on Information Systems (ECIS 2020)*. 15-17 June 2020, s.l.. Research Papers. 138. [online] Available at: <https://aisel.aisnet.org/ecis2020_rp/138> [Accessed 5 March 2024].
- Erumban, A.A. and de Jong, S.B., 2006. Cross-country differences in ICT adoption: A consequence of Culture?. *Journal of World Business*, [e-journal] 41(4), pp.302-314. <https://doi.org/10.1016/j.jwb.2006.08.005>.
- European Commission, DG for Communications Networks, Content and Technology (EC-DG Connect), 2020. *European enterprise survey on the use of technologies based on artificial intelligence*. Final report. [online] Luxembourg: Publications Office of the EU. Available at: <<https://data.europa.eu/doi/10.2759/759368>> [Accessed 4 February 2024].
- Ferrari, S. and Cribari-Neto, F., 2004. Beta regression for modelling rates and proportions. *Journal of Applied Statistics*, [e-journal] 31(7), pp.799-815. <https://doi.org/10.1080/0266476042000214501>.

- Field, A., 2018. *Discovering statistics using IBM SPSS Statistics*. 5th ed. London: Sage Publications.
- Giraud, L., Zaher, A., Hernandez, S. and Akram, A.A., 2023. The impacts of Artificial Intelligence on managerial skills. *Journal of Decision Systems*, [e-journal] 32(3), pp.566-599. <https://doi.org/10.1080/12460125.2022.2069537>.
- Grün, B., Kosmidis, I. and Zeileis, A., 2012. Extended Beta regression in R: Shaken, stirred, mixed, and partitioned. *Journal of Statistical Software*, [e-journal] 48(11), pp.1-25. <https://doi.org/10.18637/jss.v048.i11>.
- Hair, J.F., Black, W.C., Babin, B.J. and Anderson, R.E., 2009. *Multivariate Data Analysis. A global perspective*. 7th ed. New Jersey: Prentice Hall.
- Hofstede, G., Hofstede, G.J. and Minkov, M., 2010. *Cultures and Organizations: Software of the mind. Intercultural cooperation and its importance for survival*. 3rd ed. New York: McGraw-Hill.
- Hofstede Insights. The Culture Factor Group, 2024a. *Intercultural Management*. [online] Available at: <<https://www.hofstede-insights.com/intercultural-management>> [Accessed 10 January 2024].
- Hofstede Insights. The Culture Factor Group, 2024b. *Country comparison tool*. [online] Available at: <<https://www.hofstede-insights.com/country-comparison-tool>> [Accessed 10 January 2024].
- Jan, J., Alshare, K.A. and Lane, P.L., 2022. Hofstede's cultural dimensions in technology acceptance models: A meta- analysis. *Universal Access in the Information Society*, [e-journal], 23, pp.717-741. <https://doi.org/10.1007/s10209-022-00930-7>.
- Lai, C., Wang, Q., Li, X. and Hu, X., 2016. The influence of individual espoused cultural values on self-directed use of technology for language learning beyond the classroom. *Computers in Human Behavior*, [e-journal] 62, pp.676-688. <https://doi.org/10.1016/j.chb.2016.04.039>.
- Lerma, D.F.P., Kwarteng, M.A. and Pílik, M., 2023. Influence of personal cultural orientations in Artificial Intelligence adoption in small and medium-sized enterprises. In: M. Janssen, L. Pinheiro, R. Matheus, F. Frankenberger, Y.K. Dwivedi, I.O. Pappas and M. Mäntymäki eds., 2023. *New Sustainable Horizons in Artificial Intelligence and Digital Solutions. Proceedings of the 22nd IFIP WG 6.11 Conference on e-Business, e-Services and e-Society, I3E 2023*. Curitiba, Brazil, 9–11 November 2023. Cham: Springer. https://doi.org/10.1007/978-3-031-50040-4_3.
- Li, N., Zhang, X. and Limniou, M., 2023. A country's national culture affects virtual learning environment adoption in higher education: A systematic review (2001–2020). *Interactive Learning Environments*, [e-journal] 31(7), pp.4407-4425. <https://doi.org/10.1080/10494820.2021.1967408>.
- Maluf, Y.S., Ferrari, S.L.P. and Queiroz, F.F., 2022. *Robust beta regression through the logit transformation*. [online] Available at: <[arXiv:2209.11315](https://arxiv.org/abs/2209.11315)> [Accessed 24 January 2024].
- Maluf, Y.S., Ferrari, S.L.P. and Queiroz, F.F., 2024. Robust beta regression through the logit transformation. *Metrika*, [e-journal]. <https://doi.org/10.1007/s00184-024-00949-1>.
- Maslej, N., Fattorini, L., Brynjolfsson, E., Etchemendy, J., Ligett, K., Lyons, T., Manyika, J., Ngo, H., Niebles, J.C., Parli, V., Shoham, Y., Wald, R., Clark, J. and Perrault, R., 2023. *The AI Index 2023 Annual Report*. [pdf] Stanford, CA: AI Index Steering Committee, Institute for

- Human-Centered AI, Stanford University. Available at: <https://aiindex.stanford.edu/wp-content/uploads/2023/04/HAI_AI-Index-Report_2023.pdf> [Accessed 30 January 2024].
- Mooi, E., Sarstedt, M. and Mooi-Reci, I., 2018. *Market research: The process, data, and methods using Stata*. Singapore: Springer. <https://doi.org/10.1007/978-981-10-5218-7>.
- Moore, L., Lavoie, A., Bergeron, E. and Emond, M., 2007. Modeling probability-based injury severity scores in logistic regression models: The logit transformation should be used. *Journal of Trauma and Acute Care Surgery*, [e-journal] 62(3), pp.601-605. <https://doi.org/10.1097/TA.0b013e31803245b2>.
- OECD.AI, 2021. *National AI policies and strategies*. [online] Available at: <<https://oecd.ai/en/>>, <<https://oecd.ai/en/dashboards/overview>> [Accessed 20 January 2024].
- OECD.AI, 2024a. *Top AI skills worldwide*. [online] Available at: <<https://oecd.ai/en/data?selectedArea=ai-jobs-and-skills&selectedVisualization=top-ai-skills-worldwide>> [Accessed 5 January 2024].
- OECD.AI, 2024b. *AI talent concentration by country*. [online] Available at: <<https://oecd.ai/en/data?selectedArea=ai-jobs-and-skills&selectedVisualization=ai-talent-concentration-by-country>> [Accessed 5 January 2024].
- OECD.AI, 2024c. *LinkedIn data. Methodological note*. [online] Available at: <<https://oecd.ai/en/linkedin>> [Accessed 6 January 2024].
- Queiroz, F.F., Maluf, Y.S. and Ferrari, S.L.P., 2022. *Robustbetareg: Robust beta regression. R package version 0.3.0*. [online] Available at: <<https://CRAN.R-project.org/package=robustbetareg>>, <<https://cran.r-project.org/web/packages/robustbetareg/robustbetareg.pdf>> [Accessed 3 January 2024].
- R Core Team, 2023. *R: A Language and Environment for Statistical Computing*. [computer program] R Foundation for Statistical Computing. Available at: <<https://www.R-project.org/>> [Accessed 10 March 2024].
- Rubino, M., Vitolla, F., Raimo, N. and Garcia-Sanchez, I.-M., 2020. Cross-country differences in European firms' digitalisation: The role of national culture. *Management Decision*, [e-journal] 58(8), pp.1563-1583. <https://doi.org/10.1108/MD-08-2019-1120>.
- Sanders, N.R. and Wood, J.D., 2023. *The skills your employees need to work effectively with AI*. [online] Available at: <<https://hbr.org/2023/11/the-skills-your-employees-need-to-work-effectively-with-ai>> [Accessed 1 March 2024].
- Tortoise Media, 2023a. *The Global AI Index*. [online] Available at: <<https://www.tortoisemedia.com/intelligence/global-ai/>> [Accessed 6 January 2024].
- Tortoise Media, 2023b. *The Global AI Index. Methodology report*. [online] Available at: <<https://www.tortoisemedia.com/wp-content/uploads/sites/3/2023/07/AI-Methodology-2306-4.pdf>> [Accessed 8 January 2024].
- UNESCO Institute for Statistics (UIS), 2024. *STEM graduates*. [online] Available at: <<http://data.uis.unesco.org/>> [Accessed 1 February 2024].
- Vitolla, F., Raimo, N., Rubino, M. and Garegnani, G.M., 2021. Do cultural differences impact ethical issues? Exploring the relationship between national culture and quality of code of ethics. *Journal of International Management*, [e-journal] 27(1), article no. 100823. <https://doi.org/10.1016/j.intman.2021.100823>.

- World Bank, 2024. *Research and development expenditure (% of GDP)*. [online] Available at: <<https://data.worldbank.org/indicator/GB.XPD.RSDV.GD.ZS>> [Accessed 1 February 2024].
- World Economic Forum (WEF), 2023. *Future of Jobs Report 2023*. [online] Available at: <https://www3.weforum.org/docs/WEF_Future_of_Jobs_2023.pdf> [Accessed 3 March 2024].
- Wiley, 2021. *Digital Skills Gap Index 2021*. [online] Available at: <<https://dsgi.wiley.com/>> [Accessed 3 March 2024].
- Zolduoarrati, E., Licorish, S.A. and Stanger, N., 2022. Impact of individualism and collectivism cultural profiles on the behaviour of software developers: A study of stack overflow. *Journal of Systems and Software*, [e-journal] 192(2022), article no. 111427. <https://doi.org/10.1016/j.jss.2022.111427>.