



ARE AI AND ROBOTS PERCEIVED AS JOB STEALERS? A SPATIAL ECONOMETRIC ANALYSIS OF EUROPEAN REGIONS

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Abstract

Artificial intelligence and robotization are generating major occupational transformations in labor markets, affecting both the organization of work and individuals' perceptions regarding displacement risks. While existing research has primarily focused on the objective effects of digital technologies on employment, productivity, and occupational restructuring, the perceptual dimension of job displacement remains relatively underexplored, particularly at regional level. By combining an objective and subjective approach, this study investigates the determinants of perceived occupational displacement associated with robotization and AI across 228 NUTS 2 regions in the European Union. The analysis integrates perception indicators collected from Eurobarometer surveys (101.3 and 101.4) with regional macroeconomic indicators derived from Eurostat database. The methodological framework combines exploratory spatial data analysis with classical and spatial local econometric techniques. Moran's I statistic suggests significant spatial autocorrelation in the perceptions of job

displacement, indicating the existence of regional clusters. clustering processes. The Multiscale Geographically Weighted Regression (MGWR) model outperforms the classical OLS regression and reveals the spatial variability of the relationships between explanatory variables and perceived job displacement. The results indicate that unemployment rates, tertiary education levels, positive perceptions of digital skills and perceptions regarding increased work rhythm generated by AI and robotization are positively associated with fears of job displacement. In contrast, employment in knowledge intensive and high technology services, together with positive perceptions regarding the use of AI and robots in the workplace reduce the perceived occupational displacement risk. However, these factors do not have a uniform effect at regional level, which is highlighted by the MGWR local regression models. By revealing geographically differentiated patterns, this study emphasizes the need for territorially driven policies aimed at supporting workforce adaptation to emerging digital technologies.

Keywords: Artificial Intelligence, Robotization, Multiscale Geographically Weighted Regression (MGWR), Spatial Heterogeneity, Job Displacement Perceptions, Labor Market, European Union.

JEL Classification : O33, R11, J24, C21.

1. Introduction

Digitalization is a global phenomenon that involves the integration of emerging technologies into economic and occupational processes, reshaping the structure of work and how tasks are performed in the workplace. As a result, all participants in the labor market may be affected: employees, companies, and government agencies. Although the phenomenon of digitalization had already intensified before the coronavirus pandemic, the health crisis significantly accelerated this process, by increasing labor market fragmentation based on occupational relevance, the risk of infection, and unequal access to digital resources and communication technologies (Boboc et al., 2020). As a result, the pandemic increased the pace of the digital adaptation process and the importance of technological competencies across many professions.

In this context, at the employee level, there is a notable need for continuous updates in both hard skills specific to a professional activity (Anton et al., 2020) and soft skills that lead to successful integration into the labor market, such as effective communication, task management in groups, and critical thinking. Clearly, ongoing employee training programs and the simultaneous updating of knowledge in line with changes in the technologies used by multinational corporations and companies lead to increased labor productivity in a long-term perspective (Schislyaeva and Saychenko, 2022).

Consequently, the importance of digital skills is becoming increasingly relevant in the context of the expansion of automated technologies, such as robotization and artificial intelligence (AI). Robotization, derived from the evolution of digitalization, represents the process in which the use of robots and automated systems assumes and performs repetitive or precise tasks previously done by humans. In fact, there is the concept of replacing humans with clones, biorobots, or cyborgs. The way in which robotization “steals” jobs can be corrected through policies aimed to reduce wage inequalities and by reforming the education system (Dobrescu and Dobrescu, 2023).

At the same time, AI extends automated processes to cognitive activities, such as data analysis, decision-making, and fast information processing, with the aim of reducing repeated tasks accomplished by humans (Tagscherer and Carbon, 2023). Thus, AI represents a system's heuristic that uses external data that is already prepared or measured by its own sensors to achieve the desired outputs (Kaplan and Haenlein, 2019). Despite the fact that AI does not function perfectly and involves constant adaptation and learning, AI and its components can imbalance the functioning of the labor market through their ability to operate independently, to a certain extent, depending on the work context in which they are applied.

Existing research suggests that AI and robotization can create both opportunities and challenges for the labor market. On one hand, new technologies may increase labor productivity, efficiency, and the development of new jobs (Su, 2018). On the other hand, the negative effects may be determined by the replacement of certain jobs (Jung and Lim, 2020), the polarization of employment, and the accentuation of disparities between regions and economic sectors, depending on the degree of technological development and the level of digital skills. In a systematic review, Mirbabaie et al. (2022) identified the main determinants of AI-related concerns, which include reduced job security, losses related to professional status and skills, and the loss of personal autonomy. All these factors can negatively affect employee engagement, work prestige, and value and perceptions regarding future work.

In this context, this study aims to analyze the determinants of the perceived concern of job replacement through AI and robotization across NUTS 2 level in European regions, highlighting the spatial heterogeneity of these relationships by using local spatial econometric models. By combining subjective and objective perspectives within a regional approach, the study investigates how perceptions regarding AI and digital skills, together with labor market conditions, and educational characteristics influence fears related to occupational displacement driven by AI related technologies. Starting from this, the following research hypotheses are formulated:

H₁: Perceptions of job displacement associated with AI and robotization exhibit significant spatial variation across EU regions.

H₂: Perception based and regional labor market factors, including the perceived increase in work rhythm due to robotization and AI, the perceived level of digital skills, and regional unemployment rates have statistically significant and spatially heterogeneous relationships with perceived job displacement across EU regions.

H₃: The Multiscale Geographically Weighted Regression (MGWR) provides better insights for analyzing perceived occupational displacement in the context of AI and robotization compared to OLS regression.

This study contributes to the existing literature by integrating subjective perceptions on AI and robotization with objective socioeconomic indicators, using a spatial econometrics framework. While existing studies focus mainly on labor market effects of AI related technologies or on individual perceptions regarding technological changes, less attention has been given to the spatial heterogeneity of these phenomena in Europe. By applying a MGWR model at EU NUTS 2 level, we identify spatially varying relationships between perceived occupational displacement and its determinants, providing a more in-depth analysis of the regional impact related to AI-driven technologies.

The remainder of the paper is organized as follows. The next section reviews the relevant literature regarding labor market effects of AI and robotization. The third section introduces the variables used, the dataset particularities and the methodological framework applied. It is followed by the empirical results section including the exploratory analysis, spatial autocorrelation, OLS regression and the MGWR model outcomes. Last section concludes the main findings and implications of the paper.

2. Literature Review

The recent developments in artificial intelligence, automation and robotization have generated extensive debates regarding their effects on labor markets, especially in terms of employment structure and workforce adaptation. While automation and robotization refer mainly to the substitution of routine physical tasks, AI enables also the automation of analytical activities, bringing new opportunities but also challenges in the labor market. The existing literature suggests that the effects of these technologies are not uniform across occupations, sectors or regions, being influenced by economic and occupational disparities, the level of digital skills, and the innovative nature of the workplace.

Automation, accelerated by the COVID-19 pandemic, has intensified labor market reorganization by decreasing the importance of redundant jobs, increasing the demand for technological skills, and requiring continuous retraining of the workforce (WEF, 2020). In the absence of support and adaptation mechanisms, digital transformations can accentuate the already existent disparities between regional labor markets. In this context, Piroșcă et al. (2021) argue that approximately 40% of European adults were at risk of digital exclusion. Among the countries with the highest rates of low digital skills are those located in Southern and North-Eastern Europe, with Central and Northern European countries ranked at the opposite pole.

Classical labor market theories highlight the risk of technological unemployment resulted from technological change and innovation. Keynes (1963) argues that technological development is

generated by the replacement of the workforce faster than new forms of employment being created. Similarly, Leontief (1983) emphasizes the idea that most jobs will be replaced by the advancement of AI.

However, more recent empirical studies provide a more nuanced interpretation of the automation's effects on the labor market. AI and robotization have different outcomes across occupations and sectors, rather than generating a universal job destruction and unemployment crisis. For instance, this phenomenon would reduce the amount of working time and may favor increases of the supply of jobs requiring higher qualifications, as well as labor productivity (Bergeaud, 2024; Acemoglu, 2024; Aldasaro et al., 2026).

Other studies suggest that the impact of AI and robotization across occupational categories and sectors is highly heterogeneous. For instance, Chiacchio et al. (2018) show that young employees with a medium level of education are particularly affected by the robots industry, while at the occupational level, the effect of automation on technicians is positive. Hotte et al. (2023) support the idea of heterogeneity in employment rates depending on skill and competency groups, suggesting that the job displacement effect is most pronounced for individuals with average skill levels or those performing routine tasks, while the work of low-skilled or highly skilled individuals are less vulnerable to technological changes. Contrary, Acemoglu and Restrepo (2017) highlight that high-skill labor has a significant advantage on labor market compared to low-skilled labor. Felten et al. (2023) suggest that only a limited proportion of tasks (1% to 4%) are highly exposed to AI, indicating that technological substitution is often partial, not complete. In this regard, Zarifhornavar (2023) argues that the impact of AI upon a job can be classified as total, partial, or nonexistent. In this case, the most affected categories will be technicians and managers, with the military and elementary or craft-related jobs at the opposite pole. However, empirical evidence regarding the relationship between robotization and employment remains mixed. Micro-level data indicates a positive correlation, while studies based on data from the International Federation of Robotics (IFR) reveal a negative correlation between the two aspects (Klenert et al., 2023). A granular perspective would indicate more clearly which factors influence the impact of robotization, such as age, gender, a region's level of urbanization, etc. Although the results of the above-mentioned study identified the positive impact of robotization on the employment rate and a neutral impact on low-skilled workers, perspectives may differ.

Building on the heterogenous effects of AI and robotization across occupations and sectors, recent literature highlights the potential benefits of AI and its components, related to an increase in the number of jobs requiring higher qualifications, higher labor productivity, and ultimately economic growth (Aleca and Mihai, 2025; Misch et al., 2025; Aldasaro et al., 2026). Although WEF (2020)

estimated that by 2025 the number of tasks performed by machines would equal those performed by humans, the literature indicates discrepancies regarding job displacement. Contrary to theories that artificial intelligence, robotization, and digitization increase unemployment, Su (2018) argues that even though the jobs being substituted require low labor demand, they can be replaced by creating new jobs in other sectors following the introduction of well-organized policy reforms.

In this context, new jobs may be closely linked to the use of automated processes, leading to a rise in wages and employment rates in certain sectors, while labor demand will decline in other fields of activity, thereby causing higher levels of unemployment and wage disparities (Acemoglu, 2021). Although automated technologies surpass human capacity in pattern recognition, searching, and rapidly processing large volumes of data, humans remain superior in areas that require critical and rational thinking (Surden, 2019). In this regard, the most requested skills on the labour market are those that differentiate human work from automated work, such as interpersonal communication, critical thinking, responsibility and contextual interpretation (Poláková et al., 2023). At the same time, the authors point out that between 2017 and 2021, soft skills represented 40% of the total skills required in the labor market, while digital skills accounted for approximately 30%, arguing that balanced proficiency in both categories of skills is important in a technology-driven future. For example, the range of skills possessed, the complexity, and the specialization of the job influence the innovative behavior of the employee, who would be resilient to the effects of occupational substitution (Verma and Singh, 2022).

Although existing literature focuses on the economic implications of AI and robotization, less attention has been given to the spatial heterogeneity. However, the adoption and integration of AI and robotics varies significantly across regional economies. The results of the descriptive analysis conducted by Guarascio et al. (2025) suggest that in regions characterized by advanced technological services and in hub areas where manufacturing processes are well-developed, AI adoption is favorable and creates economic and employment opportunities. In contrast, regions located in the southern and eastern peripheries of Europe do not favor AI integration, as they are characterized by reduced investment and limited innovation systems. The impact of automation in these regions may lead to labor displacement. Similarly, the results of the spatial econometric models developed by Marques Santos et al. (2025) at the EU regional level highlight that regions characterized by innovation and industrial specialization tend to have greater access to European funds allocated for AI activities. In this regard, Albanesi et al. (2025) support the idea of the heterogeneity of AI's impact on the labor market through their panel econometric models, noting that automated processes mostly leads to increases in the employment rate, but their effects vary from country to country, depending on the levels of technological development, education, economic competitiveness, and policies.

Regarding geographical differences within the EU, Drago et al. (2025) used econometric methods based on panel data from 2018 to 2024 to argue that market openness confirms that interconnected economies have increased exposure to spillover effects and competitive market pressure, and that AI integration is necessary. Additionally, the authors point out that the direction and the quality of public expenditure planning are more important than the effective amount of expenditure.

Although the literature indicates mixed effects of robotization and AI on the labor market at European Union level, as the importance of jobs requiring specific qualifications and skills increase, the uncertainty associated with emerging technologies may influence the way individuals perceive the risk that their jobs will be replaced. Therefore, the process of job substitution in the context of digital technologies can be analyzed through the individuals' perceptions regarding the impact of AI on occupational displacement. For example, Wang and Lu (2025) emphasize that the perception of job replacement can be determined by demographic factors and job features. They argue that women, older employees, and highly educated individuals exhibit a higher level of concern regarding the risk of job replacement by AI. In terms of professional experience, entry-level employees exhibit low fear regarding job replacement by AI, compared to employees with rich experience in the service sector. Furthermore, the study highlights that although individuals who frequently use the internet at work fear AI's ability to take their jobs, they increase their use of digital tools, suggesting that AI facilitates the performance of work tasks rather than replacing them.

Similarly, Vasilescu et al. (2020) highlight significant differences among member countries in terms of digital skills levels, technology use, and perceptions regarding the risk of job displacement by new technologies. In general, countries in Northern and Western Europe tend to have higher levels of digital skills and favorable attitudes toward innovation, in contrast to countries from South – Eastern Europe. Furthermore, Vasilescu et al. (2020) argue that among men, the fear of job replacement by robotization is more pronounced, and age was an irrelevant factor in their analysis, suggesting that perceptions are similar regardless of the demographic group analyzed. On the other hand, the level of financial difficulties faced by individuals and low internet usage lead to a stronger perception of job displacement. The study's results show that, overall, Europeans' perception of digitalization is positive, except for those groups that are not prepared to adapt to the digital transition. Generally, people with a positive perception of robotization believe that robots can take people's jobs. On the other hand, Schoss and Ciarlante (2022) stress that the perception of technology's impact on the labor market is influenced not only by individual factors but also by those reflecting the economic context. Their results indicate that gender, community type (urban/rural), level of digital skills, and the Gini index influence negative attitudes toward AI and robots in terms of personal job security. Most of the coefficients for the exogenous variables are negative, except for the indicator of attitudes

toward the use of robots in the workplace. This suggests that as the use of emerging technologies increases, negative perceptions of AI regarding jobs will decrease.

Furthermore, factors related to the personal job situation may influence perceptions of job displacement. To identify the statistically significant factors contributing to the fear of AI, the results of the PLS-SEM models conducted by Mirbabaie et al. (2022) support the idea that the variation of the threat posed by AI to jobs can be influenced by workplace changes and loss of professional status, while past experiences with AI do not influence the perceived threat of AI.

Although existing studies examine the impact of AI and robotization on employment, most studies focus mainly on labor market outcomes on individual-level perceptions, without accounting explicitly for spatial dependence and spatial heterogeneity. To address this gap, this article analyzes the spatial heterogeneity of perceived job displacement determined by AI and robotization across Europe, using a Multiscale Geographically Weighted Regression (MGWR). Following this approach, we highlight the regional differences of the factors influencing occupational displacement, contributing to a better understanding of the spatial dimension of the AI-driven labor market transformation.

3. Data and methodology

The study used three data sources for the year 2024: the Eurobarometer (EB) surveys 101.3 and 101.4, conducted between April and May 2024, and the Eurostat database (2024). In this way, the analysis allows the integration of Europeans' perceptions and attitudes towards the labor market, in the context of robotization and AI, with the macroeconomic characteristics of regional economies. To address research hypotheses H₁ and H₃, we used NUTS 2-level data for the EU-27 countries, covering a total of 228 NUTS 2 regions. The 14 regions excluded due to data unavailability can be found in the Appendix.

The variables regarding perceptions, extracted from the EB surveys, were measured at the individual level on Likert scales. The sample for EB edition 101.3 includes 36,587 individuals, while the EB 101.4 sample contains 26,404 observations. The process of building the database involved the aggregation of data from individual level to NUTS 2 level. For each region, the total number of responses corresponding to each category was collected. Subsequently, for each response category, relative frequencies were calculated to determine its share of the total responses corresponding to that question at the regional level.

An important aspect in the process of building the database is the inconsistency between the EB data at territorial level and the data provided by Eurostat. Two major inconsistencies were identified. The first one refers to differences between the NUTS 2 regions associated with each

respondent. EB data are mostly available at the NUTS 2 level, but data for certain regions are published at the NUTS 1 or NUTS 3 level. To ensure the consistency of the statistical analysis at the NUTS 2 level, territorial aggregation or disaggregation procedures were performed as follows. The aggregation of NUTS 3 level data to NUTS 2 level was carried out by summing the responses collected at the NUTS 3 level that comprise a specific NUTS 2 region. On the other hand, territorial disaggregation was performed according to Vasilopoulou and Talving (2024), who use EB survey data published at the NUTS 1 level for NUTS 2 regions when data is unavailable (Appendix).

The second issue encountered in the data collection and processing process concerns the revisions made in 2024 to the NUTS territorial classification, which affected the delimitations of certain NUTS 2 regions compared to the previous version (2021). Since Eurostat data were published according to the NUTS 2024 nomenclature, while the EB data were available at the NUTS 2021 classification, the analysis was conducted using the NUTS 2021 format to ensure territorial comparability.

Table 1 introduces the variables used in the analysis, their descriptions, definitions, and data sources. These indicators reflect both the perceptual and the structural dimensions of the labor market transformation associated to AI and robotization. The EB variables capture the individuals' perceptions regarding job vulnerability, digital skills assessment, and potential impact of AI, while the Eurostat indicators describe the socioeconomic characteristics such as education, technological specialization and unemployment.

Table 1. Main indicators considered in the analysis at NUTS 2 level for year 2024

Variable abbreviation	Description	Unit	Source (Question)	Initial response (Perception)
JobStealP	The percentage of people who believe that robots and AI are stealing jobs	%	EB 101.4 (qb6_5)	1-Totally agree 2-Tend to agree
AISk_FJobP	The proportion of individuals who consider themselves sufficiently competent in using digital technologies to work in the future, if they are in the position of changing their job or finding another one, over the next 12 months	%	EB 101.4 (qb2_3)	1- Totally agree 2- Tend to agree
ActEmpSitN	The ratio of individuals who negatively perceive the employment situation in the reference country	%	EB 101.3 (qa2_5)	3-Rather bad 4-Very bad
EXP_JOB_N	The percentage of people who believe that workplace conditions will worsen over the next 12 months	%	EB 101.3 (qa2_6)	2-Rather bad

AIRithmP	The share of people who believe that robots and AI are increasing the rhythm in which tasks are performed at work	%	EB 101.4 (qb6_6)	1- Totally agree 2- Tend to agree
ROBOTS_P	The percentage of people who positively perceive the use of robots and AI at work	%	EB 101.4 (qb5)	1-Very positively 2-Fairly positively
Ed_Tert	The percentage of people aged 25–64 who have completed tertiary education	%	Eurostat	-
KIS	The share of employed persons in high-tech and knowledge-intensive services as a percentage of total employment	%	Eurostat	-
UNEMPL	The percentage of unemployed people aged 15–74 in the total labor force	%	Eurostat	-

Source: Eurostat and European Commission (2025)

As a starting point, the construction of the spatial weights matrix W allows the identification of spatial interactions within a geographic area by specifying a common territorial boundary or a threshold distance. Mathematically, W is a $n \times n$ matrix, where n represents the number of specified territorial units. By convention, the elements of the main diagonal (w_{ii}) are zero, so that the own neighborhood is excluded (Elhorst, 2014).

Since the results of Moran's I statistics depend on the specification of geographic neighborhood relationships, several alternative types of matrices were evaluated, including distance based matrices, inverse distance, and the k-nearest neighbors (kNN) matrix. Among these, the kNN matrix allowed the best capture of spatial dependence. The optimal number of nearest neighbors for each region follows the algorithm described by Kubara and Kopczevska (2023), which recommends iteratively testing various values of k and selecting the specification that minimizes the Akaike Information Criterion (AIC). The elements of a spatial weights matrix W using the kNN method are defined as follows:

$$\begin{cases} w_{ij}(k) = 1, \text{ if } d_{ij} \leq d_i(k) \\ w_{ij}(k) = 0, \text{ otherwise} \end{cases} \quad (1)$$

where d_{ij} represents the Euclidean distance between regions i and j , and $d_i(k)$ represents the critical distance defined for each region i , with the condition that each region has exactly k nearest neighbors.

Once the spatial weights matrix has been constructed, it is necessary to examine the spatial autocorrelation using Moran's index (Anselin and Rey, 1991). The formula for Moran's index, which is similar to Pearson's correlation coefficient, is given by the following equation:

$$IM = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{(\sum_{i=1}^n \sum_{j=1}^n w_{ij}) \sum_{i=1}^n (x_i - \bar{x})^2} \quad (2)$$

where x_i and x_j represents the values of the variable corresponding to regions i and j , n represents the total number of territorial units, and \bar{x} represents the mean value of the variable under analysis and w_{ij} are the elements of the spatial weights matrix. Moran's I values range between $[-1, 1]$. Negative values indicate dissimilarity and spatial dispersion between neighboring region, positive values indicate spatial clustering and similarity. Values close to zero suggest the absence of spatial autocorrelation (Goschin, 2017).

To reject the null hypothesis of spatial randomness, a pseudo p-value is calculated using permutation inference, representing a summary of the results from the initial distribution (Anselin, 1995; Anselin and Rey, 1991):

$$p = \frac{R+1}{M+1} \quad (3)$$

where R represents the number of calculations of Moran's I statistic for a random distribution, and M indicates the number of permutations used.

After confirming the existence of spatial autocorrelation, a classic OLS model was first applied to the dataset to estimate the linear relationship between the perceived job substitution caused by AI and robotization and the considered socioeconomic factors:

$$Y = X\beta + \varepsilon \quad (4)$$

where Y represents the $n \times 1$ vector of the dependent variable (JobStealP), X describes the matrix of independent variables (AISk_FJobP, ActEmpSitN, EXP_JOB_N, AIRithmP, ROBOTS_P, Ed_Tert, KIS, UNEMPL) of dimension $n \times p$, where n is the number of observations, p represents the number of independent variables, β is the vector of coefficients of the explanatory variables, and ε represents the error term (Woolridge, 2016).

The standard assumptions of the OLS model were also tested. These include testing for the linearity of the relationship, heteroscedasticity, the normally distributed error terms, and the absence of multicollinearity (Gujarati, 2021). To assess multicollinearity, a condition number is calculated. If this number exceeds 30, there is a possibility of multicollinearity among the independent variables. To test whether the errors are normally distributed, the Jarque-Bera test was performed. Finally, the Breusch-Pagan test was conducted to test for heteroscedasticity.

However, OLS regression involves identifying global relationships between variables without taking the spatial component into account. In order to address our research questions, we opted for Multiscale Geographically Weighted Regression (MGWR), a spatial econometric method designed to explore the geographically varying relationships. While Geographically Weighted Regression

(GWR) constrains the variation of local relationships to the same spatial scale, MGWR allows the estimation of the relationship between each explanatory variables and the dependent variable at distinct spatial scales. The MGWR model is defined as follows (Fotheringham et al., 2017):

$$y_i = \sum_{j=1}^p \beta_{bwj} x_{ij} + \epsilon_i, i = \overline{1, n} \quad (5)$$

where β_{bwj} represents the locally estimated coefficient of variable j at location i , using its specific threshold (bwj), x_{ij} represents the exogenous variable and ϵ_i is the error term.

For each region, a distinct local regression model is estimated, taking into account the information from surrounding regions within a certain distance threshold or bandwidth (de Bellefon & Floch, 2018). In this study, the spatial weights are obtained using an adaptive bi-squared kernel function. This function was selected because it allows the decreasing allocation of spatial weights for regions j as the distance from the reference region i increases, whilst the number of neighbours k remains constant for all regions (Goschin and Dimian, 2018). Furthermore, the function assumes that beyond a certain reference threshold, the value of the weights becomes null (Oshan and Fotheringham, 2018). The use of adaptive weights allows variations in the geographical area of the local model while including the same number of neighbors. Thus, the geographic area can vary depending on the surface area required to include a certain number of neighbors for all regions. The adaptive bi-squared kernel function is the following:

$$w_{ij} = \begin{cases} \left(1 - \frac{d_{ij}^2}{\Delta_{i(k)}^2}\right)^2, & \text{if } d_{ij} < \Delta_{i(k)} \\ 0, & \text{if } d_{ij} > \Delta_{i(k)} \end{cases} \quad (6)$$

where d_{ij} represents the Euclidean distance between locations i and j , and $\Delta_{i(k)}$ represents the bandwidth, which measures the distance between i and its nearest neighbor k (Oshan and Fotheringham, 2018).

The optimal bandwidth is selected by minimizing the corrected Akaike Information Criterion (AIC_c), since it can provide a useful trade-off between the adjustment and the complexity of the model (Fotheringham et al., 2017). The GWR-specific AIC_c formula is given by:

$$AIC_c = 2n \ln \hat{\sigma} + n \ln 2\pi + n \left\{ \frac{n+tr(S)}{n-2-tr(S)} \right\} \quad (7)$$

where n represents the number of observations, $\hat{\sigma}$ is the estimator of the standard deviation of the error term, and $tr(S)$ represents the trace of the smoothing matrix.

In the literature, MGWR is treated as a generalized additive model (GAM), which permits model calibration through backfitting algorithms using kernel functions similar to those in GWR (Fotheringham et al., 2017; Mollalo et al., 2020). GAM involves the iteration of a series of univariate GWR models, using at each step the partial residuals obtained in the previous step, until convergence

to a solution is achieved. At the same time, the MGWR estimation process involves identifying the optimal threshold for each explanatory variable within a predefined range for the number of neighbors. For each possible value of this threshold, the MGWR model is recalibrated, and the associated AICc information criterion is minimized. The process is repeated until the optimal set of thresholds is obtained, which allows the estimation of MGWR parameters (Oshan et al., 2019).

4. Results and Discussion

4.1. Descriptive Analysis

The descriptive statistics for the variables included in our analysis are presented in Table 2. All variables were available for a balanced sample of 228 NUTS 2 regions across EU. Preliminary analysis indicates regional heterogeneity among EU regions. The greatest variations are observed in the proportion of people who have a negative view on the national employment situation (ActEmpSitN) and in the proportion of people who have a positive view on the use of robots and AI in the workplace (ROBOTS_P). These results suggest the existence of regional disparities regarding the perceived impact of robotization and AI on the labor market.

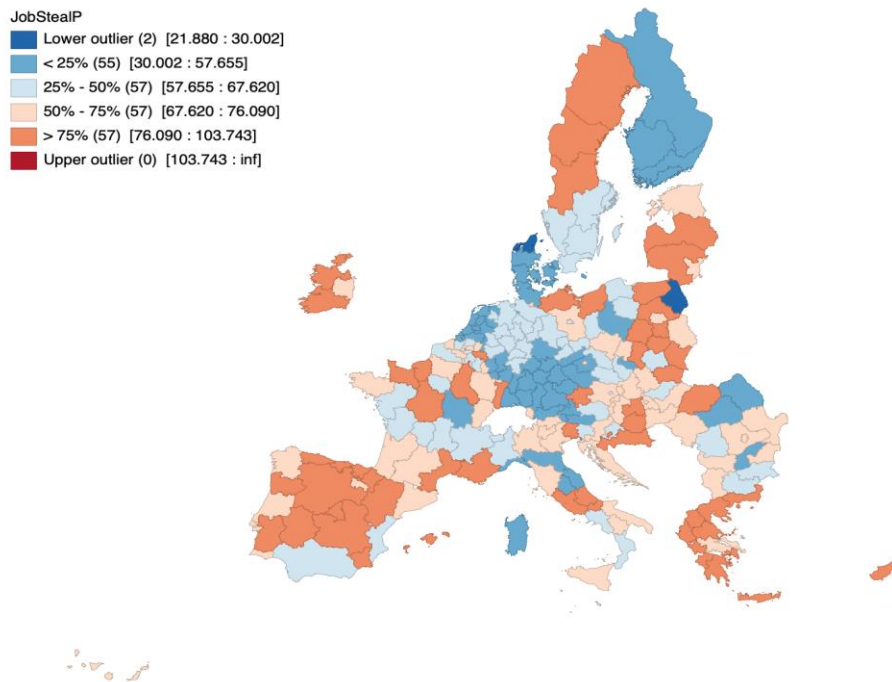
Table 2. Descriptive statistics of the variables included in the analysis

Variable	Mean	Q1	Median	Q3	Std.Dev.	Min.	Region Min.	Max.	Region Max.
JobStealP	65.3	57.84	67.62	76.01	14.24	21.88	PL84	95.83	ES43
AISk_FJobP	47.74	41.19	48.56	56.14	12.76	6.25	FRI2	88.89	DE50
ActEmpSitN	45.3	27.18	45.95	61.80	23.14	0	NL34	100	FRI2
EXP_JOB_N	9.19	3.57	6.90	9.19	8.82	0	DE30	64.13	RO21
ROBOTS_P	62.12	50.28	62.95	74.89	15.1	17.11	EL61	100	ES23
AIRithmP	72.55	65.85	74.37	82.03	13.1	22.58	ITG2	100	ES23
UNEMPL	5.65	3.38	4.80	7.60	2.98	1.3	CZ02	16.5	ES61
Ed_Tert	30.94	24.50	31.25	36.23	9.06	11.1	RO21	57.3	PL91
KIS	40.73	34.35	39.95	46.05	8.75	18.6	RO21	64.2	SE11

Source: Authors projection, using RStudio

Figure 1 depicts the percentage of respondents who perceive that AI and robotization can steal jobs. The intervals illustrated on the map are based on the quartiles and outliers, defined using the 1.5 interquartile range (IQR) criterion between the lower and upper quartile. This distribution suggests substantial spatial heterogeneity among NUTS 2 regions, with high values for the perception of job displacement due to AI and robotization concentrated in the Southern and Eastern European regions, while lower values are mainly observed in Central and North-Western regions of Europe. The visual representation in Figure 1 indicates the possibility of spatial clustering, which was further tested using Moran's I statistic.

Figure 1. Spatial distribution of variable JobStealP (Box Map)



Source: Authors projection, using GeoDa

4.2. Spatial Autocorrelation

The evaluation of spatial autocorrelation through Moran's I statistics showed strong spatial autocorrelation for: the proportion of people who view the national employment situation unfavorably (ActEmpSitN), the unemployment rate (UNEMPL) and the ratio of individuals working in high-tech and knowledge-intensive services (KIS), indicating a predominant regional clustering for these variables.

Meanwhile, the regional level of tertiary education (Ed_Tert), the proportion of people who consider themselves sufficiently digitally competent to work in the future (AISk_FJobP), the proportion of respondents with positive perceptions regarding the use of robots and AI at work (ROBOTS_P), and the percentage of people who believe that robots and AI are stealing jobs (JobStealP) exhibit moderate levels of spatial autocorrelation, so highly pronounced regional spatial concentrations are not evident. Consequently, the findings regarding the presence of spatial autocorrelation in the perception of job displacement by AI and robotization (JobStealP) support the first research hypothesis, H_1 , indicating a moderate but statistically significant spatial clustering pattern across EU regions.

Reduced spatial dependencies are observed for the ratio of people who negatively perceive the employment situation in the reference country (EXP_JOB_N) and the proportion of people who believe that automation and AI are increasing the rhythm of tasks at work (AIRithmP). Thus, these

variables are more spatially dispersed and are more likely influenced by local factors. Therefore, the variables regarding the perceived negative job situation and the benefits of AI on work suggest the need for future investigations using spatial models.

Table 3. Moran's I spatial autocorrelation index

Variable	Moran's I	Pseudo p-value (999 permutations)
JobStealP	0.353	0.001
AISk_FJobP	0.261	0.001
ActEmpSitN	0.618	0.001
EXP_JOB_N	0.180	0.002
AIRithmP	0.187	0.001
Ed_Tert	0.403	0.001
KIS	0.564	0.001
UNEMPL	0.613	0.001
ROBOTS_P	0.294	0.001

Source: Authors projection, using GeoDa

4.3. OLS Regression Model

First, the classical OLS regression model was estimated, having as dependent variable JobStealP and including all explanatory variables mentioned in Table 1. Results presented in Table 4 show several variations in the factors influencing the perceived occupational substitution in AI and robotization context.

We notice that the proportion of people who consider themselves sufficiently digitally competent to work in the future (AISk_FJobP), the proportion of people who believe that automation and AI are increasing the rhythm of tasks at work (AIRithmP), and the proportion of people who view the situation of national jobs negatively, along with the level of tertiary education in the region (Ed_Tert) and the unemployment rate (UNEMPL), are positively and significantly associated with JobStealP.

In contrast, the proportion of individuals who view their future job situation negatively (EXP_JOB_N), the ratio of individuals working in high-tech and knowledge-intensive services (KIS), and the proportion of respondents with positive perceptions regarding the use of robots and AI at work (ROBOTS_P) have statistically significant negative associations with the dependent variable. These findings partially diverge from the existing literature. In this regard, innovation-oriented regions tend to exhibit lower levels of occupational displacement (Guarascio et al., 2025). At the same time, previous studies suggest that individuals who perceive robotization as beneficial in the

workplace may simultaneously associate digital technologies with higher displacement risks (Schoss and Ciarlante, 2022).

Table 4 also reports the robustness check for the OLS regression model. The R-squared indicates moderate explanatory power, in line with general studies employing Eurobarometer perception-based data at individual level. The absence of multicollinearity and the normality of the error terms are validated by the appropriate tests, while heteroskedasticity persists, as indicated by the Breusch – Pagan test. These results are consistent with the exploratory spatial analysis suggesting the presence of spatial heterogeneity.

Table 4. Results of the OLS regression model estimation

Variable/Metric	Coefficient	p-value
Intercept	57.4815 (7.2388)	0.0000
AISk_FJobP	0.2880 (0.0704)	0.0001
ActEmpSitN	0.1071 (0.0497)	0.0322
EXP_JOB_N	-0.3154 (0.0964)	0.0013
AIRithmP	0.2635 (0.0804)	0.0012
Ed_Tert	0.4487 (0.1241)	0.0004
KIS	-0.5855 (0.1349)	0.0000
UNEMPL	0.8378 (0.3251)	0.0106
ROBOTS_P	-0.3505 (0.0750)	0.0000
R ²	0.3594	-
Adjusted R ²	0.3360	-
AIC	1773.6000	-
F-stat	15.3601	0.0000
Multicollinearity Condition Number	29.3839	-
Jarque-Bera	3.2806	0.1939
Breusch-Pagan	22.2179	0.0045

Source: Authors projection, using GeoDa

Considering the significant spatial variability of the dependent variable, we further estimate the MGWR model, that enables the analysis of the independent variables' local effects and how the identified relationships vary across European regions.

4.4 The Multiscale Geographically Weighted Regression (MGWR) Model

The results of the MGWR model show large spatial variability of most local coefficients associated to the explanatory variables (Table 5), against the global relationships provided by the OLS regression model. The bandwidth parameter is determined individually for each independent variable, allowing each relationship to vary at its own geographical scale (Fotheringham et al., 2017). This particularity of the MGWR estimation provides a better representation of the spatial heterogeneity, since the local and global varying relationships can be properly identified.

In our case, the proportion of people who view the national employment situation unfavorably (ActEmpSitN), the unemployment rate (UNEMPL), and the proportion of people employed in high-tech and knowledge-intensive services as part of total employment (KIS) display stable relationships across regions, indicating global effects of these variables. This is justified by the small range of the associated parameters and the large bandwidth used in the MGWR for these variables (Table 5).

On the contrary, the coefficients associated with variables: perception of the rhythm at which tasks are increasing at work through AI and robotization (AIRithmP), the level of positive perception of digital skills (AISk_FJobP), the tertiary education level (Ed_Tert), and the expected negative situation at work (EXP_JOB_N) show large variability at local level. This suggests that the effects of these variables on the perception of job replacement by new digital technologies varies significantly across European regions.

Table 5. Results of MGWR model

Variable	Bandwidth	Min.	Q1	Median	Q3	Max.
Intercept	43	-27.3454	23.0438	42.0384	55.2663	177.8985
AISk_FJobP	50	-0.1351	0.1566	0.3317	0.4906	1.0336
ActEmpSitN	227	0.1641	0.1702	0.1728	0.1744	0.1784
EXP_JOB_N	73	-0.7914	-0.4545	-0.2952	-0.1665	0.4215
AIRithmP	23	-1.4624	-0.0049	0.2270	0.4950	1.1741
UNEMPL	227	0.5707	0.6235	0.6594	0.6918	0.7578
ROBOTS_P	156	-0.3498	-0.3037	-0.2691	-0.2146	-0.1316
Ed_Tert	67	-0.0877	0.1628	0.3218	0.5247	0.8712
KIS	227	-0.2671	-0.2618	-0.2534	-0.2474	-0.2070

Source: Authors projection, using RStudio

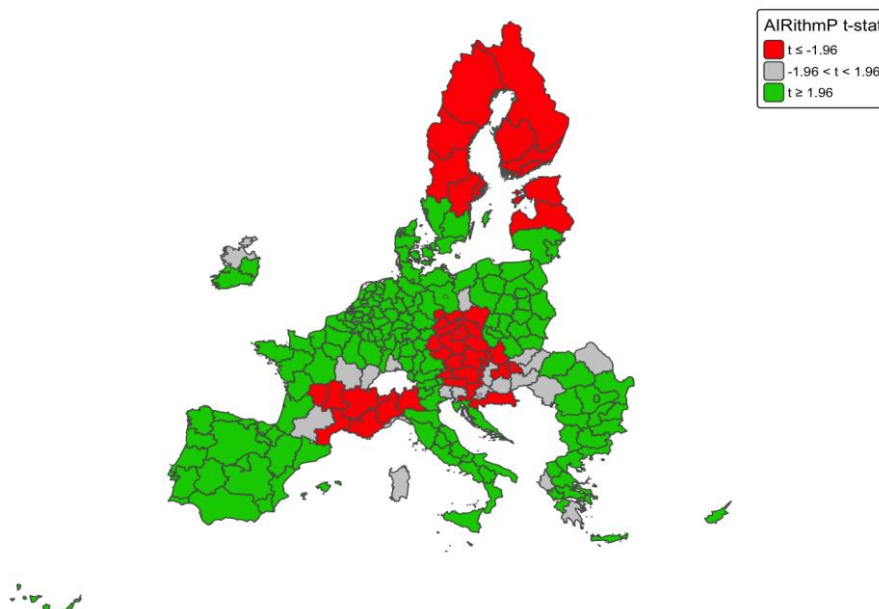
To illustrate the spatial heterogeneity of the estimated MGWR relationships, we examined the regional distribution of local t-statistics for each explanatory variable.

Table 6 reports the number of NUTS 2 regions characterized by statistically significant positive and negative local coefficients, as well as non-significant estimates. This approach allows us to examine how the direction and the strength of the determinants of perceived job substitution vary

across EU regions. Next, we will use significance maps to analyze more in depth the local impact of variables related to the perception of the increasing pace of work due to AI and robotization (AIRithmP) and the high level of confidence in digital skills for future work (AISk_FJobP).

Among all explanatory variables, AIRithmP reports the strongest local spatial heterogeneity (Table 5). In most regions, the direct and statistically significant association with the dependent variable suggests that the new digital technologies are not perceived strictly as methods for enhancing labor productivity or task performance, but may accentuate the feeling that jobs are being replaced. On the other hand, in the majority of regions in the Northern and Central European countries, Northern Italy, and Southern France (Figure 2), the identified relationship is found to be inverse. Consequently, in these geographical areas, the benefits of AI and robotization in the workplace are associated with a reduction in the perception of occupational substitution through digital technologies. The results obtained are consistent with the literature, which highlights the heterogeneous effect of AI integration and robotization in the workplace on the perception of occupational substitution (Vasilescu et al., 2020).

Figure 2. The significance map for the local coefficients associated with variable AIRithmP

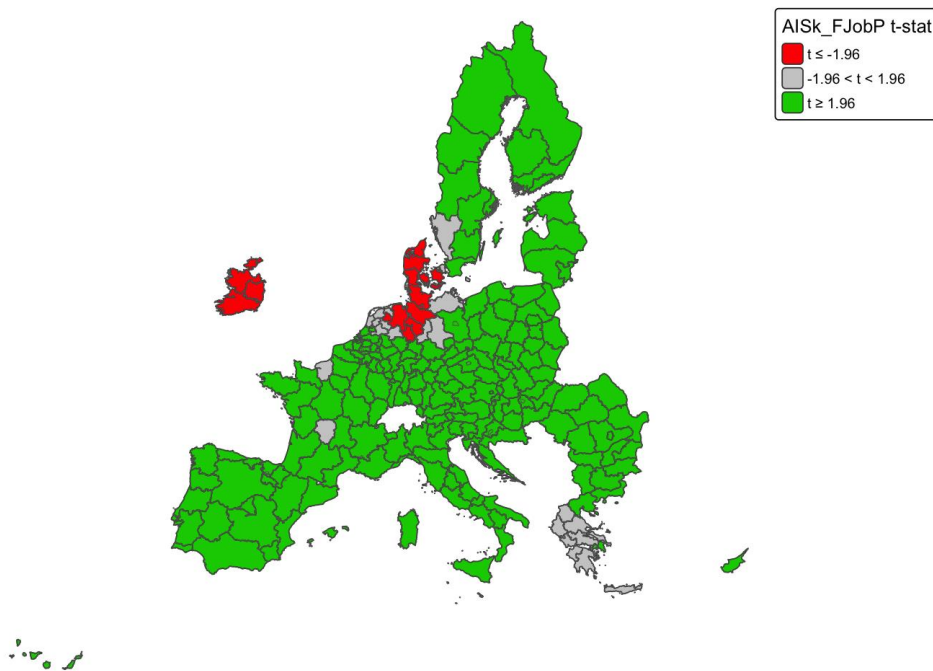


Source: Authors projection, using RStudio

The relationship between perceptions of digital skills levels (AISk_FJobP) and job displacement (JobStealP) is not uniform, as evidenced by a bandwidth of 50. In terms of the distribution of coefficients, moderate spatial heterogeneity is observed (Table 5). In most NUTS 2

regions, an increase in the perceived level of digital skills has a positive and statistically significant effect on the perceived replacement of jobs through robotization and AI. From an economic perspective, these results support the view that new digital technologies can replace the work of skilled individuals in fields requiring digital skills, such as data analysis, computer science, and Information and Communication Technology (Zarifhornavar, 2023).

Figure 3. The significance map for the local coefficients associated with variable AISk_FJobP



Source: Authors projection, using RStudio

Similarly, the education level (Ed_Tert) has a positive local effect on the perception regarding the replacement of jobs by new digital technologies (Table 6). Our findings are consistent with those of Wang and Lu (2025) who suggest that highly educated individuals perceive new digital technologies as a threat to their jobs. The only exceptions to these relationships are certain North-Western regions where educational level tends to be inversely associated with the perception of job displacement.

On the contrary, the variable ROBOTS_P has an inverse and statistically significant effect in most EU regions (Table 6). This result suggests that a positive perception of the use of AI and robots in the workplace tends to diminish the perception of job substitution in the context of emerging digital technologies, contrary to the results obtained by Vasilescu et al. (2020). In the same way, EXP_JOB_N is inversely and moderately associated with our dependent variable (Table 6). These

findings indicate that as pessimism about the future of jobs increases, the perceived relevance of job replacement by AI and automation decreases. A possible interpretation of this relationship could be linked to the fact that, in unstable professional environments, AI and automation may be perceived as having little impact on the deterioration of job conditions, given the existence of persistent vulnerabilities.

At the same time, the MGWR model indicates an overall and predominantly positive pattern regarding the UNEMPL and ActEmpSitN variables on the fear of human labor replacement (Table 6). In the case of unemployment, the results suggest that regions characterized by higher levels of labor market instability tend to have increased level of concerns regarding the replacement of labor by AI and robotization. By contrast, the KIS variable tends to exert a global, negative, and statistically significant effect on the dependent variable. This suggests that the workforce engaged in innovative activities, potentially facilitated by AI, tends to be less exposed to the effects of job displacement by emerging digital technologies (Verma and Singh, 2022).

Table 6. Regional distribution of t-statistics

Variable/Local classification	$t \leq -1.96$	$-1.96 < t < 1.96$	$t \geq 1.96$
AISk_FJobP	14	22	192
ActEmpSitN	0	25	203
EXP_JOB_N	126	98	4
AIRithmP	46	20	162
UNEMPL	0	29	199
ROBOTS_P	224	4	0
Ed_Tert	15	32	181
KIS	227	1	0

Source: Authors projection, using RStudio (The number of regions are presented in cells)

The robustness checks presented in Table 7 indicate that the MGWR model performs better than the classical OLS model in explaining the perception of job substitution across EU regions. While OLS allows for the estimation of a single set of coefficients under the assumption of spatial stationarity, the MGWR model captures local spatial heterogeneity by allowing exogenous factors to vary across different spatial scales. Thus, the MGWR model reports a higher explanatory power and lower information criteria values compared to the global OLS model. The MGWR results indicate that the determinants of the perception of job displacement due to AI and robotization are not uniformly distributed spatially, suggesting significant differences in the perceptions of the European population toward the digital transformation of labor market.

Table 7. MGWR performance

Statistics/Model	MGWR	OLS
SSR	10228.1800	29480.1000
AICc	1695.7220	1804.4600
AIC	1577.8690	1773.6000
R ²	0.7778	0.3594
Adjusted R ²	0.6521	0.3360
Number of Obs.	228	

Source: Authors projection, using RStudio

5. Conclusions

The substitution of jobs through AI and robotization has intensified in the wake of the COVID-19 pandemic, affecting not only jobs with redundant tasks but also those where AI development can take over a large share of human work, such as data analysts, computer scientists, etc. In this context, it is not only the actual displacement of jobs that must be analyzed, but also how European citizens perceive these changes in the labor market. The main objective of this study was to analyze the spatial heterogeneity of perceived occupational displacement due to AI and robotization across EU NUTS 2 regions, by identifying regional subjective and objective labor market factors influencing these perceptions. To achieve the objective, a MGWR model was used to examine the spatial variability of the relationships compared to classical OLS regression.

The findings suggest that the perceptions concerning the replacement of jobs through AI and robotization vary substantially across EU NUTS 2 regions. The statistically significant spatial autocorrelation for the aforementioned perceptions support research hypothesis H₁ and indicates the need to analyse the relationships between variables at the local level. Subsequently, the results support research hypothesis H₃ in that MGWR exhibits greater explanatory power for perceived job substitution compared to OLS regression.

Furthermore, the effects of exogenous factors on the dependent variable are heterogeneous. In the majority of European regions, factors related to the perception of the usage or integration of AI and robotization to the work environment tend to accentuate the idea of job displacement. In this context, the regional level of positive assessment of digital skills, the increasing rhythm of tasks at work in the context of new technologies, and the level of tertiary education tend to have a direct effect on the perception of job substitution in most EU regions. The results are consistent with research hypotheses H₂ and H₃ and suggest that the level of awareness regarding the effects of new technologies on the labor market is high. At the same time, this awareness indicates the persistence of public concerns.

Similarly, regional unemployment rates and perceived insecurities regarding the national job market and individual jobs are directly associated with perceptions of job displacement. Thus, these results confirm research hypothesis H₂ and may suggest that existing instabilities in regional labor markets can amplify perceived occupational substitution in the context of emerging digital technologies. On the contrary, the regions with higher shares of employment in knowledge intensive services display lower level of perceived occupational displacement, indicating better labor market adaptability to AI-driven changes.

The findings should be interpreted with several limitations. First, the aggregation of individual responses from the EB surveys led to an uneven distribution of the number of respondents across NUTS 2 regions. Although the median sample size is 100 respondents, some regions are characterized by relatively small sample sizes (Appendix), which may lead to increased variability in the indicators derived from the EB 101.3 and EB 101.4 survey data.

Second, the analysis focuses on the perceived job displacement caused by artificial intelligence and automation, which implies that regional perceptions may not reflect actual exposure to job displacement in the context of digital technology development. Finally, the analysis conducted for the year 2024 limits the formulation of the temporal dynamics of the relationships under study.

In this regard, the study highlights the need for Eurobarometer data to be uniformly available at the NUTS 2 level and the importance of such data to be collected over extended time periods.

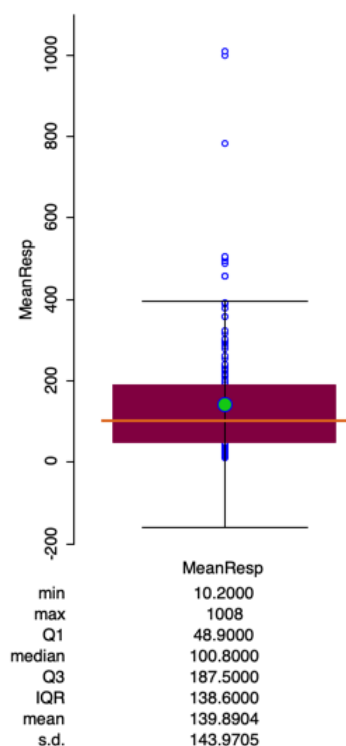
The findings also have important policy implications. Policies designed to encourage workforce adaptation within the context of AI and robotization should not be developed solely at the national level, as the impact of labor market transformation varies considerably across regions. Given the spatial heterogeneities described, public policies must focus on ensuring that the workforce is not destabilized by technological progress, but rather adapts and leverages innovative human characteristics that are currently irreplaceable by AI. The results reveal that occupational displacement is not only an economic, but also a perceptual and social challenge. We emphasize that as the use of AI and robotization expands, in the absence of differentiated and region-specific public policies, existing regional disparities will expand, and the workforce will become increasingly skeptical about their own occupations, job tasks, and skills.

Appendix

Excluded NUTS 2 level regions: Åland-Finland; Corse, Guadeloupe, Martinique, Guyane, La Réunion, Mayotte- France; Voreio Aigaio, Notio Aigaio, Ionia Nisia-Greece; Ciudad de Ceuta-Spain; Região Autónoma dos Açores, Região Autónoma da Madeira-Portugal.

Aggregated territorial units: all NUTS 2 level data from Ireland, Lithuania and Slovenia.

Disaggregated territorial units: all NUTS 2 level data from Germany, Sweden and paired NUTS 2 level regions from EB 101.3, 101.4 database: Piemonte and Valle d' Aosta, Abruzzo and Molise, Puglia and Basilicata, Provincia Autonoma di Trento and Provincia Autonoma di Bolzano, Italy.



Distribution of the average number of respondents at NUTS 2 regional level

Source: Authors projection, using GeoDa

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