Septiandri et al. *EPJ Data Science* (2025) 14:33
https://doi.org/10.1140/epjds/s13688-025-00547-9
EPJ Data Science
a SpringerOpen Journal

RESEARCH Open Access

# AI and the economic divide: How Artificial Intelligence could widen the divide in the U.S.

Ali Septiandri[1], Marios Constantinides[1,3] and Daniele Quercia[1,2*]

Handling Editor: Marton Karsai

*Correspondence:
quercia@cantab.net
[1]Nokia Bell Labs, Cambridge, UK
[2]Kings College London, United Kingdom, London, UK
Full list of author information is available at the end of the article

**Abstract**
Artificial Intelligence (AI) has been repeatedly associated with the potential for automating, or even augmenting, occupational tasks. However, the geographical impact of AI remains unclear. Building on previous work, we employed a deep learning natural language processing model to automatically identify AI patents impacting various occupational tasks. We analyzed a dataset of 17,879 task descriptions and quantified AI's potential impact at metropolitan statistical areas (MSAs) within the U.S. by examining 24,758 AI patents filed with the United States Patent and Trademark Office (USPTO) between 2015 and 2022. Our findings reveal that MSAs that will be more likely to be impacted by AI are not just hubs of creative industries but will also be characterized by a lack of economic diversity. Indeed, the U.S. MSAs that will be more likely to be impacted are those heavily specialized, with little to no efforts at diversification. These dynamics suggest that AI could amplify existing divides, hitting hardest in areas where economic opportunities are already concentrated in a few sectors, leaving many behind in the race for innovation-driven growth.

**Keywords:** Future of work; AI; Patents; Labor market; Deep learning; Geography; Natural language processing

## 1 Introduction

Artificial Intelligence (AI) has emerged as a pivotal technology in transforming occupational tasks through automation and augmentation [1–6]. It has already reshaped various industries by enhancing productivity, efficiency, and accuracy. Automation via AI involves the complete delegation of routine and repetitive tasks to intelligent systems, which can operate with precision on par with or even better than human counterparts. This has been particularly evident in manufacturing where robotic process automation and machine learning algorithms optimize production lines and quality control processes [3], or chatbots and virtual assistants have taken over routine inquiries and support functions in customer services [7]. Additionally, AI augments human capabilities by providing advanced tools that enhance decision-making and problem-solving skills, evident in sectors such as healthcare, where AI-driven diagnostic systems assist doctors by analyzing medical data with high accuracy [8]. Furthermore, the integration of AI in finance has revolutionized risk management and trading by processing vast amounts of data to identify patterns and forecast market trends [9]. These AI advancements not only optimize existing workflows but also create new paradigms of work where machines and humans collaborate [6].

While previous works have mainly focused on quantifying the impact of AI on occupational tasks [1–6], yet its impact on the geographical level remains unclear. This is particularly important as AI's adoption and benefits are often unevenly distributed across different geographical areas, leading to disparities in economic growth and labor market outcomes. In developed regions with advanced technological infrastructure and a skilled workforce, AI integration tends to drive significant economic gains and job creation in high-tech industries. Conversely, regions lacking such infrastructure may face challenges in adopting AI technologies, potentially exacerbating existing economic inequalities. For example, while metropolitan areas with robust digital ecosystems might experience a surge in AI-driven innovation and productivity, rural areas could struggle to keep pace due to limited access to necessary resources and training [10]. Therefore, in this study, we set out to quantify AI's impact on a geographical level, and in so doing, we made two main contributions:

1. We extended a measure of AI impact from previous literature, and employed a deep learning natural language processing model to automatically identify AI patents impacting various occupational tasks (Sect. 3). Using this method, we analyzed a dataset of 17,879 task descriptions and quantified AI's potential impact at industry sector and metropolitan statistical areas (MSAs within the U.S. by examining 24,758 AI patents filed with the United States Patent and Trademark Office (USPTO) between 2015 and 2022.
2. We found that, on average, the East Coast in U.S. experiences a greater impact of AI compared to the West Coast (Sect. 4). More broadly, the influence of AI extends to MSAs in the U.S. that heavily rely on industries susceptible to AI changes, often characterized by the increasing creative class employment or a lack of economic diversification.

## 2 Related work

We surveyed various lines of research that our work draws upon, and grouped them into two main areas: AI Impact on Occupational Tasks (Sect. 2.1); and Geographical Impact of AI (Sect. 2.2).

### 2.1 AI impact on occupational tasks

The impact of AI on occupational tasks has been a significant focus of research, highlighting both its potential to enhance productivity and the risks of job displacement. Huang and Rust discussed how AI-driven automation can streamline repetitive tasks, leading to increased efficiency in industries such as manufacturing and logistics [11]. Additionally, the work of Frey and Osborne [1] has been pivotal in estimating the susceptibility of jobs to automation, suggesting that nearly 47% of total U.S. employment is at risk due to AI technologies. Other studies, like those by Brynjolfsson and McAfee [10], emphasized the augmentation potential of AI, where human skills are complemented by AI, particularly in high-skill domains such as finance and healthcare. These studies collectively highlight the dual nature of AI's impact, offering both opportunities for enhanced productivity and challenges related to workforce displacement.

### 2.2 Geographical impact of AI

The geographical impact of AI is shaped by various factors, including technological diffusion, economic inequality, and economic diversification. Research using patents to study technology diffusion indicates that technological advancements often cluster in specific geographical areas [12], driven by localized interactions that facilitate the exchange and application of knowledge. However, the ability of an area to leverage these localized interactions is influenced by geographical economic conditions. For example, areas with higher inequality often experience minimal growth and development [13]. Another potential factor is what Richard Florida termed as the 'creative class' [14, 15]. In his studies, Florida found that areas with higher concentrations of creative and knowledge-based occupations are more likely to attract AI investments and innovation [16]. Economic diversification is another key determinant of how AI impacts different geographical areas. Studies have shown that areas with diverse economic bases are more resilient to economic shocks and exhibit higher stability. For example, Davies [17] found that European regions with diverse workforces recovered more swiftly from financial crisis, while Dissart [18] observed that U.S. regions with a mix of industries experienced less volatility in employment and income growth. These findings suggest that economic diversity allows geographical areas to adapt more effectively to sector-specific disruptions, as workers can transition between industries more easily [19]. Thus, the geographical impact of AI is not uniform; it is deeply influenced by local economic structures, the equitable distribution of income, and the capacity for technological innovation and adaptation.

*Research gaps* While a large body of literature has explored the broad implications of AI on occupational tasks, the impact of AI at the geographical level remains unclear. Similar to previous works that used patents to quantify AI's impact, we build upon and extend these studies to quantify the geographical impact of AI.

## 3 Methods

### 3.1 Datasets

*Occupation dataset* We obtained detailed task descriptions for a wide range of occupations from the O*NET database [20], a widely used resource in occupational studies [2, 4, 5, 21, 22]. Our data set includes 759 unique occupations and 17,879 unique tasks, as provided in the ONET 26.3 version released in May 2022. The number of tasks per occupation varies from 4 to 286, with a median of 20 tasks per occupation (Fig. 1).

*Patent dataset* To compile a corpus of AI patents, we initially retrieved 74,875 patents granted by the USPTO between 2015 and 2022, classified as AI-related according to the PATENTSCOPE AI Index [23]. To refine this collection and exclude patents only tangentially related to AI, we selected patents within the core AI applications index class. This filtering process resulted in a final corpus of 24,758 AI patents.

Out of the 24,758 AI patents granted between 2015 and 2022, the majority included the keyword "machine learning" (46%), followed by "neural network" (32%), "artificial intelligence" (9%), and "deep learning" (6%) (Table 1).

### 3.2 AII impact measure

To measure the impact of AI on occupational tasks, Septiandri et al [24] defined the AI Impact (AII) as a measure of how much AI could impact a job's tasks by looking at how

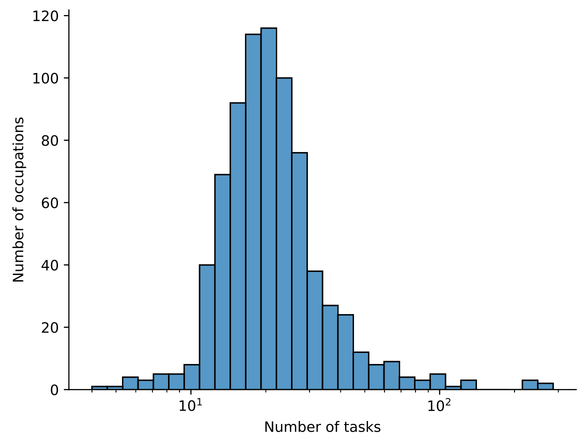


**Figure 1** Distribution of number of tasks per occupation

**Table 1** Number of patents based on keywords

| Keywords | Number of patents |
|---|---|
| machine learning | 10,904 |
| neural network | 9364 |
| artificial intelligence | 2674 |
| deep learning | 1848 |
| planning | 1050 |
| natural language processing | 917 |
| reinforcement learning | 506 |
| computer vision | 463 |
| speech processing | 126 |
| predictive analytics | 69 |
| robotics | 64 |
| control methods | 29 |
| knowledge representation | 24 |

closely these tasks are associated with patents. For each task, their method finds the patent most similar to it using a cosine similarity score. This score shows how much the task aligns with AI-related innovations. The AI impact on a task is the highest similarity score[1] between the task and any patent.

This method is based on a deep learning framework using the Sentence-T5 (ST5) architecture [25, 26] for Natural Language Processing. This framework transforms text into "semantic vector representations" (embeddings), capturing the text's meaning and allowing to measure similarity between texts. The authors used the Sentence-T5-XL model[2] for its proven effectiveness in various language tasks, including classification and similarity comparisons.

[1] The highest similarity was used to avoid including less relevant patents, which would dilute the AI impact measurement.

[2] The default model's parameters were used, that is, an Adafactor optimizer with a starting learning rate of 0.0001, linear decay after 10% of training steps, a batch size of 2048, and a softmax temperature of 0.01.

*3.2.1 AI impact on occupations*

Septiandri et al [24] computed the AI impact $x_j$ on occupation $j$ by computing the number of *AI-impacted tasks* over the total number of $j$'s tasks:

$$x_j = \frac{\sum_{t \in \text{tasks}(j)} 1_{\alpha_t > p_{90}(\alpha)}}{\sum_{t \in \text{tasks}(j)} 1}, \tag{1}$$

where $p_{90}(\alpha)$ is the 90$^{\text{th}}$ percentile of AI impact values computed on all occupations' tasks, and $1_{\alpha_t > p_{90}(\alpha)}$ is an indicator function whose value is 1, if $\alpha_t > p_{90}(\alpha)$, and 0 otherwise. Essentially, the AII measures the number of tasks within an occupation that are impacted by AI, without considering the relative importance of each task, similar to the method used in previous research [6]. The use of the 90$^{\text{th}}$ percentile as a threshold helps make the AII measure more resistant to noise, as suggested in earlier studies [27]. This is crucial because, although each task is assigned a similarity value in the initial step, the most similar patent to a task might still be unrelated. Conversely, using a stricter 95$^{\text{th}}$ percentile threshold would result in 55% of occupations having zero impacted tasks.

*3.2.2 AI impact on geographical areas*

We extended the AII measure to the geographical level. To determine the AII scores, we used the Occupational Employment and Wage Statistics (OEWS) dataset published in 2022 by the U.S. Bureau of Labor Statistics. For each MSA, we calculated a weighted average of the AII scores by weighting each occupational AII score by the number of employees in that occupation within the MSA.

$$\Omega_r = \frac{\sum_{j \in \text{occupations}(r)} x_j w_{rj}}{\sum_{j \in \text{occupations}(r)} w_{rj}}, \tag{2}$$

where $w_{rj}$ is the number of employees associated with occupation $j$ within MSA $r$. $\Omega_r$ is $r$'s geographical AII score that accounts for the potential AI impact on occupations in that geographical area and the workforce distribution. Occupations with more people in an area have a larger influence on that area's overall labor market dynamics. Weighting by the number of employees ensures that occupations with a higher workforce representation influences the geographical AII score proportionately. Moreover, some occupations might have extreme AII scores (either very high or very low). A simple average could be skewed by these outliers. By weighting sectors based on the number of employees, the measure ensures that the geographical AII score is not disproportionately affected by these smaller occupations. This method of weighted averaging aligns with methodologies in previous studies [2–4].

### 3.3 Measuring economic diversity

To measure the economic diversity of a MSA, we collected its workforce distribution data from the American Community Survey (ACS) dataset published in 2022 by the U.S. Census Bureau [28]. For each MSA, the economic diversity is computed as the entropy of the workforce distribution:

$$H(r) = -\sum_{s \in \text{sectors}(r)} \frac{w_{rs}}{N_r} \log \frac{w_{rs}}{N_r}, \tag{3}$$

where $w_{rs}$ is the number of employees associated with sector $s$ within MSA $r$ and $N_r$ is the total number of employees within MSA $r$. Industry classifications in the ACS dataset we used are based on the 2-digit NAICS (North American Industry Classification System) code, which serves as the federal standard for categorizing and analyzing business establishments across the U.S. economy.

## 4 Results

### 4.1 Most- and least-impacted geographical areas

Just as with the occupation analysis, the AII measure can be used to study the impact of AI on geographical-level outcomes. In fact, patents have been used to study the factors that influence the spread of technology among geographical areas [12], as AI is permeating urban design and planning [29]. Previous research has consistently shown that technology spillovers tend to concentrate within specific geographical areas. This concentration is often attributed to the effective transfer and dissemination of knowledge, a process facilitated by localized interactions involving communication, collaboration, social interactions, and the presence of a local pool of human capital [30, 31].

By calculating the AII measure at the MSA level, it became evident that certain states, and even at a more detailed MSA-level granularity (Fig. 2), experienced lower levels of impact compared to others. The East Coast, on average, experiences a greater impact of AI than the West Coast. However, Washington and California are exceptions to this pattern, as they are highly impacted due to the presence of Seattle and the Bay Area.

### 4.2 Factors influencing geographical impact

The extent to which local interactions can yield significant technological advancements depends on geographical capabilities that govern innovation processes. Income inequality emerges as a factor of concern, as it has been found to have adverse effects on geographical areas growth with total wages growing superlinearly as the cities increase in size [32]. Wilkinson and Pickett [13] argue that more equal societies, where income and wealth are distributed more fairly among the population, tend to have better outcomes for their citizens. We correlated the income inequality among U.S. households, calculated as the

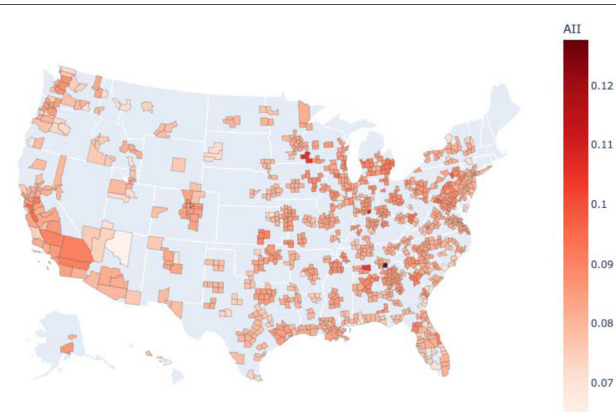


**Figure 2** Darker colors represent higher AI impact within MSAs. Grey areas indicate regions outside the boundaries of MSAs, which generally have lower population densities and are not included in the analysis due to limited data availability

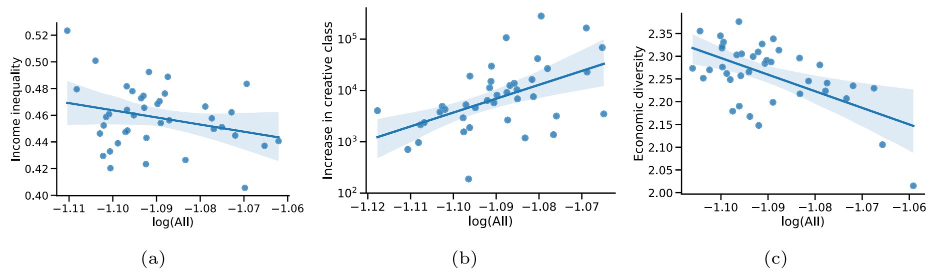


**Figure 3** Three socio-economic indicators as a function of MSA-level AII: (a) income inequality (MSAs with lower income inequality will be the most impacted); (b) attractiveness to the creative class (MSAs with a larger creative class will be the most impacted); and (c) economic diversification (MSAs with the highest diversification will be the least impacted). The binned scatterplots use 40 bins determined by the dependent variable, with each bin representing a group of observations aggregated into a single data point using the mean as the summary statistic

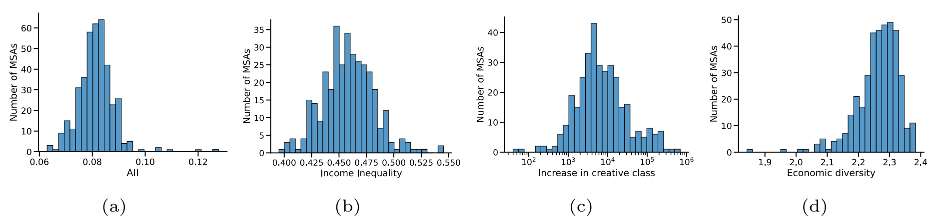


**Figure 4** Frequency distribution plots of the three socio-economic indicators and the AII measure at the MSA level

MSA's Gini coefficient from the ACS dataset published in 2022 [33] (Fig. 4b), with the AII MSA-level measure (Fig. 3a and Fig. 4a).

After controlling for total employment within each MSA, we found that higher potential AI impact is associated with lower income inequality. Specifically, areas with higher AI potential exhibited lower Gini coefficients, suggesting a more equitable income distribution. While this association aligns with emerging evidence that AI may democratize access to high-value jobs and skills, particularly in regions with investments in education and digital infrastructure [10, 34], we caution against inferring causality. It is also possible that more productive and equitable regions are better positioned to adopt and benefit from AI technologies. This highlights the need for future longitudinal research to examine how inequality evolves as AI adoption progresses. Our findings, while cross-sectional, offer a complementary perspective to existing work on the socio-economic geography of AI [35].

Another plausible explanation is that the least impacted states may not predominantly rely on the knowledge economy. Richard Florida's seminal work established a link between geographical economic prosperity and the presence of the "creative class". Florida defined the creative class as individuals engaged in creative and knowledge-based industries such as artists, designers, scientists, engineers, researchers, and professionals in fields reliant on creativity and intellectual capital [14, 15]. His theory posits that cities and geographical areas with a higher concentration of the creative class are more likely to foster innovation and economic growth. Hoyman and Faricy [36] further supported this notion by demonstrating that states with a higher percentage of the population aged twenty-five and over holding a bachelor's degree or higher in metropolitan statistical areas tend to be more economically successful. Additionally, investments in talent and technology have been shown to predict the retention of the creative class, ultimately contributing to state income growth and equality [16]. Using Florida's creative class as a proxy for the knowledge economy, we found a weak positive correlation (Pearson's $r = 0.19$) between the AII MSA-level measure and the increase in the creative class employment in ten years (Fig. 4c). This may suggest that geographical areas with a growing creative class are also those experiencing greater AI-related activity. While our findings do not speak directly to the causal impact of AI on the creative class, they indicate that regions more intensive in AI use may be more attractive to creative professionals, or that such regions foster conditions conducive to both AI adoption and creative class growth. Although the presence of the creative class has previously been associated with economic prosperity, areas that overly concentrate on knowledge-based economies will be more likely to face significant challenges in upskilling and reskilling their workforces.

However, we acknowledge that our measure of creative class growth, defined as the log of the absolute change (log($\Delta$ of the creative class)) is not scale-invariant, and alternative growth formulations may yield different patterns. Specifically, one might instead consider relative growth, defined as the change in the log of creative class ($\Delta$ (log of creative class)). When using this alternative specification, the correlation with AII is no longer statistically significant, suggesting that the observed association is sensitive to the operationalization of creative class growth. Nonetheless, our multivariate regression results based on the original formulation (i.e., absolute change) remain statistically significant and are consistent with theoretical expectations about the relationship between creative economies and AI diffusion.

A third possible explanation could be that the least impacted states include MSAs with relatively higher economic resilience. Some studies suggest that greater economic diversity at the MSA-level may contribute to greater economic resilience. Davies [17] analyzed regional economies across Europe and found that geographical areas with more diversity in their workforce composition exhibited higher stability and faster recovery from the 2008-2010 global financial crisis. Similarly, Dissart [18] found that U.S. geographical areas with greater diversity across sectors saw lower volatility in employment and income growth, indicating higher economic resilience. The proposed mechanism in these studies is that diverse geographical economies allow for greater adaptability and adjustment to sector-specific economic shocks. When a recession damages an individual sector, an area with diverse industries can absorb the shock better as workers can shift to unaffected sectors more easily [19]. Similarly, one can hypothesize that when a sector is affected due to automation, an area that diversifies its workforce will be more economically resilient. In contrast, specialized economies centered around one or a few dominant industries have been found to be more vulnerable to sector-specific disruptions. Martin [37] found that during recessions, regions in Europe with less complex, less diverse economies suffered greater rises in unemployment rates due to their concentration in a small number of industries that were severely impacted (e.g., manufacturing). This closer examination allowed us to delve into how localized geographical capabilities correlate with the impact of AI. In so doing, we correlated a measure of economic diversity (computed as the entropy of workforce distribution by sector within an MSA, as detailed in Sect. 3.3 and shown in Fig. 4d) with the AII MSA-level measure (Fig. 3b). Two distinct groups of MSAs of resilient economies

**Table 2** Most- and least-impacted MSAs. The MSA-level AII is calculated as the employment-weighted average of occupation-level AII scores. For each MSA, we also report the economic diversity (higher values indicate greater diversity)

| Rank | Most-impacted | Economic diversity | Least-impacted | Economic diversity |
|---|---|---|---|---|
| 1 | Dalton, GA | 2.20 | Daphne-Fairhope-Foley, AL | 2.34 |
| 2 | Columbus, IN | 2.13 | Coeur d'Alene, ID | 2.32 |
| 3 | Rochester, MN | 1.95 | Hinesville, GA | 2.28 |
| 4 | Huntsville, AL | 2.21 | Rapid City, SD | 2.27 |
| 5 | Winchester, VA-WV | 2.30 | Missoula, MT | 2.27 |
| 6 | San Jose-Sunnyvale-Santa Clara, CA | 2.21 | Bloomington, IL | 2.20 |
| 7 | Charleston, WV | 2.24 | St. George, UT | 2.28 |
| 8 | Rockford, IL | 2.23 | Manhattan, KS | 2.20 |
| 9 | Detroit-Warren-Dearborn, MI | 2.23 | Walla Walla, WA | 2.21 |
| 10 | Stockton-Lodi, CA | 2.37 | Hot Springs, AR | 2.27 |
| 11 | Kankakee, IL | 2.23 | Guayama, PR | 2.26 |
| 12 | Ann Arbor, MI | 2.03 | Lawrence, KS | 2.17 |
| 13 | Augusta-Richmond County, GA-SC | 2.29 | Watertown-Fort Drum, NY | 2.26 |
| 14 | Riverside-San Bernardino-Ontario, CA | 2.33 | Grants Pass, OR | 2.33 |
| 15 | Boulder, CO | 2.17 | Kingston, NY | 2.27 |
| 16 | Palm Bay-Melbourne-Titusville, FL | 2.28 | Santa Fe, NM | 2.25 |
| 17 | York-Hanover, PA | 2.32 | Barnstable Town, MA | 2.25 |
| 18 | Iowa City, IA | 2.06 | Pocatello, ID | 2.18 |
| 19 | Harrisburg-Carlisle, PA | 2.30 | Jacksonville, NC | 2.30 |
| 20 | Gainesville, FL | 2.08 | Flagstaff, AZ | 2.18 |

emerged (Table 2). The first group comprises MSAs with diversified economies where the workforce is engaged in a wide range of industry sectors. In fact, diversified metropolitan areas tend to experience more economic growth [38]. The second group consists of MSAs where the workforce specializes in industry sectors that are least impacted such as education. In contrast, MSAs concentrated in sectors most vulnerable to disruption, such as manufacturing and healthcare, bear the costs of this over-specialization. The most affected U.S. metropolitan areas are those disproportionately reliant on a specific sector, with little to no attempts at diversifying their economic base. This narrow focus leaves them particularly exposed to the transformative and potentially destabilizing impacts of AI. This monotonic relationship may be driven by the fact that economically less diversified MSAs tend to concentrate employment in a small number of sectors (e.g., manufacturing, transportation, or administrative services) that are highly susceptible to automation. These sectors are typically associated with routine and predictable tasks, which existing AI systems are increasingly capable of performing. Conversely, more economically diverse MSAs often balance across sectors with varying degrees of AI exposure or have a larger share of employment in less automatable sectors such as education, arts, and professional services.

To move beyond correlational analysis and verify our findings, we constructed multivariate regression models that controlled for total employment. These models revealed statistically significant relationships between AII and all three previously analyzed factors: income inequality, economic diversity, and creative class growth (Table 3). The Adj. $R^2$ values for these models indicate varying levels of explanatory power. Specifically, the model for income inequality has a relatively low Adj. $R^2$ value of 0.051, suggesting that the relationship between AII and income inequality is weakly explained by the model. In contrast, the model for creative class growth has a high Adj. $R^2$ of 0.790, indicating a strong fit and suggesting that AII explains a substantial portion of the variance in creative class

**Table 3** Multivariate regression analysis showing the relationship between AII and factors influencing geographical impact. Adj. $R^2$ values show differences in the explanatory power of the models: income inequality (Adj. $R^2$ = 0.051), economic diversity (Adj. $R^2$ = 0.089), and creative class growth (Adj. $R^2$ = 0.790), indicating the strongest model fit for creative class growth. Beta coefficients highlight significant relationships: a negative association between AII and income inequality (*beta* = –0.102, $p < 0.01$), a negative association with economic diversity (*beta* = –0.576, $p < 0.01$), and a strong positive association with creative class growth (*beta* = 1.929, $p < 0.01$). Total employment and its change are included as control variables. Numbers in parentheses represent standard errors

| | Income inequality | Economic diversity | log(Δ Creative class) |
|---|---|---|---|
| Intercept | 0.295*** | 1.435*** | 2.937*** |
| | (0.044) | (0.156) | (0.571) |
| log(AII) | –0.102*** | –0.576*** | 1.929*** |
| | (0.036) | (0.125) | (0.504) |
| log(Total employment) | 0.010*** | 0.039*** | |
| | (0.003) | (0.009) | |
| log(Δ Total employment) | | | 0.751*** |
| | | | (0.024) |
| Observations | 342 | 302 | 283 |
| $R^2$ | 0.056 | 0.095 | 0.792 |
| Adjusted $R^2$ | 0.051 | 0.089 | 0.790 |
| Residual Std. Error | 0.023 (df = 339) | 0.069 (df = 299) | 0.284 (df = 280) |
| F Statistic | 10.146*** (df = 2; 339) | 15.784*** (df = 2; 299) | 531.656*** (df = 2; 280) |

***Note***: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

growth. The economic diversity model shows an intermediate Adj. $R^2$ of 0.089, highlighting a modest explanatory power. The negative coefficient for AII and income inequality (*beta* = –0.102, $p < 0.01$) aligns with the earlier correlation analysis, suggesting that areas with higher AII scores tend to have lower levels of income inequality. Similarly, the negative coefficient for economic diversity (*beta* = –0.576, $p < 0.01$) corroborates the correlation analysis, indicating that MSAs with higher economic diversity will be less likely to be impacted by AI. The strong positive coefficient for creative class growth (*beta* = 1.929$p$ < 0.01) is consistent with the observed correlation, emphasizing that MSAs with higher creative class growth will be more likely to be impacted by AI.

## 5 Discussion

### 5.1 Main findings

By employing a deep learning natural language processing model to analyze 17,879 task descriptions and 24,758 AI patents, we found that the impact of AI on various occupations across the U.S. varies. In particular, the influence of AI extends to MSAs in the U.S. that heavily rely on industries susceptible to AI changes, often characterized by economic inequality or a lack of economic diversification. Contrary to the expectation that AI would primarily impact areas with high concentrations of tech industries, our findings show that areas heavily dependent on industries susceptible to AI-driven changes (e.g., manufacturing and healthcare) are equally affected. Additionally, the East Coast experiences a greater overall impact of AI compared to the West Coast, with notable exceptions such as Seattle and the Bay Area

### 5.2 Implications

From a theoretical standpoint, our study advances our understanding of the diffusion of AI technology and its uneven impact across different geographical areas. Previous literature has largely focused on the automation potential of AI in specific industries and occupations, often highlighting the risks of job displacement and the benefits of productivity enhancement. For example, tasks such as programming or diagnostics, initially perceived as prime candidates for automation, often evolve into augmented roles that require advanced judgment and adaptive skills such as troubleshooting networks or designing AI-enhanced workflows [1, 4]. Our study extends this body of work by incorporating a geographical perspective, showing that the economic and technological landscapes of areas significantly influence how AI impacts local labor markets. This aligns with theories of technological diffusion that suggest innovations tend to cluster in certain areas due to localized interactions and knowledge spillovers [12].

Moreover, our findings highlight the role of economic inequality and industrial diversification in shaping the geographical impacts of AI [13, 19]. MSAs with higher economic inequality tend to experience more pronounced impacts, which may exacerbate existing disparities. Conversely, economically diverse areas will be more likely to be resilient to the disruptive effects of AI, supporting theories that link economic diversification with geographical stability and adaptability.

From a practical perspective, our study's findings have implications for policymakers and business leaders. For policymakers, the uneven geographical impact of AI suggests the need for targeted interventions to support areas most at risk of adverse effects, such as those heavily reliant on manufacturing or healthcare sectors. Investment in retraining programs, infrastructure improvements, and incentives for tech adoption in less affected areas could help mitigate these disparities. For businesses, understanding the geographical nuances of AI impact can inform strategic decisions regarding location, workforce development, and technology investments. Companies operating in high-impact areas may need to invest more in employee reskilling and new technologies to remain competitive. Additionally, businesses in less affected areas might find opportunities to leverage AI to gain a competitive edge.

### 5.3 Limitations and future work

This study has three limitations that should be addressed in future research. First, our analysis is based on patent data, which may not capture all forms of AI-related innovations, particularly those that are proprietary and not patented. Moreover, our reliance on patent data inherently captures current technological capabilities but may overlook the societal and economic shifts that shape AI adoption. As Webb notes [3], these shifts often include labor shortages and industry-specific adaptations that influence whether AI augments or replaces human labor. Therefore, while our measure effectively maps present susceptibilities, it has limited predictive power for future developments driven by emergent technologies and socio-economic factors. Second, the study focuses on the United States, and the findings may not be generalizable to other countries with different economic structures and technological adoption rates. Future research could expand the geographical scope to include international comparisons, which would provide a more comprehensive understanding of the global impact of AI. Additionally, longitudinal studies could examine how the impact of AI evolves over time, especially as new technologies emerge and existing ones mature. Finally, incorporating qualitative data, such as interviews with industry experts and policymakers, could enrich our understanding of the nuanced ways in which AI influences regional economies.

## 6 Conclusion

The impact of AI on U.S. occupations extends beyond knowledge-centric areas, significantly affecting those reliant on specific industry sectors. The East Coast generally experiences a higher impact than the West Coast, except for tech hubs like Seattle and the Bay Area. These findings highlight the importance of geographical economic structures, with economically diverse areas showing greater resilience to AI-driven changes. Policymakers should consider specific strategies to support areas most at risk, while companies should prioritize through strategic decisions their locations and workforce development.

**Abbreviations**
AI, Artificial Intelligence; US, United States; USPTO, United States Patent and Trademark Office; AII, AI Impact; ST5, Sentence-T5; MSA, Metropolitan Statistical Area; OEWS, Occupational Employment and Wage Statistics; ACS, American Community Survey.

**Acknowledgements**
Not applicable.

**Author contributions**
AS collected the data and conducted the analysis. AS, MC, and DQ conceived the experiments and wrote the manuscript.

**Funding information**
Nokia Bell Labs provided support in the form of salaries for authors [AS, MC, DQ], but did not have any additional role in the study design, data collection and analysis, decision to publish, or preparation of the manuscript. The specific roles of these authors are articulated in the 'author contributions' section.

**Data availability**
Data and code is provided within a link in the manuscript.

## Declarations

**Ethics approval and consent to participate**
This study was approved by Nokia Bell Labs.

**Consent for publication**
All authors have reviewed and approved the manuscript for publication.

**Competing interests**
The authors declare no competing interests.

**Author details**
[1]Nokia Bell Labs, Cambridge, UK. [2]Kings College London, United Kingdom, London, UK. [3]CYENS Centre of Excellence, Nicosia, Cyprus.

Received: 13 September 2024 Accepted: 28 March 2025 Published online: 17 April 2025

**References**

1. Frey CB, Osborne MA (2017) The future of employment: how susceptible are jobs to computerisation? Technol Forecast Soc Change 114:254–280. https://doi.org/10.1016/j.techfore.2016.08.019
2. Felten E, Raj M, Seamans R (2021) Occupational, industry, and geographic exposure to artificial intelligence: a novel dataset and its potential uses. Strateg Manag J 42(12):2195–2217. https://doi.org/10.1002/smj.3286
3. Webb M (2019) The impact of artificial intelligence on the labor market. SSRN Electron J. https://doi.org/10.2139/ssrn.3482150
4. Brynjolfsson E, Mitchell T, Rock D (2018) What can machines learn and what does it mean for occupations and the economy? AEA Pap Proc 108:43–47. https://doi.org/10.1257/pandp.20181019
5. Autor DH, Handel MJ (2013) Putting tasks to the test: human capital, job tasks, and wages. J Labor Econ 31(S1):59–96. https://doi.org/10.1086/669332
6. Autor D, Chin C, Salomons AM, Seegmiller B (2022) New frontiers: the origins and content of new work, 1940–2018. Technical report, National Bureau of Economic Research
7. Kannan PV, Bernoff J (2019) Does your company really need a chatbot? Harvard Business Review. Accessed 14 Sep 2023
8. Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, Thrun S (2017) Dermatologist-level classification of skin cancer with deep neural networks. Nature 542(7639):115–118
9. Nguyen DK, Sermpinis G, Stasinakis C (2023) Big data, artificial intelligence and machine learning: a transformative symbiosis in favour of financial technology. Eur Financ Manag 29(2):517–548
10. Brynjolfsson E, McAfee A (2014) The second machine age: work, progress, and prosperity in a time of brilliant technologies. Norton, New York

11. Huang M-H, Rust RT (2018) Artificial intelligence in service. J Serv Res 21(2):155–172
12. Straccamore M, Loreto V, Gravino P (2023) The geography of technological innovation dynamics. Sci Rep 13(1):21043
13. Wilkinson RG, Pickett K (2009) The spirit level. Why more equal societies almost always do better. Allen Lane, London, p 331
14. Florida R (2002) The rise of the creative class, vol 9. Basic Books, New York
15. Florida R (2003) Cities and the creative class. City Community 2(1):3–19. https://doi.org/10.1111/1540-6040.00034
16. Florida R, Mellander C, Stolarick K (2008) Inside the black box of regional development—human capital, the creative class and tolerance. J Econ Geogr 8(5):615–649
17. Davies S (2011) Regional resilience in the 2008–2010 downturn: comparative evidence from European countries. Camb J Reg Econ Soc 4(3):369–382
18. Dissart JC (2003) Regional economic diversity and regional economic stability: research results and agenda. Int Reg Sci Rev 26(4):423–446
19. Chapple K, Lester TW (2010) The resilient regional labour market? The US case. Camb J Reg Econ Soc 3(1):85–104
20. O*NET Resource Center, National Center for O*NET Development (2023) O*NET® database releases archive. https://www.onetcenter.org/db_releases.html
21. Goos M, Manning A, Salomons A (2009) Job polarization in Europe. Am Econ Rev 99(2):58–63. https://doi.org/10.1257/aer.99.2.58
22. Felten EW, Raj M, Seamans R (2023) How will language modelers like ChatGPT affect occupations and industries? SSRN Electron J. https://doi.org/10.2139/ssrn.4375268
23. WIPO (2019) WIPO technology trends 2019: artificial intelligence. World Intellectual Property Organization, Geneva. https://www.wipo.int/edocs/pubdocs/en/wipo_pub_1055.pdf
24. Septiandri AA, Constantinides M, Quercia D (2024) The potential impact of AI innovations on US occupations. PNAS Nexus 3(9):pgae320. https://doi.org/10.1093/pnasnexus/pgae320
25. Reimers N, Gurevych I (2019) Sentence-BERT: sentence embeddings using Siamese BERT-networks. In: Proceedings of the 2019 conference on empirical methods in natural language processing and the 9th international joint conference on natural language processing (EMNLP-IJCNLP). Association for Computational Linguistics, Hong Kong, pp 3982–3992. https://doi.org/10.18653/v1/D19-1410
26. Ni J, Hernandez Abrego G, Constant N, Ma J, Hall K, Cer D, Yang Y (2022) Sentence-t5: scalable sentence encoders from pre-trained text-to-text models. In: Muresan S, Nakov P, Villavicencio A (eds) Findings of the Association for Computational Linguistics: ACL 2022. Association for Computational Linguistics, Dublin, pp 1864–1874. https://doi.org/10.18653/v1/2022.findings-acl.146
27. Chaturvedi S, Prytkova E, Ciarli T, Nomaler Ö (2023) What is the future of automation? Using semantic analysis to identify emerging technologies. Technical report. https://www.h2020-pillars.eu/node/1174
28. U.S. Census Bureau (2023) Industry for the civilian employed population 16 years and over. https://data.census.gov/table/ACSSE2023.K202403?q=industry&g=010XX00US31000M1&moe=false&tp=true. Accessed 3 Dec 2024
29. Batty M (2023) The emergence and evolution of urban AI. AI Soc 38(3):1045–1048
30. Alcácer J, Chung W (2014) Location strategies for agglomeration economies. Strateg Manag J 35(12):1749–1761
31. Bonaventura M, Aiello LM, Quercia D, Latora V (2021) Predicting urban innovation from the us workforce mobility network. Humanit Soc Sci Commun 8(1):1–9
32. Shutters ST, Applegate J, Wentz E, Batty M (2022) Urbanization favors high wage earners. npj Urban Sustain 2(1):6
33. U.S. Census Bureau (2022) Gini index of income inequality. https://data.census.gov/table/ACSDT5Y2022.B19083?q=gini. Accessed 3 Dec 2024
34. Agrawal A, Gans J, Goldfarb A (2022) Prediction machines, updated and expanded: the simple economics of artificial intelligence. Harvard Business Review Press, Brighton
35. Chui M, Manyika J, Miremadi M (2016) Where machines could replace humans-and where they can't (yet). The McKinsey Quarterly, 1–12
36. Hoyman M, Faricy C (2009) It takes a village: a test of the creative class, social capital, and human capital theories. Urban Aff Rev 44(3):311–333
37. Martin R (2012) Regional economic resilience, hysteresis and recessionary shocks. J Econ Geogr 12(1):1–32
38. Straccamore M, Bruno M, Monechi B, Loreto V (2023) Urban economic fitness and complexity from patent data. Sci Rep 13(1):3655


## Publisher's note