Economic Geography of AI Skill Demand: Evidence from U.S. Job Postings

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Abstract

This paper examines the spatial patterns and changing geography of artificial intelligence (AI) labor demand through the use of job posting data. Job postings are linked to identified AI skills established through a bibliometric analysis of keywords from published academic journal articles on the subject. Using Lightcast job postings from 2014, 2018, 2022, and 2024, we calculate state-level location quotients with an Empirical Bayes adjustment to account for the low number of postings in earlier years and identify regions with high AI skill demand. We also construct spatial Lorenz curves to measure patterns of geographic concentration. Results indicate that demand for AI skills became more geographically dispersed between 2014 and 2024. By 2024, the spatial concentration of AI-related job postings was similar to that of employment in broad occupational groups such as sales and administrative occupations, suggesting that demand for AI skills is not confined to a small number of regions.

1 Introduction

The rapid advancement of artificial intelligence (AI) has profound implications for labor markets, economic development, and regional innovation systems. As technological innovation continues to reshape economic landscapes, understanding the geography of AI activity has become increasingly important. Recent studies have examined AI innovation and adoption (McElheran et al., 2024), employment (Damioli et al., 2024), patents (Toole et al., 2020), and productivity (Filippucci et al., 2024). While these studies focus on realized AI activity, the geography of AI skill demand, measured through job postings, may provide an earlier indication of emerging spatial patterns, as firms seek AI-related capabilities before they are reflected in broader economic outcomes.

This paper examines the economic geography of job postings requiring AI skills as a measure of AI skill demand and compares spatial patterns over time to assess changes in their geographic concentration. Using the AI skill taxonomy developed by Hunt and Crawley (2026) and job postings data from Lightcast, we calculate state-level location quotients to identify regions with high AI skill demand and construct spatial Lorenz curves to measure geographic concentration. Our findings indicate that demand for AI skills became more geographically dispersed between 2014 and 2024. These results contribute to the growing literature on the geography of technological change during a period of rapid AI expansion.

2 Growth and Spatial Patterns of AI

Between 2010 and 2019, job postings requiring AI skills increased tenfold (Alekseeva et al., 2021), signaling a dramatic shift in firms' demand for AI capabilities. Some scholars and commentators have described this transformation as the beginning of a new industrial revolution (Grant, 2023), with AI emerging as a fundamental driver of economic change. However, the growth of AI has not been evenly distributed across regions.

For example, Bloom et al. (2021) find that more than 40 percent of U.S. patents in emerging and disruptive technologies are concentrated in five places: San Jose, San Francisco, New York, Seattle, and Boston. These "pioneer locations" are not only leading innovation but are also adopting AI technologies more rapidly than the rest of the country (McElheran et al., 2024). (Muro and Liu, 2021) attribute this concentration to agglomeration economies, which provide firms with access to deep pools of highly skilled workers needed to develop and implement AI technologies. Despite the current concentration of AI activity, (Bloom et al., 2021) suggest that AI will eventually diffuse geographically, estimating that it could take as long as 50 years for the technology to evolve from a complex, skill-intensive innovation to one that is broadly accessible in lower-skill or resource-constrained regions. Until then, access to AI is likely to remain uneven, with regional adoption depending heavily on existing labor market characteristics.

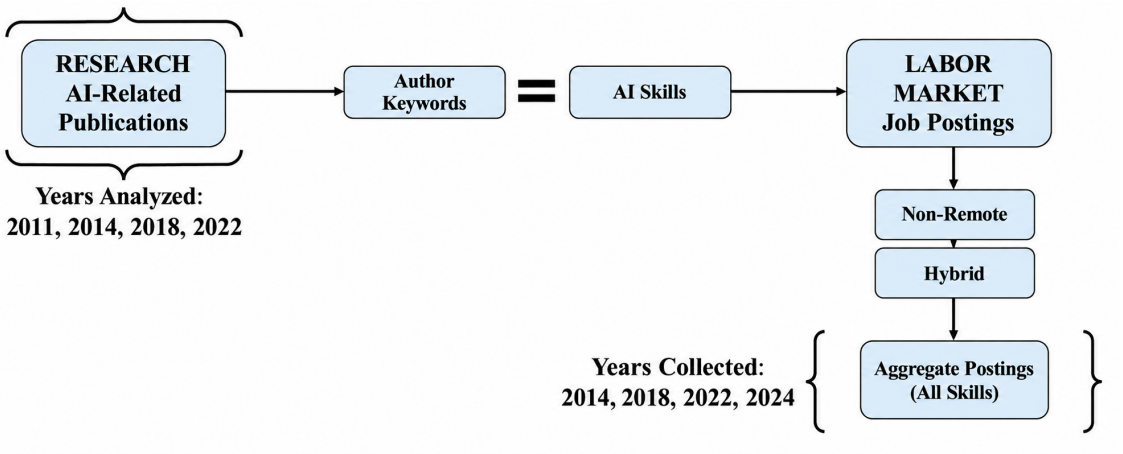
The COVID-19 pandemic led to modest decentralization of technological employment, but it did not fundamentally alter the geographic concentration of AI-related jobs (Muro and Liu, 2021). Bessen et al. (2021) notes that firms continue to face greater difficulty filling AI-related positions outside of established innovation hubs. Although regions outside of innovation hubs may adopt AI technologies as they mature, they risk remaining one step behind the technological frontier. By the time earlier generations of AI tools become widely accessible, leading innovation centers are likely to have shifted to newer technologies (Salemink et al., 2017). This path dependency may contribute to a persistent "AI divide," in which less technologically advanced regions remain disadvantaged, exacerbating both economic and geographic inequality (McElheran et al., 2024).

3 Data and Analysis

Our analysis uses job postings data from Lightcast, one of the leading sources of U.S. labor market information. Because our focus is on the specific location of labor demand, we restrict the analysis to non-remote and hybrid job postings[1]. We identify AI skills using the taxonomy developed by Hunt and Crawley (2026), which uses keywords from AI-related academic publications as proxies for emerging labor market skills. Publications from 2011, 2014, 2018, and 2022 were analyzed to capture the evolution of AI research while avoiding redundancy. In total, 1,925 AI-related skills were identified and used to filter Lightcast job postings.

[1]Fully remote postings make up on average 9% of total AI postings in 2024.

Figure 1: Outline of Data Collection Methodology



We then match the AI skill taxonomy to Lightcast job postings for all 50 states[2]. Although the bibliometric analysis covers 2011 through 2022, we analyze job postings from 2014 to 2024 to capture more recent labor market trends even though publication data for 2024 was not yet available. To examine the economic geography of AI skill demand, we calculate Empirical Bayes (EB) adjusted state-level location quotients for 2014, 2018, 2022, and 2024, along with spatial Lorenz curves for each year. Because AI-related job postings were relatively sparse in some states during the early years of the sample, traditional location quotients may produce inaccurate estimates (Crawley et al., 2013). To stabilize early/sparse years, we apply an EB shrinkage estimator (Cressie, 1992). The EB-adjusted location quotient (LQ) for state (s) in year (t) is:

$$LQ_{s,t}^{EB} = \frac{\tilde{\rho}_{s,t}}{\rho_{US,t}} \tag{1}$$

Where $\rho_{US,t}$ is the U.S. share of job postings that require AI skills (similar to a traditional location quotient). The EB-adjusted share of state-level job postings that require AI skills is:

$$\tilde{\rho}_{s,t} = \frac{y_{s,t} + k \cdot \rho_s^{prior}}{n_{s,t} + k} \tag{2}$$

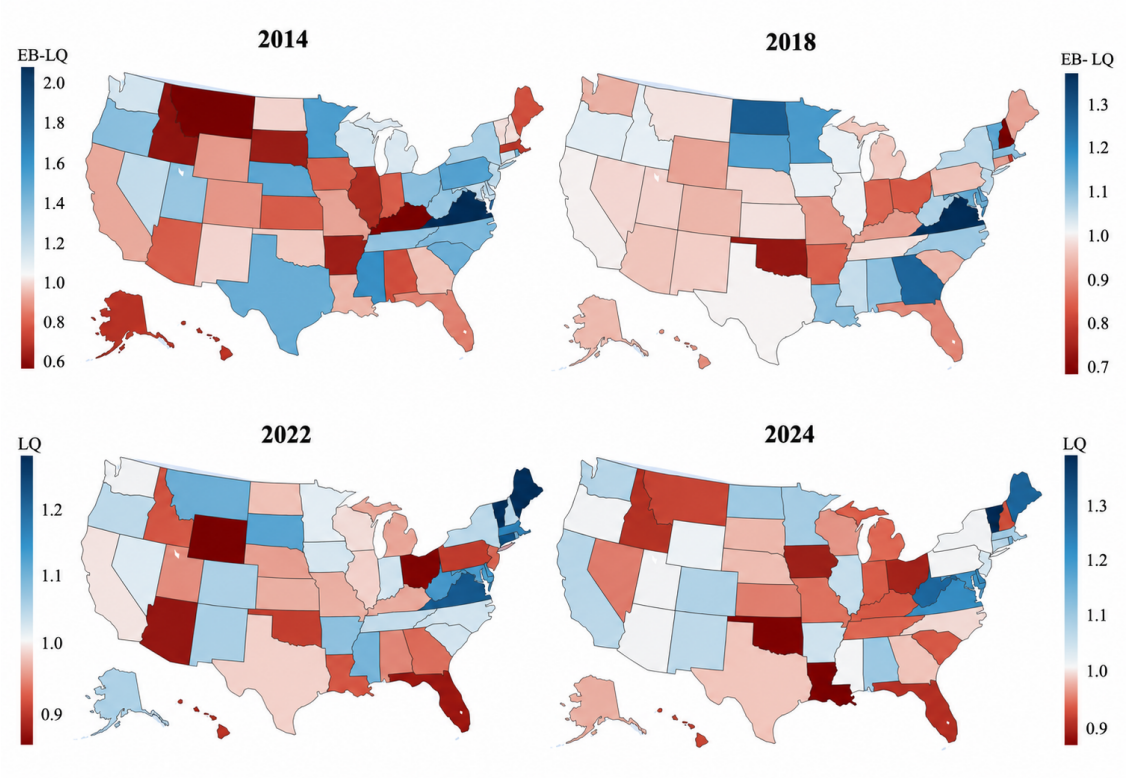
Where, $y_(s,t)$ is the number of job postings that require AI skills, $n_(s,t)$ is the total number of postings in a state, and p_s^{prior} is a state-specific Bayesian prior defined as the mean observed AI share in 2014 and 2018. We set the prior strength to (k=100) pseudo-counts, providing stability in low-count states while preserving meaningful cross-state variation[3]. The EB-adjusted location quotients identify states with relatively high AI skill demand while reducing spurious extremes caused by low counts of job postings.

Figure 2 shows the location quotients for AI skill demand over the period of 2014 to 2024 (EB-adjusted for 2014 and 2018), with the values presented in Appendix 2, Table A2.1 through Table A2.4. Values greater than 1.0 indicate that the state has an above average demand for AI skills for a given year, while values less than 1.0 suggest that demand for these types of skills is below average in the state. The top three states by EB-adjusted location quotient in 2014 are Virginia (2.04), Mississippi (1.47), and Minnesota (1.44). Notable by their absence, large innovation-intensive states (e.g., California, Massachusetts, New York) are not among the top regions by location quotient. This pattern is consistent with an early-stage technology in which large, diversified regions exhibit lower LQs even as they produce frontier innovation and have highly specialized talent (e.g., PhD-intensive roles that generate fewer job postings).

[2]The authors acknowledge that, by using states, some spatial variation may be lost. However, due to the paucity of data at a lower spatial scale, comparative metrics would be difficult to calculate.

[3]To aid in the choice of pseudo value, a series of robustness checks involving different values was carried out. Please see Appendix 2 for more details.

Figure 2: Location Quotients for AI Skill Demand (EB-Adjusted for 2014 and 2018)

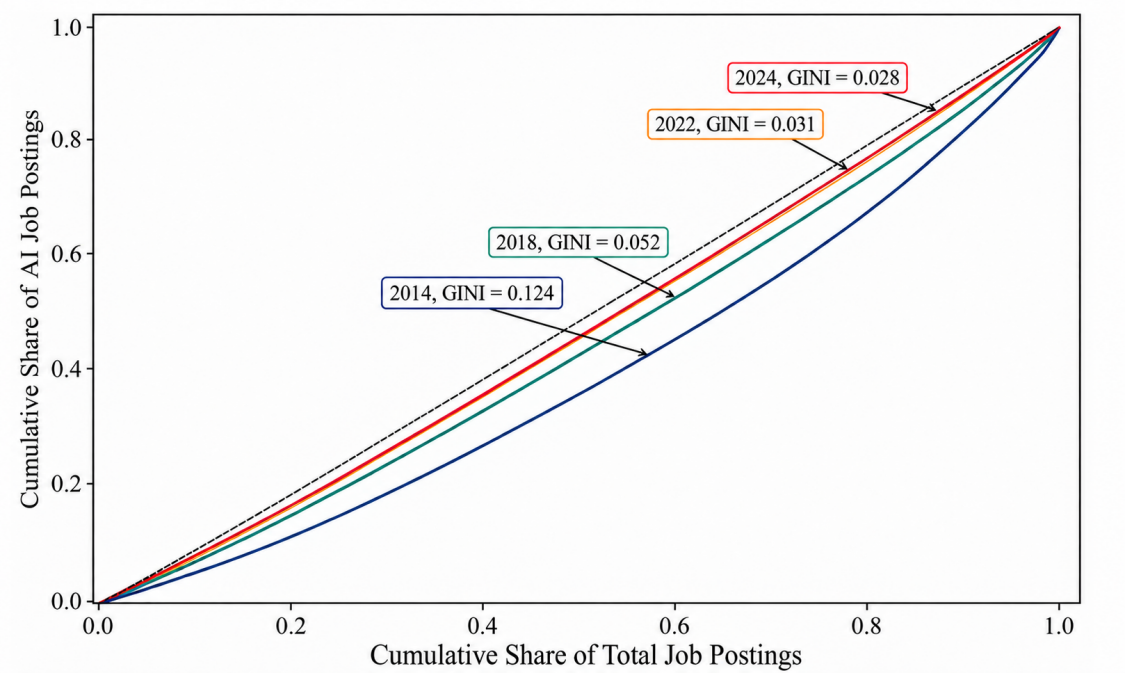


Virginia, a state known to have significant numbers of data centers[4], maintained the highest level of demand in 2018, although its location quotient declined from 2.04 to 1.35. The cross-state variance in location quotients also declined between 2014 and 2018 (from 0.09 to 0.02), indicating a more even distribution of AI skill demand. This trend continued in later years, with a lower variance in location quotients in both 2022 (variance of 0.01) and 2024 (variance of 0.01). As of 2024, the top three states by location quotient are Vermont (1.34), Maine (1.25), and West Virginia (1.23), with Virginia, the top-ranked state in earlier years, having the fifth-highest location quotient (1.17). Historically, these states have had a low matching efficiency whereby the supply of available workers has not met the regional demand. The LQ is capturing their aspirational demand and does not offer insight into whether a position has been filled. At the other end of the distribution, only two states have location quotients below 0.90 in 2024. Collectively, these results suggest that demand for AI skills has become increasingly dispersed across U.S. states.

Figure 3 provides additional evidence on the geographic concentration of AI job postings using spatial Lorenz curves[5]. The 45-degree line represents a distribution in which AI job postings are proportional to total job postings across states. Deviations from this line indicate differences between the spatial distribution of AI-related job postings and overall labor demand, with larger deviations reflecting greater geographic concentration. Over time, the Lorenz curves move progressively closer to the 45-degree line, indicating that AI job postings became more evenly distributed across states. Likewise, Krugman (1991) locational Gini coefficients, a related measure of geographic concentration, declined from 0.12 in 2014 to 0.03 in 2024.

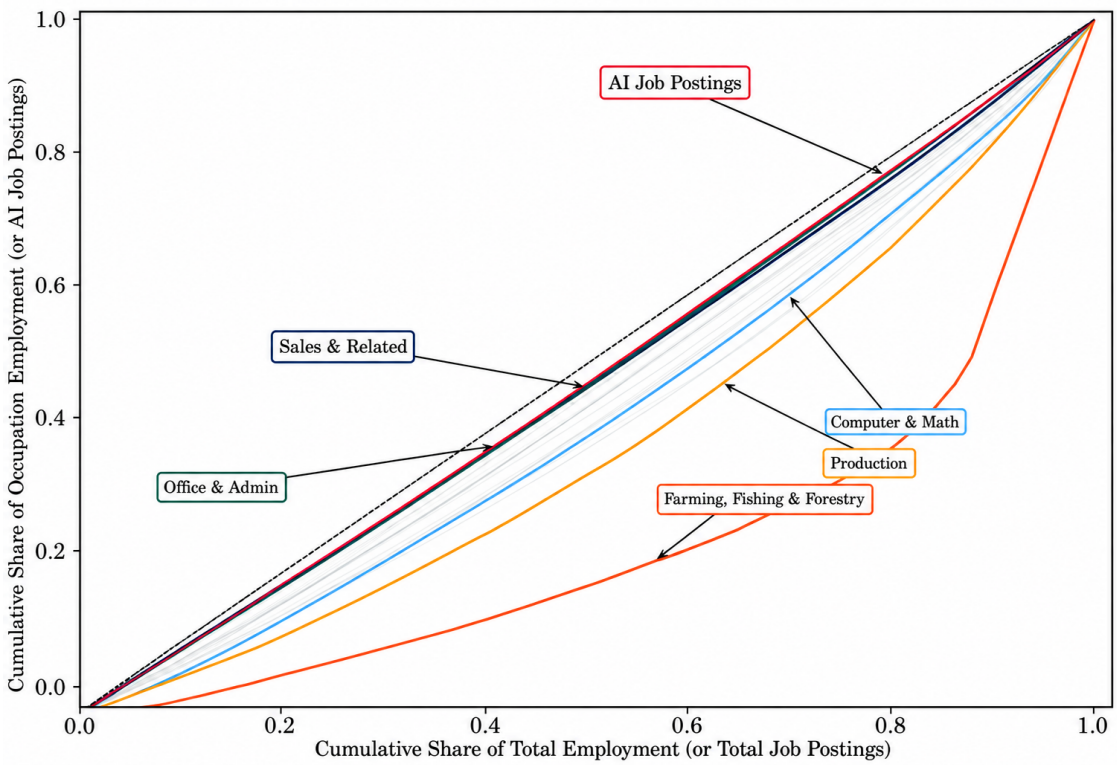
[4]https://virginiamercury.com/2026/07/06/how-virginia-became-the-worlds-data-center-capital-and-how-its-going/
[5]To construct the Lorenz curves, states are ranked in order of their share of total job postings.

Figure 3: Lorenz Curves Showing the Geographic Concentration of AI Skill Demand



To place AI job postings in context, Figure 4 compares their geographic concentration with state-level employment across major occupational categories using data from the U.S. Bureau of Labor Statistics. The three most geographically concentrated occupational groups are farming, fishing, and forestry; production; and life, physical, and social science occupations, which is consistent with past studies on industry and occupational agglomeration (Ellison et al., 2010; Gabe and Abel, 2012). In contrast, the geographic concentration of AI job postings is similar to that of occupations such as sales (and related) occupations and office and administrative support. This finding suggests that demand for AI skills has become a ubiquitous feature of labor markets across nearly all states.

Figure 4: Lorenz Curves Showing the Geographic Concentration of AI Skill Demand



4 Conclusions

This study examined the economic geography of AI job postings across U.S. states between 2014 and 2024 using a novel measure of AI skill demand derived from a bibliometric analysis of the academic AI literature. The results indicate that demand for AI skills became more geographically dispersed over time. By 2024, the spatial concentration of AI-related job postings was similar to employment in broad occupational groups such as sales and administrative support. This suggests that employer demand for AI skills extends beyond a small number of innovation hubs, making workforce preparedness relevant to a wider range of states.

These findings suggest that policies supporting AI development should be complemented by efforts to strengthen the capacity of firms and workers to adopt and use AI across regions. Investments in leading research centers may support innovation, but meeting geographically dispersed demand also requires accessible education and training, support for business adoption, and collaboration between employers, educational institutions, and economic development organizations. For regions outside established technology hubs, the findings point to a role for economic development strategies that help existing industries integrate AI, alongside efforts to attract new technology firms. Job posting data can help inform these strategies by identifying the AI skills employers seek and how demand changes across regional economies.

Although the dispersal of AI skill demand does not establish that adoption or its economic benefits are equally distributed, it strengthens the case for policies that enable a wider range of regions to participate in technological change. As AI develops, regional outcomes will depend both on the forces that concentrate innovation and on the capacity of firms, workers, and institutions to translate its diffusion into productivity gains and economic opportunity.

Acknowledgments

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Appendix 1

Figure A1.1: Bibliometric Classification Procedure

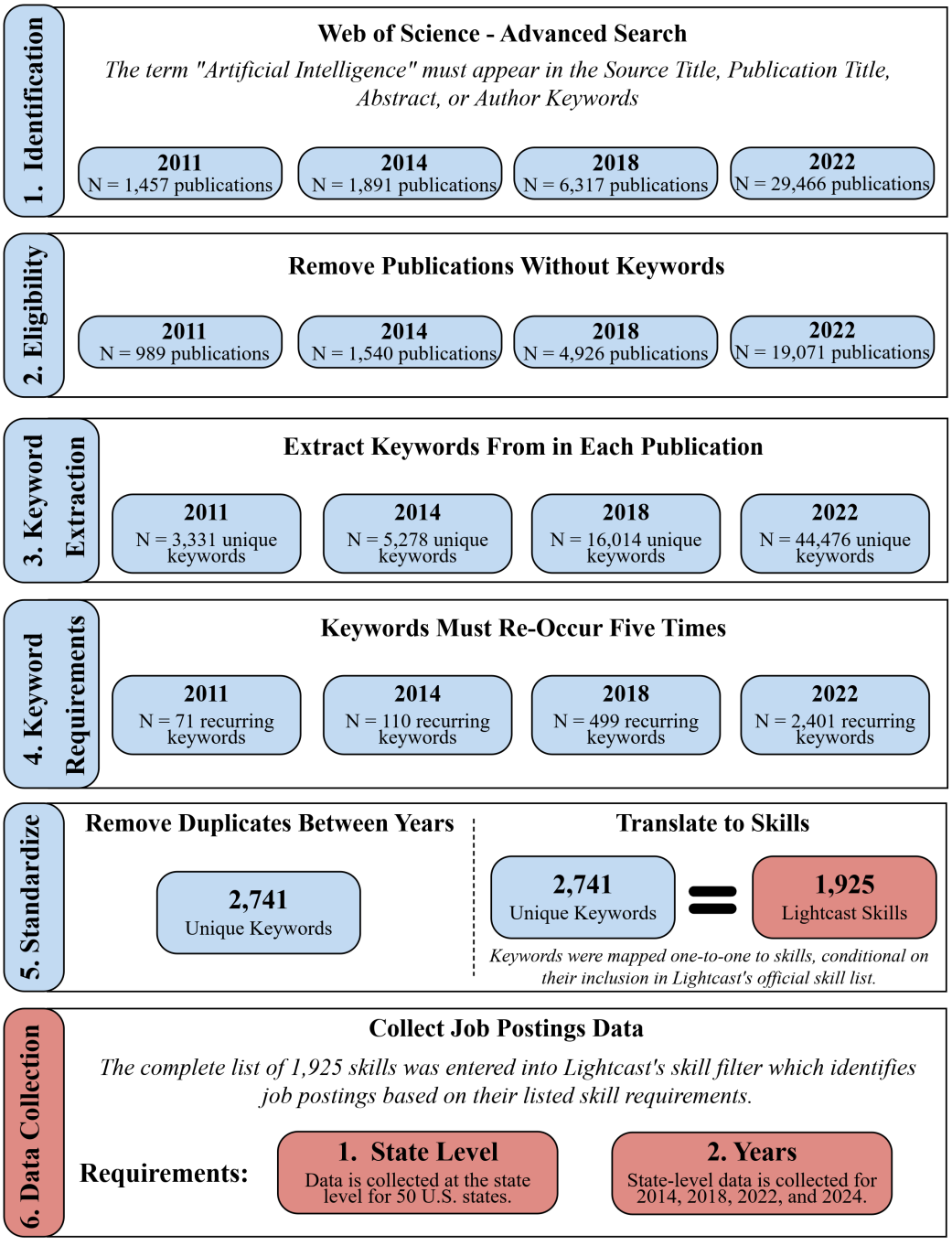
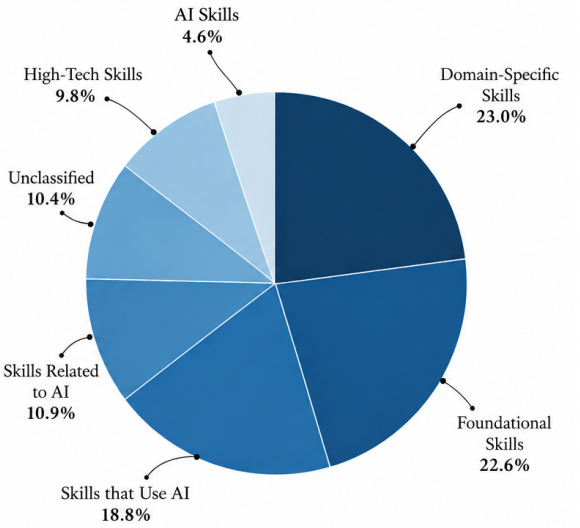


Figure A1.2: Classification and Distribution of Identified AI Skills by Type

Skill Category	Description
AI Skills	Core mathematical, algorithmic, and computational skills used to develop, train, and optimize AI systems.
Skills that Use AI	Technical skills used to apply AI systems to automate tasks, support decision-making, and optimize workflows.
Skills Related to AI	Technical competencies providing computational, data, software, and infrastructure to develop and deploy AI systems.
High-Tech Skills	Specialized technical skills involving engineering, automation, digital infrastructure, and other technologies complementary to AI.
Foundational Skills	Transferable analytical and technical skills that apply across technologies, industries, and domains.



Notes: Skill categories are defined based on their relationship to AI technologies and their intended use. Percentages represent the share of total AI skills (n = 1,925). "Unclassified" includes skills that could not be assigned to a specific category.

For a fuller discussion, please see https://econdatavizme.com/the-ai-skills-ecosystem-dashboard/.

Appendix 2

To stabilize early/sparse years, we apply an Empirical Bayes (EB) style shrinkage estimator[6]. The estimator combines an observed local value with a prior benchmark, giving the benchmark more weight when the local sample is small. As such small samples receive more shrinkage while large samples retain more of their observed value. This is particularly useful for a Location Quotient (LQ) as it reduces the extreme estimates caused by small denominators.

The state-specific prior share is defined as the mean of the AI posting shares observed in 2014 and 2018. The prior strength, (k), represents the number of pseudo-observations assigned to this prior. We assessed alternative values of (k), through a sensitivity analysis and selected a value (100) that stabilized estimates in years with small posting counts while preserving cross-state variation. The selected value therefore balances the reduction of extreme early-year LQs caused by small counts against the preservation of variation supported by the observed data. The EB-adjusted share is now given as:

$$\tilde{\rho}_{s,t} = \frac{y_{s,t} + k \cdot \rho_s^{prior}}{n_{s,t} + k} \tag{A2.3}$$

Where ρ_s^{prior} is the state-specific prior, defined as the mean of the observed state shares in 2014 and 2018, and k=100 pseudo-counts. The EB-smoothed location quotient is formalized as:

$$LQ_{s,t}^{EB} = \frac{\tilde{\rho}_{s,t}}{\rho_{US,t}} \tag{A2.4}$$

This procedure retains the relative high LQ values while damping spurious extremes due to small denominators, paralleling standard EB smoothing in small-area rate estimation.

[6]For more details on the Empirical Bayes see the work of Cressie (1992)

Table A2.1: Sensitivity of State AI Posting Location Quotients to Empirical Bayes Prior Strength, 2014

State	k=0	k=100	k=250	k=500	k=1000	k=2000	Crosses 1?
Alabama	0.687	0.761	0.845	0.943	1.058	1.166	No
Alaska	0.671	0.705	0.750	0.814	0.910	1.030	No
Arizona	0.785	0.793	0.803	0.821	0.851	0.901	No
Arkansas	0.585	0.644	0.718	0.811	0.935	1.066	No
California	0.894	0.896	0.898	0.902	0.910	0.924	No
Colorado	0.854	0.863	0.875	0.895	0.929	0.986	No
Connecticut	1.037	1.045	1.055	1.072	1.102	1.152	No
Delaware	1.009	1.069	1.139	1.221	1.318	1.410	No
Florida	0.843	0.847	0.852	0.860	0.875	0.902	No
Georgia	0.926	0.935	0.949	0.969	1.006	1.064	No
Hawaii	0.640	0.700	0.770	0.854	0.955	1.053	No
Idaho	0.520	0.585	0.666	0.766	0.896	1.031	No
Illinois	0.691	0.695	0.703	0.714	0.736	0.776	No
Indiana	0.764	0.780	0.802	0.835	0.891	0.971	No
Iowa	0.766	0.783	0.807	0.843	0.903	0.992	No
Kansas	0.780	0.800	0.828	0.868	0.932	1.020	No
Kentucky	0.533	0.571	0.622	0.692	0.796	0.925	No
Louisiana	0.893	0.915	0.944	0.985	1.047	1.125	No
Maine	0.701	0.771	0.856	0.964	1.105	1.251	No
Maryland	1.078	1.085	1.097	1.114	1.145	1.196	No
Massachusetts	0.732	0.740	0.752	0.772	0.808	0.871	No
Michigan	1.033	1.038	1.044	1.054	1.071	1.101	No
Minnesota	1.442	1.443	1.443	1.444	1.446	1.449	No
Mississippi	1.471	1.470	1.470	1.469	1.469	1.468	No
Missouri	0.861	0.877	0.900	0.933	0.985	1.055	No
Montana	0.423	0.559	0.706	0.865	1.039	1.190	No
Nebraska	1.396	1.392	1.386	1.379	1.370	1.359	No
Nevada	1.109	1.126	1.147	1.176	1.217	1.265	No
New Hampshire	0.934	0.975	1.019	1.066	1.117	1.160	No
New Jersey	1.121	1.125	1.131	1.140	1.156	1.182	No
New Mexico	0.870	0.960	1.049	1.137	1.224	1.293	No
New York	1.179	1.183	1.189	1.199	1.216	1.243	No
North Carolina	1.307	1.311	1.317	1.325	1.339	1.358	No
North Dakota	0.856	0.965	1.072	1.176	1.278	1.358	No
Ohio	1.264	1.262	1.259	1.255	1.248	1.237	No
Oklahoma	0.913	0.941	0.974	1.012	1.057	1.098	No
Oregon	1.273	1.282	1.293	1.309	1.331	1.357	No
Pennsylvania	1.419	1.416	1.412	1.405	1.394	1.377	No
Rhode Island	1.353	1.355	1.357	1.359	1.361	1.362	No
South Carolina	1.387	1.384	1.381	1.378	1.373	1.369	No
South Dakota	0.495	0.650	0.812	0.980	1.155	1.300	No
Tennessee	1.260	1.267	1.276	1.289	1.309	1.333	No
Texas	1.381	1.381	1.381	1.381	1.380	1.380	No
Utah	1.233	1.239	1.247	1.257	1.271	1.286	No
Vermont	0.638	0.973	1.192	1.347	1.462	1.535	No
Virginia	2.048	2.039	2.027	2.010	1.980	1.937	No
Washington	1.073	1.081	1.092	1.108	1.136	1.176	No
West Virginia	1.160	1.227	1.288	1.346	1.399	1.439	No
Wisconsin	1.036	1.049	1.065	1.090	1.129	1.182	No
Wyoming	0.648	0.869	0.987	1.060	1.110	1.140	No

Notes: $k = 0$ denotes the unadjusted location quotient; higher k values indicate stronger empirical Bayes prior weighting. "Crosses 1?" indicates whether the location quotient crosses the threshold of 1 between $k = 0$ and $k = 100$.

Table A2.2: Sensitivity of State AI Posting Location Quotients to Empirical Bayes Prior Strength, 2018

State	k=0	k=100	k=250	k=500	k=1000	k=2000	Crosses 1?
Alabama	1.042	1.084	1.130	1.181	1.238	1.288	No
Alaska	0.921	0.938	0.962	0.996	1.052	1.127	No
Arizona	0.952	0.955	0.960	0.967	0.981	1.005	No
Arkansas	0.815	0.853	0.901	0.964	1.049	1.144	No
California	0.993	0.994	0.995	0.997	1.000	1.007	No
Colorado	0.932	0.936	0.943	0.953	0.973	1.007	No
Connecticut	0.877	0.896	0.922	0.961	1.026	1.120	No
Delaware	1.136	1.189	1.249	1.317	1.396	1.468	No
Florida	0.887	0.889	0.892	0.897	0.906	0.923	No
Georgia	1.224	1.226	1.230	1.237	1.248	1.268	No
Hawaii	0.883	0.905	0.934	0.972	1.027	1.089	No
Idaho	0.986	1.012	1.044	1.085	1.140	1.199	Yes
Illinois	1.002	1.005	1.009	1.016	1.029	1.051	No
Indiana	0.851	0.860	0.872	0.892	0.927	0.983	No
Iowa	1.004	1.013	1.025	1.045	1.079	1.131	No
Kansas	0.967	0.979	0.995	1.019	1.058	1.115	No
Kentucky	0.889	0.902	0.920	0.946	0.990	1.052	No
Louisiana	1.087	1.097	1.109	1.128	1.159	1.201	No
Maine	0.854	0.916	0.991	1.085	1.204	1.326	No
Maryland	1.124	1.129	1.138	1.151	1.175	1.215	No
Massachusetts	1.074	1.078	1.085	1.096	1.115	1.150	No
Michigan	0.951	0.955	0.962	0.973	0.994	1.028	No
Minnesota	1.150	1.154	1.160	1.169	1.186	1.215	No
Mississippi	1.007	1.042	1.086	1.143	1.218	1.299	No
Missouri	0.883	0.890	0.901	0.917	0.946	0.993	No
Montana	0.932	0.986	1.049	1.123	1.211	1.295	No
Nebraska	0.955	0.970	0.991	1.022	1.069	1.132	No
Nevada	0.968	0.978	0.992	1.014	1.051	1.107	No
New Hampshire	0.625	0.668	0.722	0.792	0.888	0.994	No
New Jersey	1.042	1.045	1.051	1.059	1.074	1.101	No
New Mexico	0.925	0.954	0.991	1.041	1.111	1.194	No
New York	1.043	1.047	1.051	1.059	1.073	1.099	No
North Carolina	1.068	1.071	1.077	1.085	1.101	1.130	No
North Dakota	1.214	1.258	1.303	1.348	1.394	1.431	No
Ohio	0.838	0.841	0.845	0.852	0.866	0.889	No
Oklahoma	0.717	0.731	0.750	0.778	0.825	0.892	No
Oregon	1.010	1.016	1.026	1.041	1.069	1.113	No
Pennsylvania	0.943	0.945	0.949	0.956	0.968	0.990	No
Rhode Island	0.761	0.808	0.866	0.940	1.038	1.143	No
South Carolina	0.908	0.927	0.952	0.989	1.045	1.120	No
South Dakota	1.088	1.147	1.211	1.281	1.358	1.426	No
Tennessee	0.966	0.973	0.982	0.998	1.026	1.071	No
Texas	0.995	0.997	0.999	1.002	1.008	1.020	No
Utah	0.955	0.968	0.986	1.012	1.053	1.111	No
Vermont	1.040	1.130	1.223	1.320	1.422	1.506	No
Virginia	1.347	1.351	1.356	1.365	1.382	1.412	No
Washington	0.932	0.936	0.942	0.952	0.970	1.002	No
West Virginia	0.993	1.052	1.119	1.195	1.284	1.365	Yes
Wisconsin	1.001	1.008	1.017	1.033	1.061	1.105	No
Wyoming	0.840	0.913	0.978	1.037	1.091	1.130	No

Notes: $k = 0$ denotes the unadjusted location quotient; higher k values indicate stronger empirical Bayes prior weighting. "Crosses 1?" indicates whether the location quotient crosses the threshold of 1 between $k = 0$ and $k = 100$.

Table A2.3: Sensitivity of State AI Posting Location Quotients to Empirical Bayes Prior Strength, 2022

State	k=0	k=100	k=250	k=500	k=1000	k=2000	Crosses 1?
Alabama	0.945	0.944	0.942	0.939	0.934	0.923	No
Alaska	1.046	1.045	1.044	1.042	1.038	1.031	No
Arizona	0.870	0.869	0.869	0.868	0.866	0.864	No
Arkansas	1.066	1.063	1.059	1.052	1.039	1.017	No
California	0.993	0.993	0.993	0.993	0.992	0.991	No
Colorado	1.043	1.042	1.041	1.040	1.038	1.034	No
Connecticut	1.212	1.211	1.208	1.205	1.198	1.184	No
Delaware	1.138	1.132	1.124	1.112	1.091	1.059	No
Florida	0.870	0.870	0.870	0.869	0.869	0.868	No
Georgia	0.936	0.936	0.936	0.935	0.934	0.932	No
Hawaii	0.895	0.894	0.892	0.889	0.884	0.873	No
Idaho	0.926	0.924	0.922	0.917	0.909	0.895	No
Illinois	0.983	0.982	0.982	0.981	0.980	0.977	No
Indiana	1.019	1.019	1.018	1.017	1.015	1.011	No
Iowa	1.016	1.015	1.014	1.011	1.006	0.997	No
Kansas	0.971	0.970	0.968	0.965	0.960	0.949	No
Kentucky	0.963	0.962	0.959	0.956	0.949	0.936	No
Louisiana	0.921	0.921	0.920	0.919	0.917	0.913	No
Maine	1.275	1.266	1.253	1.233	1.198	1.146	No
Maryland	1.110	1.109	1.109	1.107	1.105	1.101	No
Massachusetts	1.145	1.144	1.144	1.143	1.140	1.136	No
Michigan	0.962	0.962	0.961	0.960	0.957	0.952	No
Minnesota	1.008	1.008	1.007	1.006	1.003	0.998	No
Mississippi	1.082	1.077	1.070	1.059	1.040	1.010	No
Missouri	0.970	0.969	0.969	0.967	0.965	0.961	No
Montana	1.093	1.084	1.072	1.054	1.025	0.983	No
Nebraska	0.963	0.963	0.962	0.960	0.958	0.952	No
Nevada	1.014	1.013	1.012	1.011	1.008	1.002	No
New Hampshire	1.029	1.028	1.026	1.023	1.016	1.004	No
New Jersey	0.924	0.924	0.923	0.922	0.920	0.916	No
New Mexico	1.046	1.044	1.039	1.033	1.020	0.998	No
New York	1.034	1.034	1.033	1.033	1.031	1.028	No
North Carolina	1.014	1.014	1.014	1.013	1.011	1.009	No
North Dakota	0.976	0.976	0.975	0.973	0.971	0.966	No
Ohio	0.858	0.857	0.857	0.856	0.854	0.850	No
Oklahoma	0.915	0.913	0.910	0.906	0.898	0.884	No
Oregon	1.034	1.034	1.032	1.030	1.026	1.019	No
Pennsylvania	0.908	0.907	0.907	0.906	0.904	0.900	No
Rhode Island	1.103	1.102	1.099	1.095	1.087	1.072	No
South Carolina	1.016	1.015	1.015	1.013	1.010	1.005	No
South Dakota	1.103	1.102	1.101	1.098	1.093	1.082	No
Tennessee	1.033	1.032	1.032	1.030	1.028	1.023	No
Texas	0.983	0.983	0.983	0.983	0.982	0.981	No
Utah	0.948	0.946	0.944	0.941	0.934	0.922	No
Vermont	1.237	1.230	1.219	1.203	1.175	1.132	No
Virginia	1.199	1.199	1.198	1.198	1.196	1.194	No
Washington	1.004	1.003	1.003	1.002	0.999	0.995	No
West Virginia	1.122	1.111	1.096	1.074	1.039	0.993	No
Wisconsin	0.991	0.991	0.989	0.987	0.984	0.977	No
Wyoming	0.847	0.846	0.844	0.842	0.837	0.827	No

Notes: $k = 0$ denotes the unadjusted location quotient; higher k values indicate stronger empirical Bayes prior weighting. "Crosses 1?" indicates whether the location quotient crosses the threshold of 1 between $k = 0$ and $k = 100$.

Table A2.4: Sensitivity of State AI Posting Location Quotients to Empirical Bayes Prior Strength, 2024

State	k=0	k=100	k=250	k=500	k=1000	k=2000	Crosses 1?
Alabama	1.077	1.076	1.075	1.074	1.071	1.065	No
Alaska	0.976	0.976	0.976	0.976	0.975	0.975	No
Arizona	1.001	1.001	1.001	1.001	1.000	1.000	No
Arkansas	1.026	1.026	1.026	1.025	1.023	1.020	No
California	1.041	1.041	1.041	1.041	1.041	1.041	No
Colorado	1.058	1.058	1.058	1.058	1.058	1.057	No
Connecticut	1.045	1.045	1.045	1.045	1.045	1.046	No
Delaware	1.224	1.223	1.221	1.218	1.212	1.202	No
Florida	0.920	0.920	0.920	0.920	0.920	0.920	No
Georgia	0.978	0.978	0.978	0.978	0.978	0.978	No
Hawaii	0.926	0.926	0.926	0.925	0.924	0.922	No
Idaho	0.922	0.922	0.922	0.922	0.922	0.922	No
Illinois	1.032	1.032	1.031	1.031	1.031	1.031	No
Indiana	0.941	0.941	0.941	0.941	0.941	0.941	No
Iowa	0.908	0.908	0.908	0.908	0.909	0.910	No
Kansas	0.955	0.955	0.955	0.955	0.955	0.954	No
Kentucky	0.940	0.940	0.940	0.940	0.939	0.939	No
Louisiana	0.883	0.884	0.884	0.884	0.885	0.886	No
Maine	1.245	1.243	1.239	1.234	1.225	1.209	No
Maryland	1.150	1.150	1.150	1.149	1.149	1.148	No
Massachusetts	1.063	1.063	1.063	1.063	1.063	1.063	No
Michigan	0.948	0.948	0.948	0.948	0.948	0.948	No
Minnesota	1.060	1.060	1.060	1.060	1.059	1.059	No
Mississippi	1.000	1.000	1.000	1.001	1.001	1.002	No
Missouri	0.949	0.948	0.948	0.948	0.948	0.948	No
Montana	0.933	0.933	0.934	0.935	0.937	0.941	No
Nebraska	0.980	0.980	0.980	0.980	0.979	0.978	No
Nevada	0.955	0.955	0.955	0.955	0.955	0.955	No
New Hampshire	0.930	0.930	0.930	0.929	0.928	0.927	No
New Jersey	1.022	1.022	1.022	1.022	1.022	1.021	No
New Mexico	1.038	1.038	1.038	1.037	1.036	1.035	No
New York	1.003	1.003	1.003	1.003	1.003	1.003	No
North Carolina	0.988	0.988	0.988	0.988	0.988	0.988	No
North Dakota	1.068	1.068	1.068	1.067	1.066	1.064	No
Ohio	0.911	0.911	0.911	0.911	0.910	0.910	No
Oklahoma	0.893	0.893	0.893	0.893	0.892	0.891	No
Oregon	1.002	1.002	1.002	1.002	1.002	1.002	No
Pennsylvania	1.000	1.000	1.000	0.999	0.999	0.999	No
Rhode Island	1.097	1.096	1.096	1.094	1.092	1.088	No
South Carolina	0.941	0.941	0.941	0.941	0.941	0.941	No
South Dakota	0.979	0.979	0.980	0.982	0.985	0.990	No
Tennessee	0.947	0.947	0.947	0.947	0.947	0.947	No
Texas	0.979	0.979	0.979	0.979	0.979	0.978	No
Utah	1.001	1.001	1.001	1.000	1.000	0.999	No
Vermont	1.343	1.337	1.328	1.316	1.294	1.264	No
Virginia	1.165	1.165	1.165	1.165	1.165	1.166	No
Washington	1.042	1.042	1.041	1.041	1.041	1.040	No
West Virginia	1.233	1.229	1.224	1.216	1.201	1.179	No
Wisconsin	0.968	0.968	0.968	0.968	0.968	0.967	No
Wyoming	1.008	1.002	0.995	0.984	0.966	0.939	No

Notes: $k = 0$ denotes the unadjusted location quotient; higher k values indicate stronger empirical Bayes prior weighting. "Crosses 1?" indicates whether the location quotient crosses the threshold of 1 between $k = 0$ and $k = 100$.