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U.S. AI Workforce

Labor Market Dynamics

CSET Issue Brief

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AUTHORS
Diana Gehlhaus
Ilya Rahkovsky

Executive Summary

A lack of good data on the U.S. artificial intelligence workforce limits the potential effectiveness of policies targeted at growing and cultivating this cadre of talent. We bridge this information gap by providing new analysis on the state of the U.S. AI workforce.

Our analysis on the dynamics of the U.S. AI workforce finds:

- The AI workforce is geographically concentrated.
- The AI workforce, about 9 percent of total U.S. employed in 2019, has grown rapidly over 2015 to 2019 with technical occupations growing the fastest.
- Growth in demand for AI workers over 2015 to 2019 matches growth in demand for all U.S. workers.
- Key AI occupations have divergent labor market trends.
- There is evidence of strong future growth in demand for AI workers and AI-related skills.
- More efforts are needed to elevate the legitimacy of alternative pathways into AI occupations outside of a four-year degree.

Our analysis also provides new insight on the ongoing concern over talent shortages in the AI workforce. While we do not directly state the presence of shortages, our findings suggest some segments of the AI workforce have a greater likelihood than others to be experiencing a supply-demand gap. Considering the core roles and responsibilities of those working in the design, development, implementation, and scaling of AI and AI-enabled capabilities:

- The extremely strong employment and wage growth for computer and information research scientists over 2015 to 2019 likely indicates that there is more demand than supply.
- In other “high-demand” occupations such as software developers and data scientists, we find evidence that

existing talent development pipelines are working to meet demand.

- In the case of project management specialists and user experience designers, we do not find evidence of a notable gap in demand relative to supply.

This is the second paper in a three-part series. The first paper defined the U.S. AI workforce and characterized the supply of AI talent in the United States. The third paper will assess what federal, state, and local government policy levers are available to facilitate a sufficient domestic AI workforce pipeline.

Table of Contents

Introduction

The concern about an artificial intelligence workforce shortage in the United States is a key issue in many workforce, technology, and national security policymaking circles. Various news media and business literature report acute AI talent shortages, calling for immediate action in order to stay globally competitive. These calls have prompted urgency to grow the U.S. AI workforce and highlighted the potential challenges policymakers face in doing so.

The idea that an AI workforce shortage exists is so commonly accepted that it has become a strategic priority of the Biden administration and the U.S. Department of Defense. Many legislative proposals, including those based on the recommendations of the National Security Commission on Artificial Intelligence, have the goal of growing and cultivating the domestic AI workforce based on this premise.

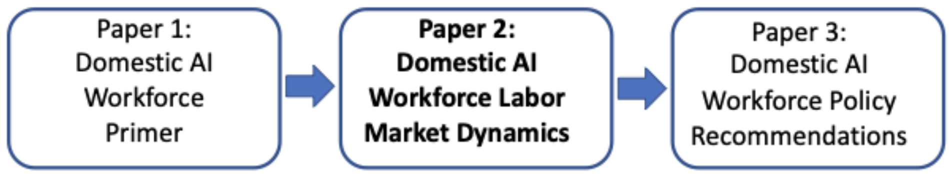
However, any evidence on which these claims are based is incomplete. There is little data on actual U.S. AI labor market dynamics to inform whether there is an AI workforce shortage, and if so, to what extent. Moreover, the data that is available does not have a standard definition of "AI workforce." This makes it difficult, if not impossible, to determine which workers are in short supply and how great the shortage may be.

Given the scale and complexities of U.S. education and workforce policy, there is a large cost to such incomplete information. Without being appropriately targeted, investments may bring little in return. Worse, a mistaken policy may disrupt existing talent pipelines, resulting in an adverse effect on the vitality of the AI workforce.

This issue brief seeks to bridge the existing information gap on the labor market dynamics of the U.S. AI workforce. We provide a preliminary assessment of the state of the U.S. AI labor market, providing new data-driven insights on the question of AI talent shortages. We review labor market dynamics related to supply and demand, and look longitudinally at changes in the AI workforce over 2015 to 2019.

This is the second installment of a three-part paper series on the U.S. AI workforce. It is a follow-up to the first brief, "The U.S. AI Workforce: Understanding the Supply of Domestic Talent."[1] The final report in this series will be a policy report with actionable recommendations in the short-, medium-, and long-term to more effectively grow and cultivate the domestic AI workforce. The series is depicted in Figure 1.

Figure 1: CSET Research on U.S. Domestic AI Workforce.



Source: CSET.

Research Approach and Methods

The analysis in this brief uses the same definition of AI workforce as described in the first paper of the series, "The U.S. AI Workforce: Understanding the Supply of Domestic Talent."

To assess AI workforce dynamics, we explore several data sources. First, we use one-year microdata from the 2015 and 2019 waves of the U.S. Census Bureau's American Community Survey, using the appropriate survey weights.[2] We use ACS data to assess the location of AI workers, along with fundamental measures of labor market dynamics including employment and wage growth, and occupational unemployment. Second, we analyze data from Burning Glass, an online jobs posting aggregation platform, to assess the dynamics of AI labor demand over time. Third, we analyze data from LinkedIn Insights regarding a set of selected occupations core to the development of AI. We consider job tenure and top employers, along with current and fastest growing skills. Finally, for another forward-looking indicator, we consider occupational employment projections from the U.S. Bureau of Labor Statistics.

We note here that analysis using LinkedIn data for select occupations is based on job titles and U.S. workers with LinkedIn profiles.[3] For example, "software engineer," "full stack engineer," and "application developer" are just some of the job titles associated with software developers. Job titles are not a one-to-one match to occupational employment, which can comprise many job titles.[4] However, we are confident that our approach includes a majority of workers employed in the select AI occupations, and that many of these workers are represented given LinkedIn's high U.S. penetration rate.[5]

In addition to a current assessment of the AI workforce, this brief also provides some forward-looking insight. We consider the fastest growing skills for selected key occupations as an indicator of the future of these occupations. We also consider occupational employment projections to assess one commonly used indicator of future demand.

The U.S. AI Workforce

A range of roles and responsibilities are involved in the designing, development, and deployment of AI products and applications. This includes the technical AI workers who are at the center of the AI development process, who develop, train, and apply AI algorithms; workers who play a critical role as part of the product team; and workers necessary at the institution or organizational level that perform commercial functions.[6]

Previous CSET research defined the AI workforce as "the set of occupations that include people who are qualified to work in AI or on an AI development team, or have the requisite knowledge, skills, and abilities (KSAs) such that they could work on an AI product or application with minor training." (The full list of occupations is in Appendix A of "The U.S. AI Workforce: Understanding the Supply of AI Talent.")

For our analysis of the AI workforce, we distinguish AI workers through four occupational categories:

(1) Technical Team 1 (Tech 1): occupations that are or could be actively working in AI, needed to provide technical inputs into AI applications, or could laterally move into an AI development role.

(2) Technical Team 2 (Tech 2): occupations that have the related KSAs to perform technical roles on an AI team, either as is or with some minimal additional training.

(3) Product Team: occupations that complement AI technical occupations in product development (such as project or product managers and legal compliance officers).

(4) Commercial Team: occupations that provide support for the scaling, marketing, or acquisition of AI at the organizational level.

As noted in the first paper of this series, we count entire occupations, regardless of the share actively working in AI. This is because we are interested in the total pool of possible AI talent—the set of people that have the requisite KSAs to work in AI or on an AI development team with minor training. Although it is not possible to estimate the exact shares working actively in AI, it is likely that some occupations will have higher shares than others.[7]

This paper's analysis includes some components that are focused on the employed segment of the AI workforce, and others that are focused on the entire AI workforce (employed and unemployed). When reporting data on employment and wages, along with data on employment projections, we are looking at employed persons. When considering unemployment rates, we consider the population of employed and unemployed persons. Data from LinkedIn Insights does not distinguish between employed and unemployed, and job postings data from Burning Glass is solely an indicator of demand.

Understanding Workforce Shortages

Media reports have long proclaimed the existence of workforce shortages—in fields such as nursing, high-tech manufacturing, computer and information technology, and more recently, AI. But what does it mean for there to be a workforce shortage? And how can we measure the degree to which one exists?

There is no standard typology, but generally workforce shortages come in two distinct forms.[8] These are worth delineating because the nature and reason for these shortages are different, as are the solutions for addressing them.

The first is a skills shortage in the traditional economic sense. Here, there is an insufficient supply of talent with specific, in-demand skills. It is a human capital shortage where there are labor market indicators economy-wide that the supply of workers with these skills is scarce relative to demand. These shortages can be persistent or temporary, depending on if and how quickly workforce development pipelines are able to adapt to changes in skill demand.[9]

High barriers to entry in an occupation are the main reason for skills shortages.[10] Literature suggests, for example, that the shortage of nurses has been particularly persistent.[11] Many nursing programs across the country have a limited number of available openings, resulting in long wait-lists. If only a limited number of education or training programs exist to prepare workers with specific skills, such as in advanced manufacturing, that can also limit available supply.

High barriers to entry are known to exist for occupations that require advanced education or many years of training and experience. This includes some AI occupations such as computer and information research scientists, and occupations with national or state-mandated licensing requirements such as select types of engineers. These occupations will inherently have a more limited supply and could be more vulnerable to a shortage. For highly technical occupations, the result has been a reliance on foreign talent to fill the gap. However, this could also be a barrierenhancing shortage because of caps and other restrictions imposed by U.S. immigration laws.[12]

Yet another type of barrier to entry is occupational stigma. Research shows a shrinking talent supply and pipeline for trade occupations such as electricians, mechanics, and plumbers due to limited interest and alternative tracking in high school.[13] Many who would have normally pursued trade careers are being funneled into college instead.[14]

The second type is a local talent shortage, in an organization or geographic area.[15] Here, a sufficient supply of talent with the needed skills exists in other areas or other organizations, but specific organizations or geographic areas may be experiencing acute challenges recruiting and retaining these workers.[16] There could be several reasons for these workforce rigidities, including workers' geographic preferences, stricter state occupational licensing requirements, and, at the organizational level, limited career advancement opportunities, poor hiring practices, uniquely specific skills and/or experience requirements, below market average wages and compensation, restrictions on competitor firm hiring ("noncompete" employment contracts), and a less competitive brand or reputation.[17]

For example, much has been written about the federal government's inability to recruit sufficient civilian talent—in many career fields, ranging from AI and cybersecurity to health professions and shipbuilding.[18] Similarly a small business may not be able to find the right talent for their needs, or an organization employing an otherwise declining occupation may struggle as workers move into other fields to set themselves up for better long-term opportunities.

The question is what type of shortage it is and therefore what can be done to address it. The small business may not be able to compensate at market rates,[19] may lack an inspiring brand or mission, or may be located in an undesirable area. The federal government may similarly struggle to be a competitive employer along compensation and branding lines, for a myriad of reasons,[20] but this is not itself indicative of a skills shortage across the economy. Moreover, for certain positions, the employee must be a U.S. citizen, which could be a limiting factor for some highly technical skill sets.[21] The exception is when the entity is the main employer. For example, shipbuilding employment is primarily driven by the federal government, and maintaining a pool of this talent is challenging because of the irregular demand and uncertain budgeting.

Because of the specific KSAs needed for more technical occupations—barriers to entry—it is technical occupations that generally have the most risk of experiencing skills shortages. Nontechnical occupations have many pathways to entry, allowing more workers to be qualified or quickly move into these roles. That said, 2020 has shown that more widespread workforce shortages could affect even nontechnical occupations; for example, warehouse and fulfillment center workers and delivery workers saw tremendous spikes in demand during the rapid and unexpected labor market shift during the COVID-19 pandemic.

Measuring Workforce Shortages

There is no universal way to measure a workforce shortage.[22] Instead, there are a variety of data points economists consider that indicate a shortage exists, and the severity of such a shortage.

One common data point is through business surveys and anecdotal evidence as reported by the business literature, consulting firms, and news media. For example, a 2019 Deloitte survey found that 21 percent of companies surveyed (globally) reported having a "major" or "extreme" shortage in AI talent.[23] A 2020 survey of about 1,000 executives by RELX found 39 percent said they were not using AI because of "a lack of technical expertise."[24] Other reports focus on the top tier AI talent—computer research scientists and machine learning (ML) engineers—when making claims of shortages.[25]

For evidence of skills shortages, economists generally turn to more official data points.[26] Here they consider labor market indicators such as changes in occupational unemployment rates, average real earnings, and job vacancy and turnover rates relative to all occupations.[27] According to a paper from the U.S. Bureau of Labor Statistics, measuring shortages are "…focused on the entire labor market process and evaluated, to the extent possible, factors such as trends in employment and earnings, current demand and supply, and even factors such as hiring practices." Since there is no accepted threshold for determining a shortage, the author created one:

> "the occupation's employment growth rate was at least 50 percent faster than average employment growth, the wage increase was at least 30 percent faster than average, and the occupation's unemployment rate was at least 30 percent below average."[28]

While this brief does not directly state whether there is a shortage in AI talent, it does provide some key indicators of supply and demand dynamics that will better inform policy discussions.

Labor Market Dynamics of the U.S. AI Workforce

Effective education and workforce policy requires understanding the relevant labor market dynamics, including insights on the existence of any workforce shortages.

To assess the state of the AI workforce, including the existence of talent shortages, this report considers five broad labor market signals. Each signal contains a set of indicators that provide important context for the current state and trends in the U.S. AI workforce.

Signal #1: The AI Workforce is Geographically Concentrated

Much of the discussion around the location of workers in AI occupations—particularly those in technical occupations—is that they are geographically concentrated in a few urban hubs. Media reports frequently note tech hubs in the United States have taken over a small number of cities,[29] with economic and social spillover effects felt across the country[30]. On one hand, talent clustering is good for innovation and growth in these areas, which have experienced large economic gains over the last decade. On the other hand, the concentration of economic wealth and activity in these areas is exacerbating the have/have-not divide for everyone else, including those living in these clusters that do not have high earnings.[31]

For this analysis we considered geographic distribution in two ways: (1) the share of AI employment as a share of total U.S. county employment,[32] and (2) the share of total group employment by U.S. county (e.g., all AI occupations, Tech 1 occupations, etc.). Each map shows color gradation between blue and red, with blue having the smallest shares and red the largest.[33] (The methodology of creating these maps, along with top five tables by share of county employment and by group employment, are provided in the Appendix A of this brief. All maps were created in Tableau.)

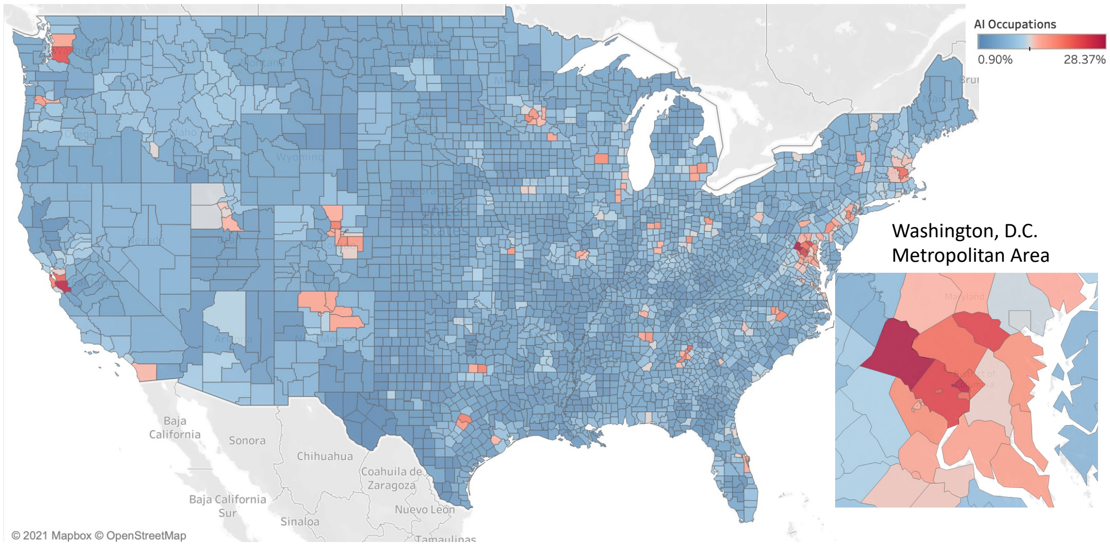
The maps presented in this section visualize the geographic distribution of:

- The total AI workforce—that is, Technical Team 1, Technical Team 2, Product Team, and Commercial Team occupations combined (Figures 2 and 3).[34]
- Technical Team 1 occupations (Figure 4).
- Product Team occupations (Figure 5).

We focus here on the total AI workforce, Technical Team 1, and Product Team occupations because of their immediate relevance to AI product development and the AI workforce policymaking communities. We also focus more on share of county employment as a way to make meaningful comparisons across counties and groups. (The geographic distribution of group employment for Technical Team 1 and Product Team occupations, along with both types of geographic distributions for Technical Team 2 and Commercial Team occupations, are provided in Appendix B.)

Beginning with the overall AI workforce, Figures 2 and 3 show AI workers are generally concentrated around major U.S. cities. Figure 2 shows the percentage of each county's workers that are employed in AI occupations as defined above. As a share of total employment in the associated county(s), among the top counties are those containing Seattle (King County, WA), the Washington, D.C. metropolitan area (Arlington, Fairfax, and Loudoun Counties, VA), and San Francisco (San Francisco and Santa Clara Counties, CA). The top county by share is Loudoun County, VA, where the share of AI workers as a share of total employment is 28 percent.[35]

Figure 2: County Employment Share in AI is Higher in Major Cities.
Share of county employment in AI occupations.



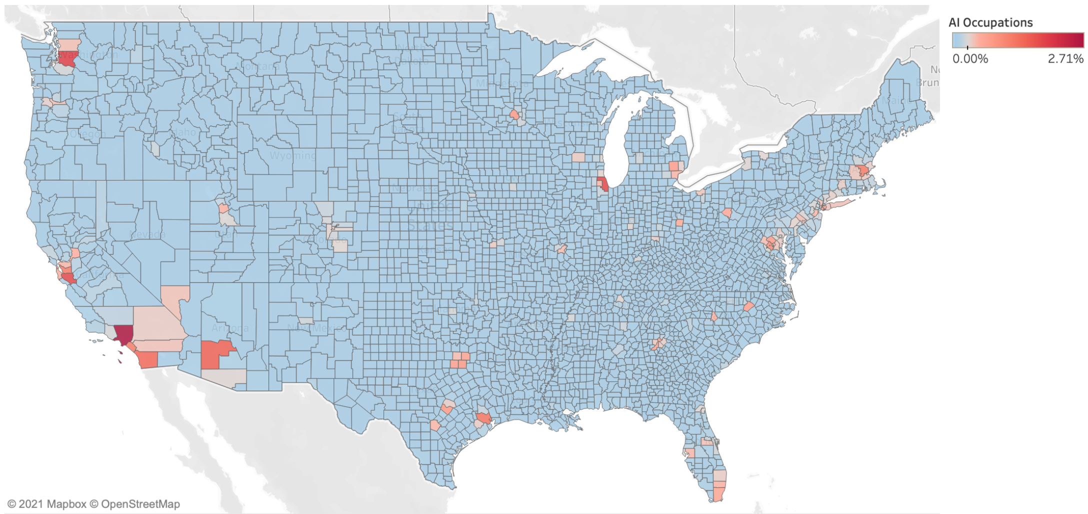
Source: American Community Survey 2019, CSET.

However, instead of AI workers all being solely in the top five hubs highlighted in many news stories—Boston, New York, San Francisco, Seattle, and Washington, D.C.—we also see pockets of other metro areas across the country that have high shares of employment in AI occupations. For example, areas including Ann Arbor (MI), Atlanta (GA), Austin (TX), Denver (CO), and Minneapolis (MN) are also featured on the map. Moreover, we see several less densely populated areas having high shares of AI employment, such as in New Mexico where there are two national research labs.

Figure 3 presents a similar map looking at the share of AI employment by U.S. county. We see representation in key metro areas as in Figure 2 with two notable differences. First, the expansion in Southern California, which has a large share of AI workers. Second, the few low-density areas such as northern New Mexico that were on the map in Figure 2 now fall off in Figure 3. That is because these areas may have a high share of county employment in AI occupations, but a small number of AI workers. These counties have small populations and it takes fewer workers to comprise a high share of total employment.

Figure 3: AI Employment is Generally Concentrated in Large U.S. Metropolitan Areas.

Share of AI Occupational Employment by County.

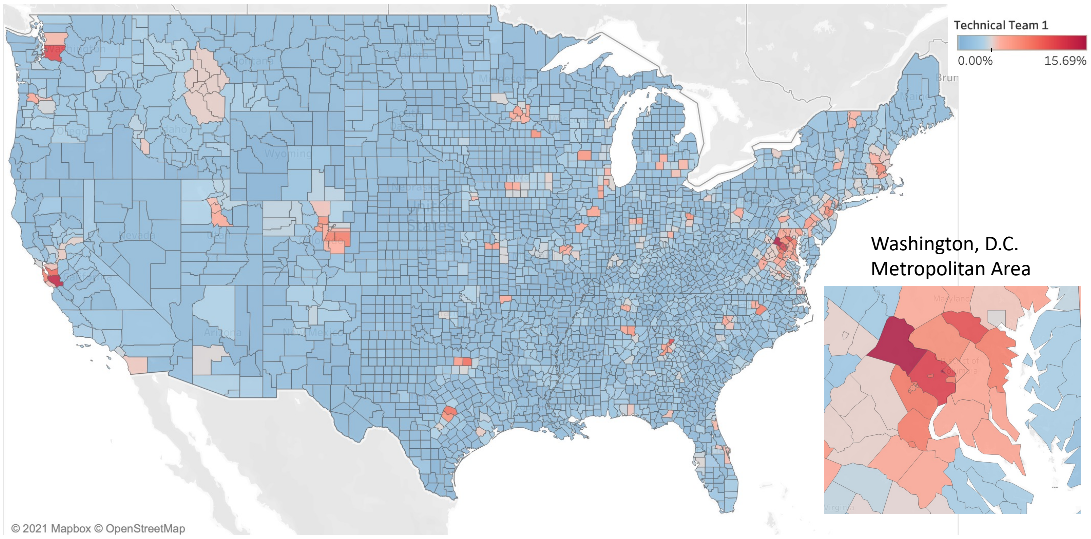


Source: American Community Survey 2019, CSET.

When looking at Technical Team 1 occupations, we see these workers are also concentrated in key U.S. metropolitan areas. Figure 4 provides a mapping of Tech 1 occupations by share of county employment. The top five counties are in two urban areas: Washington, D.C. and San Francisco. Interestingly, four of the top five by county share are in the Washington, D.C. metropolitan area, with Loudoun County and the City of Falls Church taking the first two spots with shares of over 15 percent. Santa Clara, CA, followed by Fairfax and Arlington Counties, VA round out the list.

Figure 4: Tech 1 Workers Have Higher County Employment Shares in Known AI Hubs.

Share of county employment in Technical Team 1 occupations.



Source: American Community Survey 2019, CSET.

The urban concentration of Tech 1 workers suggests that when it comes to technical AI occupations, these workers do resemble what is reported in the media and literature on AI clusters.[36] That said, we still see notable concentrations of this talent in cities such as Atlanta, Austin, Denver, and Salt Lake City. Moreover, even though Tech 1 workers comprise high shares of total county employment in the top five counties, these counties still accounted for a small share of total Tech 1 employment (see Table A2 in Appendix A).

When looking at the distribution of Tech 1 workers without adjusting to county employment, we find a more concentrated employment story (see Figure B1 in Appendix B). The Washington, D.C. metropolitan area no longer dominates, instead seeing the highest levels of Tech 1 employment in Los Angeles, San Francisco, and Seattle.

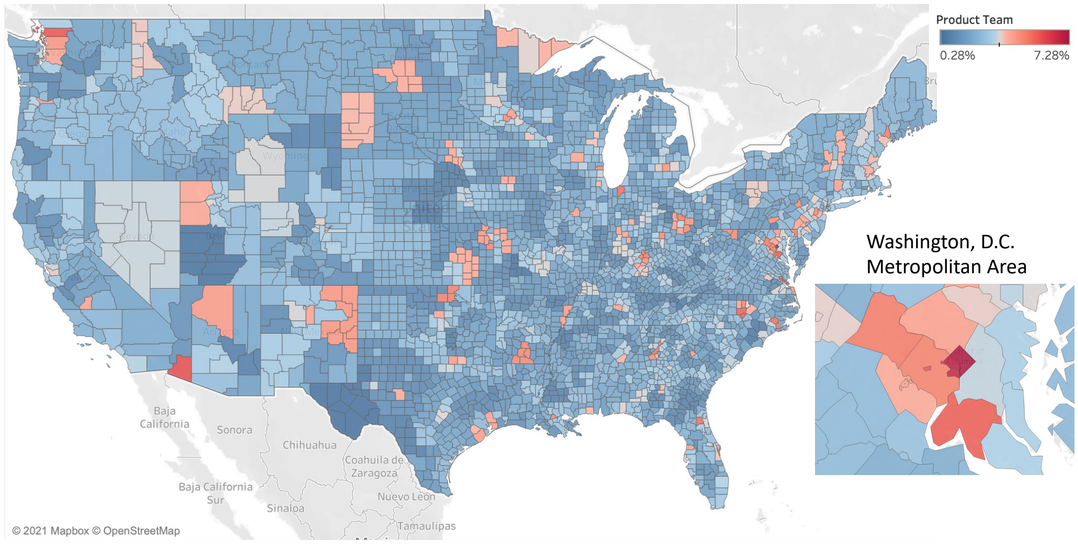
However, by not adjusting to county size, the analysis is also slightly misleading. The inherently smaller counties in the eastern part of the United States make a large difference. For example, the Washington, D.C. metropolitan area consists of many small counties. While this means it takes fewer Tech 1 workers to make Tech 1 employment a large share, it also means considering adjacent counties may be a more appropriate way to compare employment levels in Los Angeles, San Francisco, and Seattle. Adding total Tech 1 employment in Arlington, Fairfax, and Loudoun Counties, we find once again that the Washington, D.C. metropolitan area ranks in the top five, now overtaking Los Angeles for third highest (see Table A2 in Appendix A).

The implication is that Tech 1 workers are concentrated geographically, but are found across many metropolitan areas outside of the core known and discussed “tech hubs.” Moreover, the Washington, D.C. metropolitan area is a top area for these workers, which suggests more talent is in this area and Washington, D.C.-based companies and industries than previously thought.

Perhaps most interestingly, Product Team occupations are among the most spread out geographically. This likely reflects the wider range of industries employing these workers, as noted in our previous brief.

Figure 5 provides a map of Product Team occupations by their share of county employment. We can see workers in these occupations are fairly distributed across the country, not only in core urban clusters. In fact, these workers do not make up more than 7 percent of total employment in any U.S. county. Given that, the top four locations for Product Team workers relative to total county employment are in the Washington, D.C. metropolitan area, with Yuma, AZ, rounding out the list.[37] Together the top five counties accounted for just 1 percent of total Product Team employment in 2019 (see Table A4 in Appendix A).

Figure 5: Product Team Workers are More Spread Out.
Share of county employment in Product Team occupations.



Source: American Community Survey 2019, CSET.

When looking solely at the distribution of Product Team employment without adjusting for county size, the sheer large size of counties such as Los Angeles makes these areas dominate (see Figure B2 in Appendix B). It is more evident that low-density regions that had high shares of county employment, such as Yuma, do not have a large number of Product Team workers.

The differences in geographic concentration of AI workers suggests product team talent may be easier to attract and recruit in terms of location.[38] Specifically, those employed in Product Team occupations are more geographically distributed, and therefore may be more accessible. Organizations and communities not in the known "tech hubs" wishing to invest in developing AI capabilities, as opposed to acquiring "off-the-shelf" commercial solutions, may have to worry about relocation related to attracting technical talent more than the rest of the needed team. However, organizations and communities wishing to invest in acquiring instead of developing AI capabilities may already have a running start in local access to talent.

Signal #2: The AI Workforce is Growing Rapidly

U.S. AI employment grew rapidly over 2015 to 2019 relative to total U.S. employment.[39] Table 1 shows the growth in employment of the AI workforce compared to total U.S. employment. The number of employed AI workers increased over 20 percent, to 14 million in 2019, with Tech 1 occupations seeing the largest increase.[40] In contrast, over this period total U.S. employment grew by 5.6 percent.

Table 1: U.S. AI Employment Increased 21.4 Percent Over 2015 to 2019.

	2015 Employment	2019 Employment	2015–2019 Percentage Change	2019 Unemployment Rate	2019 Unemployment Rate, Bachelor's Degree or Higher
Technical Team 1	4,048,950	5,095,130	25.8%	2.2%	1.9%
Technical Team 2	2,779,460	3,221,890	15.9%	2.2%	1.8%
Product Team	3,548,900	4,314,070	21.6%	2.9%	2.5%
Commercial Team	1,716,980	2,047,510	19.3%	2.9%	2.7%
Total AI Workforce	12,094,290	14,678,600	21.4%	2.5%	2.1%
Total U.S.	151,593,280	160,034,580	5.6%	4.5%	2.5%

Note: Project management specialist (part of Product Team) is a new occupation as of 2018. In 2015, the occupation was split across “Business Occupations, All Other” (Product Team), “Computer Occupations, All Other” (Tech 1), and “Managers, All Other (Not included in this analysis). The share that was devoted to each to estimate approximate 2015 employment is unknown. These comparisons are therefore not exact. Other classification differences over 2015 to 2019 are adjusted using a proportionality approach; the share of an occupation relative to its aggregate in 2019 was applied to the aggregate in 2015 if the occupation was not available. This was done for geoscientists (Tech 2), web developers (Tech 2), web and digital interface designers (Product Team), graphic designers (Product Team), and marketing managers (Commercial Team). These classification complications also limit the reliability of unemployment rate estimates for 2015.

Source: American Community Survey 2015 and 2019, CSET.

Unemployment in 2019 was also notably lower across AI occupation groups relative to the entire U.S. workforce. While unemployment for the AI workforce averaged 2.5 percent, the unemployment rate for all U.S. workers was two percentage points higher, averaging 4.5 percent in 2019.[41]

However, this difference reduces when looking at the unemployment rates for those with a bachelor's degree or higher.[42] Product and Commercial Team occupational unemployment rates become comparable to the national unemployment rate. The difference for Technical Team occupations goes from over 50 percent less to about 25 percent less than the national average. This difference is still notable, but less than the 30 percent threshold used by the U.S. Bureau of Labor Statistics.

Signal #3: Demand for AI Workers Matched All Workers

One way traditional economics measures changes in labor supply relative to changes to labor demand is by looking at the relationship between the job vacancy rate and the unemployment rate.[43] However, official data on job vacancies are not available at the occupation level.[44] We therefore investigate job postings data from Burning Glass, which is available at the occupation level.[45]

This analysis does not consider job postings as a share of the labor force, nor the change in occupational unemployment rates over time. The required data is not available on the supply side, and is too noisy on the demand side. Job postings do not necessarily reflect specific jobs or even one job, nor do they mean a new job has been created. Employers could be posting to collect resumes for future jobs or use one post for multiple vacancies. Job postings are therefore not the same as job vacancy rates and would not be a sufficient proxy.

Instead, we present a general assessment of AI labor demand using job postings data over 2015 to 2019. This is consistent with economic literature, which uses job postings data to showcase the change in demand for a given occupation or group of occupations.[46]

Table 2 shows a strong increase in demand for AI occupations over 2015 to 2019. Over this time, AI workforce job postings increased almost 30 percent, to over 7 million postings in 2019, with similar growth rates in each of the four AI categories.

However, the strong increase in AI occupation job postings was commensurate with the increase in total U.S. job postings over 2015 to 2019. This suggests that growth in AI workforce job demand by this measure was no faster—if anything slightly slower—than that for all U.S. jobs over this period.

Table 2: AI-Related Job Openings Grew as Fast as All U.S. Job Postings.

	U.S. Job Postings, 2015	U.S. Job Postings, 2019	Growth 2015–2019
Technical Team 1	2,577,416	3,323,496	29%
Technical Team 2	967,693	1,169,402	21%
Product Team	563,404	769,330	37%
Commercial Team	1,439,055	1,843,296	28%
AI Workforce	5,547,568	7,105,524	28%
U.S. Workforce	26,608,490	35,487,110	33%

Source: Burning Glass, CSET.

Of the AI occupation groups, Product Team occupation postings grew the fastest, at 37 percent. Product Team occupations were also the only group to see postings increase more than the total U.S. rate.

Importantly, job postings data should not be compared directly to supply-side measures such as employment growth to answer the question of talent shortages.[47] This is because in addition to the noisiness of job postings data there is also a natural rate of churn (turnover) in labor markets. In many cases workers are simply changing jobs but no new jobs were added to the economy.[48]

Signal #4: Key AI Occupations Have Divergent Trends

The next set of indicators take a deeper dive on five AI occupations that are of key interest to organizations and policymakers seeking to design, develop, and deploy AI-enabled products and applications. We spotlight these occupations because they are critical in the AI development process, and therefore are prominently featured in the business literature and federal workforce policymaking discussions. These occupations are: computer research scientists (Tech 1), software developers (Tech 1), mathematicians/statisticians/data scientists (Tech 1), project management specialists (Product Team), and user experience designers (Product Team).[49]

Table 3 highlights employment, average wage, and educational attainment in 2019 for these key occupations. It also provides the change over 2015 to 2019 in employment and average wage, inflation adjusted,[50] as well as average tenure for workers in these occupations (how long an individual stays in one job on average).[51] All data is calculated using the American Community Survey with the exception of Average Tenure, which comes from LinkedIn Insights.

Table 3: Key AI Occupations Grew Rapidly Over 2015 to 2019.

	2019 Employment	2019 Unemployment Rate	2019 Mean Wage	2015–2019 Employment Change	2015–2019 Change in Mean Wage	2019 Share with Bachelor's or Higher	Average Tenure
Computer Research Scientists	35,230	N/A+	108,230	72.9%	27.3%	91.0%	1.3 years
Software Developers	1,651,990	1.9%	117,600	38.9%	13.4%	85.9%	1.3 years
Mathematicians/ Statisticians/ Data Scientists*	184,290	2.0%	82,850	251.9%	-12.1%	82.7%	0.8 years
Project Management Specialists**	663,230	2.1%	90,150	N/A++	N/A++	70.7%	2.2 years
User Experience Designers***	396,720	3.8%	45,650	4.0%	N/A++	65.8%	1.3 years
Total AI Employed	14,678,600	2.5%	86,230	21.4%	N/A++	67.6%	N/A+++
Total U.S. Employed	160,034,580	4.5%	52,110	5.6%	7.0%	35.7%	N/A+++

+N/A = Not reported due to small sample size.

++N/A = Not available due to changes in occupation classification.

+++N/A = Not available due to non-correspondence to LinkedIn Insights.

*American Community Survey (ACS) microdata classifies mathematicians, statisticians, and data scientists as part of "Mathematical Science Occupations, All Other." The ACS data in this table are for this "All Other" occupation; average tenure includes job titles for all three occupations. Also, data scientists were added to this occupation with the 2018 classification update. This resulted in a reclassification of some workers previously included in other occupations into this occupation, which is partly why there is a large increase in employment and a corresponding decrease in real average earnings.

**Project management specialists are a new occupation as of 2018, previously contained in multiple occupational categories. Therefore, data is not available for 2015. However, 2019 employment actually decreased from 2018.

***User experience designers are defined as graphic designers plus web and digital interface designers. Both are new breakout occupations as of 2018. While we can use proportionality assumptions to estimate employment change, we are unable to estimate change in earnings.

Source: American Community Survey 2015 and 2019, LinkedIn Insights (Data Accessed December 2020), CSET.

It is worth noting that growth rates in employment for the highlighted Tech 1 occupations are much faster than for total U.S. employment, and even for the growth in all AI workers. Computer and information research scientists, for example, grew quite rapidly over 2015 to 2019, increasing 73 percent. The category of mathematical science occupations that includes data scientists grew over 250 percent over 2015 to 2019 (noting the classification changes for this group). This suggests that the supply of these workers is increasing steadily to meet demand.

The situation is a bit different for real average wage growth in each occupation.[52] Computer and information research scientists saw large wage growth alongside employment growth, growing almost four times faster than the national average. Real wage growth for software developers was not as fast, but still almost two times the national average.

In contrast, mathematical science occupations showed a decline in real average wages. However, we acknowledge that may not completely reflect reality—the displayed decline is due, in part, to the creation of the data scientist occupation (which reclassified some workers previously classified in other occupations). Still, the proliferation in college degree programs related to data science[53] could have resulted in a large number of more junior (and lower paid) talent entering this occupation.

Each of the selected occupations also have a much higher educational attainment than the average for all employed U.S. workers. More than 80 percent of computer and information research scientists, software developers, and data scientists had at least a four-year college degree, and more than 70 percent of project management specialists had a bachelor's degree (compared to 35 percent for total U.S. employed).

Importantly, this data provides clear insight on the ability to enter these AI occupations through pathways other than a four-year college degree. For project management specialists and user experience designers, some alternate pathways clearly exist, given that nearly a third of those employed workers do not hold a four-year degree. However, options outside of a traditional four-year degree are far fewer for the more technical AI occupations. The lack of alternate pathways for these professions suggests talent is potentially being left behind (or on the table) if there are individuals who can perform these functions but lack a four-year college degree.[54] Such talent could be tapped if portfolios and/or certifications were to become acceptable to employers in lieu of college degrees. It is likely that a concerted effort is needed to effectively expand these career pathways.

Given the high share of college graduates, one way to assess the health and response of the United States' talent pipeline is to look at degrees conferred. This is particularly the case for Tech 1 occupations, which are more technical and therefore have a clearer link to specific fields of study.[55] As noted in the first brief of this series, about half of workers employed in Tech 1 occupations studied computer science or engineering.

Looking at data from the U.S. Department of Education, computer science and engineering were the fastest growing undergraduate degrees over 2015 to 2018 (the most recent year available). While total degrees conferred increased 4.5 percent, the number of degrees conferred in computer science and engineering increased by 34 percent and 25 percent, respectively, far more than any other field of study.[56] This equates to an additional 44,000 graduates combined over this three-year period, and in 2018 these two degrees accounted for 10.2 percent (or 201,550) of all four-year degrees conferred.[57]

In terms of tenure, there was a range across occupations. Those with job titles on LinkedIn related to project management specialists had the longest job tenure, at 2.2 years. Those with job titles related to mathematicians, statisticians, and data scientists had the least, at less than 10 months. There are several reasons this could be the case, from high demand to age—for example, many data scientists may be younger and are more likely to move on quickly to advance their careers.[58] Still, this suggests there may be considerable churn in these occupations, making retention a common issue.[59] It also suggests that employee retention may in itself not be the optimal goal for organizations, a point we will explore further in subsequent research.

It is noteworthy that while a critical occupation to the advancement of new AI-enabled applications, computer and information research scientists are among the smallest AI occupations. In 2019, just 35,320 workers were classified in this occupation, compared to 1.65 million software developers and 2.6 million in all Technical Team 1 occupations. This suggests that while these workers garner the most attention within the AI workforce, they may not be truly representative of the supply-demand dynamics for the rest of the AI workforce.

Given the differences in occupational size, and employment and wage growth across the AI workforce, it is likely the nature and extent of gaps in the AI workforce pipeline vary by occupation. In the case of computer and information research scientists, employment and wages have grown rapidly relative to the national average. At the same time, high educational attainment is a significant barrier to entry. It is therefore possible that potential shortages for this occupation—while a very small part of the AI workforce—may be a critical challenge for some employers, at least in the near-term. However, it may not be a challenge for other employers engaged in AI, nor may these workers comprise the majority of AI talent on AI product teams.

For software developers it appears that supply increased alongside demand, evidenced by the growth in real earnings and employment. The question becomes whether the increase in demand was larger than the increase in supply. For mathematical science occupations, it could be that the increase in supply was actually faster than the increase in demand (partially explaining the decline in real average earnings). Similarly, although the data is more limited, we find little evidence of any significant workforce gaps for project management specialists and user experience designers.[60]

Signal #5: Evidence of Strong Future Growth in Demand

One forward looking demand-side indicator is projected job growth. The U.S. Bureau of Labor Statistics produces 10-year occupational forecasts by detailed occupation.[61] These projections are for the 2019–2029 period, and we note that the COVID-19 pandemic may have impacted these projections. However, we believe that if anything, the COVID-19 pandemic accelerated demand for many AI occupations. This is due to several factors, including the shift to remote work, the rapid adoption of automated process and operations solutions, and the high demand for technologically-driven services. Therefore, it is more likely these projections are a conservative estimate than an overstatement.

Table 4 shows strong projected demand for AI occupations relative to all occupations, with demand for AI occupations projected to grow twice as fast as for all U.S. occupations. The projected increase in AI occupations amounts to almost 17 percent of the total projected increase in U.S. employment. Still, there is variety among the AI occupation groups. Technical Team 1 occupations are projected to have the fastest growth, while Commercial Team occupations the least.

Table 4: AI Occupations Projected to Grow Faster than All Occupations

	Projected Employment Change, 2019–2029	Projected Employment Growth, 2019–2029
Technical Team 1	550,400	13%
Technical Team 2	164,500	6%
Product Team	216,800	7%
Commercial Team	73,600	3%
Total AI Workforce	1,005,300	8%
Total US Employed	6,039,100	4%

Note: Project management specialists are counted with business occupations, all other in commercial team occupations; web and digital interface designers are counted with web developers in Technical Team 2 occupations.

Source: U.S. Bureau of Labor Statistics, CSET.

It is worth nothing that several of these occupations are also projected to grow rapidly over the next decade, although not necessarily in large numbers. This is shown in Table 5.

Table 5: Several Key Occupations are Projected to Grow Rapidly.

	Projected Employment Change, 2019–2029	Projected Employment Growth, 2019–2029
Computer and Information Research Scientists	5,000	15.4%
Software Developers*	316,000	21.5%
Mathematicians, Statisticians, Data Scientists**	25,200	31.9%

*Includes “Software Quality Assurance Analysts and Testers.”
**Includes “Mathematical Science Occupations, all Other.”

Source: U.S. Bureau of Labor Statistics, CSET.

Finally, looking at the top current skills relative to the fastest growing skills, we see evidence of growth in skills related to AI. Table 6 shows the top five skills people with related job titles on LinkedIn currently list as having in our five key occupations.

Table 6: Most Common Skills are Highly Technical.

Top Five Current Skills					
Rank	**Computer Research Scientists**	**Software Developers**	**Mathematicians, Statisticians, Data Scientists**	**Project Management Specialists**	**User Experience Designers**
1	Python	Software Development	Data Analysis	Program Management	Graphic Design
2	Machine Learning	Java	Data Science	Engineering	Adobe Photoshop
3	C++	JavaScript	Python	Product Management	Adobe Illustrator
4	Matlab	SQL	Data Mining	Process Improvement	Adobe Creative Suite
5	Engineering	C++	SQL	Business Analysis	Web Design

Source: LinkedIn Insights, CSET (Data accessed December 2020).

Not surprisingly, many of the top skills are related to computer programming. For each of our key occupations, the top skills fall in line with their typically-associated roles and responsibilities. Interestingly, for project management specialists engineering is listed as a top skill, suggesting a fair number of these workers may have some technical background or expertise.

We see a movement toward more AI-specific skills when looking at the fastest growing skills as shown in Table 7. Across each of these occupations, we see the fastest growing skills over the last year are not only highly technical, but many are directly related to the AI or ML development process. Even for project management specialists, the fastest growing skills are related to software development teams, including the rising importance of the user experience role.

Table 7: Fastest Growing Skills are Moving Toward an AI Focus.

Top Five Fastest Growing Skills					
Rank	**Computer Research Scientists**	**Software Developers**	**Mathematicians, Statisticians, Data Scientists**	**Project Management Specialists**	**User Experience Designers**
1	Data Analytics	Full-Stack Development	Data Analytics	Jira	Design
2	PyTorch	Back-End Web Development	Pandas	Project Coordination	Prototyping
3	Data Science	TypeScript	Artificial Intelligence (AI)	User Experience (UX)	Brand Identity
4	Pandas	React.js	NumPy	Scrum	Sketch App
5	Data Visualization	Docker Products	Data Visualization	Agile Project Management	Branding

Growth is over the last 12 months from the date of data extraction, measured by LinkedIn as the number of user profiles with the specified job titles listing this skill.

Source: LinkedIn Insights, CSET (Data accessed December 2020).

Conclusion

The concern of an AI workforce shortage is a key issue in many policymaking circles, but good data on AI labor market dynamics is limited. We bridge this information gap by providing new analysis on the state of the AI workforce. We use an occupation-based definition of the AI workforce, enabling analysis using occupation data collected by the federal government over time.

Our analysis finds several new insights on the dynamics of the U.S. AI workforce: (1) The AI workforce is geographically concentrated, (2) The AI workforce has grown rapidly over 2015 to 2019, with technical occupations growing the fastest, (3) Growth in demand for AI workers over 2015 to 2019 matches growth in demand for all U.S. workers, (4) Key AI occupations have divergent labor market trends, (5) There is evidence of strong future growth in demand for AI workers and AI-related skills, and (6) More efforts are needed to elevate the legitimacy of alternative pathways into AI occupations outside of a four-year degree.

It is quite likely that some segments of the AI workforce have a greater likelihood than others to be experiencing a supply-demand gap. Although we do not answer directly whether shortages exist, we find this issue is far more nuanced than a simple “yes” or “no.” This is based on analysis of changes in employment, real earnings, and job postings, along with unemployment rates—traditional economic measures used to indicate occupational shortages.

For example, overall evidence is mixed when considering AI occupations in aggregate. In terms of supply, AI occupations experienced a rapid increase in employment relative to non-AI occupations over 2015 to 2019. We find AI workforce employment grew almost five times faster than total U.S. employment, while the unemployment rate was almost half of the national unemployment rate in 2019. In terms of demand, however, we find that while demand for workers in AI occupations is strong, as measured by job postings, it is roughly in line with the rise in postings across all occupations.

Within the key AI occupations of interest explored here, the extremely strong employment and wage growth for computer and information research scientists likely indicates that there is more demand than supply. Still, we find that this is a very small—albeit important—occupation within the AI workforce. The implication then becomes that there could be a shortage, but not of a scale large enough to preoccupy or dominate AI education and workforce policy.

We also find that in high-demand occupations such as software developers and data scientists, talent development pipelines are working to meet increased demand. While there has been a rapid increase in employment, there has also been a rapid increase in the number of college graduates with degrees in computer science, engineering, and mathematics. We also find mixed evidence related to the growth in real earnings. It may be the case that for some of these more technical occupations, demand still outstrips supply. However, this could be because demand increased very rapidly very quickly and these pipelines are continuing to catch up. It could also be because these occupations are fairly concentrated in U.S. metropolitan areas, leading to geographic differences in the nature of any gaps.

Moreover, our analysis suggests not all AI occupations have a supply-demand gap. In the case of project management specialists and user experience designers, the change in employment, wages, and unemployment rates do not suggest any notable gap in demand relative to supply.

We note several factors could affect the degree or extent of any AI workforce gap. These include barriers to entry for the occupation (e.g., educational attainment), geographic location (e.g., access to talent), and average rates of job tenure (e.g., turnover or churn). Our analysis suggests high rates of turnover in technical occupations, affecting the ability to retain talent. One possible implication is that employment policies focused on retention may be shortsighted and employers should instead focus on talent management more holistically. More research is needed and future research will explore this further.

In the quest to expand the talent pipeline outside of four-year degrees, for occupations such as software developers and data scientists, the prevailing wisdom of the need for a four-year college degree should be carefully considered. Currently there is a proliferation of certifications, coding academies, and other online courses aimed at upskilling U.S. workers to have the requisite KSAs to perform these functions. However, if employers do not accept these alternative credentials, as suggested by the high rates of four-year degrees in these professions, there is a risk of leaving many potentially qualified workers on the sidelines. It could also have serious implications in the quest to increase economic equity. Future CSET research will also explore this further.

Finally, in a forward-looking indicator, among our key occupations of interest we find many of the fastest growing skills are AI-specific. This could suggest workers in these jobs are actively training to work in AI, and that they are experiencing labor market signals that indicate such skills will be in demand going forward.

This paper is the second in a three-part series. The third paper will assess what federal, state, and local government policy levers are available to facilitate a sufficient domestic AI workforce pipeline. Additional future research related to this series will explore other topical issues on domestic AI talent pipelines and career pathways, such as the perceived rise of AI-related certifications. It will also include an examination of broader manpower and personnel policy implications for the U.S. Department of Defense and broader national security community.

Appendix A: Mapping the Location of AI Workers

This Appendix provides: (1) additional detail on creating the geographic maps and (2) tables of the top five locations by share of county employment and share of group employment.

To create the geographic maps for this report, we had to crosswalk several data elements using American Community Survey and other U.S. Census Bureau data. ACS compiles and publishes data on geographic location of survey respondents in terms of public use microdata area in its household survey. We first crossed this PUMA data to Census tract, a geographic classification scheme also maintained by the U.S. Census Bureau. We then crosswalked Census tract to U.S. counties, using another Census-provided crosswalk.

Since PUMAs cross multiple Census tracts and multiple counties, we employed a proportionality assumption to assign workers across county borders. That is, when multiple PUMAs constituted a single county, or when a single PUMA overlapped multiple counties, we created a weighted average. Each PUMA in a given county had a weighted average based on the PUMA population it was a part of serving as the weight.

The total employment numbers used in creating the maps and these Appendix tables are slightly different than those presented elsewhere in the report. This is because geographic data is included only in the household portion of ACS; we therefore used household weights. This has the effect of making employment totals slightly lower than those provided in the rest of the report, which use person weights.

The remainder of this Appendix provides the top five tables for each group: All AI Occupations (Table A1), Technical Team 1 Occupations (Table A2), Technical Team 2 Occupations (Table A3), Product Team Occupations (Table A4), and Commercial Team Occupations (Table A5).

Table A1: AI Workforce Top Five, 2019.

County	State	Total Employment	Share of Group Employment	Share of County Employment
Share of Total County Employment				
Loudoun County	VA	60,610	0.4%	28.4%
City of Falls Church	VA	1,830	*	27.8%
Santa Clara County	CA	258,150	1.8%	27.0%
Arlington County	VA	40,100	0.3%	26.5%
San Francisco County	CA	116,070	0.8%	23.4%
Total		476,760	3.4%	
Share of Total Group Employment				
Los Angeles County	CA	383,130	2.7%	8.1%
King County	WA	275,070	1.9%	22.3%
Cook County	IL	260,610	1.8%	10.6%
Santa Clara County	CA	258,150	1.8%	27.0%
Maricopa County	AZ	213,640	1.5%	10.5%
Total		1,390,600	9.9%	

*Less than 0.1 percent.

Source: American Community Survey 2019, U.S. Census Bureau, CSET.

Table A2: Technical Team 1 Occupations Top Five, 2019.

County	State	Total Employment	Share of Group Employment	Share of County Employment
Share of Total County Employment				
Loudoun County	VA	33,510	0.7%	15.7%
City of Falls Church	VA	1,010	*	15.4%
Santa Clara County	CA	136,780	2.8%	14.3%
Fairfax County	VA	73,450	1.5%	12.4%
Arlington County	VA	18,070	0.4%	11.9%
Total		262,820	5.3%	
Share of Total Group Employment				
King County	WA	145,030	3.0%	11.7%
Santa Clara County	CA	136,780	2.8%	14.3%
Los Angeles County	CA	110,390	2.2%	2.3%
Cook County	IL	95,930	2.0%	3.9%
Alameda County	CA	80,460	1.6%	9.9%
Total		568,590	11.6%	

*Less than 0.1 percent.

Source: American Community Survey 2019, U.S. Census Bureau, CSET.

Table A3: Technical Team 2 Occupations Top Five, 2019.

County	State	Total Employment	Share of Group Employment	Share of County Employment
Share of Total County Employment				
Rio Arriba County	NM	1,210	*	9.0%
Taos County	NM	990	*	9.0%
San Miguel County	NM	880	*	9.0%
Los Alamos County	NM	540	*	9.0%
Mora County	NM	150	*	9.0%
Total		3,770	0.1%	
Share of Total Group Employment				
Los Angeles County	CA	81,100	2.6%	1.7%
Santa Clara County	CA	74,890	2.4%	7.8%
San Diego County	CA	59,740	1.9%	3.9%
King County	WA	51,730	1.7%	4.2%
Middlesex County	MA	50,870	1.6%	6.0%
Total		318,330	10.2%	

*Less than 0.1 percent.

Source: American Community Survey 2019, U.S. Census Bureau, CSET.

Table A4: Product Team Occupations Top Five, 2019.

County	State	Total Employment	Share of Group Employment	Share of County Employment
Share of Total County Employment				
District of Columbia	DC	24,950	0.6%	7.3%
Arlington County	VA	10,570	0.3%	7.0%
City of Alexandria	VA	6,280	0.2%	6.7%
City of Falls Church	VA	410	*	6.3%
Yuma County	AZ	4,090	0.1%	5.9%
Total		46,300	1.1%	
Share of Total Group Employment				
Los Angeles County	CA	123,520	3.0%	2.6%
Cook County	IL	74,870	1.8%	3.1%
Maricopa County	AZ	61,210	1.5%	3.0%
Harris County	TX	53,820	1.3%	2.5%
King County	WA	49,920	1.2%	4.0%
Total		363,340	8.8%	

*Less than 0.1 percent.

Source: American Community Survey 2019, U.S. Census Bureau, CSET.

Table A5: Commercial Team Occupations Top Five, 2019.

County	State	Total Employment	Share of Group Employment	Share of County Employment
Share of Total County Employment				
San Francisco County	CA	21,690	1.1%	4.4%
Brown County	WI	5,440	0.3%	3.9%
Limestone County	AL	1,620	0.1%	3.8%
Coweta County	GA	2,430	0.1%	3.7%
Loudoun County	VA	7,320	0.4%	3.4%
Total		38,500	2.0%	
Share of Total Group Employment				
Los Angeles County	CA	68,120	3.5%	1.4%
Cook County	IL	39,500	2.0%	1.6%
King County	WA	28,390	1.4%	2.3%
Orange County	CA	27,480	1.4%	1.8%
Harris County	TX	26,990	1.4%	1.2%
Total		190,480	9.7%	

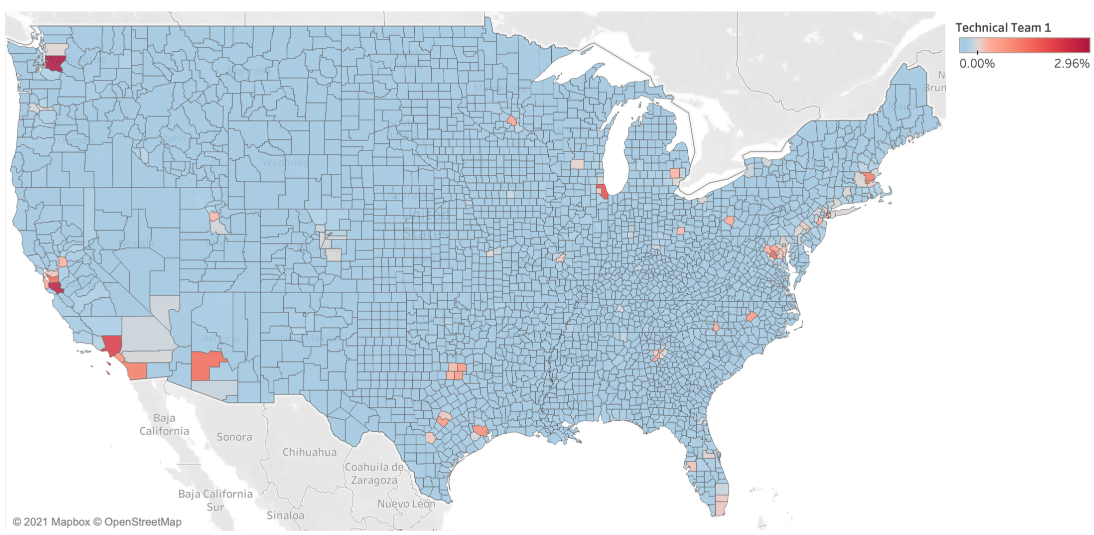
Source: American Community Survey 2019, U.S. Census Bureau, CSET.

Appendix B: Supplemental Employment Distribution Geographic Maps

This appendix provides supplemental maps of the geographic distribution for our AI occupational categories. We present geographic distribution in two ways: (1) the share of AI workers by U.S. county as a share of total county employment, and (2) share of employment in that group by county. Each map shows color gradation between blue and red, with blue having the smallest shares and red the largest.

Figures B1 and B2 provide the share of group employment by county for Technical Team 1 occupations and Product Team occupations, respectively. (Figures 4 and 5 in this report provide county employment share maps.) Figures B3 and B4 map Technical Team 2 occupations in both ways noted above. Figures B5 and B6 do the same for Commercial Team occupations.

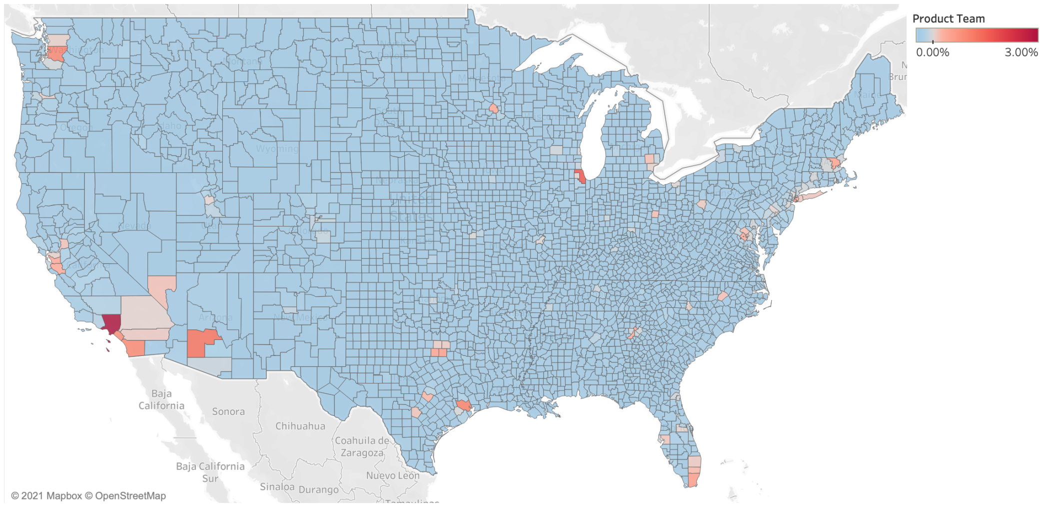
Figure B1: Share of Technical Team 1 Employment by County.
Employment in Tech 1 occupations as a share of total Tech 1 employment.



Source: American Community Survey 2019, CSET.

Figure B2: Share of Product Team Employment by County.

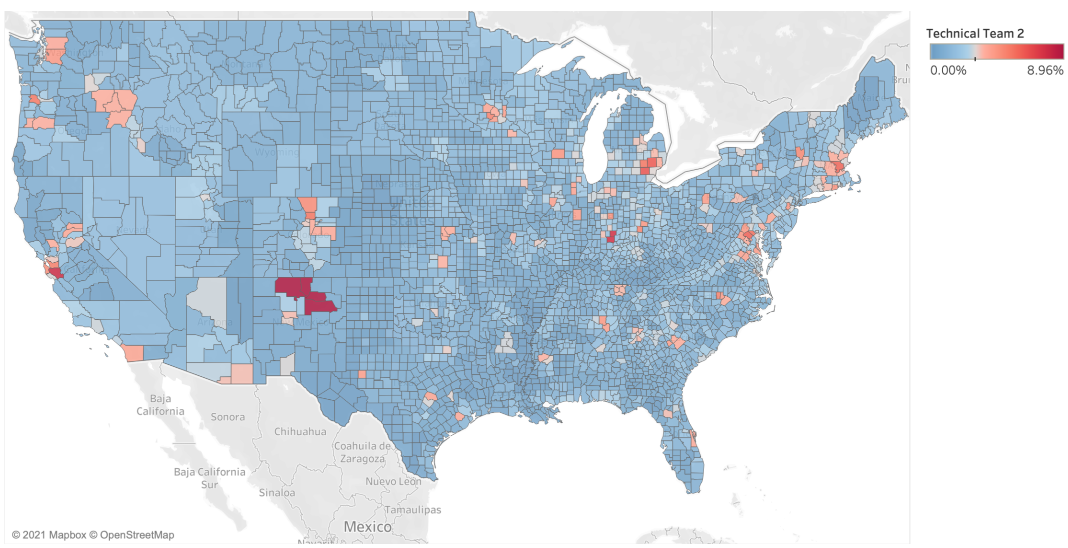
Employment in Product Team occupations as a share of total Product Team employment.



Source: American Community Survey 2019, CSET.

Figure B3: Technical Team 2 Occupations by County Share.

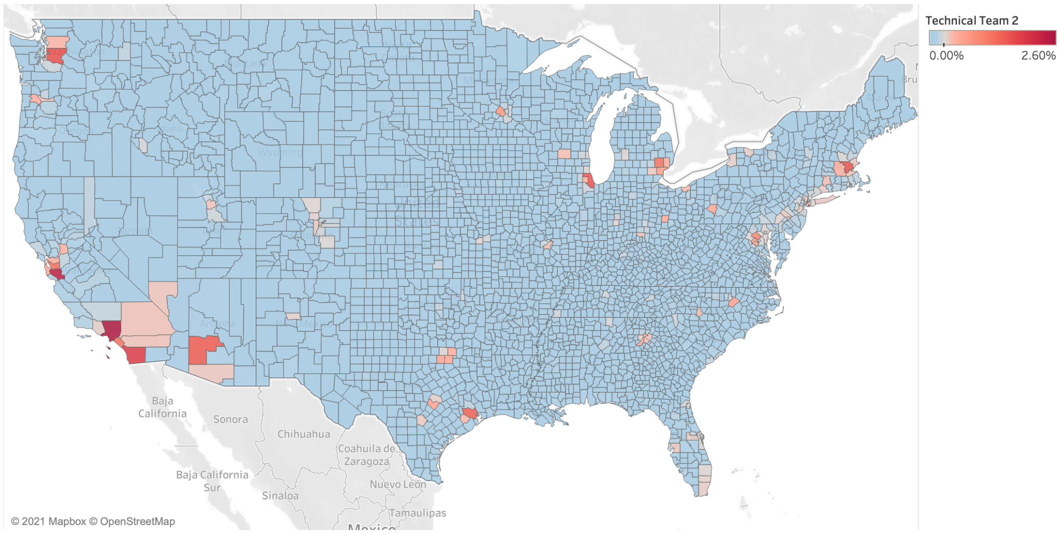
Share of county employment in Technical Team 2 occupations.



Source: American Community Survey 2019, CSET.

Figure B4: Share of Technical Team 2 Employment by County.

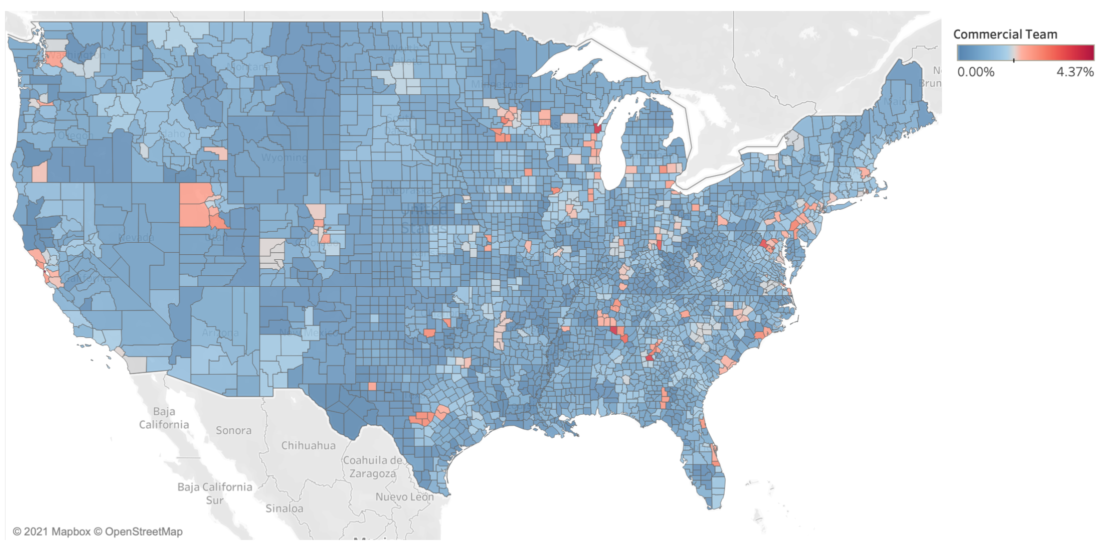
Employment in Tech 2 occupations as a share of total Tech 2 employment.



Source: American Community Survey 2019, CSET.

Figure B5: Commercial Team Occupations by County Share.

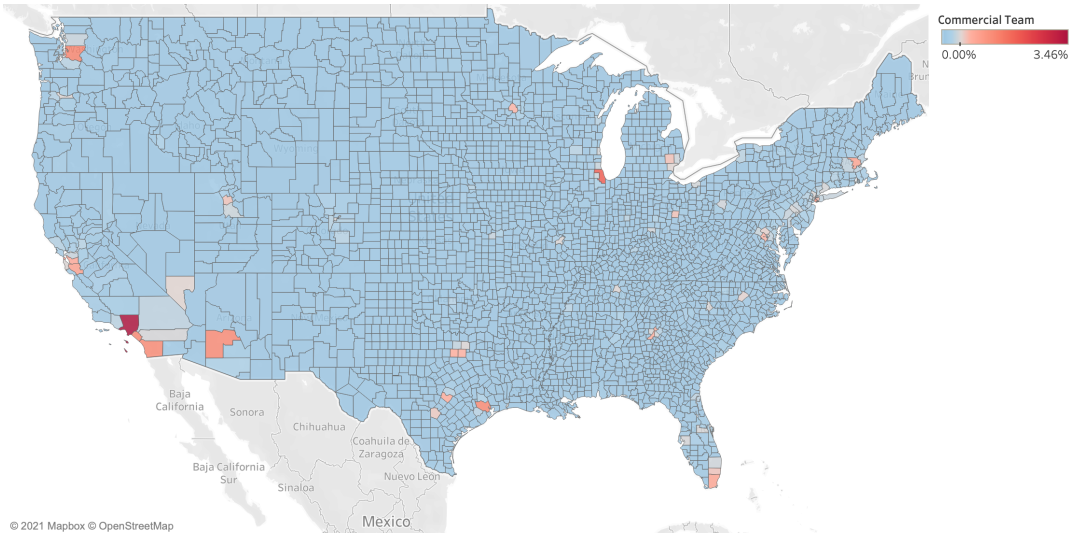
Share of county employment in Commercial Team occupations.



Source: American Community Survey 2019, CSET.

Figure B6: Share of Commercial Team Employment by County.

Employment in Commercial Team occupations as a share of total Commercial Team employment.



Source: American Community Survey 2019, CSET.

Appendix C: Top Employers

Table C1 shows the top employers listed for each of the selected occupations.

Table C1: Tech Companies are Not the Only Top Employers.

Rank	Computer Research Scientists	Software Engineers	Mathematicians, Statisticians, Data Scientists	Project Management Specialists	User Experience Designers*
1	Apple	Google	Microsoft	Microsoft	Self-Employed
2	Adobe	Microsoft	Facebook	Amazon	Google
3	Georgia Tech Research Institute	Amazon	IBM	AT&T	Facebook
4	Ford Motor Company	IBM	Wells Fargo	Google	Amazon
5	Southwest Research Institute	Facebook	U.S. Census Bureau	IBM	Apple
6	Facebook	Amazon Web Services (AWS)	Amazon	United States Air Force	Conscience VC
7	United States Air Force	Apple	Apple	Boeing	Microsoft
8	Intel Corporation	Lockheed Martin	Google	Hewlett Packard Enterprise	IBM
9	Lawrence Livermore National Laboratory	Oracle	Booz Allen Hamilton	Wells Fargo	AT&T
10	United States Department of Defense	Northrop Grumman	UnitedHealth Group	Cognizant	General Motors

*Defined as graphic designers plus web and digital interface designers. Several entries in the top 10 were related to self-employed and freelance; we removed duplication for this list.

Source: LinkedIn Insights, CSET (Data accessed December 2020).

Across the key AI occupations of interest, technology companies dominate the list of top employers. Amazon, Google, IBM, and Microsoft are top employers for all occupations except computer and information research scientists, and Apple and Facebook are top employers for all occupations except project management specialists. Other technology companies, such as Adobe, Oracle, Intel, and Hewlett-Packard, also make the list of top employers for select occupations. Non-technology companies Wells Fargo and AT&T also each appear as top employers in two occupations.

However, the U.S. government and defense industrial base are also among the top employers for key AI occupations. Expanding the list of top employers from five to 10, we find the federal government and DIB are top employers of computer and information research scientists; software developers; mathematicians, statisticians and data scientists; and project management specialists. It is possible many user experience designers also work for the federal government, but in a freelance or contract capacity.

For example, the U.S. Air Force and Department of Defense appear as computer research and information scientists' seventh and tenth top employers, respectively. Lawrence Livermore National Laboratory, a federally-funded research lab, is the ninth top employer. The U.S. Census Bureau is the fifth largest employer of data scientists, mathematicians, and statisticians—outranking Amazon, Apple, and even Google. Project management specialists are more diverse in terms of geography and industry, and this is also reflected in employers. Still, the U.S. Air Force falls sixth on the list of top employers.

The strong showing of DIB employers on the list provides another indicator of the U.S. government's ability to reach workers in key AI occupations. For example, even though the U.S. government is not listed as a top employer of software developers, two of their top contractors are—Lockheed Martin and Northrop Grumman. In addition to Lockheed Martin, ranked first among the top ten federal contractors, and Northrop Grumman, ranked fourth, Boeing, which ranks second, is also listed as a top employer of project management specialists.

It is worth noting that computer and information research scientists, perhaps the most critical in the advancement of AI, has the largest variety of top employers. While the other key AI occupations are dominated by “big tech”, computer and information research scientists’ top employers include other technology players Adobe, Ford Motors, Intel, and several research labs. In addition to Lawrence Livermore National Laboratory, two independent research labs, Georgia Tech Research Institute and Southwest Research Institute, are also in the top ten.

Still, the dominance of technology companies on the list suggests that the U.S. government faces strong competition from the private sector in all five of the AI occupations listed in table C1. This implies that the U.S. government should continue to prioritize its own competitive position as an employer to attract, recruit, and retain key AI workers. Moreover, the presence of government as a top employer in some cases shows AI talent is not completely out of reach to government employers as to have little to no competitive standing. Not only does the U.S. government appear multiple times on the list of top ten employers, they also have close ties to many of the private companies listed above.

Authors

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Endnotes

[1] Diana Gehlhaus and Santiago Mutis, "The U.S. AI Workforce: Understanding the Supply of AI Talent" (Center for Security and Emerging Technology, January 2021), https://cset.georgetown.edu/wp-content/uploads/US-AI-Workforce_Brief-2.pdf.

[2] We choose this period because AI development and deployment advanced considerably in just the last five years, along with movement of technical talent into these occupations (e.g., growing and cultivating talent pipelines). We use the one-year files over five-year average files for more timely analysis.

[3] For each spotlight occupation, we created a list of job titles to search and aggregate results on for analysis. The results aggregated every worker in the United States with a LinkedIn profile with one of these job titles as of the date accessed. We started with the occupation name and used LinkedIn's automated search suggestions for additional titles. We also consulted a list of job titles by occupation provided by the U.S. Census Bureau to ensure we were including as many related titles as possible.

[4] Moreover, job titles may not be unique to one occupation. The U.S. Census Bureau classifies people into occupations based on their reported job titles and detailed job tasks, so that the same job title could be assigned to different occupations.

[5] In the United States, there are more than 174 million LinkedIn users. This is greater than total U.S. employment because nonworkers such as students and retirees have accounts, and people may have multiple accounts. See https://news.linkedin.com/about-us#Statistics.

[6] Gehlhaus and Mutis, "The U.S. AI Workforce."

[7] In fact, it is likely that few jobs are 'strictly AI' in terms of products and programs workers may be involved in. That means counting jobs that are 100 percent focused on AI development would be undercounting the true AI workforce.

[8] We note here there are a range of typologies provided in the literature, and this is the author's interpretation of the nature of workforce shortages. For one example of the literature discussion on shortages, see Michael S. Teitelbaum, *Falling Behind?: Boom, Bust, and the Global Race for Scientific Talent* (Princeton, NJ: Princeton University Press, 2014), https://www.jstor.org/stable/j.ctt5hhq5c.

[9] For example, a rapid increase in demand happens unexpectedly due to a technological disruption.

[10] Although there can be other reasons, such as a sudden economic shock or labor market tightness that arises as an economy approaches full employment.

[11] Rebekah L. Fox and Kathleen Abrahamson, "A Critical Examination of the U.S. Nursing Shortage: Contributing Factors, Public Policy Implications," *Nursing Forum* 44, no. 4 (October/December 2009): 235-244, https://onlinelibrary.wiley.com/doi/epdf/10.1111/j.1744-6198.2009.00149.x. Also see Anthony P. Carnevale et al., "Nursing: Supply and Demand Through 2020" (Georgetown University Center on Education and the Workforce, 2015), https://cew.georgetown.edu/cew-reports/nursingprojections.

[12] Tina Huang and Zachary Arnold, "Immigration Policy and the Global Competition for AI Talent" (Center for Security and Emerging Technology, June 2020), https://cset.georgetown.edu/research/immigration-policy-and-the-global-competition-for-ai-talent/.

[13] Ashley Gross and John Marcus, "High-Paying Trade Jobs Sit Empty, While High School Grads Line Up For University," *National Public Radio* (*NPR*), April 25, 2018, https://www.npr.org/sections/ed/2018/04/25/605092520/high-paying-trade-jobs-sit-empty-while-high-school-grads-line-up-for-university.

[14] We do not get into the merits of such funneling here. However, with the resurgence of career and technical education in U.S. high schools this may be starting to change.

[15] Note not being in shortage is not the same as having a surplus.

[16] For example, recruiting "high quality" STEM teachers in certain school districts.

[17] There are also quality differences across workers within an occupation, which can be important in fields such as AI, but we do not get into that here.

[18] Yvonne D. Jones, "Human Capital: Improving Federal Recruiting and Hiring Efforts," Testimony to the Subcommittee on Regulatory Affairs and Federal Management, Committee on Homeland Security and Governmental Affairs, July 30, 2019, https://www.gao.gov/assets/710/700657.pdf.

[19] Market rates being wages and compensation. This is assuming these rates are stable and have not experienced large increases. Large increases in market rates are one indicator of a talent shortage.

[20] In addition to a branding challenge, many government agencies are competing against each other for the same talent, even within the same agency or department. The maze of entry points for service in the DOD, for example, could confuse or overwhelm prospective applicants. The time it takes to obtain a security clearance and onboard is another, as is duty station location for some military installations.

[21] Remco Zwetsloot, "Strengthening the U.S. AI Workforce" (Center for Security and Emerging Technology, September 2019), https://cset.georgetown.edu/research/strengthening-the-u-s-ai-workforce/.

[22] Sue Richardson, "What is a skills shortage?" (National Center for Vocational Educational Research, February 2007), https://files.eric.ed.gov/fulltext/ED495918.pdf.

[23] David Jarvis, "The AI talent shortage isn't over yet," Deloitte Insights, September 2020, https://www2.deloitte.com/us/en/insights/industry/technology/ai-talent-challenges-shortage.html. Total company shares computed using data provided in the corresponding detailed methodology.

[24] Joe McKendrick, "Artificial intelligence skills shortages re-emerge from hiatus," *ZDNet*, October 22, 2020, https://www.zdnet.com/article/artificial-intelligence-skills-shortages-re-emerge/.

[25] Element AI, "2020 AI Global Talent Report," accessed January 10, 2021, https://jfgagne.ai/global-ai-talent-report-2020/.

[26] If there is no evidence of a skills shortage, but an organization or geographic area is experiencing recruiting challenges, it is more likely a local talent shortage.

[27] Other countries have independent panels of economists that assess shortages for the purpose of immigration priority (which people to exempt from labor assessment requirements etc.). For example, see: https://www.gov.uk/government/publications/full-review-of-the-shortage-occupation-list-may-2019.

[28] Carolyn M. Veneri, "Can occupational labor shortages be identified using available data?," *Monthly Labor Review*, U.S. Bureau of Labor Statistics, March 1999, https://www.bls.gov/opub/mlr/1999/03/art2full.pdf.

[29] "AI Across the World: Top 10 Cities in AI 2020," *Re-Work Blog*, accessed January 10, 2021, https://blog.re-work.co/top-10-cities-in-ai-2020/.

[30] For these cities and for the rest of the United States that is not in a hub. See Mark Muro and Robert Maxim, "Big tech's role in regional inequality," Brookings, October 9, 2018, https://www.brookings.edu/blog/the-avenue/2018/10/09/big-techs-role-in-regional-inequality/.

[31] Certainly, the rise of remote work due to the COVID-19 pandemic could change the need for clustering. There is already some evidence that technical talent is moving out of these urban areas.

[32] We chose this measurement because it provides a better assessment of how concentrated these workers are. Here we can assess whether the share of AI workers in each county is large or small; for example, knowing a large share of AI workers are in Seattle by itself is not as meaningful as knowing it is a large share of total employment in Seattle. This allows for more meaningful and direct comparisons across counties and states.

[33] We include only the continental United States in our maps as there was little U.S.-based AI employment outside of this region.

[34] In terms of where these workers reside.

[35] Loudoun County, VA, is an area with many federal government contractors. However, this and other surrounding counties constitute the suburbs of Washington, D.C. where many of these workers working within the Washington, D.C. metropolitan area may reside.

[36] William R. Kerr and Frédéric Robert-Nicoud, "Tech Clusters," National Bureau of Economic Research, Working Paper 27421, June 2020.

[37] Yuma, AZ, being a low-density county with multiple military installations housing functions known to require Product Team relevant KSAs.

[38] Of course, with the increasing prevalence of remote work, location may be less relevant in attracting and recruiting AI-relevant talent.

[39] For analysis using the American Community Survey (ACS) we consider employed only, with the exception of unemployment rates. There we consider the entire AI and U.S. workforce, consisting of employed and unemployed workers.

[40] We note classification differences from 2015 to 2019 are adjusted using a proportionality approach; the share of an occupation relative to its aggregate in 2019 was applied to the aggregate in 2015 if the occupation was not available. This was done for geoscientists (Tech 2), web developers (Tech 2), web and

digital interface designers (Product Team), graphic designers (Product Team), and marketing managers (Commercial Team).

[41] We note this is higher than the official unemployment rate from the U.S. Bureau of Labor Statistics for 2019. Similarly, our U.S. employment totals are slightly higher than published BLS civilian labor force totals. This is likely for several reasons, including differences in survey frame and weighting (BLS totals are derived from the Current Population Survey), seasonal adjustments made by BLS, and population composition. For example, our analysis includes active duty military.

[42] We make this comparison due to the high rate of AI workers with at least a bachelor's degree relative to the total U.S. workforce: 67.6 percent versus 35.7 percent. These estimates are provided in Table 3.

[43] In economic theory, the "Beveridge Curve" maps job vacancies as a share of the labor force to unemployment, noting a decline in unemployment rates when the number of postings increase (exponential decay). It is actively used in the economics literature regarding assessments on the state of the labor market. See for example: Peter A. Diamond and Ayşegül Şahin, "Disaggregating the Matching Function," National Bureau of Economic Research, Working Paper 22965, December 2016, https://www.nber.org/system/files/working_papers/w22965/w22965.pdf. Still, it is an imperfect indicator: this relationship quickly fell apart in 2020, and notably shifted outward after the Great Recession from the decline in labor force participation. For more on the importance of the Beveridge Curve in assessing the labor market, see Thomas A. Lubik and Karl Rhodes, "Putting the Beveridge Curve Back to Work," (Federal Reserve Bank of Richmond, September 2014), https://www.richmondfed.org/-/media/richmondfedorg/publications/research/economic_brief/2014/pdf/eb_14-09.pdf.

[44] Official data on job vacancies comes from the U.S. Bureau of Labor Statistics' Job Openings and Labor Turnover Survey.

[45] Available documentation from Burning Glass notes that while it includes all types of job postings regardless of hiring intent, it does execute algorithms to remove duplicate postings across job posting sites.

[46] Raymond Perrault et al., "Artificial Intelligence Index: 2019 Annual Report" (Stanford University Human-Centered Artificial Intelligence Institute, December 2019), https://hai.stanford.edu/sites/default/files/ai_index_2019_report.pdf.

[47] It would be incorrect, for example, to assess that because the U.S. workforce grew at one-sixth the rate of all U.S. job postings from 2015 to 2019 that there was a shortage of U.S. workers.

[48] Interestingly many employers of AI occupations have publicly noted retention challenges for this talent. That could be a reason for postings to be growing faster for AI jobs, yet, they are not.

[49] User experience (UX) designer is not a formal occupation in the Standard Occupational Classification system. Here we define UX designers as graphic designers plus web and digital interface designers, which are SOC occupations.

[50] We adjusted nominal wages in two ways, which yielded identical results. First, we applied the Consumer Price Index adjustment factor provided by IPUMS (an administrator of ACS microdata) which puts wages in constant 1999 dollars. Second, we estimated the Personal Consumption Expenditure price deflator using data on real disposable income per capita (in 2012 chain weighted dollars) from the Bureau of Economic Analysis's National Income and Product Accounts, indexed the deflator to 2019, and applied the resulting factor to nominal wages.

[51] Here we use tenure as an indicator for job turnover, or churn.

[52] Of course, average wages are not a perfect measure for labor shortages. See James Bessen, "Employers Aren't Just Whining – the "Skills Gap" Is Real," *Harvard Business Review*, August 25, 2014, https://hbr.org/2014/08/employers-arent-just-whining-the-skills-gap-is-real.

[53] Zackary Bennett, "Why Colleges Are Offering Data Science Programs," *US News & World Report*, September 18, 2020, https://www.usnews.com/education/best-colleges/articles/why-more-colleges-are-offering-data-science-programs.

[54] We have also conducted interviews with employers of AI workers for the next paper in this series. While not a random or generalizable sample, these interviews also validated that hires for technical occupations must at least have a four-year degree.

[55] Mapping fields of study to occupations is known to be imprecise and difficult, since most fields of study can flow into employment in many occupations. Only a few more technical occupations have a clear link to specific undergraduate majors, and even then some people in these occupations have non-technical undergraduate degrees. They move into these occupations after graduation with additional training and experience. Moreover, even for those with technical degrees, for example in STEM fields, many do not ultimately pursue careers in

technical occupations. See "Where Do College Graduates Work?" from the U.S. Census Bureau (https://www.census.gov/dataviz/visualizations/stem/stem-html/) and "Revisiting the STEM Workforce" from the National Science Foundation (https://www.nsf.gov/pubs/2015/nsb201510/nsb201510.pdf).

[56] With the exception of military technology, which comprised just 0.03 percent of all undergraduate degrees in 2018. Mathematics and statistics was the next fastest growing degree over 2015 to 2018, with the number of conferred degrees increasing by about 16 percent, or 3,400 graduates.

[57] See "2020 Digest of Education Statistics," U.S. Department of Education, https://nces.ed.gov/programs/digest/d19/tables/dt19_322.10.asp?current=yes. The total number of graduates increased by about 86,000 over 2015 to 2018; we do not say half of the increase was in these two fields as some majors saw declines.

[58] A large volume of survey research finds younger generations change jobs faster than older generations. For example, a 2019 Gallup survey found "21% of millennials say they've changed jobs within the past year, which is more than three times the number of non-millennials who report the same." See Amy Adkins, "Millennials: The Job-Hopping Generation," Gallup, https://www.gallup.com/workplace/231587/millennials-job-hopping-generation.aspx#:~:text=A%20recent%20Gallup%20report%20on,millennials%20who%20report%20the%20same.&text=For%20businesses%2C%20this%20suggests%20that,see%20a%20future%20with%20them.

[59] According to LinkedIn, technology sector (software) employees have the highest turnover rate of any industry. See Michael Booz, "These 3 Industries Have the Highest Talent Turnover Rates," *LinkedIn Talent Blog*, March 15, 2018, https://business.linkedin.com/talent-solutions/blog/trends-and-research/2018/the-3-industries-with-the-highest-turnover-rates.

[60] We have also conducted interviews with employers of AI workers for the next paper in this series. While not a random or generalizable sample, none of these interviews noted hiring difficulties for nontechnical AI occupations.

[61] For the latest BLS occupational employment projections data, see "Employment by detailed occupation," U.S. Bureau of Labor Statistics, https://www.bls.gov/emp/tables/emp-by-detailed-occupation.htm.