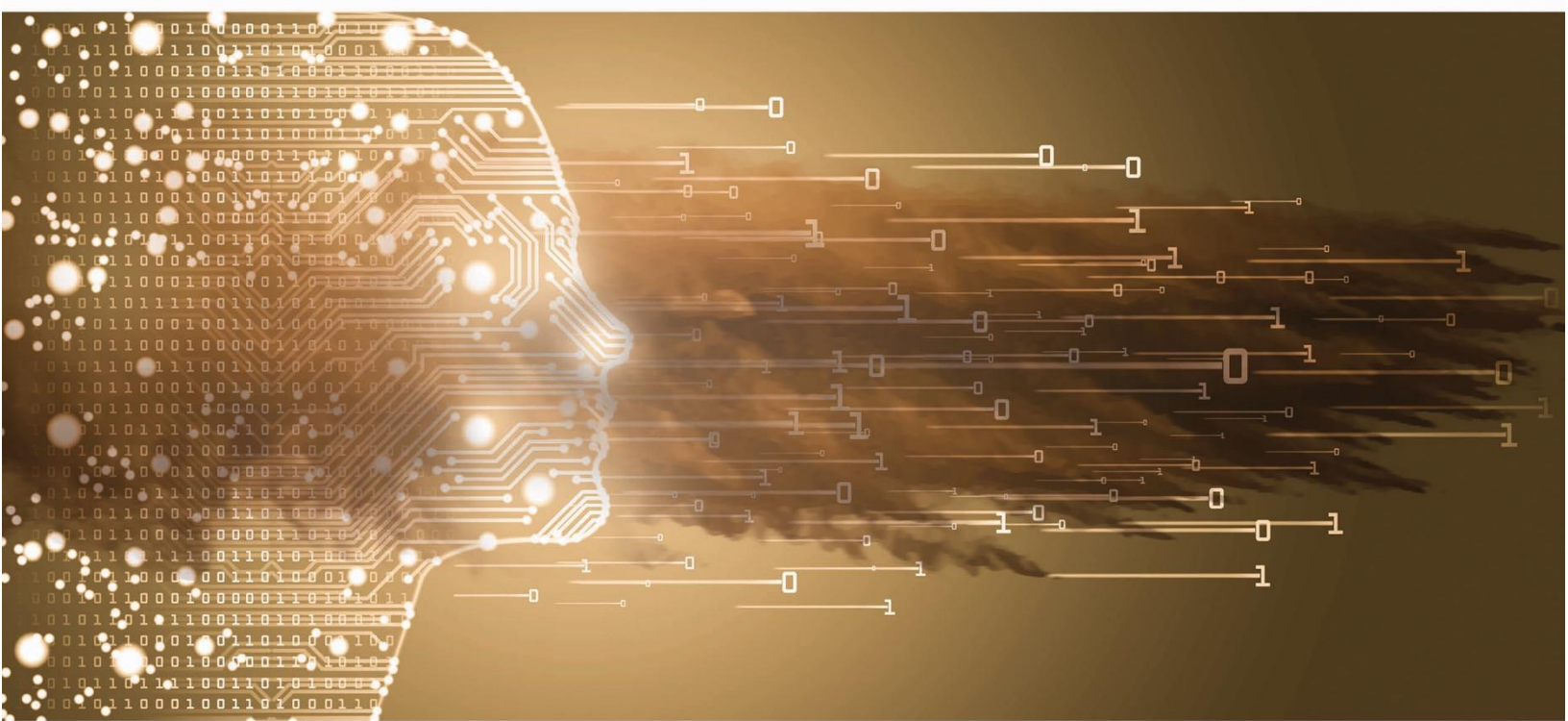




THE WIND SHIFTS BEFORE A SANDSTORM



Measuring the impact on artificial intelligence on the Inland Empire/Desert Region's labor market

CENTER OF EXCELLENCE FOR LABOR MARKET RESEARCH | SEPTEMBER 2026



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EXECUTIVE SUMMARY: WHEN THE WIND STARTS TO SHIFT

Artificial intelligence (AI) has reached the Inland Empire/Desert Region's workforce, but not in the places or at the pace the national conversation would suggest. This report measures what can be observed in terms of the exposure to AI and its impact on the regional labor market today using three instruments: traditional labor market information, which establishes what work exists and at what scale; online job postings, which register employer demand once a skill is explicit enough to name in a listing; and a measure built from observed AI usage at the task level, which records what is being done with the technology now rather than what history predicts. When an emerging technology is successfully used by a worker to augment or automate a specific aspect of their work, that occupational task becomes "exposed" to AI. Every occupation has a set number of occupational tasks, so the more of its tasks are exposed to AI the higher its overall exposure rate will be.

15.1%

of regional work is exposed to AI,
against 18.3% statewide

0.5%

of regional job postings
name an AI skill

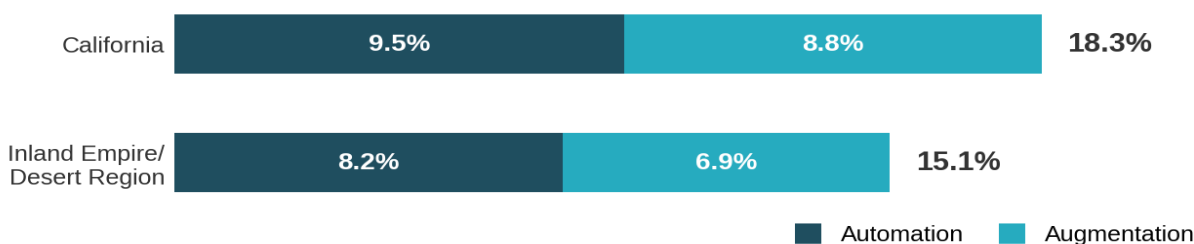
71.7%

of net job growth is in sectors
sending little AI signal

How exposed is the region?

- **The region is less exposed to the effects of AI than California overall.** That gap reflects what the region's residents do for a living rather than any regional difference in how a given job is performed.
- **Exposure is not displacement.** Nearly every occupation involves tasks that AI is observed performing, as well as tasks it is not. Consequently, the more likely near-term outcome is that AI will redistribute work within roles rather than eliminating roles outright.
- **Lower exposure is not lower risk.** Regional residents are less likely to hold a bachelor's degree (15.7% versus 22.6%) or a graduate degree (8.9% versus 14.5%). That attainment profile lowers measured exposure and also narrows access to the productivity gains AI offers more credentialed workers.

Exhibit ES.1: AI exposure of task-weighted employment, Inland Empire/Desert Region and California, 2025

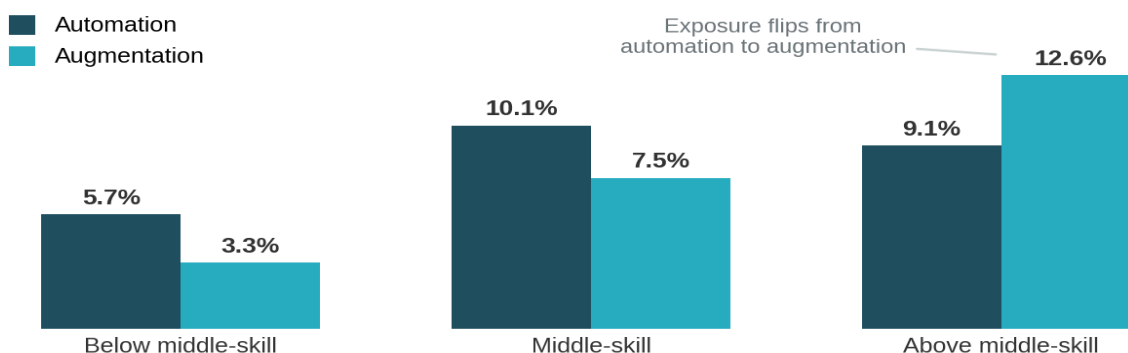


Source: COE analysis of Lightcast data (2026.3) and Anthropic Economic Index data (2026)

Where does that exposure concentrate?

- Exposure follows the nature of the work rather than the employer. Across major occupational groups, the most exposed group carries roughly sixteen times the automation exposure of the least exposed, from 1.7% in Construction and Extraction to 27.6% in Computer and Mathematical occupations. Across industry sectors, that high-to-low gap narrows to roughly three times, from 5.4% in Accommodation and Food Services to 15.7% in Management of Companies and Enterprises.
- Automation exposure peaks at the middle-skill level, the tier that accounts for 42.7% of regional employment and that community colleges serve most directly. Above middle-skill work carries nearly as much automation exposure (9.1% versus 10.1%), but the balance inverts: augmentation (12.6%) exceeds automation there, meaning AI is observed supporting that work rather than performing it.
- Office and Administrative Support occupations are the region's clearest single concentration of exposed work: the second-highest automation exposure of any occupational group at 23.8% and the second-largest workforce at 180,720 workers. However, employer demand for AI skills is below the regional average.

Exhibit ES.2: AI exposure by occupational skill level, Inland Empire/Desert Region, 2025



Source: COE analysis of Lightcast data (2026.3) and Anthropic Economic Index data (2026)

What are employers actually asking for?

- Employer demand for AI skills is verified, concentrated, and small. Five industry sectors accounted for roughly 69% of the region's AI postings.
- When regional employers post jobs that include AI, they want workers to operate the technology rather than to build it. AI Operator roles account for 55% of AI postings, AI Builder roles for 29%, and AI Assisted Worker roles for 16%, amounting to roughly 400 Builder openings a year across all regional industries.
- Job posting data measures hiring signals, not adoption; they set a floor beneath the real figure. They exclude every employer that adopted AI by training existing staff, that received AI features through a vendor's software update, or that described the requirement in language a skill taxonomy does not recognize.

Exhibit ES.3: Regional job postings seeking AI skills, July 2025 through June 2026

All regional job postings



Carry an AI skill tag

3,395 (1.19%)

Verified as genuinely seeking AI skills

1,425 (0.50%)

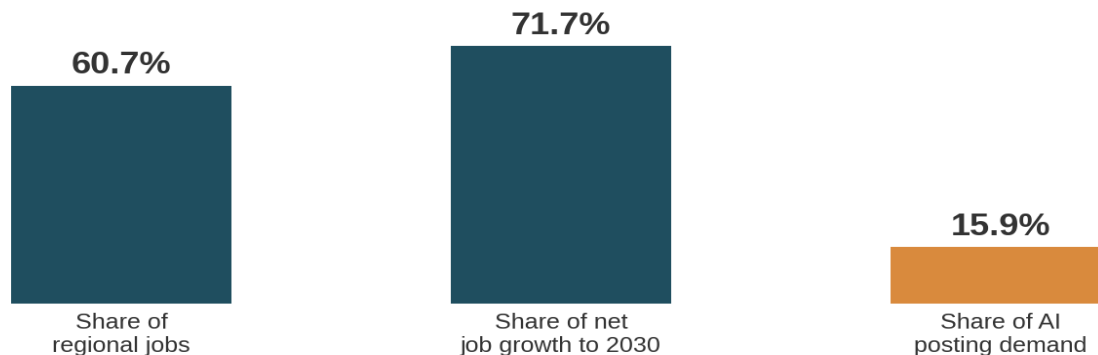
Source: COE analysis of Lightcast data (2026.3) and Anthropic Economic Index data (2026)

Where do capability and demand diverge?

- Each industry sector is plotted against two regional averages: the share of its occupational tasks AI can perform, and the share of its job postings seeking AI skills. Four categories result: Insulated (below average on both), Latent (above-average exposure, below-average demand), Applied (below-average exposure, above-average demand), and Adopting (above average on both).
- Regarding the relationship between exposure and demand, sectors in the Latent and Insulated quadrants hold most of the region's jobs and nearly all of its projected growth, while accounting for a small fraction of its AI posting demand. Most of the region's workforce sits where employers are not yet signaling a demand for AI skills.
- Health Care and Social Assistance is the widest gap: 15.8% of regional employment, 37% of projected net job growth, above-average exposure at 16.2%, and 0.2% of postings seeking AI skills. It holds the largest share of the region's AI-exposed employment of any sector, at 17.0%.
- Transportation and Warehousing is the region's defining specialization, with an employment concentration of 2.46, yet it registers the weakest signal on both exposure and AI posting demand. That result is an artifact of scope, not evidence of low risk: warehouse robotics,

automated material handling, and autonomous vehicles are the technologies most likely to reshape this sector, and none of them appear in the usage data behind these estimates.

Exhibit ES.4: Latent and Insulated quadrant sectors, share of employment, growth, and AI posting demand



Source: COE analysis of Lightcast data (2026.3) and Anthropic Economic Index data (2026)

What does this ask of the region's institutions?

- The most exposed work inside every sector examined is the coordination layer, records, billing, coding, scheduling, dispatch, documentation, and drafting, rather than the sector's clinical or technical core. These programs commonly sit in business and office administration program areas rather than in the department that serves the sector, so program review organized by sector may not surface them.
- The region's students and those under 25 are already being impacted by this technology's effects. The region has proportionally more residents age 24 and under than California overall, at 33.1% versus 30.2%, and effects observed nationally have concentrated among workers aged 22 to 25 through slowed hiring rather than displacement of incumbents. The near-term risk is less that graduates lose jobs than that the entry-level positions they train for are filled less often.

The response is within reach of existing programs.

What separates workers who benefit from AI from those displaced by it is domain knowledge deep enough to direct the tool, evaluate its output, and recognize when it is wrong. That is an extension of what programs already develop within a discipline rather than a separate technical curriculum.

Section 2.9 consolidates the regional findings supporting this summary. Section 3.2 presents findings for each of the four sectors examined in detail, and Section 3.3 presents the patterns visible across all four.

Other Summary Materials

- **View an online presentation.** The IE/D COE Team has created an Executive Summary presentation that is available online and makes sharing the findings with your colleagues as easy as forwarding the link. Click [here](#) to view.
- **View a short video.** There is also a short video available online that highlights the key findings in an engaging, seven-minute summary of the report's main points. This has also been made to be easily shared with your contacts in the IE/D region. Click [here](#) to view.



SECTION 1: HOW DESERT WINDS BECOME A DUST STORM

1.1: What's Stirring Up the Dust

Dust storms are nothing new in the Inland Empire Desert Region (IE/D), a region spanning millions of acres of desert terrain alongside a diverse set of industries and subregional economies. Most storms pass with little lasting effect. Occasionally, one reshapes the ground it crosses. Artificial intelligence has the potential to be the second kind, and the winds have already reached the region's workforce. This report examines what we can observe about that change in the IE/D labor market today, identifies where the region's workers are most exposed, and offers findings for community college and K-12 practitioners preparing students for the economy on the other side.

Artificial intelligence (AI) refers to computer systems capable of performing tasks that typically require human cognition, such as learning from data, recognizing patterns, making predictions, and generating content, with varying degrees of autonomy.¹ In the context of this report, AI encompasses a spectrum of technologies and disciplines, including machine learning, natural language processing, robotics, and generative AI, which are increasingly embedded in workplace tools and processes across occupations and industries.² Refer to subsection 2.1 for a detailed introduction to these disciplines and how they have been used in our research through a skills-based taxonomy. This research focuses on the labor market implications of AI, highlighting adoption signals through traditional labor market information and job posting data, as well as an innovative framework that centers on both explicit task automation (substitution) and tools that enhance worker productivity and decision-making (augmentation).

Artificial intelligence is developing faster than conventional labor market data used to measure the effect on work. This report draws on three instruments, each answering a different question and each representing a different relationship to the present moment. Traditional labor market information, which includes employment counts and projections by industry and occupation, establishes what work exists in the region and at what scale, through projection extend historical staffing patterns forward and do not anticipate a technology without precedent in those patterns. Job posting data registers employer demand, but only once a skill becomes explicit and operationalized enough for an employer to name it in a listing, so this may be a conservative and lagging signal. The third, built from observed AI usage at the task level, was added for that reason, to measure what is being done with AI now rather than what employers have named or what history predicts.³ This difference in vantage point is one reason credible sources reach different conclusions about AI's workforce impact, and it is why this report separates what can be measured in the region today from what current evidence suggests may come.

¹ Stanford University Human-Centered Artificial Intelligence (HAI). Artificial Intelligence Index Report 2026. Retrieved from: https://hai.stanford.edu/assets/files/ai_index_report_2026.pdf

² Ibid.

³ Handa, K., Tamkin, A., McCain, M., Huang, S., Durmus, E., Heck, S., Mueller, J., Hong, J., Ritchie, S., Belonax, T., Troy, K. K., Amodei, D., Kaplan, J., Clark, J., & Ganguli, D. (2025). *Which economic tasks are performed with AI? Evidence from millions of Claude conversations*. Anthropic.

Vantage point is not the only reason conclusions differ. Researchers also approach the question from different perspectives, so their findings are not competing estimates of the same quantity, but answers to different questions about how AI affects work. Three approaches recur in the literature.

The first approach estimates impact from technical capability, asking which tasks large language models can perform at or above human level. This reasoning underlies headlines such as “Dario Amodei, CEO of Anthropic: AI Could Eliminate 50% of Entry-Level White-Collar Jobs”.⁴

The second approach comes from labor economics, holding that when technology completes a task more efficiently than a worker, organizations substitute technology for labor and displacement follows, while also recognizing that “the displacement effect of automation is offset by technologies that create new tasks,” producing augmented and entirely new roles. The World Economic Forum’s Future of Jobs Report 2025 quantifies both sides: 92 million roles displaced worldwide by 2030, and 170 million new roles created for workers who acquire the right skills by that same year.⁵

The third approach comes from observed usage, setting aside what AI might do in order to measure how it is actually being applied, task by task. This approach cannot forecast, but it is the only one of the three grounded in what is already occurring rather than what is technically possible or economically projected.⁶ This report draws on all three and relies on the third for its regional exposure estimates.

Occupations are bundles of tasks, each requiring its own mix of skills, and AI’s effect is better understood at the task level than at the occupation level. Some tasks can be completed by AI with little human involvement, such as generating a first-draft summary. Others can be meaningfully assisted but still require human judgment to reach a final outcome. Still, others depend on physical presence, relational trust, or situational awareness, and cannot be replicated by current AI. Because most occupations combine all three kinds of work, an occupation’s exposure is best expressed as the share of its tasks that can be automated or augmented, rather than as a binary judgment about whether the occupation survives.

A quantified measure of task-level exposure is not by itself sufficient to advise an education practitioner on modifying a course or program. The two things we hope practitioners most need to know, include how the work is changing, and what employers are asking for, are measured by different instruments, and those instruments do not always agree. A task can be exposed to automation or augmentation without any employer naming an AI skill in a job posting, and an employer can advertise an AI skill for work whose underlying tasks have barely changed. Where the two diverge, offers information about the change already factored into hiring and change arriving ahead of any market signal. This report treats those differences as findings rather than data to reconcile.

This report organizes its analysis around three intersecting lenses, each drawn from the instruments described earlier:

⁴ <https://www.axios.com/2025/05/28/ai-jobs-white-collar-unemployment-anthropic>

⁵ World Economic Forum. “Future of Jobs Report 2025.” World Economic Forum, January 2025.

⁶ Massenkoff, M., & McCrory, P. (2026, March 5). *Labor market impacts of AI: A new measure and early evidence*. Anthropic. <https://www.anthropic.com/research/labor-market-impacts>

- **Industry:** what work exists in the region, and at what scale, established through traditional labor market information.
- **Occupation:** what tasks that work comprises and how exposed those tasks are to AI.
- **Worker category:** whether the role builds AI systems, operates them as a core function, or uses AI as an optional productivity tool that may not be named in a job requirement. This third relationship is the one that employers have the least reason to state in a job posting and is the hardest to observe.

The region's exposure profile is distinctive because its industry and occupational composition is distinctive from other California regions. The IE/D is not a single economy, but a set of subregional economies with different industry concentrations, and skill requirements for the same occupational title may vary by industry and worker category. Because regional exposure is the weighted sum of these differences, task-level analysis is meaningful only when anchored in the region's actual labor force. This report provides that foundation by detailing the region's demographic and educational characteristics and its industry and occupational composition.

1.2: The Ground Beneath the Storm, A Regional Overview

The Inland Empire/Desert Region contained 4.74 million residents, or approximately 12.1% of the statewide population in 2025. The region's population is projected to grow by 2.3% through 2030, adding nearly 110,200 residents, more than all other metropolitan statistical areas (MSAs) in California. Regional growth contradicts the projected statewide population decline through 2030, which is expected to result in the loss of over 3,500 residents. The Inland Empire/Desert Region sits within Southern California, but its population characteristics and industry composition differ from the surrounding regions. Because AI exposure depends on what work exists in a region and who performs it, statewide or national estimates cannot capture the region's exposure profile. This subsection establishes that foundation in three parts: the region's population, including the age and educational characteristics of its workforce; the industries that determine what work exists in IE/D and at what scale; and the occupations that determine what tasks that work comprises. Each part identifies the characteristics most relevant to AI exposure. In section 2, we will present the exposure analysis based on this foundation.

The age of the Inland Empire/Desert region's population is important context for understanding how artificial intelligence may impact the region. Exhibit 1.2.1 shows the region's age distribution compared with California's overall population. Research indicates that artificial intelligence is most likely to replace routine tasks that are most exposed to automation.⁷

Research indicates that artificial intelligence's employment effects have so far concentrated among workers at the earliest stages of their careers in occupations whose current tasks large language models can most easily replicate.⁸ In a report titled "Canaries in the Coal Mine", Brynjolfsson and colleagues find a 6% to 16% decline in employment among workers aged 22 to 25 in the most exposed occupations, attributable primarily to slowed hiring rather than to displacement of workers already in those jobs. The mechanism matters for educators since the risk to the region's students is less that they will lose jobs, but that the entry-level positions they train

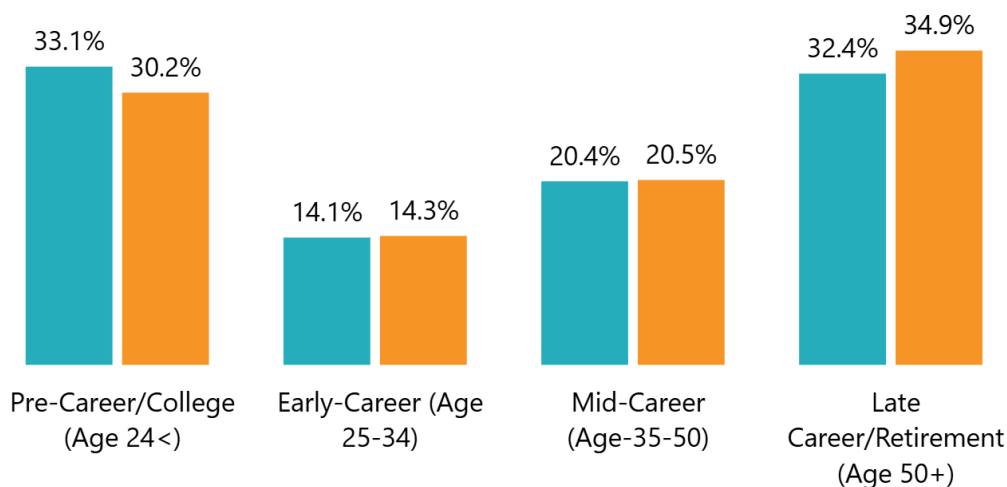
⁷ Brynjolfsson, Erik, et al. "Canaries in the Coal Mine: Generative AI and the Earnings and Employment of Early-Exposed Workers." Stanford Digital Economy Lab, August 2026.

⁸ Ibid.

for will be filled less often. A region with proportionality more residents approaching labor market entry therefore has proportionally more residents exposed to that effect.⁹

Exhibit 1.2.1: Age Distribution of the Population, IE/D vs. California, 2025

● Inland Empire/Desert Region ● California



Source: Lightcast 2026.3 – Demographic Overview

Approximately one-third (33.1%) of the regional population falls into the pre-career/college cohort (age 24 and under), compared to 30.2% statewide, suggesting the region has a somewhat larger share of residents entering the workforce at the career stage most associated with AI exposure.

The remaining cohorts closely follow the state's overall trend. Early-career residents (aged 25-34) constitute 14.1% of the region, compared to 14.3% statewide. Mid-career residents (aged 35-50) make up 20.4% of the region, while 20.5% of the state's workforce falls into this age group. This suggests that the region's AI exposure risk is not primarily concentrated in a significantly older or younger workforce, but rather in this relatively larger entry-level cohort.

The region's population age 50 and over is somewhat smaller than the state's, at 32.4% compared with 34.9%. Age appears to shape outcomes more than exposure itself: workers in the most exposed occupations tend to be older and more credentialed, yet Brynjolfsson and colleagues find that workers aged 30 and over in high-exposure roles saw employment rise 6% to 12% during the same period that employment for workers aged 22 to 25 in those same roles declined.¹⁰ Accumulated domain knowledge and institutional context appear to determine whether AI substitutes for a worker or amplifies one. This divergence is examined further in the COE's AI Practitioner analysis, which explores what distinguishes workers who benefit from AI adoption from those displaced by it.¹¹

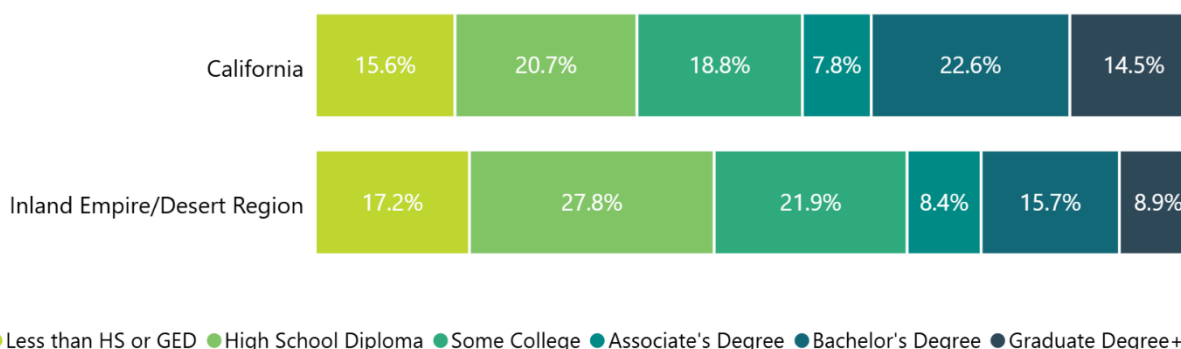
⁹ Ibid.

¹⁰ Ibid.

¹¹ AI Practitioner Analysis. (2026). Inland Empire/Desert Region Center of Excellence for Labor Market Research (COE). Retrieved from: <https://coeccc.net/inland-empire-desert/2026/07/ai-practitioner-analysis/>

The Inland Empire/Desert Region differs from California as a whole with regard to educational attainment. Exhibit 1.2.2 displays the educational attainment of the Inland Empire compared to California.

Exhibit 1.2.2: Educational attainment of the Inland Empire/Desert Region and California, 2025



Source: Lightcast 2026.3 – Educational Attainment Overview

Regional residents are less likely to hold a bachelor's degree (15.7% versus 22.6%) or a graduate degree (8.9% versus 14.5%), and more likely to have a high school diploma or less as their highest educational attainment (45.0%) as compared to state level education attainment (36.3%).

Anthropic's analysis of AI exposure indicates that workers with a bachelor's or graduate degree are most likely to face exposure to AI automation or augmentation, since these credentials tend to correspond with occupations concentrated in cognitive tasks such as research, analysis, writing, and coding that current AI systems handle well. Based on the above analysis, the region's workforce, with its lower educational attainment and occupations with different task compositions, may experience a slower pace of AI-driven disruption compared to the state as a whole. However, this educational gap could also hinder the region's ability to capitalize on the productivity gains and augmentation benefits that AI offers to more credentialed workers because employers could have less financial incentive to be "early adopters". Additionally, as stated above, entry-level workers in a younger age group may bear the brunt of any regional disruption, even if the region is less impacted than other regions of California whose workforce has a higher level of educational attainment.

The two characteristics of age and education pull against each other. By age, the region carries more residents at the career stage where AI's employment effects have been observed. By credential, it carries fewer workers in the occupations where task exposure may be concentrated. Demographic composition alone cannot settle whether the region is more or less exposed than California overall; it depends on what work the region's residents actually do. Section 2 takes up that question directly.

Industry employment information provides insight into the types of businesses that employ the region's residents. Exhibit 1.2.3 displays current and projected employment by industry sectors, along with each sector's employment concentration relative to the nation.

Exhibit 1.2.3: Current and projected employment by industry sector, 2025-2030

Industry Sector (NAICS)	2025 Jobs ▼	2025 - 2030 Change	2025 - 2030 % Change	2025 Employment Concentration
Government (90)	307,021	19,290	6%	1.09
Health Care and Social Assistance (62)	306,974	47,744	16%	1.15
Transportation and Warehousing (48)	208,887	17,155	8%	2.46
Retail Trade (44)	193,150	6,135	3%	1.08
Accommodation and Food Services (72)	169,397	12,286	7%	1.05
Construction (23)	141,254	4,317	3%	1.25
Administrative and Support and Waste Management and Remediation Services (56)	123,851	1,463	1%	1.11
Manufacturing (31)	99,966	-278	0%	0.70
Other Services (except Public Administration) (81)	93,808	6,388	7%	0.98
Wholesale Trade (42)	68,242	2,608	4%	1.00
Professional, Scientific, and Technical Services (54)	62,522	3,608	6%	0.46
Educational Services (61)	31,923	3,991	13%	0.63
Arts, Entertainment, and Recreation (71)	31,044	2,980	10%	0.87
Real Estate and Rental and Leasing (53)	29,816	1,270	4%	0.88
Finance and Insurance (52)	26,511	-1,173	-4%	0.34
Information (51)	14,772	1,817	12%	0.44
Agriculture, Forestry, Fishing and Hunting (11)	14,256	-729	-5%	0.65
Management of Companies and Enterprises (55)	8,204	-449	-5%	0.28
Utilities (22)	5,627	52	1%	0.83
Mining, Quarrying, and Oil and Gas Extraction (21)	1,658	199	12%	0.25

Source: Lightcast 2026.3 – Industry Table, QCEW Employees, Non-QCEW Employees, and Self-Employed

In 2025, the IE/D region supported 1.94 million jobs, making it the third largest metropolitan statistical area (MSA) in California, following Los Angeles-Long Beach-Anaheim and San Francisco-Oakland-Fremont. Regional employment is projected to grow by 6.6% by 2030, adding nearly 128,600 jobs and outpacing California’s projected growth rate of 4.2%.

The region's seven largest industry sectors collectively account for nearly three-quarters of all jobs. Notably, these sectors are more concentrated within the region than in California and the nation as a whole, meaning each sector contributes a larger share of regional employment than its share of employment statewide or nationally.

The Transportation and Warehousing sector is the third largest sector by job count and shows the region's strongest degree of industry specialization, with an employment concentration of 2.46, nearly two and a half times the statewide average share for that sector, at 0.96. In addition to the

specialization in logistics, the region's two largest sectors by job count are Government and Healthcare and Social Assistance, together accounting for nearly one-third of regional employment. These sector concentration levels (1.09 and 1.15, respectively) closely mirror their statewide employment shares rather than reflecting distinct regional specialization. Healthcare and Social Assistance is also the fastest-growing sector over the next five years, projected to grow 16% and add 47,744 jobs to the region.

This industry mix matters for AI exposure because the region's leading sectors carry very different task compositions. Transportation and Warehousing, along with Retail Trade and Administrative and Support Services, tend to concentrate physical, location-dependent tasks, such as driving, material handling, and in-person customer service, that remain comparatively insulated from current AI capabilities, even as some scheduling, routing, and administrative tasks within these sectors become increasingly augmentable. Healthcare and Social Assistance, on the other hand, presents a more diverse landscape. It encompasses a range of tasks, from highly protected hands-on care and clinical judgment to substantial documentation, diagnostic support, and administrative responsibilities that are more readily automated or augmented. Government employment spans a similarly wide range of tasks, from constituent-facing services to back-office functions with high automation potential. Section 2 quantifies how these differences translate into measured exposure.

The scale and mix of industries are critical to understanding AI exposure in the region because leading sectors have very different task compositions. Understanding how AI will affect the region requires moving beyond industry sector to the occupation and task level. Occupations are not confined to single sectors: office and administrative support work is performed in logistics warehouses, hospitals, business offices, and county agencies alike. We cannot assume the skills required for an occupation are identical across different work contexts; records and scheduling work in a distribution center may not be the same as in a clinic, even when jobs fall under the same occupational code. Sector analysis alone therefore says little about the content of the work being performed, and occupational analysis has its own variation. The region's occupational profile is another key starting point to understanding AI exposure in the region.

The region's occupational profile can be initially assessed using high-level occupational groups, which provide a comprehensive overview of the scale and diversity of occupations within the region's overall labor market. These occupational groups complement and contrast industry-level data by presenting the scale and composition of jobs in the region, categorized by shared work activities and contexts. While the region's occupational composition shows similar patterns as the industry level, it diverges when no longer organized by employer focus. (To learn more about the differences between Industry and Occupations, including the SOC hierarchy, the IED COE's LMI 201 online training series is a useful resource.)

Exhibit 1.2.4 displays the current and projected employment by major (2-digit) occupational group.

Exhibit 1.2.4: Current and projected employment by major occupational group, 2025-2030

Major Occupational Group (SOC2)	2025 Jobs ▼	2025 - 2030 Change	2025 - 2030 % Change
Transportation and Material Moving Occupations (53-0000)	285,904	18,667	7%
Office and Administrative Support Occupations (43-0000)	180,720	4,902	3%
Food Preparation and Serving Related Occupations (35-0000)	172,579	12,333	7%
Sales and Related Occupations (41-0000)	156,517	2,644	2%
Healthcare Support Occupations (31-0000)	151,597	27,736	18%
Educational Instruction and Library Occupations (25-0000)	114,566	8,598	8%
Management Occupations (11-0000)	110,130	7,599	7%
Construction and Extraction Occupations (47-0000)	102,744	3,524	3%
Healthcare Practitioners and Technical Occupations (29-0000)	102,621	11,479	11%
Business and Financial Operations Occupations (13-0000)	82,795	4,019	5%
Production Occupations (51-0000)	77,605	895	1%
Installation, Maintenance, and Repair Occupations (49-0000)	71,952	4,311	6%
Building and Grounds Cleaning and Maintenance Occupations (37-0000)	70,252	2,977	4%
Personal Care and Service Occupations (39-0000)	59,630	4,612	8%
Protective Service Occupations (33-0000)	49,697	3,486	7%
Community and Social Service Occupations (21-0000)	39,985	4,738	12%
Arts, Design, Entertainment, Sports, and Media Occupations (27-0000)	25,869	1,782	7%
Computer and Mathematical Occupations (15-0000)	22,073	1,882	9%
Architecture and Engineering Occupations (17-0000)	18,027	822	5%
Life, Physical, and Social Science Occupations (19-0000)	13,076	1,127	9%
Farming, Fishing, and Forestry Occupations (45-0000)	10,760	-307	-3%
Legal Occupations (23-0000)	9,536	485	5%

Source: Lightcast 2026.3 – Occupation Table, QCEW Employees, Non-QCEW Employees, and Self-Employed

Transportation and Material Moving Occupations is the region's largest occupational group by a wide margin, accounting for 285,904 jobs in 2025 and projected to grow by 7% through 2030, consistent with the region's pronounced concentration in Transportation and Warehousing. Office and Administrative Support Occupations is the second-largest group at 180,720 jobs, though its projected growth is 3%, which contrasts with the similar Industry of Administrative and Support and Waste Management and Remediation Services (56), which is ranked only the seventh-largest in the region. Food Preparation and Serving Related Occupations (172,579 jobs) and Sales and Related Occupations (156,517 jobs) round out the region's largest groups, both reflecting the region's substantial retail and accommodation and food services presence.

Healthcare Support Occupations stands out as the fastest-growing major occupational group, projected to grow 18% and add 27,736 jobs by 2030, a pace consistent with the broader growth of the Healthcare and Social Assistance sector as shown in Exhibit 1.2.3. Healthcare Practitioners

and Technical Occupations (102,621 jobs, 11% growth) and Community and Social Service Occupations (39,985 jobs, 12% growth) show similarly strong growth, further underscoring the expanding role of care-related work in the regional economy. By contrast, smaller occupational groups such as Computer and Mathematical Occupations (22,073 jobs) and Life, Physical, and Social Science Occupations (13,076 jobs) represent a modest but growing share of regional employment, at 9% growth each, while Farming, Fishing, and Forestry Occupations is the only major group projected to decline (-3%) over the same period.

The industry determines the work available in a region, while occupations define the tasks that comprise that work. Neither of these describes the relationship between a worker and the technology itself in terms of whether AI is something a worker builds, something the job requires them to operate, or something they adopt on their own initiative. That relationship shapes how AI reaches a given worker, and it is not visible in either an industry or an occupational code.

1.3: Who Stands in the Path of the Wind

To better understand how artificial intelligence is currently impacting regional employment, this report applies the third lens, which describes the worker’s relationship to the technology. Drawing on the analysis of regional job postings, the COE identifies three categories of AI-impacted roles: AI Builder, AI Operator, and AI Assisted Worker. Positions within each of these categories are uniquely affected by the employer and industry adoption and integration of emerging technologies. (The COE has published a presentation that provides more context for the research that led to this categorization here.)

The following table displays the workforce categories assigned to jobs based on their use of AI, either as a direct work task or how a work task interacts with the technology, and how each category typically presents itself when reviewing occupational data.

AI BUILDER What the job actually does: The job builds AI. The role designs, develops, trains, or engineers AI systems themselves; specialized AI skills are the core requirement. Remove the AI and the job does not exist. Typical roles: Machine-learning engineers, data scientists, AI researchers, AI software developers.	AI OPERATOR What the job actually does: The job requires the use of AI. AI is an operational part of doing the work; the worker runs, applies, or works within AI-powered systems and is expected to. Includes “AI-adjacent” roles such as a technician maintaining AI-driven equipment. Typical roles: Analysts, HR professionals, radiologists, educators operating AI-powered tools.	AI ASSISTED WORKER What the job actually does: The job uses AI to assist. AI is an optional productivity aid the worker adopts to do ordinary work better; it is not a stated requirement. Typical roles: Any role using ChatGPT for drafting, Copilot for code, or similar to improve output.
NONE No genuine relationship. No credible tie between the role and the skill in the posting text.		

These categories are critical to continuing to analyze the technology and its relation to the current labor market. With any new technology's adoption, especially one as transformative as AI, it will have ripple effects across industries and occupations; it will affect positions in different ways and to different degrees. The first three categories describe the relationship between the worker and AI, with "none" representing those job postings where there appeared to be no credible relationship between the role and the AI skills.

The ways and degrees will largely depend on either how directly applicable the technology is to core work tasks (such as AI software developers who create the technology) or how quickly workers and employees can find ways to successfully use the technology to either automate or augment work tasks not directly related to AI (such as administrative assistants who use AI to record meeting minutes). While AI Builders are generally clustered in leading technology companies that are primarily not based in the region, AI Operators and AI Assisted Workers, by contrast, are already at work across the region's employers.

This distinction holds significant regional importance. AI Builders cluster in the technology firms that develop these systems, few of which are based in the Inland Empire/Desert Region, consistent with Computer and Mathematical Occupations accounting for roughly 1% of regional employment. AI Operators and AI Assisted Workers, by contrast, are already at work across the region's employers, in logistics, healthcare, government, and administrative workplaces. For regional educators, the practical question is less how to produce AI Builders than how to prepare graduates who will enter the workforce as AI Operators and AI Assisted Workers.

These categories also differ in how readily they can be observed. AI Builder and AI Operator roles have a relationship to AI, because it is a condition of the job and warrants these categories. Typically, an employer would not advertise for a machine learning engineer without naming the technology. An AI Assisted Worker job may not have such an explicit relationship to AI due to it being optional, and an employer may not mention it explicitly within a job posting. Section 2 addresses what this means for measuring each category in the regional labor market.

Students entering the workforce in the coming years will likely find employment in one of these three job categories. By understanding these relationships and their respective requirements, we can identify the skills that will position graduates for success. This report leverages these categories, along with industry and occupation, as lenses to examine the current and future impact of AI on the regional labor market.

1.4: When the Weather Meets the Land

The preceding subsections provide context for our region in terms of the industries and occupations likely to be affected by AI. This includes a definition of the technology, a description of the regional labor force, and a framework for understanding the relationships between workers and AI.

The following sections use this data to assess how Artificial Intelligence will impact the Inland Empire's regional economy, especially the labor market, in the months and years to come. This report uses two instruments from two different perspectives.

The first instrument includes online job postings, which gauge potential employer demand by capturing regional employers' requests for AI skills across occupations, industries, and scales. It

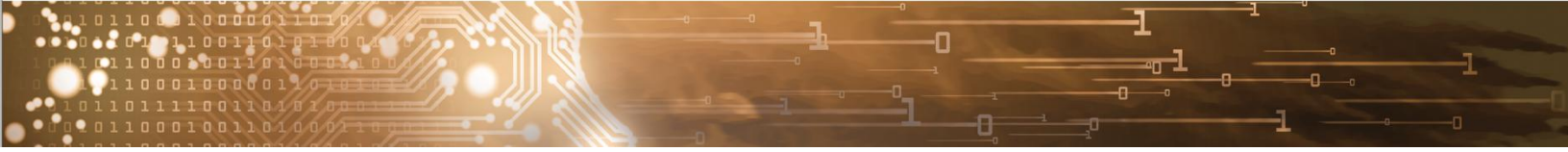
represents a record of employer-stated intent, yet it only captures what employers have explicitly designated as relevant skills and only after AI has become sufficiently prominent to be included in job descriptions.

The second instrument comes from a different source entirely. Anthropic, the developer of the AI assistant Claude, publishes analysis of how its system is used in practice, mapping millions of real conversations to the specific work tasks that make up occupations. This produces a record of which tasks AI is performing in practice, and whether it is completing them outright or assisting a person who remains in the loop. Applied to the region's occupational composition, we can estimate how exposed the regional workforce is to automation and augmentation, independent of whether any employer has named an AI skill.

Neither instrument is sufficient alone to tell the story of how AI may and is impacting the IED region. Nor should we expect that the results should be similar. Employer demand for AI skills in the region is currently modest and concentrated in a small number of sectors and occupations. Task exposure is considerably broader, and it reaches occupations where employers have named no AI skill in any job posts. Both findings are accurate. Read together, the gap between them is the most useful signal that the following Section 2 produces. Section 2 distinguishes change already reflected in hiring from change that may arrive ahead of any market signal that we can detect.

Job posting data and task exposure are not equally predictive and reading them the same way would mislead. Postings record what has already happened; employers wrote those listings, and the demand they express is real, if narrower than actual adoption. Task exposure records what is possible: work that AI is technically capable of performing, which becomes changed work only through decisions and investments employers have not yet made. Where demand and exposure both run high, the market is already signaling, and programs can respond to it. Where demand is low and exposure is high, it is also an opportunity for decisions to be made on program design.

Not all disruption results in net job loss. The evidence assembled in Section 2 points more to job reshaping than elimination: tasks are redistributed within occupations rather than occupations disappearing. But reshaped work still requires differently prepared workers, and the region's educators are positioned to determine how prepared they are. The sections that follow examine where the change is already visible, where it is arriving, and what it asks of the institutions preparing the region's future workforce.



SECTION 2: HOW FAR THE DUST TRAVELS, AI'S REACH ACROSS THE REGIONAL ECONOMY

2.1: A New Way to Measure the Approaching Storm

Most attempts to estimate AI's effect on work begin with expert judgment. A researcher examines a list of job tasks, considers what current systems can do, and rates each task for whether it could be performed by AI. This approach produces theoretical exposure estimates, and it has real value. This estimate-based approach establishes an outer boundary for what is technically possible.¹²

However, it does not tell us what is happening. A task can be entirely feasible for AI and never actually performed by it. This portion of the analysis takes a different approach, one grounded in observed behavior rather than expert estimations. It draws on research published by Anthropic, the developer of AI assistant Claude, which examines a large, anonymized sample of real conversations between people and AI models and maps each conversation to the specific work task that person was trying to accomplish.¹³ Rather than asking what AI might do, this method asks what people are actually using it for at a task level.

What a “task” means

Those tasks are drawn from O*NET, the U.S. Department of Labor's standard catalog of the activities that make up American jobs.¹⁴ (For an overview of the O*NET datasets and their relation to each other, see the O*NET Content Model.) O*NET organizes all work under Standard Occupational Classification codes (SOCs) or occupations. Each occupation is defined as a unique combination of knowledge, skills, abilities, work activities, and task statements.

Task statements are the most granular level: specific duties performed in a job; each linked to exactly one occupation. Every occupation has a set of core tasks central to the role and supplemental tasks performed less frequently. As an example, one of the core task statements for Registered Nurses (SOC 29-1141) is “record patients' medical information and vital signs,” and one of the supplemental tasks is “engage in research activities related to nursing.”¹⁵ A single occupation may have dozens of such statements, and they vary significantly in how amenable they are to AI. Recording vital signs into a chart is a fundamentally different activity from assessing whether a patient's condition is deteriorating, even though both belong to the same occupation. This is why task-level measurement matters. Asking whether AI will “replace nurses” produces a debate. Asking which of the nurse's specific documented tasks are showing in observed AI use produces an answer.

Automation and augmentation are not the same thing

For each task, the data records not only how often AI is used but how it is used, whether AI completes the work directly with minimal human involvement, or whether it collaborates with, checks, or advises a person who remains responsible for the outcome. The first pattern is

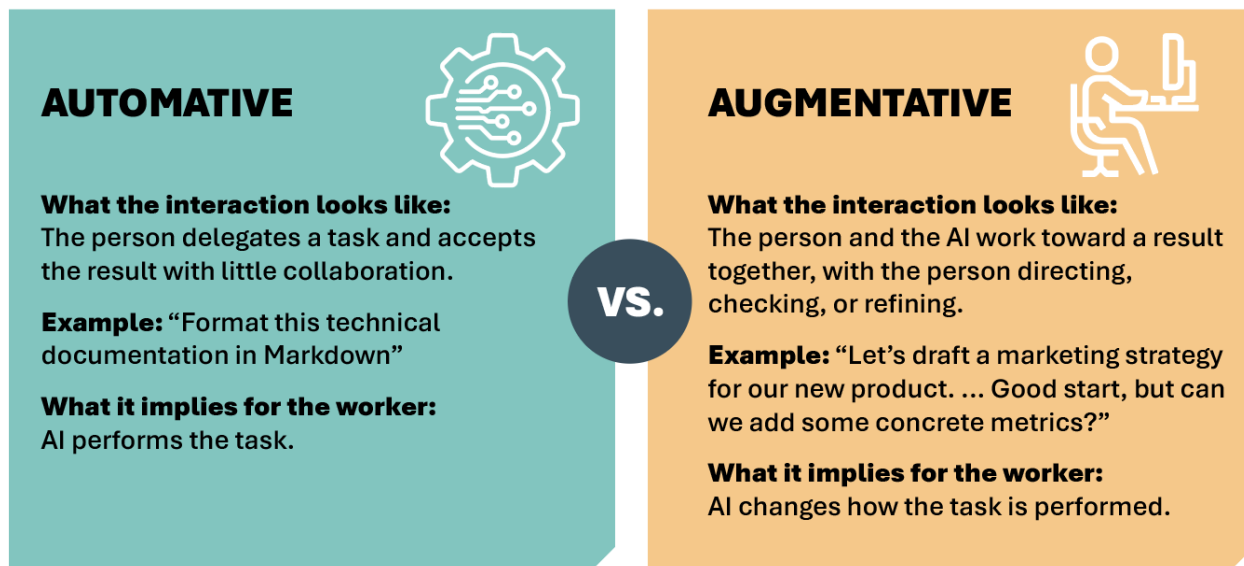
¹² Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2023). *GPTs are GPTs: An early look at the labor market impact potential of large language models* (arXiv:2303.10130). arXiv. <https://arxiv.org/abs/2303.10130>

¹³ Handa, K., Tamkin, A., McCain, M., Huang, S., Durmus, E., Heck, S., Mueller, J., Hong, J., Ritchie, S., Belonax, T., Troy, K. K., Amodei, D., Kaplan, J., Clark, J., & Ganguli, D. (2025). Which economic tasks are performed with AI? Evidence from millions of Claude conversations. Anthropic.

¹⁴ National Center for O*NET Development. (n.d.). *The O*NET content model*. U.S. Department of Labor, Employment and Training Administration. <https://www.onetcenter.org/content.html>

¹⁵ National Center for O*NET Development. (n.d.). *Summary report for: 29-1141.00 — Registered nurses*. O*NET OnLine. <https://www.onetonline.org/link/summary/29-1141.00>

described as automative, the second as augmentative. This distinction matters because the two imply very different consequences for a worker: one substitutes for the work, the other changes how the work is performed.



These patterns are derived from the structure of the conversation itself, whether a person handed over a task and accepted the result, or worked collaboratively toward it.

From a national perspective to a regional one

The published data is national. To translate this data to our regional economy required two additional steps.

First, because O*NET records which tasks belong to which occupations, the individual task scores were rolled up to the occupation level. This produced an AI exposure profile for each occupation, a measure of what share of that occupation’s work is showing up in observed AI use, separating the degree to which AI tends to automate its work from the degree to which it augments it.

Second, those occupational profiles were applied to regional staffing patterns, which include the actual mix of occupations employed across the Inland Empire and Desert region. This step is what makes the analysis regional rather than national. An occupation that is highly exposed but barely present in the region contributes little to the regional picture, while an occupation that is both exposed and a major source of jobs heavily influences it. Using staffing patterns, we can directly connect the scale of an occupation’s AI exposure to the scale of each occupation in the context of an Industry.

The figures resulting from this analysis are presented throughout this section as shares of task-weighted employment. It’s important to note that the fact that a certain percentage of task-weighted employment is exposed does not necessarily imply that the corresponding percentage of jobs is at risk. In other words, if we were to sum up all the tasks performed across the regional workforce, weighted by the number of individuals who perform each one, the share of the total that comprises tasks appearing in the observed AI use would be distributed across various occupations in partial amounts, rather than being concentrated in a subset of jobs that disappear. This exposure

analysis finds that 8.2% of task-weighted employment in the Inland Empire/Desert Region is exposed to automation, while 6.9% is exposed to augmentation, for a regional exposure rate of 15.1%.

What this measure can and cannot tell us

This is the most direct evidence available about AI's current relationship to real work, and it has three limitations.

It reflects the usage of one company's AI systems. The picture is strongest for the kinds of work an AI assistant can handle, including reading, writing, analysis, coding, and summarization. Technologies that operate on the physical world, including warehouse robotics and autonomous vehicles, fall largely outside it. For a region whose defining specialization is logistics, that is a meaningful gap and is addressed again in the sector analysis that follows.

It measures potential, not outcomes. A task appearing in observed AI use tells us AI is being applied to that kind of work somewhere. It does not tell us that a regional employer has adopted it, that a regional worker's job has changed, or that anyone has been displaced. Researchers examining this gap are explicit on the point that a theoretical capability routinely fails to translate into use because of model limitations, legal constraints, software requirements, and human verification steps. One task rated as fully feasible, such as authorizing prescription refills and providing information to pharmacies, has never been observed being performed.¹⁶

The measure does not capture the decisions that stand between capability and adoption.

Whether exposure ever reaches a regional worker depends on factors no dataset observes. Whether employers understand what the technology does, whether they invest in it, whether workflows are redesigned to accommodate it, whether the underlying data is in usable form, and whether the cost of the tool is justified against the cost of the labor it would change.

What follows is a map of where AI could reach the region's work, the outer edge of the storm rather than a forecast of where it will land.

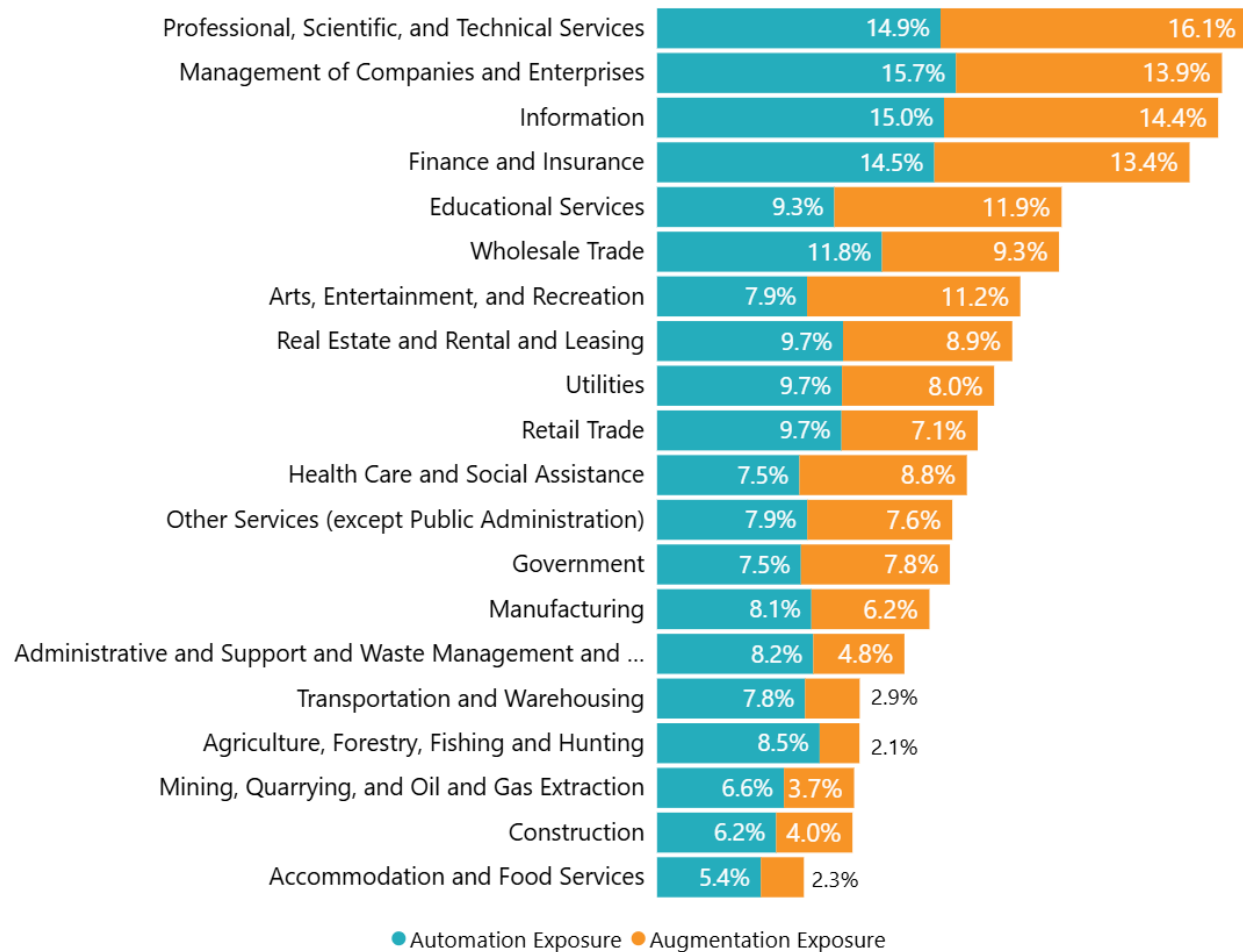
2.2: What Anthropic Data Reveals: Industry Exposure

Artificial Intelligence does not reach every industry in the same way since exposure depends on tasks a job actually contains; industries differ according to the mix of work their employees perform. How much of the work involves reading, writing, analyzing, and processing information, and how much involves physical presence, direct services, or judgment exercised in the moment.

Exhibit 2.2.1 presents AI exposure for each of the region's industry sectors, showing the share of tasks that AI systems are observed completing directly (automation) and the share AI is observed assisting with (augmentation).

¹⁶ Massenkoff, M., & McCrory, P. (2026, March 5). *Labor market impacts of AI: A new measure and early evidence*. Anthropic. <https://www.anthropic.com/research/labor-market-impacts>

Exhibit 2.2.1: Automation/Augmentation exposure by industry sector, Inland Empire/Desert Region, 2025



Source: COE analysis of Lightcast staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

Where exposure concentrates

AI's potential impact varies considerably across industries, driven less by the industry itself than by the nature of the work performed within it. Employment composition significantly affects overall exposure. This exposure analysis finds that 9.5% of task-weighted employment in California is exposed to automation, while 8.8% is exposed to augmentation, for a statewide exposure rate of 18.3%. The Inland Empire (15.1%) is thus less exposed to LLM-driven change than California (18.3%) as a whole, a gap that reflects the region's occupational composition rather than any regional difference in how a given job is performed.

Automation exposure is highest in knowledge-intensive sectors, such as Management of Companies and Enterprises (15.7%); Information (15.0%); Professional, Scientific, and Technical Services (14.9%); and Finance and Insurance (14.5%), where administrative, analytical, and information-processing tasks align closely with current AI capabilities. Sectors centered on physical labor, in-person service, or dynamic environments cluster at the other end of the range: Accommodation and Food Services (5.4%), Construction (6.2%), Mining,

Quarrying, and Oil and Gas Extraction (6.6%), Health Care and Social Assistance (7.5%), Government (7.5%), and Transportation and Warehousing (7.8%), all show automation exposure at roughly half the level of the top sectors.

Share is not the same as scale

This ranking reflects the share of tasks exposed within each industry, not the number of workers affected, and the two can diverge sharply. Management of Companies and Enterprises has the region's highest automation exposure at 15.7% and employs 8,204 people. Health Care and Social Assistance (7.5%) employs 306,974. A lower share of a much larger workforce can represent a far greater volume of exposed work.

Both ends of this spectrum are useful, and they answer different questions. Share identifies which industries face the most fundamental change in how their work is performed. Scale identifies where that change will reach the largest number of workers. An educator deciding whether to revise a program needs the first, and an educator estimating how many students are affected needs the second.

What kind of change, not just how much

Comparing automation and augmentation sheds light on an aspect that the combined figures fail to capture, not just the extent of AI's influence on an industry, but the nature of its relationship with the work itself.

In most sectors, automation exposure exceeds augmentation exposure, meaning a larger share of tasks are ones AI is observed completing directly than ones it is observed assisting with. The gap between automation and augmentation is widest in Agriculture, Forestry, Fishing and Hunting (8.5% automation exposed versus 2.1% augmentation exposed), Transportation and Warehousing (7.8% versus 2.9%), Administrative and Support Services (8.2% versus 4.8%), and Accommodation and Food Services (5.4% versus 2.3%).

Four sectors invert this pattern, with augmentation exceeding automation: Arts, Entertainment, and Recreation (11.2% augmentation versus 7.9% automation), Educational Services (11.9% versus 9.3%), Health Care and Social Assistance (8.8% versus 7.5%), and Professional, Scientific, and Technical Services (16.1% versus 14.9%). In these industries, AI more often works alongside a person than completes work independently. Government (7.5% automation, 7.8% augmentation) and Other Services (except Public Administration) (7.9% automation, 7.6% augmentation) stand apart as the sectors where the two measures are nearly identical, suggesting a roughly even mix.

This distinction matters for educational program planning. When automation dominates, the question for a worker is whether a portion of their task load is transferred to a system. Conversely, when augmentation dominates, the question becomes whether they can effectively direct that system, leading to different instructional responses.

What the figures do not say

These estimates indicate the share of tasks that are potential candidates for AI automation or augmentation. However, they do not describe the share of jobs that are likely to be displaced, and it is crucial to distinguish between the two.

Nearly every occupation combines tasks AI is observed performing with tasks it is not. The more probable near-term outcome is that AI reshapes the composition of work within roles

rather than eliminating roles outright, which is a pattern consistent with current employment evidence, which has not yet shown systemic displacement in the most exposed occupations, though it has shown slowed hiring for workers at the entry level.^{17 18}

Industry sector-level data groups employers, not work. Since a single industry employs workers across many different occupations, a sector-level figure averages together work that has little in common. As an example, one industry code is for hospitals, which employ surgeons, medical coders, food service staff, and IT administrators. The following subsection examines the same exposure data organized by occupation, which brings the analysis closer to the actual content of the work and, for educators, closer to the program that prepares people for it.

2.3: What Anthropic Data Reveals: Occupation Exposure

Industry describes who employs a worker. Occupation describes what that work does. For this research, we use major occupation groups to better align with educational programs for similar occupations. The analysis of major occupational groups reinforces that exposure to AI is driven primarily by the type of work performed, not solely by the industry in which that work takes place. Exhibit 2.3.1 displays the automation and augmentation exposure of each occupational group in the Inland Empire/Desert Region.

¹⁷ Massenkoff, M., & McCrory, P. (2026, March 5). *Labor market impacts of AI: A new measure and early evidence*. Anthropic. <https://www.anthropic.com/research/labor-market-impacts>

¹⁸ Brynjolfsson, E., Chandar, B., & Chen, R. (2026). *Canaries in the coal mine? Six facts about the recent employment effects of artificial intelligence*. Stanford Digital Economy Lab, p. 11

Exhibit 2.3.1: Automation/Augmentation exposure by occupational group, Inland Empire/Desert Region, 2025



Source: COE analysis of Lightcast staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

Where exposure concentrates

Automation exposure is highest in office and knowledge-based occupations: Computer and Mathematical occupations lead at 27.6%, followed by Office and Administrative Support occupations at 23.8%, both well above the next tier of occupational groups, including Business and Financial Operations (12.3%), Sales and Related (12.2%), Arts, Design, Entertainment, Sports, and Media (10.9%), and Management (10.8%). These occupations share a common foundation: tasks centered on documentation, information management, data analysis, and written communication.

Occupations built around physical labor, equipment operation, hands-on service, or direct interaction with people show far lower automation exposure. Construction and Extraction have the lowest share of automatable tasks (1.7%), followed by Building and Grounds Cleaning and Maintenance (2.4%), Educational Instruction and Library (3.6%), Healthcare Support (3.6%), Production (4.3%), Life, Physical, and Social Science (4.4%), Installation, Maintenance, and Repair (4.8%), and Food Preparation and Serving Related (5.1%). Legal occupations have low automation exposure (3.9%), despite being more closely associated with office and knowledge-based occupations, which have high automation exposure.

Occupational exposure varies far more than industry exposure does. Across the region's industry sectors, automation exposure ranged from 5.4% to 15.7%, a meaningfully narrow difference. Across occupational groups, the same measure runs from 1.7% in Construction and Extraction to 27.6% in Computer and Mathematical occupations. The most exposed occupational group carries roughly sixteen times the automation exposure of the least exposed, with the widest industry gap closer to three times. This data confirms that exposure follows the nature of the work rather than the employer and is the reason occupation is the more useful unit of measure for this research.

Transportation and Material Moving presents the opposite case: a modest 6.3% automation share, but spread across 285,904 workers, the region's largest occupational group by a wide margin. Even at that lower rate, the size of the workforce means the absolute volume of exposed work is considerable.

One occupational group stands out on both measures

Office and Administrative Support has the second-highest automation exposure of any occupational group (23.8%) and the second-largest workforce in the region at 180,720 workers. No other group combines a high exposure share with employment at this scale. Whether measured by how much of the work is exposed or by how many workers perform it, this occupational group is where AI's potential impact in IE/D is greatest.

What kind of change, not just how much

Comparing the share of both automation and augmentation exposure also reveals how AI is likely to affect different types of work, beyond just the size of the effect. Legal occupations show by far the widest gap in favor of augmentation (3.9% automation versus 25.9% augmentation), followed by Architecture and Engineering (6.7% versus 16.0%), Life, Physical, and Social Science (4.4% versus 11.2%), Arts, Design, Entertainment, Sports, and Media (10.9% versus 17.6%), Educational Instruction and Library (3.6% versus 10.0%), and Healthcare Support (3.6% versus 9.8%). In these occupations, AI is more likely to serve as a productivity-enhancing tool that supports research, drafting, analysis, and decision-making than to complete tasks independently.

The reverse pattern, automation exposure well ahead of augmentation, is most pronounced in Office and Administrative Support (23.8% versus 9.7%), suggesting routine administrative and clerical tasks are among the most susceptible to direct automation. Notably, Computer and Mathematical occupations show a similar pattern despite ranking highest overall (27.6% versus 16.3%).

Office and Administrative Support therefore ranks near the top on three separate measures: exposure share, workforce size, and the degree to which that exposure takes the form of automation rather than augmentation.

What these figures do not say

As with the industry analysis in subsection 2.2.1, these estimates describe the share of tasks within an occupation that have the potential for automation or augmentation, not the share of jobs expected to be displaced. Most occupations combine exposed and unexposed work. The

more likely near-term outcome is that AI changes how work is performed by reallocating tasks within roles, rather than eliminating occupations outright.¹⁹

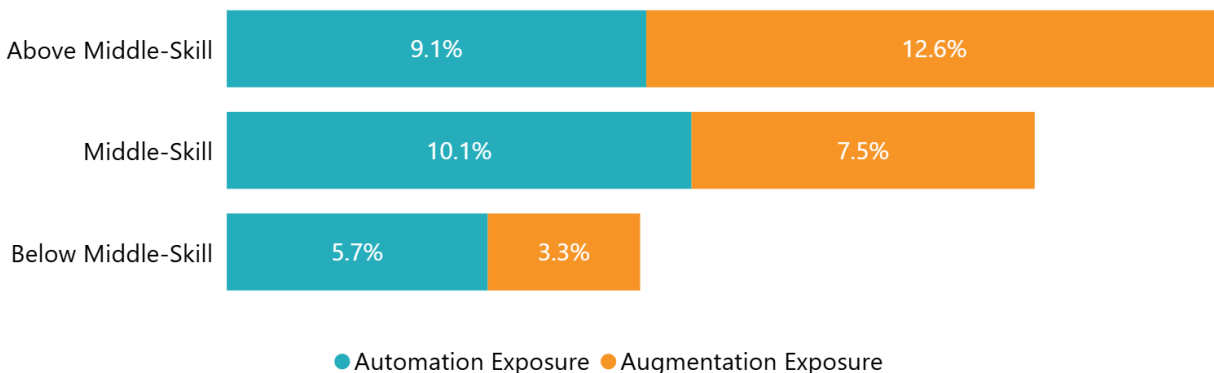
Occupational groups are still broad categories and can mask the nuances of the differences in type of work. The Office and Administrative Support group covers work as different as medical records specialists, customer service representatives, and shipping clerks, and the figure reported for the group is an average across all of them. The next subsection approaches the same data from a different direction, grouping occupations by the level of education they typically require, which maps more directly to educational programs.

2.4: What Anthropic Data Reveals: Skills/Education Level Exposure

The preceding subsections organized exposure by industry and by occupation. This section organizes exposure by the level of education an occupation typically requires, which corresponds most directly to what community colleges and K-12 career pathways provide.

Of the 1.94 million jobs in the Inland Empire/Desert Region, approximately 42.7% typically require an education associated with community college training programs. 19.6% of regional jobs typically require a bachelor's degree or more, while 37.7% of jobs typically require less than a community college-level education. Exhibit 2.4.1 displays the share of tasks that could be augmented or automated by artificial intelligence, broken out by skill level.

Exhibit 2.4.1: Automation/Augmentation exposure by skill level, Inland Empire/Desert Region, 2025



Source: COE analysis of Lightcast staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

Automation exposure peaks at the middle-skill level

Automation exposure does not rise steadily with education. The data suggests that AI's impact on higher-skill occupations is driven primarily by augmentation rather than automation. Automation exposure is highest for Middle-Skill workers (10.1%), slightly lower for Above Middle-Skill (9.1%) jobs, and lowest for Below Middle-Skill roles at 5.7%.

¹⁹ Massenkoff, M., & McCrory, P. (2026, March 5). *Labor market impacts of AI: A new measure and early evidence*. Anthropic. <https://www.anthropic.com/research/labor-market-impacts>

Automation exposure is greater for middle-skill occupations. This reflects the task content of that work: middle-skill roles concentrate structured, procedural, information-handling activity such as processing records, coding claims, scheduling, preparing documents, entering and reconciling data, which AI is observed completing.²⁰ Above middle-skill work involves more judgment, interpretation, and accountability that AI is observed supporting rather than performing, while below middle-skill work involves more physical presence and direct service, which it does neither.

What this means for the region's education pipeline

Community college programs serve the most exposed education tier. Middle-skill occupations account for 42.7% of regional employment, which is roughly 828,000 jobs and the largest of the three groups. They also carry the highest automation exposure of any education level. Together, these two facts identify where AI's measured potential and the education system's mission overlap most directly.

The comparison between the two measures adds a further distinction. At the middle-skill level, automation exposure (10.1%) exceeds augmentation exposure (7.5%) by nearly 3%. At the above middle-skill level, the relationship inverts, with augmentation at 12.6% exceeding automation at 9.1%.

K–12 pathways lead to the least exposed education tier, although these pathways are rarely the final destination for workers. Occupations requiring less than a community college credential exhibit the lowest exposure of any level on both measures: 5.7% automation and 3.3% augmentation.

For pathways that directly lead students into the workforce, this lower exposure persists. However, most K–12 CTE pathways are not terminal; instead, they serve as on-ramps into community college programs, which are located in the tier with the highest automation exposure. A student following a business or health administration pathway from high school into a regional community college program moves from the least exposed segment of the labor market to the most exposed one.

Two findings from Section 1 demonstrate this pattern. The region has a larger share of residents age 24 and under than California overall (33.1% versus 30.2%), meaning proportionally more of its population is at or approaching labor market entry. As noted in Section 1.2, the employment effects observed so far have concentrated among workers aged 22 to 25 in the most exposed occupations, and the mechanism is slowed hiring rather than displacement of incumbents.²¹ The region's K–12 students are the cohort entering the labor market at the point where these measurable effects have appeared.

2.5: Reading the Drift: Using Job Posting Data

Job postings serve as a near-real-time indicator of employer demand. When an employer creates a job listing, they are essentially describing the job responsibilities, presenting a record of stated needs rather than a comprehensive list of technical requirements. However, job postings can also be incomplete for various reasons. For instance, a job posting may not explicitly mention an AI skill, even if AI is indeed present in the workplace, due to factors such

²⁰ Handa, K., Tamkin, A., McCain, M., Huang, S., Durmus, E., Heck, S., Mueller, J., Hong, J., Ritchie, S., Belonax, T., Troy, K. K., Amodei, D., Kaplan, J., Clark, J., & Ganguli, D. (2025). *Which economic tasks are performed with AI? Evidence from millions of Claude conversations*. Anthropic.

²¹ Brynjolfsson, E., Chandar, B., & Chen, R. (2025). *Canaries in the coal mine? Six facts about the recent employment effects of artificial intelligence*. Stanford Digital Economy Lab.

as the employer's lack of investment in the technology or the hiring manager or human resources staff's unfamiliarity with the terminology. Additionally, the listing might describe the requirement as familiarity with a specific software product rather than as an AI skill. Furthermore, an employer that adopts AI by training existing staff instead of hiring new employees will not create a job posting at all.²² A sector showing few job postings may show little AI activity, or considerable AI activity that employers have not included. For these reasons, job posting data is used to establish a floor on employer demand for AI skills, not a measure of AI adoption.

Why a skills-based approach

Artificial intelligence is not explicitly included in occupational classification systems that organize most labor market data. No AI industry code and no AI occupation code exist. A machine learning engineer, a nurse using an AI-assisted diagnostic tool, and a warehouse supervisor overseeing automated routing all sit under different codes, and none of those codes identifies AI as a specific skill or activity. Counting AI work therefore requires looking at the skills employers include in job postings rather than the occupational categories they hire for.

This report uses the AI skill clusters developed by Lightcast, originally created to support the Stanford Institute for Human-Centered AI and its annual AI Index Report. The taxonomy organizes 354 individual AI skills into ten clusters that distinguish the different kinds of work the term "artificial intelligence" includes:²³

- 1) **AI Agent (29 skills):** Skills related to software that can carry out tasks or hold conversations semi-independently on a person's behalf, such as chatbots and virtual assistants. (ex. ChatGPT)
- 2) **AI Ethics, Governance, and Regulation (8 skills):** Skills related to the safe, responsible, and compliant use and oversight of AI systems. (ex. AI Safety)
- 3) **Intelligence (43 skills):** A broad cluster covering general AI knowledge, tools, and applications not captured by the more specialized clusters below. (ex. Cognitive Automation)
- 4) **Autonomous Driving (14 skills):** Skills specific to self-navigating vehicles, including sensing, mapping, and route planning. (ex. Autonomous Vehicles)
- 5) **Artificial Intelligence [General] (20 skills):** Skills related to using AI to create new content, such as text, images, or code, rather than simply analyzing existing data. (ex. Prompt Engineering)
- 6) **Machine Learning (105 skills):** The largest cluster, covering the technical methods, algorithms, and platforms that allow AI systems to learn patterns from data. (ex. Machine Learning Model Training)
- 7) **Natural Language Processing (59 skills):** Skills that enable computers to understand, generate, and respond to human language, from speech recognition to text summarization. (ex. Natural Language Programming)
- 8) **Neural Networks (29 skills):** Skills related to the layered, brain-inspired architecture underlying most modern AI systems. (ex. Deep Learning)

²² Microsoft & LinkedIn. (2024). *AI at work is here. Now comes the hard part: 2024 work trend index annual report*. Microsoft.

²³ Lightcast. Beyond the Buzz. (2025). Retrieved from: https://www.datocms-assets.com/62658/1753230742-beyond_the_buzz_final23.pdf

9) Robotics (19 skills): Skills related to programming and operating physical machines that can sense, move through, and act on their environment. (ex. Robotic Process Automation)

10) Visual Image Recognition (28 skills): Skills that enable computers to interpret images or video, including facial and object detection. (ex. Computer Vision)

To identify differences in how employers demand AI skills across the regional economy, we pulled job postings for each AI skill cluster, grouped by industry sector. We classified job postings mentioning at least one AI skill as an “AI job.” However, because postings typically mention several skills, they can also include more than one AI skill cluster. As a result, summing job ads across AI skill clusters could create duplication, with some postings flagged as AI-related in multiple clusters. Beyond the distribution of AI skill clusters across the region, this report assesses aggregate demand for AI skill clusters, identifying how combined skill clusters affect industries and occupations.

This analysis identified the occupations with the highest frequency of AI skill demand. By comparing job postings that required AI skills to all postings, we determined the percentage of postings that required AI skills for each occupation, occupational group, and industry sector. This analysis offers valuable insight into the extent to which demand for AI skills has already penetrated different areas of the regional labor market. The same postings also support a second classification, and the type of role workers have with this technology, which is presented in Subsection 2.8.

The tagging problem, and how this analysis addresses it

Lightcast processes each online job posting, identifies the skills it references, and associates a set of standardized skill labels, referred to as tags. The tag is an inference drawn from the posting text, not something the employer supplied. For example, a listing that includes the following statement, “must be proficient in Excel and have experience with SQL,” is tagged with those two skills, even though the employer never used the word “skill.” This mechanism enables a skills-based analysis at scale. Instead of reading several hundred thousand postings, an analyst can filter for every posting that carries a tag from the AI skill list and run those results through this process.

Skill tags are imperfect, and the most common failure in this data has a specific and identifiable cause. Employers increasingly include equal employment opportunity and hiring-process language disclosing that AI is used in resume screening. A tagging system reading that text registers an AI skill, even though the posting describes the employer’s hiring practice rather than the job’s requirements. Treating every tagged posting as genuine demand for AI skills overstates the scale of employer demand.

To address this, the Center of Excellence developed a documented scoring methodology that reads the job posting rather than relying on the skill tag. The approach is deliberately rule-based rather than model-based, so that every result carries a plain-language audit trail and can be explained and defended. Each posting is assessed against two questions: where in the posting is the skill mentioned, and what surrounds that mention?

- Mentions inside legal, EEO, or hiring-process language are excluded, because they describe the employer rather than the job.
- Mentions tied to duty or requirement language such as “experience with,” “develop,” “deploy,” “lead these initiatives” carry a greater weight.
- Corroborating technical terms and related skills elsewhere in the posting add supporting evidence.

Each posting receives a quality tier: High (strong evidence of genuine AI work), Medium (partial evidence, requiring review before use), or Low (high-confidence false positive). These tiers are combined into a confidence rate, weighting High at 1.0, Medium at 0.75, and Low at zero.

The scored sample yields a confidence rate, or the share of tagged postings that genuinely involve AI, which is then applied to the full tagged count for that industry. The AI-related posting counts throughout this report are therefore confidence-adjusted estimates, not raw tagged counts of job postings. It is important to note that job postings measure hiring demand, the openings employers are advertising, and not the number of people currently working in these roles and may serve as an early indicator of where demand is heading.

Taken together, these methods produce a conservative estimate that represents the postings in which regional employers explicitly mentioned that AI skills were integral to the duties of a particular job. The subsequent subsections assess the demand across the region's industries, occupations, and the type of role workers have with this technology.

2.6: Tracking the Drift: Industry Job Posting Analysis

Between July 2025 and June 2026, employers in the Inland Empire/Desert region posted 286,073 unique job postings across all industries and occupations. Of these job postings, 3,395 were tagged with AI skills, accounting for 1.19% of regional job postings. Applying the scoring methodology described above indicates that about 1,425 job postings, or 42% of tagged postings, genuinely sought individuals with AI skills. As a result, only 0.5% of total postings in the Inland Empire/Desert Region genuinely sought individuals with AI skills.

It is important to note that this is not an estimate of how many regional employers use AI. It is a count of how many regional employers wrote AI into the duties of a job they were hiring for, and it excludes every form of adoption described in the preceding subsection. While this share may seem low for the region as a whole, certain industries and occupations show higher concentrations of AI-skill demand in job postings. Exhibit 2.6.1 displays the number of AI job postings, total unique postings, and share of AI postings by industry sector from job postings in the Inland Empire/Desert region over the last 12 months.

Exhibit 2.6.1: AI job postings count and share by industry, Inland Empire/Desert Region, July 2025 – June 2026

Industry Sector (NAICS)	AI Skill Job Postings ▼	Total Job Postings	AI Share of Postings
Professional, Scientific, and Technical Services (54)	453	15,233	3.0%
Manufacturing (31)	168	15,271	1.1%
Real Estate and Rental and Leasing (53)	163	5,852	2.8%
Educational Services (61)	117	12,246	1.0%
Information (51)	87	3,424	2.5%
Health Care and Social Assistance (62)	82	42,779	0.2%
Other Services (except Public Administration) (81)	65	10,439	0.6%
Retail Trade (44)	57	30,927	0.2%
Wholesale Trade (42)	57	8,838	0.6%
Finance and Insurance (52)	40	5,850	0.7%
Public Administration (92)	36	7,022	0.5%
Administrative and Support and Waste Management and Remediation Services (56)	28	10,313	0.3%
Construction (23)	27	7,241	0.4%
Accommodation and Food Services (72)	15	20,129	0.1%
Transportation and Warehousing (48)	13	10,074	0.1%
Utilities (22)	9	1,336	0.7%
Arts, Entertainment, and Recreation (71)	6	3,976	0.2%
Agriculture, Forestry, Fishing and Hunting (11)	2	298	0.7%
Management of Companies and Enterprises (55)	2	359	0.6%
Mining, Quarrying, and Oil and Gas Extraction (21)	0	452	0.0%

Source: COE analysis of Lightcast job posting data (2026.3)

Demand concentrates in a small number of sectors

Three sectors show AI-skill demand well above the regional average of 0.50%: Professional, Scientific, and Technical Services (3.0%); Real Estate and Rental and Leasing (2.8%); and Information industry (2.5%). Despite having relatively low AI shares, employers in the Manufacturing (1.1%) and Educational Services (1.0%) sectors have posted over 100 AI-related job openings in the past year, placing them among the top five industry sectors in total AI-related job postings.

Together, these five sectors, Professional, Scientific, and Technical Services; Manufacturing; Real Estate and Rental and Leasing; Educational Services; and Information, accounted for approximately 69% of all AI job postings in the region, indicating a strong concentration of AI skill demand within a small number of industries. The ten sectors with the fewest AI postings together accounted for less than 10% of the regional total. Notably, Health Care and Social Assistance and Retail Trade represent some of the largest total job posting volumes in the region, yet AI postings account for 0.2% of sector

job postings. Demand is not distributed across the regional economy and is concentrated in a handful of industries.

The region's largest employers are not the ones hiring for AI skills

The sectors generating the most AI postings are not the sectors that employ the most people. Professional, Scientific, and Technical Services produced 453 AI postings, the most of any sector, from 15,233 total postings, and employs 62,522 workers, roughly 3% of regional employment. Real Estate and Rental and Leasing, second by share, employs 29,816. Information employs 14,772.

The region's four largest sectors by job count show a different pattern entirely. Health Care and Social Assistance, with 306,974 jobs in 2025, produced 82 AI postings across 42,779 total postings, a 0.2% share. Retail Trade, with 193,150 jobs, produced 57 AI postings from 30,927 job postings, also 0.2%. Transportation and Warehousing, the region's defining specialization with 208,887 jobs, produced 13 AI postings across 10,074 total, a share of 0.1%. Accommodation and Food Services, at 169,397 jobs, produced 15.

Taken together, these four sectors employ approximately 878,000 people, which is roughly 45% of regional employment, and account for 167 AI postings, or about 12% of the regional total.

What this pattern does and does not indicate

The concentration described here reflects where employers are stating a need for AI skills in the jobs they are posting. It should not be interpreted as a map of where AI is presented in regional workplaces.

The preceding subsection identified several reasons a sector might show few AI postings, including employers adopting the technology through existing staff rather than new hires, hiring managers who do not describe the work in the vocabulary a skill taxonomy recognizes, and roles advertised through staffing agencies and attributed to a different sector. Each of these applies with particular force to the sectors that provide the highest employment above. A hospital system introducing AI-assisted documentation trains the medical records staff it already employs. A distribution center adopting automated routing does not necessarily advertise for it, and a substantial share of warehouse hiring in this region moves through staffing firms classified under administrative and support services.

The data does establish where employers state a need for AI skills: in a small number of knowledge-intensive sectors, and rarely in the industries where most of the region's workforce is employed. Whether that absence reflects low adoption or unstated adoption is a question that job posting data alone cannot answer. The occupational analysis that follows approaches the same postings from a different lens, examining the types of work, rather than employers, attached to stated AI demand.

2.7: Tracking the Drift: Occupation Job Posting Analysis

While industry-specific job posting data may provide insight into employer adoption and integration of artificial intelligence, they do not identify which types of roles are most likely to require AI skills. Exhibit 2.7.1 displays the number of AI job postings, total postings, share of AI postings by major occupational group, and the major occupational group's share of regional AI postings. Major occupational groups reflect similar themes to the industry-level data but reveal how AI skill concentration differs by role.

Exhibit 2.7.1: AI job postings count and share by major occupational group, Inland Empire/Desert Region, July 2025 – June 2026

Major Occupational Group (SOC2)	2025 Jobs ▼	Automation Exposure	AI Job Postings	Total Job Postings	AI Share of Postings
Transportation and Material Moving (53-0000)	285,904	6.3%	52	24,435	0.2%
Office and Administrative Support (43-0000)	180,720	23.8%	65	24,921	0.3%
Building and Grounds Cleaning and Maintenance (37-0000)	172,579	2.4%	4	7,328	0.1%
Sales and Related (41-0000)	156,517	12.2%	90	37,765	0.2%
Healthcare Support (31-0000)	151,597	3.6%	18	15,416	0.1%
Educational Instruction and Library (25-0000)	114,566	3.6%	56	9,986	0.6%
Management (11-0000)	110,130	10.8%	189	26,573	0.7%
Protective Service (33-0000)	102,744	6.1%	8	7,512	0.1%
Healthcare Practitioners and Technical (29-0000)	102,621	5.6%	86	35,926	0.2%
Business and Financial Operations (13-0000)	82,795	12.3%	117	13,160	0.9%
Production (51-0000)	77,605	4.3%	17	8,118	0.2%
Installation, Maintenance, and Repair (49-0000)	71,952	4.8%	75	13,320	0.6%
Food Preparation and Serving Related (35-0000)	70,252	5.1%	4	18,342	0.0%
Personal Care and Service (39-0000)	59,630	7.1%	7	5,426	0.1%
Construction and Extraction (47-0000)	49,697	1.7%	8	4,868	0.2%
Community and Social Service (21-0000)	39,985	9.6%	39	7,211	0.5%
Arts, Design, Entertainment, Sports, and Media (27-0000)	25,869	10.9%	32	6,928	0.5%
Computer and Mathematical (15-0000)	22,073	27.6%	388	5,355	7.2%
Architecture and Engineering (17-0000)	18,027	6.7%	81	3,340	2.4%
Life, Physical, and Social Science (19-0000)	13,076	4.4%	52	3,518	1.5%
Farming, Fishing, and Forestry (45-0000)	10,760	8.1%	0	578	0.0%
Legal (23-0000)	9,536	3.9%	7	1,698	0.4%

Source: COE analysis of Lightcast job posting and staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

Demand is concentrated in technical occupations

Computer and Mathematical occupations show by far the highest share of job postings requiring AI skills, at 7.2%, nearly three times the next-highest group of occupations and roughly fourteen times the regional average of 0.50%.

Only two other occupational groups exceed 1.0%. Architecture and Engineering (2.4%) and Life, Physical, and Social Science (1.5%). Every remaining occupational group in the region falls below that threshold.

By volume rather than share, two additional groups stand out. Management occupational group included 189 postings, and Business and Financial Operations posted 117; each had more than 100 AI-related job postings over the last 12 months, despite comparatively modest AI shares of 0.7% and 0.9%, respectively.

Together, the top five occupational groups by posting volume, Computer and Mathematical; Management; Business and Financial Operations; Sales and Related; and Healthcare Practitioners and Technical, accounted for approximately 61% of all AI job postings in the region, indicating a strong concentration of AI skill demand within a small number of occupational groups. Notably, two of these top five groups, Sales and Related and Healthcare Practitioners and Technical, carry some of the lowest AI shares in the table (0.2% each), echoing the industry-level pattern in which high posting volume and high AI skill concentration do not necessarily move together.

Where stated demand and measured exposure diverge

Subsection 2.3 reported which occupational groups carry the highest AI task exposure. Placing those findings alongside those in this section shows that the two measures agree in some cases and diverge sharply in others.

These two measures agree at the highest levels of exposure. Computer and Mathematical occupations rank first on both with 27.6% automation exposure and 7.2% of postings. This work is both technically applicable to AI and explicitly named in hiring.

They also agree at the lowest. Construction and Extraction (1.7% automation exposure, 0.2% of postings), Building and Grounds Cleaning and Maintenance (2.4%, 0.1%), and Food Preparation and Serving Related (5.1%, 0.0%) show low values on both measures. Neither the exposure data nor the posting data indicates substantial AI activity in this work.

The two measures diverge at moderate exposure levels, and the divergence is substantial.

Office and Administrative Support carries the second-highest automation exposure of any occupational group at 23.8%, however only 0.3% of its postings seek AI skills, under the regional average. It employs 180,720 workers, the second-largest group in the region.

The pattern repeats elsewhere. Sales and Related shows 12.2% automation exposure against 0.24% of postings, across 156,517 workers. Management shows 10.8% automation exposure against 0.7% of postings, across 110,130 workers. Transportation and Material Moving, the region's largest group at 285,904 workers, shows 6.3% automation exposure against 0.21% of postings.

Office and Administrative Support, Sales and Related, Management, and Transportation and Material Moving together employ approximately 733,000 workers, which is roughly 38% of regional employment. In each, the exposure data indicates that AI is observed performing a measurable share of the tasks the work involves, while the posting data shows employers naming AI skills at or below the regional average.

How to read that gap

Two explanations are consistent with the evidence, and they are not mutually exclusive.

The first is timing. Employers may not yet be hiring for AI skills in these occupations because adoption has not reached them, or because it is occurring through existing staff rather than new hires, which was described in subsection 2.5.

The second is that AI skills are not the hiring criterion in these roles. An employer filling an administrative position may value the same underlying capabilities regardless of whether a candidate uses AI to exercise them and may see no reason to name a tool in the posting.

What the gap does not say is that these occupations are unaffected. Exposure and stated demand measure different things, and these four groups point in different directions.

For educators, this is the most consequential pattern in the posting data. Where exposure and demand both run high, employers are signaling what they need, and programs can respond to that signal. Where exposure is high, and demand is low or absent, curriculum decisions rest on evidence about the work itself rather than on what employers are currently asking for. Office and Administrative Support, which is the region's second-largest occupational group, sits in that position.

Subsection 2.8 approaches these same postings from a third direction, examining not which occupations carry AI demand but what relationship to the technology employers describe within them.

2.8: Storm Chasers: AI Worker Types in the Inland Empire

The preceding subsections analyzed AI-related postings by industry and occupation. The following subsection asks a different question of the same postings. When a regional employer does include AI skills in a job, what are they asking the worker to do with it?

How postings are classified

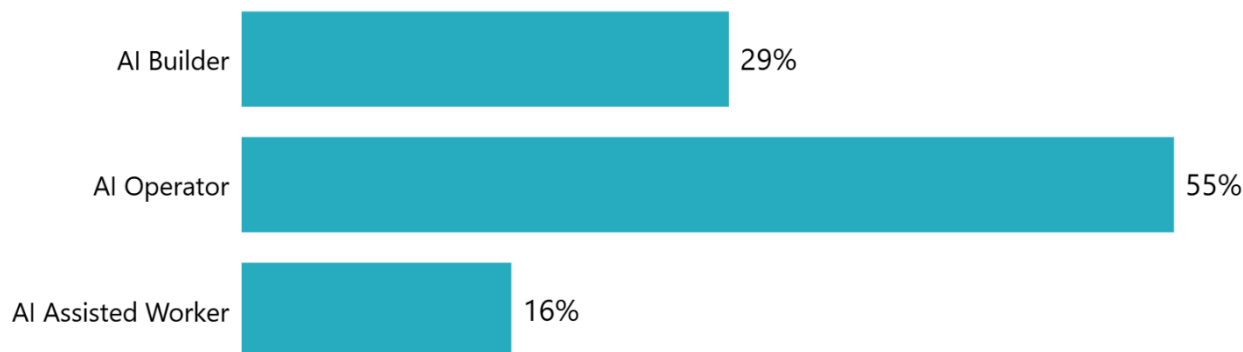
Section 1.3 introduced three ways a job can relate to AI. The scoring methodology assigns each posting to one of them based on the duty language in the job description, corroborated by the skills tagged on the posting record.

- **AI Builder:** the job posting asks the worker to design, develop, train, or engineer AI systems. Build-or-develop language must appear, and an AI-development skill must be present on the record; a build verb alone does not qualify.
- **AI Operator:** the posting requires the worker to run, apply, or work within AI-powered systems to perform the role's tasks. This includes maintaining or supporting AI-driven equipment.
- **AI Assisted Worker:** the posting names AI as an optional aid rather than a requirement, through language such as "familiarity with," "a plus" or "nice to have."

Two rules resolve postings that show evidence of more than one category. A posting containing both build language and application language is classified as Builder, since building the technology is the more specific relationship. A posting containing a genuine mention accompanied by optional language such as "a plus," or "nice to have" is classified as Assisted Worker rather than Operator, since the requirement is not binding. These categories describe the role employers advertised, not the AI activity occurring in the region's workplace. A posting is a record of one opening, not a measure of how many workers hold that relationship to the technology.

What the region's AI postings say

Exhibit 2.8.1: AI workforce categories in AI job postings, Inland Empire/Desert Region, July 2025 – June 2026



Source: COE analysis of Lightcast staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

The majority of the region’s AI-related postings (55%) describe AI Operator roles as jobs where using an AI-powered system is part of performing the work, which is a different job function than building an AI system. AI Builder roles accounted for 29% of total job postings, and AI Assisted Worker roles represented 16%. The practical reading is that when a regional employer advertises for AI, they are typically hiring someone to work with the technology rather than to create it. This is consistent with the region’s industry composition. The occupational and industry groups where AI development work is represented faintly are Computer and Mathematical occupations, which account for roughly 1% of regional employment, and both Information and Professional, Scientific, and Technical Services show employment concentrations below half the national average.

Why Assisted Workers are the hardest to count

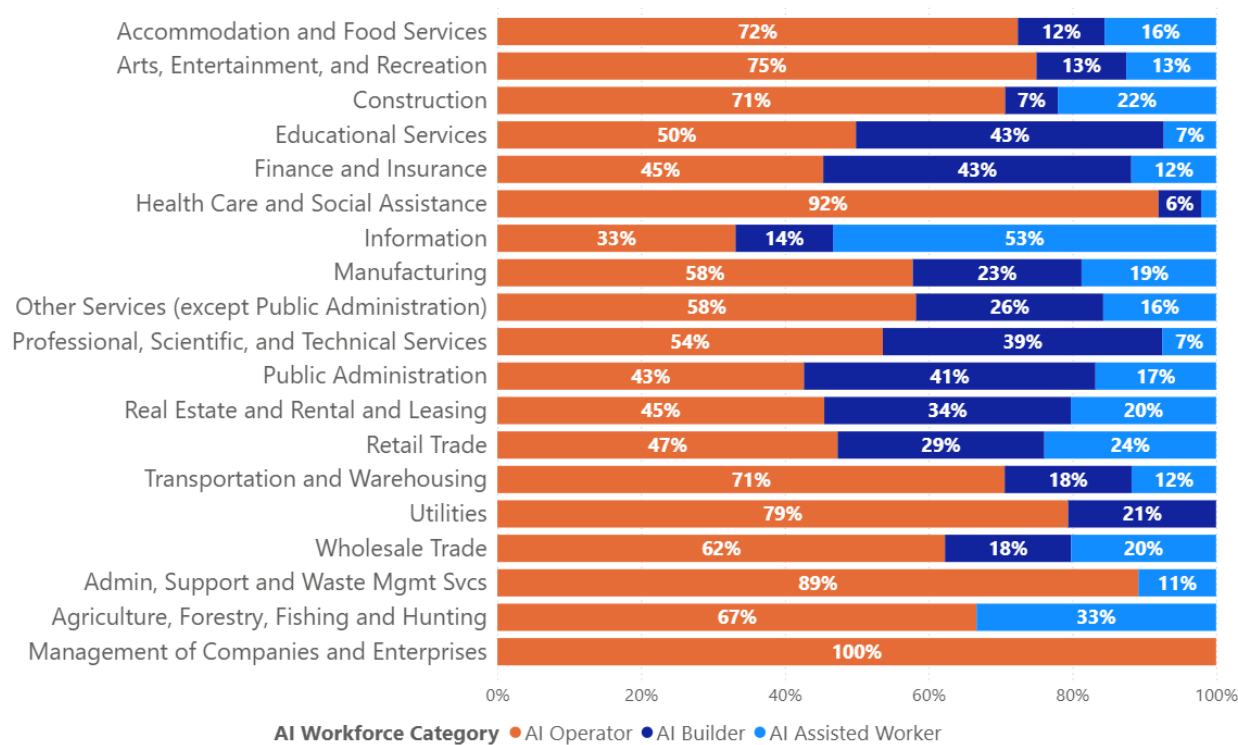
The three categories are not equally visible in posting data, and the difference is systematic. A Builder or Operator relationship must be stated, because it is a condition of employment. An employer cannot advertise for a machine learning engineer without naming the technology and cannot require a worker to operate an AI-driven system without describing it. An Assisted Worker relationship carries no such requirement. It is optional by definition; it does not screen candidates, and employers have little reason to mention it.

The 16% figure therefore represents the postings in which an employer chose to mention an optional tool, not an estimate of how many regional workers use AI to do ordinary work more effectively. National survey evidence suggests informal, worker-initiated adoption is far more common than any employer-stated measure would indicate.²⁴ This category of worker is the one most likely to grow, and the one this instrument is least able to see.

The same three relationships look different by sector

²⁴ Microsoft & LinkedIn. (2024). *AI at work is here. Now comes the hard part: 2024 work trend index annual report*. Microsoft.

Exhibit 2.8.2: AI workforce categories in AI job postings by industry sector (2-digit), Inland Empire/Desert Region, July 2025 – June 2026



Source: COE analysis of Lightcast job posting data (2026.3)

Operator roles are the majority in thirteen of the nineteen sectors with AI postings, but the composition varies substantially.

Builder demand concentrates in a small group of sectors.

Educational Services (43%), Public Administration (41%), and Professional, Scientific, and Technical Services (39%) show the highest share of AI Builder workers. In these sectors, roughly two in five AI postings ask workers to develop the technology rather than apply it.

Several large-employment sectors show no Builder demand at all.

Health Care and Social Assistance, Administrative and Support Services, and Agriculture recorded no Builder postings during the year. Health Care is the clearest case: 92% of its AI postings describe Operator roles, workers required to use AI-powered systems in clinical, administrative, or documentation work. Information is the only sector where Assisted Worker postings form a majority at 53%. Its AI-related postings are more likely to describe AI as an optional aid than as a requirement, which is the reverse of the pattern elsewhere.

Transportation and Warehousing follows the Operator-dominant pattern, at 71% Operator, 18% Builder, and 12% Assisted Worker. The sector’s AI posting volume is very small, so these shares rest on a few postings and should be read with corresponding caution.

What this means for regional educators

This distribution carries a direct implication for program design. AI Builder roles account for 29% of AI postings in a region that produces roughly 1,425 such postings a year, so the estimated number of Builder openings is modest, at approximately 400 a year across all industries.

The Operator type job is where the region's demand concentrates, and it is the type of job most compatible with community college and K-12 preparation. An Operator does not need to build a model. They are asked to apply a model competently within their occupation, which requires understanding what the system does, recognizing when its output is wrong, and exercising the domain judgment the tool cannot supply.

The Assisted Worker relationship is the smallest category in the posting data, including no employer mandate and no job requirement, only a worker who recognizes that a tool can improve their work and knows how to use it well. What distinguishes these workers is not tool familiarity. Anyone can open a chatbot. The difference is domain knowledge deep enough to evaluate when to use a tool for a specific use case, how it applies to their work, and how to use it effectively.

Educators should take note of this finding. The capabilities that make an Assisted Worker effective, evaluating output, verifying accuracy, exercising judgment about where a tool fits, are extensions of what programs already develop within a discipline, not a separate technical skill set.

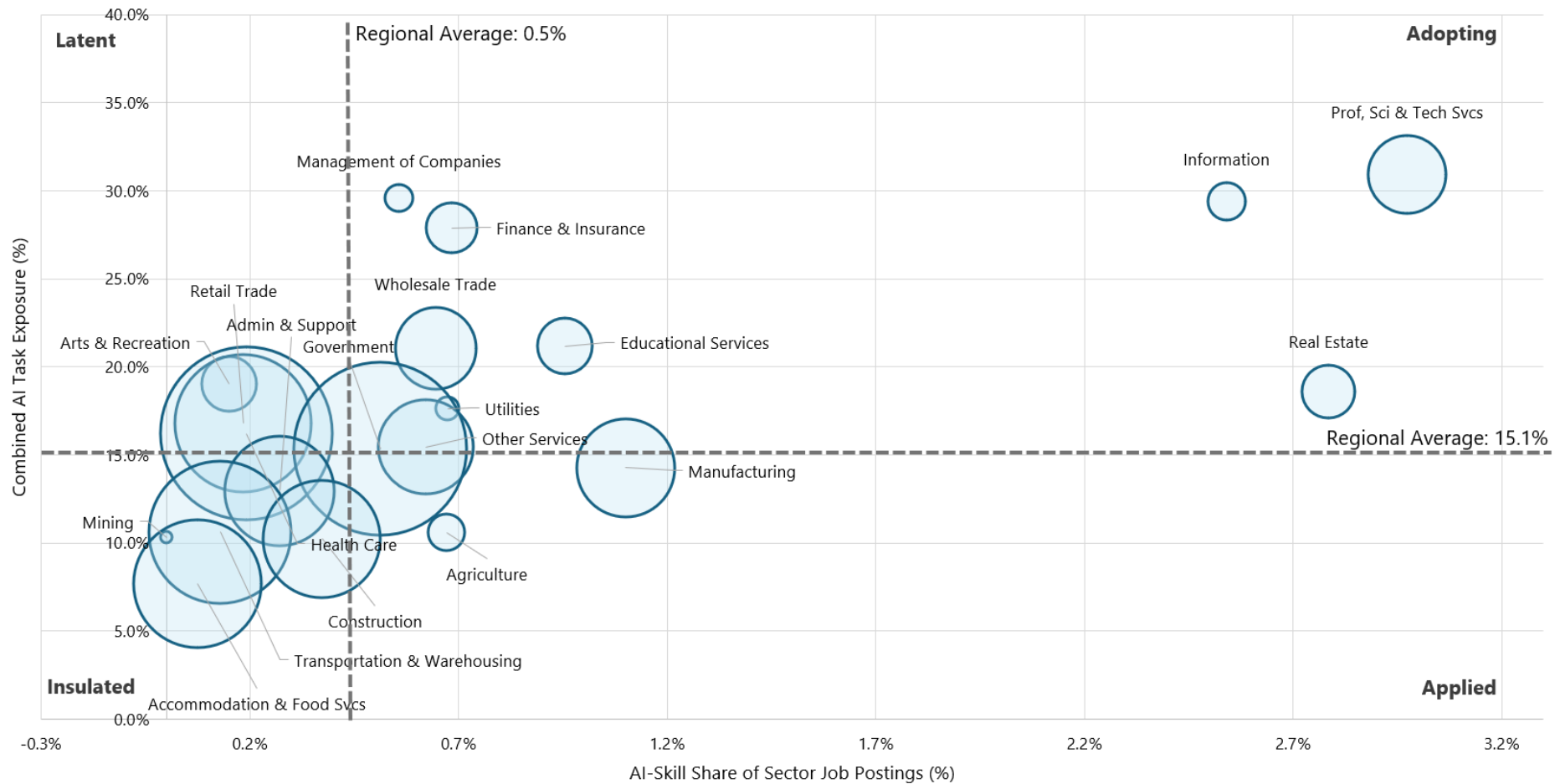
Three lenses have now been applied to the region's AI-related postings: which industries generate them, which occupations they describe, and what relationship to the technology they describe. Each answers a different question, and all three describe employer-stated demand.

In conjunction with the exposure analysis in Subsections 2.2 through 2.4, a pattern emerges that neither instrument produces alone. The sectors where AI could reach the most work are not consistently the sectors where employers are hiring for it. The final subsection places both measures on the same axes and examines what their agreement and disagreement indicate for the region.

2.9: Where Potential and Demand Diverge

The two instruments used in this analysis measure different things. Task exposure describes what current AI systems could plausibly do in the work performed across the region. Job postings describe what employers are actually hiring for. Neither forecasts the future impact AI may have on the regional labor market, and where they disagree, however the disagreement is informative unto itself. Exhibit 2.9.1 plots every industry sector against both Task exposure and the share of AI-skill Job postings, with bubble size representing 2025 employment. Sectors are assigned to quadrants by whether they fall above or below the regional average on each measure: 15.1% combined task exposure on the vertical axis, and a 0.5% AI-skill share of postings on the horizontal axis. This four-quadrant framework was developed by the Center of Excellence for this analysis; the labels are descriptive rather than drawn from an established typology.

Exhibit 2.9.1: Industry exposure vs job posting demand, Inland Empire/Desert Region, 2025



Source: COE analysis of Lightcast job posting and staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

Industry sectors fall within four categories of AI adoption:

- **Adopting sectors** show above-average exposure and above-average job posting demand. In these sectors, the work that AI can plausibly perform is also the work employers are actively recruiting AI skills to do. Professional, Scientific, and Technical Services and Information anchor this group, joined by Finance and Insurance, Management of Companies, Wholesale Trade, Educational Services, Real Estate, Utilities, Other Services, and Government.
- **Latent sectors** show above-average exposure, but limited job posting demand. These sectors represent the widest gap between what AI could do and what employers currently need. Health Care and Social Assistance, Retail Trade and Arts, Entertainment, and Recreation show the greatest disconnect.
- **Applied sectors** show below-average exposure overall, but concentrated job posting demand. Manufacturing has exposure below the regional average but the second-highest number of AI job postings in the region, which may indicate that AI is applied to specific functions rather than diffusing across the sector's workforce. Agriculture, Forestry, Fishing, and Hunting also falls into this quadrant.
- **Insulated sectors** show below-average exposure and limited job posting demand, making them insulated from the impacts of AI in the near-term. Transportation and Warehousing, Construction, Administrative and Support Services, Accommodation and Food Services, and Mining are less exposed than other sectors and demonstrate limited job posting demand.

Employment and AI demand sit in different quadrants.

Nearly three-quarters of the region's projected job growth is in sectors where employers are not currently advertising for AI skills, and more than half of that growth is in sectors where AI exposure is above average. The quadrants above are defined entirely by two data points: what share of a sector's tasks are exposed, and what share of its postings seek AI skills. Neither account for a sector's size. Bubble size in Exhibit 2.9.2 gives a visual sense of scale, but the quadrant assignment does not depend on it. Adding employment and projected growth answers a different question about how much of the region's workforce sits in each quadrant and not where AI activity is concentrated.

Exhibit 2.9.2: AI exposure and demand by quadrant, Inland Empire/Desert Region, 2025

Quadrant - Industry Sector	2025 Jobs	2025-2030 Change	Share of Regional AI Exposure	Share of AI Postings
Adopting (high exposure, high demand)	648,446	37,401	42.0%	72.1%
Government	307,021	19,290	16.1%	2.5%
Other Services (except Public Administration)	93,808	6,388	5.0%	4.6%
Wholesale Trade	68,242	2,608	4.9%	4.0%
Professional, Scientific, & Technical Services	62,522	3,608	6.6%	31.8%
Educational Services	31,923	3,991	2.3%	8.2%
Real Estate & Rental & Leasing	29,816	1,270	1.9%	11.5%
Finance and Insurance	26,511	-1,173	2.5%	2.8%
Information	14,772	1,817	1.5%	6.1%
Management of Companies & Enterprises	8,204	-449	0.8%	0.1%
Utilities	5,627	52	0.3%	0.6%
Latent (high exposure, low demand)	531,168	56,858	30.1%	10.1%
Health Care & Social Assistance	306,974	47,744	17.0%	5.8%
Retail Trade	193,150	6,135	11.1%	4.0%
Arts, Entertainment, & Recreation	31,044	2,980	2.0%	0.4%
Applied (low exposure, high demand)	114,222	-1,006	5.4%	12.0%
Manufacturing	99,966	-278	4.9%	11.8%
Agriculture, Forestry, Fishing & Hunting	14,256	-729	0.5%	0.2%
Insulated (low exposure, low demand)	645,047	35,419	22.5%	5.8%
Transportation & Warehousing	208,887	17,155	7.6%	0.9%
Accommodation & Food Services	169,397	12,286	4.5%	1.0%
Construction	141,254	4,317	4.9%	1.9%
Admin, Support & Waste Mgmt Services	123,851	1,463	5.5%	2.0%
Mining, Quarrying, & Oil & Gas Extraction	1,658	199	0.1%	0.0%

Source: COE analysis of Lightcast job posting and staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

The Latent and Insulated quadrants hold 60.7% of regional jobs and are projected to generate 71.7% of net job growth through 2030, while accounting for 15.9% of AI posting demand. Most of the region's workforce, and most of where its new jobs are coming from, is in sectors sending little hiring signal about AI.

This key finding is what matters for program planning.

Sectors in the Insulated quadrant show below-average exposure and little hiring signal around AI. The two instruments agree, and IE/D's educational system offering programs that support these sectors has a defensible basis for treating AI as a longer-term consideration.

Sectors in the Latent quadrant show above-average exposure, meaning a meaningful share of the tasks these workers perform are tasks where AI is observed performing, while employers advertise AI skills at below-average rates. The fact that this is where the region's growth is concentrated - Latent sectors are projected to generate 44.2% of net job growth, the largest share of any quadrant, from 27.4% of current employment necessitates a focus on the future state of educational program design for jobs in these sectors. As presented in earlier sections, the below-average advertised AI skills signal can be driven by many factors. Employers in these sectors may not have adopted the technology. Employers may have adopted AI in ways that generate no postings, such as through existing staff, through software their vendors have updated, or without describing it in terms a job listing would capture.

Any of these reasons, given the findings from the data, lead to the same conclusion. A sector in the Adopting quadrant is telling colleges what it needs through its hiring. A sector in the Latent quadrant is not sending the same signal and will not until the change is already underway within their organizations. Programs serving Latent sectors have no employer signal to respond to, which means decisions about those programs rest on evidence about the work itself rather than on what employers are currently asking for.

Taken together, Sections 1 and 2 describe a region where AI exposure and employer hiring signal do not line up, and where the gap between them is widest in the sectors carrying the most jobs and the most growth. Regional totals alone cannot tell an educator which programs to build or change. To move from measurement to conclusions educators can act on, the report shifts to the industry level. Section 3 reports what four sectors show when examined at the occupational and industry group level, drawing on the full sector analyses presented in Appendices 1 through 4.



SECTION 3: INTRODUCTION TO THE INDUSTRY SECTIONS

3.1: Assessing How AI Impacts Key Sectors

The region has approximately 1.94 million jobs and 1,425 AI-impacted job postings. Section 2 established that those postings were concentrated in sectors that employ a small share of the regional workforce, while the sectors driving most of the region's employment and projected growth generate little AI hiring signal.

The finding sets the question this section answers. Knowing which sectors show a gap between exposure and demand does not tell an educator which programs are affected. Each sector-level exposure figure is an average across every occupation an industry employs and the number of jobs for each. A hospital system employs surgeons, medical coders, food service workers, and IT administrators under a single industry code, and the single figure reported for that sector describes none of them precisely.

The same limitation applies to the quadrant framework. A sector can post for AI skills at well above the regional rate while sending no signal at all to the credential level K12 and community colleges serve, as Professional, Scientific, and Technical Services does.

This is not a flaw in the sector-level analysis, but it does limit what that analysis can tell a program designer. This section therefore reports findings for four sectors examined at the industry group and occupational level, where the variation that sector averages conceal becomes evident and where findings can be matched to specific programs. The full analysis supporting these findings is presented sector by sector in Appendices 1 through 4, and readers whose programs serve a particular sector will find the detail there.

3.2: The Four Sectors and Why They Were Selected

Sectors were selected on regional economic weight, with employment volume and projected employment growth carrying the greatest weight. We also considered employment concentration, AI exposure, AI job posting demand, and alignment with regional educational programs serving each sector.

The four sectors selected are:

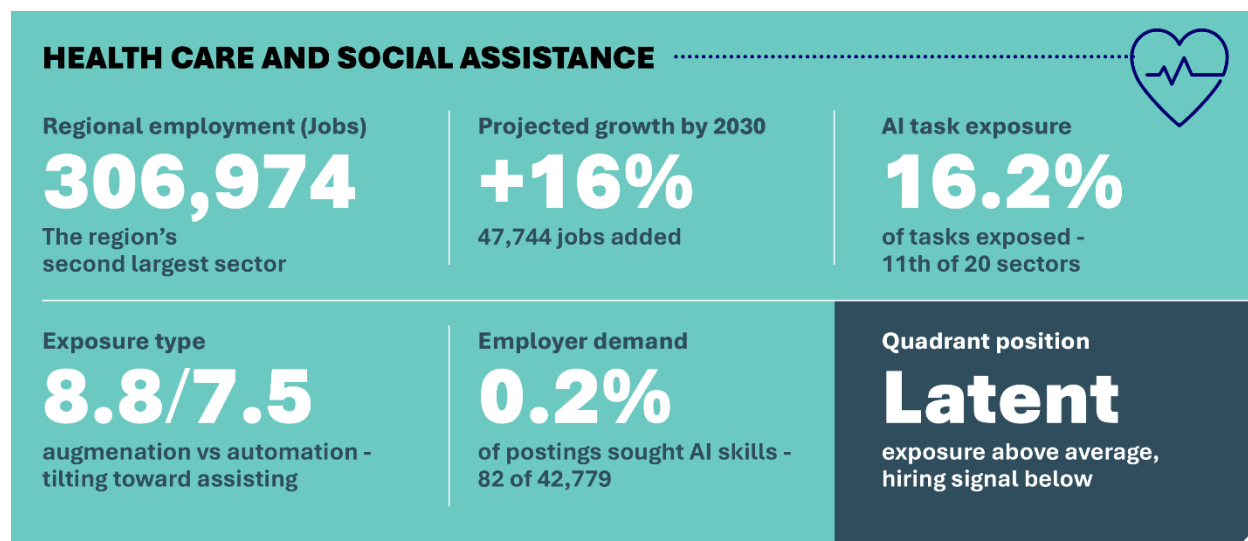
- Health Care and Social Assistance
- Transportation and Warehousing
- Professional, Scientific, and Technical Services
- Manufacturing

Together, these sectors employ a substantial share of the regional workforce and include the region's most concentrated industry specialization. Based on our analysis, each sector also occupies a different position in the exposure-demand framework, allowing the analysis in Appendices 1 through 4 to cover the full range of relationships between what AI could reach and what employers are asking for.

Health Care and Social Assistance

Within the sector's core middle-skill occupations, exposure concentrates in administrative work. Clerking, billing, and administrative occupations account for four of the five most exposed. At the other end, ten core occupations show no measurable AI exposure in the underlying data, including several centered on ophthalmology and direct patient treatment. The industry groups carrying the most exposed employment are Offices of Physicians and Offices of Other Health Practitioners, both at 21%, followed by Child Care Services and Outpatient Care Centers at 17%.

The 82 AI-related postings the sector produced also differ in character from the region overall. Ninety-two percent describe AI Operator roles, work requiring a person to use an AI-powered system, against 55% regionally. AI Builder postings account for 6% versus 29% regionally, and AI Assisted Worker postings account for 2% versus 16%. Where this sector hires for AI, it hires people to use it, not to build it.



Transportation and Warehousing

Within the sector's core middle-skill occupations, exposure concentrates entirely in office-based work: management and office operations occupations account for all five of the most exposed. Twelve core occupations show no measurable AI exposure in the underlying data, the majority focused on railroad and aircraft operations. The industry groups carrying the most exposed employment are Warehousing and Storage and Freight Transportation Arrangement, both at 19%, followed by Taxi and Limousine Services at 18% and Support Activities for Air Transportation at 15%.

The sector produced 13 AI-related postings over twelve months, the second-lowest count of any sector. That volume is too small to support firm conclusions about composition, but the pattern is consistent with the region's other large employers: 71% describe AI Operator roles against 55% regionally, with AI Builder postings at 18% and AI Assisted Worker postings at 12%.

TRANSPORTATION AND WAREHOUSING



Regional employment (Jobs)

208,887

The region's most concentrated sector

Projected growth by 2030

+8%

17,155 jobs added

AI task exposure

10.6%

of tasks exposed - 5th lowest of 20 sectors

Exposure type

2.9/7.8

augmentation vs automation - tilting toward performing

Employer demand

0.1%

of postings sought AI skills - 13 of 10,074

Quadrant position

Insulated

exposure and hiring signal both below average

Professional, Scientific, and Technical Services

Within the sector's core middle-skill occupations, exposure spans the widest range of any sector examined. Legal occupations account for two of the three most exposed, while veterinary science occupations are the two least exposed, a contrast that reflects the difference between document-centered work and work requiring physical handling of animals. The industry groups carrying the most exposed employment are Accounting, Tax Preparation, Bookkeeping, and Payroll Services at 40%, followed by Computer Systems Design and Related Services at 33%, Legal Services at 32%, and Management, Scientific, and Technical Consulting Services at 29%.

The sector produced 453 AI-related postings, more than any other in the region, and their composition differs from the regional pattern. Thirty-nine percent describe AI Builder roles against 29% regionally, the highest Builder share of any sector, while AI Assisted Worker postings account for 7% against 16%. AI Operator postings sit at 54%, almost exactly the regional rate. Where this sector hires for AI, it is more likely than any other to hire people to build it.

PROFESSIONAL, SCIENTIFIC, AND TECHNICAL SERVICES



Regional employment (Jobs)

62,522

3.2% of regional employment

Projected growth by 2030

+6%

3,608 jobs added

AI task exposure

31%

of tasks exposed - highest of 20 sectors

Exposure type

16.1/14.9

augmentation vs automation - tilting toward assisting

Employer demand

3.0%

of postings sought AI skills - 453 of 15,233

Quadrant position

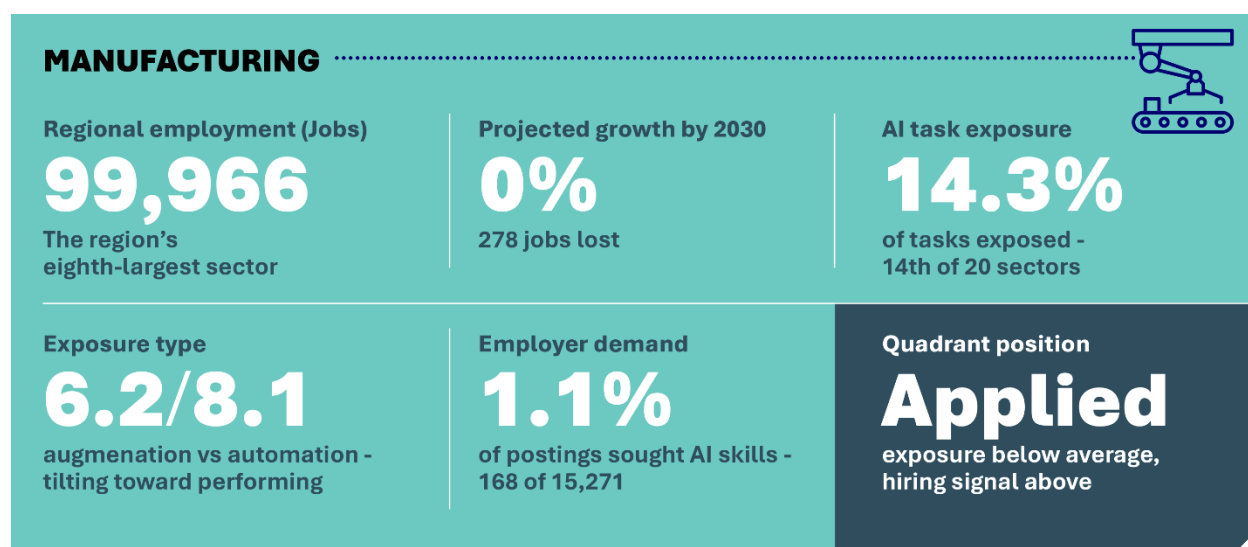
Adopting

exposure and hiring signal both above average

Manufacturing

Within the sector's core middle-skill occupations, exposure concentrates in technical and coordinating work: drafting, measuring, and management operations occupations account for three of the four most exposed. Eleven core occupations show no measurable AI exposure in the underlying data, with machine tending and laboratory operations making up five of the eleven. The industry groups carrying the most exposed employment are Bakeries and Tortilla Manufacturing at 23%, followed by Other Food Manufacturing and Other Miscellaneous Manufacturing at 20% each, and Architectural and Structural Metals Manufacturing at 19%.

The sector produced 168 AI-related postings, the second-highest count of any sector, and its composition closely tracks the region overall: AI Operator roles at 58% against 55% regionally, AI Builder roles at 26% against 29%, and AI Assisted Worker roles at 16%. Unlike the other three sectors examined, Manufacturing's AI hiring looks like the regional average in kind and differs mainly in volume.



3.3: Findings Across the Four Sectors

Section 3.2 presents findings for each of the four sectors individually. Read alongside one another, the four sector analyses show three patterns that no single sector section makes visible.

The most exposed occupations within each sector perform coordination work rather than the sector's defining activity.

The four sectors occupy four different positions in the quadrant framework and share almost no occupational overlap. The most exposed Industry Core middle-skill occupations within each one are nonetheless the same kind of work.

Exhibit 3.3.1: Most exposed Industry Core middle-skill occupations in the four sectors examined, Inland Empire/Desert Region, 2025

Industry Sector	Most Exposed Industry Core Occupations	Total AI Exposure
Health Care and Social Assistance	Receptionists and Information Clerks	56%
	Billing and Posting Clerks	36%
Transportation and Warehousing	Transportation, Storage, and Distribution Managers	30%
	First-Line Supervisors of Transportation and Material Moving Workers	29%
Professional, Scientific, and Technical Services	Paralegals and Legal Assistants	33%
	Legal Secretaries and Administrative Assistants	29%
Manufacturing	Mechanical Drafters	33%
	First-Line Supervisors of Production and Operating Workers	25%

Source: COE analysis of Lightcast staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

The Industry Core occupations showing no measured exposure are equally consistent across sectors and consistently hands-on. They include ophthalmic occupations, surgical technologists, phlebotomists, and physical therapist aides in Health Care and Social Assistance; railroad and aircraft operations in Transportation and Warehousing; machine tending and laboratory technician occupations in Manufacturing; and veterinary occupations in Professional, Scientific, and Technical Services (see Appendices 1.2, 2.2, 3.2, and 4.2).

This pattern has implications for program review. The exposed programs are frequently not the ones housed in the department that serves the sector. A hospital system's exposure concentrates in medical records and health information, billing and coding, scheduling and intake, patient access, and care coordination (see Appendix A1.5). A distribution center's exposure concentrates in dispatch and load planning, freight and customs documentation, billing and claims, and customer service (see Appendix A2.5). These programs commonly sit within business and office administration program areas rather than within allied health or logistics. Program review organized by sector may not surface them.

A sector's quadrant position describes a signal that may not reach the credential level community colleges serve.

Section 2.9 places Professional, Scientific, and Technical Services in the Adopting quadrant because its employers post for AI skills at approximately six times the regional rate. Examined at the middle-skill level, the sector behaves differently. Across its four most exposed industry groups, AI-related postings run between 0.25% and 0.64%, at or below the regional average (see Appendices 3.3 and 5.3). The sector's AI hiring is concentrated in roles requiring a bachelor's degree or more.

The industry group analysis makes the same point at the occupational level. In Legal Services, three notable middle-skill occupations generated 439 postings over twelve months, of which two genuinely requested AI skills. In Accounting, Tax Preparation, Bookkeeping, and Payroll Services, the most exposed industry group in the sector at 39% total exposure, three notable middle-skill occupations generated 1,994 postings, of which five genuinely requested AI skills, or 0.2%.

A sector can therefore be adopting AI at a rate well above the regional average while sending no signal at all to the credential level a community college serves. Read the quadrant position as a sector-level descriptor rather than guidance for middle-skill program design.

Whether exposure appears as automation or as augmentation may track an occupation's accountability for the outcome.

Within the same industry group, occupations at comparable levels of total exposure divide sharply by the direction of that exposure. Paralegals and Legal Assistants show 33% exposure, effectively all of it augmentation, while Legal Secretaries and Administrative Assistants show 29% exposure that is automation-led, at 21%. Bookkeeping, Accounting, and Auditing Clerks show 46% exposure driven primarily by automation, and Computer User Support Specialists show 56% exposure on the same pattern. General and Operations Managers, Civil Engineering Technologists and Technicians at 29%, and Mechanical Drafters at 33% are all augmentation-led. Receptionists and Information Clerks show 56% exposure, with 39% automation-led.

These figures suggest a pattern: where an occupation carries responsibility for a judgment others rely on, exposure appears as augmentation; where an occupation produces a record for others to act on, exposure appears as automation.

This is offered as an observation rather than a finding, and it has at least one visible counterexample. Billing and Posting Clerks are augmentation-led in both sectors where the occupation appears, despite being a records-producing role (see Appendix A1.2). If the pattern holds under further testing, it would give program designers a way to reason about occupations for which no observed exposure data yet exists.

These three patterns, together with the sector findings above, complete the industry-level evidence this report presents. Section 4 sets out the report's conclusions, drawing on the regional findings of Sections 1 and 2 and the industry-level findings of this section.



SECTION 4: THE ONLY WAY OUT IS THROUGH

4.1: Regional Impact

1. The Inland Empire/Desert Region is less exposed to AI than California overall, but lower exposure is not the same as lower risk.

Approximately 15.1% of task-weighted employment in the region is exposed to AI, consisting of 8.2% exposed to automation and 6.9% to augmentation, compared with 18.3% statewide (see Section 2.2). That gap reflects the region's occupational composition rather than any regional difference in how a given job is performed.

The same composition that produces the lower figure also limits the region's access to AI's benefits. Regional residents are less likely to hold a bachelor's degree (15.7% versus 22.6%) or a graduate degree (8.9% versus 14.5%), and more likely to hold a high school diploma or less as their highest attainment (45.0% versus 36.3%) (see Section 1.2). Above middle-skill work is where exposure takes the form of augmentation rather than substitution (see Section 2.4). A region with proportionally fewer credentialed workers is therefore positioned for a slower pace of AI-driven disruption and for a smaller share of the productivity gains that accompany it.

2. Exposure follows the nature of the work rather than the employer.

Across the region's industry sectors, automation exposure ranges from 5.4% to 15.7%, a spread of roughly three times. Across major occupational groups, the same measure ranges from 1.7% in Construction and Extraction to 27.6% in Computer and Mathematical occupations, a spread of roughly sixteen times (see Sections 2.2 and 2.3).

Industry establishes how much work exists in the region and where it is located. Occupation establishes what that work consists of. Because a single industry code covers a hospital's surgeons, medical coders, food service staff, and IT administrators alike, a sector-level exposure figure averages together work with little in common. Findings intended to inform decisions about a specific program require the occupational view.

3. Automation exposure peaks at the middle-skill level, the education tier regional community colleges serve most directly.

Automation exposure does not rise steadily with education. It is highest for middle-skill occupations at 10.1%, slightly lower for above middle-skill occupations at 9.1%, and lowest for below middle-skill occupations at 5.7% (see Section 2.4). Middle-skill occupations account for 42.7% of regional employment, or approximately 828,000 jobs, the largest of the three tiers.

The direction of exposure also inverts across tiers. At the middle-skill level, automation exposure (10.1%) exceeds augmentation exposure (7.5%). At the above middle-skill level, the relationship reverses, with augmentation at 12.6% exceeding automation at 9.1%. Middle-skill work concentrates structured, procedural, information-handling activity such as processing records, coding claims, scheduling, preparing documents, and reconciling data, which is the work AI is observed completing. Above middle-skill work concentrates on the judgment, interpretation, and accountability that AI is observed supporting rather than performing.

The distinction between work AI substitutes for and work AI amplifies therefore appears to track how much of the work carries responsibility for the outcome, and that in turn corresponds in part to credential level. This is where the exposure measure and the mission of the region's educational institutions intersect most directly.

4. The region's K-12 career pathways lead from the least exposed education tier into the most exposed one.

Occupations requiring less than a community college credential show the lowest exposure of any tier on both measures, at 5.7% automation and 3.3% augmentation (see Section 2.4). Most K-12 CTE pathways, however, are not terminal. They serve as on-ramps into community college programs, which sit in the tier carrying the highest automation exposure. A student following a business and finance pathway from high school into a regional community college program moves from the least exposed segment of the labor market into the most exposed one.

Two findings from Section 1 compound this pattern. The region has a larger share of residents age 24 and under than California overall, at 33.1% versus 30.2%, meaning proportionally more of its population is at or approaching labor market entry (see Section 1.2). The employment effects observed nationally to date have concentrated among workers aged 22 to 25 in the most exposed occupations, and the mechanism has been slowed hiring rather than displacement of workers already in those roles. Workers aged 30 and over in those same high-exposure occupations saw employment rise 6% to 12% over the same period. The near-term risk to the region's students is therefore less that they will lose jobs than that the entry-level positions they train for will be filled less often.

5. Employer demand for AI skills in the region is verified, concentrated, and small.

Regional employers listed 286,073 unique job postings between July 2025 and June 2026. Of these, 3,395 carried an AI skill tag, or 1.19% of the total. Applying the scoring methodology described in Section 2.5, which reads the posting text rather than relying on the skill tag and excludes AI mentions appearing in legal, EEO, and hiring-process language, indicates that approximately 1,425 postings genuinely sought AI skills. That is 0.5% of all regional postings (see Sections 2.5 and 2.6).

Demand is also narrowly distributed. Five industry sectors accounted for approximately 69% of all AI postings, and the top five major occupational groups accounted for approximately 61% (see Sections 2.6 and 2.7). The ten sectors with the fewest AI postings together accounted for less than 10% of the regional total.

This figure establishes a floor on employer demand rather than a measure of AI adoption. It counts employers who wrote AI into the duties of a job they were advertising. It excludes employers who adopted AI by training existing staff rather than hiring, employers whose vendors introduced AI functions through software updates, and hiring managers who described a requirement in terms a skill taxonomy does not recognize as AI.

6. When regional employers hire for AI, they hire workers to operate it rather than to build it.

Of the region's AI-related postings, 55% describe AI Operator roles, 29% describe AI Builder roles, and 16% describe AI Assisted Worker roles (see Section 2.8). At approximately 1,425 AI postings a year, AI Builder demand amounts to roughly 400 openings annually across all industries, consistent with Computer and Mathematical occupations accounting for approximately 1% of regional employment (see Section 1.3).

The AI Operator category is both where regional demand concentrates and what community college and K–12 preparation is positioned to supply. An AI Operator is not asked to build a model. They are asked to apply one competently within an occupation, which requires understanding what the system does, recognizing when its output is wrong, and supplying the domain judgment the tool cannot.

The 16% AI Assisted Worker figure should be read as the least reliable of the three. AI Builder and AI Operator relationships must be stated in a posting because they are conditions of employment. An optional productivity aid does not screen candidates, so employers have little reason to name it. National survey evidence suggests that informal, worker-initiated adoption is considerably more common than any employer-stated measure indicates (see Section 2.8). This is the category most likely to grow and the one this instrument is least able to observe.

7. Office and Administrative Support is the region's clearest single concentration of exposed work, and the occupational group about which employers say the least.

The group ranks near the top of the regional analysis on four separate measures (see Sections 2.3 and 2.7):

- Exposure share: the second-highest automation exposure of any major occupational group, at 23.8%.
- Workforce size: the second-largest occupational group in the region, at 180,720 workers.
- Direction of exposure: automation exceeds augmentation by more than two to one, at 23.8% versus 9.7%.
- Employer signal: 0.3% of the group's postings seek AI skills, below the 0.5% regional average.

No other occupational group combines an exposure share of this magnitude with employment at this scale. Whether measured by how much of the work is exposed, by how many regional workers perform it, or by how little employers are currently saying about it, this group is where AI's measured potential in the Inland Empire/Desert Region is greatest.

8. Most of the region's employment, and nearly all of its projected growth, sits in sectors sending little AI hiring signal.

The quadrant framework introduced in Section 2.9 categorizes Industry Sectors by whether they fall above or below the regional average on task exposure, at 15.1%, and on AI-skill share of postings, at 0.5%. The distribution of regional employment across those quadrants is the most consequential regional pattern the two instruments produce together. The Latent and Insulated quadrants hold 60.7% of regional jobs and are projected to generate 71.7% of net job growth through 2030, while accounting for 15.9% of AI posting demand. The Latent quadrant alone, showing above-average exposure and below-average demand, is projected to generate 44.2% of net job growth from 27.4% of current employment.

A sector in the Adopting quadrant is describing what it needs through its hiring. A sector in the Latent quadrant is not and will not until the change is already underway inside its organizations. Programs serving Latent sectors therefore have no employer signal to respond to, which means

decisions about those programs rest on evidence about the work itself rather than on what employers are currently asking for.

9. Exposure share and exposure scale identify different sectors, and the region's largest volumes of exposed work sit in sectors with below-average shares.

Management of Companies and Enterprises carries the region's highest automation exposure at 15.7% and employs 8,204 people. Health Care and Social Assistance carries automation exposure of 7.5% and employs 306,974 (see Section 2.2). Converted from share to volume, the ranking reverses. Health Care and Social Assistance holds 17.0% of all AI-exposed employment in the region, the largest share of any sector, on an exposure rate only modestly above the regional average (see Appendix A1.5). Transportation and Warehousing, whose exposure rate is the fifth-lowest of any sector, still accounts for approximately 7.6% of the region's AI-exposed tasks on the strength of its size alone (see Appendix A2.5).

Both measures are valid, and they answer different questions. Share identifies which industries face the most fundamental change in how their work is performed. Scale identifies where that change will reach the largest number of workers. A practitioner revising the content of a program needs the first; a practitioner estimating how many students are affected needs the second.

10. The largest limitation of this analysis falls on the region's most concentrated industry.

The exposure measure used throughout this report is built from observed usage of one company's AI assistant. It is strongest for work involving reading, writing, analysis, coding, and summarization, and it does not capture technologies that act on the physical world, including warehouse robotics, automated material handling, machine vision, process automation, and autonomous vehicles (see Sections 2.1, Appendix A3.5, and A4.5).

These technologies align with the region's defining specialization. Transportation and Warehousing holds an employment concentration of 2.46, nearly twice that of the next most concentrated sector, employs 10.8% of regional jobs, and is projected to supply 13.3% of regional job growth through 2030 (see Appendix A2.1 and A2.5). The sector's Insulated classification is accurate within the framing of this report and should not be read as a forecast of low disruption. Industry groups such as Warehousing and Storage already carry the highest automation exposure within the sector and are the likeliest first point of contact with improving robotics capability. The sector's exposure to technologies outside the scope of this measure warrants further investigation.

4.2: Recommendations

The preceding sections describe what can be measured in the Inland Empire/Desert Region today. This section sets out what those measurements ask of the institutions that will act on them.

How to Read These Recommendations

The following are conclusions the evidence supports rather than a strategic plan, and they are bounded by what the two instruments can observe. Neither measures program enrollment, completion, or wage outcomes, nor how deeply any individual employer has adopted the technology. One caution governs everything below: exposure is not displacement (see Sections 2.2, 2.3, and 4.1). Every recommendation here concerns what a program teaches rather than

whether a program should continue to exist, and none of them supports directing students toward less exposed occupations, since lower exposure is not lower risk.

This report is also a snapshot. The exposure measure records observed usage at one point in time, and the posting measure sets a floor on employer demand rather than measuring adoption (see Sections 2.5 and 2.8). A program decision made against this baseline should be revisited against the next one. Reproducing the analysis annually or biennially would show direction and rate of change rather than a single level, and further research on technologies that act on the physical world would close the gap that falls hardest on the region's most concentrated industry.

RECOMMENDATIONS FOR INSTITUTIONS

1. Establish a minimum AI standard for every student

Nearly every occupation in the region combines exposed and unexposed tasks, so the question for a graduate is not whether AI reaches their field but whether they can work competently alongside it when it does. Regional demand argues for a general standard rather than a specialist one: AI Operator roles account for 55% of the region's AI postings compared with 29% for AI Builder roles (see Section 2.8), and an Operator is asked to apply an AI system competently within an occupation rather than build one.

Waiting for employers to specify the requirement is not a workable alternative, because sectors projected to generate 71.7% of net job growth through 2030 account for 15.9% of the region's AI posting demand (see Section 2.9). What the standard should develop is domain knowledge deep enough to direct a tool, evaluate its output, and recognize when it is wrong, which is an extension of what programs already build within a discipline rather than a separate technical curriculum.

2. Conduct a program-level AI review

The most exposed work inside every sector examined is the coordination layer rather than the sector's technical core (see Section 3.4), and those programs commonly sit within business and office administration program areas. Sector-based program review will not surface these programs, which makes the program rather than the academic department or CCCC sector the right unit of review.

A useful review establishes three things: what share of the destination occupation's tasks are exposed and in which direction, whether the exposed tasks are the ones graduates are hired to perform, and how many students the program enrolls and completes. The last is not available in this report and is what turns the review from description into a basis for prioritization. The purpose is to establish what a program teaches and how that should change, not to identify programs for reduction, since a program whose exposure is augmentation-led may be preparing students for work that becomes more valuable rather than less.

RECOMMENDATIONS FOR PROGRAM DESIGN

3. Read exposure at the occupation-level

A sector-level figure averages every occupation an industry employs and describes none of them precisely (see Section 3.1). Across major occupational groups, automation exposure runs from 1.7% in Construction and Extraction to 27.6% in Computer and Mathematical

occupations, a spread of roughly sixteen times against roughly three times across industry sectors (see Sections 2.2 and 2.3). A program owner working from a sector number may be working from a figure that does not describe their students' destination occupation at all.

Two cautions apply when going to the source. Anthropic's Economic Index is organized by task and usage pattern rather than as an occupational lookup table, so it will not directly reproduce the figures in Exhibit 2.3.1, which are the COE's analysis of Index data crossed against Lightcast regional staffing patterns. Furthermore, an occupation showing no measured exposure should be read as an absence of observed usage rather than as evidence of safety; between 10 and 12 Industry Core occupations in each of the four sectors examined return no exposure in this data (see Appendices A1.2, A2.2, A3.2, and A4.2).

4. Address programs by the type of exposure, not a single score

Automation and augmentation call for different instructional responses (see Section 2.2) and combining them into a single score can produce the wrong priority order. Legal occupations illustrate the problem. At 3.9% automation exposure, they rank among the region's least exposed groups, and a ranking built on automation share would place legal programs at the back of the queue. Their augmentation exposure is 25.9%, the highest of any occupational group in the region (see Section 2.3). The work is not moving away from paralegals; what paralegals are expected to produce is changing.

A low score carries its own caveat. This measure does not capture technologies that act on the physical world (see Sections 2.1 and 4.1), and Production and Transportation and Material Moving are precisely the occupational groups those technologies target. For physical rather than informational work, a low score does not forecast low disruption.

5. Audit the entry-level tasks a program's graduates are hired to perform

The employment effects observed nationally have concentrated among workers aged 22 to 25 through slowed hiring rather than displacement of incumbents (see Sections 1.2 and 4.1), so the near-term risk to the region's students is less that they will lose jobs than that the positions they train for will be filled less often. That narrows the question a program should ask not whether the occupation is exposed, but whether the exposed tasks are the ones a new graduate is hired to do. An occupation can be stable in aggregate while its entry-level workforce thins, because the tasks typically assigned to a first-year employee are frequently the structured, high-volume, checkable ones that AI is observed completing.

Where that entry-level workforce thins, work-based learning becomes more valuable. Internships and apprenticeships supply the supervised early practice that a narrowing set of entry-level positions no longer provides at scale, which for most programs is a reallocation of existing effort rather than new curriculum.

4.3: Where to Go from Here

The detailed analysis

The appendices contain the sector-level analysis this report summarizes. Each of the four sectors examined is presented in five parts: overall exposure and its composition (An.1), the sector's Industry Core middle-skill occupations ranked by exposure (An.2), exposure by industry group (An.3), the AI worker types that employers are hiring for (An.4), and the sector's position relative to regional averages (An.5).

The Industry Core tables are the most directly useful for program work. They list named occupations with their automation and augmentation exposure separately, which is the level at which a program owner can determine whether the exposed tasks are the ones their graduates are hired to perform. A reader whose programs serve one of the four sectors will find more in that sector's appendix than in this section.

The scoring methodology used to verify AI job postings is documented and reproducible. It screened out 58% of AI-tagged postings, narrowing 3,395 tagged postings to 1,425 that genuinely sought AI skills. Section 2.5 covers the rule set, tier definitions, and how postings are treated when AI appears in hiring-process language rather than in job duties.

What this report does not settle

Three questions fall outside what the evidence in this report can address. Each is stated below, including the reason the available data cannot resolve it.

The first is adoption. This report measures what AI can do with the region's work and what employers have written into job postings. Neither observes what regional employers have actually deployed. The gap between capability and adoption is decided by investment, workflow redesign, vendor availability, verification requirements, and cost, none of which appear in either instrument.

The second is the physical technologies. The exposure measure does not capture robotics, automated material handling, machine vision, or autonomous vehicles, and those technologies are directed at the region's most concentrated industry. Transportation and Warehousing's Insulated classification is accurate within the scope of this measure and should not be read as a forecast.

The third is program content. This analysis identifies which occupations carry exposure and which AI skills employers advertise, but it cannot determine which of those skills regional programs already teach. Exposure is measured at the task level and demand at the skill level, while programs are observable only by title, award, and program code. No crosswalk connects a course sequence to the O*NET tasks or Lightcast skill tags used throughout this report. The analysis can therefore identify a program whose target occupation is exposed; it cannot establish whether that program's existing coursework already addresses the exposure, or where the gap sits.

A closing note

A goal for this report was to answer a narrow question: what can actually be measured about artificial intelligence's relationship to work in the Inland Empire/Desert Region today. The answer is less dramatic than the national conversation and more specific. Exposure is real, concentrated in identifiable occupations, and largest in the middle-skill tier the region's colleges serve most directly. Employer demand is verifiable, small, and located almost entirely outside the sectors where most of the region's workers are employed. The two measures disagree, and the disagreement is the finding.

None of this research forecasts what will happen. It establishes a baseline against which change can be measured, which is a more useful thing for an institution making decisions on a multi-year horizon. The Center of Excellence intends to reproduce this analysis so that the next

version shows direction and rate rather than a single level and welcomes inquiries from regional practitioners working through what these findings mean for a specific program.

APPENDIX A1: HEALERS IN THE EYE OF THE STORM (HEALTH CARE AND SOCIAL ASSISTANCE)

A1.1: Overview

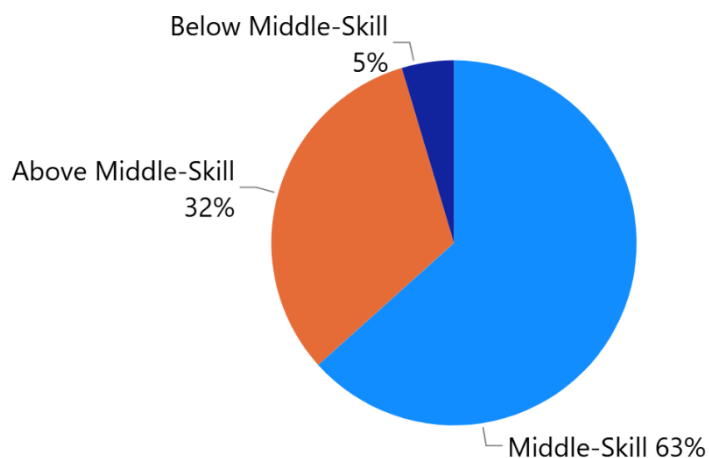
Industry with Most Middle-Skill Jobs in the Region

The Health Care and Social Assistance sector is one of the region's largest industry sectors and is projected to account for about 37% of regional job growth over the next five years, making it a key driver of regional employment. This industry sector falls into the latent quadrant, with above-average exposure (16.2%) and below-average AI job posting demand (0.2%). As a result, the Health Care and Social Assistance sector shows a wide gap between what AI could do and what employers currently need.

Health Care and Social Assistance (NAICS 62) covers businesses that provide health care and social assistance, or both, to individuals.²⁵ Establishments in this sector deliver services provided by trained professionals, typically requiring advanced education, training, or licensure. The sector is large relative to the regional economy. With approximately 307,000 jobs in 2025, it accounts for 15.8% of employment in the Inland Empire/Desert Region.

Exhibit A1.1.1 displays the distribution of Health Care and Social Assistance sector employment in 2025 by skill level. Approximately 63% of those jobs, nearly 211,100, are middle-skill, while 32% are above middle-skill and 5% are below middle-skill. The share of workers requiring a postsecondary education for employment confirms the advanced education and training requirements typically required in this sector.

Exhibit A1.1.1: Skill-level distribution in the health care and social assistance sector, Inland Empire/Desert Region, 2025



Source: COE analysis of Lightcast occupation data (2026.3)

²⁵ Health Care and Social Assistance Industry Sector Definition. (2026). North American Industry Classification System (NAICS). Retrieved from: <https://www.census.gov/naics/?input=62&year=2022&details=62>

Across all occupations in this Industry Sector, about 7.5% of tasks are susceptible to automation and 8.8% to augmentation, for 16.2% overall AI exposure. (For context, the regional average across industry sectors is 15.1% AI Exposure.)

Also, the remainder of this chapter focuses on middle-skill occupations, which typically require more than a high school diploma but less than a bachelor's degree. This segment of the labor market is what regional K-12 institutions and community colleges are positioned to serve directly through associate degrees, certificates, and other credentials, making it the level at which findings can most readily inform program decisions.

A1.2: Industry Core Occupations

Exhibit A1.2.1 shows the AI exposure for the core occupations in this Industry Sector. This report defines “Industry Core” occupations as those which are middle skill, have greater than 10 jobs in the Industry, greater than 50 jobs in the region, and whose jobs in the region are heavily concentrated in this Industry, meaning a third or more of its regional jobs are found in this single Industry Sector. By focusing on the “Industry Core” occupations, as opposed to all middle-skill occupations in this Industry, AI exposure can be compared across the jobs that are most critical to employers in this field.

Exhibit A1.2.1: AI exposure and employment estimates for core middle-skill occupations in the health care and social assistance industry group, Inland Empire/Desert Region, 2025

Description	Automation Exposure %	Augmentation Exposure %	Total AI Exposure %	Jobs in Industry (2025)	Jobs in Region (2025)	Share of Industry Employment
Receptionists and Information Clerks	38.9%	16.7%	56%	3,215	7,467	43.06%
Billing and Posting Clerks	14.3%	21.4%	36%	1,261	2,834	44.48%
Medical Secretaries and Administrative Assistants	26.7%	6.7%	33%	9,422	10,599	88.90%
Interviewers, Except Eligibility and Loan	25.0%	6.3%	31%	1,255	2,040	61.54%
Social and Human Service Assistants	10.5%	15.8%	26%	3,220	5,402	59.60%
Dietetic Technicians	15.4%	7.7%	23%	480	628	76.39%
Childcare Workers	8.3%	12.5%	21%	6,157	14,061	43.79%
Residential Advisors	10.0%	10.0%	20%	211	371	56.86%
Nuclear Medicine Technologists	17.6%	0.0%	18%	131	152	86.11%
Emergency Medical Technicians	8.3%	8.3%	17%	1,611	2,354	68.46%
Switchboard Operators, Including Answering Service	15.8%	0.0%	16%	267	474	56.24%
Home Health and Personal Care Aides	3.8%	11.5%	15%	106,046	111,455	95.15%
Medical Transcriptionists	13.3%	0.0%	13%	369	562	65.72%
Psychiatric Technicians	6.3%	6.3%	13%	1,191	1,485	80.20%
Nursing Assistants	3.0%	9.1%	12%	8,788	10,652	82.50%
Medical Records Specialists	11.8%	0.0%	12%	900	1,386	64.89%
Clinical Laboratory Technologists and Technicians	7.1%	3.6%	11%	1,312	1,690	77.63%
Medical Assistants	5.0%	5.0%	10%	10,313	11,434	90.19%
Occupational Therapy Assistants	9.1%	0.0%	9%	333	408	81.75%
Radiation Therapists	4.5%	4.5%	9%	441	513	86.05%
Magnetic Resonance Imaging Technologists	0.0%	8.3%	8%	263	317	82.78%
Paramedics	0.0%	7.7%	8%	331	828	39.98%
Dental Hygienists	0.0%	6.3%	6%	1,908	1,950	97.83%
Health Information Technologists and Medical Registrars	6.3%	0.0%	6%	134	223	59.82%
Preschool Teachers, Except Special Education	0.0%	5.9%	6%	2,424	4,434	54.67%
Psychiatric Aides	5.9%	0.0%	6%	131	320	41.06%
Diagnostic Medical Sonographers	5.0%	0.0%	5%	876	1,006	87.12%
Cardiovascular Technologists and Technicians	4.8%	0.0%	5%	405	477	84.80%
Physical Therapist Assistants	4.8%	0.0%	5%	807	890	90.68%
Licensed Practical and Licensed Vocational Nurses	0.0%	4.5%	5%	6,621	8,396	78.86%
Orderlies	4.5%	0.0%	5%	483	607	79.57%
Respiratory Therapists	4.5%	0.0%	5%	1,695	2,172	78.06%
Radiologic Technologists and Technicians	3.3%	0.0%	3%	1,801	2,210	81.48%
Dental Assistants	0.0%	0.0%	0%	5,187	5,344	97.06%
Health Technologists and Technicians, All Other	0.0%	0.0%	0%	2,190	2,454	89.22%
Healthcare Practitioners and Technical Workers, All Other	0.0%	0.0%	0%	195	320	60.91%
Healthcare Support Workers, All Other	0.0%	0.0%	0%	1,121	2,217	50.53%
Medical Equipment Preparers	0.0%	0.0%	0%	665	811	82.00%
Ophthalmic Medical Technicians	0.0%	0.0%	0%	195	217	89.80%
Opticians, Dispensing	0.0%	0.0%	0%	505	891	56.74%
Phlebotomists	0.0%	0.0%	0%	1,251	1,416	88.35%
Physical Therapist Aides	0.0%	0.0%	0%	702	753	93.23%
Surgical Technologists	0.0%	0.0%	0%	1,017	1,206	84.36%

Source: COE analysis of Lightcast staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

Receptionists and Clerks Are Most Exposed

Clerking occupations are the most AI exposed occupations in this sector. Receptionists and Information Clerks are the most exposed occupation, with 56% of all tasks found to be within reach of Anthropic's Claude product, while Billing and Posting Clerks are the second highest at 36% of all tasks exposed. Additionally, Billing and Posting Clerks are also the most impacted by

Augmentation, which accounts for 21.4% of its AI exposure. While Receptionists and Information Clerks are the most impacted by Automation, which exposes more than 38.9% of all their occupational tasks to AI.

In contrast, ten Industry Core occupations do not currently show any AI exposure from Claude usage. However, this data is a point in time and limited by Anthropic's current dataset, so it may not be accurate across all AI products and will undoubtedly change as adoption increases across fields. However, among the ten occupations shown above, two relate to ophthalmology, suggesting low disruption in this field overall. Other occupations include Surgery Technicians, Phlebotomists, and Physical Therapist Aides, all of which involve direct patient examination and treatment. This may denote that occupations requiring direct client interaction are less exposed at this stage of the technology's capabilities and perhaps that adjacent fields will be more resistant to adopting the technology in the near term.

Overall, it appears that occupations involved in clerking, billing, and administrative tasks are more exposed, with four in the top five Industry Core occupations for AI exposure. In contrast, occupations in ophthalmology and others less focused on administrative tasks are less exposed, with ten occupations showing no AI exposure in Claude's dataset. This difference may be explained by differences in common work activities between the groups. Clerking, billing, and administrative tasks are more likely to involve data entry, drafting and reviewing documents, or scheduling appointments, while many of the ten occupations showing no exposure are related to direct patient examination/treatment. Administrative tasks are substantially more exposed to AI augmentation or automation than direct patient care, given the current use of the Claude product.

A1.3: Industry Groups

So far, the report has presented exposure and employment estimates at the sector level when discussing Industry data. Sector-level exposure figures are weighted averages that can mask variation among the businesses within them. Because AI exposure reflects the occupational mix of a workforce rather than the sector label itself, businesses in the same sector can differ substantially.

The following sections shift to industry groups, a finer classification that shows how exposure varies among businesses within a sector. Industry groups offer the detail needed to observe those differences while keeping regional employment estimates reliable. Industry Groups are a lower level of the NAICS data taxonomy. For example, this Industry Sector is Health Care and Social Assistance (NAICS 62), and an Industry Group within the sector is General Medical and Surgical Hospitals (NAICS 6221). For an overview of the NAICS taxonomy and its relation to each other, see the North American Industry Classification System (NAICS) at BLS²⁶, or visit the IED COE's LMI 201 online training series as a useful resource.)

Exhibit A1.3.1 shows the number of middle-skill jobs by industry group in the Health Care and Social Assistance industry sector in 2025.

²⁶ <https://www.bls.gov/bls/naics.htm>

Exhibit A1.3.1: Middle-skill jobs by industry group in the health care and social assistance, Inland Empire/Desert Region, 2025

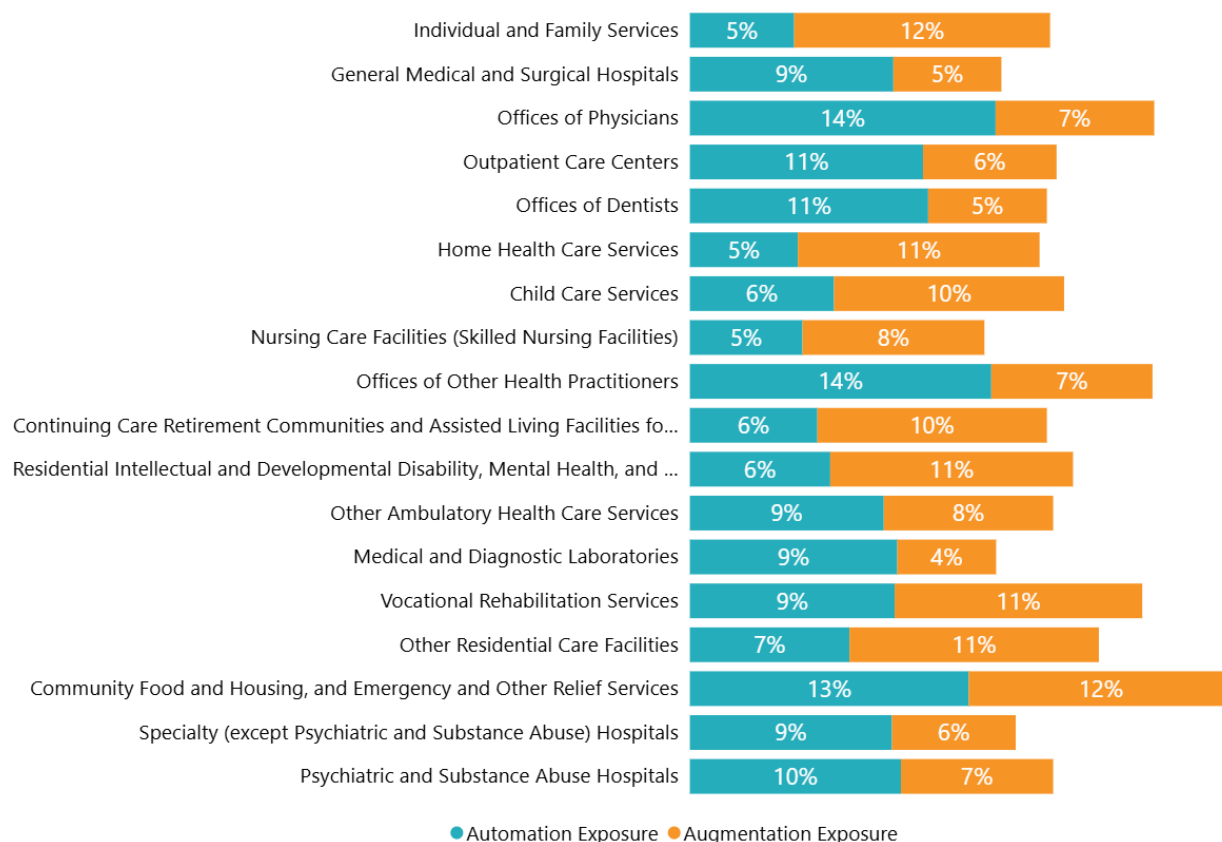
Industry Group	2025 Jobs	Middle-Skill Jobs	Middle-Skill Share of Jobs
Individual and Family Services	106,603	95,819	90%
General Medical and Surgical Hospitals	49,833	21,306	43%
Offices of Physicians	26,647	15,369	58%
Outpatient Care Centers	26,212	12,883	49%
Offices of Other Health Practitioners	16,748	6,194	37%
Nursing Care Facilities (Skilled Nursing Facilities)	13,535	8,669	64%
Offices of Dentists	13,411	11,118	83%
Home Health Care Services	12,853	10,607	83%
Child Care Services	10,559	9,285	88%
Continuing Care Retirement Communities and Assisted Living Facilities for the Elderly	8,989	6,173	69%
Residential Intellectual and Developmental Disability, Mental Health, and Substance Abuse Facilities	7,133	4,879	68%
Other Ambulatory Health Care Services	4,364	3,094	71%
Medical and Diagnostic Laboratories	3,141	2,243	71%
Vocational Rehabilitation Services	2,328	1,066	46%
Community Food and Housing, and Emergency and Other Relief Services	1,362	651	48%
Other Residential Care Facilities	1,271	838	66%
Specialty (except Psychiatric and Substance Abuse) Hospitals	1,145	506	44%
Psychiatric and Substance Abuse Hospitals	841	355	42%

Source: COE analysis of Lightcast staffing pattern data (2026.3)

While total exposure is useful for comparison, automation and augmentation exposure figures may provide greater insight into the potential impacts of increasing AI adoption. Exhibit A1.3.2 displays the automation and augmentation exposure for middle-skill workers in the top 10 industry groups in the Health Care and Social Services industry sector. The industry groups have varying shares of automation and augmentation exposures.

The middle-skill workforce in the Offices of Physicians and Offices of Other Health Care Practitioners industry groups has the greatest automation exposure at 14%, with 7% augmentation exposure. These shares indicate that a meaningful share of tasks are likely to be replaced with AI tools rather than enhanced by them. Conversely, the middle-skill workforce in the Individual and Family Services and Home Health Care Services industry groups have between 11% and 12% of task-weighted employment that can be augmented by AI. Workers in these industry groups may use AI to improve the quality of service delivery.

Exhibit A1.3.2: Middle-skill AI task exposure by industry group in the health care and social assistance industry sector, Inland Empire/Desert Region, 2025



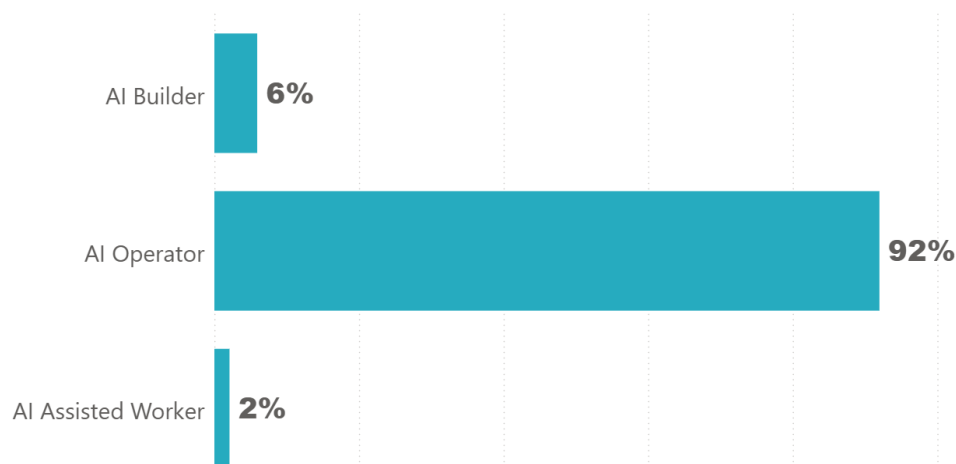
Source: COE analysis of Lightcast staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

The widest spread is in the Offices of Physicians industry group, where 14% of middle-skill tasks are automation-exposed, and 7% are augmentation-exposed. This distribution is reflected in the middle-skill workforce in the Offices of Other Health Practitioners industry group.

A1.4: What Employers Are Telling Us With Job Posts

As noted in section 2.6, the Health Care and Social Assistance sector produced the sixth most AI postings (82), which equates to 0.2% of all sector job postings in the assessed window of time. Exhibit A1.4.1 shows the breakdown of AI Worker Types from the 82 job posts from sector employers.

Exhibit A1.4.1: AI workforce categories in industry sector AI job postings, Inland Empire/Desert Region, July 2025 – June 2026



Source: COE analysis of Lightcast staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

The job posts follow the regional trend, with the majority tied to AI Operators (92%), followed by AI Builders (6%), and finally AI Assisted Workers (2%). However, this sector shows a much higher concentration of AI Operators than the region as a whole: 92% vs. 55%. This sector had considerably fewer AI Builders (6%) and AI Assisted Workers (2%).

The higher concentration of AI Operators suggests this industry uses AI products, such as Claude, to enhance operations rather than developing the technology itself. This sector also has fewer ads for AI Assisted Workers, which may reflect regulations such as HIPAA, whose privacy restraints may limit AI use.

A1.5: Where The Industry Falls In The Quadrant Model

As described in section 2.9, the Health Care and Social Assistance sector is in the “Latent” quadrant. This means the sector has above-average AI exposure and below-average AI job-posting demand. The gap between what the technology can do and what regional employers are asking for is wider here than anywhere else in the IE/D economy.

Going further, the Health Care and Social Assistance sector holds the single largest share of the region’s AI-exposed workforce of any Industry Sector, with 17.0% of all AI-exposed employment in the IE/D region. This is due to scale rather than intensity. The sector’s AI exposure by occupational tasks is 16.2%, only modestly above the regional average of 15.1%, but employs nearly 307,000 workers, or 15.8% of all regional employment. Only 0.2% of the sector’s job postings required AI skills, well below the regional average of 0.5%. Put differently, Health Care and Social Assistance accounts for 15.8% of the region’s jobs, but only 5.8% of AI job posts, approximately one-third the rate its employment share would predict.

The AI-exposed work appears concentrated in administrative and information-handling occupations, including medical records and health information, billing and coding, scheduling and intake, patient access, and care coordination, while direct-care occupations that dominate industry employment remain less exposed.

While current trends do not guarantee future results, as of this publication date, the IE/D Health Care and Social Assistance sector represents the largest cohort of exposed workers with the lowest relative rate of employer AI demand.

APPENDIX A2: DRIVING THROUGH THE DUST (TRANSPORTATION AND WAREHOUSING)

A2.1: Overview

Most Concentrated Industry in the Region

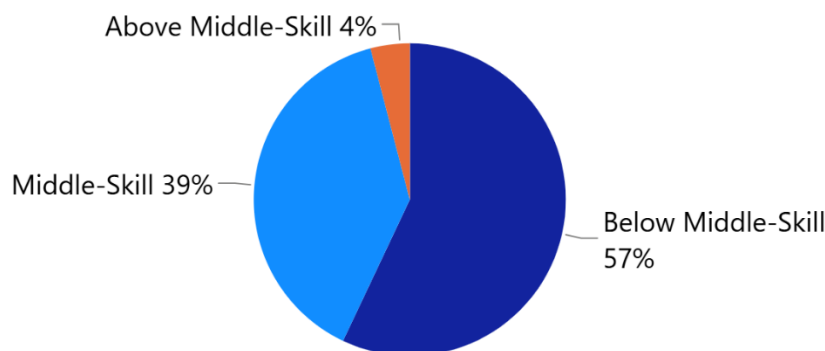
The Transportation and Warehousing sector is one of the region's largest industry sectors and is projected to add nearly 17,200 jobs over the next five years. This industry sector falls into the insulated quadrant, with below-average exposure (10.6%) and below-average AI job posting demand (0.1%). That classification is based on the sector-level data. Analysis of the industry groups and occupations that make up the sector is likely to reveal segments with exposure above 10.6%. Given the number of jobs in this sector, even a below-average exposure rate may affect many jobs.

Transportation and Warehousing (NAICS 48) covers businesses that provide transportation of passengers and cargo, warehousing and storage for goods, scenic and sightseeing transportation, and support activities related to modes of transportation.²⁷ The sector is the third-largest and most concentrated in the region, underscoring its importance to the regional economy. With approximately 208,900 jobs in 2025, it accounts for 10.8% of employment in the Inland Empire/Desert Region.

Exhibit A2.1.1 displays the distribution of Transportation and Warehousing sector employment in 2025 by skill level. Approximately 39% of those jobs, nearly 81,300, are middle-skill, while 4% are above middle-skill and 57% are below middle-skill. The share of workers requiring a postsecondary education for employment suggests this sector offers many opportunities for entry-level workers.

²⁷ Transportation and Warehousing Industry Sector Definition. (2026). North American Industry Classification System (NAICS). Retrieved from: <https://www.census.gov/naics/?input=48&year=2022&details=48>

Exhibit A2.1.1: Skill-level distribution in the transportation and warehousing sector, Inland Empire/Desert Region, 2025



Source: COE analysis of Lightcast occupation data (2026.3)

Across all occupations in this Industry Sector, approximately 7.8% of tasks are susceptible to automation and 2.9% to augmentation, for a total AI exposure of 10.6%. (For context, the regional average across Industry Sectors is 15.1% AI Exposure.)

The remainder of this chapter also focuses on middle-skill occupations, which typically require more than a high school diploma but less than a bachelor's degree. This segment of the labor market is what regional K-12 institutions and community colleges are positioned to serve directly through associate degrees, certificates, and other credentials, making it the level at which findings can most readily inform program decisions.

A2.2: Industry Core Occupations

Exhibit A2.2.1 shows the AI exposure for the core occupations in this Industry Sector. This report defines “Industry Core” occupations as those which are middle skill, have greater than 10 jobs in the Industry, greater than 50 jobs in the region, and whose jobs in the region are heavily concentrated in this Industry, meaning a third or more of its regional jobs are found in this single Industry Sector. By focusing on the “Industry Core” occupations, as opposed to all middle-skill occupations in this Industry, AI exposure can be compared across the jobs that are most critical to employers in this field.

Exhibit A2.2.1: AI exposure and employment estimates for core middle-skill occupations in the transportation and warehousing industry group, Inland Empire/Desert Region, 2025

Description	Automation Exposure %	Augmentation Exposure %	Total AI Exposure %	Jobs in Industry (2025)	Jobs in Region (2025)
Transportation, Storage, and Distribution Managers	13.3%	16.7%	30%	2,065	3,725
First-Line Supervisors of Transportation and Material Moving Workers, Except Aircraft Cargo Handling Supervisors	20.0%	9.2%	29%	6,379	11,593
Reservation and Transportation Ticket Agents and Travel Clerks	9.5%	14.3%	24%	289	414
Weighers, Measurers, Checkers, and Samplers, Recordkeeping	11.1%	5.6%	17%	916	1,425
Dispatchers, Except Police, Fire, and Ambulance	16.7%	0.0%	17%	1,761	3,374
Electrical and Electronics Installers and Repairers, Transportation Equipment	13.3%	0.0%	13%	47	82
Baggage Porters and Bellhops	11.8%	0.0%	12%	109	317
Transportation Inspectors	5.9%	5.9%	12%	85	196
Shipping, Receiving, and Inventory Clerks	9.1%	0.0%	9%	6,278	15,011
Cargo and Freight Agents	8.3%	0.0%	8%	1,899	2,004
Heavy and Tractor-Trailer Truck Drivers	6.9%	0.0%	7%	34,006	45,894
Couriers and Messengers	6.7%	0.0%	7%	2,082	2,375
Aircraft Cargo Handling Supervisors	0.0%	0.0%	0%	278	285
Aircraft Mechanics and Service Technicians	0.0%	0.0%	0%	952	2,129
Airfield Operations Specialists	0.0%	0.0%	0%	110	217
Locomotive Engineers	0.0%	0.0%	0%	627	636
Petroleum Pump System Operators, Refinery Operators, and Gaugers	0.0%	0.0%	0%	51	123
Rail Car Repairers	0.0%	0.0%	0%	365	371
Rail Yard Engineers, Dinkey Operators, and Hostlers	0.0%	0.0%	0%	63	67
Railroad Brake, Signal, and Switch Operators and Locomotive Firers	0.0%	0.0%	0%	187	198
Railroad Conductors and Yardmasters	0.0%	0.0%	0%	790	853
Rail-Track Laying and Maintenance Equipment Operators	0.0%	0.0%	0%	252	268
Signal and Track Switch Repairers	0.0%	0.0%	0%	127	168
Transportation Workers, All Other	0.0%	0.0%	0%	48	68

Source: COE analysis of Lightcast staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

Supervisors and Managers Are Most Exposed

Management occupations are the most AI exposed occupations in this sector. Transportation, Storage, and Distribution Managers are the most exposed occupation, with 30% of all tasks found to be within reach of Anthropic’s Claude product, while First-Line Supervisors of Transportation and Material Moving Workers (Except Aircraft Cargo Handling Supervisors) are the second highest at 29% of all tasks exposed. Additionally, First-Line Supervisors of Transportation and Material Moving Workers (Except Aircraft Cargo Handling Supervisors) are also the most impacted by Augmentation, which accounts for 20% of its AI exposure. Transportation, Storage, and Distribution Managers are the most impacted by Automation, which accounts for 16.7% of their AI exposure. The other three occupations in the top five for AI exposure are all related to office operations, including: Reservation and Transportation Ticket Agents and Travel Clerks; Weighers, Measurers, Checkers, and Samplers (Recordkeeping); and Dispatchers (Except Police, Fire, and Ambulance).

As a contrast, 12 Industry Core occupations do not currently show any AI exposure from Claude usage. However, this data is a point in time and limited by Anthropic's current dataset, so it may not be accurate across all AI products and will undoubtedly change as adoption increases across fields. However, among the 12 occupations shown above, seven relate to railroad operations, and three relate to aircraft operations, suggesting low disruption in these fields overall. This may denote that occupations requiring direct operation of large-scale cargo transportation are less exposed at this stage of the technology's capabilities and perhaps that adjacent fields will be more resistant to adopting the technology in the near term.

Overall, it appears that occupations involved in transportation management and office operations are more exposed, composing all the top five Industry Core occupations for AI exposure. In contrast, occupations in railroad or aircraft operations are less exposed, making up 10 of the 12 occupations showing no AI exposure in Claude's dataset. This difference may be explained by differences in common work activities between the groups. Supervisory and other administrative tasks are more likely to involve data entry, communication, drafting and reviewing documents, or scheduling activities, while the majority of the 12 occupations showing no exposure are related to the movement of cargo-hauling trains/aircraft. Administrative tasks are substantially more exposed to AI augmentation or automation than heavy equipment operation or maintenance, given the current use of the Claude product.

A2.3: Industry Groups

So far, the report has presented exposure and employment estimates at the sector level when discussing Industry data. Sector-level exposure figures are weighted averages that can mask variation among the businesses within them. Because AI exposure reflects the occupational mix of a workforce rather than the sector label itself, businesses in the same sector can differ substantially.

The following sections shift to industry groups, a finer classification that shows how exposure varies among businesses within a sector. Industry groups offer the detail needed to observe those differences while keeping regional employment estimates reliable. Industry Groups are a lower level of the NAICS data taxonomy. For example, this Industry Sector is Transportation and Warehousing (NAICS 48), and an Industry Group within the sector is Warehousing and Storage (NAICS 4931). For an overview of the NAICS taxonomy and their relation to each other, see the North American Industry Classification System (NAICS) at BLS²⁸ or visit the IED COE's LMI 201 online training series as a useful resource.)

Exhibit A2.3.1 shows the number of middle-skill jobs by industry group in the Transportation and Warehousing sector in 2025.

²⁸ <https://www.bls.gov/bls/naics.htm>

Exhibit A2.3.1: Middle-skill jobs by industry group in the transportation and warehousing, Inland Empire/Desert Region, 2025

Industry Group	2025 Jobs	Middle-Skill Jobs	Middle-Skill Share of Jobs
Warehousing and Storage	118,269	28,156	24%
General Freight Trucking	28,915	23,550	81%
Couriers and Express Delivery Services	22,905	6,727	29%
Specialized Freight Trucking	8,973	7,282	81%
Support Activities for Air Transportation	5,771	3,191	55%
Freight Transportation Arrangement	4,232	2,747	65%
Rail Transportation	3,667	3,082	84%
Taxi and Limousine Service	3,307	118	4%
Local Messengers and Local Delivery	3,124	1,280	41%
Support Activities for Road Transportation	2,957	2,228	75%
School and Employee Bus Transportation	1,842	320	17%
Scheduled Air Transportation	897	431	48%
Other Transit and Ground Passenger Transportation	897	311	35%
Support Activities for Rail Transportation	812	475	59%
Other Support Activities for Transportation	597	276	46%
Urban Transit Systems	463	400	86%
Postal Service	331	153	46%
Charter Bus Industry	222	175	79%
Pipeline Transportation of Natural Gas	217	129	60%
Nonscheduled Air Transportation	157	61	39%
Other Pipeline Transportation	115	81	70%
Scenic and Sightseeing Transportation, Land	65	28	43%
Scenic and Sightseeing Transportation, Other	42	23	54%
Scenic and Sightseeing Transportation, Water	41	13	31%
Deep Sea, Coastal, and Great Lakes Water Transportation	26	15	56%
Support Activities for Water Transportation	22	12	54%
Interurban and Rural Bus Transportation	13	11	86%
Inland Water Transportation	7	3	46%
Pipeline Transportation of Crude Oil	0	0	

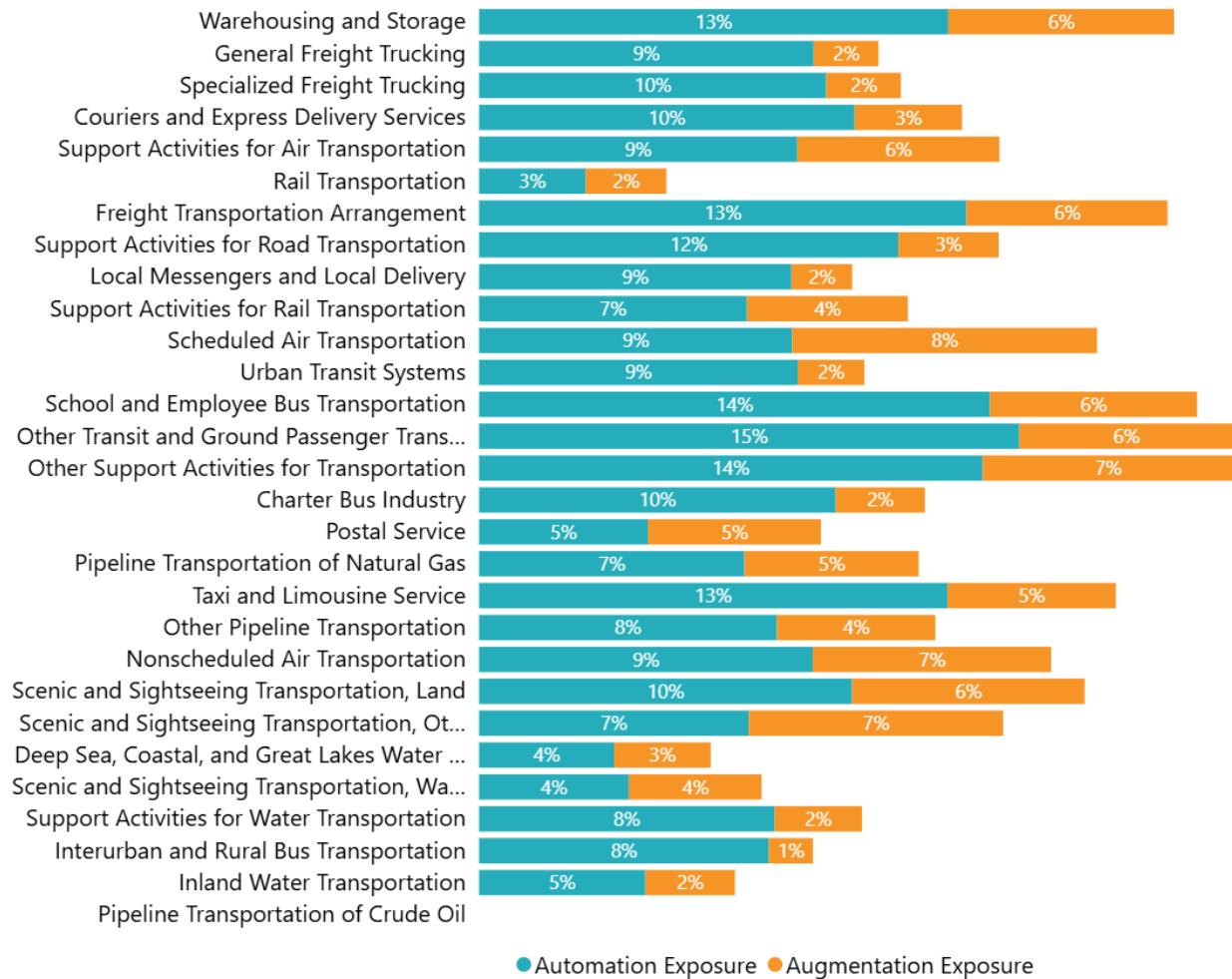
Source: COE analysis of Lightcast staffing pattern data (2026.3)

While total exposure is useful for comparison, automation and augmentation exposure figures may provide greater insight into the potential impacts of increasing AI adoption. Exhibit A2.3.2 displays the automation and augmentation exposure for middle-skill workers in the top 10 industry groups in the Transportation and Warehousing industry sector. Each industry group displayed has a greater share of tasks susceptible to automation than to augmentation for the middle-skill workforce. Most of the industry groups displayed have AI exposure rates greater than the sector average.

The three most automation-exposed industry groups in this sector include Warehousing and Storage, Freight Transportation Arrangement, and Taxi and Limousine Services, each with

approximately 13% of tasks exposed to automation. The Warehousing and Storage, Freight Transportation Arrangement, and Support Activities for Air Transportation have the greatest shares of tasks that can be augmented in this sector, suggesting these workers may use AI to enhance their work.

Exhibit A2.3.2: Middle-skill AI task exposure by industry group in the transportation and warehousing industry sector, Inland Empire/Desert Region, 2025



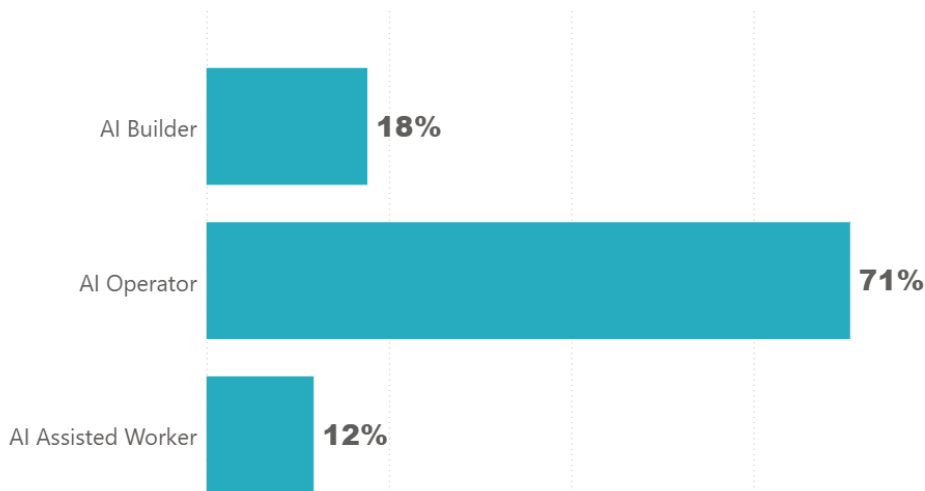
Source: COE analysis of Lightcast staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

The widest spread is in the Support Activities for Road Transportation industry group, where 12% of middle-skill tasks are automation-exposed, and 3% are augmentation-exposed. While this distribution is greater than that of other industry groups displayed, this pattern is consistent throughout the sector.

A2.4: What Employers Are Telling Us With Job Posts

As noted in section 2.6, the Transportation and Warehousing sector produced only 13 AI postings, which equates to 0.1% of all sector postings in the assessed window of time. Exhibit A2.4.1 shows the breakdown of AI Worker Types from the 13 job posts from sector employers.

Exhibit A2.4.1: AI workforce categories in industry sector AI job postings, Inland Empire/Desert Region, July 2025 – June 2026



Source: COE analysis of Lightcast staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

The job postings follow the regional trend, with the majority tied to AI Operators (71%), followed by AI Builders (18%), and finally AI Assisted Workers (12%). However, this sector shows a greater concentration of AI Operators than the region as a whole, 71% vs 55%. AI Builders and AI Assisted Workers have a lower share in the Transportation and Warehousing sector than in the region overall.

A2.5: Where The Industry Falls In The Quadrant Model

As described in section 2.9, the Transportation and Warehousing sector is in the “Insulated” quadrant. This means the sector shows below-average AI exposure and below-average AI job posting demand. Therefore, neither the sector’s task composition nor its employers’ current hiring behavior points toward near-term disruption from AI capabilities.

Going further, the Transportation and Warehousing sector is the most consequential example of an insulated industry sector in the IE/D, not because of its exposure, but because of its significance to the regional economy. It is the third largest sector in the region, with a regional concentration of 2.46, nearly twice that of the next most concentrated industry, Construction, at 1.25. Its AI exposure by occupational tasks is 10.6%, well below the 15.1% regional average, and only 0.1% of job postings sought individuals with AI skills, also below the 0.5% regional average.

While this sector may appear insulated from AI impacts, its scale turns the low exposure rate into significant absolute exposure, accounting for approximately 7.6% of the region’s AI-exposed tasks. The exposure appears concentrated in office and coordination occupations, including dispatch and load planning, freight and customs documentation, billing and claims,

and customer service, rather than the driving, handling, and material-movement work that accounts for the majority of jobs.

Please note that this sector is “Insulated” only within the framing of this report structure. Warehouse robotics, automated material handling, and autonomous and semi-autonomous vehicles are not associated with Claude usage and therefore are not captured in this analysis. Given that this sector is projected to grow by 8.2%, accounting for 13.3% of regional job growth, its exposure to robotics should be the subject of further investigation. Industry groups such as Warehousing and Storage have high automation exposure and may be the first to experience the impact of increasing robotics capabilities.

While current trends do not guarantee future results, as of the publication date, the IE/D Transportation and Warehousing sector shows the weakest signal of near-term AI disruption among major regional sectors. This sector's insulated status gives workforce training partners more time to prepare for AI's impacts.

APPENDIX A3: WHERE THE DUST SETTLES THICKEST (PROFESSIONAL, SCIENTIFIC, AND TECHNICAL SERVICES)

A3.1: Overview

Most Exposed Industry in the Region

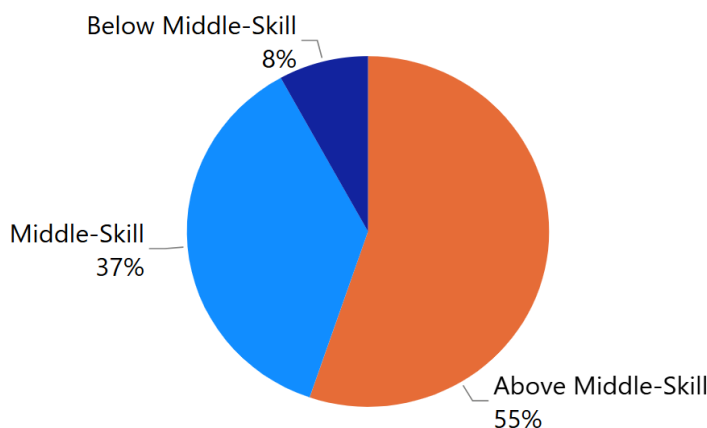
The Professional, Scientific, and Technical Services sector is the region's most exposed industry sector by task composition, and employers in this sector posted more AI-related job postings over the last 12 months than employers in any other sector. Together, these factors make this sector a strong candidate for further examination.

Professional, Scientific, and Technical Services (NAICS 54) covers businesses that provide specialized expertise to other organizations and, sometimes, to individuals.²⁹ The work generally requires advanced education, training, or licensure. Examples include law, accounting, engineering, architecture, computer and IT services, consulting, research, advertising and design, and veterinary services. With approximately 62,500 jobs in 2025, it accounts for 3.2% of employment in the Inland Empire/Desert Region.

Exhibit A3.1.1 displays the distribution of Professional, Scientific, and Technical Services sector employment in 2025 by skill level. Approximately 37% of those jobs, nearly 23,000, are middle-skill, while 55% are above middle-skill and 8% are below middle-skill. The share of workers requiring a postsecondary education for employment confirms the advanced education and training requirements typically required in this sector.

²⁹ Professional, Scientific, and Technical Service Industry Sector Definition. (2026). North American Industry Classification System (NAICS). Retrieved from: <https://www.census.gov/naics/?input=54&year=2022&details=54>

Exhibit A3.1.1: Skill-level distribution in the professional, scientific, and technical services sector, Inland Empire/Desert Region, 2025



Source: COE analysis of Lightcast occupation data (2026.3)

Given the extent of AI exposure and employer demand for workers with AI skills, the Professional, Scientific, and Technical Services industry sector serves as a good leading indicator of regional AI adoption, despite its small regional size. Across all occupations in this Industry Sector, approximately 14.9% of tasks are susceptible to automation, and 16.1% are susceptible to augmentation, which equals 31% overall AI exposure. (For context, the regional average across Industry Sectors is 15.1% AI Exposure.)

Also, the remainder of this chapter focuses on middle-skill occupations, which typically require more than a high school diploma but less than a bachelor's degree. This segment of the labor market is what regional K-12 institutions and community colleges are positioned to serve directly through associate degrees, certificates, and other credentials, making it the level at which findings can most readily inform program decisions.

A3.2: Industry Core Occupations

Exhibit A3.2.1 shows the AI exposure for the core occupations in this Industry Sector. This report defines “Industry Core” occupations as those which are middle skill, have greater than 10 jobs in the Industry, greater than 50 jobs in the region, and whose jobs in the region are heavily concentrated in this Industry, meaning a third or more of its regional jobs are found in this single Industry Sector. By focusing on the “Industry Core” occupations, as opposed to all middle-skill occupations in this Industry, AI exposure can be compared across the jobs that are most critical to employers in this field.

Exhibit A3.2.1: AI exposure and employment estimates for core middle-skill occupations in the professional, scientific, and technical services industry group, Inland Empire/Desert Region, 2025

Description	Automation Exposure %	Augmentation Exposure %	Total AI Exposure %	Jobs in Industry (2025)	Jobs in Region (2025)
Paralegals and Legal Assistants	0.0%	33.3%	33%	1,778	2,608
Civil Engineering Technologists and Technicians	7.1%	21.4%	29%	276	803
Legal Secretaries and Administrative Assistants	21.4%	7.1%	29%	723	1,108
Architectural and Civil Drafters	10.7%	14.3%	25%	563	860
Environmental Engineering Technologists and Technicians	15.4%	7.7%	23%	103	256
Title Examiners, Abstractors, and Searchers	6.3%	12.5%	19%	141	309
Photographers	7.1%	7.1%	14%	1,300	1,627
Surveying and Mapping Technicians	6.7%	6.7%	13%	262	447
Veterinary Technologists and Technicians	3.2%	3.2%	6%	851	940
Veterinary Assistants and Laboratory Animal Caretakers	3.6%	0.0%	4%	1,164	1,287

Source: COE analysis of Lightcast staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

Paralegals and Legal Assistants Are Most Exposed

Paralegals and Legal Assistants are the most AI exposed occupation at 33% of all tasks found to be within reach of Anthropic’s Claude product. Additionally, Paralegals and Legal Assistants are also the most impacted by Augmentation, which encompasses the full 33% of its AI exposure. However, Legal Secretaries and Administrative Assistants are the most impacted by Automation, which exposes more than 21% of all their occupational tasks to AI. Legal Secretaries and Administrative Assistants, along with Civil Engineering Technologists and Technicians, are the second most AI exposed as 29% of their tasks are within reach of Claude.

In contrast, occupations in the field of veterinary science are the least impacted of the group. Veterinary Assistants and Laboratory Animal Caretakers are the least exposed at 4% of all tasks, while Veterinary Technologists and Technicians are the second least exposed at 6% of all tasks within reach of Claude.

Overall, it appears that occupations in the legal field are more exposed, with two in the top three Industry Core occupations for AI exposure. While occupations in the veterinary science field are less exposed, with the two lowest core Industry middle-skill occupations for AI exposure. The difference in the two fields is possibly explained by the differences in common work activities between the two groups. Legal services are more likely to involve drafting and reviewing documents, while veterinary science is more likely to involve either directly working with animals or operating scientific equipment. Document drafting and review are substantially more exposed to AI augmentation or automation than direct patient care or equipment operation, by nature of the current form of the Claude product.

A3.3: Industry Groups

So far, the report has presented exposure and employment estimates at the Sector level when discussing Industry data. Sector-level exposure figures are weighted averages that can mask variation among the businesses within them. Because AI exposure reflects the occupational

mix of a workforce rather than the sector label itself, businesses in the same sector can differ substantially.

The following sections shift to industry groups, a finer classification that shows how exposure varies among businesses within a sector. Industry groups offer the detail needed to observe those differences while keeping regional employment estimates reliable. Industry Groups are a lower level of the NAICS data taxonomy. For example, this Industry Sector is Professional, Scientific, and Technical Services (NAICS 54), and an Industry Group within the sector is Legal Services (NAICS 5411). For an overview of the NAICS taxonomy and their relation to each other, see the North American Industry Classification System (NAICS) at BLS³⁰, or visit the IED COE's LMI 201 online training series as a useful resource.)

Exhibit A3.3.1 displays the number of middle-skill jobs by each industry group in the Professional, Scientific, and Technical Services industry sector in 2025.

Exhibit A3.3.1: Middle-skill jobs by industry group in the professional, scientific, and technical services, Inland Empire/Desert Region, 2025

Industry Group	2025 Jobs ▼	Middle-Skill Jobs	Middle-Skill Share of Jobs
Management, Scientific, and Technical Consulting Services	13,980	3,625	26%
Architectural, Engineering, and Related Services	12,166	4,359	36%
Accounting, Tax Preparation, Bookkeeping, and Payroll Services	8,399	2,899	35%
Legal Services	7,972	4,036	51%
Other Professional, Scientific, and Technical Services	7,087	5,031	71%
Computer Systems Design and Related Services	5,538	1,740	31%
Advertising, Public Relations, and Related Services	3,474	718	21%
Specialized Design Services	3,183	395	12%
Scientific Research and Development Services	723	188	26%

Source: COE analysis of Lightcast staffing pattern data (2026.3)

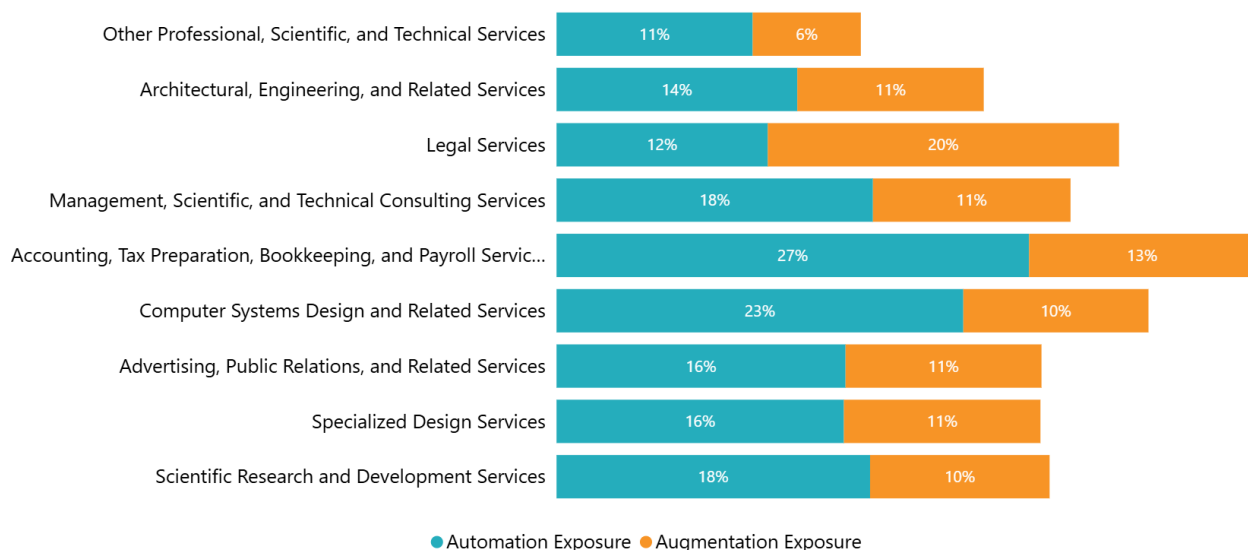
Middle-skill employment and AI exposure aren't clearly correlated. Other Professional, Scientific, and Technical Services has by far the highest middle-skill employment share (71%) in the sector, yet the lowest total exposure for those jobs (17%). Meanwhile, Accounting, Tax Preparation, Bookkeeping, and Payroll Services has only a moderate middle-skill share (35%) but the highest total exposure of any group (39%), driven almost entirely by automation (27%). So, the size of an industry's middle-skill workforce doesn't predict how exposed that workforce is to AI; what matters more is the underlying task composition of the specific occupations involved. For example, while middle-skill tasks in the Accounting, Tax Preparation, Bookkeeping, and Payroll Services industry group are more exposed than those in the Legal Services industry group, the Legal Services industry group has more workers whose tasks are exposed to AI.

While total exposure is useful for comparison, automation and augmentation exposure figures may provide greater insight into the potential impacts of increasing AI adoption. Exhibit A3.3.2 displays the automation and augmentation exposure for middle-skill workers in each industry group in the Professional, Scientific, and Technical Services industry sector. Each industry

³⁰ <https://www.bls.gov/bls/naics.htm>

group's middle-skill workforce has more tasks susceptible to automation than to augmentation, except for Legal Services.

Exhibit A3.3.2: Middle-skill AI task exposure by industry group in the professional, scientific, and technical services industry sector, Inland Empire/Desert Region, 2025



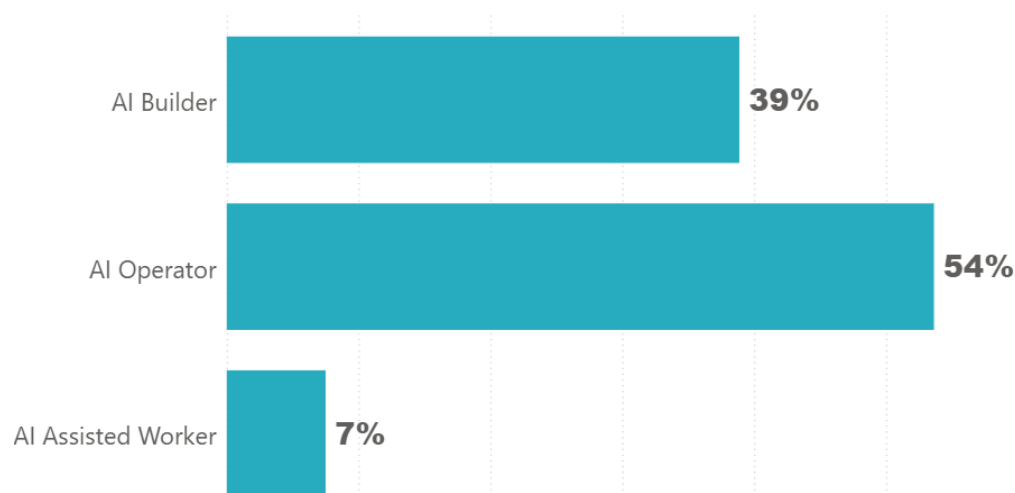
Source: COE analysis of Lightcast staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

The widest spread is in the Accounting, Tax Preparation, Bookkeeping, and Payroll Services industry group, where 27% of middle-skill tasks are automation-exposed, and 13% are augmentation-exposed. This distribution is reflected in the middle-skill workforce in the Computer Systems Design and Related Services industry group.

A3.4: What Employers Are Telling Us With Job Posts

As noted in section 2.6, the Professional, Scientific, and Technical Services sector produced the most AI postings (453), which equates to 3.0% of all sector job postings in the assessed window of time. Exhibit A3.4.1 shows the breakdown of AI Worker Types from the 453 job posts from sector employers.

Exhibit A3.4.1: AI workforce categories in industry sector AI job postings, Inland Empire/Desert Region, July 2025 – June 2026



Source: COE analysis of Lightcast staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

The job posts follow the regional trend, with the majority tied to AI Operators (54%), followed by AI Builders (39%), and finally AI Assisted Workers (7%). However, this sector shows a far greater concentration of AI Builders when compared to the region as a whole, 39% vs. 29%. Similarly, AI Assisted Workers show a lower concentration when compared to the region, 7% vs. 16%. However, AI Operators are nearly equal when the sector is compared to the region, 54% vs. 55%.

The greater concentration of AI Builders demonstrates that this industry is not merely using AI products, such as Claude, but is creating its own instances of this technology rather than merely requiring workers to adopt the technology to assist their work. However, other sectors such as Finance and Insurance or Education Services have higher concentrations of AI Builders in their own posts, so this sector is by no means uniquely focused on AI Builders in the region.

A3.5: Where The Industry Falls In The Quadrant Model

As described in section 2.9, the Professional, Scientific, and Technical Services sector is in the “Adopting” quadrant. This means the sector shows above-average AI exposure and above-average AI job posting demand; therefore, the work that AI can plausibly perform is also the work employers are actively recruiting workers with AI skills to use.

Going further, the Professional, Scientific, and Technical Services sector is the most extreme example of an Industry “Adopting” AI technology. This is because it has both the highest share of regional AI job posts (31.8%) and the highest rate of AI exposure by occupational tasks (31%). (For context, the regional average across all Industries for AI job posts is 0.5%, while for AI exposure by occupational tasks it is 15%.)

Though a minority of IE/D employers in this field are currently posting jobs requiring or preferring AI skills, middle-skill workers in this Industry Sector can expect to be at the vanguard of AI disruption in the region overall. Due to the high density of AI exposed middle skill,

occupations in this sector, employers will likely have more incentive to adopt AI products, such as Claude, to complement their current technology stack. Also, middle skill workers in the most exposed Industry Groups, such as Accounting, Tax Preparation, Bookkeeping, and Payroll Services; or Computer Systems Design and Related Services, can expect to be even further disrupted because of its high concentration of AI exposed occupations.

While current trends do not guarantee future results, as of this publication date, the IE/D Professional, Scientific, and Technical Services sector is within reach of disruption by AI the most aggressively because of both advances in the technology's capabilities and the needs of regional employers.

APPENDIX A4: DUST IN THE GEARS (MANUFACTURING)

A4.1: Overview

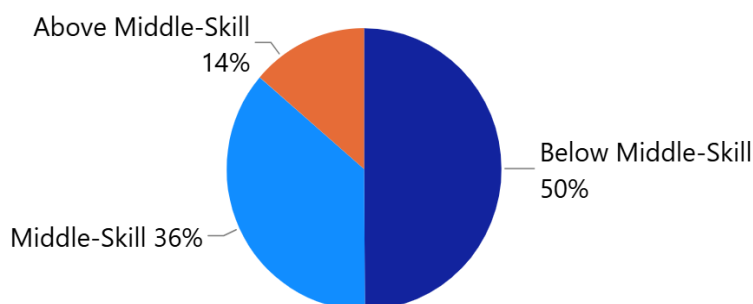
Industry with Second Most AI Demand in the Region

The Manufacturing sector is a mid-sized sector in the Inland Empire/Desert Region. This industry sector falls into the applied quadrant, with below-average exposure (14.3%) and above-average AI job posting demand (1.1%). That classification is based on the sector-level data. Analysis of the industry groups and occupations that make up the sector is likely to reveal segments with exposure above 14.3%.

Manufacturing (NAICS 31-33) covers businesses engaged in the mechanical, physical, or chemical transformation of materials, substances, or components into new products.³¹ The sector is the eighth largest in the region by 2025 job counts. With approximately 100,000 jobs in 2025, it accounts for 5.2% of employment in the Inland Empire/Desert Region.

Exhibit A4.1.1 displays the distribution of Manufacturing sector employment in 2025 by skill level. Approximately 36% of those jobs, over 36,200, are middle-skill, while 14% are above middle-skill and 50% are below middle-skill. The share of workers requiring a postsecondary education for employment suggests this sector offers many opportunities for entry-level workers.

Exhibit A4.1.1: Skill-level distribution in the manufacturing sector, Inland Empire/Desert Region, 2025



Source: COE analysis of Lightcast occupation data (2026.3)

³¹ Manufacturing Industry Sector Definition. (2026). North American Industry Classification System (NAICS). Retrieved from: <https://www.census.gov/naics/?input=31&year=2022&details=31>

Across all occupations in this Industry Sector, about 8.1% of tasks are susceptible to automation and 6.2% to augmentation, for 14.3% overall AI exposure. (For context, the regional average across Industry Sectors is 15.1% AI Exposure.)

Also, the remainder of this chapter focuses on middle-skill occupations, which typically require more than a high school diploma but less than a bachelor's degree. This segment of the labor market is what regional K-12 institutions and community colleges are positioned to serve directly through associate degrees, certificates, and other credentials, making it the level at which findings can most readily inform program decisions.

A4.2: Industry Core Occupations

Exhibit A4.2.1 shows the AI exposure for the core occupations in this Industry Sector. This report defines “Industry Core” occupations as those which are middle skill, have greater than 10 jobs in the Industry, greater than 50 jobs in the region, and whose jobs in the region are heavily concentrated in this Industry, meaning a third or more of its regional jobs are found in this single Industry Sector. By focusing on the “Industry Core” occupations, as opposed to all middle-skill occupations in this Industry, AI exposure can be compared across the jobs that are most critical to employers in this field.

Exhibit A4.2.1: AI exposure and employment estimates for core middle-skill occupations in the manufacturing industry sector, Inland Empire/Desert Region, 2025

Description	Automation Exposure %	Augmentation Exposure %	Total AI Exposure %	Jobs in Industry (2025)	Jobs in Region (2025)
Mechanical Drafters	6.7%	26.7%	33%	168	374
First-Line Supervisors of Production and Operating Workers	10.0%	15.0%	25%	3,310	5,282
Mechanical Engineering Technologists and Technicians	6.7%	16.7%	23%	77	155
Inspectors, Testers, Sorters, Samplers, and Weighers	12.9%	6.5%	19%	3,010	6,059
Chemical Technicians	6.3%	12.5%	19%	171	389
Computer Numerically Controlled Tool Programmers	6.3%	12.5%	19%	217	262
Food Science Technicians	12.5%	6.3%	19%	257	377
Industrial Engineering Technologists and Technicians	3.3%	13.3%	17%	172	232
Machinists	0.0%	10.3%	10%	1,574	2,040
Electro-Mechanical and Mechatronics Technologists and Technicians	3.6%	3.6%	7%	36	83
Prepress Technicians and Workers	6.7%	0.0%	7%	75	104
Industrial Machinery Mechanics	6.3%	0.0%	6%	1,269	2,898
Tool and Die Makers	0.0%	5.9%	6%	253	284
Computer Numerically Controlled Tool Operators	3.7%	0.0%	4%	1,681	1,944
Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic	3.4%	0.0%	3%	1,682	1,855
Aerospace Engineering and Operations Technologists and Technicians	0.0%	0.0%	0%	76	113
Chemical Equipment Operators and Tenders	0.0%	0.0%	0%	376	404
Dental Laboratory Technicians	0.0%	0.0%	0%	209	273
Drafters, All Other	0.0%	0.0%	0%	61	161
Engine and Other Machine Assemblers	0.0%	0.0%	0%	101	121
Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders	0.0%	0.0%	0%	95	114
Maintenance Workers, Machinery	0.0%	0.0%	0%	189	462
Medical Appliance Technicians	0.0%	0.0%	0%	54	100
Ophthalmic Laboratory Technicians	0.0%	0.0%	0%	42	113
Plant and System Operators, All Other	0.0%	0.0%	0%	98	260
Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders	0.0%	0.0%	0%	660	838

Source: COE analysis of Lightcast staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

Mechanical Drafters Are Most Exposed

Mechanical Drafters are the most AI exposed occupation at 33% of all tasks found to be within reach of Anthropic’s Claude product. Additionally, Mechanical Drafters are also the most impacted by Augmentation, which comprises 26.7% of its AI exposure. However, Inspectors, Testers, Sorters, Samplers, and Weighers are the most impacted by Automation, which exposes 12.9% of all their occupational tasks to AI. First-Line Supervisors of Production and Operations Workers are the second most AI exposed as 25% of their tasks are within reach of Claude.

As a contrast, 11 Industry Core occupations do not currently show any AI exposure from Claude usage. However, this data is a point in time and limited by Anthropic’s current dataset, so it may not be accurate across all AI products and will undoubtedly change as adoption increases across fields. However, among the 11 occupations shown above, three relate to machinery operation/tending, and two others relate to laboratory technicians, suggesting low disruption in these fields overall. This may denote that occupations requiring direct interaction with heavy machinery and careful calibration of specialized equipment are less exposed at this stage of the technology’s capabilities and perhaps that adjacent fields will be more resistant to adopting the technology in the near term.

Overall, it appears that occupations involved in drafting, measuring, and management operations are more exposed, composing three of the top four Industry Core occupations for AI exposure. In contrast, occupations in machine tending and laboratory operations are less exposed, making up 5 of the 11 occupations showing no AI exposure in Claude’s dataset. This difference may be explained by differences in common work activities between the groups. Drafting, measuring, and management tasks are more likely to involve computer usage, communication, or drafting and reviewing documents, while the majority of the 11 occupations showing no exposure are related to machinery and equipment operation. Computer-based tasks are substantially more exposed to AI augmentation or automation than machinery and equipment operation, given the current use of the Claude product.

A4.3: Industry Groups

So far, the report has presented exposure and employment estimates at the Sector level when discussing Industry data. Sector-level exposure figures are weighted averages that can mask variation among the businesses within them. Because AI exposure reflects the occupational mix of a workforce rather than the sector label itself, businesses in the same sector can differ substantially.

The following sections shift to industry groups, a finer classification that shows how exposure varies among businesses within a sector. Industry groups offer the detail needed to observe those differences while keeping regional employment estimates reliable. Industry Groups are a lower level of the NAICS data taxonomy. For example, this Industry Sector is Manufacturing (NAICS 31-33), and an Industry Group within the sector is Plastics Product Manufacturing (NAICS 3261). For an overview of the NAICS taxonomy and its relation to each other, see the North American Industry Classification System (NAICS) at BLS³², or visit the IED COE’s LMI 201 online training series as a useful resource.)

Exhibit A4.3.1 shows the number of middle-skill jobs by industry group in the Manufacturing sector in 2025.

³² <https://www.bls.gov/bls/naics.htm>

Exhibit A4.3.1: Middle-skill jobs by industry group in the manufacturing, Inland Empire/Desert Region, 2025

Industry Group	2025 Jobs ▼	Middle-Skill Jobs	Middle-Skill Share of Jobs
Plastics Product Manufacturing	8,948	3,902	44%
Architectural and Structural Metals Manufacturing	5,603	2,029	36%
Bakeries and Tortilla Manufacturing	4,560	779	17%
Beverage Manufacturing	4,394	1,426	32%
Cement and Concrete Product Manufacturing	4,318	2,035	47%
Other Wood Product Manufacturing	4,064	1,183	29%
Other Food Manufacturing	3,827	1,022	27%
Other Miscellaneous Manufacturing	3,798	1,337	35%
Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	3,725	2,289	61%
Medical Equipment and Supplies Manufacturing	2,854	1,285	45%
Other Fabricated Metal Product Manufacturing	2,449	960	39%
Printing and Related Support Activities	2,264	672	30%
Aerospace Product and Parts Manufacturing	2,175	924	43%
Converted Paper Product Manufacturing	2,145	546	25%
Household and Institutional Furniture and Kitchen Cabinet Manufacturing	1,922	585	30%
Animal Slaughtering and Processing	1,897	336	18%
Pharmaceutical and Medicine Manufacturing	1,750	697	40%
Motor Vehicle Parts Manufacturing	1,736	650	37%
Fruit and Vegetable Preserving and Specialty Food Manufacturing	1,641	442	27%
Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	1,622	559	34%
Other General Purpose Machinery Manufacturing	1,523	566	37%
Semiconductor and Other Electronic Component Manufacturing	1,516	479	32%
Soap, Cleaning Compound, and Toilet Preparation Manufacturing	1,494	621	42%
Motor Vehicle Body and Trailer Manufacturing	1,469	430	29%
Other Electrical Equipment and Component Manufacturing	1,291	400	31%
Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	1,181	441	37%
Iron and Steel Mills and Ferroalloy Manufacturing	1,097	459	42%
Office Furniture (including Fixtures) Manufacturing	1,062	331	31%
Metalworking Machinery Manufacturing	1,041	611	59%
Boiler, Tank, and Shipping Container Manufacturing	1,034	375	36%
Other Nonmetallic Mineral Product Manufacturing	1,027	472	46%
Commercial and Service Industry Machinery Manufacturing	974	354	36%
Coating, Engraving, Heat Treating, and Allied Activities	969	292	30%
Electric Lighting Equipment Manufacturing	932	330	35%
Alumina and Aluminum Production and Processing	892	340	38%
Forging and Stamping	882	353	40%

Industry Group	2025 Jobs ▼	Middle-Skill Jobs	Middle-Skill Share of Jobs
Grain and Oilseed Milling	824	295	36%
Veneer, Plywood, and Engineered Wood Product Manufacturing	792	242	30%
Electrical Equipment Manufacturing	789	237	30%
Basic Chemical Manufacturing	774	400	52%
Dairy Product Manufacturing	719	241	34%
Steel Product Manufacturing from Purchased Steel	704	261	37%
Animal Food Manufacturing	684	248	36%
Other Textile Product Mills	606	163	27%
Rubber Product Manufacturing	601	212	35%
Other Furniture Related Product Manufacturing	598	171	29%
Foundries	596	310	52%
Glass and Glass Product Manufacturing	587	264	45%
Sugar and Confectionery Product Manufacturing	518	131	25%
Other Chemical Product and Preparation Manufacturing	510	261	51%
Spring and Wire Product Manufacturing	476	186	39%
Other Transportation Equipment Manufacturing	419	140	33%
Industrial Machinery Manufacturing	412	151	37%
Petroleum and Coal Products Manufacturing	396	199	50%
Paint, Coating, and Adhesive Manufacturing	394	155	39%
Agriculture, Construction, and Mining Machinery Manufacturing	351	131	37%
Motor Vehicle Manufacturing	322	66	21%
Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	321	161	50%
Clay Product and Refractory Manufacturing	302	132	44%
Resin, Synthetic Rubber, and Artificial and Synthetic Fibers and Filaments Manufacturing	290	145	50%
Communications Equipment Manufacturing	276	92	33%
Nonferrous Metal (except Aluminum) Production and Processing	265	99	37%
Pulp, Paper, and Paperboard Mills	254	88	35%
Ship and Boat Building	250	65	26%
Engine, Turbine, and Power Transmission Equipment Manufacturing	189	84	44%
Cutlery and Handtool Manufacturing	178	69	39%
Sawmills and Wood Preservation	173	43	25%
Computer and Peripheral Equipment Manufacturing	167	52	31%
Hardware Manufacturing	152	59	39%
Textile Furnishings Mills	124	37	30%
Other Leather and Allied Product Manufacturing	70	12	17%
Lime and Gypsum Product Manufacturing	64	30	47%
Audio and Video Equipment Manufacturing	59	15	25%
Apparel Accessories and Other Apparel Manufacturing	47	9	18%
Textile and Fabric Finishing and Fabric Coating Mills	45	6	13%
Household Appliance Manufacturing	36	9	26%

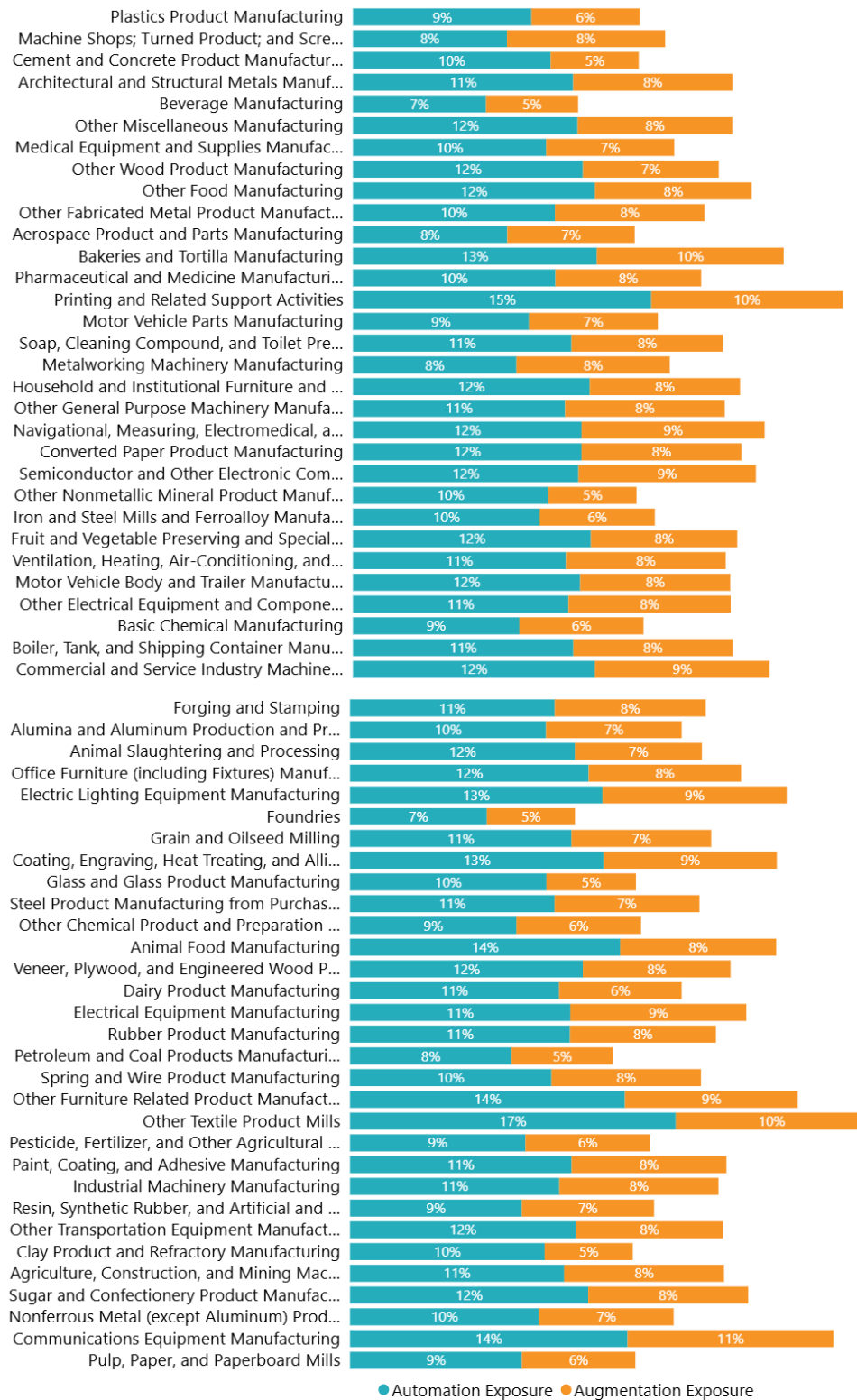
Industry Group	2025 Jobs ▼	Middle-Skill Jobs	Middle-Skill Share of Jobs
Seafood Product Preparation and Packaging	30	7	23%
Manufacturing and Reproducing Magnetic and Optical Media	25	6	25%
Fiber, Yarn, and Thread Mills	20	11	53%
Footwear Manufacturing	13	2	12%
Apparel Knitting Mills	10	3	33%
Fabric Mills	5	2	44%
Leather and Hide Tanning and Finishing	4	1	18%
Railroad Rolling Stock Manufacturing	2	0	21%
Tobacco Manufacturing	1	0	49%

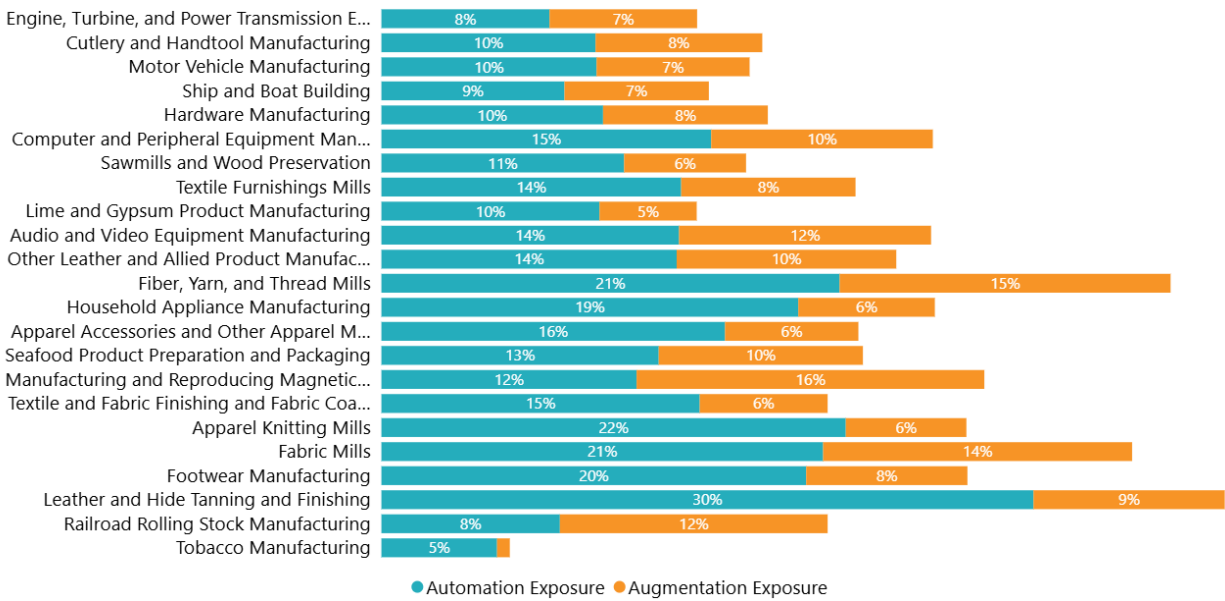
Source: COE analysis of Lightcast staffing pattern data (2026.3)

While total exposure is useful for comparison, automation and augmentation exposure figures may provide greater insight into the potential impacts of increasing AI adoption. Exhibit A4.3.2 displays the automation and augmentation exposure for middle-skill workers in each industry group in the Manufacturing industry sector. Automation and augmentation exposure is nearly evenly split across industry groups, with most industry groups more exposed to automation, mirroring the sector distribution.

The widest spread is in the Cement and Concrete Product Manufacturing, where 10% of tasks are automation-exposed, and 5% are augmentation-exposed. AI exposure in manufacturing industry groups typically leans toward automation, suggesting current AI models could successfully complete a meaningful share of tasks. The Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing industry sector is the only industry group in this sector that has an even distribution of automatable and augmentable tasks.

Exhibit A4.3.2: Middle-skill AI task exposure by industry group in the manufacturing industry sector, Inland Empire/Desert Region, 2025



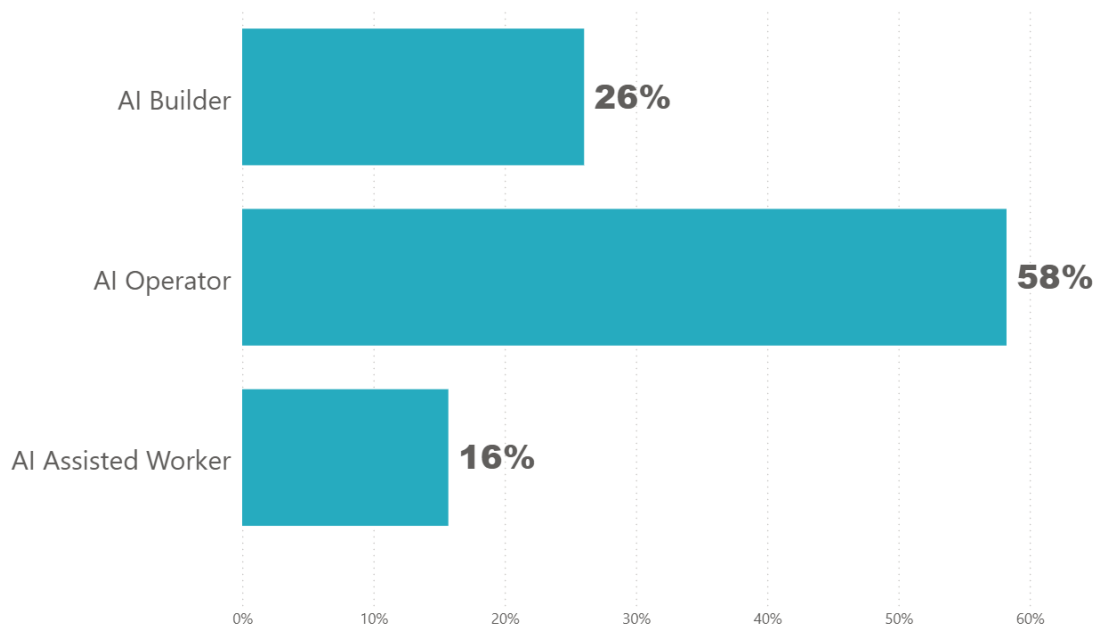


Source: COE analysis of Lightcast staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

A4.4: What Employers Are Telling Us With Job Posts

As noted in section 2.6, the Manufacturing sector produced the second most AI postings (168), which equates to 1.1% of all sector job postings in the assessed window of time. Exhibit A4.4.1 shows the breakdown of AI Worker Types from the 168 job posts from sector employers.

Exhibit A4.4.1: AI workforce categories in industry sector AI job postings, Inland Empire/Desert Region, July 2025 – June 2026



Source: COE analysis of Lightcast staffing pattern data (2026.3) and Anthropic Economic Index automation/augmentation data (2026)

The job posts follow the regional trend, with the majority tied to AI Operators (58%), followed by AI Builders (26%), and finally AI Assisted Workers (16%). However, this sector shows a slightly lower concentration of AI Assisted Workers than the region as a whole (16% vs. 19%). This sector shows a slightly smaller concentration of AI Builders when compared to the region as a whole, 26% vs. 29%.

A4.5: Where The Industry Falls In The Quadrant Model

As described in section 2.9, the Manufacturing sector is in the “Applied” quadrant. This means the sector shows below-average AI exposure, but above-average AI job posting demand. Therefore, employers are actively recruiting workers with AI skills at a rate that outpaces what the sector’s underlying task profile would predict.

Going further, the Manufacturing sector is the most significant example of an industry applying AI technology in the region, accounting for the majority of employment in the Applied quadrant. Manufacturing’s AI job posting rate of 1.1% is more than double the 0.5% regional average, and the fourth highest among the sectors, while its AI exposure by occupational tasks is 14.3%, below the 15.1% regional average. This sector had the second highest number of AI job postings in the region.

Please note that the exposure measures used in this report capture tasks that large language models, such as Claude, can perform currently, and do not capture the tasks outside of Claude’s scope, such as physical robotics, machine vision, or process automation, which are important to this sector.

While current trends do not guarantee future results, as of this publication date, the IE/D Manufacturing sector is the clearest regional case of employer AI demand outpacing measured task exposure. Employers here appear to be adopting AI products, such as Claude, to complement engineering and operations functions rather than substitute for production work, a pattern that rewards middle-skill workers who can pair existing process knowledge with AI fluency.