California's AI Workforce Advantage

Building a Precision Intelligence System

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Executive Summary

The global race to lead in artificial intelligence will be determined not only by advances in models, chips, and capital investment, but also by how effectively governments and employers prepare workers to adapt as AI changes the nature of work. California has a first-mover opportunity that no other state can yet claim: to build a workforce readiness strategy precise enough to match how AI is actually reshaping work at the level of tasks, skills, hiring demand, and training needs. Realizing this advantage depends on acting before comparable data capabilities and planning frameworks emerge elsewhere.

AI reshapes occupations from the inside, augmenting some tasks, transforming others, and raising the value of the distinctly human capabilities that remain. A workforce strategy calibrated to occupational headcounts will miss the changes already underway. On the other hand, a strategy calibrated to tasks and skills can target investment with precision and put California ahead of the change.

California's existing workforce institutions and data infrastructure, including 45 local workforce development boards, 116 community colleges, nearly $1 billion in annual workforce investment, and one of the nation's most extensive public workforce data systems, position the state to build a task- and skill-based analytical framework unmatched elsewhere in the country. By connecting these assets through a shared data layer, California can identify workforce transitions earlier and direct training and workforce investments with greater precision.

California's first-mover window is open, but it is narrow. The technical building blocks for a task-and-skill data system already exist. The question is whether California will assemble them before another state does.

Section by Section Preview

This report makes that case across five sections and translates it into concrete recommendations for policymakers and industry leaders alike.

Section 1 establishes the foundational framework: AI changes tasks within occupations, not entire occupations at once. Effective workforce strategy must operate at three levels of granularity: occupations, tasks, and skills, and the analytical tools to do so already exist.

Section 2 examines what the current labor market research shows. The picture is nuanced since AI demand is growing sharply while junior opportunity in certain sectors is evolving. Neither trend alone captures the full picture, and policy calibrated to the broader transformation will lead the market.

Section 3 maps California's workforce readiness opportunity. The state has significant infrastructure that can be enhanced with the task-and-skill data that would allow existing systems to respond to AI-driven changes with analytical depth.

Section 4 benchmarks California against Washington, New York, and Massachusetts, each of which has a large concentration of technology talent and has made significant progress in workforce modernization. The objective is not to rank states, but to identify strategies that California can adapt.

Section 5 translates the analysis into a set of prioritized recommendations for policymakers and for employers. The public and private recommendations are designed to reinforce each other since the analytical infrastructure that improves public workforce targeting also gives California employers a stronger foundation for their own talent decisions.

01

From Work Transformation to Task Evolution

AI is reshaping work at the task level, not the occupational level. The workforce data systems that can see inside occupations, identifying which tasks AI augments and which capabilities remain distinctly human, are the ones that will strengthen workforce readiness, target public investment, and give California employers a strategic framework for their own talent decisions.

The latest industry research demonstrates that the most important fact about AI's effect on work is that it reorganizes the tasks and skills within occupations rather than replacing occupations themselves. Generative AI, agentic systems, and physical AI are changing the composition of jobs at the task and skill level, in small ways and large, across every sector of California's economy. The workforce strategy that tracks this task-level change is the one that will find the greatest opportunities for investment.

This is not an abstract distinction, as it directly shapes how California deploys nearly $1 billion in annual workforce development investment, how community colleges design curriculum, and how employers approach talent acquisition and role design.

Why task-level analysis informs the strategic picture

Consider two of California's largest workforce segments: registered nurses and software developers. At an occupation-level lens, they appear to have similar potential to be affected by AI-related trends, but a task-level analysis reveals a more differentiated pattern of impact.

For nurses, AI is primarily an augmentation tool as it handles documentation, scheduling, and administrative tasks. Consequently nurses can spend more time on the patient-facing, judgment-intensive work that defines the profession's value. For developers, some coding and testing tasks are increasingly AI-enabled, while team leadership, stakeholder communication, and complex architectural judgment grow in importance. These are two occupations that present entirely different readiness pictures, and therefore call for different investment strategies for the state's workforce programs and the companies that employ these workers.

The analytical foundations for this task-level approach are well established in the research literature. Eloundou et al. (2023) introduced a task-based framework for assessing how large language models intersect with work across U.S. occupations. They find that roughly 80 percent of U.S. workers could see at least 10 percent of their tasks affected, and that approximately 19 percent may see at least 50 percent of their tasks impacted, with higher-wage roles more exposed than lower-wage ones. AI is affecting work across the income spectrum, creating opportunities to prepare workers at every level of the economy.

Building on these task-level effects across the economy, multiple AI providers have published occupation-level mappings of real-world conversation data, including OpenAI's analysis of ChatGPT usage (Chatterji et al., 2025), Microsoft's analysis of Copilot usage (Tomlinson et al., 2025), and Anthropic's analysis of Claude usage (Handa et al., 2025). Massenkoff and McCrory (2026) extend this work by combining platform usage data with the Eloundou et al. capability rubric to construct an "observed exposure" metric that identifies occupations where AI is actively augmenting or altering tasks today. Collectively, this evidence suggests that AI's labor market effects are already visible in shifting patterns of task demand, hiring, and skill requirements. More importantly for California, it demonstrates that these changes can now be measured with sufficient granularity to support earlier and more targeted workforce planning than traditional occupation-level indicators allow. Since underlying usage data vary by platform and user base, individual datasets should be interpreted as one lens within a broader, converging empirical picture.

Three levels of granularity: occupations, tasks, and skills

Given the task-level nature of AI's impact on work, effective workforce analysis requires deconstructing jobs into three levels of granularity, each of which illuminates different dimensions of AI readiness and investment opportunity.

Level	Definition	Example
Occupation	Broadest description of a job	Lawyer
Task	Observable units of work performed within an occupation	Courtroom advocacy, contract review, litigation support
Skill	Capabilities equired to execute the task	Oral argumentation, legal research, case retrieval

Table 1a. Deconstructing jobs into occupations, tasks, and skills

The skills picture reinforces why this granularity matters. Research on skill adjacency shows that capabilities cluster into networks, where skills that co-occur across tasks represent natural transition pathways between occupations (Alabdulkareem et al., 2018). For example, legal research skills used in contract review may have strong adjacency with litigation support tasks, which may evolve to define the lawyer's role as generative AI advances.

Workforce programs that incorporate skill adjacency can better align workers with higher-value work within their existing expertise, enabling smoother transitions for workers, stronger returns on public investment, and more efficient talent pipelines for employers.

The evolution of AI readiness assessment frameworks

The analytical toolkit for assessing AI readiness has evolved rapidly over the past decade, shifting from occupation-level estimates to task-level frameworks and, more recently, to empirically grounded measures based on observed AI usage in real-world settings, a progression reflected in the major frameworks used to assess AI exposure over time (Table 1b).

Year	Framework	Unit of Analysis	Key Contribution
2017	Frey & Osborne	Occupation	Estimated automation probability for 702 occupations
2018	Brynjolfsson, Mitchell & Rock	Task	Task-level rubric distinguishing AI exposure from automation risk
2023	Eloundou et al.	Task	LLM capability mapped to O*NET tasks; ~80% of workers have ≥10% exposure
2024	Saxena et al.	Task	Reinforcement learning simulation of AI learnability by task type
2025	MIT Media Lab Iceberg Index	Skill	Skills-centered framework revealing cross-sector AI exposure patterns
2026	Massenkoff & McCrory	Task	Observed exposure = structural exposure + real-world Claude usage data

Table 1b. Evolution of AI exposure assessment frameworks (selected)

The practical significance of this evolution is that today's most advanced frameworks offer California two complementary vantage points. The composite observed-exposure measures, drawing on real usage data from multiple AI platforms (Handa et al., 2025; Chatterji et al., 2025; Tomlinson et al., 2025; Massenkoff & McCrory, 2026), capture current patterns of AI use in the labor market. The MIT Media Lab's Iceberg Index (Chopra et al., 2025) complements this with a forward-looking, skills-centered simulation of where AI capabilities technically overlap with human tasks even before that capability shows up in adoption data. These frameworks carry direct implications for where workforce investment will have the greatest near-term impact.

A complementary framework would develop a workforce readiness profile that distinguishes routine cognitive tasks from work requiring physical expertise and human judgment, providing a strategic foundation for talent planning and targeted workforce investments. Together, these frameworks can supply the conceptual and empirical scaffolding for a workforce data system that California has not yet fully assembled.

A workforce data infrastructure that is accessible to employers, through public APIs, shared data standards, and co-investment mechanisms, transforms the alignment between public and private interests into a structural advantage for California's workforce.

02

What Emerging Labor Market Research Shows

AI is accelerating the transformation of work, and it is opening sector-specific opportunities for more targeted workforce investment. For policymakers and employers ready to navigate the transition with analytical confidence, the signal is already there to read.

A growing body of research on AI's labor market effects is can inform California workforce policy by providing evidence on how tasks are being reallocated and how AI-related productivity gains may be associated with changes in work organization. California enters this transition from a position of strength, with the infrastructure to navigate it well.

What the research shows: five key findings

1. AI demand is real and growing, but concentrated

The UMD-LinkUp AI Maps project (2026), analyzing approximately 155 million U.S. job postings since 2018, finds that demand for AI-related job postings has increased sharply since the launch of ChatGPT. In this research, an "AI job posting" is defined as one requiring technical AI skills, for example, training or fine-tuning a machine learning model, rather than merely involving the use of AI tools, such as a chatbot, in the course of the work. The share of AI-specific job postings rose from 0.28 percent of all postings in Q4 2022 to 1.13 percent in Q4 2025, a roughly fourfold increase over this period. This growth remains concentrated in a relatively narrow set of specialized technical roles. However, in California, these measures likely capture only a subset of total AI-related labor demand. In 2024, the state accounted for 15 percent of all U.S. AI job postings, and the Bay Area attracted a large share of national AI venture investment, with AI-related roles comprising 42 percent of tech job postings in the region (California State Senate, 2025; CBRE, 2025).

AI-related job postings capture only part of the picture, as many roles affected by AI are not explicitly labeled as such in job postings data. These include semiconductor design engineers, hardware and chip architects, enterprise AI integration specialists, and technical sales and solutions engineers supporting AI deployments. California's semiconductor workforce, which includes approximately 47,000 workers and more than 2,000 businesses and leads the nation with 627 semiconductor manufacturing establishments, illustrates how AI-related demand extends across adjacent technical sectors beyond explicitly coded AI roles (Semiconductor Industry Association, 2021; Office of Governor Gavin Newsom, 2026).

These patterns suggest that AI-related demand is broader than job postings alone capture. The policy implication is that California should not focus solely on expanding direct AI-sector employment, but also prioritize broad-based AI readiness, enabling workers across industries to adopt and apply AI capabilities as the technology diffuses throughout the economy.

2. Economy-wide job postings have not collapsed

Although AI has become a prominent driver of labor market change, aggregate employment indicators present a more nuanced picture. According to the same UMD-LinkUp analysis, total U.S. job postings in late 2025 remained above any pre-pandemic quarter. The authors also note that workforce reductions attributed to AI often occur alongside broader factors, including post-pandemic hiring corrections, cost containment, and organizational restructuring.

This matters for California policymakers because more precise understanding of workforce changes enables more effective allocation of strategic resources. In particular, distinguishing AI adoption effects from broader economic cycles is essential for interpreting labor market signals and avoiding misattribution in workforce planning. The monthly labor market report from Challenger, Gray & Christmas (2026) supports this need for caution, noting that while AI adoption is increasingly cited in announced workforce restructuring, these changes are occurring alongside mergers, acquisitions, bankruptcies, and broader corporate restructuring, making it difficult to attribute workforce adjustments to any single driver.

3. Entry-level opportunities are evolving in occupations undergoing significant AI-enabled change

The analysis of millions of job postings, done by Levanon et al. (2025), finds that entry-level white-collar job postings requiring fewer than three years of experience have contracted since 2022 in occupations most exposed to AI, including business operations, finance, and project management. The report identifies four structural drivers of this trend: the AI-driven reconfiguration of junior-level tasks, post-pandemic lean staffing practices, productivity gains from AI augmentation of experienced workers, and an oversupply of college graduates relative to degree-requiring entry-level demand. This pattern is concentrated in AI-exposed occupations and is not observed to the same extent in lower-exposure occupations, suggesting that AI may be influencing how entry-level work is structured within occupations rather than uniformly reducing entry-level hiring.

Evidence on early-career labor market outcomes shows a similar pattern. There are early signs of softening job-finding rates for workers aged 22 to 25 entering AI-exposed occupations and Brynjolfsson, Chandar, and Chen (2025) report suggestive evidence of employment declines for young workers in these roles.

In a February 2026 update, the authors sharpen this picture: with the broadest set of controls, the decline becomes statistically significant only from 2024 onward and rules out competing explanations like interest rates. Relative to otherwise-similar experienced workers, employment for 22-25-year-olds in AI-exposed occupations has fallen by roughly 16 percent since late 2022 and the gap continues to widen rather than close. The authors, who track these trends monthly via ADP payroll data, remain careful not to claim AI as the sole cause. While not conclusive, the evidence points to a meaningful impact on early-career professionals.

Within this transition, employer expectations for entry-level roles also appear to be shifting. PwC's Global AI Jobs Barometer (2026) finds that AI-exposed entry-level roles are seven times more likely than the least AI-exposed junior roles to require traditionally senior skills such as leadership and strategic thinking. This divide is visible across occupations: entry-level openings for roles like junior software developers, which sit in highly AI-exposed fields, have contracted, while entry-level demand has grown fastest in human dependent and place-based occupations such as construction roles that are less exposed to AI substitution. Where AI exposure is high, the nature of entry-level work itself is changing rather than disappearing: at some organizations, graduates are already directing teams of AI agents, setting task priorities and scrutinizing their outputs. These are responsibilities that resemble orchestration and judgment more than the routine execution traditionally expected of junior staff. In the United States, AI-exposed "seniorized" entry-level roles increased by 35 percent between 2019 and 2025, while comparable non-seniorized roles declined by 10 percent, indicating a shift in the skill composition of entry-level work rather than a uniform reduction in opportunity.

For California, this transition presents an opportunity to improve the precision of workforce investment. The state's 116 community colleges and large workforce development infrastructure are well positioned to align training with evolving employer demand. At a time of constrained public resources, recalibrating curriculum, success metrics, and employer partnerships toward emerging skill requirements can help ensure workforce investments prepare Californians for the types of entry-level roles that are increasingly shaping the state's labor market.

4. AI is changing hiring requirements, not just headcounts

Research on AI-adopting firms consistently finds shifts in hiring toward non-routine analytical and interpersonal skills, indicating that AI changes the composition of work within occupations by increasing demand for higher-value tasks.

This shift in hiring requirements is accompanied by broader changes in how work is organized and executed within firms. PwC's 2026 Global AI Jobs Barometer finds that companies most exposed to AI achieved 34 percent productivity growth from 2018 to 2025, compared to 24 percent for companies least exposed, suggesting that AI adoption is associated with changes in task execution and work organization rather than simply changes in employment levels. Over the same period, headcount growth at AI-exposed firms also outpaced less-exposed firms (52 percent versus 36 percent), reinforcing the pattern that AI exposure is linked to internal restructuring of work rather than net job reduction. The Barometer further identifies a "two-track" labor market, in which "professionalized" roles, where AI automates routine tasks and elevates human judgment, are growing faster than "democratized" roles, where AI lowers barriers to entry.

While PwC captures firm-level outcomes associated with AI exposure, the BCG Henderson Institute (2026) examines how these changes manifest at the occupational level across the U.S. labor market. The BCG Henderson Institute, analyzing approximately 165 million U.S. jobs across roughly 1,500 roles, provides complementary evidence at the occupational level. It estimates that 50 to 55 percent of positions will be substantially affected by AI over the next two to three years, while 10 to 15 percent will require more extensive transition as core tasks are redesigned.

These occupational-level patterns also depend on how organizations redesign roles and implement AI in practice. Deloitte's 2026 Global Human Capital Trends report reinforces this interpretation from an organizational perspective. While 65 percent of leaders report that AI requires significant cultural change, only 6 percent report meaningful progress in designing human–AI interaction. Firms prioritizing technology over human-centered design are 1.6 times more likely to fall short of expected returns, underscoring that successful AI adoption depends on redesigning roles and hiring requirements around human capabilities, not simply reducing headcount.

5. Emerging indicators of AI-related labor market change

Multiple emerging data sources point toward early labor market signals in AI-exposed occupations. The Massenkoff–McCrory (2026) composite observed-exposure measure finds that highly exposed occupations are projected by the Bureau of Labor Statistics to grow more slowly through 2034, with early evidence also indicating a roughly 14 percent softening in job-finding rates for workers aged 22 to 25 entering those occupations. Complementary occupation-level usage mappings from OpenAI and Microsoft point in a broadly consistent direction, even as estimates vary depending on platform coverage and methodology.

These patterns should be interpreted as early indicators rather than confirmed long-run trends. Their value lies in their convergence across different measurement approaches: capability-based mapping, observed usage data, and worker-reported surveys. These methods provide a more actionable signal than any single data source alone, and represent the kind of early warning indicators that workforce systems are increasingly able to leverage.

The policy implication: neither narrative is sufficient

A workforce strategy grounded in opportunity must prioritize AI literacy and productivity augmentation as central pillars of California's economic approach, while remaining attentive to emerging signals of labor market adjustment. MIT economist David Autor's framework offers a useful lens for this balance: AI's central promise lies in extending the reach of human expertise, enabling a broader set of workers to engage in higher-stakes decision-making tasks that were once confined to a narrower set of specialized professionals (Autor, 2024).

AI readiness policy is most powerful when it focuses on preparing workers to use AI productively. The evidence base supports this priority, and a strategy that targets these transitions will lead the market.

03

California's Workforce Readiness Opportunity

California’s opportunity is to add analytical depth to the workforce infrastructure it has already built. The state operates one of the most comprehensive workforce development systems in the country. The next step is to refine that system’s focus from the occupational level to the task and skill level where AI is actively reshaping work. The scale of investment is already substantial; the opportunity now lies in improving how precisely it is targeted.

California’s workforce development system is, by any reasonable measure, one of the most extensive in the United States. The state’s 45 local workforce boards coordinate federally funded services across every region, while its 116 community colleges serve more than 2 million students annually and maintain deep employer partnerships across major industry sectors.

This system is supported by a layered set of tools and data infrastructure. CalJOBS connects job seekers with training resources and labor market information, while CareerZone provides occupational profiles, wage data, and career pathway exploration. The Cradle-to-Career Data System offers a longitudinal backbone linking K–12, postsecondary, and workforce outcomes, and the CTE LaunchBoard tracks employment and earnings outcomes for Career Technical Education completers. The California Career Passport Program is further advancing toward skills-based credentialing.

The opportunity is not to expand this infrastructure, but to increase the precision with which existing investments are deployed. Specifically, the next step is to integrate a shared analytical layer that enables these systems to respond more directly to changes in the composition of work driven by AI.

Questions California's systems are well-positioned to answer next

California's current workforce architecture cannot readily answer the questions that would most improve readiness and resource allocation in an AI-reshaping economy.

For example:

- Which specific tasks within a growing occupation are distinctly human, and therefore the most effective focus for training investment and role design?
- Which workers are well positioned to move laterally into higher-resilience roles by leveraging existing skills with minimal additional training?
- Which regional economies have the highest concentration of workers in AI-exposed occupations, and which employers in those regions have the greatest stake in workforce transitions?
- Which community college programs are building durable, human-centric capabilities that AI augments rather than replaces, and how can employers validate and co-invest in those programs?
- Where are the most productive opportunities for public–private co-investment, where employer workforce needs and public workforce investments are sufficiently aligned to support shared program design?

These questions are addressable, but only with analytical systems that integrate task-level data, and skill-adjacency modeling.

The four key components

A. Task-level AI readiness assessment integrated into CalJOBS and CareerZone

CalJOBS currently uses ONET SOC codes to classify job postings, and CareerZone integrates ONET data across more than 900 occupations. O*NET (Occupational Information Network) is the U.S. Department of Labor's standardized taxonomy of occupations, tasks, and skills used to describe the structure of work across the economy. O*NET itself provides 1,016 occupational titles, each decomposed into 10 to 25 task statements and mapped to approximately 120 cross-occupation skill descriptors, forming a robust foundational structure.

The next layer is an AI readiness assessment: a systematic scoring of each task based on its exposure to AI augmentation, automation, or resilience. Connecting California's existing O*NET-based infrastructure to contemporary AI exposure measures would transform these systems from descriptive tools into forward-looking readiness systems.

B. Real-time job postings data as a labor market signal

California's current labor market intelligence relies primarily on survey-based data, which introduces reporting lags. The UMD-LinkUp AI Maps research demonstrates the added value of job postings data, enabling near real-time visibility into changes in skill demand, employer hiring behavior, and AI-related role growth.

Integrating job postings data into California's existing data infrastructure would allow earlier detection of AI-driven shifts before they appear in traditional employment statistics. Governor Newsom's Executive Order N-6-26, directing EDD to develop a sector-level AI employment dashboard, provides a natural starting point for this integration.

C. Skills-adjacency modeling for transition pathway planning

Skill adjacency models, pioneered by Alabdulkareem et al. (2018), represent skills as networks in which co-occurrence across tasks defines transition pathways between occupations.

For workforce programs, this enables identification of roles workers can move into with minimal additional training and strong employment growth prospects. For employers, it identifies internal pathways into emerging or AI-augmented roles and the targeted skills needed to bridge transitions.

California's Cradle-to-Career Data System provides the longitudinal data backbone on which a skills-adjacency modeling layer could be built, particularly given its ability to link community college training completion to labor market outcomes.

The key constraint is not data availability, but the absence of a shared task-and-skill standard that would allow Cradle-to-Career, CalJOBS, CareerZone, and LaunchBoard to operate within a unified analytical framework.

D. Employer-facing access to the same intelligence

The private sector has developed advanced proprietary skill taxonomies. Platforms such as Lightcast and LinkedIn maintain continuously updated frameworks containing tens of thousands of skills derived from job postings and resumé data. These tools are widely used by California's large employers for enterprise workforce planning but they are not consistently accessible to workers, community colleges, or small businesses.

A public task-and-skill infrastructure, built through open APIs, shared data standards, and co-investment mechanisms, would close this gap while establishing a common analytical foundation across stakeholders. As a shared public good, such infrastructure enables a more complete and dynamic view of the labor market than any single private system can provide, aligning workforce development, education, and employer planning around a common data language.

No other state has yet built this. California has the largest tech workforce of any comparable state and the highest concentration of AI-native companies, nearly $1 billion in annual workforce spending, and cross-agency data infrastructure already in progress. Taken together, it is the strongest first-mover candidate in the country.

04

Lessons from Comparable States

California can benchmark itself not to rank states, but to learn fast and adapt. Washington, New York, and Massachusetts each offer concrete models for capabilities California is working to build, and each has made choices California can learn from and improve upon.

Three states with strong technology workforces and active workforce modernization efforts offer California the most relevant benchmarks: Washington, New York, and Massachusetts. Each has developed capabilities California can learn from and adapt to its own context.

Feature	California	Washington	New York	Massachusetts
Public skills-matching portal	Partial (CareerZone)	Established (WA Workforce Portal)	Established (Career Development Portal)	Established (MassHire)
Real-time job postings integration	Limited	Established	Partial	Partial
AI-specific literacy initiative	In development (EO N-6-26)	Emerging	Partial	Established (Google partnership)
Sector-based AI readiness programs	Pilot stage	Established	Established	Established
Cross-agency data standards	In development (Cradle-to-Career)	Established	Established	Established

Table 4a. State Workforce Modernization Benchmarks

Washington: Real-time skills matching and public-facing intelligence

Washington State has built one of the most integrated public-facing workforce data systems among the benchmark states. The Washington Workforce Portal connects job seekers with training programs and employers using real-time skill demand data, representing a level of integration that California has not yet achieved. Washington Workforce Watch, produced by the state Workforce Training Board, further translates labor market data into accessible public reporting on trends and program outcomes.

Washington demonstrates that real-time labor market intelligence and public-facing accessibility can be developed together. Its system shows that workforce effectiveness improves when workers, employers, and policymakers operate from shared, continuously updated skill demand data.

New York: Cross-agency coordination and sector-based training

New York's workforce modernization strategy is defined by cross-agency coordination and structured sector-based programming. Its career development portal integrates skills assessment, credential recognition, and training pathways into a unified system for job seekers, offering a more consolidated public-facing experience than California currently provides. Initiatives such as the SCION illustrate how a state can build cross-agency partnerships and shared data systems to align workforce services around specific populations and needs.

New York's systematic approach to workforce innovation, including sector-based training programs, skills gap interventions, and employer partnerships coordinated through the state Department of Labor, provides evidence that the institutional coordination challenges California faces are solvable. California's workforce system involves more actors, more regions, and more institutional complexity than New York's, but the coordination model New York has built offers a template for how intentional cross-agency effort can create something more coherent than the sum of its parts.

Massachusetts: Public-private AI literacy at scale

Massachusetts offers California the most directly transferable model for rapid deployment of AI literacy training through existing workforce infrastructure. In 2025, Governor Healey and Google announced a statewide partnership to provide free AI training to Massachusetts residents, coordinated through the MassHire Career Center network. The implementation details such as course availability and eligibility structured through existing career centers, offer an operational model for how state workforce centers can serve as distribution channels for AI literacy programs that neither the state nor private partners could scale alone.

This approach highlights three design principles: public-private partnerships can scale quickly when governance alignment exists; existing workforce institutions can serve as effective delivery channels for new capabilities; and private-sector partners contribute both technical content and labor market legitimacy. California is particularly well positioned to replicate and scale this model given its deeper concentration of AI-native firms and established workforce infrastructure.

What California can do

Across these benchmarks, a clear distinction emerges between incremental modernization and system-level integration. California's advantage lies not in any single component but in the combination of:

- the largest concentration of AI-native firms among U.S. states,
- the most extensive community college system in the country,
- and an emerging cross-agency data infrastructure, including Cradle-to-Career, CTE LaunchBoard, and the Career Passport initiative.

These assets create the foundation for a more advanced task- and skill-level workforce intelligence system than any other state has yet assembled. The states that lead in AI workforce readiness will be those that move from fragmented infrastructure to integrated intelligence systems capable of tracking task-level change and directing investment with precision. California already has the underlying components; the opportunity is to connect them into a coherent system of insight.

California has a clear opportunity to translate its existing assets into national leadership. The states that will lead on AI workforce readiness are the ones that move from infrastructure to insight, building systems that can see inside occupations, track task-level change in real time, and direct investment with precision. California has everything it needs to be first.

05

Recommendations for Policymakers and Employers

The opportunity before California is not to react to workforce changes after they occur. It is to build the analytical and training infrastructure that allows policymakers and employers to navigate the transition, investing where readiness gaps are largest and transition opportunity is clearest.

The recommendations in this section are organized for two audiences whose interests converge on a shared goal. Policymakers and workforce boards will benefit from more sophisticated analytical tools to allocate the state's workforce development resources with greater precision and impact. Employers benefit from a strategic framework for navigating AI-related talent decisions, including role redesign, upskilling investment, onboarding for AI-assisted work, and talent pipeline co-investment with community colleges and workforce boards. Where these interests align, the recommendations identify opportunities for co-investment and co-design that neither sector can realize independently.

For Policymakers and Workforce Boards

Recommendation 1: Build a shared task-and-skill intelligence layer across existing workforce systems

California's most important workforce modernization investment is not a new program but a shared data standard and analytical layer that connects CalJOBS, CareerZone, the Cradle-to-Career Data System, and the CTE LaunchBoard around a common task-and-skill vocabulary. The ONET foundation is already embedded in California's systems. The next step is to augment ONET task data with AI readiness assessments, drawing on the Eloundou, Massenkoff-McCrory, and MIT Iceberg frameworks, and make that dataset available across the state's workforce ecosystem.

This does not require building new systems from scratch. The path forward runs through intentional data standards and connectivity decisions that EDD, the Labor and Workforce Development Agency, and the Chancellor's Office make jointly. Governor Newsom's Executive Order N-6-26 directs EDD to launch a sector-level AI employment dashboard. That dashboard is a natural starting point, and designing it from the outset to interoperate with systems already operated by the California Community Colleges system would significantly increase its impact.

Recommendation 2: Launch pilot sector-based AI readiness programs through community colleges

The Massachusetts-Google model offers a template California can extend and improve upon. California's community colleges already have employer relationships, credentialing infrastructure, and statewide reach. A structured pilot, involving selecting three to five regional economies with high concentrations of occupations undergoing significant AI-enabled change, partnering with employers on curriculum and credentialing, and delivering programs through existing community college infrastructure, would generate an evidence base needed to scale efficiently.

This direction aligns with emerging federal policy attention. Congressman Sam Liccardo (CA-16), joined by Congressman Jimmy Panetta, recently introduced the Supporting Knowledge Through Industry-Led Learning (SKILL) Act, which would incentivize private sector investment in community colleges and public universities through tax credits for co-created workforce training programs. The bill proposes a $2,500 tax credit per student completion, and an additional $2,500 for employers who hire program graduates, directly aligning employer incentives with workforce outcomes. The SKILL Act's model is closely aligned with the co-design approach California's own pilot programs should pursue.

The Hamilton Project's (2026) framework for pro-worker AI design provides the normative direction: workforce programs are most effective when they augment worker capabilities rather than simply preparing workers for AI-mediated roles. Employer-designed curriculum, paired with recognized credentialing, creates clear labor market signaling value. California's Career Passport Program provides a potential credentialing backbone. The remaining gap is content, particularly sector-specific AI literacy curricula that are both practically relevant and validated by employers with sufficient labor market credibility. Here, SVLG members are natural validation partners.

Recommendation 3: Establish shared data standards and open APIs for employer access

California's analytical infrastructure becomes most powerful when it extends beyond state systems. Providing access through open APIs allows employers to integrate task-and-skill data directly into their workforce planning systems, aligning private hiring and training decisions with public workforce investments.

This creates a shared data layer that functions as a coordination mechanism: employers and public agencies operate from the same underlying understanding of task-level workforce change, enabling more efficient alignment between training programs, hiring demand, and investment.

For Employers

Recommendation 4: Map how AI is changing work internally before drawing workforce-redesign decisions

The BCG Henderson Institute’s finding that 50 to 55 percent of positions will be substantially changed by AI, while only 10 to 15 percent will require near-term transition, is a useful starting point for internal workforce planning. For each major role cluster, employers benefit from conducting task-level analysis: which tasks AI is augmenting, which tasks it is automating, and which human capabilities are increasing in strategic value. Conducted systematically, this approach produces a different talent strategy than occupation-level assessments and helps identify where upskilling investment will generate the highest return.

The same task-level mapping that improves internal talent decisions also generates the employer-side signal California’s public workforce systems most need: which skills are employers actually demanding in AI-reshaping roles, and which community college programs are producing graduates with those capabilities? Sharing that signal through structured partnerships with local workforce boards and community colleges is one of the highest-leverage contributions employers can make.

Recommendation 5: Invest in AI literacy across the workforce, not just for technical roles

David Autor’s (2024) argument that AI can extend the value of human expertise across a broader set of workers depends on the development of AI literacy that enables effective augmentation. AI literacy is not primarily a technical skill, it is the capacity to work effectively with AI tools within a given domain: knowing when to rely on AI outputs, knowing when to verify them, prompting effectively for domain-specific tasks, and exercising judgment where AI capability is limited.

For employers, the strongest approach embeds AI literacy investment in role-specific onboarding and ongoing professional development, rather than treating it as a standalone technical training program. The challenge is not access to AI tools. Rather, it is ensuring workers are equipped to use them effectively enough that organizations realize productivity gains while supporting an inclusive transition across roles.

Recommendation 6: Strengthen onboarding for AI-assisted work

The entry-level evolution is not only a public policy issue but an employer talent pipeline challenge. If AI is reshaping many of the junior tasks that historically served as entry points to professional roles, employers who do not redesign their onboarding will risk weakening their talent pipelines and constraining future mid-level capability development.

Effective onboarding for AI-assisted work requires deliberate scaffolding of the judgment and interpersonal skills that complement AI capabilities, alongside structured training in the tools workers will use in practice. This is particularly important for roles where junior tasks are increasingly AI-mediated rather than fully manual.

Employers are well-positioned to co-design these onboarding programs with California community colleges, particularly given the California Career Passport Program's goal to create portable, employer-recognized skill credentials. Employers who participate in credential validation will influence the skills community college graduates bring to the labor market while giving colleges clear signals about evolving workforce needs.

Recommendation 7: Partner with public workforce institutions on curriculum and talent pipelines

The alignment between public workforce investment and private employer needs is increasingly important, but often operationally fragmented. SVLG members have the scale, technical expertise, and domain knowledge to ensure California's community college AI readiness programs reflect real labor market demand. Public workforce boards, in turn, provide the reach, credentialing infrastructure, and regional networks needed to scale these programs beyond what employers can achieve independently.

The Massachusetts–Google model provides a useful template, but California employers can extend it further by contributing curriculum design, industry-recognized credentialing, hiring commitments for program completers, and ongoing feedback loops that allow training programs to evolve alongside AI capabilities and labor market demand. Shared program design and co-funded curriculum development are the mechanisms that transform isolated partnerships into durable workforce infrastructure.

The public and private sector interests here are closely aligned and increasingly interdependent. California's workforce data becomes more valuable as employers contribute real-time signals about skill demand and task change. At the same time, employer talent strategies become more effective as public programs produce workers with task-level capabilities aligned to evolving work. This creates a structural co-investment opportunity. It is the mechanism through which California can convert its first-mover position into a durable advantage in workforce intelligence and talent development.

Conclusion

The case for a task-and-skill data system in California is, at its core, a case for workforce readiness: building the systems that allow policymakers, employers, and workers to navigate an AI-reshaping economy with the information needed to make consequential decisions with greater precision.

AI reshapes occupations at the task and skill level, and it does so unevenly across sectors, occupations, regional economies, and the specific mix of tasks within roles. A workforce strategy calibrated to occupation-level trends will systematically miss this granularity. In a period of budget discipline, that precision is not a constraint on action; it is the argument for it. California's nearly $1 billion in annual workforce investment is a significant asset, and directing it with task-and-skill precision is how the state can increase its impact, promote more inclusive growth, and maintain our global competitiveness.

The technical building blocks for this kind of system already exist. The occupational task decomposition foundation provided by frameworks is already embedded in California's workforce systems. Massenkoff and McCrory, along with parallel work from OpenAI and Microsoft, show that real-world AI usage data drawn from multiple platforms can be incorporated into labor market analysis. The MIT Media Lab's Iceberg Index and related frameworks demonstrate that skills-centered approaches can surface AI exposure patterns that traditional occupational indicators miss. California's Career Passport, Cradle-to-Career Data System, and CTE LaunchBoard provide a foundation on which a shared analytical layer can be built. No other state has assembled this combination of assets.

California also holds structural advantages that strengthen its position: the largest tech workforce in the country, a high concentration of AI-native companies, the most extensive community college system, and a cross-agency data infrastructure already in development. Governor Newsom's Executive Order N-6-26 establishes an institutional mandate for action. The alignment between public workforce investment and employer talent needs creates a narrow but meaningful window for coordinated implementation.

The question is not whether California can build this system. It is whether it can move quickly enough to lead in building it.

The opportunity is immediate. Shifts in hiring, skill demand, and the organization of work are already underway, and California's leaders are making consequential decisions today about talent development, workforce programs, and public–private partnerships. A shared task-and-skill data layer would enable those decisions to be made with greater precision and impact. Building it is one of the most consequential near-term steps California can take to strengthen workforce readiness and secure a durable first-mover advantage in the AI economy.

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