Center for AI Policy

Preparing for AI's Economic and Workforce Impacts: NAIAC Comment

The Center for AI Policy is preparing a report on the potential upcoming effects of increasingly capable AI systems on the US job market. We are sharing our preliminary ideas on this topic in response to the National AI Advisory Committee (NAIAC) Workforce and Opportunity Working Group's call for public feedback on "ways the nation can support people's lifetime employment and career success as they navigate changes in jobs and the economy brought on by AI, automation, and other factors."

The Harm

We currently lack high-quality data on AI-driven job loss and creation. The current best we have to go on may be the recurring reports from the outplacement firm Challenger, Gray, & Christmas. To date, these reports have identified 4,628 AI-caused jobs cuts in the US since May 2023, but this number is certainly an undercount, since companies have incentives to avoid reporting AI layoffs.

Beyond missing data, the Challenger data is focused solely on the past, and fails to account for how the frenetic pace of AI progress could quickly bring new AI capabilities that displace extraordinary amounts of human labor. For example, OpenAI is aiming to build "highly autonomous systems that outperform humans at most economically valuable work," and a recent survey of AI experts that such systems could plausibly arrive in the next decade. Once such systems exist, it will be very challenging for businesses to justify employing humans rather than machines.

To understand the potential scale of this change, consider US employment numbers from the Bureau of Labor Statistics (BLS). Its May 2022 data found:

- 2,879,840 Customer Service Representatives
- 1,984,180 Heavy and Tractor-Trailer Truck Drivers
- 1,826,710 Secretaries and Administrative Assistants, Except Legal, Medical, and Executive
- 1,534,790 Software Developers
- 1,402,420 Accountants and Auditors
- 1,059,840 Light Truck Drivers

If upcoming AI systems displace just ten percent of these jobs over the next decade, this would already amount to over one million Americans. And the employees in the bulleted occupations account for just 7% of all the US workers in the BLS data.

Thus, if future AI systems truly surpass human labor capabilities, there could be tens of millions of Americans out of work. Further, an economic analysis found that the transition to such systems could occur rapidly, over the span of years rather than decades; this would leave US government leaders with little time to respond.

We can't confidently predict which precise jobs will be lost, which might be created, or what the people caught up in that change might experience, but we can begin to take steps now to address these risks. There are a number of promising proposals in this space, but here we focus on just two: **data collection** on job loss from AI, and **focus worker support** on at-risk jobs.

The Need for Better Data

The lack of data on existing AI job loss hinders the government's abilities to understand labor market trends and proactively address labor disruptions. NAIAC has previously found that without these abilities, "it is possible to witness stark increases in inequality even as productivity rises."

If we want to understand and predict how AI will affect employment, we need granular data that tracks which jobs are being created or displaced by AI, how many, and the fates of workers in those jobs.

Raw numbers of jobs lost and gained will not be sufficient, because such numbers miss important information such as the relative pay and quality of the jobs, the skills required to transition to new jobs, and demographics of workers that are more likely to need to transition. For instance, some applications of AI might not lead to greater unemployment but instead force workers into lower-paying, lower-quality jobs.

To solve this issue, the US Government should establish an initiative to collect such data and create a publicly available and easily accessible database, which can enable more effective policy making and research into projections of potential future effects. The data should be presented in a way that protects any sensitive information from the reporting companies.

At a minimum, the initiative should aim to answer:

- **Job Loss and Creation:** What sectors (or specific professions) are seeing job loss? What sectors are seeing new jobs as a result of AI?

- **Skill Requirements:** What worker skills are being obviated by AI and where is AI being used to augment worker skills?

On top of these efforts, there is also opportunity here to track trends from the worker side of things, attempting to answer:

- **Worker Transitions:** For those who have lost their job as a result of AI, what is their current employment status? What job are they doing?
- **Wage Differences:** How much are they earning relative to before the transition?

Collecting basic demographic data of affected workers will also help researchers (or potentially the data collectors themselves) identify trends in how the effects depend on factors, e.g. geography or age, which could help more effectively identify vulnerable groups. Such data could also be labeled with Bureau of Labor Statistics (BLS) task descriptions to arrive at more concrete understandings of which skills are becoming obsolete.

There are a number of ways this task could be done, such as delegating collection to the BLS, or including these questions as part of the Annual Business Survey run by the Census Bureau, which is already tracking the number of firms adopting AI.

Such an effort would enable research of AI's effects on employment to be crowdsourced. Predictions could be made and scrutinized with the understanding that everyone is starting with the same data. Moreover, this data would be invaluable to a program aimed at retraining programs for those affected, an issue to which we now turn.

Focus Worker Support on Jobs at Risk of Displacement

If the US Government aims to support workers who could lose jobs due to AI-driven change, then it will need to identify who those workers are.

Some current research has focused on trying to map current or projected AI capabilities to specific job tasks, extrapolating out from there to determine which jobs (or skills) are most at risk. Such research has helped paint some broad generalizations that, for now, represent our best guess at the contours of what is likely to come.

- One finding is that jobs which involve repetition or routine tasks are significantly more exposed than others. Whereas in the past routine physical tasks were automated, routine cognitive tasks now seem to be those most exposed.
- Some analyses have found greater exposure to jobs likely to be at the higher end of the wage scale, with a particular concentration of exposure to AI between the 75th and 90th percentile.

- Two studies have found jobs that require greater education are likely to be more exposed, often with highest projections of exposure for jobs that require a bachelor's degree or higher.
- One study finds workers older than 30 are likely to be most exposed. The oldest workers are particularly at risk, as they're likely to be less mobile and able to adapt to drastic change.

Thus, a rough idea of the groups most at risk—from AI systems similar to existing AI systems—are the older workforce or those in jobs that are repetitive, well-paid, or require greater education. Studies have identified a wide range of jobs potentially at risk; Mckinsey (2023) looked at exposure by types of work and sector (see Figure 1 in the Appendix) and RAND (2023) listed highly exposed jobs by AI technique (see Figure 2 in the Appendix). Unfortunately, specific predictions can range from study to study.

But given the environment of rapid change that we're likely to have, we cannot simply wait for further research. We need to start now in identifying opportunities based on the above commonalities between studies, and there are actually still a number of promising directions we can head in. For instance, we can begin supporting worker transitions to jobs that seem unlikely to be quickly automated, such as jobs that involve social skills (e.g. nurses, caretakers, babysitters).

Given the diversity of professions likely to be affected, the government might need to focus on more general workforce transition projects. Here, it could take inspiration from previous efforts by the federal government, like the US Highschool Movement or the 1944 GI Bill, which were both largely successful pushes to support the American public in light of changing circumstances.

We Need Lasting Solutions

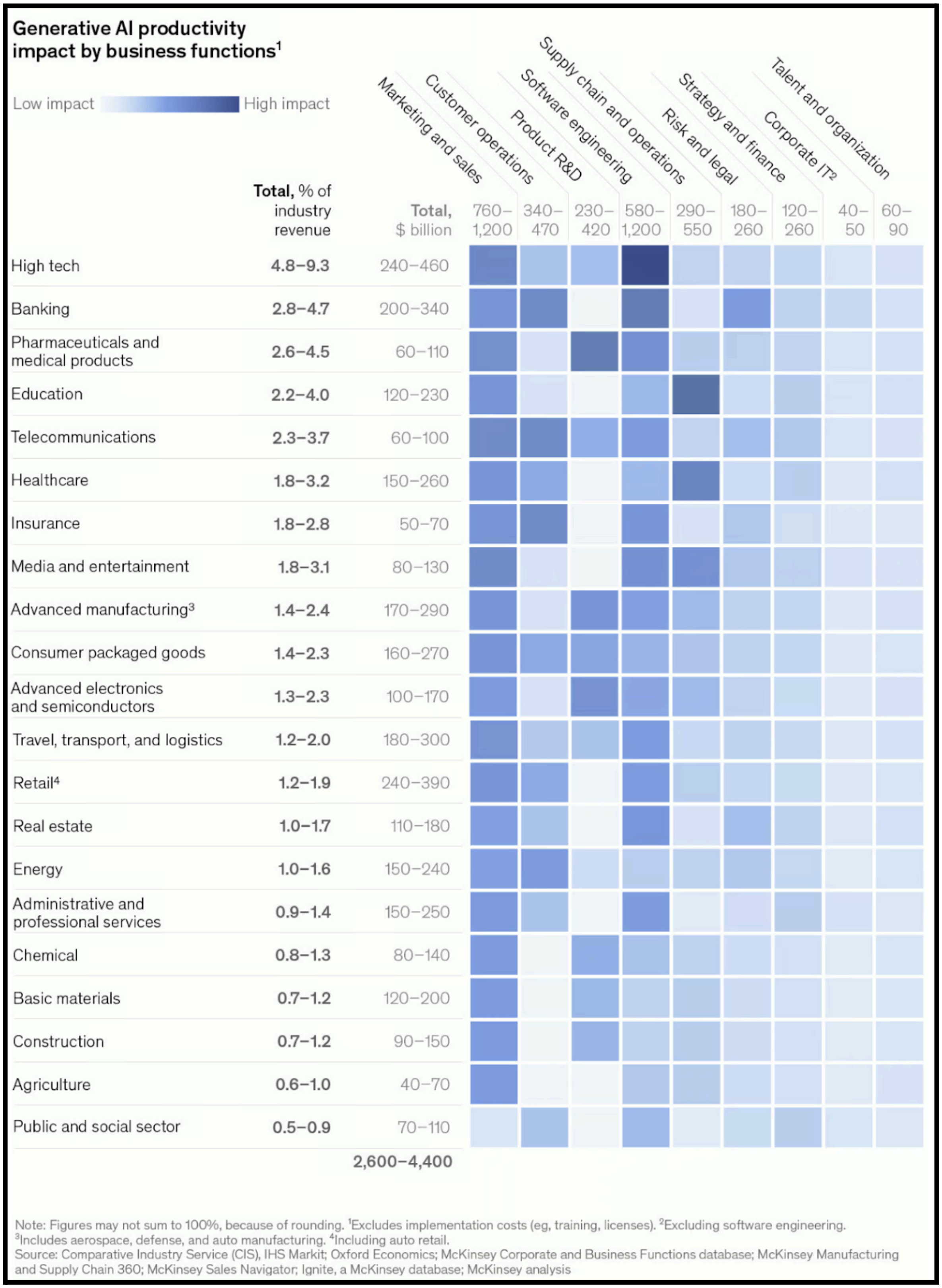
It is important to recognize that targeted worker support is not a permanent solution. AI systems will continue to become cheaper and more capable, and so ultimately all the jobs are at risk. When an AI system becomes more cost effective than a human at any job that they could have, then that human will not be able to find any job. This could very quickly lead to massive unemployment that is very difficult to reduce. We must develop proactive policy solutions to head this off at the outset.

We've only outlined some tentative suggestions based on limited current findings. As the number of jobs automated by AI rises, and we have a chance to see and measure the effects rather than make projections based on tasks and current capabilities, we will be better able to project what effects we are likely to see in the future.

Sincerely,
Jason Green-Lowe
Executive Director
Center for AI Policy

Appendix

Figure 1: [Mckinsey (2023)]



Generative AI productivity impact by business functions[1]

Low impact — High impact

	Total, % of industry revenue	Total, $ billion	Marketing and sales	Customer operations	Product R&D	Software engineering	Supply chain and operations	Risk and legal	Strategy and finance	Corporate IT[2]	Talent and organization
			760–1,200	340–470	230–420	580–1,200	290–550	180–260	120–260	40–50	60–90
High tech	4.8–9.3	240–460									
Banking	2.8–4.7	200–340									
Pharmaceuticals and medical products	2.6–4.5	60–110									
Education	2.2–4.0	120–230									
Telecommunications	2.3–3.7	60–100									
Healthcare	1.8–3.2	150–260									
Insurance	1.8–2.8	50–70									
Media and entertainment	1.8–3.1	80–130									
Advanced manufacturing[3]	1.4–2.4	170–290									
Consumer packaged goods	1.4–2.3	160–270									
Advanced electronics and semiconductors	1.3–2.3	100–170									
Travel, transport, and logistics	1.2–2.0	180–300									
Retail[4]	1.2–1.9	240–390									
Real estate	1.0–1.7	110–180									
Energy	1.0–1.6	150–240									
Administrative and professional services	0.9–1.4	150–250									
Chemical	0.8–1.3	80–140									
Basic materials	0.7–1.2	120–200									
Construction	0.7–1.2	90–150									
Agriculture	0.6–1.0	40–70									
Public and social sector	0.5–0.9	70–110									
		2,600–4,400									

Note: Figures may not sum to 100%, because of rounding. [1]Excludes implementation costs (eg, training, licenses). [2]Excluding software engineering. [3]Includes aerospace, defense, and auto manufacturing. [4]Including auto retail.
Source: Comparative Industry Service (CIS), IHS Markit; Oxford Economics; McKinsey Corporate and Business Functions database; McKinsey Manufacturing and Supply Chain 360; McKinsey Sales Navigator; Ignite, a McKinsey database; McKinsey analysis

Figure 2: RAND (2023)

TABLE 2

Top Ten Occupations Most Exposed to AI Technologies

Computer Vision	Evolutionary Computation	AI Hardware	Knowledge Processing	Machine Learning	NLP	Planning and Control	Speech Recognition
GIS technologists and technicians	Nondestructive testing specialists	Search marketing strategists	Search marketing strategists	Audiologists	Captioners	Search marketing strategists	Captioners
Search marketing strategists	Machinists	Information security analysts	Statisticians	Statisticians	Marketing strategists	Online merchants	Special education teachers, secondary
Captioners	Cytotechnologists	Statisticians	Geological technicians	Critical care nurses	Special education teachers, secondary	Sales agents	Interpreters and translators
Statisticians	Ophthalmic technologists	Document management specialists	Audiologists	Search marketing strategists	Speech and language pathology assistants	Clinical nurse specialists	Speech and language pathology assistants
Special education teachers, secondary	Search marketing strategists	Web administrators	Clinical nurse specialists	Geneticists	Document management specialists	Treasurers and controllers	Search marketing strategists
Radiologic technicians	Statisticians	Data warehousing specialists	Online merchants	Speech and language pathology assistants	Interpreters and translators	Advanced practice psychiatric nurses	Speech and language pathologists
Physicians, pathologists	Geological technicians	Special education teachers, middle school	GIS technologists and technicians	Special education teachers, secondary	English teachers, postsecondary	Bookkeeping clerks	Hearing aid specialists
Document management specialists	Ophthalmic technicians	Telecom engineering specialists	Advanced practice psychiatric nurses	Special education teachers, middle school	GIS technologists and technicians	Web administrators	Music directors and composers
Special effects artists and animators	Astronomers	Special education teachers, secondary	Web administrators	Clinical nurse specialists	Speech and language pathologists	Claims adjusters	English teachers, postsecondary
Speech and language pathologists	Substance abuse counselors	GIS technologists and technicians	Special education teachers, middle school	Captioners	Telecom engineering specialists	Critical care nurses	Statisticians

SOURCES: Author calculations from O*NET and AIPD data.

NOTE: GIS = geographic information systems. Exposure is measured as the cumulative exposure by 2020. Occupation names have been shortened from their original length in the O*NET database. Green cells indicate that the occupation has a bright outlook according to O*NET.