How Will AI Affect Students' Employability?
Implications for Equity in Education

Jennifer L. Steele
Professor of Education
American University
Washington, DC
steele@american.edu

Working Paper in Progress
August 2023

Abstract

I use data from the U.S. Department of Labor's Occupational Information Network (O*NET), which provides detailed information in the skills, tasks, work activities of 873 civilian jobs. Examining the importance and level of each of 34 work activities in each job, I rate the automation risk of each job on a 0 to 1 scale. I project that across jobs, about 30% of work is vulnerable to automation by AI, with modestly higher risks in lower-skilled jobs. This pattern may increase labor market inequity but to a lesser extent than previous waves of automation. Results highlight the importance of teaching students to leverage rather than compete with AI.

Objectives

Recent innovations in generative artificial intelligence (AI), including the November 2022 release of OpenAI's ChatGPT, have left schools and universities scrambling to consider the implications for education. In Steele (2023a, 2023b), I argue that generative artificial intelligence challenges three pillars of our education systems: measurement, information accuracy/freedom from bias, and the market value of skills. This paper focuses on the third challenge, projecting the impacts of a new generation of automation tools on the demand for jobs in the U.S. in the next two decades, as today's high school and college students enter the middle phases of their careers.

Here, I use data from the U.S. Department of Labor's Occupational Information Network (O*NET), which provides detailed information in the skills, tasks, work activities, work contexts, prevalence, and compensation for 873 civilian jobs. Examining the importance and level of each of 34 work activities in each job, I rate the automation risk of each job across 5 conceptual work activity categories and one overall category. The resulting automation risk score, ranging from 0 to 1 for each job, can be roughly interpreted as the fraction of work that is vulnerable to automation in that job. I then examine the sensitivity of these risk scores to the mix of work activities in job. Next, I examine how automation risk varies by employment sector, educational requirements, and average earnings. These questions have important implications for racial and socioeconomic equity and for the skill sets young people are given the opportunities to acquire.

Literature Review

In the past three decades, the labor market effects of automation have fallen disproportionately on blue-collar workers (Autor, 2014; Autor et al., 2003). As factory jobs became scarce, workers without college degrees increasingly found themselves in lower-paying service sector jobs. Meanwhile, the digital revolution raised earnings premiums for so-called knowledge workers, especially in the booming technology and scientific sectors (Goldin & Katz, 2008).

These converging forces—increasing demand for knowledge workers and reduced demand for workers in routinized, assembly-line manufacturing jobs—sharply widened the wage gap between individuals with and without postsecondary degrees (Oreopoulos & Petronijevic, 2013; Psacharopoulos & Patrinos, 2018). The consequences fell especially hard on Black and Brown individuals whose access to postsecondary degrees had been constrained by systematic discrimination and economic marginalization (Carnevale & Rose, 2013).

But by the late 2010s, forecasters were warning of a new wave of automation on the horizon—one that was coming for desk jobs. In 2022, the high-paying U.S. technology sector laid off about 150,000 workers, with cuts continuing into 2023. The layoffs may have been a partial readjustment following the hiring spree of technology workers during the COVID-19 pandemic, but it may also be a precursor of increasing technology company investments in job automation via generative artificial intelligence (AI).

In November 2022, OpenAI made its generative AI writing tool, ChatGPT-3.5, publicly available at no cost. Educational institutions reacted with concern, and some school systems and universities imposed bans on generative AI tools (Castillo, 2023). The concern is that generative AI makes it hard to measure students' skills, particularly in areas of writing, reading, information analysis, and computer programming. But the rise of AI also raises larger questions about the long-term value of these skills in an economy where they can be rapidly automated. To understand the implications of generative AI on the skills we teach in K-12 and postsecondary settings, this study undertakes projections of the labor market impact of the new generation of automation tools.

Data

I use 34 O*NET generalized work activities data for 873 jobs in the 2010 O*NET content model (O"NET Resource Center, 2023). The activity descriptions are based on qualitative coding of tasks reported on routinely updated surveys of job incumbents (Hansen et al., 2014). Data on the labor market prevalence and earnings of each job are based on 2002 data from the U.S. Bureau of Labor Statistics (BLS) based on Standard Occupational Classification (SOC) 6-digit codes, which are also used as occupational codes in O*NET.

I employ 34 of 41 generalized work activities along with incumbents' ratings of their importance to the job (ranging from 1 to 5) and level of sophistication and complexity required for a given activity (ranging from 0 to 7). O*NET rescales these ratings from 0 to 100 for both the importance and level scales. I use the new scales to create a ranking of automation risk based on the following assumptions:

1) AI generates probabilistic writing that models millions of extant texts and is not driven by an underlying intelligence (Newport, 2023). Thus, generative AI is likely to improve over time but to remain in the sphere of high-fidelity, low-creativity mimicry in the foreseeable future.
2) As with prior waves of automation, the less sophisticated and more predicable a task, the easier it is to automate (Levy & Murnane, 2004; Murnane & Levy, 1996).
3) Generative AI is skilled at tasks of data aggregation and processing, summarizing, rewriting/interpreting for different audiences, and explaining, as well as adhering to genre conventions. It is less skilled at tasks that are particularly human or interpersonal (such as nursing, mentoring, or coaching), idiosyncratically physical (such as replacing a faucet, cutting hair, or installing cabinetry), or creative and strategic (such as writing a moving book of essays, reassigning staff to projects based on their ineffable qualities, or launching a company) (Schneider, 2023).

Analytic Methods

Guided by earlier-wave studies that have used job characteristics in automation prediction strategies (Frey & Osborne, 2013), I generate an automation risk score based on the work activity category and its level of sophistication. For activity categories deemed difficult to automate per assumption 3 above (categories I deem as humanistic, physical, or creative), I calculate risk as:

$$\text{Risk}_{\text{protective}} = (1 - (\text{importance}/100)) * (1 - (\text{level}/100)) \qquad (1)$$

For categories deemed easier to automate (analytic and mechanistic), I calculate risk as:

$$\text{Risk}_{\text{programmable}} = (\text{importance}/100) * (1 - (\text{level}/100)) \qquad (2)$$

Note that for both formulas, a higher skill level is always linked to reduced automation risk. For protective activities, a higher importance is also linked to lower defined risk. For programmable or automatable activities, higher importance yields higher risk, though higher skill levels remain more protective.

Results to Date

I average these skills into skill category composite means based on definitions shown in the Appendix. These means range from 0.21 across jobs for mechanistic risk to 0.4 across jobs for risk due to the physical and idiosyncratic aspects of the job. The equally weighted composite risk level among the five types of component risks is 0.300, with a range from 0.123 to 0.540. The rough interpretation of a risk score is as the fraction of work in that category (or overall, for overall risk) that is vulnerable or amenable to automation.

These estimates suggest that it is only a fraction of the work—usually a small minority of the work—of any given job is vulnerable or amenable to automation in the coming years. For some workers, especially those working at higher levels of skill, a risk score of 0.25 could mean that they will become 25% more productive by automating a quarter of their work. But for other jobs, it could suggest a 25% contraction of the workforce as fewer people are required for the same amount of work.

To understand *who* is likely to be most affected, I break jobs into risk terciles (thirds) by job zone and 22 job sectors (SOC families). Job zones roughly indicate the education levels required for each job, where 5 is an advanced degree, 4 is a bachelor's degree, 3 is an associate's degree or some colleges, 2 is a high school diploma, and 1 is less than a diploma. The question here is which education levels are likely to be hit hardest.

In Table 1, I find that risk scores are moderately higher in lower-skilled and lower-paying occupations, which may further widen opportunity gaps and social inequities. This is because, *ceteris paribus*, complexity varies inversely with automation risk and underscores the importance of preparing all students, especially students of color and students from disadvantaged backgrounds, for complex and idiosyncratic tasks. We can also teach students to utilize AI to perform more complex tasks, so that they are among those equipped to view it as a tool rather than a labor market competitor.

[Table 1 about here]

Moreover, because AI will fall heavily on white collar occupations, Table 1 shows less of a relationship with education level than we have seen in past automation rounds, where the impact fell almost entirely on workers with less than a bachelor's degree (Autor et al., 2003).

Figure 1 shows the likely risk in each of 22 sectors or job families. Pie sections are sorted by labor market share and shaded by the extent of automation risk. We find by far the highest automation risk in legal, sales, office support, business/finance, and production. Table 2 shows particular risks in each sector.

[Figure 1 about here]

Implications to Date

In the coming years, as schools have more time to grapple with the encroachment of AI, they will need to consider the likely impact of AI on the skills students will need to thrive in an evolving labor market. This study begins to highlight the vulnerability of work activities to automation, and consequent effects on the equitable distribution of jobs in the U.S. labor market.

References

Autor, D. H. (2014). Skills, education, and the rise of earnings inequality among the "other 99 percent." *Science*, *344*(6186), 843–851. https://doi.org/10.1126/science.1251868

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, *118*(4), 1279–1333. https://doi.org/https://doi.org/10.1162/003355303322552801

Carnevale, A. P., & Rose, S. J. (2013). *Socioeconomic Status, Race/Ethnicity, and Selective College Admissions*. https://repository.library.georgetown.edu/handle/10822/559296

Castillo, E. (2023, March 27). These schools have banned ChatGPT and similar AI tools. *Best Colleges*. https://www.bestcolleges.com/news/schools-colleges-banned-chat-gpt-similar-ai-tools/

Frey, C. B., & Osborne, M. (2013). *The future of employment: How susceptible are jobs to computerisation?* https://www.oxfordmartin.ox.ac.uk/downloads/academic/future-of-employment.pdf

Goldin, C., & Katz, L. F. (2008). *The race between education and technology*. Belknap Press.

Hansen, M. C., Norton, J. J., Gregory, C. M., Meade, A. W., Thompson, L. F., Rivkin, D., Lewis, P., & Nottingham, J. (2014). *O*NET work activities project technical report.* https://www.onetcenter.org/dl_files/DWA_2014.pdf

Levy, F., & Murnane, R. J. (2004). *The new division of labor: How computers are creating the next job market.* Russell Sage Foundation.

Murnane, R. J., & Levy, F. (1996). *Teaching the new basic skills*. Free Press.

Newport, C. (2023). What kind of mind does ChatGPT have? *The New Yorker*. https://www.newyorker.com/science/annals-of-artificial-intelligence/what-kind-of-mind-does-chatgpt-have

O"NET Resource Center. (2023). *Work Activities*. https://www.onetcenter.org/dictionary/27.3/excel/work_activities.html

Oreopoulos, P., & Petronijevic, U. (2013). Making college worth it: A review of the returns to higher education. *The Future of Children*, *23*(1), 41–65. http://muse.jhu.edu/journals/future_of_children/v023/23.1.oreopoulos.pdf

Psacharopoulos, G., & Patrinos, H. A. (2018). Returns to investment in education: A decennial review of the global literature. *Education Economics*, 1–14. https://doi.org/10.1080/09645292.2018.1484426

Schneider, M. (2023). Do we need humans anymore? *U.S. Department of Education, Institute of Education Sciences*. https://ies.ed.gov/director/remarks/01-04-2023.asp

Steele, J. L. (2023a). To GPT or not GPT: Empowering our students to learn with AI. *Computers & Education: Artificial Intelligence*, *5*. https://doi.org/https://doi.org/10.1016/j.caeai.2023.100160

Steele, J. L. (2023b, July 20). Don’t ban ChatGPT: Teach students to do what it can’t do. *The Hill*. https://thehill.com/opinion/technology/4105892-dont-ban-chatgpt-teach-students-to-do-what-it-cant-do/

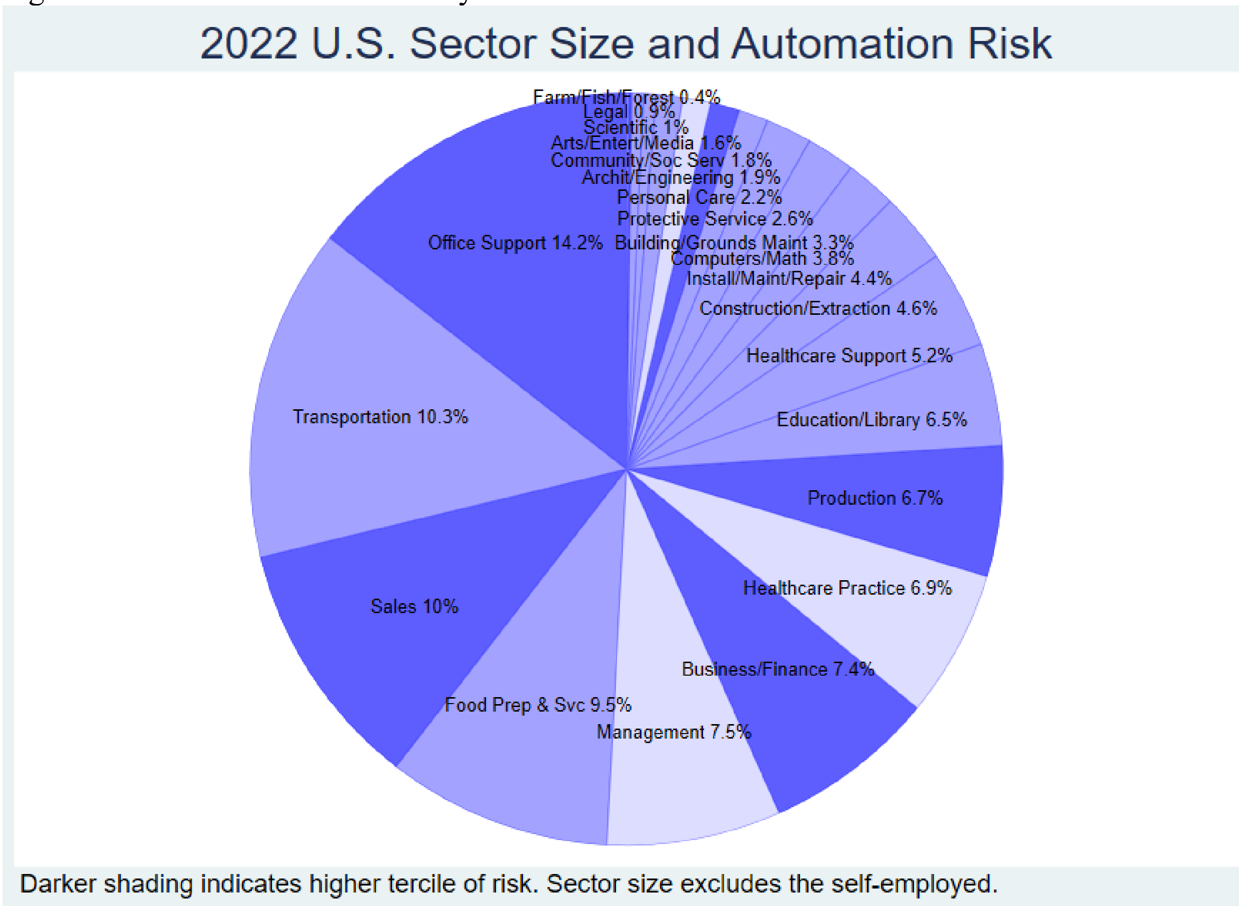
Table 1. Overall risk scores by job zone

Job zone	Mean
Less than high school	0.332
High school	0.322
Associate or similar	0.289
Bachelors	0.291
Advanced	0.281
Total	0.300

Table 2. Average estimated automation risk by SOC job family

Job Family	Risk Score
Architecture and Engineering Occ	0.265
Arts, Design, Entertainment, Spo	0.31
Building and Grounds Cleaning an	0.306
Business and Financial Operation	0.324
Community and Social Service Occ	0.297
Computer and Mathematical Occupa	0.313
Construction and Extraction Occu	0.284
Educational Instruction and Libr	0.293
Farming, Fishing, and Forestry O	0.318
Food Preparation and Serving Rel	0.312
Healthcare Practitioners and Tec	0.259
Healthcare Support Occupations	0.298
Installation, Maintenance, and R	0.279
Legal Occupations	0.393
Life, Physical, and Social Scien	0.285
Management Occupations	0.26
Office and Administrative Suppor	0.374
Personal Care and Service Occupa	0.324
Production Occupations	0.321
Protective Service Occupations	0.276
Sales and Related Occupations	0.343
Transportation and Material Movi	0.314
Total	0.300

Figure 1. Automation risk terciles by labor market sector size



Appendix

The 5 skill categories as presently defined (AM-CHP), before evaluation of sensitivity tests.

Analytic

Analyzing Data or Information	anay
Documenting Recording Information (output)	docu
Evaluating Information to Determine Compliance with Standards	eval
Interpreting the Meaning of Information for Others (under communic/interact)	inte
Processing Information	proc
Scheduling Work and Activities (reasoning)	sche
Performing administrative activities (interacting with others: administering)	prof
Monitoring processes, materials, or surrounding (input)	mont
Estimating the quantifiable characteristics of products, events or info (information input--id and eval releve info)	esti
Identifying objects, actions, and events (information input--id and eval releve info)	iden

Mechanistic

Controlling machines and processes (output-physical)	cont
Operating vehicles, mechanized devices, or equipment (output-physical)	oper

Creative

Developing Objectives and Strategies	deve
Making Decisions and Solving Problems	maki
Judging the Qualities of Objects, Services, or People	judg
Thinking Creatively	thin
Monitoring and controlling resources (interacting with others: administering)	moni
Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment (output: complex and technical activities)	draf

Humanistic

Assisting and Caring	assi
Coaching and Developing	coac

Establishing and Maintaining Interpersonal Relationships	esta
Providing Consultation and Advice to Others	prov
Resolving Conflicts and Negotiating with Others	reso
Selling or Influencing Others	sell
Training and Teaching Others	Trai
Developing and Building Teams	dvel
Staffing organizational units (interacting with others: administering)	staf
Coordinating the work and activities of others	coor
Guiding, directing, and motivating subordinates	guid

Physical

Handling and moving objects	hand
Performing general physical activities	pefo
Repairing and maintaining mechanical equipment (complex and technical)	repa
Repairing and maintaining electrical equipment (complex and technical)	rpai
Performing for or working directly w/ the public	perf
Inspecting Equipment, Structures, or Materials	insp