# AI and the Future of Work in Illinois

## An Assessment of Workers at Risk by Automated Technologies


Photo: Matthew Horwood/Getty Images

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# EXECUTIVE SUMMARY

- The rapid development of artificial intelligence (AI) and other automating technologies generates concerns among scholars, policymakers, and workers' representatives. AI is expected to bring profound transformations to the workplace, and preparing for these changes will facilitate a smoother transition into the future.
- In 2022, the Illinois Task Force on the Future of Work produced a comprehensive report highlighting areas for attention regarding how new technologies will impact the workforce, acknowledging potential impacts on wages, occupational trends, and the nature of work itself.
- This Project for Middle Class Renewal report advances the Taskforce's effort towards assessing workers' vulnerability to computerization and AI, identifying occupations, industries, and areas that may face more substantial impacts, and the demographic characteristics of the workers in these jobs.
- Workers are considered *at risk* if they are likely to be impacted by computer-based technology, including AI, based on similarities between what they do and the potential of new technologies. This report applies two risk measures (Frey and Osborne, 2017 and Webb, 2020) to the Illinois context to identify workers at risk.
- Technologies may augment the productivity of some workers and replace others. There is also a time lag between technology availability and adoption, which delays impacts. Given the time lag, risk does not necessarily entail displacement, and this report does not attempt to predict displacement rates. Instead, it assesses the occupational identity of workers at risk to provide a roadmap to who may need support transitioning into a more AI-structured future of work.
- The results show that between 14 to 25 percent of the Illinois employed labor force are at *high risk* of being impacted by automating technologies, corresponding to 0.9 to 1.5 million workers. Furthermore, 237,000 to 417,000 workers are at *very high risk* (4 to 7 percent).
- The demographic characteristics of AI-vulnerable workers vary significantly across both risk measures, emphasizing the complexity of predicting specific impacts.
- Manufacturing appears particularly susceptible compared to most other industries in the state. Likewise, the energy sector, particularly its renewable segment, seems to be at higher risk. In contrast, industries such as Healthcare and Social Assistance, and Educational Services are at relatively lower risk.
- Industries with lower union coverage and median income face *high risk* according to one of the measures but not the other.
- Spatial analysis reveals that the risk is evenly distributed across the state, with higher-risk areas primarily concentrated within the Chicago-Naperville-Elgin area and near the Saint Louis borders.
- Considering the contrasting findings, the report recommends that Illinois policymakers preemptively prepare all workers to cope with technology and AI disruptions, particularly in *high-risk* industries. The state should also closely monitor the evolving employment landscape as technology adoption expands.

# Table of Contents

# About the Authors

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# ABOUT THE PROJECT FOR MIDDLE CLASS RENEWAL

The Project for Middle Class Renewal's mission is to investigate the working conditions of workers in today's economy and elevate public discourse on issues affecting workers with research, analysis and education in order to develop and propose public policies that will reduce poverty, provide forms of representation to all workers, prevent gender, race, and LGBTQ+ discrimination, create more stable forms of employment, and promote middle-class paying jobs. Each year, the Project publishes critical research studies and holds education forums on contemporary public policies and practices impacting labor and workplace issues. If you would like to partner with the Labor Education Program in supporting the work of the Project or have questions about the Project please contact Robert Bruno, Director of the Labor Education Program, at (312) 996-2491.

# Introduction

Discussion regarding how emerging technologies, such as artificial intelligence (AI) and new forms of automation, will affect workers has received increased attention. The Biden Administration issued guidance on AI that explicitly addressed "Supporting Workers" through data collection to mitigate job displacement and ensure job quality (White House, 2023). AI is a field of computer science focused at developing machines capable of performing human like tasks. While no consensus exist as to what precisely is meant by "artificial intelligence," it is generally recognized as a subset of automation that usually incorporates digitalization. Concerns about AI and the future of work grow out of the commonly understood definition of automation as the "substitution of non-human value for human production value (Gallup, 2020). AI algorithms can learn how to complete tasks by identifying patterns in the data as opposed to following human instructions.

As AI adoption rates increase, displacement and changes in existing jobs will follow (Frank et al. 2019; Fossen and Sorgner 2022; Acemoglu and Restrepo 2019). Understanding these impacts allows for proactive preparation of workforce development initiatives, reducing stress associated with job transitions. While some studies have focused on this question at national levels, impacts are likely to vary across states, given their individual economic and institutional structure (Muro, Maxim, and Whiton 2019).

In 2022, the Illinois Task Force on the Future of Work produced a 58-page report that included a focus area on "The Impact of New Technology and the Future of Tech in Illinois." The report stated:

> *"New technologies and innovation continue to advance and shape the future of work. In particular, advancements in automation technologies and artificial intelligence (AI) are impacting the nature of work and the workplace itself. As machines carry out more tasks done by humans, complement the work that humans do, and even perform some tasks that surpass what humans can do, there will continue to be drastic shifts in wages and occupational trends (Illinois Future of Work Task Force Report, May 31, 2022)."*

It acknowledged that "the most profound concern around innovation is its impact on current and future labor markets. At the most simplistic level, this sentiment is captured by the fear of robots displacing human workers."

The report also noted what the national literature on technology adoption has found:

> *"The rise of technology, however, does not threaten all groups at the same rate."*

What the report did not do is either estimate the degree of overall labor market vulnerability to AI in the state or the possible technology impacts on workers based on demographics or occupations.

The Project for Middle Class Renewal aims to advance the Task Force's work by assessing the vulnerability of workers in Illinois to new technological developments, identifying occupations and industries that may face stronger impacts, as well as the demographic characteristics of the workers in these jobs. Anticipating and preparing for the potential consequences of AI across industrial sectors and occupations would help to facilitate a smoother transition into the future of work.

This report examines the potential industrial and occupational risk of automating technologies based on two risk measures: the susceptibility to computerization by Frey and Osborne (2017) and the exposure to artificial intelligence by Webb (2020)[1]. Overall, between 14 and 25 percent of workers in Illinois are in occupations that will likely be impacted by AI.

# Introduction

It is important to note that assessing risk does not equal job displacement. There is a lag between technology availability and generalized adoption. Additionally, viewing occupations as a "bundle of tasks" suggests the potential for AI technologies to perform some tasks of an occupation, while human beings continue to execute other tasks (Gallup, 2020). Further, once technologies are incorporated, they may augment the productivity of some workers and replace the work done by others (Autor, Levy, and Murnane 2003; Frank et al. 2019). While it is likely that the nature of jobs will undergo significant changes, not all impacted workers will be displaced – a realization that, once again, reinforces the need for anticipatory reskilling initiatives across the board.

# Assessing AI Risk

For the past decades, the focus of the scholarship on technology and employment has been on the impacts of computerization and automation on workers. From the 1970s, automation development led to a phenomenon known as "hollowing of the middle" – a large-scale displacement of workers performing routine jobs and the disappearance of middle-paying jobs in industries such as Manufacturing. In its place, the services industry rapidly expanded, polarized between low- and high-pay jobs (Autor, Levy, and Murnane 2003; Autor and Price 2013).

More recently, artificial intelligence (AI) developments and their potential impacts on workers became a new source of concern, one with many similarities with prior moments of technological disruption in human history (Brynjolfsson and McAfee 2014; Schwab 2017). AI's potential to perform human-like jobs is expected to significantly disrupt employment and many other areas of human interaction. Moreover, AI raises new concerns about ethics and biases, which has prompted the publication of over a hundred normative AI ethics documents across various sectors (Schiff et al. 2021).

The fear of disruptive impacts on the labor market stimulated the development of various predictive risk measures. Frey and Osborne (2017) developed an occupational susceptibility to computerization measure based on expert knowledge of the technology potential within the job and estimated that about half of the US employment was at a 70 percent or higher risk of AI impact. Frey and Osborne observed a strong and negative relationship between the probability of computerization and wages and education. However, tasks involving perception and manipulation, creative intelligence, and social intelligence were considered less susceptible to AI engineering.

Webb (2020) identified jobs with high exposure to AI by analyzing the overlap between patent and occupational descriptions. Compared to previous automating technologies (e.g., industrial robots and software), he found more substantial exposure to AI among workers with higher educational levels, unlike the earlier cases of technology adoption.

More recently, Felten, Raj, and Seamans (2021) developed the AI Occupational Exposure assessment by linking specific AI applications to occupational abilities (as opposed to tasks). This index captures relationships between AI applications and occupations but does not "measure how substitutable or automatable an occupation is" as the authors are "agnostic about whether or when AI will augment or replace human labor."

The various risk measures can naturally lead to conflicting predictions, given their distinct methodologies and assumptions. In a conciliation attempt, Fossen and Sorgner (2019, 2022) combined two measures (Frey and Osborne 2017 and Felten, Raj, and Seamens 2018) to generate a map of the digitalization of occupations. In relying on both Frey and Osborne and Webb, our report contributes to a better understanding of the sensitivity of findings to various methodologies.

Furthermore, risk measures built on occupations have been criticized for overestimating automatability, as high-risk occupations may still contain substantial non-automatable tasks. Another criticism is that these studies overlook how tasks vary across jobs (Arntz, Gregory, and Zierahn 2017). Arntz, Gregory, and Zierahn claim that accounting for task heterogeneity reduces Frey and Osborne's predictions of at-risk jobs to 9 percent on average across 21 countries in the Organization for Economic Co-operation and Development (OECD). For the US, Frey and Oborne's predicted risk was 47 percent.

In assessing automating technology risks, it is essential to acknowledge the lag time between a technology's potential and its adoption. AI adoption outside the tech sector is currently at early, often experimental stages (Bughin et al. 2017). Acemoglu et al. (2022) observe a rapid growth in AI job postings pushed by establishments that already engage in tasks compatible with current AI development. Although there is evidence that these jobs reduce hiring in non-AI positions at the establishment level, the aggregate impact is too small to be detectable. Investments in AI are also found to be stronger among firms with higher cash reserves, R&D investments, and markups [2](Babina et al., n.d.; Alekseeva et al. 2021). Across the board, these studies find increased productivity for early AI adopters but evidence that many firms face barriers to incorporating new technologies.

Furthermore, even once technologies are incorporated into workplaces, their effects on workers vary beyond the displacement possibility. There is evidence that AI has negative impacts on on-the-job training and worker motivation (Li et al. 2023), but also that it often complements workers (Hatzius et al. 2023) and enhances their productivity when executed in a collaborative manner (Sowa, Przegalinska, and Ciechanowski 2021). By and large, how technologies are incorporated and the broader job context directly affect worker well-being (Nazareno and Schiff 2021). The analysis presented herein takes a first step in understanding how AI's potential exposure impacts Illinois workers and identifies groups with higher vulnerability.

# Data and Methodology

The methodology of this report combines recently developed scales of automation risk with worker data from the 2019 American Community Survey (ACS) for Illinois (Ruggles et al. 2023)[3]. Linking risk measures with the ACS allows for studying at-risk population groups, their demographic and employment characteristics, and place of residence, for example[4].

Frey and Osborne and Webb assess risk based on task similarity between what workers typically do in their occupations and the capabilities of new technologies, although the criteria employed differed. While Frey and Osborne relied on a panel of experts to identify skill sets that would require human action, Webb used patent descriptions to discern which tasks new technologies can perform to determine risk exposure[5]. Both measures are based on technology capabilities and share a predictive nature. Our analysis establishes two risk measures from theirs: "high risk" are workers at or above the 75th risk percentile, and "very high risk" are those above the 90th percentile. Notably, these risk measures serve the purpose of identifying potential impacts rather than predicting technological displacement. Indeed, as new technologies are incorporated into the workplace, they may become complements or substitutes for workers.

This report examines the technology/AI risks based on the workers' gender (see, Appendix Table A2 for the demographic characteristics of workers in Illinois), race, level of education, age, industry and occupation. Also noted were differences regarding worker economic conditions and bargaining power (union or nonunion). Lastly, it investigates spatial variations in concentrated risk across the state and by occupational projected growth

Both Frey and Osborne's and Webb's scales were developed using O*NET Standard Occupational Classification (SOC), allowing easy conversion to the Census harmonized occupation code (occ2010) using occupational crosswalks. The matching between the O*NET and the Census occupational classifications is imperfect, and O*NET provides a more granular classification. Whenever multiple O*NET codes matched a single code in the Census, the scores were averaged as in Nazareno and Schiff (2021).

The ACS sample includes all employed workers, except for those in military occupations.

# Findings:
## Assessing Workers at Risk

Table 1 shows the number of at-risk workers (above the 75th and 90th thresholds) in Illinois and the United States. About one-quarter of Illinois workers (1.5 million) are at a high risk based on Frey and Osborne, and about 15 percent (1.0 million) based on Webb. Those at very high risk range from roughly 4 (Webb) to 7 (Frey and Osborne) percent (237,000 to 418,000). Interestingly, projections for the state of Illinois show remarkable proximity to the entire United States.

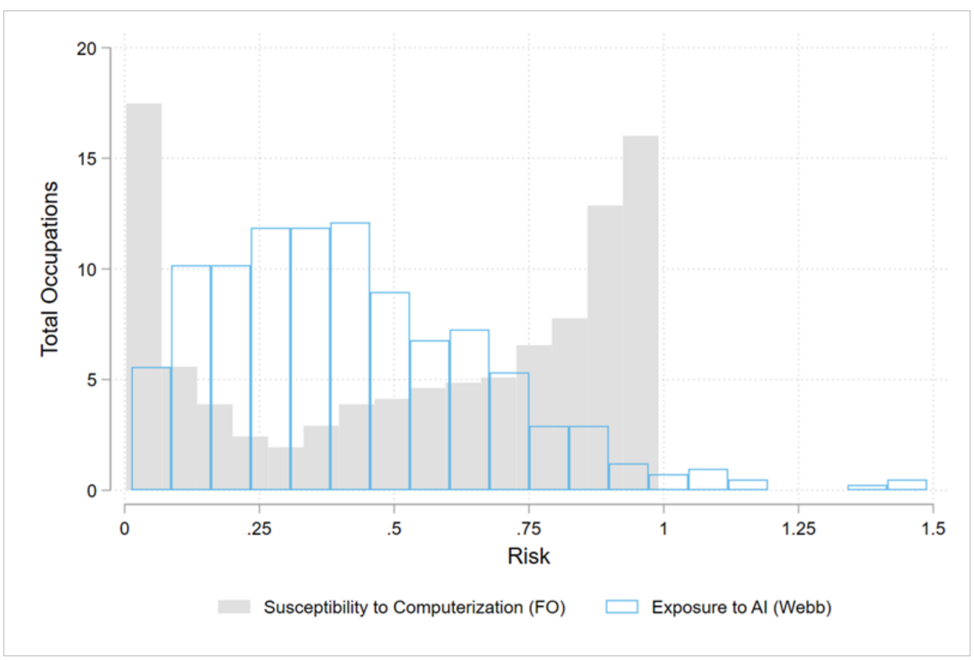
**Table 1. Workers At Risk by New Technologies**

| Risk percentile | Total Occupations | Illinois | | United States | |
|---|---|---|---|---|---|
| | | Total Workers | Percent of Employment | Total Workers | Percent of Employment |
| Above 75th (FO) | 145 | 1,519,548 | 24.3% | 37,099,540 | 23.9% |
| Above 75th (W) | 154 | 912,211 | 14.6% | 23,033,758 | 14.8% |
| Above 90th (FO) | 36 | 417,550 | 6.7% | 10,025,111 | 6.5% |
| Above 90th (W) | 44 | 237,373 | 3.8% | 10,025,111 | 6.5% |

*Note: FO stands for Frey and Osborne's (2017) susceptibility to computerization and W for Webb's exposure to artificial intelligence. Sources: Authors' tabulations using FO and W's measures, combined with the American Community Survey 2019 5-years estimates for Illinois.*

Figure 1 provides a histogram of 422 occupations across each measure, emphasizing their differences. Frey and Osborne accumulate significantly more occupations at the upper end of the risk distribution than Webb. Furthermore, Frey and Osborne's risk distribution resembles a U-shaped format where Webb is closer to a bell curve.

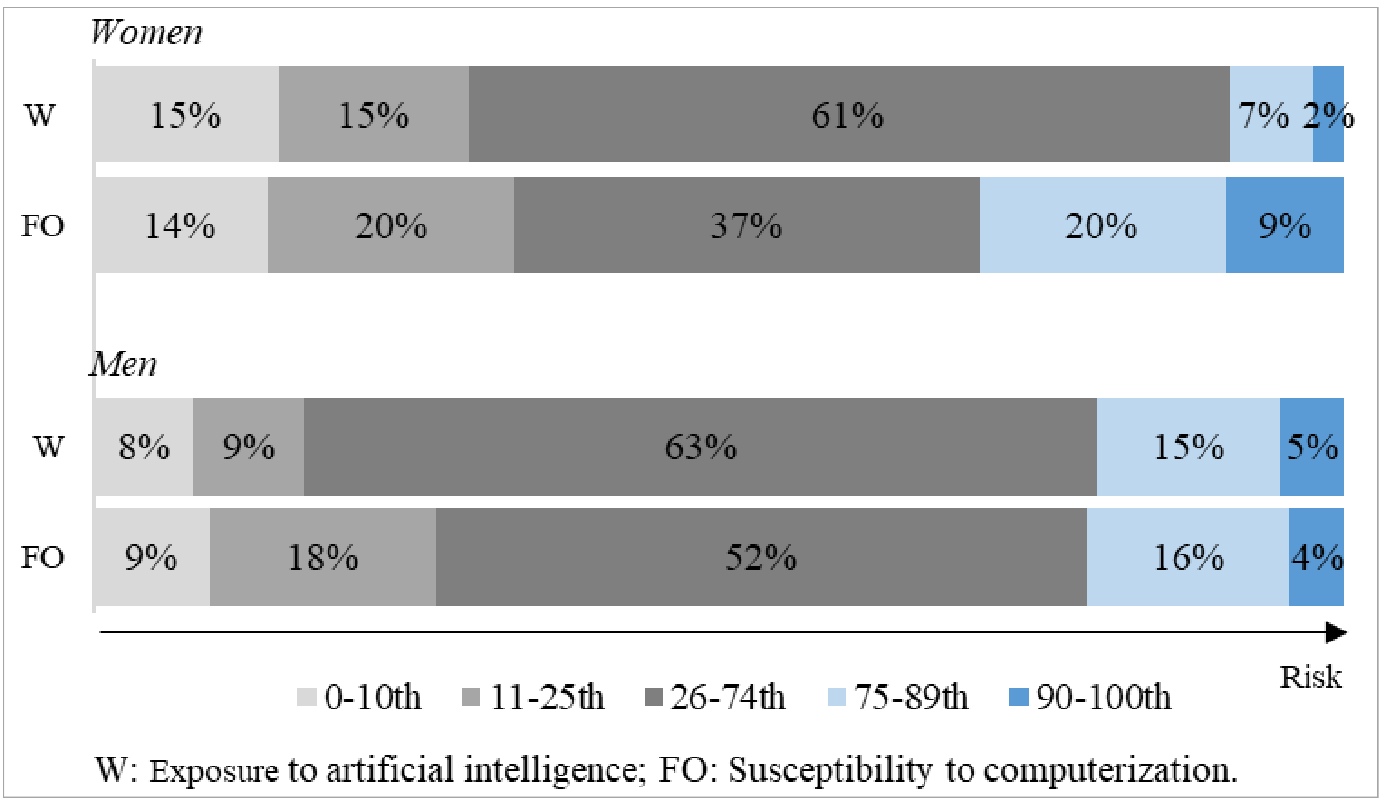
**Figure 1. Occupational Distribution by Estimated Risk**



### Demographic Portrait

This section turns to understanding the demographic profile of workers at risk. Throughout the analysis, Frey and Osborne show a higher proportion of workers at risk, as expected from the occupational distribution shown in Figure 1. Predictions, however, differ beyond the total number of workers at risk, as the demographic profile of these portrayed by each measure varies significantly. For example, Figure 2 illustrates similar shares of male workers at risk in Frey and Osborne and Webb (roughly 20 percent). But the impact on women ranges from nine to 29 percent. Hence, Frey and Osborne and Webb anticipate a gendered impact.

**Figure 2. Workers at Risk by New Technologies by Sex**

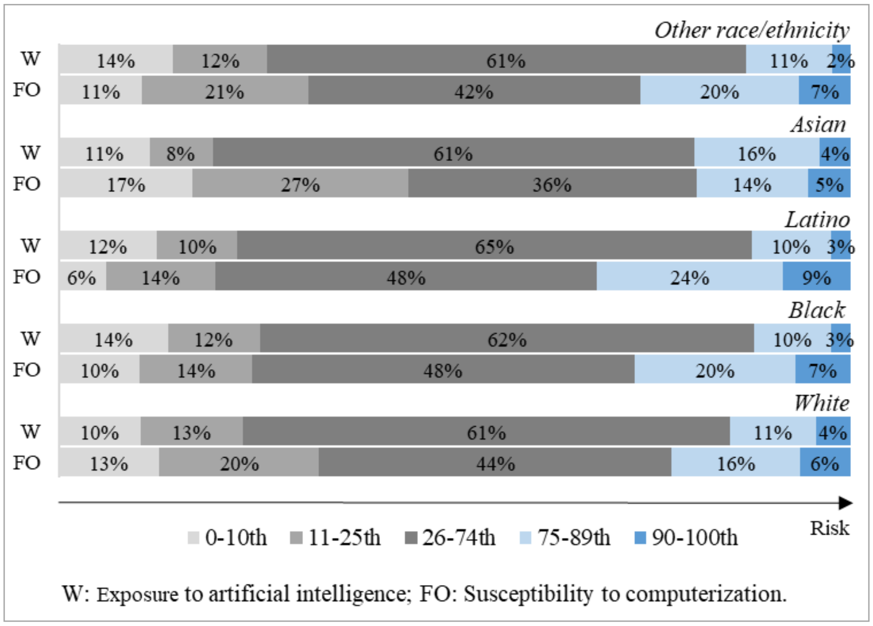



*Note: FO stands for Frey and Osborne's (2017) susceptibility to computerization and W for Webb's exposure to artificial intelligence. Sources: Authors' tabulations using FO and W's measures, combined with the American Community Survey 2019 5-year estimates for Illinois.*

# Findings:
## Assessing Workers at Risk

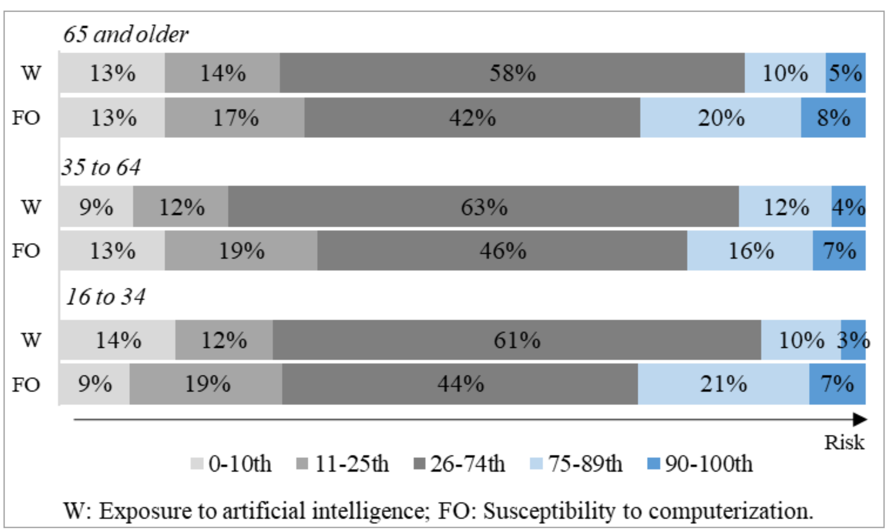
Heterogeneous predictions also show up regarding race and ethnicity, as per Figure 3. On the one hand, Frey and Osborne predict higher risk across all categories, especially for Latino (33 percent), Black (27 percent), and other race/ethnicity (27 percent) workers. On the other hand, in Webb, the variation of workers at risk is stable across categories (13-15 percent), except for Asians, which peaks at 20 percent.

**Figure 3. Percent of Workers at Risk by New Technologies by Race**




There is not much variation in workers at risk by age based on Webb, as illustrated by Figure 4. In contrast, Frey and Osborne predict higher risk for young and older workers, with nearly 30 percent at high risk (above the 75th percentile).

**Figure 4. Workers at Risk by New Technologies by Age**

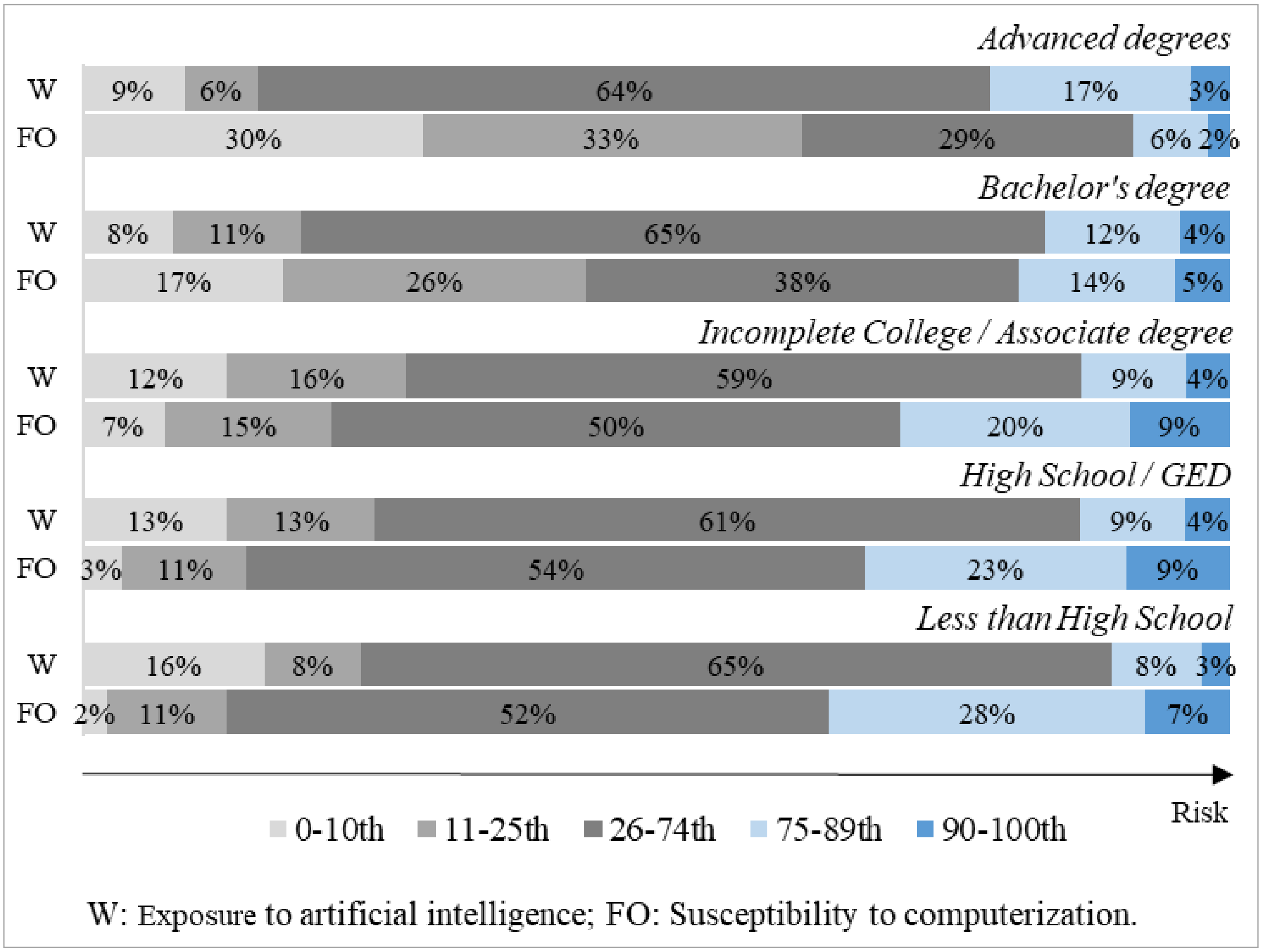



*Note: FO stands for Frey and Osborne's (2017) susceptibility to computerization and W for Webb's exposure to artificial intelligence. Sources: Authors' tabulations using FO and W's measures, combined with the American Community Survey 2019 5-year estimates for Illinois.*

# Findings:
## Assessing Workers at Risk

Differences in educational attainment levels are even more striking (Figure 5). Webb predicts that highly educated workers will face higher risk, whereas Frey and Osborne identify higher risk for less educated workers.

**Figure 5. Workers at Risk by New Technologies by Educational Attainment Levels**




*Note: FO stands for Frey and Osborne's (2017) susceptibility to computerization and W for Webb's exposure to artificial intelligence. Sources: Authors' tabulations using FO and W's measures, combined with the American Community Survey 2019 5-year estimates for Illinois.*

# Findings:
# Assessing Workers at Risk

## Industry Outlook

This section centers on workers at risk at the industry level. It begins by examining industries at a higher aggregate level and then breaks up some targeted groups of interest. As shown in Table 2, the largest industries in Illinois in terms of total employment are Health Care and Social Assistance (13.7 percent of the employed workers), Manufacturing (12.0 percent) Professional, Scientific, and Management, and Administrative and Waste Management Services (11.9 percent), Retail (10.6 percent), and Educational Services (9.3 percent).

Considering these top five industries, Manufacturing features an elevated concentration of workers at high risk, ranging from 25.1 (Webb) to 35.0 (Frey and Osborne) percent. Likewise, both measures predict roughly a third of the workers in Professional Services industries are at a high risk. However, the retail sector features a high concentration of workers at risk in Frey and Osborne but not in Webb. Meanwhile, Health Care and Social Assistance, and Educational Services concentrate relatively lower fractions of at-risk workers in both measures.

Industries with a smaller number of workers with elevated concentration of risk (above the 75th percentile) in Frey and Osborne but not in Webb are Accommodation and Food Services (39.1 percent), Finance, Insurance, and Real State, and Rental and Leasing (38.1 percent), and Transportation and Warehousing, and Utilities (22.9 percent). Industries with elevated risk in Webb but not Frey and Osborne are Public Administration (30.5 percent) and Construction (27.1 percent). Finally, although concentrating only 1.0 percent of workers in Illinois, Agriculture, Forestry, Fishing, Hunting, and Mining concentrate significant shares of workers at risk in both Frey and Osborne (29.5 percent) and Webb (68.7 percent).

## Unionization and Income

At the industry level certain industries are more vulnerable to automation. But are there variables that mitigate against vulnerability? Given the potential disruptive impact of new technologies in the workplace, assessing to what extent union protection is in place is relevant. As shown in Table 2, when analyzed by union density, the industries with more extensive union coverage in Illinois (e.g., Public Administration, Educational Services, Construction, and Transportation and Warehousing, and Utilities) concentrate lower shares of workers at risk than industries with union coverage below 7 percent in either measure. These associations suggest that workers with reduced bargaining power are more likely to be impacted by emerging technologies. Additionally, Frey and Osborne predict higher risk in industries with the lowest median incomes, although the relationship between income and risk is not as clear in Webb.

# Findings:
## Assessing Workers at Risk

**Table 2. Workers At-Risk by New Technologies by Industry**

| | Percent above 75th | | Percent above 90th | | Industry size | | Median income | Percent covered by union |
|---|---|---|---|---|---|---|---|---|
| Industry | FO | W | FO | W | Workers | Percent of employed | | |
| Agriculture, Forestry, Fishing, and Hunting, and Mining | 29.5 | 68.7 | 3.0 | 62.5 | 65,205 | 1.0 | 40,000 | 0.0 |
| Construction | 9.7 | 27.1 | 2.3 | 6.9 | 334,827 | 5.4 | 50,000 | 34.9 |
| Manufacturing | 35.0 | 25.1 | 14.4 | 6.4 | 750,111 | 12.0 | 47,481 | 12.1 |
| Wholesale | 18.5 | 12.9 | 7.7 | 1.8 | 187,614 | 3.0 | 50,000 | 11.1 |
| Retail | 42.3 | 5.8 | 4.6 | 0.9 | 660,732 | 10.6 | 23,988 | 6.1 |
| Transportation and Warehousing, and Utilities | 22.9 | 12.1 | 4.5 | 5.0 | 412,541 | 6.6 | 45,815 | 28.8 |
| Information | 16.7 | 14.6 | 6.9 | 3.3 | 115,172 | 1.8 | 53,268 | 10.0 |
| Finance and Insurance, and Real Estate, and Rental and Leasing | 38.1 | 14.1 | 16.1 | 3.3 | 452,165 | 7.2 | 60,430 | 1.0 |
| Professional, Scientific, and Management, and Administrative, and Waste Management Services | 26.5 | 27.3 | 6.4 | 3.8 | 742,405 | 11.9 | 53,000 | 4.4 |
| Educational Services | 9.9 | 5.1 | 3.0 | 0.9 | 579,438 | 9.3 | 41,946 | 42.9 |
| Health Care and Social Assistance | 11.6 | 9.0 | 5.9 | 3.7 | 859,993 | 13.7 | 36,086 | 7.5 |
| Arts, Entertainment, and Recreation | 22.2 | 5.0 | 4.1 | 1.0 | 130,401 | 2.1 | 20,362 | 8.5 |
| Accommodation and Food Services | 39.1 | 1.1 | 3.6 | 0.1 | 439,397 | 7.0 | 17,266 | 3.3 |
| Other Services, Except Public Administration Services | 12.9 | 4.3 | 4.2 | 1.0 | 295,406 | 4.7 | 30,000 | 8.0 |
| Public Administration | 15.3 | 30.5 | 5.8 | 3.8 | 225,395 | 3.6 | 64,746 | 48.1 |
| Military (excluding workers in military occupations) | 7.1 | 17.4 | 3.5 | 3.0 | 7,320 | 0.1 | 45,000 | - |

*Note: FO stands for Frey and Osborne's (2017) susceptibility to computerization and W for Webb's exposure to artificial intelligence. Sources: Authors' tabulations using FO and W's measures, combined with the American Community Survey 2019 5-year estimates for Illinois. Median income in 2019-dollar values. Union coverage was obtained from the Current Population Survey for Illinois in 2019.*

### Selected Industries Breakdown

Tables 3 to 6 break down "Health Care and Social Assistance," "Educational Services," "Energy," and the "Automotive" sectors into subcategories for a more nuanced understanding of AI impacts on these fields of employment. Health Care and Social Assistance and Educational Services are two of the largest employers in the state of Illinois. The Energy and Automotive sectors were examined and constructed as a combination of subcategories of various industries to observe how sectors expected to substantially change in the upcoming years due to the Illinois' Climate and Equitable Jobs Act (Illinois General Assembly 2021) would be subject to AI risk.

Three industries account for half of the employment in the Health Care and Social Assistance domain: "general medical and surgical hospitals," "nursing care facilities," and "offices of physicians." Frey and Osborne, and Webb identify a relatively small fraction of hospital workers at high risk, peaking between 11 and 12 percent (Table 3). By comparison, the percentage of high-risk employees working at "Outpatient care centers" is larger than hospital workers. Optometrists offices appear among the highest risk, while employees providing "Child day care services" are at nearly zero risk.

# Findings:
## Assessing Workers at Risk

**Table 3. Workers at Risk by New Technologies in Health Care and Social Assistance**

| | Percent above 75th | | Percent above 90th | | Industry size | |
|---|---|---|---|---|---|---|
| Industry | FO | W | FO | W | Workers | Percent of employed |
| General medical and surgical hospitals, and specialty (except psychiatric and substance abuse) hospitals | 11.8 | 10.6 | 4.9 | 4.1 | 296,125 | 34.4 |
| Nursing care facilities (skilled nursing facilities) | 6.3 | 5.5 | 2.6 | 1.5 | 87,086 | 10.1 |
| Offices of physicians | 22.4 | 7.9 | 14.8 | 2.1 | 66,235 | 7.7 |
| Child day care services | 1.9 | 0.3 | 0.8 | 0.1 | 64,130 | 7.5 |
| Individual and family services | 8.0 | 3.3 | 3.5 | 0.7 | 63,639 | 7.4 |
| Outpatient care centers | 14.3 | 20.6 | 8.7 | 13.9 | 62,713 | 7.3 |
| Home health care services | 4.8 | 4.0 | 2.8 | 1.8 | 53,822 | 6.3 |
| Residential care facilities, except skilled nursing facilities | 10.0 | 5.1 | 3.6 | 1.8 | 43,145 | 5.0 |
| Other health care services | 12.7 | 17.1 | 6.6 | 8.6 | 41,522 | 4.8 |
| Offices of dentists | 21.0 | 3.4 | 14.3 | 0.3 | 37,284 | 4.3 |
| Offices of other health practitioners | 12.3 | 38.4 | 7.3 | 3.3 | 13,178 | 1.5 |
| Vocational rehabilitation services | 33.1 | 11.7 | 11.7 | 1.2 | 7,479 | 0.9 |
| Offices of chiropractors | 26.0 | 1.6 | 17.0 | 0.4 | 7,429 | 0.9 |
| Community food and housing, and emergency services | 16.1 | 9.3 | 7.1 | 1.9 | 6,314 | 0.7 |
| Offices of optometrists | 24.3 | 30.9 | 15.3 | 24.9 | 5,639 | 0.7 |
| Psychiatric and substance abuse hospitals | 13.0 | 8.8 | 1.5 | 2.9 | 4,253 | 0.5 |
| Total | 11.6 | 9.0 | 5.9 | 3.7 | 859,993 | 100.0 |

*Note: FO stands for Frey and Osborne's (2017) susceptibility to computerization and W for Webb's exposure to artificial intelligence. Sources: Authors' tabulations using FO and W's measures, combined with the American Community Survey 2019 5-year estimates for Illinois.*

Within the Educational Services industries, employees at "Colleges, universities, and professional schools" face the highest risk of AI impacts (Table 4). The remaining categories include a relatively low share of workers at risk.

**Table 4. Workers at Risk by New Technologies in Educational Services**

| | Percent above 75th | | Percent above 90th | | Industry size | |
|---|---|---|---|---|---|---|
| Industry | FO | W | FO | W | Workers | Percent of employed |
| Elementary and secondary schools | 7.3 | 2.5 | 1.4 | 0.5 | 355,017 | 61.3 |
| Colleges, universities, and professional schools, including junior colleges | 15.2 | 10.5 | 5.9 | 1.7 | 189,980 | 32.8 |
| Other schools and instruction, and educational support services | 7.2 | 1.8 | 3.2 | 0.7 | 30,236 | 5.2 |
| Business, technical, and trade schools and training | 9.0 | 5.7 | 1.8 | 0.0 | 4,205 | 0.7 |
| Total | 9.9 | 5.1 | 3.0 | 0.9 | 579,438 | 100.0 |

*Note: FO stands for Frey and Osborne's (2017) susceptibility to computerization and W for Webb's exposure to artificial intelligence. Sources: Authors' tabulations using FO and W's measures, combined with the American Community Survey 2019 5-year estimates for Illinois.*

# Findings:

## Assessing Workers at Risk

The Energy sector reveals a medium to high share of workers at high risk, ranging from 7 to 37 percent (Table 5). "Construction, and mining and oil and gas field machinery manufacturing" and "Electric power generation, transmission and distribution" account for over 70 percent of the total employment and have a predicted high risk of 16-21 percent (Frey and Osborne) and 22-29 percent (Webb). Importantly, these two energy industries are also the most likely to generate employment associated with renewable sources, in contrast to almost all other categories, which are almost fully engaged in oil and gas activity (GEPI 2023)[6].

**Table 5. Workers at Risk by New Technologies in the Energy Sector**

| | Percent above 75th | | Percent above 90th | | Industry size | |
|---|---|---|---|---|---|---|
| Industry | FO | W | FO | W | Workers | Percent of employed |
| Construction, and mining and oil and gas field machinery manufacturing | 21.0 | 21.6 | 11.5 | 4.0 | 24,791 | 36.2 |
| Electric power generation, transmission and distribution | 15.6 | 29.2 | 4.9 | 13.8 | 24,447 | 35.7 |
| Petroleum refining | 19.1 | 36.7 | 8.1 | 15.1 | 6,063 | 8.8 |
| Natural gas distribution | 21.4 | 20.8 | 12.7 | 3.6 | 4,929 | 7.2 |
| Support activities for mining | 12.0 | 20.8 | 7.8 | 3.8 | 2,602 | 3.8 |
| Petroleum and petroleum products merchant wholesalers | 16.1 | 7.8 | 9.3 | 1.9 | 2,360 | 3.4 |
| Electric and gas, and other combinations | 18.2 | 26.0 | 12.5 | 12.9 | 1,251 | 1.8 |
| Pipeline transportation | 20.3 | 14.7 | 4.5 | 3.7 | 1,089 | 1.6 |
| Oil and gas extraction | 6.6 | 30.0 | 1.3 | 2.9 | 1,024 | 1.5 |
| Total | 18.2 | 25.2 | 8.5 | 8.5 | 68,556 | 100.0 |

*Note: FO stands for Frey and Osborne's (2017) susceptibility to computerization and W for Webb's exposure to artificial intelligence. Sources: Authors' tabulations using FO and W's measures, combined with the American Community Survey 2019 5-year estimates for Illinois. The categories included as part of the energy sector combine subcategories in Agriculture, Forestry, Fishing, and Hunting, and Mining, Manufacturing, Wholesale, and Transportation and Warehousing, and Utilities.*

# Findings:
## Assessing Workers at Risk

Finally, in the Automotive sector[7], most industries face a high risk as assessed by Frey and Osborne. Meanwhile, in Webb's assessment, most industries face a low risk, except for motor vehicles and motor vehicle equipment manufacturing – coinciding with the largest employer in this sector (Table 6).

**Table 6. Workers at Risk by New Technologies in the Automotive Sector**

| | **Percent above 75th** | | **Percent above 90th** | | **Industry size** | |
|---|---|---|---|---|---|---|
| Industry | FO | W | FO | W | Workers | Percent of employed |
| Motor vehicles and motor vehicle equipment manufacturing | 45.3 | 21.0 | 30.2 | 5.8 | 52,552 | 25.1 |
| Automotive repair and maintenance | 17.5 | 4.1 | 4.8 | 1.0 | 51,288 | 24.5 |
| Automobile dealers | 38.5 | 6.7 | 11.3 | 2.0 | 47,667 | 22.7 |
| Gasoline stations | 49.8 | 2.6 | 1.6 | 0.4 | 22,910 | 10.9 |
| Automotive parts, accessories, and tire stores | 34.8 | 6.6 | 16.2 | 0.6 | 16,138 | 7.7 |
| Motor vehicle and motor vehicle parts and supplies merchant wholesalers | 22.8 | 11.0 | 12.3 | 0.9 | 9,296 | 4.4 |
| Automotive equipment rental and leasing | 22.5 | 6.3 | 16.6 | 2.7 | 6,511 | 3.1 |
| Other motor vehicle dealers | 30.0 | 6.5 | 8.5 | 0.7 | 3,422 | 1.6 |
| Total | 34.7 | 9.4 | 13.9 | 2.4 | 209,784 | 100.0 |

*Note: FO stands for Frey and Osborne's (2017) susceptibility to computerization and W for Webb's exposure to artificial intelligence. Sources: Authors' tabulations using FO and W's measures, combined with the American Community Survey 2019 5-year estimates for Illinois. The categories included as part of the automotive sector combine subcategories in Manufacturing, Other Services (except Public Administration), Retail Trade, Wholesale Trade, Finance and Insurance, and Real Estate, and Rental and Leasing.*

# Findings:
## Assessing Workers at Risk

### Occupation Projections Growth

Table 7 details risk thresholds for the fastest expanding and declining occupations in Illinois[8] (see Appendix, Table A1 for a list of all occupations at risk). Light blue shades highlight those between the 75th to 89th risk percentiles (high risk), and dark blue for those at risk above the 90th percentile (very high risk). Growth rates between 2022 and 2032 range from -39 to 28 percent, and there is a clear contrast between the risk measures. In Webb, several of the top twenty fastest-growing occupations are at high risk. Contrarily, Frey and Osborne predict the shrinking occupations to be at high risk. Once again, the implications point to opposite responses. The fastest expanding occupations encompass various health and technology-related positions, while the declining ones appear to reflect a lot of machine operation.

**Table 7. Workers at Risk by New Technologies by Projected Occupation Growth**

| Ranking | Occupation | Risk Percentile | | Workers (2019) | Projected Growth (2032) |
|---|---|---|---|---|---|
| | | FO | W | | |
| 1 | Medical and Health Services Managers | < 10 | 75-89 | 26,005 | 28.4 |
| 2 | Physician Assistants | 11 to 25 | 11 to 25 | 3,583 | 26.5 |
| 3 | Actuaries | 26 to 74 | > 90 | 2,413 | 23.2 |
| 4 | Software Developers, Applications and Systems Software | 11 to 25 | 75 to 89 | 51,555 | 23.0 |
| 5 | Operations Research Analysts | 11 to 25 | 26 to 74 | 5,095 | 22.5 |
| 6 | Personal Care Aides | 26 to 74 | < 10 | 58,075 | 21.7 |
| 7 | Personal Care and Service Workers, All Other | NA | NA | 10,242 | 20.5 |
| 8 | Veterinarians | 11 to 25 | 75 to 89 | 2,654 | 19.7 |
| 9 | Financial Examiners | 26 to 74 | 26 to 74 | 844 | 19.5 |
| 10 | Speech Language Pathologists | < 10 | 11 to 25 | 7,690 | 19.3 |
| 11 | Computer Scientists and Systems Analysts/Network systems Analysts/Web Developers | 11 to 25 | 26 to 74 | 76,392 | 19.2 |
| 12 | Mathematical science occupations, nec | 11 to 25 | 75 to 89 | 4,932 | 18.8 |
| 14 | Massage Therapists | 26 to 74 | 11 to 25 | 6,453 | 18.3 |
| 13 | Logisticians | < 10 | 75 to 89 | 6,099 | 18.3 |
| 15 | Registered Nurses | < 10 | 26 to 74 | 141,870 | 16.4 |
| 16 | Financial Managers | 11 to 25 | 26 to 74 | 54,582 | 16.0 |
| 17 | Animal Trainers | 11 to 25 | 26 to 74 | 1,687 | 16.0 |
| 18 | Nonfarm Animal Caretakers | 26 to 74 | < 10 | 10,402 | 15.5 |
| 19 | Computer and Information Systems Managers | 11 to 25 | 26 to 74 | 27,278 | 15.4 |
| 20 | Physical Therapists | < 10 | > 90 | 11,378 | 15.1 |

| Ranking | Occupation | Risk Percentile | | Workers (2019) | Projected Growth (2032) |
|---|---|---|---|---|---|
| | | FO | W | | |
| 403 | Office Machine Operators, Except Computer | 75 to 89 | 75 to 89 | 1,645 | -14.2 |
| 404 | New Account Clerks | > 90 | 11 to 25 | 604 | -14.4 |
| 405 | Bank Tellers | > 90 | 26 to 74 | 13,728 | -14.5 |
| 406 | Tailors, Dressmakers, and Sewers | 75 to 89 | 26 to 74 | 2,963 | -14.7 |
| 407 | Sewing Machine Operators | 75 to 89 | 26 to 74 | 4,889 | -15.2 |
| 408 | Mining Machine Operators | 26 to 74 | 75 to 89 | 1,707 | -15.5 |
| 409 | Door-to-Door Sales Workers, News and Street Vendors, and Related Workers | 75 to 89 | 11 to 25 | 6,354 | -15.9 |
| 410 | File Clerks | > 90 | < 10 | 6,898 | -16.0 |
| 411 | Cutting Workers | 26 to 74 | 26 to 74 | 2,876 | -16.2 |
| 413 | Payroll and Timekeeping Clerks | > 90 | < 10 | 6,277 | -16.4 |
| 412 | Structural Metal Fabricators and Fitters | 26 to 74 | 26 to 74 | 1,238 | -16.4 |
| 414 | Molders and Molding Machine Setters, Operators, and Tenders, Metal and Plastic | 26 to 74 | 26 to 74 | 2,876 | -16.9 |
| 415 | Prepress Technicians and Workers | > 90 | > 90 | 1,139 | -17.1 |
| 416 | Engine and Other Machine Assemblers | 26 to 74 | 11 to 25 | 674 | -18.9 |
| 417 | Telemarketers | > 90 | < 10 | 2,139 | -20.6 |
| 418 | Pressers, Textile, Garment, and Related Materials | 26 to 74 | 11 to 25 | 1,030 | -21.8 |
| 419 | Switchboard Operators, Including Answering Service | > 90 | 26 to 74 | 894 | -25.1 |
| 420 | Data Entry Keyers | > 90 | > 90 | 14,156 | -26.0 |
| 421 | Telephone Operators | > 90 | 26 to 74 | 1,231 | -26.6 |
| 422 | Word Processors and Typists | 26 to 74 | < 10 | 9,508 | -38.6 |

*Note: The table displays the twenty occupations with higher projected growth and decline in the period 2022-2032. Light blue shades highlight those between the 75th to 89th risk percentiles (high risk), and dark blue for those at risk above the 90th percentile (very high risk). Source: Authors' calculations combining the American Community Survey 2019 5-year estimates for Illinois and the Occupation Projections 2022-2032 for the United States, enabled by the Bureau of Labor and Statistics (BLS) Employment Projections Program (BLS 2023).*

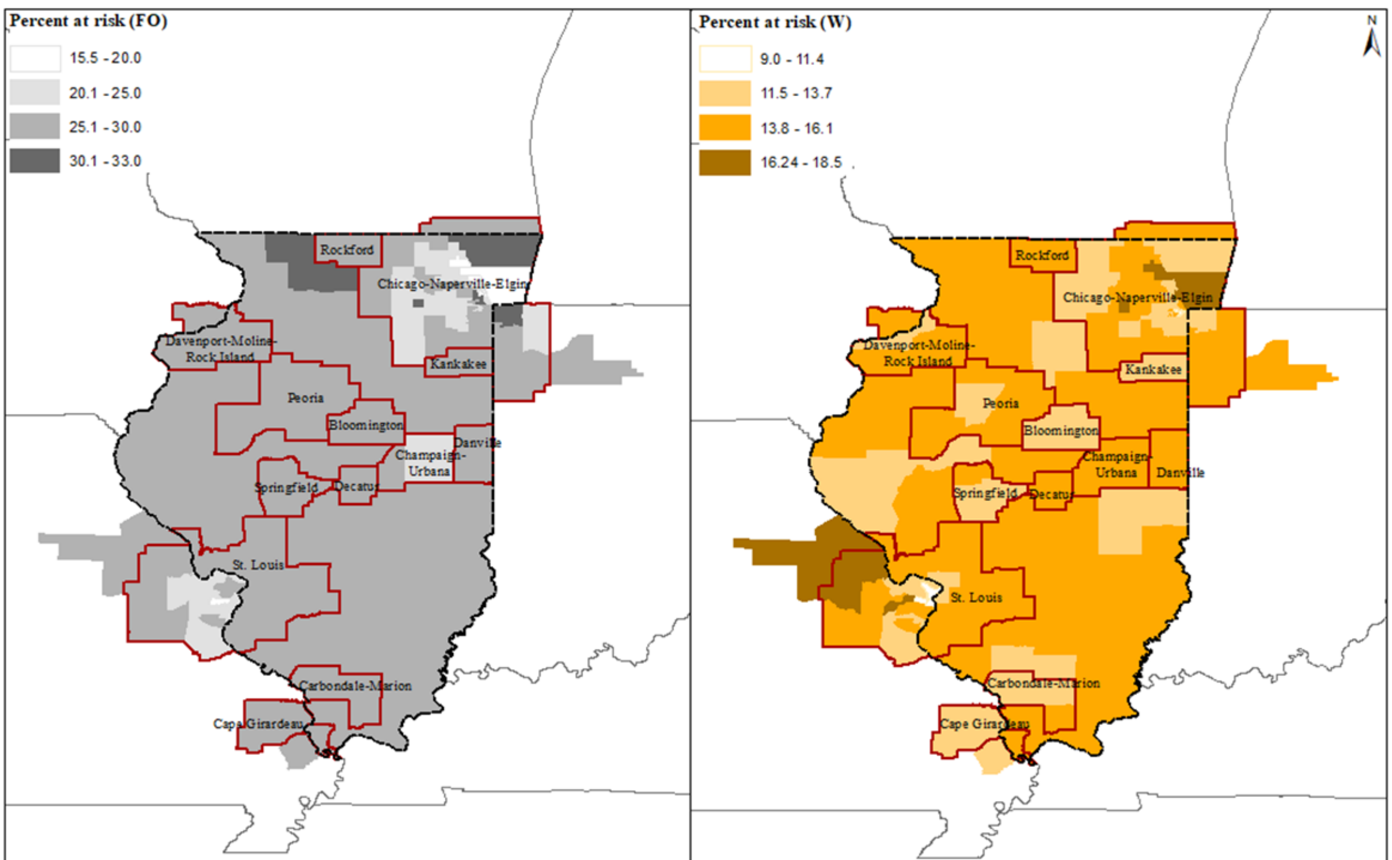
# Findings:
## Assessing Workers at Risk

### Spatial Variation

Lastly, this section explores the concentration of high and very high risk workers across geographical locations. Figure 6 illustrates the share of workers at the 75th percentile or higher in Frey and Osborne and Webb in each Public Use Microdata Area (PUMA) – the smallest geographic unit available in the ACS microdata[9]. While PUMAs do not fit perfectly within metropolitan area boundaries, the Figure shows these boundaries for reference, including those that extend across state borders.

The spatial distribution of risk is somewhat even. Across areas, predictions of workers at high risk range from 15 to 33 percent (Frey and Osborne), and from ten to 19 percent (Webb). Most areas are within the middle-risk categories, and very few fit into the category with the lowest risk. The highest-risk areas are mainly located within Chicago-Naperville-Elgin and Saint Louis metropolitan area borders.

**Figure 6. Share of Workers at High Risk (above 75th percentile)**




a. Percentage of workers at or above the 75th percentile risk in Frey and Osborne (2017)

b. Percentage of workers at or above the 75th percentile risk in Webb (2020)

Source: Author's tabulations using FO and W's measures, combined with the American Community Survey 5 years estimates 2019, and 2019 TIGER/Line Shapefiles prepared by the U.S. Census Bureau.

# Synthesis

Table 8 synthesizes the findings in a logit regressions framework, indicating the predicted probability that a worker is in an occupation considered high-risk or very high-risk.

Considering columns 1 and 2 (high risk), Frey and Osborne's risk measure suggests that women are more likely to be at risk than men, with a probability of 31 percent versus 19 percent. Risk is also higher for all racial-ethnic groups than for white workers (at 23 percent), and for young (26 percent) and older workers (29 percent) as opposed to workers aged 35 to 64 (23 percent), as well as those with lower levels of education (30-31 percent for High School degree holders or less). In contrast, Webb predicts higher risk for men (17 percent), Asians (18 percent), and workers with higher levels of education (22 percent for advanced degree holders). These opposing findings remain mostly consistent for very high risk (columns 3 and 4).

Predicted high risk for industries ranges from 8 to 41 percent in Frey and Osborne, and from 1 to 67 percent in Webb. Manufacturing exhibits a higher predicted risk than most industries in both classifications, ranging from 24 (Webb) to 35 percent (Frey and Osborne). Industries with a higher risk than manufacturing in Frey and Osborne are 1) Retail (37 percent) and 2) Finance and Insurance, and Real Estate, and Rental and Leasing (41 percent). In Webb, the exceptions are 1) Agriculture, Forestry, Fishing, and Hunting, and Mining (67 percent), 2) Construction (26 percent), and 3) Public Administration (28 percent). (Full logit models' results are available in Table A3 in the Appendix).

**Table 8. Predicted Probabilities of Being a Worker at Risk**

| | Above 75th | | Above 90th | |
|---|---|---|---|---|
| **Variables** | **(1) FO** | **(2) W** | **(3) FO** | **(4) W** |
| | | | | |
| Male | 0.19 | 0.17 | 0.04 | 0.04 |
| Female | 0.31 | 0.11 | 0.10 | 0.03 |
| White | 0.23 | 0.14 | 0.07 | 0.04 |
| Black | 0.26 | 0.15 | 0.06 | 0.03 |
| Latino | 0.27 | 0.14 | 0.07 | 0.03 |
| Asian | 0.24 | 0.18 | 0.07 | 0.04 |
| Other race/ethnicity | 0.26 | 0.14 | 0.07 | 0.03 |
| 16 to 34 years old | 0.26 | 0.15 | 0.07 | 0.04 |
| 35 to 64 years old | 0.23 | 0.15 | 0.06 | 0.04 |
| 65+ years old | 0.29 | 0.14 | 0.08 | 0.04 |
| Less than High School | 0.31 | 0.10 | 0.08 | 0.03 |
| High School / GED | 0.30 | 0.12 | 0.09 | 0.03 |
| Incomplete College / Associate degree | 0.28 | 0.14 | 0.09 | 0.04 |
| Bachelor's degree | 0.18 | 0.15 | 0.04 | 0.04 |
| Advanced degrees | 0.10 | 0.22 | 0.02 | 0.04 |
| Agriculture, Forestry, Fishing, and Hunting, and Mining | 0.31 | 0.67 | 0.04 | 0.59 |
| Construction | 0.11 | 0.26 | 0.03 | 0.07 |
| Manufacturing | 0.35 | 0.24 | 0.15 | 0.06 |
| Wholesale | 0.20 | 0.12 | 0.09 | 0.02 |
| Retail | 0.37 | 0.06 | 0.04 | 0.01 |
| Transportation and Warehousing, and Utilities | 0.23 | 0.12 | 0.05 | 0.05 |
| Information | 0.18 | 0.13 | 0.08 | 0.03 |
| Finance and Insurance, and Real Estate, and Rental and Leasing | 0.41 | 0.13 | 0.17 | 0.03 |
| Professional, Scientific, and Management, and Administrative, and Waste Management Services | 0.29 | 0.25 | 0.07 | 0.04 |
| Educational Services | 0.12 | 0.05 | 0.04 | 0.01 |
| Health Care and Social Assistance | 0.10 | 0.10 | 0.05 | 0.04 |
| Arts, Entertainment, and Recreation | 0.21 | 0.05 | 0.04 | 0.01 |
| Accommodation and Food Services | 0.31 | 0.01 | 0.03 | 0.00 |
| Other Services, Except Public Administration Services | 0.11 | 0.05 | 0.04 | 0.01 |
| Public Administration | 0.17 | 0.28 | 0.07 | 0.03 |
| Military (excluding workers in military occupations) | 0.08 | 0.15 | 0.04 | 0.03 |

*Note: FO stands for Frey and Osborne's (2017) susceptibility to computerization and W for Webb's exposure to artificial intelligence. Sources: Authors' tabulations using FO and W's measures, combined with the American Community Survey 2019 5-year estimates for Illinois. The table columns represent predicted probabilities of being at risk, estimated using margins from the logit regressions shown in Table A3 in the Appendix. The sample includes 6,258,122 employed workers living in Illinois. Standard errors clustered at the PUMA level. Table A3 in the Appendix illustrates predicted probabilities using margins (p<0.01 for all values).*

# Conclusion

The development of AI has generated concerns among scholars, policymakers, and worker representatives. Although the pace of adoption has been slow (Bughin et al. 2017; Acemoglu et al. 2022), as intelligent systems become incorporated in the workplace at a large scale, they are expected to profoundly transform the nature of work, changing tasks workers perform, and making some jobs obsolete.

This report combined data from the American Community Survey with two AI risk measures (Frey and Osborne 2017; Webb 2020) to identify which Illinois workers, industries and areas in the state of Illinois are most likely impacted.

While the demographic characteristics of AI vulnerable workers vary significantly across both measures and exhibit no distinct spatial patterns, the findings concerning industries reveal similarities. Notably, once again, the Manufacturing sector appears more susceptible to substantial technological impacts compared to most other industries. The Energy sector, particularly two of its largest component industries with a significant presence of renewable energy-related jobs, also anticipates robust AI impacts. This is noteworthy considering Illinois' Climate and Equitable Jobs Act. Conversely, larger employers in sectors such as Health Care and Social Assistance, and Educational Services, are expected to experience relatively lower AI impacts.

Given the contrasting findings discussed in the analysis, rather than providing a unifying perspective, this report highlights the limitations of making definitive predictions based solely on the available measures. However, considering the rapid pace of technological change, the report recommends that policymakers begin preparing workers of all demographics for potential AI disruptions. Initiatives to proactively enhance worker technology literacy and related skills should be designed in high and very high-risk occupations, especially energy related. This step aligns with the Task Force's realization that technology is "already impacting the everyday lives of Illinoisans, but more intentional preparation is necessary to ensure that its benefits reach all workers and not just those who are already highly educated and well compensated." This report offers a profile of what workers and industries should be getting the necessary training.

In addressing the adoption of new technology and AI into the workplace, the Illinois Task Force on the Future of Work (FOW) recommended partnerships with "employers and technology training providers to develop more effective tech certification" for workers to transition into employment or re-employment. The state should evaluate whether partnerships have been created within those industries identified in this report where workers are at high or very high risk of AI exposure. Where a void still exists in meeting the training needs of workers at risk of AI disruption or displacement, partnerships should be prioritized.

Additionally, setting up a monitoring system to closely watch employment trends as technology adoption continues to expand would provide an early warning system to policymakers of AI's potential disruption. The Future of Work Task Force noted that "[j]ust as automation and AI can 'disrupt' traditional businesses and services, Illinois' data infrastructure could be leveraged" to alert state agencies to address high and very high-risk workers. Based on our risk assessment, we strongly encourage the state to abide by the FOW Report's recommendation to "Invest in data collection specifically on job quality in order to understand whether state funding for workforce development is placing Illinoisans into quality jobs." Our AI risk assessment suggests areas to prioritize information gathering on advanced workplace technology adoption. After collecting the data from employers, as the FOW Report calls for, "State agencies, in partnership with universities and other research institutions, should produce semi-annual reports on future of work outcomes."

In summary, the risk profile assessed using Frey and Osborne and Webb paints divergent conclusions and almost reverse demographic portraits. Neither of their risk levels are a prediction of job automation. Importantly however for policy makers, both approaches only account for what is technologically doable. They do not account for what is economically feasible in AI adoption. They leave unanswered the question of what economic incentives companies will have to produce or embrace human labor replacing technologies. But it bares clearly noting that technological advancements do not occur independent of political forces. In other words, what state elected leaders do will influence the way AI impacts the lives of working people. As such, rather than a unifying view, this report underlines the limits of relying on a single measure to assess at-risk workers. In this scenario – and given the fast pace expected for new technologies to be incorporated into the workplace – it would be wise for state policy makers to preemptively design programs that improve technology literacy and related skills, for all workers.

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# APPENDIX

**Table A1. Occupations Highly Likely to be Impacted by New Technologies**
(Check marks indicate if the occupation is considered at risk according to each criterion)

| | Percentile 75th + | | Percentile 90th + | | Workers | |
|---|---|---|---|---|---|---|
| **Title** | **FO** | **Webb** | **FO** | **Webb** | **Freq.** | **Percent** |
| Administrative Services Managers | | ✓ | | | 5,923 | 0.09 |
| Industrial Production Managers | | ✓ | | | 12,222 | 0.20 |
| Transportation, Storage, and Distribution Managers | | ✓ | | | 12,384 | 0.20 |
| Farmers, Ranchers, and Other Agricultural Managers | | ✓ | | ✓ | 25,078 | 0.40 |
| Constructions Managers | | ✓ | | ✓ | 22,372 | 0.36 |
| Medical and Health Services Managers | | ✓ | | | 26,005 | 0.42 |
| Buyers and Purchasing Agents, Farm Products | | ✓ | | ✓ | 537 | 0.01 |
| Wholesale and Retail Buyers, Except Farm Products | | ✓ | | | 7,917 | 0.13 |
| Claims Adjusters, Appraisers, Examiners, and Investigators | ✓ | | ✓ | | 13,509 | 0.22 |
| Logisticians | | ✓ | | | 6,099 | 0.10 |
| Accountants and Auditors | ✓ | | | | 88,565 | 1.42 |
| Appraisers and Assessors of Real Estate | ✓ | ✓ | | ✓ | 3,823 | 0.06 |
| Budget Analysts | ✓ | | | | 1,424 | 0.02 |
| Credit Analysts | ✓ | ✓ | ✓ | ✓ | 1,750 | 0.03 |
| Personal Financial Advisors | | ✓ | | | 17,813 | 0.28 |
| Insurance Underwriters | ✓ | ✓ | ✓ | | 6,770 | 0.11 |
| Tax Examiners and Collectors, and Revenue Agents | ✓ | | | | 1,617 | 0.03 |
| Tax Preparers | ✓ | ✓ | ✓ | ✓ | 4,120 | 0.07 |
| Financial Specialists, nec | | ✓ | | | 1,927 | 0.03 |
| Computer Programmers | | ✓ | | ✓ | 18,979 | 0.30 |
| Software Developers, Applications and Systems Software | | ✓ | | | 51,555 | 0.82 |
| Computer Support Specialists | | ✓ | | | 27,917 | 0.45 |
| Network and Computer Systems Administrators | | ✓ | | | 8,782 | 0.14 |
| Actuaries | | ✓ | | ✓ | 2,413 | 0.04 |
| Mathematical science occupations, nec | | ✓ | | | 4,932 | 0.08 |
| Architects, Except Naval | | ✓ | | | 10,207 | 0.16 |
| Surveyors, Cartographers, and Photogrammetrists | | ✓ | | | 1,450 | 0.02 |
| Chemical Engineers | | ✓ | | ✓ | 2,332 | 0.04 |
| Civil Engineers | | ✓ | | | 12,531 | 0.20 |
| Computer Hardware Engineers | | ✓ | | ✓ | 2,134 | 0.03 |
| Electrical and Electronics Engineers | | ✓ | | | 7,944 | 0.13 |

# Appendix

| | Percentile 75th + | | Percentile 90th + | | Workers | Workers |
|---|---|---|---|---|---|---|
| **Title** | **FO** | **Webb** | **FO** | **Webb** | **Freq.** | **Percent** |
| Environmental Engineers | | ✓ | | | 954 | 0.02 |
| Industrial Engineers, including Health and Safety | | ✓ | | | 9,352 | 0.15 |
| Marine Engineers and Naval Architects | | ✓ | | ✓ | 96 | 0.00 |
| Materials Engineers | | ✓ | | ✓ | 1,812 | 0.03 |
| Petroleum, mining and geological engineers, including mining safety engineers | | ✓ | | | 548 | 0.01 |
| Engineers, nec | | ✓ | | | 20,018 | 0.32 |
| Engineering Technicians, Except Drafters | | ✓ | | | 13,827 | 0.22 |
| Surveying and Mapping Technicians | ✓ | | ✓ | | 1,224 | 0.02 |
| Medical Scientists, and Life Scientists, All Other | | ✓ | | | 4,189 | 0.07 |
| Astronomers and Physicists | | ✓ | | ✓ | 850 | 0.01 |
| Atmospheric and Space Scientists | | ✓ | | ✓ | 183 | 0.00 |
| Chemists and Materials Scientists | | ✓ | | | 4,121 | 0.07 |
| Environmental Scientists and Geoscientists | | ✓ | | | 1,206 | 0.02 |
| Physical Scientists, nec | | ✓ | | | 11,533 | 0.18 |
| Economists and market researchers | | ✓ | | | 887 | 0.01 |
| Psychologists | | ✓ | | | 9,253 | 0.15 |
| Urban and Regional Planners | | ✓ | | | 839 | 0.01 |
| Social Scientists, nec | | ✓ | | | 1,383 | 0.02 |
| Agricultural and Food Science Technicians | ✓ | | ✓ | | 1,563 | 0.02 |
| Biological Technicians | | ✓ | | ✓ | 665 | 0.01 |
| Lawyers, and judges, magistrates, and other judicial workers | | ✓ | | | 56,925 | 0.91 |
| Paralegals and Legal Assistants | ✓ | ✓ | | | 15,509 | 0.25 |
| Library Technicians | ✓ | | ✓ | | 1,911 | 0.03 |
| Technical Writers | ✓ | | | | 2,025 | 0.03 |
| Photographers | | ✓ | | ✓ | 6,850 | 0.11 |
| Optometrists | | ✓ | | ✓ | 1,881 | 0.03 |
| Audiologists | | ✓ | | | 796 | 0.01 |
| Occupational Therapists | | ✓ | | ✓ | 5,376 | 0.09 |
| Physical Therapists | | ✓ | | ✓ | 11,378 | 0.18 |
| Veterinarians | | ✓ | | | 2,654 | 0.04 |
| Clinical Laboratory Technologists and Technicians | | ✓ | | ✓ | 11,609 | 0.19 |
| Medical Records and Health Information Technicians | ✓ | | | | 6,602 | 0.11 |
| First-Line Supervisors of Correctional Officers | | ✓ | | | 1,883 | 0.03 |
| Fire Inspectors | | ✓ | | | 416 | 0.01 |
| Police Officers and Detectives | | ✓ | | | 39,137 | 0.63 |
| Security Guards and Gaming Surveillance Officers | ✓ | ✓ | | | 41,686 | 0.67 |
| Combined Food Preparation and Serving Workers, Including Fast Food | ✓ | | | | 24,417 | 0.39 |
| Waiters and Waitresses | ✓ | | | | 81,792 | 1.31 |

# APPENDIX

| | Percentile 75th + | | Percentile 90th + | | Workers | Workers |
|---|---|---|---|---|---|---|
| **Title** | **FO** | **Webb** | **FO** | **Webb** | **Freq.** | **Percent** |
| Food preparation and serving related workers, nec | ✓ | | | | 14,335 | 0.23 |
| Host and Hostesses, Restaurant, Lounge, and Coffee Shop | ✓ | | ✓ | | 12,394 | 0.20 |
| First-Line Supervisors of Housekeeping and Janitorial Workers | ✓ | | | | 8,211 | 0.13 |
| Pest Control Workers | | ✓ | | ✓ | 2,395 | 0.04 |
| Grounds Maintenance Workers | ✓ | | | | 44,719 | 0.71 |
| Gaming Services Workers | ✓ | | | | 2,563 | 0.04 |
| Ushers, Lobby Attendants, and Ticket Takers | ✓ | | ✓ | | 2,242 | 0.04 |
| Cashiers | ✓ | | | | 131,044 | 2.09 |
| Counter and Rental Clerks | ✓ | | ✓ | | 3,429 | 0.05 |
| Parts Salespersons | ✓ | | ✓ | | 3,621 | 0.06 |
| Retail Salespersons | ✓ | | | | 129,837 | 2.07 |
| Insurance Sales Agents | ✓ | | | | 23,547 | 0.38 |
| Real Estate Brokers and Sales Agents | ✓ | | | | 28,690 | 0.46 |
| Telemarketers | ✓ | | ✓ | | 2,139 | 0.03 |
| Door-to-Door Sales Workers, News and Street Vendors, and Related Workers | ✓ | | | | 6,354 | 0.10 |
| Switchboard Operators, Including Answering Service | ✓ | | ✓ | | 894 | 0.01 |
| Telephone Operators | ✓ | | ✓ | | 1,231 | 0.02 |
| Bill and Account Collectors | ✓ | | | | 5,663 | 0.09 |
| Billing and Posting Clerks | ✓ | | ✓ | | 19,644 | 0.31 |
| Bookkeeping, Accounting, and Auditing Clerks | ✓ | | ✓ | | 43,930 | 0.70 |
| Payroll and Timekeeping Clerks | ✓ | | ✓ | | 6,277 | 0.10 |
| Procurement Clerks | ✓ | | ✓ | | 1,955 | 0.03 |
| Bank Tellers | ✓ | | ✓ | | 13,728 | 0.22 |
| Credit Authorizers, Checkers, and Clerks | ✓ | | ✓ | | 1,264 | 0.02 |
| File Clerks | ✓ | | ✓ | | 6,898 | 0.11 |
| Hotel, Motel, and Resort Desk Clerks | ✓ | | | | 4,758 | 0.08 |
| Interviewers, Except Eligibility and Loan | ✓ | | | | 5,581 | 0.09 |
| Library Assistants, Clerical | ✓ | | | | 5,694 | 0.09 |
| Loan Interviewers and Clerks | ✓ | | | | 5,206 | 0.08 |
| New Account Clerks | ✓ | | ✓ | | 604 | 0.01 |
| Correspondent clerks and order clerks | ✓ | | | | 6,573 | 0.11 |
| Human Resources Assistants, Except Payroll and Timekeeping | ✓ | | | | 2,649 | 0.04 |
| Receptionists and Information Clerks | ✓ | | ✓ | | 47,759 | 0.76 |
| Cargo and Freight Agents | ✓ | | ✓ | | 1,337 | 0.02 |
| Couriers and Messengers | ✓ | | | | 11,024 | 0.18 |
| Dispatchers | | ✓ | | ✓ | 12,498 | 0.20 |
| Postal Service Clerks | ✓ | | | | 5,106 | 0.08 |
| Shipping, Receiving, and Traffic Clerks | ✓ | ✓ | ✓ | | 29,671 | 0.47 |

# Appendix

| | Percentile 75th + | | Percentile 90th + | | Workers | |
|---|---|---|---|---|---|---|
| **Title** | **FO** | **Webb** | **FO** | **Webb** | **Freq.** | **Percent** |
| Weighers, Measurers, Checkers, and Samplers, Recordkeeping | ✓ | | | | 3,639 | 0.06 |
| Secretaries and Administrative Assistants | ✓ | | | | 126,944 | 2.03 |
| Data Entry Keyers | ✓ | ✓ | ✓ | ✓ | 14,156 | 0.23 |
| Insurance Claims and Policy Processing Clerks | ✓ | | ✓ | | 15,212 | 0.24 |
| Mail Clerks and Mail Machine Operators, Except Postal Service | ✓ | ✓ | | | 3,425 | 0.05 |
| Office Clerks, General | ✓ | | ✓ | | 57,508 | 0.92 |
| Office Machine Operators, Except Computer | ✓ | ✓ | | | 1,645 | 0.03 |
| Proofreaders and Copy Markers | | ✓ | | ✓ | 572 | 0.01 |
| First-Line Supervisors of Farming, Fishing, and Forestry Workers | | ✓ | | ✓ | 1,122 | 0.02 |
| Agricultural Inspectors | ✓ | ✓ | | ✓ | 226 | 0.00 |
| Agricultural workers, nec | ✓ | ✓ | | ✓ | 15,505 | 0.25 |
| First-Line Supervisors of Construction Trades and Extraction Workers | | ✓ | | | 19,347 | 0.31 |
| Carpenters | | ✓ | | | 46,755 | 0.75 |
| Cement Masons, Concrete Finishers, and Terrazzo Workers | ✓ | | | | 2,267 | 0.04 |
| Glaziers | | ✓ | | | 1,207 | 0.02 |
| Roofers | ✓ | | | | 8,649 | 0.14 |
| Construction and Building Inspectors | | ✓ | | ✓ | 2,919 | 0.05 |
| Elevator Installers and Repairers | | ✓ | | ✓ | 798 | 0.01 |
| Fence Erectors | ✓ | | | | 555 | 0.01 |
| Rail-Track Laying and Maintenance Equipment Operators | ✓ | | | | 870 | 0.01 |
| Mining Machine Operators | | ✓ | | | 1,707 | 0.03 |
| First-Line Supervisors of Mechanics, Installers, and Repairers | | ✓ | | ✓ | 8,840 | 0.14 |
| Electrical and electronics repairers, transportation equipment, and industrial and utility | | ✓ | | | 754 | 0.01 |
| Automotive Body and Related Repairers | ✓ | | | | 5,209 | 0.08 |
| Coin, Vending, and Amusement Machine Servicers and Repairers | ✓ | | | | 1,486 | 0.02 |
| Riggers | ✓ | ✓ | | ✓ | 217 | 0.00 |
| First-Line Supervisors of Production and Operating Workers | | ✓ | | ✓ | 40,122 | 0.64 |
| Assemblers and Fabricators, nec | ✓ | | ✓ | | 48,303 | 0.77 |
| Bakers | ✓ | | | | 10,534 | 0.17 |
| Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders | ✓ | | | | 316 | 0.01 |
| Food Cooking Machine Operators and Tenders | | ✓ | | | 809 | 0.01 |
| Computer Control Programmers and Operators | | ✓ | | | 8,853 | 0.14 |
| Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic | ✓ | | | | 1,180 | 0.02 |

# Appendix

| | Percentile 75th + | | Percentile 90th + | | Workers | |
|---|---|---|---|---|---|---|
| **Title** | **FO** | **Webb** | **FO** | **Webb** | **Freq.** | **Percent** |
| Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic | ✓ | ✓ | | | 2,058 | 0.03 |
| Machinists | ✓ | ✓ | | | 15,404 | 0.25 |
| Metal workers and plastic workers, nec | ✓ | | | | 29,309 | 0.47 |
| Bookbinders, Printing Machine Operators, and Job Printers | ✓ | ✓ | | | 10,497 | 0.17 |
| Prepress Technicians and Workers | ✓ | ✓ | ✓ | ✓ | 1,139 | 0.02 |
| Sewing Machine Operators | ✓ | | | | 4,889 | 0.08 |
| Tailors, Dressmakers, and Sewers | ✓ | | | | 2,963 | 0.05 |
| Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders | ✓ | ✓ | ✓ | | 275 | 0.00 |
| Textile, Apparel, and Furnishings workers, nec | | ✓ | | | 221 | 0.00 |
| Cabinetmakers and Bench Carpenters | ✓ | | | | 1,346 | 0.02 |
| Woodworking Machine Setters, Operators, and Tenders, Except Sawing | ✓ | ✓ | ✓ | | 189 | 0.00 |
| Woodworkers including model makers and patternmakers, nec | ✓ | ✓ | | ✓ | 820 | 0.01 |
| Power Plant Operators, Distributors, and Dispatchers | | ✓ | | ✓ | 2,022 | 0.03 |
| Stationary Engineers and Boiler Operators | ✓ | | | | 6,685 | 0.11 |
| Water Wastewater Treatment Plant and System Operators | | ✓ | | ✓ | 2,913 | 0.05 |
| Plant and System Operators, nec | | ✓ | | | 1,068 | 0.02 |
| Crushing, Grinding, Polishing, Mixing, and Blending Workers | ✓ | | | | 3,413 | 0.05 |
| Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders | ✓ | | | | 1,116 | 0.02 |
| Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders | | ✓ | | ✓ | 160 | 0.00 |
| Inspectors, Testers, Sorters, Samplers, and Weighers | ✓ | ✓ | ✓ | | 33,639 | 0.54 |
| Jewelers and Precious Stone and Metal Workers | ✓ | | | | 1,344 | 0.02 |
| Packaging and Filling Machine Operators and Tenders | ✓ | | ✓ | | 16,014 | 0.26 |
| Photographic Process Workers and Processing Machine Operators | ✓ | ✓ | ✓ | | 927 | 0.01 |
| Adhesive Bonding Machine Operators and Tenders | ✓ | ✓ | | | 471 | 0.01 |
| Etchers, Engravers, and Lithographers | ✓ | | ✓ | | 324 | 0.01 |
| Molders, Shapers, and Casters, Except Metal and Plastic | ✓ | | | | 1,127 | 0.02 |
| Tire Builders | ✓ | | | | 1,158 | 0.02 |
| Other production workers including semiconductor processors and cooling and freezing equipment operators | ✓ | | | | 60,291 | 0.96 |
| Taxi Drivers and Chauffeurs | ✓ | | | | 30,798 | 0.49 |
| Locomotive Engineers and Operators | ✓ | ✓ | | ✓ | 3,238 | 0.05 |

# Appendix

| | Percentile 75th + | | Percentile 90th + | | Workers | |
|---|---|---|---|---|---|---|
| **Title** | **FO** | **Webb** | **FO** | **Webb** | **Freq.** | **Percent** |
| Ship and Boat Captains and Operators | | ✓ | | | 1,090 | 0.02 |
| Parking Lot Attendants | | ✓ | | | 2,892 | 0.05 |
| Transportation Inspectors | ✓ | ✓ | | ✓ | 1,515 | 0.02 |
| Transportation workers, nec | ✓ | ✓ | | ✓ | 1,361 | 0.02 |
| Crane and Tower Operators | ✓ | ✓ | | | 2,025 | 0.03 |
| Conveyor operators and tenders, and hoist and winch operators | | ✓ | | ✓ | 597 | 0.01 |
| Industrial Truck and Tractor Operators | ✓ | | | | 37,881 | 0.61 |
| Machine Feeders and Offbearers | ✓ | | | | 1,154 | 0.02 |
| Packers and Packagers, Hand | | ✓ | | | 30,415 | 0.49 |
| Refuse and Recyclable Material Collectors | ✓ | | | | 4,858 | 0.08 |
| 190 occupations (out of 422) | 109 | 110 | 36 | 44 | 2,235,102 | 35.72 |

*Note: FO stands for Frey and Osborne's (2017) susceptibility to computerization, and W for Webb's exposure to artificial intelligence. Sources: Authors' tabulations using FO and W's measures, combined with the American Community Survey 5 years estimates 2019 for Illinois.*

**Table A2. Characteristics of Workers in Illinois (2019)**

| Variable | Workers | Percent |
|---|---|---|
| Sex | | |
| Male | 3,267,633 | 52.2 |
| Female | 2,990,489 | 47.8 |
| Race | | |
| White | 4,034,852 | 64.5 |
| Black | 727,385 | 11.6 |
| Latino | 1,029,676 | 16.5 |
| Asian | 370,051 | 5.9 |
| Other | 96,158 | 1.5 |
| Age | | |
| 16 to 34 | 2,213,027 | 35.4 |
| 35 to 65 | 3,702,009 | 59.2 |
| 65 and older | 343,086 | 5.5 |
| Education | | |
| Less than High School | 510,961 | 8.2 |
| High School / GED | 1,411,641 | 22.6 |
| Incomplete College / Associate Degree | 1,951,374 | 31.2 |
| Bachelor's Degree | 1,486,472 | 23.8 |
| Advanced degree | 897,674 | 14.3 |

Source: American Community Survey 5 years estimates 2019.

### Table A3. Log-Likelihood of Being a Worker at Risk

| Variables | Above 75th (1) FO | (2) W | Above 90th (3) FO | (4) W |
|---|---|---|---|---|
| Female | 0.72*** | -0.60*** | 1.06*** | -0.38*** |
| | (0.02) | (0.02) | (0.03) | (0.03) |
| Black | 0.15*** | 0.02 | -0.05 | -0.26*** |
| | (0.02) | (0.03) | (0.04) | (0.06) |
| Latino | 0.20*** | -0.05 | 0.12*** | -0.31*** |
| | (0.02) | (0.03) | (0.03) | (0.05) |
| Asian | 0.07* | 0.32*** | 0.10* | 0.09 |
| | (0.04) | (0.05) | (0.05) | (0.06) |
| Other race/ethnicity | 0.14*** | -0.02 | 0.06 | -0.40*** |
| | (0.05) | (0.06) | (0.10) | (0.15) |
| 35 to 64 years old | -0.22*** | -0.00 | -0.22*** | 0.12*** |
| | (0.02) | (0.02) | (0.03) | (0.03) |
| 65+ years old | 0.19*** | -0.07** | 0.09** | 0.15*** |
| | (0.03) | (0.04) | (0.04) | (0.05) |
| High School / GED | -0.05** | 0.24*** | 0.19*** | 0.33*** |
| | (0.02) | (0.04) | (0.04) | (0.06) |
| Incomplete College / Associate degree | -0.17*** | 0.36*** | 0.10** | 0.48*** |
| | (0.03) | (0.04) | (0.04) | (0.06) |
| Bachelor's degree | -0.81*** | 0.54*** | -0.72*** | 0.66*** |
| | (0.04) | (0.04) | (0.07) | (0.06) |
| Advanced degrees | -1.53*** | 1.02*** | -1.55*** | 0.57*** |
| | (0.04) | (0.05) | (0.07) | (0.07) |
| Agriculture, Forestry, Fishing, and Hunting, and Mining | -0.20*** | 1.91*** | -1.63*** | 3.15*** |
| | (0.06) | (0.10) | (0.11) | (0.14) |
| Construction | -1.59*** | 0.11*** | -1.85*** | 0.07 |
| | (0.05) | (0.03) | (0.08) | (0.08) |
| Wholesale | -0.83*** | -0.84*** | -0.67*** | -1.37*** |
| | (0.04) | (0.05) | (0.05) | (0.09) |
| Retail | 0.10** | -1.58*** | -1.62*** | -1.98*** |
| | (0.04) | (0.04) | (0.05) | (0.07) |
| Transportation and Warehousing, and Utilities | -0.65*** | -0.88*** | -1.32*** | -0.24*** |
| | (0.05) | (0.04) | (0.07) | (0.06) |
| Information | -0.95*** | -0.74*** | -0.81*** | -0.76*** |
| | (0.07) | (0.07) | (0.08) | (0.10) |
| Finance and Insurance, and Real Estate, and Rental and Leasing | 0.27*** | -0.77*** | 0.14*** | -0.75*** |
| | (0.04) | (0.04) | (0.05) | (0.06) |

| | | | | |
|---|---|---|---|---|
| Professional, Scientific, and Management, and Administrative, and Waste Management Services | -0.29*** | 0.03 | -0.86*** | -0.58*** |
| | (0.03) | (0.04) | (0.04) | (0.05) |
| Educational Services | -1.43*** | -1.94*** | -1.62*** | -2.05*** |
| | (0.04) | (0.08) | (0.07) | (0.09) |
| Health Care and Social Assistance | -1.68*** | -1.10*** | -1.39*** | -0.47*** |
| | (0.04) | (0.04) | (0.05) | (0.05) |
| Arts, Entertainment, and Recreation | -0.79*** | -1.80*** | -1.60*** | -1.90*** |
| | (0.05) | (0.08) | (0.10) | (0.18) |
| Accommodation and Food Services | -0.19*** | -3.18*** | -1.96*** | -3.77*** |
| | (0.05) | (0.09) | (0.07) | (0.26) |
| Other Services, Except Public Administration Services | -1.54*** | -1.93*** | -1.68*** | -1.81*** |
| | (0.05) | (0.07) | (0.07) | (0.13) |
| Public Administration | -1.03*** | 0.22*** | -0.98*** | -0.62*** |
| | (0.06) | (0.06) | (0.07) | (0.07) |
| Military (excluding workers in military occupations) | -1.92*** | -0.61** | -1.44*** | -0.86* |
| | (0.26) | (0.27) | (0.38) | (0.46) |
| Constant | -0.49*** | -1.35*** | -1.99*** | -3.04*** |
| | (0.04) | (0.05) | (0.06) | (0.07) |

*Note: FO stands for Frey and Osborne's (2017) susceptibility to computerization and W for Webb's exposure to artificial intelligence. Sources: Authors' tabulations using FO and W's measures, combined with the American Community Survey 2019 5-year estimates for Illinois. Table columns represent differences in log odds, estimated using logit regressions with ACS individual weights. The Sample includes 6,258,122 employed workers living in Illinois. Manufacturing is the industry reference group. Standard errors clustered at the PUMA level. Table 8 illustrates predicted probabilities using margins. *** p<0.01, ** p<0.05, * p<0.1*

# Endnotes

1. Frey and Osborne's susceptibility to computerization assesses the risk of AI (including machine learning and other sub-fields) and mobile robotics. Webb's exposure focuses on AI alone.
2. The ratio of sales to costs of goods. In general, higher markups correspond to higher revenues.
3. Both Frey and Osborne's and Webb's scales were developed using O*NET Standard Occupational Classification (SOC), allowing easy conversion to the Census harmonized occupation code (occ2010) using occupational crosswalks. The matching between the O*NET and the Census occupational classifications is imperfect, and O*NET provides a more granular classification. Whenever multiple O*NET codes matched a single code in the Census, the scores were averaged as in Nazareno and Schiff (2021).
4. The ACS sample includes all employed workers, except for those in military occupations.
5. Frey and Osborne (2017) asked panelists to rate an occupation as automatable based on the answer to the following question: "Can the tasks of this job be sufficiently, conditional on the availability of big data, to be performed by state-of-the-art computer equipment?"
6. Using granular employment data from the Statistics of US Businesses, GEPI (2023) estimates that the entirety of the following industries has jobs directly related to fossil fuel: support activities for mining, petroleum refining, oil and gas extraction, pipeline transportation, and natural gas distribution. About 62 percent of petroleum and petroleum products merchant wholesalers, and 44 percent of construction, and mining and oil and gas field machinery manufacturing jobs are also attributable to fossil fuel. Electric power generation, transmission and distribution, and Electric and gas, and other combinations are not considered fossil fuel industries.
7. The EPA suggests a narrow definition of the automotive sector that includes vehicle manufacturing, sales and salvage, and repair and maintenance services (EPA 2023). Here, we adopt an expanded definition that also incorporates gasoline stations and rental and leasing.
8. The Occupational Employment Projections Data estimate the occupation growth for a ten-year period at the country level, which were assumed to be similar for Illinois. The projections are originally available in the National Employment Matrix (NEM) occupation codes and were translated into ACS 2010 occupation codes using crosswalks provided by the BLS. Whenever multiple NEM codes matched a single code in the ACS, the projections were averaged.
9. PUMAs are the smallest geographical areas available in the ACS microdata. PUMAS are nonoverlapping partitions of states containing at least 100 thousand people, and do not PUMAs do not fit perfectly within metropolitan area boundaries. Some PUMAs extend over more than one metropolitan area, and some metropolitan areas only extend over parts of PUMAs.