

RESEARCH ARTICLE

Digital Automation and Employment Dynamics: Evidence from the 2019 Annual Business Survey

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Abstract

This paper examines how the adoption of artificial intelligence (AI), cloud-based computing, and robotics was associated with workforce outcomes among U.S. employer firms. The analysis uses the 2019 Annual Business Survey, administered by the U.S. Census Bureau for the National Center for Science and Engineering Statistics, which asked firms about technology use during the 2016–2018 reference period. The study reports descriptive results for three outcomes: changes in the number of workers, changes in the overall skill level of workers, and changes in workers' science, technology, engineering, and mathematics (STEM) skills. Most technology-using firms reported no change in workforce size. Among firms reporting a change, increases in employment were more common than decreases for all three focal technologies, although the margin was smallest for robotics. Reported skill increases were more frequent than reported skill decreases, especially among AI-using firms. The findings do not establish causal effects, but they provide firm-level evidence that these technologies were more often associated with workforce stability and upskilling than with reported net employment reductions during the period studied.

Keywords — Digital automation; Artificial intelligence; Cloud computing; Robotics; Workforce development; Employment

1 Introduction

Digital automation has renewed an old question in labor economics and organizational studies: when firms adopt new production technologies, do they reduce labor demand, reorganize work, or raise the skills required of workers? The question is especially salient for artificial intelligence (AI), cloud-based computing, and robotics because these technologies can alter both physical and cognitive tasks. Some accounts emphasize substitution and worker displacement [1,2]. Others stress complementarity, arguing that automation changes the task content of jobs and can raise demand for workers whose activities are made more productive by new tools [3,4].

A large share of the literature relies on forecasts, task-based exposure measures, or macroeconomic comparisons. These approaches are useful, but they do not directly show what firms say happened to their workforce after adopting a technology. The 2019 Annual Business Survey (ABS) provides a useful source for this narrower question. Its technology module asked U.S. employer firms about the use of five advanced technologies during 2016- 2018 and about reported effects on workforce size and skill requirements [5,6].

This paper uses the ABS data to describe workforce outcomes among firms that used AI, cloud-based computing, and robotics. The analysis focuses on three questions. First, what share of technology-using firms reported increases, decreases, or no change in the number of workers? Second, what share reported increases, decreases, or no change in overall workforce skill levels? Third, how did firms report changes in STEM skills? The study is descriptive rather than causal. It is intended to clarify what the survey data show and to avoid overstating the implications of cross-sectional, self-reported responses.

2 Literature Review

Research on automation often begins with the possibility of labor substitution. Frey and Osborne [2] estimated that many U.S. occupations contained work activities susceptible to computerization, and Ford [1] argued that AI and robotics could extend automation beyond routine manual work into cognitive and professional tasks. Later studies using task-level methods produced more moderate estimates of automation risk, but reached a similar conclusion: workers differ substantially in their exposure to technological change [7,8].

Empirical work on robotics also points to displacement risks in some settings. Acemoglu and Restrepo [9] found negative local labor-market effects associated with industrial robot exposure in the United States. Dauth et al. [10], studying Germany, found that robots reduced manufacturing employment while generating adjustment across sectors. These findings indicate that automation can reduce demand for particular tasks or occupations even when aggregate employment effects are harder to observe.

Technology adoption can also affect workers who remain employed. Studies of technostress show that new information systems may increase perceived overload, job insecurity, and uncertainty when workers must adapt quickly to unfamiliar tools [11,12]. Grace et al. [13] show that expert expectations about AI capabilities vary widely, but forecasts of rapid task-level progress can still shape workplace anxiety.

A second body of work emphasizes complementarity. Autor [3] argues that automation substitutes for some tasks while complementing others, especially nonroutine analytical, interpersonal, and judgment-intensive work.

Table 1: Employer firms represented in the technology-specific ABS estimates.

Technology group	Employer firms
Artificial intelligence	8,172
Cloud-based computing	52,975
Robotics	9,683
Specialized software	95,401
Specialized equipment	39,529

Note. Values are all-industry estimates from the 2019 Annual Business Survey technology impact tables [27].

Autor, Levy, and Murnane [14] similarly show that technological change altered the skill content of work by reducing demand for routine tasks and raising demand for other activities.

Bessen [4] shows that automation can increase employment when it raises demand for products or services strongly enough to offset labor-saving effects. Brynjolfsson and McAfee [15] and Schwab [16] frame recent digital technologies as part of a broader transformation in production and coordination, while Raj and Seamans [17] distinguish AI and robotics by the tasks they perform and the organizational changes they require.

The skill implications of automation are central to this complementarity view. Deming [18] documents the growing labor-market value of social skills, and Frank et al. [19] argue that understanding AI's labor-market effects requires linking technologies to tasks, skills, and occupations. Organizational research reaches a similar point: digital transformation often redesigns work roles rather than simply eliminating them [20, 21]. Reports by the McKinsey Global Institute and the OECD also emphasize that automation is likely to change the composition of skill demand, even where total employment does not fall [22, 23].

Firm-level evidence is important because adoption decisions are made by organizations of different sizes, industries, workforces, and strategic goals. Davenport and Ronanki [24] note that firms often introduce AI for specific business processes rather than as a wholesale replacement for labor. Wright and Schultz [25] argue that these organizational choices raise ethical and managerial questions about workforce planning. Georgieff and Hye [26] likewise call for granular evidence on how AI adoption relates to employment outcomes.

The ABS technology module helps address this gap by asking firms directly about the workforce effects associated with their use of advanced technologies. Acemoglu et al. [6] use the same survey module to document technology adoption, automation motives, productivity differences, and workforce exposure. The present paper focuses more narrowly on the reported employment and skill outcomes in the public ABS tables.

3 Study

The data come from the 2019 Annual Business Survey, which covers data year 2018 and includes a technology module with questions about the use of advanced technologies during 2016–2018 [5]. The ABS is administered by the U.S. Census Bureau for the National Center for Science and Engineering Statistics. The public tables used here report estimates for employer firms by industry and for all industries combined. Because some detailed cells are suppressed for confidentiality, this analysis uses the all-industry aggregate estimates reported in the public ABS tables [27].

The ABS technology module asked firms about five technology groups: artificial intelligence, cloud-based computing systems and applications, robotics, specialized software, and specialized equipment. The main text focuses on AI, cloud-based computing, and robotics because those technologies are central to current debates about digital automation. Results for specialized software and specialized equipment are retained in Appendix ??.

For each technology used, firms reported whether the technology increased, decreased, or did not change the number of workers. They also reported whether it increased, decreased, or did not change workers' overall skill level. For STEM skills, the response options were increased, decreased, did not change, and not applicable. The analysis reports percentages within each technology group. These percentages should be read as the distribution of firm responses, not as changes in the number of employees.

The analysis is descriptive. Percentages from the public ABS tables were summarized by technology group and outcome. No causal model is estimated. The data are self-reported and cross-sectional, so the results cannot establish whether technology adoption caused changes in employment or skills. They show how technology-using firms characterized the workforce effects associated with each technology during the 2016–2018 reference period.

4 Results

Table 1 reports the number of employer firms represented in the all-industry estimates for each technology group, and Figure 1 displays these counts visually. Table 2 reports the workforce outcome percentages for AI, cloud-based computing, and robotics.

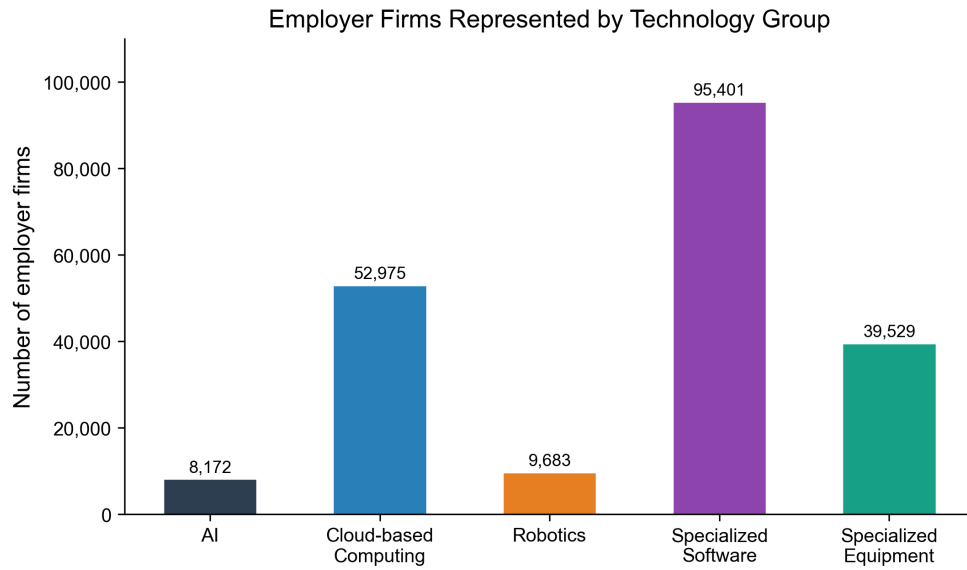


Figure 1: Number of employer firms represented in the ABS technology impact estimates, by technology group.

Table 2: Reported workforce effects among firms using AI, cloud-based computing, and robotics.

Reported effect	AI	Cloud-based	Robotics
<i>Number of workers</i>			
Increased	15.0	12.5	10.0
Decreased	6.3	3.7	8.1
Did not change	78.8	83.8	81.9
<i>Overall skill level of workers</i>			
Increased	40.9	28.2	23.6
Decreased	1.8	0.8	2.3
Did not change	57.3	70.9	74.1
<i>STEM skills of workers</i>			
Increased	31.2	15.8	20.3
Decreased	1.1	0.5	1.6
Did not change	39.8	42.3	54.4
Not applicable	27.9	41.4	23.7

Note. Values are percentages of firms using the relevant technology. Percentages may not sum to exactly 100 because of rounding. Source: 2019 Annual Business Survey, Tables 95–99 and 104–105 [27].

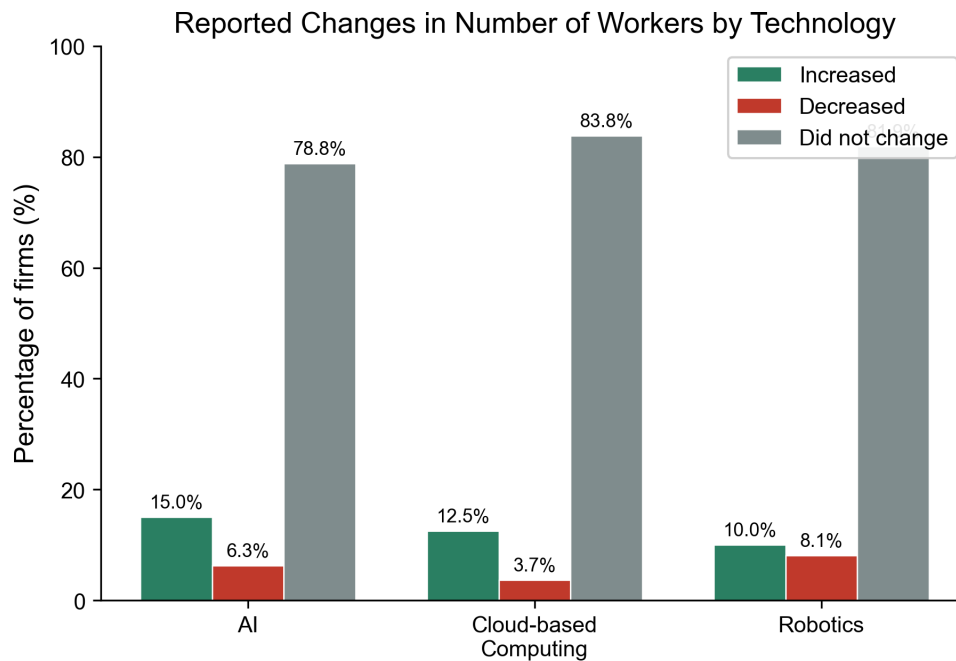


Figure 2: Reported changes in the number of workers among firms using AI, cloud-based computing, and robotics. Values are percentages of technology-using firms.

The most common reported outcome was no change in the number of workers. This was reported by 78.8% of AI-using firms, 83.8% of cloud-using firms, and 81.9% of robotics-using firms. Among firms reporting a change, increases were more common than decreases across technologies. AI-using firms reported a 15.0% increase and a 6.3% decrease. Cloud-using firms reported a 12.5% increase and a 3.7% decrease.

Robotics had the smallest positive margin. A workforce increase was reported by 10.0% of robotics-using firms, while 8.1% reported a decrease. This pattern is consistent with prior evidence that physical automation can substitute directly for some manual tasks [9, 10]. Still, the ABS results show that even among robotics-using firms, "no change" was reported much more often than workforce reductions. Figure 2 illustrates the distribution of reported workforce-size changes across the three focal technologies.

Reported skill effects were stronger than reported headcount effects. AI-using firms were the most likely to report an increase in the overall skill level of workers: 40.9% reported an increase, compared with 28.2% of cloud-using firms and 23.6% of robotics-using firms. Reported decreases in overall skill level were uncommon across all three technologies: 1.8% for AI, 0.8% for cloud-based computing, and 2.3% for robotics.

These results are consistent with the view that technology adoption can raise the skill demands placed on workers. They do not, however, show the mechanism. A reported increase in skills could reflect training of existing employees, hiring workers with different skills, changes in task assignments, or some combination of these processes. Figure 3 presents the distribution of reported overall skill-level changes.

The STEM-skill results show a similar but more uneven pattern. AI-using firms reported the highest rate of increases in STEM skills, at 31.2

The not-applicable category is important for interpreting these results. It was selected by 41.4% of cloud-using firms, 27.9% of AI-using firms, and 23.7% of robotics-using firms. Because cloud-based services are used broadly across industries and business functions, many cloud users may not have considered STEM skills relevant to their workforce. The ABS tables do not provide worker-level detail sufficient to test this interpretation directly. Figure 4 shows the full response distribution, including the not-applicable category.

Table 3 summarizes the main comparative patterns. The net employment measure is the percentage of firms reporting an increase in the number of workers minus the percentage reporting a decrease. It is a response-share difference, not an estimate of net jobs created.

Figure 5 visualizes these comparative metrics side by side. Three points follow from the comparison. First, all three technologies show a positive response-share difference for employment, but the robotics margin is much smaller than the AI and cloud margins. Second, AI stands out in reported skill increases, both overall and STEM-specific. Third, low rates of reported skill decreases suggest that firms more often experienced technology adoption as a skill-upgrading process than as a skill-reducing process.

Table 4 reports the same employment and skill outcomes for specialized software and specialized equipment. The additional technology groups follow the same broad pattern as the focal technologies. For both special-

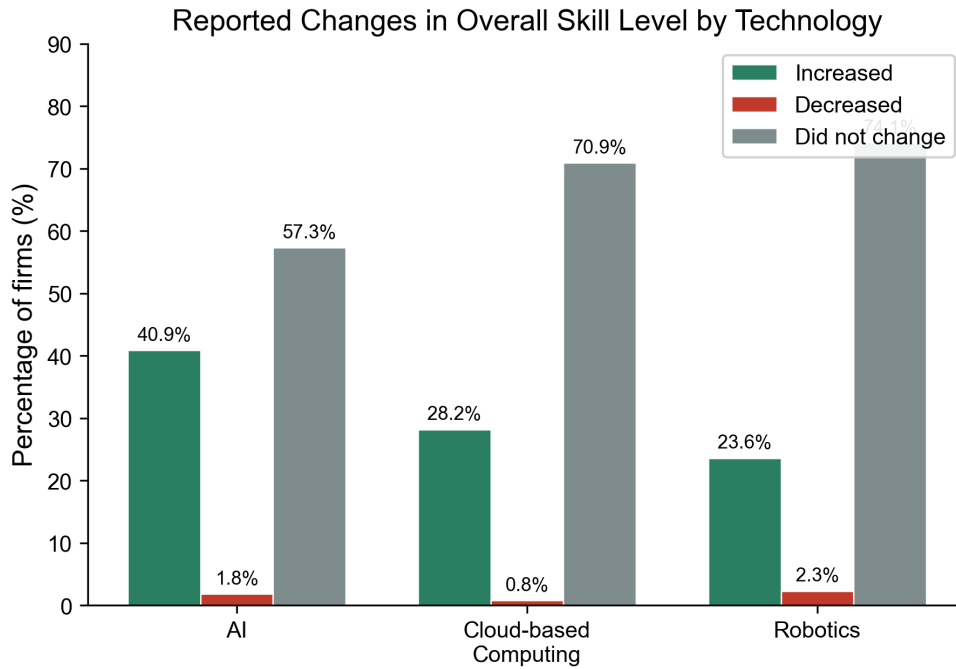


Figure 3: Reported changes in overall skill level among firms using AI, cloud-based computing, and robotics. Values are percentages of technology-using firms.

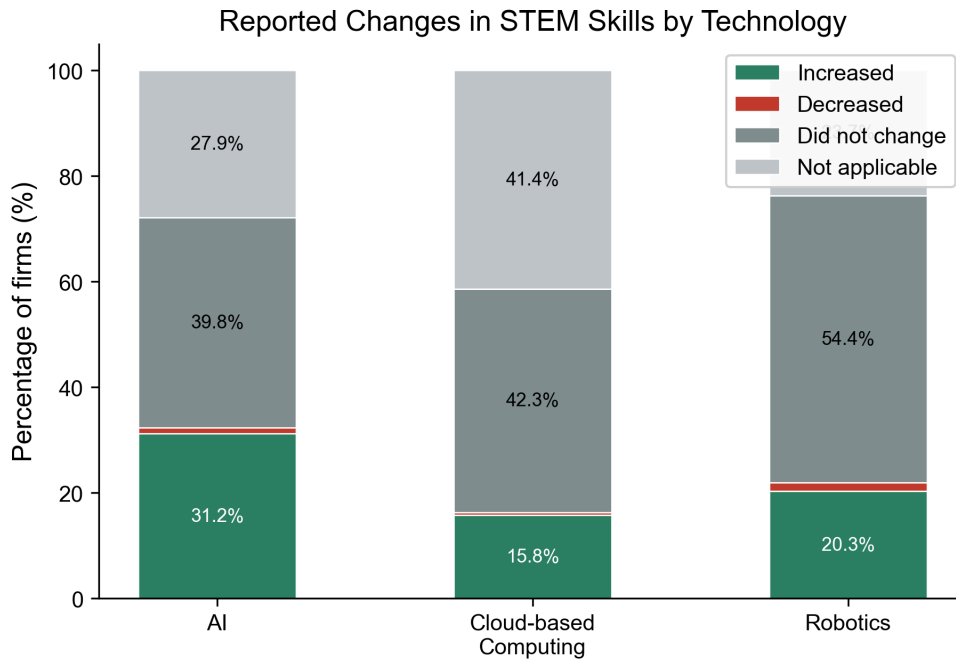


Figure 4: Reported changes in STEM skills among firms using AI, cloud-based computing, and robotics. Stacked bars include the not-applicable category. Values are percentages of technology-using firms.

Table 3: Summary comparison of reported workforce effects.

Metric	AI	Cloud	Robotics
Workers increased	15.0	12.5	10.0
Workers decreased	6.3	3.7	8.1
Response-share difference: workers increased minus decreased	+8.7	+8.8	+1.9
Overall skill level increased	40.9	28.2	23.6
STEM skills increased	31.2	15.8	20.3

Note. Values are percentages of technology-using firms. The response-share difference is descriptive and does not measure employment headcount changes. Source: 2019 Annual Business Survey technology impact tables [27].

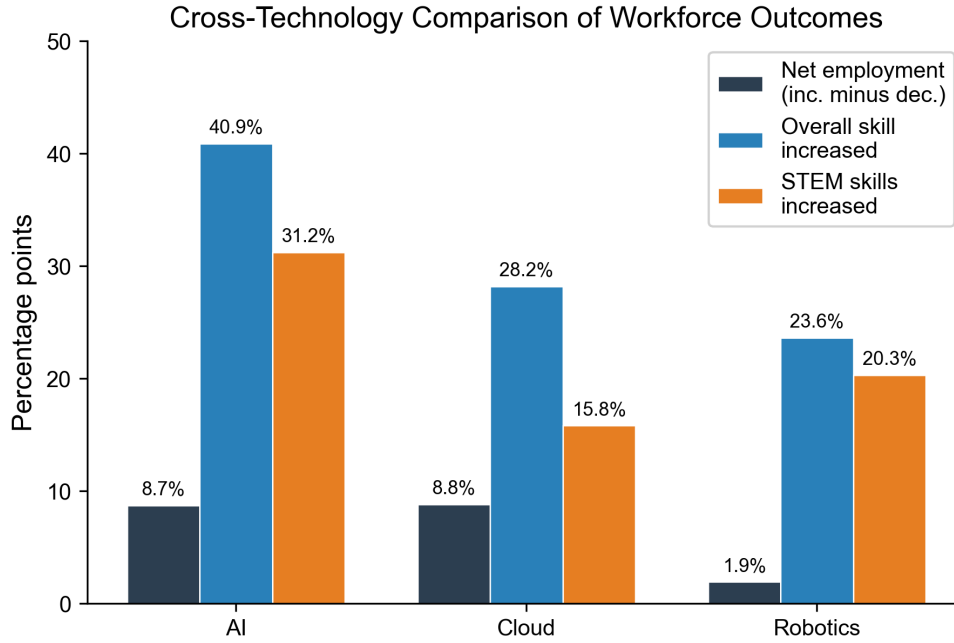


Figure 5: Cross-technology comparison of workforce outcomes: net employment response-share difference, percentage of firms reporting increased overall skill level, and percentage reporting increased STEM skills.

Table 4: Reported workforce effects among firms using specialized software and specialized equipment.

Reported effect	Spec. software	Spec. equipment
<i>Number of workers</i>		
Increased	10.2	8.9
Decreased	2.5	3.8
Did not change	87.3	87.3
<i>Overall skill level of workers</i>		
Increased	18.4	15.7
Decreased	0.6	1.2
Did not change	81.0	83.1
<i>STEM skills of workers</i>		
Increased	11.3	12.1
Decreased	0.4	0.9
Did not change	47.8	50.6
Not applicable	40.5	36.4

Note. Values are percentages of firms using the relevant technology. Source: 2019 Annual Business Survey, Tables 101–102 and 107–108 [27].

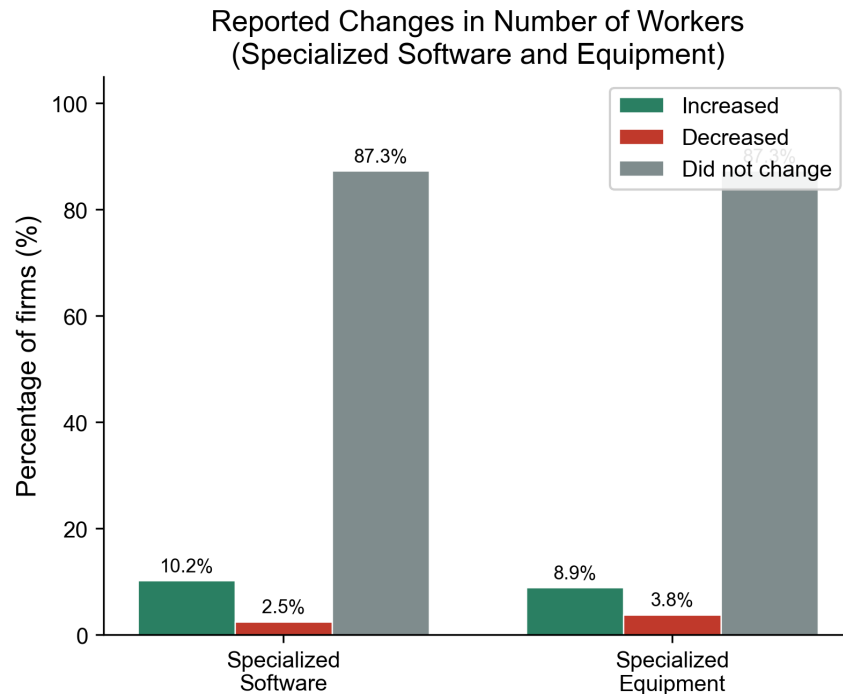


Figure 6: Reported changes in the number of workers among firms using specialized software and specialized equipment.

ized software and specialized equipment, 87.3% of firms reported no change in the number of workers. Reported skill increases were less common than among AI-using firms, but they were still more common than reported skill decreases. Figures 6–8 present these results graphically.

5 Discussion

The central finding is that most firms using AI, cloud-based computing, or robotics reported no change in workforce size during the 2016–2018 reference period. Where firms did report headcount changes, increases were more common than decreases. These results align with the complementarity argument that automation often changes the organization of work rather than simply reducing employment [3, 4].

The findings should not be read as evidence that no workers were displaced. A firm reporting no net change in worker count could have eliminated some jobs while creating others. A firm reporting increased skill levels could have trained existing workers, changed hiring patterns, or replaced some workers with others. The ABS public tables do not show within-firm reallocations, separations, or worker-level transitions. For that reason, the paper avoids claims about net job creation or causal effects.

The robotics results deserve particular caution. Robotics had the highest reported workforce-decrease rate among the focal technologies, at 8.1%, and the smallest positive response-share difference. This is consistent with the idea that robotics is more directly tied to automation of physical tasks than cloud-based computing and many AI applications [9, 17]. At the same time, the majority of robotics-using firms still reported no change in workforce size.

The skill results suggest that technology adoption was often accompanied by upskilling. AI-using firms were especially likely to report increases in overall and STEM skills. This pattern aligns with research showing that digital technologies can increase demand for analytical, technical, and complementary interpersonal skills [14, 18, 19]. The ABS data do not show whether these skill increases came from training, hiring, or changes in job composition.

5.1 Practical Implications

For managers and human resource professionals, the results point to the importance of workforce planning alongside technology adoption. A firm implementing AI, cloud systems, or robotics may not reduce employment, but it may still need different skills. Training, internal mobility, job redesign, and communication with employees are therefore central implementation issues, not secondary concerns [21, 25].

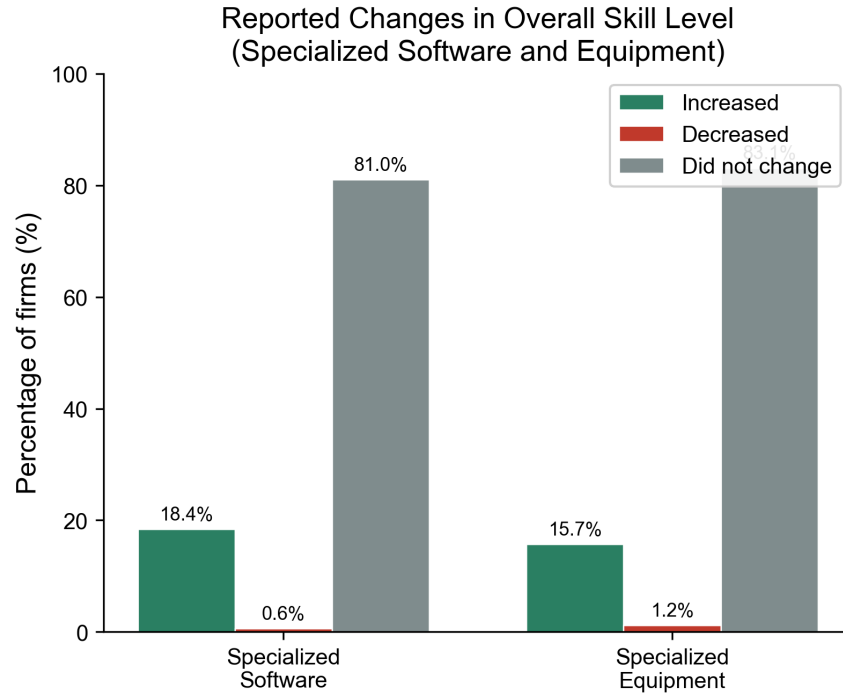


Figure 7: Reported changes in overall skill level among firms using specialized software and specialized equipment.

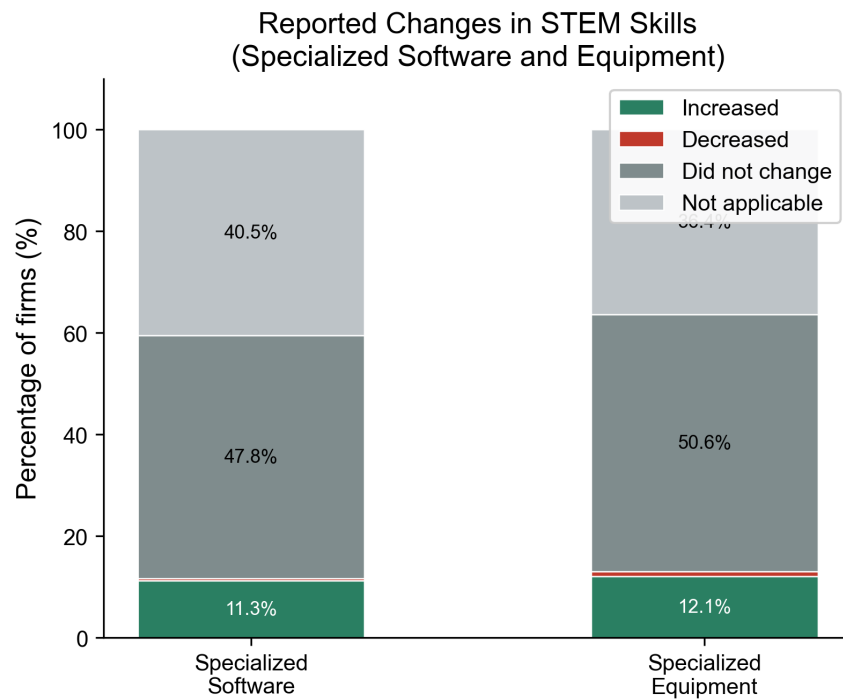


Figure 8: Reported changes in STEM skills among firms using specialized software and specialized equipment. Stacked bars include the not-applicable category.

For workers and career-development professionals, the findings support continued investment in skills that complement automated systems. These include data interpretation, system monitoring, exception handling, process improvement, and communication across technical and nontechnical teams. The evidence does not imply that every worker needs advanced STEM training, but it does show that many firms associate the use of technology with higher skill requirements.

For educators, the findings support applied technology training across a broader set of programs than traditional computer science or engineering. Because firms in many industries use cloud-based systems and other digital tools, graduates in business, health, logistics, design, and public service fields may also need experience working with data-rich and automated systems.

Several limitations constrain the interpretation. First, the public tables report firm-level response categories rather than worker-level employment flows. Second, the all-industry estimates mask sector-specific differences. Also, the reference period was 2016–2018; the patterns may differ in later periods as AI tools, robotics, and cloud infrastructure mature.

6 Conclusion

Using public tables from the 2019 Annual Business Survey, this paper examined reported workforce effects among U.S. employer firms using AI, cloud-based computing, and robotics during 2016–2018. The main result is straightforward: most technology-using firms reported no change in the number of workers. Among firms reporting a change, increases were more common than decreases for all three technologies, although the margin was smallest for robotics. Skill increases were also more common than skill decreases, particularly for AI.

These findings do not settle the broader debate over automation and employment. They do, however, provide firm-level descriptive evidence that the use of these technologies was more often associated with workforce stability and skill upgrading than with reported net workforce reductions during the period studied. The results are best understood as evidence about reported firm experiences, not as proof of causal employment effects.

Our future work research should link technology adoption to longitudinal employer and worker records where possible. Such data would make it easier to distinguish training from hiring, net employment stability from internal reallocation, and temporary adjustment from persistent change. Sector-specific analysis would also be useful, especially in industries where robotics and AI are more directly connected to production processes. Qualitative work could complement these data by showing how firms manage implementation, redesign jobs, and communicate changes to employees.

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