



HHS Public Access

Author manuscript

J Occup Rehabil. Author manuscript; available in PMC 2024 July 02.

Published in final edited form as:

J Occup Rehabil. 2024 June ; 34(2): 299–315. doi:10.1007/s10926-023-10164-w.

Assistive Technology's Potential to Improve Employment of People with Disabilities

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Abstract

Purpose—This study investigates how access to assistive technologies affects employment and earnings among people with disabilities.

Methods—We first document employment and earnings gaps associated with specific impairments and activity limitations using 2017–2021 American Community Survey and 2014 Survey of Income and Program Participation data. We then use accommodations data from the 2012, 2019, and 2021 Current Population Survey (CPS) Disability Supplements to examine employment and earnings growth for people with disabilities related both to any, and to technology-based, accommodations. We also provide short descriptions of three developing assistive technologies that assist people with upper body impairments, visual impairments, and anxiety conditions.

Results—Almost all impairments and activity limitations are linked to lower employment and earnings, with especially low employment among people with mobility impairments and particularly low earnings among those with cognitive impairments. About one-tenth of workers with disabilities received any accommodations, and 3–4% received equipment-based accommodations in the 2012–2021 period; these figures increased slightly over the period. The occupations with the highest disability accommodations rates had greater disability employment growth from 2012 to 2021, but disability pay gaps did not decrease more in these occupations. The

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Author contributions Douglas Kruse and Lisa Schur wrote the main text in section I to IV, with input and review by Hazel-Anne Johnson and Lauren Gilbert. Antonio Di Gallo, Weibo Gao, and Hao Su contributed to section V. All authors reviewed and edited the manuscript.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

Ethical Approval All data are from analysis of secondary data in publicly available government datasets, so no ethical approval is required.

three developing assistive technologies we describe illustrate the potential to reduce the estimated employment and earnings deficits.

Conclusion—Assistive technology accommodations have potential for improving employment outcomes for people with disabilities.

Keywords

Disability; Employment; Assistive technology; Accommodations

Introduction

Can assistive technology (AT) mitigate the employment and earnings disparities faced by people with disabilities (PWDs)? [1, 2]. There has been a tremendous increase in the use of AT in general over the past several decades, helping disabled people in a wide range of activities, and many have also benefited the general population [3, 4]. This includes a vast expansion of technologies that can help the employment of PWDs, illustrated by thousands of ATs referenced at the Job Accommodations Network [5].

While there are many examples of how AT can help the employment of PWDs, there has been little systematic and representative evidence on its effects on employment, pay, and job retention. Prior literature focuses on the causes or consequences of accommodations analyzed at the individual level. Here we take a different approach, by focusing on occupation-level measures that reflect the potential availability of accommodations in different occupations, and assessing how these measures relate to employment outcomes for PWDs over the past decade.

In this paper, we present a) new estimates of the employment and earnings gaps associated with disability, b) an occupation-level analysis of the relationship between AT accommodations and the employment and earnings of PWDs over the 2012–2021 period, and c) brief descriptions of three developing assistive technologies to illustrate AT's potential. While there are no data on the employment effects of specific assistive technologies, we use our estimates on the functional deficits addressed by these technologies to illustrate the potential for improving employment outcomes among PWDs.

Literature Review

The value of accommodations in general is indicated by Maestas et al., who find that “47 to 58 percent of accommodation-sensitive individuals lack accommodation and would benefit from some kind of employer accommodation to either sustain or commence work” [6]. They find that among individuals who could benefit from accommodations, those who were accommodated in 2014 were 13.2 percentage points more likely to work in 2018 than unaccommodated individuals in 2014.

The literature is generally consistent with this finding of favorable effects of employer accommodations. Two recent reviews found strong evidence that accommodations for PWDs are linked to continued employment and faster return to work [7, 8]. Longitudinal comparisons find that employer accommodations are linked to increased employment

duration with the current employer and delayed labor force exits [9–13]. Accommodations appear to speed the return to work [14–16] and slow applications for disability insurance benefits, but do not reduce subsequent claims for these benefits [11, 13]. PWDs themselves report positive effects of employer accommodations [17]. A review of 37 studies on pandemic-related workplace accommodations found that the pandemic had both positive impacts (e.g., reduced stigma from accommodations, and more rapid implementation) and negative impacts (e.g., new accommodation needs) on accommodations for PWDs [18]. These benefits and costs may be particularly salient for certain groups such as neurodiverse individuals, for whom telework has been found to help create accessible workspaces and resolve tensions between productivity and wellbeing, but also create communication problems in a virtual environment [19–21].

The provision of accommodations by employers reflects characteristics of employers (size and industry) and workers (age, gender, education, union status, and pre-injury wage), although employer characteristics appear to be much more important [22–24]. Among employers, there is significant variation by industry, and large employers are more likely than smaller employers to provide accommodations [22, 25].

The findings are less robust with respect to specific accommodations involving AT. The Assistive Technology Act of 2004 defines AT as “any item, piece of equipment, or product system.. that is used to increase, maintain, or improve functional capabilities of individuals with disabilities” [26]. AT can be as simple as a cane or as complex as a sophisticated computer system. One early review provides mixed results and cautions regarding the effects of AT on employment of PWDs [27]. Two subsequent studies analyzed the effects of new equipment combined with other accommodations: one found that “provision of equipment/assistance” had effects that were as favorable for continued employment as other accommodations [13], while another found that “special equipment or office remodeling” had positive but insignificant effects on employment duration [12].

Case study literature on AT provides more insights. One study found positive effects of AT on job performance and skills [28], and another found benefits for productivity and self-esteem [17]. Collins et al. found that AT enhanced job outcomes for young adults with intellectual disabilities [29]. Several authors, however, argue that an individualized approach of providing AT neglects many employment challenges and barriers faced by PWDs [30], and the successful provision of AT is complicated by employers’ perspectives, the accessibility of AT, and the availability of support from vocational and rehabilitation services [31]. The costs of AT are found to be no more on average than the costs of other accommodations [32].

Regarding access to AT in general (not just for employment), Black workers appear to have higher use but lower growth in access to AT [33], and Ward-Sutton et al. argue that access to AT among PWDs reflects historical inequities between African Americans and Whites [34], although Brucker et al. find no significant racial difference in employer accommodations after controlling for other characteristics [25]. Access to AT is lower among people of color and those with low educational attainment, low household income, later disability onset, and a mental rather than physical disability [35].

An additional important factor is co-worker reactions. While most co-workers support disability accommodations, they can sometimes generate jealousy and resentment [36]. Employer policies and practices as well as supervisor knowledge and support are critical in ensuring PWDs have the accommodations they need and that they are part of a workplace “culture of inclusion” [37–39].

Data and Methods

We use three datasets based on surveys conducted by the U.S. Census Bureau: the 2017–2021 American Community Survey (ACS), the 2014 Survey of Income and Program Participation SSA Supplement (SIPP), and the 2012, 2019, and 2021 Current Population Survey Disability Supplements (CPS).

The 2017–2021 ACS has a very large sample (9,246,283 million people age 18–64), representing a repeated cross-section of about 1% of U.S. households sampled once during a year. It includes six disability questions identifying four impairments (hearing, vision, cognitive, and mobility) and two activity limitations (difficulty dressing or bathing, and difficulty going outside home alone). These questions are reproduced in Appendix A. The ACS data also allow construction of current employment status and hourly wages for jobs held in the past 12 months. The hourly pay values were winsorized at the upper and lower 1% levels to reduce the influence of outliers.

The 2014 SIPP is less recent and has a smaller sample (20,120 people age 18–64), but has the advantage of more detailed disability questions, allowing a finer look at physical and mental conditions that accommodations may help to address. While SIPP is designed as a longitudinal survey, the SSA Supplement was conducted one time only on 2014 Wave 1 respondents during September to November 2014. The 17 disability questions we use on impairments, activity limitations, and mental or cognitive conditions are reproduced in Appendix A. Like the ACS, the SIPP data permit the construction of employment status and hourly pay, and the pay values were winsorized at the upper and lower 1% levels.

The CPS Disability Supplements were added to the monthly CPS surveys in May 2012, July 2019, and July 2021. In these supplements, all employees were asked “Have you ever requested any change in your current workplace to help you do your job better? For example, changes in work policies, equipment, or schedules.” If yes, employees were asked what types of changes they had requested, and whether the request was fully or partially granted. Here we assess both any type of accommodation, and an accommodation based on “new or modified equipment.” Note that “new or modified equipment” is a broader category than AT, since the equipment may not be specifically designed to address a disability; as we will see, however, employees with disabilities were more likely than employees without disabilities to request and be granted new or modified equipment, so it is very likely that much of this equipment is AT. We do not know if the accommodation was made for a new or existing employee. The disability measure is based on the same six questions used in the ACS, identifying four impairment types and two activity limitations. The 2012, 2019, and 2021 supplements have sample sizes of 54,113, 43,167, and 40,498 respectively, including 2,092, 1,740, and 1,664 employees with disabilities respectively.

To examine disability employment and pay gaps in the ACS and SIPP data we predict employment using linear probability models and the natural logarithm of hourly pay using a Heckman selection model. The control variables are listed at the bottom of Table 1, with complete results in Tables 5 and 6 (including the excluded variables used to identify the Heckman equations). These techniques allow ready translation of the results into percentage differences in employment and pay associated with the disability variables.

To analyze the potential effect of accommodations on disability employment and pay gaps, we use occupation-level measures that reflect the potential availability of accommodations in different occupations (in contrast to prior literature which focuses on assessing accommodations at the individual level), and see how these measures relate to employment outcomes for PWDs over the past decade. We assess three outcomes:

1. Disability employment growth: Percentage change in total number of PWDs employed in a given occupation, measured as $((\text{year 2 disability employment}) / (\text{year 1 disability employment}) - 1) * 100$
2. Disability representation change: Change in percentage of people within an occupation who have a disability, measured as $((\text{year 2 disability employment}) / (\text{year 2 total employment}) - ((\text{year 1 disability employment}) / (\text{year 1 disability employment}))) * 100$
3. Disability pay gap change: Change in disability pay gap, measured as the difference between the disability coefficients predicting $\ln(\text{hourly pay})$ in year 1 and year 2. For each year, $\ln(\text{hourly pay})$ was regressed on the control variables listed in Table 1, plus disability interacted with occupational dummies in order to estimate an occupation-specific disability pay gap in each year. We do not need to do inflation adjustments since we are comparing percentage pay gaps within each year.

For all three outcomes, we combined CPS data for all 12 months in the calendar year of the relevant disability supplement (2012, 2019, and 2021). We tested two different occupational coding systems with different levels of detail: one that included 137 occupations that each had at least five employees with disabilities responding to the accommodations question in 2012, and a broader code that included 42 occupations that each had at least 14 employees with disabilities responding to the accommodations question in 2012. The second occupational coding system is used in results presented in Table 3 and 4, but results were similar between the two coding systems.

All results use sample weights supplied with the datasets. The data were analyzed using Stata version 17.0.

Results

Employment and Earnings Gaps

Almost all disability types and conditions are linked to lower employment and earnings, as shown in Table 1. ACS data in columns 1 and 3 show the smallest (but still highly significant) deficits for people with visual or hearing impairments. The largest employment

deficits are among people with mobility impairments (0.343 lower employment probability, or 34.3 percentage points, compared to people without disabilities) and those otherwise limited in going outside alone (35.9 points lower). Among the employed, the largest pay deficits exist for cognitive impairments (-0.193 log points which translates to 17.6% lower pay) and being limited in going outside alone (16.8% lower pay).

The SIPP employment results in column 2 of Table 1 show reduced employment probabilities of more than 0.10 (10 percentage points) among those who have difficulty walking 3 blocks, standing for one hour, or lifting and carrying 10 pounds, and those who have a speech impairment, developmental disability, or Alzheimer's, senility, or dementia. All the other conditions are associated with reduced employment except for difficulty in sitting for one hour.

The SIPP pay results in column 4 show pay deficits of 10% or more associated with an intellectual disability (-0.536 log points which translates to 41.5% lower pay), visual impairment (11.7% lower pay), "other" mental/emotional condition (11.3% lower pay), difficulty picking up a glass or grasping a pencil (11.0% lower pay), and difficulty walking three blocks (10.9% lower pay). Some conditions appear to significantly limit employment but not the pay of those who become employed with those conditions, such as difficulty lifting and carrying 10 pounds, standing for one hour, and pushing or pulling large objects.

Accommodation Rates

To assess how accommodations may help to reduce these employment and earnings gaps we turn to data from the CPS Disability Supplements. Table 2 shows that in 2012, 12.7% of employees with disabilities requested accommodations, and 10.2% had these requests fully or partially granted (column 1). These numbers each went up slightly in 2019 and 2021, so that 15.1% requested accommodations and 12.4% had them granted in 2021 (column 5). These increases between 2012 and 2021 are significant at the $p < 0.10$ level (column 7). Among employees without disabilities, the requested and granted accommodations in 2012 were just over half the rates among employees with disabilities (column 2), while these figures went down significantly by 2021 (columns 6 and 8).

Broken down by disability type, granted accommodations were highest among those with cognitive (12.1%) or mobility (13.0%) impairments in 2012 (column 1). This figure increased significantly by 2021 to 19.0% among employees with cognitive impairments, and increased non-significantly to 14.4% among employees with mobility impairments (column 5).

Turning to equipment-based accommodations, 4.2% of employees with disabilities requested such accommodations in 2012 and 3.3% had them granted in full or part (column 1). The numbers also increased slightly (but not significantly) to 4.8% and 4.1% in 2021 (column 5). As with accommodations in general, employees without disabilities saw a significant decline in equipment-based accommodation requests and grants from 2012 to 2021.

The rate of equipment-based accommodations does not vary substantially by disability type. Employees with mobility impairments were the most likely to receive such accommodations

in both 2012 (4.0%) and 2021 (5.0%)(columns 1 and 5). The likelihood of such accommodations increased slightly across all disability types, especially among people with cognitive impairments (2.0% in 2012 to 4.4% in 2021). This suggests that technological advances may have particularly benefited people with cognitive impairments.

How do these accommodations vary by occupation? Table 3 presents an occupational breakdown of the percent who were granted accommodations, averaged across all three years. Among employees with disabilities, those doing personal care excluding childcare and home care were the most likely to receive any accommodations (27.3%), followed by those doing health support excluding diagnosis and technicians (23.2%)(column 1). Farming/ranching managers were the least likely to receive any accommodations (0.8%). The accommodation rate was higher among employees with disabilities than among those without disabilities (column 2) in every occupation except for construction managers, food prep excluding cooks, installation/repair, and farming/ranching managers.

Equipment-based accommodations were most likely for employees with disabilities in health support excluding diagnosis and technicians (13.1%), computer/math (12.1%), and administrative assistants (11.0%). Several occupations had no instances of equipment-based accommodations for employees with disabilities: childcare services, laborers/package/movers, maids, and farming/forestry/fishing.

Accommodations and Employment Outcomes

As seen in Table 4, occupations in which employees with disabilities had more accommodations in 2012 also had significantly greater disability employment growth in 2012–2019 and 2012–2021 (column 2). There is also a positive correlation between equipment-based accommodations in 2012 and disability employment growth in 2012–2021 (column 3). Both results are consistent with the idea that a higher accommodations rate favored employment growth among PWDs.

The above results may simply reflect greater employment growth in general in more accommodating occupations, but we also find a significant positive correlation between the disability accommodations rate in 2012 and the change in disability representation in an occupation. A positive correlation also exists between this outcome and equipment-based correlations, but this is not statistically significant.

A different story emerges with respect to changes in pay gaps. While the accommodations rate in 2012 is positively linked to improvements (i.e., reductions) in the disability pay gap in 2012–2019, the correlation is significantly negative when looking at the 2012–2021 period. It is possible that accommodations help draw in lower-skill workers who contribute to greater disability pay gaps, or employers are lowering wages of accommodated workers. The pattern indicates that accommodations were linked to greater pay disparities in the 2019–2021 pandemic period, reflecting greater difficulties for workers with disabilities who managed to hang onto their jobs in the pandemic.

Do the potential effects of accommodation availability vary by type of disability? Table 4 reports similar correlations for 2012–2021 changes in employment growth and disability

percent in occupation for people with hearing, vision, cognitive, and mobility impairments. As can be seen, the only significant correlation is a positive one, indicating that people with cognitive impairments had greater employment growth in occupations where they received more accommodations in 2012. All the correlations with equipment-based accommodations, however, do not reach statistical significance.

These data are generally consistent with the idea that disability accommodations help increase employment growth for PWDs, and for people with cognitive impairments in particular. To probe the results, we tested whether there were differential effects associated with *changes* in accommodation rates over the 2012–2021 period, or differences between the accommodation rates of people with and without disabilities, but we did not find significant correlations (not reported here).

We recognize there are limitations to using occupation-level data as a measure of accommodations availability, especially when looking at changes in accommodation rates over time. In particular, technological change varies among occupations, and many new technologies may make jobs more accessible for PWDs without the need for special accommodations. For example, many new computer software programs now have accessibility built in so that extra programs or peripherals are not necessary. Requesting accommodations may be stressful and even risky [36], so PWDs may gravitate to occupations where no extra equipment or other accommodations are necessary. In addition, employers may be more reluctant to hire PWDs in occupations where extra equipment is needed to accommodate their disabilities. Both these employee-driven and employer-driven effects would dampen the correlation between accommodation rates and employment growth.

We are also mindful that our data include the first 16 months of the pandemic (from March 2020 to the survey done in July 2021), and it is possible that the adoption and effects of assistive technologies may be affected by the pandemic recession. In fact we find that the results on disability employment growth are strongest when looking across the entire 2012–2021 period instead of just the 2012–2019 period. This suggests that for the more accommodating occupations in 2012, employers were more prepared and/or willing to retain or rehire PWDs in the early stages of the recession in 2020–2021. The use of assistive technologies in the pandemic may be related to the large increase in telework, due both to the development of new technologies to enable telework and to employer willingness to experiment with and accept new methods of completing the work.

Examples of Developing Assistive Technologies

AT can be low-tech (e.g., canes for blind people, sliding boards for wheelchair transfers), medium-tech (e.g., manual wheelchairs, screen magnifiers), or high-tech (devices using complex digital or electronic components). Here, we provide three examples of developing high-tech assistive technologies that have potential to improve disability-related employment outcomes, and discuss how they relate to the employment and earnings deficits identified in Table 1. These three technologies are designed to assist people with upper body impairments, visual impairments, and anxiety conditions.

Wearable Robot for People with Upper Body Impairments

Wearable robots, also referred to as “exoskeletons” or “exosuits,” are devices that are designed to support or augment the physical capabilities of the wearer [40]. They have shown potential to benefit both able-bodied and disabled users in a variety of scenarios, such as at work (e.g., reducing the risk of injuries in physically demanding jobs), in rehabilitation (accelerating the recovery of physical capabilities), or in daily living (helping individuals with mobility impairments to regain independence) [41–45].

A wearable robot is pictured in Fig. 1. It is designed to aid shoulder and arm functions in individuals with residual volitional movement ability, so that the user retains control of the motion, while the device helps to compensate for the effects of gravity [46]. The robot is relatively easy to put on and take off and is worn as a backpack with additional straps around the forearms. The adjustable straps and dimensions of the wearable structure can fit individuals with varying body types and sizes. The device has a total weight of 4 kg (9 pounds), with most of the mass being concentrated at the waist level, to minimize the inertial penalty on the wearer. This mass distribution is achieved using cable-driven transmission, which allows the device to deliver assistance to the arms while the actuators (the heaviest components) are located close to the center of mass of the human body. The assistance supports arm elevation in both shoulder abduction and flexion. The exoskeleton controller detects residual volitional movements of the limbs using motion sensors placed on the wearer’s forearms and computes the force required to supplement the user’s effort.

The robot is portable and capable of providing human-scale forces assistance, which makes it suitable for community use by people with arm weakness as well as able-bodied individuals. For this purpose, it uses high-torque density motors and cable-drive transmission to significantly reduce mass and mechanical resistance [47, 48].

With the intuitive assistance strategy of gravity compensation, the wearable robot is designed to be user-friendly without any specific training. Once the wearer initiates the motion, the robot reacts in real time to support arm elevation in both shoulder abduction and flexion. Therefore, unloaded from gravity, the user can better leverage any residual capacity to actively control other degrees of freedom, such as shoulder horizontal flexion.

This form of assistance can help alleviate cognitive and physical workload by facilitating the restoration of arm functions in subjects with upper-limb impairments. For example, the exoskeleton can augment the wearers’ range of motion and assist them in reaching and grasping objects in various directions, even at shoulder height or overhead. This ability can be very useful, and reduce fatigue and physical stress, in job-related tasks that involve picking and placing, lifting, or manipulating objects, which are common tasks in warehouses or retail stores. Additionally, the exoskeleton might improve other capabilities such as moving objects across surfaces, pushing and pulling objects horizontally, or using various tools and objects.

This device can address some of the disability-related employment and earnings deficits identified earlier. Table 1 indicates that employment rates are 10.3 percentage points lower among people who have difficulty lifting and carrying 10 pounds, 3.3 points lower among

people who have difficulty reaching overhead, and 9.3 points lower among people who have difficulty pushing or pulling large objects. These functional deficits are not associated with lower earnings for those who become employed, but employed people who have difficulty picking up a glass or grasping a pencil have 12.4% lower earnings. A wearable robot such as the one described here can reduce some of these significant employment and earnings deficits.

These potential benefits do not, of course, mean that wearable robots will be readily adopted or accepted by employers. A companion paper in this special issue explores employer reactions to this specific device in an experimental setting, finding that presentation of this device in a hypothetical job interview creates great interest among employers but also concerns about risk, and more enthusiastic language creates greater openness to seeing the positive aspects of this device. In follow-up work we will interview HR and public policymakers to explore the potential of such a device for improving employment and productivity of PWDs, along with employer concerns about costs and other barriers to widespread adoption of such technologies.

Facial, Object, and Text Recognition for Blind and Visually-Impaired People

Several tools have been developed to aid blind and visually-impaired people in facial recognition, object detection, and the reading of text [49]. For example, object detection has been built into “smart canes” to identify potential obstacles and guide cane users away from them [50]. Here, we focus on a technology that more broadly helps blind and visually impaired people negotiate their environments, with the help of either remote human volunteers or artificial intelligence.

This AT operates through an app connected to a camera. In 2015 an app named “Be My Eyes” was introduced that pairs blind or visually-impaired users with sighted volunteers, by feeding images from the user’s camera to the volunteers who may be anywhere in the world, and the volunteer describes the images to the user. More than 6 million people were acting as volunteers in 2023 [51].

This technology is now being adapted so that AI interprets the images and provides assistance without the need for human volunteers. Such a system, described by Lakhani et al., [49] is based on image processing and deep learning to recognize and interpret three types of input. The first component is facial recognition. The system engages in facial detection to distinguish a facial image from non-facial content, and then uses a similarity-based learning approach to compare facial features with faces stored in an existing data-base. Based on unique facial features identified by a trained neural network, a similarity score is generated, and if the score exceeds a threshold, the person is identified and their name is revealed to the user. Testing of the system showed that faces were accurately identified 99.38% of the time, and the results were not affected by hairstyles, the presence or absence of glasses, or the person’s pose [49]. Apart from recognizing people, such a system can even describe their appearance and how they are feeling [52].

The second component of the system is object detection. The system will first detect objects in the camera image, and then calculate distance to identify potential obstacles.

While distance measurement is typically done with two cameras for measurement based on triangulation, this system uses the concept of “triangle similarity” to compare the actual and apparent width of an object to calculate its distance from the camera. Testing showed very small differences between the actual and estimated distances to a car, door, backpack, bottle, and chair.

The third component of the system is optical character recognition (OCR) for reading. The system described by Lakhani et al. uses the open-source engine called Tesseract. An image is processed and the pixels are concatenated into “Blobs” which are organized into text lines, with distinct words identified by spacing, and an adaptive classifier then classifies letters, characters, and words drawing on a data-base of multiple fonts. The system can then read the text to the user.

The power of such a system augmented by AI is illustrated by a blind user who had his app scan the menu at a restaurant, and then asked it to read only the chicken dishes, which it did [51]. He nonetheless was reluctant about relying solely on AI, and said it could be a good complement to human volunteers.

Such AT can help people relate to co-workers, physically navigate through the workplace, read and process written material, meet new people, and perform many types of job tasks. As described in Table 1, people with visual impairments have employment rates about 5 points lower, and pay rates 8–12% lower, than those of otherwise-similar individuals without disabilities. While we cannot project how much these gaps may be reduced, this AT appears to have strong potential to increase independence and productivity, and reduce many obstacles that blind and visually impaired people face in the workplace.

Wearable Device for Detection and Treatment of Anxiety

Anxiety disorders are common: 7% of all adult Americans, and 15% of young adults, experienced anxiety in 2018, and both figures increased since 2008 [53]. Anxiety is often associated with depression [54]. It can clearly affect work performance, particularly in jobs that require interaction with co-workers or customers.

A number of assistive devices have been developed to detect the onset of anxiety attacks, and provide treatment [55, 56]. The assistive devices measure physiological symptoms such as heart rate, heart rate fluctuation, respiration, and skin temperature. Based on a variety of signals, the devices can assess the likelihood of an anxiety attack, and take action either by alerting the user or providing a biofeedback intervention such as a breathing exercise.

Devices can vary both in what symptoms are measured, and the types of biofeedback and treatment provided. Some wrist devices are effective in reducing anxiety by providing acupressure or a slow heartbeat rhythm on the wrist [57, 58] or by providing false feedback to change users’ perceptions of their heart rate [59]. Reviewing several types of devices, Hunkin et al. conclude that “The literature suggests potential benefits of heart rate variability (HRV) biofeedback devices, while other modalities (aided meditation, false physiological feedback, electrodermal biofeedback, and respiration biofeedback) are less supported” [55]. Low HRV indicates the autonomic nervous system is imbalanced and there is reduced

cardiac adjustment to environmental stressors, leading to poor emotion regulation and stress tolerance, and increased social anxiety.

Here we describe one promising device based on HRV detection, which is a patch worn near the heart under one's clothes so is not visible to others [60]. When the patch detects low HRV, it provides vibration feedback both directly and to a smartphone app, signaling that the user should begin a 3-min biofeedback breathing exercise, over which real-time visual guidance is available. The app then presents data to the user on HRV over the 3-min period. Chung et al. assessed the results of using the patch in combination with biweekly stress management coaching sessions over eight weeks, and found that symptoms of anxiety and depression were strongly reduced [60].

The ACS and SIPP surveys do not specifically measure anxiety, which would fall under "other mental/emotional conditions" in SIPP. Table 1 shows that this category is associated with a 6.8 point lower employment rate, and 11.3% lower pay rate among the employed. The results from the patch and similar devices indicate that this type of AT has potential to reduce these deficits by helping people regulate anxiety and improving their ability to function productively in a consistent way.

Conclusion

There has been an explosion of assistive technologies to help PWDs be more productive in the workplace, and help reduce the substantial employment and earnings deficits they continue to face. Our descriptions of three developing technologies illustrate the potential of AT to increase employability and productivity of PWDs.

There has been growth among employees with disabilities of both accommodations in general and equipment-based accommodations from 2012 to 2021. Unlike prior studies of accommodations that use individual-level data, we focus on occupation-level accommodations data over the 2012 to 2021 period, examining whether the higher availability of accommodations in certain occupations is linked to employment and earnings growth among PWDs in those occupations. We find the occupations with higher rates of all accommodations, and equipment-based accommodations, in 2012 had greater disability employment growth over the 2012–2021 period, but did not have decreases in the disability pay gap (possibly due to greater availability of accommodations drawing lower-skill workers into the occupation).

We remain cautious about concluding there is a causal link. As noted earlier, substantial technological change has occurred over this period which could increase workplace accessibility without specialized accommodations. Many new technologies use a universal design approach that "bakes in" accessibility so they can be readily used by people across the spectrum of abilities, as is embodied in many new software programs. PWDs may be drawn to occupations where they can perform the work with standard equipment and no need for accommodations. In addition, despite the ADA requirements and greater AT availability, employers may be reluctant to hire PWDs in jobs where accommodations are

required. The link between accommodations and employment growth may be dampened by both these employee- and employer-driven effects.

As also noted, we are mindful that our data span the first 16 months of the pandemic recession, and the results for disability employment growth are strongest when we include this period. The adoption and effects of assistive technologies may be affected by the state of the labor market—for example, employers may have been more likely to retain accommodated employees in the early stages of the pandemic. Recent evidence on the positive role of telework in the strong employment growth of PWDs in 2021–2022 indicates that employers are more willing to make new accommodations in a tight labor market [61, 62].

Clearly there is more room for research in the fast-developing world of assistive technologies. It will be valuable not only to look at the effects of specific technologies such as the one described here, but also to examine the institutional, attitudinal, policy, and economic barriers that inhibit adoption of assistive technologies. One of the key factors is who bears the cost of these new technologies—will employers be willing to bear the cost based on expected higher productivity, or will workers or government be required to foot some or all of the bill (e.g., through VR agencies or tax incentives)? Will the costs and other barriers decline significantly as new types of AT become more widely adopted? The ongoing employment and earnings gaps faced by PWDs raise the importance of such research.

Funding

This study is funded by “NSF 20-515 Future of Work at the Human-Technology Frontier,” under National Science Foundation (NSF) award number 2026622. This line of study was also supported in part by a grant from the National Institute on Disability, Independent Living, and Rehabilitation Research (NIDILRR) for the Rehabilitation Research & Training on Employment Policy: Center for Disability-Inclusive Employment Policy Research Grant #90RTEM0006-01-00 and by the RRTC on Employer Practices Leading to Successful Employment Outcomes Among People with Disabilities, Douglas Kruse PI, Grant #90RTEM0008-01-00. The views provided herein do not necessarily reflect the official policies of NSF or NIDILRR, nor do they imply endorsement by the Federal Government.

Appendix A: Disability question wordings

Disability questions used in ACS and CPS:

1. Hearing impairment: “Is this person deaf or does he/she have serious difficulty hearing?”
2. Visual impairment: “Is this person blind or does he/she have serious difficulty seeing even when wearing glasses?”
3. Cognitive impairment: “Because of a physical, mental, or emotional condition, does this person have serious difficulty concentrating, remembering, or making decisions?”
4. Mobility impairment: “Does this person have serious difficulty walking or climbing stairs?”
5. Other limit in dressing or bathing: “Does this person have difficulty dressing or bathing?”

6. Other limit in going outside: “Because of a physical, mental, or emotional condition, does this person have difficulty doing errands alone such as visiting a doctor’s office or shopping?”

Disability questions used in SIPP:

- a. Hearing impairment: “Is person deaf or does he/she have serious difficulty hearing (even when wearing a hearing aid)?”
- b. Visual impairment: “Is person blind or does he/she have serious difficulty seeing, even when wearing glasses or contacts?”
- c. Speech impairment: “Does person have difficulty having his/her speech understood in the language spoken in the home?”
- d. Climbing 10 stairs: “Does person have any difficulty walking up a flight of 10 stairs?”
- e. Walking 3 blocks: “Does person have any difficulty walking a quarter mile—about three city blocks?”
- f. Standing for one hour: “Does person have any difficulty standing or being on his/her feet for one hour?”
- g. Sitting for one hour: “Does person have any difficulty sitting for one hour?”
- h. Stooping, crouching, or kneeling: “Does person have any difficulty stooping, crouching, or kneeling?”
- i. Reaching over head: “Does person have any difficulty reaching over his/her head?”
- j. Lifting and carrying 10 lbs.: “Does person have any difficulty lifting and carrying something as heavy as 10 pounds—such as a bag of groceries?”
- k. Pick up glass or grasp pencil: “Does person have difficulty using his/her hands and fingers to do things such as picking up a glass or grasping a pencil?”
- l. Pushing or pulling large objects: “Does person have any difficulty pushing or pulling large objects such as a living room chair?”
- m. Learning disability: “Does person have a learning disability such as dyslexia?”
- n. Alzheimer’s, senility, or dementia: “Does person have Alzheimer’s disease or any other serious problem with confusion or forgetfulness?”
- o. Intellectual disability: “Does person have an intellectual disability? (Formerly known as mental retardation)”
- p. Developmental disability: “Does person have a developmental disability such as autism or cerebral palsy?”
- q. Other mental/emotional condition: “Does person have any other mental or emotional condition?”

See appendix Tables 5 and 6

Table 5
Regression results and descriptive statistics for ACS data in Table 1

	<u>Linear probability predicting employment</u>		<u>Heckman model predicting ln(hourly pay)</u>				Mean (4)	(s.d.)
	(1)		<u>Pay coefficients</u>		<u>Selection model</u>			
Disability type								
Vision impairment	-0.053	(0.002)	-0.079	(0.004)	-0.179	(0.005)	0.021	(0.142)
Hearing impairment	-0.032	(0.002)	-0.046	(0.003)	-0.113	(0.005)	0.020	(0.141)
Cognitive impairment	-0.289	(0.001)	-0.193	(0.003)	-0.870	(0.003)	0.049	(0.217)
Mobility impairment	-0.343	(0.001)	-0.139	(0.003)	-1.015	(0.003)	0.049	(0.217)
Other limit in dressing or bathing	-0.196	(0.007)	-0.081	(0.017)	-0.585	(0.022)	0.001	(0.030)
Other limit in going outside	-0.359	(0.003)	-0.185	(0.008)	-1.053	(0.009)	0.005	(0.068)
Gender and marital status								
Male sep/div	-0.081	(0.001)	-0.150	(0.002)	-0.353	(0.004)	0.054	(0.226)
Male widowed	-0.134	(0.003)	-0.157	(0.007)	-0.525	(0.011)	0.004	(0.064)
Male never married	-0.118	(0.001)	-0.257	(0.001)	-0.546	(0.003)	0.204	(0.403)
Female married	-0.177	(0.001)	-0.318	(0.001)	-0.743	(0.002)	0.248	(0.432)
Female sep/div	-0.077	(0.001)	-0.356	(0.002)	-0.388	(0.003)	0.071	(0.256)
Female widowed	-0.171	(0.002)	-0.404	(0.004)	-0.640	(0.006)	0.012	(0.108)
Female never married	-0.105	(0.001)	-0.354	(0.001)	-0.533	(0.003)	0.175	(0.380)
Education								
Some HS	-0.038	(0.001)	0.087	(0.003)	-0.223	(0.005)	0.069	(0.254)
HS or GED degree	0.088	(0.001)	0.237	(0.003)	0.155	(0.004)	0.269	(0.443)
Some college, no degree	0.119	(0.001)	0.396	(0.003)	0.303	(0.004)	0.228	(0.419)
Associate's degree	0.176	(0.001)	0.471	(0.003)	0.453	(0.005)	0.087	(0.282)
Bachelor's degree	0.201	(0.001)	0.781	(0.003)	0.535	(0.005)	0.201	(0.401)
Master's degree	0.227	(0.001)	0.976	(0.003)	0.655	(0.005)	0.080	(0.272)
Prof. degree	0.240	(0.002)	1.266	(0.004)	0.681	(0.008)	0.017	(0.130)
Ph/D	0.261	(0.002)	1.167	(0.004)	0.789	(0.009)	0.012	(0.108)
Race/ethnicity								
Black non-Hispanic	-0.037	(0.001)	-0.143	(0.001)	-0.116	(0.002)	0.130	(0.336)
Hispanic	0.021	(0.001)	-0.138	(0.001)	0.017	(0.002)	0.186	(0.389)
Native/Pacific Islander	-0.074	(0.002)	-0.117	(0.004)	-0.252	(0.007)	0.008	(0.089)

	<u>Linear probability predicting employment</u>		<u>Heckman model predicting ln(hourly pay)</u>					
			<u>Pay coefficients</u>		<u>Selection model</u>	<u>Mean</u>	<u>(s.d.)</u>	
	(1)	(2)	(2)	(3)	(4)			
Asian	-0.043	(0.001)	-0.033	(0.002)	-0.196	(0.003)	0.062	(0.241)
Other race	-0.014	(0.001)	-0.062	(0.002)	-0.040	(0.004)	0.030	(0.172)
Age								
18–34	0.142	(0.001)					0.156	(0.363)
35–44	0.147	(0.001)					0.227	(0.419)
45–54	0.154	(0.001)					0.207	(0.405)
55–64	0.035	(0.001)					0.201	(0.401)
							0.208	(0.406)
58 labor market experience dummies	No		Yes		Yes			
50 state dummies	Yes		Yes		Yes			
4 year dummies	Yes		Yes		Yes			
Selection identifiers								
Live alone					-0.231	(0.002)	0.135	(0.341)
Family size					-0.028	(0.001)	2.930	(1.679)
Kids < 6 years old					-0.171	(0.002)	0.171	(0.377)
Kids 6–17 years old					0.019	(0.002)	0.315	(0.464)
Other family income					0.000	(0.000)	55,588	(84,663)
Other family income squared					0.000	(0.000)	1.03E + 10	-5.E + 10
Selection parameters								
/athrho					0.074	(0.003)		
/lnsigma					-0.418	(0.001)		
rho					0.074			
sigma					0.658			
lambda					0.049			
Dependent variables								
Employment							0.707	(0.455)
Ln(hourly pay)							3.074	(0.792)

Standard errors in parentheses in columns 1–3

Table 6

Regression results and descriptive statistics for SIPP data in Table 1

	<u>Linear probability predicting employment</u>		<u>Heckman model predicting ln(hourly pay)</u>					
	(1)		<u>Pay coefficients</u>		<u>Selection model</u>	<u>Mean</u>	<u>(s.d.)</u>	
			(2)		(3)	(4)		
Disability type								
Vision impairment	-0.048	(0.018)	-0.124	(0.057)	-0.230	(0.064)	0.041	(0.197)
Hearing impairment	-0.013	(0.017)	-0.005	(0.042)	0.002	(0.060)	0.038	(0.191)
Speech impairment	-0.105	(0.026)	-0.133	(0.085)	-0.563	(0.108)	0.017	(0.131)
Difficulty with physical activities:								
Climbing 10 stairs	-0.043	(0.020)	-0.055	(0.045)	-0.130	(0.063)	0.087	(0.281)
Walking 3 blocks	-0.129	(0.020)	-0.115	(0.050)	-0.316	(0.061)	0.092	(0.289)
Standing for one hour	-0.134	(0.019)	0.024	(0.039)	-0.334	(0.057)	0.115	(0.320)
Sitting for one hour	0.005	(0.018)	0.015	(0.046)	-0.004	(0.064)	0.072	(0.259)
Stooping, crouching, or kneeling	-0.033	(0.015)	-0.059	(0.029)	-0.047	(0.047)	0.143	(0.350)
Reaching over head	-0.033	(0.018)	-0.011	(0.046)	-0.095	(0.064)	0.064	(0.245)
Lifting and carrying 10 lbs	-0.103	(0.021)	0.037	(0.051)	-0.330	(0.066)	0.077	(0.267)
Pick up glass or grasp pencil	-0.010	(0.019)	-0.117	(0.050)	-0.065	(0.069)	0.046	(0.210)
Pushing or pulling large objects	-0.093	(0.018)	-0.007	(0.039)	-0.288	(0.055)	0.108	(0.310)
Mental or cognitive impairment:								
Learning disability	-0.023	(0.019)	0.015	(0.049)	-0.171	(0.070)	0.037	(0.188)
Alzheimer's, senility, or dementia	-0.104	(0.023)	-0.059	(0.085)	-0.287	(0.101)	0.026	(0.158)
Intellectual disability	-0.097	(0.037)	-0.536	(0.149)	-0.185	(0.139)	0.013	(0.115)
Developmental disability	-0.104	(0.048)	-0.094	(0.147)	-0.268	(0.168)	0.007	(0.085)
Other mental/emotional condition	-0.068	(0.018)	-0.120	(0.046)	-0.236	(0.065)	0.045	(0.207)
Female	-0.099	(0.007)	-0.250	(0.013)	-0.198	(0.024)	0.518	(0.500)
Education								
Some HS	-0.069	(0.023)	0.144	(0.050)	-0.255	(0.071)	0.086	(0.280)
HS or GED degree	0.064	(0.020)	0.367	(0.045)	0.169	(0.064)	0.261	(0.439)
Some college, no degree	0.095	(0.021)	0.436	(0.046)	0.172	(0.066)	0.204	(0.403)
Associate's degree	0.143	(0.022)	0.640	(0.047)	0.403	(0.072)	0.087	(0.282)
Bachelor's degree	0.163	(0.021)	0.877	(0.045)	0.462	(0.068)	0.206	(0.404)
Master's degree	0.185	(0.022)	1.101	(0.047)	0.619	(0.076)	0.091	(0.288)
Prof. degree	0.176	(0.030)	1.286	(0.068)	0.419	(0.119)	0.013	(0.114)

	<u>Linear probability predicting employment</u>		<u>Heckman model predicting ln(hourly pay)</u>					
	(1)	(2)	Pay coefficients		Selection model		Mean	(s.d.)
			(2)	(3)	(3)	(4)	(4)	(4)
Ph/D	0.265	(0.026)	1.273	(0.065)	0.842	(0.128)	0.014	(0.118)
Race/ethnicity								
Black non-Hispanic	-0.057	(0.012)	-0.135	(0.021)	-0.133	(0.040)	0.130	(0.336)
Hispanic	-0.036	(0.011)	-0.125	(0.021)	-0.074	(0.036)	0.170	(0.376)
Asian	-0.122	(0.016)	-0.017	(0.032)	-0.381	(0.051)	0.062	(0.240)
Other race	-0.083	(0.022)	-0.099	(0.041)	-0.170	(0.070)	0.024	(0.155)
Age								
25-34	0.144	(0.014)	0.390	(0.026)	0.417	(0.042)	0.223	(0.416)
35-44	0.176	(0.014)	0.657	(0.025)	0.666	(0.044)	0.203	(0.402)
45-54	0.202	(0.013)	0.708	(0.025)	0.793	(0.042)	0.213	(0.409)
55-64	0.094	(0.014)	0.697	(0.026)	0.498	(0.041)	0.196	(0.397)
Selection identifiers								
Family size					0.034	(0.014)	2.926	(1.628)
Kids < 18 years old					-0.077	(0.019)	0.767	(1.118)
Other household income					0.000	(0.000)	5108	(12,797)
Other household income squared					0.000	-2.6E-11	1.90E + 08	-5.E + 09
Selection parameters								
/athrho					0.172	(0.033)		
/lnsigma					-0.530	(0.015)		
rho					0.170	(0.032)		
sigma					0.589	(0.009)		
lambda					0.100	(0.018)		
Dependent variables								
Employment							0.684	(0.465)
Ln(hourly pay)							2.892	(0.731)

Standard errors in parentheses in columns 1-3

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Fig. 1. Portable robotic exoskeleton for powered assistance during arms elevation. The robot detects residual volitional movements of the wearer's limbs and provides support to offload the limbs from the effects of gravity, helping to restore arm functions in people with upper-limb impairments

Table 1

Disability-related Employment and Pay Gaps

Figures represent regression coefficients (s.e. in parentheses)

Dependent variable:	Ln(hourly pay)			
	Employed ACS (1)	SIPP (2)	ACS (3)	SIPP (4)
Disability type				
Visual impairment	-0.053** (0.002)	-0.048*** (0.0183)	-0.079** (0.004)	-0.124** (0.0571)
Hearing impairment	-0.032** (0.002)	-0.013 (0.0166)	-0.046** (0.003)	-0.005 (0.0425)
Cognitive impairment	-0.289** (0.001)		-0.193** (0.003)	
Mobility impairment	-0.343** (0.001)		-0.139** (0.003)	
Other limit in dressing or bathing	-0.196** (0.007)		-0.081** (0.017)	
Other limit in going outside	-0.359** (0.003)		-0.185** (0.008)	
Speech impairment		-0.105*** (0.0257)		-0.133 (0.0853)
Difficulty with physical activities:				
Climbing 10 stairs		-0.043** (0.0201)		-0.055 (0.0446)
Walking 3 blocks		-0.129*** (0.0203)		-0.115** (0.0505)
Standing for one hour		-0.134*** (0.0192)		0.024 (0.0386)
Sitting for one hour		0.005 (0.0179)		0.015 (0.0457)
Stooping, crouching, or kneeling		-0.033** (0.0149)		-0.059** (0.0289)
Reaching over head		-0.033* (0.0182)		-0.011 (0.0456)
Lifting and carrying 10 lbs		-0.103*** (0.0205)		0.037 (0.0514)
Pick up glass or grasp pencil		-0.010 (0.0188)		-0.117** (0.0503)
Pushing or pulling large objects		-0.093*** (0.0180)		-0.007 (0.0390)
Mental or cognitive impairment:				
Learning disability		-0.023 (0.0189)		0.016 (0.0494)
Alzheimer's, senility, or dementia		-0.104*** (0.0232)		-0.059 (0.0848)
Intellectual disability		-0.097*** (0.0365)		-0.536*** (0.149)
Developmental disability		-0.104** (0.0476)		-0.094 (0.147)
Other mental/emotional condition		-0.068*** (0.0183)		-0.120*** (0.0462)
Observations	9,246,283	20,120	8,598,128	18,569

Columns 1 and 2 are based on linear probability regressions, and columns 3 and 4 are based on Heckman models. All regressions control for education, race/ethnicity, and gender; the ACS regressions also control for gender interacted with marital status, state of residence, and year; the SIPP regressions and the ACS employment regression also control for age, while the ACS pay regression controls for labor market experience. See Tables 5 and 6 for fuller results and descriptive statistics.

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Table 2

Disability and Non-disability Accommodations, 2012–2021

	2012		2019		2021		2012–2021 change	
	Disability (1)	No disability (2)	Disability (3)	No disability (4)	Disability (5)	No disability (6)	Disability (7)	No disability (8)
<i>Any accommodations</i>								
Requested change	12.7% **	8.6%	14.2% **	9.2%	15.1% **	6.8%	2.4% ^	-1.8% ^^
Granted in full	8.6% **	5.3%	10.9% **	6.1%	11.0% **	4.7%	2.4% ^^	-0.6% ^^
Granted in part	1.7%	1.6%	1.2%	1.5%	1.4%	1.0%	-0.3%	-0.6% ^^
Granted in full or part	10.2% **	6.9%	12.1% **	7.6%	12.4% **	5.7%	2.2% ^	-1.2% ^^
<i>Granted in full or part if:</i>								
Hearing impairment	7.3%		6.8%		7.8%		0.4%	
Vision impairment	7.9%		15.1% **		7.1%		-0.8%	
Cognitive impairment	12.1% **		14.9% **		19.0% **		6.9% **	
Mobility impairment	13.0% **		14.7% **		14.4% **		1.3%	
<i>New or modified equipment</i>								
Requested change	4.2% **	3.1%	4.7% **	3.3%	4.8% **	2.6%	0.6%	-0.5% ^^
Granted in full	2.6% *	1.9%	3.4% **	2.1%	4.0% **	1.8%	1.4% ^^	-0.1%
Granted in part	0.7%	0.7%	0.6%	0.7%	0.2% **	0.5%	-0.5% ^^	-0.3% ^^
Granted in full or part	3.3%	2.7%	4.0% **	2.9%	4.1% **	2.2%	0.9%	-0.4% ^^
<i>Granted in full or part if:</i>								
Hearing impairment	3.4%		3.4%		4.2% *		0.8%	
Vision impairment	3.6%		6.0% *		4.1%		0.5%	
Cognitive impairment	2.0%		3.9%		4.4% **		2.4% **	
Mobility impairment	4.0% *		4.6% *		5.0% **		1.0%	
Sample size	2,092	52,021	1,740	41,427	1,664	36,834		
Hearing impairment	756		664		572			
Vision impairment	310		238		212			
Cognitive impairment	470		440		494			

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	2012		2019		2021		2012–2021 change	
	Disability (1)	No disability (2)	Disability (3)	No disability (4)	Disability (5)	No disability (6)	Disability (7)	No disability (8)
Mobility impairment	809		627		581			

Figures represent percent of employees who requested or were granted accommodations

* Difference between disability and non-disability samples is significant at $p < 0.10$

** $p < 0.05$

^ Change between 2012 and 2021 is significant at $p < 0.10$

^^ $p < 0.05$

Table 3

Disability and Non-disability Accommodations, 2012–2021

	Any accommodations		Eq. accommodations	
	Disability	No disability	Disability	No disability
	(1)	(2)	(3)	(4)
Total	11.7%	6.8%	3.8%	2.6%
Personal care excl. child & home care	27.3%	4.8%	4.9%	1.9%
Health support excl. diagnosis and technicians	23.2%	7.7%	13.1%	2.3%
Computer/math	22.5%	10.6%	12.1%	4.6%
Admin assistants	20.9%	7.2%	11.0%	2.4%
Social services	20.4%	10.3%	7.8%	3.8%
Education	18.5%	8.2%	4.6%	3.2%
Business operations	18.1%	9.4%	6.7%	3.6%
Scientists	18.0%	10.1%	7.8%	4.8%
Architects/engineers	16.9%	9.3%	7.2%	4.5%
Home or health aides	15.1%	5.4%	2.6%	0.9%
Bus drivers	14.8%	4.2%	0.4%	1.6%
Customer reps	14.6%	7.3%	2.8%	1.8%
Legal	14.6%	10.7%	9.7%	4.5%
Cashiers	14.0%	4.8%	2.6%	0.5%
Misc. managers	13.6%	9.6%	4.1%	4.0%
Health technicians	13.4%	7.9%	5.6%	2.1%
Admin. support excl. admin assistants	13.0%	6.0%	4.5%	2.0%
Health diagnosis	12.9%	8.9%	1.6%	3.1%
Cooks	12.8%	4.9%	1.6%	1.6%
Top executives	11.9%	10.1%	7.5%	4.5%
Arts and entertainment	11.3%	9.7%	3.1%	4.3%
Sales supervisors	11.0%	5.7%	4.9%	1.5%
Financial specialists	11.0%	7.2%	4.1%	2.8%
Protective services	10.0%	6.3%	1.9%	2.4%
Production	9.9%	5.5%	5.7%	2.6%

	Any accommodations		Eqt. accommodations	
	Disability (1)	No disability (2)	Disability (3)	No disability (4)
Retail sales excl. cashiers	9.5%	4.5%	2.4%	0.6%
Receptionists	9.2%	5.4%	0.8%	2.2%
Non-bus vehicle operators	8.6%	4.7%	2.1%	1.9%
Misc. transportation	7.9%	3.9%	1.6%	1.8%
Childcare services	7.9%	3.3%	0.0%	0.3%
Non-retail sales	7.6%	5.6%	1.3%	1.9%
Construction managers	7.2%	8.1%	3.7%	3.7%
Laborers/packagers/movers	6.7%	2.8%	0.0%	1.2%
Automotive	6.2%	5.6%	1.8%	3.1%
Janitors	6.1%	3.7%	1.2%	1.9%
Maintenance excl. janitors	6.0%	3.5%	0.8%	1.8%
Construction/extraction	5.2%	3.4%	1.5%	1.9%
Maids	4.8%	3.3%	0.0%	0.8%
Food prep excl. cooks	3.7%	4.4%	0.5%	0.7%
Farming/forestry/fishing	3.7%	2.8%	0.0%	1.9%
Installation/repair	3.6%	6.7%	2.5%	3.5%
Farm/ranch managers	0.8%	4.4%	0.6%	2.8%

Percent of employees granted accommodations averaged across 2012–2021, ranked by disability accommodations rate

Table 4

Occupation-level Correlations of Accommodations and Employment Outcomes

	Correlation of outcome at left with:		
	Mean (s.d.)	Accommodation rate among employees with disabilities in base year	Equipment-based accommodation rate among employees with disabilities in base year
	(1)	(2)	(3)
All disabilities			
Disability employment growth (percent)			
2012–2019	12.54 (18.99)	0.289	0.054 (0.737)
2019–2021	16.32 (24.85)	0.196	0.110 (0.490)
2012–2021	3.39 (14.17)	0.448	0.314 (0.043)**
Change in percentage with disability within occupation			
2012–2019	0.12 (0.54)	0.079	-0.114 (0.471)
2019–2021	0.34 (0.67)	0.210	0.037 (0.816)
2012–2021	0.22 (0.47)	0.260	0.105 (0.507)
Change in disability pay gap (percent point)			
2012–2019	-2.78 (7.21)	0.290	0.086 (0.588)
2019–2021	2.01 (18.48)	-0.227	-0.210 (0.182)
2012–2021	4.79 (21.56)	-0.278	-0.137 (0.388)
By disability type			
Disability employment growth (percent), 2012–2021			
Hearing	0.03 (26.22)	-0.204	-0.181 (0.252)
Vision	10.90 (38.22)	0.240	0.223 (0.156)
Cognitive	62.79 (65.37)	0.316	-0.180 (0.255)**
Mobility	-4.49 (23.67)	0.052	0.049 (0.759)
Change in percentage with disability within occupation, 2012–2021			
Hearing	-0.09 (0.32)	-0.160	-0.103 (0.516)
Vision	0.01 (0.17)	0.149	0.088 (0.579)
Cognitive	0.45 (0.42)	0.082	-0.192 (0.224)
Mobility	-0.13 (0.32)	0.052	-0.042 (0.791)

Correlation of outcome at left with:			
Mean	(s.d.)	Accommodation rate among employees with disabilities in base year	Equipment-based accommodation rate among employees with disabilities in base year
(1)	(2)	(2)	(3)
42	42	42	42
N			

All figures weighted by number of people with disabilities in occupation in 2012 P= values in parentheses in columns 2 and 3

* p < 0.10,

** p < 0.05