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AI Utilization, Disability, and Discrimination

By

Kayleigh Truman, Ph.D Student, School of Management and Labor Relations

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DISABLED WORKERS FIGHT A RIGGED AI BASED SYSTEM

As of 2024, there are over 70 million disabled individuals in the United States, and only 22% are working, in any capacity. As artificial intelligence (AI) use and algorithmic management expand, disabled workers face new forms of discrimination; from hiring criteria and assessment metrics to potentially hazardous working conditions[1]. In this paper, I review some of the current issues faced by differently abled workers, including the heavily biased medical models of disability commonly used in AI and algorithmic management (AM) systems.

Cautions of Artificial Intelligence

Without proper understanding of the limitations of AI tools, systematic inequities that already exist in our current social structure will be perpetuated and even exacerbated; unless human oversight and intentionality are built into AI training and implementation. Commonly called the "Black Box theory", AI and computationally complicated systems tend to earn trust more readily than humans performing similar work[2]. Without explanations of the system's choices, the lack of understanding and/or knowledge of the system's reasoning can lead to poorly applied and unaligned design choices that have a direct impact on all workers, with or without disabilities.

At their core, AI and large language models (LLMs) are algorithmic systems that are trained using specific input; then utilized in various ways to complete a certain task or generate a certain output. This training material fundamentally changes how AI systems serve their designed functions. Thus, "AI systems model the world based on what's in the data they're given"[3]. If the training data is biased, or incorrect, the products of the AI's algorithm will likely mimic and/or perpetuate those same systematic inequalities. This can be seen in everything from voice recognition issues on your phone to medical assessments on individuals with different skin colors[4].

The Dangers of the Medical Model of Disability

Even outside of medically relevant applications, AI systems tend to be exclusively

[1] (Bennett & Keyes, 2020; Trewin, 2018; Whittaker et al., 2019)
[2] (Afroogh et al., 2024)
[3] (Whittaker et al., 2019, p. 9)
[4] (Adamson & Smith, 2018; Tatman, 2017)

trained on what is called the "medical model of disability". This model places the center of disability as a problem within an individual; meaning they are the direct cause or center of whatever their condition may be.[5] Placing the onus of their condition within the individual labels disabled workers as intrinsically having problems, being less capable, and potentially even dangerous.[6] What this doesn't do is acknowledge that many disabled individuals can function perfectly well. "Disability is often less about physical or mental impairment than it is about how society responds to impairments"[7]. If their *environment* works with their disability instead of against, they may not be necessarily considered "less than" other workers. With the unilateral application of AI systems, disabled workers are fundamentally put at a disadvantage by them being accessed based on their functionality in an environment innately not designed for them. In addition, without clear knowledge of AI utilization, surveillance mechanisms or assessment metrics, disabled workers may not know what accommodations to ask for to allow them to perform to the best of their abilities.

In contrast, AI and algorithmic management could utilize the "social model of disability". Unlike the medical model, the social model of disability centers the problems experienced by differently abled individuals as contingent on their environment. Rather than being fundamental issues they must fix, disabilities manifest the strongest when environments are not designed with them in mind, thus accentuating their "shortcomings". Is someone who is hard of hearing inherently less skilled in meetings than a worker with normal hearing? With subtitles or a sign language interpreter they could easily be just as capable. Would a cashier be worse at their job if they could sit down as needed? The medical model considers these "deficits" as being the individual's problem, not that of the environment, employer or anyone else.

In addition to the disparaging medical model of disability, unlike other protected classes like race, age, and so on, disabilities do not fall as neatly into isolated, nor permanent categories. Broken legs cannot all be quantified the same way, nor can the symptoms or daily impacts of depression or lupus. The breadth of facets that disabilities affect in workers leaves AI's confused and unable to properly account for all possible variables under one single disability identifier[8]. These large swaths of

[5] (Marks, 1997)

[6] (Whittaker et al., 2019)

[7] (Burch & Sutherland, 2006)

[8] (Parker, 2015)

manifested complexities combined with known issues of intersectionality within AI systems perpetuate inequitable systems that exist in many of our current work and social environments.

Workplace Concerns

These issues are becoming even more of a concern as more workplaces rely on AI and automated employment decision tools (AEDTs) for hiring and promotion decisions. New York City passed one of the earliest laws regulating AEDTs which first went active in 2023. Here, most organizations using AEDTs must conduct bias audits annually, make the published reports publicly available and give notice to all applicants prior to AI utilization in the appraisal of a job application[9]. While this law makes great strides in regulation, and visibility of AI utilization outcomes, it is still highly limited, particularly when it comes to disabled workers. This provision only protects specific categories such as sex, ethnicity, and race. Disability as a protected attribute is explicitly not included. Disabled workers are already limited in their ability to hold current or potential employers accountable for discriminatory practices, but given the opaque understanding of AI and AEDTs, this leaves disabled workers even more susceptible to discrimination. While many commonly used AEDT's have their own self-determined accountability measures and bias mitigation techniques, most AIs are considered proprietary and thus cannot be publicly accessed or easily scrutinized by workers, management or the public[10].

Workplace Concerns for Disabled Workers

Even once hired, disabled employees are at the mercy of the AI systems in place. Something as simple as a walker or wheelchair may create a potential hazard when AI is poorly trained or incorrectly implemented. Self-driving cars have been found to have trouble identifying even bicyclists as humans[11], let alone individuals with walkers or wheelchairs[12]. This leads pedestrians and workers to have to pass a "reverse Turing-test;" meaning they must prove to the AI they are human to be treated as such, or they risk being misidentified entirely[13]. If autonomous automobiles, meant to directly interact with a variety of public conditions on the road, are unable to accurately identify

[9] (Subchapter 25: Automated Employment Decision Tools, § 20-870:, 2021)
[10] (Whittaker et al., 2019)
[11] (Griggs & Wakabayashi, 2018)
[12] (Kraemer & Benton, 2015)
[13] (Whittaker et al., 2019)

people, the potential implication for workers is of dire concern. Can an AI system that's developed to screen appropriate personal protective equipment on a construction site tell the difference between rated safety goggles and basic prescription glasses? If wearable technological devices are given to workers to help them stay aware of exhaustion levels, would the technology label workers with chronic fatigue as lazy, or label those with kidney problems of taking too many water breaks?

Continuing still, these issues lead to the issue of privacy and disability disclosure. Workers commonly don't disclose their disabilities out of fear of prejudice and rejection. Similar issues are occurring for other marginalized demographics. Trans workers are finding that poorly trained AI systems are outing them to their employers and potentially costing them their jobs[14]. Unilaterally implementing AI systems without an understanding of the symptoms or manifestation of disorders or living conditions, leaves swaths of workers in the precarious position of being systematically predisposed to failure.

Where from here?

Fixing this problem on a coordinated macro scale is likely not currently feasible. However, firms can begin by questioning the material their AI systems are trained on and requesting the social model be included in that training. They should involve differently abled workers in the AI design and implementation process. Taking their recommendations as pertinent considerations; not just ticking a box of diverse involvement.

Here, the employer would gain insight into what accommodations workers could potentially ask for, thus helping even the playing field. For example, curb cuts on sidewalks were originally implemented to assist wheelchair users, however, *everyone* benefits from them; people with strollers, laundry carts, amazon workers, etc. Employers may find similar situations in their own workplaces. They should be explicit about AI utilization to all workers, disabled or otherwise; share how, where, and when the AI systems are being utilized and for what purpose. What are the metrics being measured? The *how and what* are key for workers to accurately request accommodation instead of floundering in uncertainty.

[14] (Urbi, 2018)

With a lack of supporting evidence behind the struggles of disabled workers, they are left as forgotten and invisible labor. That's why researchers and academics should carefully assess workplaces with AI and algorithmic management systems to detect and measure systematic bias as well as identify its source. Creating scales and metrics that can be demonstrated as hard facts to employers would reveal where the onus of inequities lies. Workplaces would likely appreciate these findings in terms of potentially preventing discriminatory cases as time and legislation progress. Or taking the value creation standpoint and positioning the findings as changes that could result in improvements in efficiency, value creation when accommodation is implemented. Further, if the data supports the possibility that these accommodations may produce secondary benefits, those should be highlighted as a potential source of competitive advantage.

Some may feel this identification is "ticking the box," as it were, on finding the problem. Once isolated, employers will begin to initiate changes that adjust for changing legislative or regulatory requirements… right? Identifying biases and inequalities is merely the first step, researchers and worker organizations cannot stop here. Without some form of enforcement, opposition or regulatory body, the problem is likely to continue unchecked. As we know too well, our legal and regulatory systems lag far behind with regards to immerging worker issues. Unions, worker centers and community organizations need to take an early stand in identifying and seeking remedies for the sources of these inequities. In workplaces covered by collective bargaining agreements, pursue grievances that arise from disabled workers interacting with AI systems just as you would your other workers. Overtime, unions should make preventative discrimination measures an active contract negotiation point, not just for disabled workers or legally "protected classes". In the ever-changing state of labor, we cannot standby as employers get farther ahead of us with new, unregulated technology. While the legal system spins its wheels, workers are struggling now. As unionists and worker advocates we need to practice the solidarity that we preach, visibly or invisibly disabled workers deserve protections from bias like the rest of us. Remember, an attack on one is an attack on all.

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