Toward a taxonomy of negative outcomes from the use of AI-driven systems for people with disabilities

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Abstract

For the past decade, *AI-driven systems* are being introduced into our society at a tremendous speed. As a result, we are seeing more and more incidents of their use leading to *negative outcomes* for people with disabilities. We use the term *negative outcomes* to capture, in a broad sense, any difficulty caused by the use of AI-driven systems, ranging from mere inconvenience to material harm. *In this paper, we seek to understand in what ways AI-driven systems create negative outcomes for people with disabilities.* To answer this question, we used five publicly available and current AI incident databases to compile a data set of 79 negative outcomes of AI-driven systems for people with disabilities. We then categorized these negative outcomes into nine broad categories. Based on these categories, we then discuss five areas for future research and to design better AI-driven systems with respect to people with disabilities.

CCS Concepts

• **Human-centered computing** → **Accessibility technologies**.

Keywords

accessibility, AI, disability

1 Introduction

In 2019 a doctoral student and wheelchair user was trapped on Forbes Avenue in Pittsburgh in the US when a Starship robot blocked her access to the sidewalk, posing an extreme safety hazard [132]. In 2020, the company ProctorU's system to automate the proctoring of exams to prevent cheating was found to disproportionately accuse disabled students of cheating [19]. In 2024, an autistic 14-year-old became dependent on a Character.AI chatbot representing the character Daenerys Targaryen from the show Game of

Thrones and committed suicide in order to be with the character [91]. These examples illustrate some of the ways in which the use of *AI-driven systems* can create serious negative consequences for people with disabilities. We use **AI-driven systems** as an umbrella term to describe systems that incorporate technologies - such as machine/deep learning, large language models, computer vision, and affective computing - for things like making predictions, generating content, and decision-making.

Over the past decade, both public and private organizations have been increasingly integrating AI-driven systems into their products and services [60]. As a result, we are seeing many incidents of their use leading to *negative outcomes*, including for people who are already marginalized by society in some way [40, 57]. We use the term *negative outcomes* to capture, in a broad sense, any difficulty caused by the use of an AI-driven system, ranging from causing confusion or inconvenience (e.g., a screen reader's incorrect description of the image of bullet points on a website) to causing material harm (e.g., making incorrect welfare service eligibility determinations). **In this paper, we seek to understand in what ways AI-driven systems create *negative outcomes* for a specific marginalized group - people with disabilities.** Further, we take a broad view of disability and do not focus on any specific kind of disability.

There has been much work in recent years that draws on AI incident databases to categorize and understand problems emanating from the use of what we call AI-driven systems [55, 69, 103]. In the absence of any serious regulation of AI-driven systems [23], the AI incident databases are the closest thing we have that can act as a public watchdog (in the US at least) in the interim. These incident databases are currently among the best sources for basing our work on real world problems from the introduction of AI-driven systems. Many negative affects of AI-driven systems, especially on the marginalized, only become visible once deployed and cannot easily be foreseen during development [83]. Each incidents in the AI incident databases includes multiple articles from major reputable news sources. The AI incident databases classify the incidents and provide a search function, which allows their users to identify incidents of interest. For the present study, we view the AI incident databases through a disability-focused lens.

In this paper, we seek to determine in what ways AI-driven systems create negative outcomes for people with disabilities, writ large, in the real world. We specifically eschew speculating on negative outcomes and, instead, ground our work in the real world consequences of using AI-driven systems. To this end, we pulled from five AI incident databases to curate our dataset of incidents

where AI-driven systems negatively affected people with disabilities. These databases are public-interest initiatives based on new reports around adverse incidents involving AI (broadly defined). Their aim is to ensure transparency, openness, and accountability around AI-driven systems. The incident databases we consulted included: AI, Algorithmic, and Automation Incidents and Controversies (AIAAIC) [3]; the AI Incident Database (AIID) [5]; the OECD AI Incident Monitor [94]; the Database of AI Litigation (DAIL) [33]; and Where in the World is AI? [6]. These databases have a combined total of over 17,700 entries. From these databases we extracted a *dataset* of *79 incidents* where people with disabilities had experienced negative outcomes from the use of an AI-driven system. By analyzing the situations in each of these 79 incidents, we then developed a **taxonomy** of negative outcomes from the use of an AI-driven system. Our taxonomy includes nine broad categories of negative outcomes: (1) denying people with disabilities of vital resources; (2) falsely accusing people with disabilities of serious offenses; (3) disrespecting the privacy of people with disabilities; (4) suppressing the voices of people with disabilities; (5) providing skewed content to people with disabilities; (6) causing distress to people with disabilities; (7) fostering prejudice about people with disabilities; (8) impersonating people with disabilities; and (9) limiting access for people with disabilities. Based on our taxonomy, we then suggest five ways to better design AI-driven systems in order to minimize their negative consequences for people with disabilities and thus better meet society's needs. Ultimately, we would like to position this work as a start of a conversation. We want to push back against the current ableist disregard of people with disabilities, their needs, and way of life, when it comes to the introduction of AI-driven systems, often in the name of efficiency and productivity. We believe this is the opportune moment to talk about these issues as a way to prevent, or at least reduce future harm, since the AI-driven systems are still (somewhat) emerging.

Before getting to the rest of the paper, we would like to delve a bit more into why we used AI incident databases to create our taxonomy. Our reasons for using these databases included the following. (1) AI databases allowed us to ground our work in real, documented, and substantiated cases of AI-driven systems producing outcomes of negative valence [69]. (2) Using the AI incident databases prevented us from resorting to speculation on the negative outcomes, as has become common in recent years [89]. (3) Furthermore, AI incident databases can be effective at ethically gathering information on sensitive topics, such as physical and emotional harm, from around the world. (4) Finally, the use of AI incident databases has advantages over researcher-led inquiries (e.g., interviews, focus groups), namely in that it prevents researchers from inadvertently influencing participant responses.

2 Related work

The taxonomy we created for this paper showcases the various ways in which AI-driven systems create negative outcomes for people with disabilities. Consequently, we divide the related work section into the following three broad categories: AI incident databases; existing taxonomies of AI-driven systems; and prior work on the negative effects of AI-driven systems on people with disabilities.

2.1 AI incident databases

For the past few years, numerous online databases are being maintained to document incidents reported around the negative outcomes of deployed AI-driven systems. One of the most popular among these is the AI, Algorithmic, and Automation Incidents and Controversies (AIAAIC) database [3]. AIAAC is an open-source database that captures a snapshot of negative outcomes for individuals, communities, and society at large relating to AI and related technologies and applications. For each incident, it tracks around 10-12 pieces of information related to the incident, including: the incident description; details of the AI-driven system involved, including the developer and its deployer; the location of the incident; the time frame of the incident; the type of harm caused; and links to documented reports. Several other databases also exist that track similar details about negative effects of deployed AI incidents include the AI Incident Database (AIID) [5], OECD AI Incident database [94], AI Risk Repository [10], AI Vulnerability Database [12], AI Badness, which specializes on negative effects of generative AI [4], and Where in the World is AI? which maps the incidents to a map of the world [6]. A slightly different type of database that tracks the negative effects of deployed AI-driven systems is one called the database of AI litigation, which tracks instances of ongoing litigation around deployed AI-driven systems [33]. In this work, we searched through all of these databases to identify cases where AI-driven systems had negatively outcomes people with disabilities. As discussed later, only five of these eight databases ultimately yielded at least one incident, which used in this study.

2.2 Prior taxonomies of AI-driven systems

Numerous previous studies have attempted to create taxonomies of various issues around AI-driven systems. These fall into two camps in terms of their source of information: taxonomies derived from prior literature and taxonomies derived from incident databases. The prior taxonomies created from literature reviews include work on: identifying risks posed by large language models (LLMs) [51, 128, 129]; identifying risks posed by text-to-image generative models [15]; identifying personalized risks specific to LLMs, based on user feedback [64]; identifying potential harm from algorithmic systems [35, 118]; identifying the various definitions of fairness used to reduce bias, as experienced by end-users in AI-driven systems [80, 111]; identifying the various forms of hallucination in LLMs [54]; identifying harm caused by deepfakes [127]; and identifying autonomy in human-robot interactions [63].

Other efforts have looked at incident databases to develop their taxonomies. This group includes efforts that investigate: privacy risks posed by AI-driven systems, based on the incidents from the AIAAC and AID databases [69]; pathways to harm caused by AI-based speech generators, based on the reported incidents from the AIAAC, AID, and OECD AI incident databases [55]; support failure cause analysis, based on incidents from the AID database [103]; the variety of ways in which AI-driven systems fail, based on the AIAAC database [109]; and common topics of interest for developers interacting with ChatGPT, based on the DevGPT dataset [114]. For the present work, we also examined incident databases. Ours, however, very specifically focuses on how AI-driven systems

harmed people with disabilities, which heretofore has not been studied.

2.3 Prior work on the negative effects of AI-driven systems on people with disabilities

Despite statuary requirements (e.g., Americans with Disabilities Act (ADA) [81]) that mandate the provision of appropriate information technology access to people with disabilities, inaccessibility of such technologies is still a major ongoing problem for the disability community [18]. The accessibility literature is replete with papers that talk about how information technology often leaves people with disabilities behind. Examples range from the inaccessible website building tools [86, 99, 102] to physical interfaces [68], voice interfaces [58, 71, 72], and virtual reality [65, 68]. It is not therefore surprising, unfortunately, that AI-driven systems also similarly inaccessible for people with disabilities. In recent years some work has been done toward understanding how AI-driven systems affect with people with disabilities. In [47], the paper focuses on how people with disabilities perceive LLMs, trained on real-world data, in terms of perpetuating harmful biases toward those who are marginalized. In [75], the authors look at disability representation in text-to-image generative-AI-driven systems and how such representation often reflects societal biases and stereotypes. Finally, [87] focused on understanding real-life interactions that people with disabilities have with LLMs. While extremely useful, these efforts generally focus on one specific type of generative-AI-driven system. Our work seeks to understand, in a much broader manner, how AI-driven systems impact people with disabilities. As a result we neither limit the type of AI-driven systems that we consider in this work nor the type of disability - as long as there is a documented incident of the system's use causing a negative outcome for someone with a disability.

3 Methodology

In this work, we seek to identify the negative outcomes of AI-driven systems for people with disabilities. To this end, we started with eight AI incident databases to find documented incidents where an AI-driven system produced some form of negative outcome for someone with a disability. The idea was to curate our own *dataset* of such negative outcomes. Figure 1 provides an overview of our dataset curation process. The AI incident databases we consulted included: AI, Algorithmic, and Automation Incidents and Controversies (AIAAIC); the AI Incident Database (AIID); the OECD AI Incident Monitor; the Database of AI Litigation (DAIL); Where in the World is AI? [6]; the AI Risk Repository [10]; the AI Vulnerability Database [12]; and AI Badness [4][1].

None of these databases included tags related to disability, so we searched[2] for disability-related incidents using a set of keywords around disability and its various forms that we also used in our prior work [70]. Our set of keywords, which we adapted from the

keyword list in [106], can be found in Table 1. As we are interested in exploring how AI-driven systems affect people with any kind of disability, our keyword list includes terms relating to many kinds of disabilities. We also included temporary disabilities, such as rehabilitation from a surgery, as well as health conditions related to advanced age. Only five of the eight databases contained at least one incident regarding someone with a disability. Thus the AI Risk Repository [10], the AI Vulnerability Database [12], and AI Badness [4] did not end up contributing to our dataset.

After searching for each keyword in the databases and compiling the results, we had a total of 102 entries. We then manually went through each entry to ensure it was indeed relevant and could be included in our final dataset. We did this by first checking if each entry met our *inclusion criteria.* An incident was included in out dataset if it met <u>all</u> of the following conditions: (1) the described incident was about an AI-driven system; (2) the AI-driven system involved in the incident affected one or more people with a disability; and (3) the outcome on the person with a disability was negative. We then removed entries that met <u>any</u> of the following *exclusion criteria*: (1) the person's disability was caused by an AI-driven system (e.g., a self-driving vehicle injuring someone non-disabled); (2) the incident description was too vague to determine whether someone with a disability was affected or not; and (3) the incident described was one where AI was being used for the diagnosis or management of a medical condition.

We sometimes found multiple entries for a particular incident in the same database. In such cases, we combined the entries into one incident. We followed the same procedure when we found the same incident across multiple databases. Thus we counted any particular incident only once in our dataset. At the end of this process, we ended up with a total of N = 79 incidents in our dataset. The Appendix of the paper lists all the incidents in our dataset along with the associated URLs from the respective incident database. Table 2 shows the number of relevant incidents from each of the five databases that we used to curate our dataset.

3.1 Analyzing the dataset

In this work we seek to better understand how AI-driven systems create negative outcomes for people with disabilities. The authors performed a reflective thematic analysis (RTA) of the incidents. We used Braun and Clark's six-step recursive approach to thematic analysis of our work [21]. RTA is considered a reflection of the researcher's interpretive analysis of the data located at the intersection of the dataset, their expectations about the dataset, and their analytical skills. With RTA, codes represent the authors' collective interpretations of patterns of meaning across the dataset. RTA therefore recognizes that no two researchers will be alike in all three criteria and therefore it eschews the expectation that codes or themes produced by one researcher would be reproduced by another. Thus in RTA researchers collaborate in order to attain richer analysis rather than attempting to achieve consensus. Consequently, in this work the authors performed the coding and analysis as per the RTA method and the taxonomy presented in the paper reflects our finalized codes. In total, we created a final codebook of nine types of negative outcomes. We will define these in Section 4 in detail, as part of our taxonomy of negative outcomes.

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[1]As of May 2025, this database is no longer active.

[2]The Where in the World is AI? database used a different interface from the others and did not include a search feature. Consequently, we went through each incident in it manually to find relevant instances for our dataset. As of early April 2025, this database is no longer active.
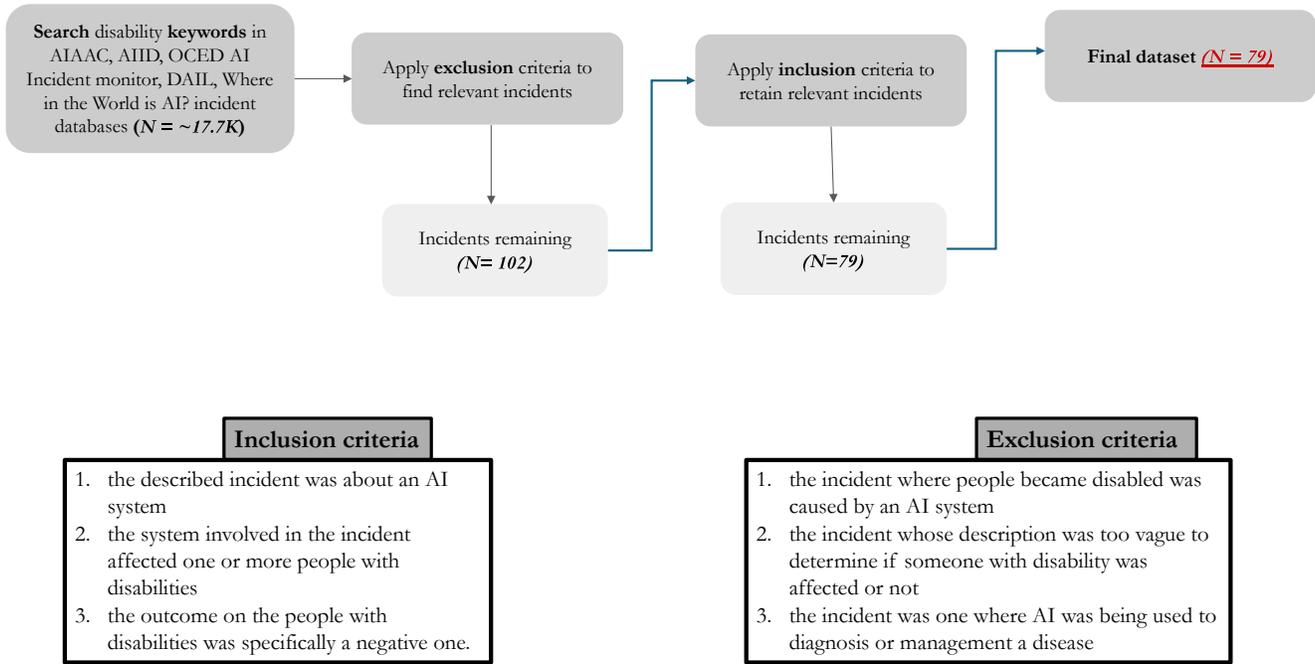
Inclusion criteria

1. the described incident was about an AI system
2. the system involved in the incident affected one or more people with disabilities
3. the outcome on the people with disabilities was specifically a negative one.

Exclusion criteria

1. the incident where people became disabled was caused by an AI system
2. the incident whose description was too vague to determine if someone with disability was affected or not
3. the incident was one where AI was being used to diagnosis or management a disease

Figure 1: How we curated our dataset of negative outcomes from AI-driven systems on people with disabilities using databases of AI incidents

AAC, accessibility, accessible, Alzheimer, Alzheimer's, amnesia, amnestic, amputation, amputee, amyotrophic lateral sclerosis, aphasia, apraxia, arthritis, assistive technology, ataxia, augmentative communication, autism, autistic, blind, blindness, caregiver, cochlear implant, congenital amputation, congenital amputee, deaf, dementia, diabetic retinopathy, disabilities, disability, disabled, Down syndrome, dysarthria, dyslexic, dystonia, epilepsy, essential tremor, fibromyalgia, Friedreich ataxia, Friedreich's ataxia, glaucoma, handicap, handicapped, hard of hearing, hearing aid, hearing device, hearing loss, hemiplegia, hemiplegic, impaired, impairment, impairments, lateral sclerosis, lisp, Lou Gehrig's disease, Lou Gehrig, macular degeneration, mobility, multiple sclerosis, muscular dystrophy, muscular rheumatism, myopathy, neurological disorder, neurological vision impairment, neuromuscular disorders, nursing home, paralysis, paralyzed, paraplegia, paraplegic, Parkinson, Parkinson's disease, Parkinsonism, quadriplegia, quadriplegic, sclerosis, seizure disorder, short term memory, sigmatism, SMA, speaking disorder, special needs, speech impediment, speech therapy, spinal bifida, spinal cord injury, spinal muscular atrophy, stroke, stutter, TBI, traumatic brain injury, tremor, tremors, vision, walker, wheelchair, bedridden, disease, injuries, injury, limited vision, no vision, non-verbal, nonverbal, poor vision, rehab, rehabilitation, surgeries, surgery, wheelchair, bed-ridden

Table 1: Disability-related keywords we used to identify relevant incidents for inclusion in our dataset

Database	Number of relevant incidents found
AIAAIC [3]	33
AI Incident Database (AIID) [5]	21
OECD AI Incidents Monitor (AIM) [94]	18
The Database of AI Litigation (DIAL) [33]	6
Where in the World is AI? [6]	1

Table 2: The number of relevant incidents from each database used to curate our dataset

3.2 Overview of our dataset

Before getting to the details of our taxonomy, we first present a broad overview of our dataset. In this regard, we present four characteristics of our dataset: the types of AI-driven systems included in it, the kinds of disabilities in the people who were negatively affected, the sectors within which the offending AI-driven systems were deployed, and the eventual actions taken (or lack there of)

against the offending AI-driven systems, once the incidents were reported.

Types of AI-driven systems in our dataset: Table 3 shows the types of AI-driven systems and the number of incidents that featured each system. Overall, *we classified the AI-driven systems from our dataset into 11 types.* In our classification, the most common type of AI-driven system was what we refer to as *predictive AI* (i.e., the use of machine learning to identify and anticipate user behavior and forecast events [89]) - which was present in 34 incidents. This was followed by *generative AI* (i.e., the use of generative models primarily to produce text and images), with 17 incidents. The next most common types were biometrics (i.e., the use of innate human facial and body characteristics to identify someone) and web accessibility (i.e., the use of automated tools to make websites accessible to blind and low-vision individuals), both with seven incidents each. There were fewer than five incidents per type for the other kinds of AI-driven systems, including: social media recommendation engines (i.e., the use of information filtering to recommend relevant

AI-driven system type	Count	AI-driven system type	Count
Predictive AI	34	Affective computing	2
Generative AI	17	Natural language processing (NLP)	2
Biometrics	8	Speech recognition	1
Web accessibility	7	Image processing	1
Recommendation systems	4	Brain-computer interface (BCI)	1
Robotics	4		

Table 3: Distribution of our classification of the types of AI-driven systems in our dataset. The total number of entries in this table is greater than the number of incidents in our dataset because one incident involved two types of AI-driven systems.

content on social media platforms, primarily TikTok, Instagram, and Facebook); robotics (i.e., a collective term we use for incidents with robo-taxis, delivery robots, and companion robots); affective computing (i.e., attempting to determine someone's emotions, feelings, or mood, often based on external characteristics [101]); natural language processing (i.e., specifically around automated "toxicity" detection in texts); image processing (i.e., specifically in the context of the automated cropping of non-salient elements of an image); speech recognition (i.e., specifically voice assistants recognizing a user's commands); and brain-computer interfaces (i.e., limb-free cursor control on a computer screen via a neural implant).

Classes of disabilities affected by AI-driven systems in our dataset: Since our focus in this work is on people with disabilities, we next wanted to see what kind of disabilities were represented in our dataset. Table 4 shows the distribution of the nine classes of disabilities found. *The classes of disability listed here are taken from how the disability was described in the incident report.* Not all incidents in our dataset included a description of the exact kind of disability in detail. Such cases often described the underlying chronic or genetic condition that caused the disability instead. We therefore present an aggregate overview of the classes of disabilities present in our dataset.

Type of disability	Count	Type of disability	Count
Broadly, all disabilities	19	Speech impairment	7
Cognitive disability	16	Mental disability	5
Vision impairment	15	Hearing disability	2
Motor disability	15	Learning disability	1
Unspecified	7		

Table 4: Distribution of the types of disability present in our dataset, as reported in the original incident databases. The total number of entries in this table is greater than the number of incidents in our dataset, as some incidents affected multiple kinds of disability.

Most of these terms are self-explanatory. Cognitive disabilities include instances of intellectual and developmental disabilities, autism, Down Syndrome, Alzheimer's disease, and dementia. Motor disabilities include both upper body and lower body mobility impairments (e.g., cerebral palsy and Tourette's syndrome). Speech impairments include individuals whose disability caused speech impairment, such as cerebral palsy, Amyotrophic lateral sclerosis (ALS), and Dysarthria. Mental disabilities include individuals with depression, attention deficit disorder, and bipolar disorders. There was only one instance of a learning disability, which was Dyslexia.

The term 'Broadly all' is used to describe cases where all classes of disability were likely to be affected by the AI-driven system, per the incident report. Lastly, the term 'Unspecified' is used for incidents where it was clear that someone with a disability was affected by the use of an AI-driven system but not enough detail was available about the type of disability affected.

Sectors that deployed the AI-driven systems in our dataset: Next, *we broke down our dataset in terms of the sectors within which the AI-driven systems causing negative outcomes were deployed.* Table 5 shows the various sectors involved. In our breakdown, we recorded a total of 23 different sectors represented in our dataset. Welfare and social services was the most common sector where AI-driven systems caused negative consequences for people with disabilities. This is followed, in descending order, by: education, social media, technology involving chatbots and web-accessibility tools, employment, healthcare, and law enforcement. The other sectors each had fewer than 3 incidents. The entries categorized in the technology sectors are essentially tools that are used by individual users as part of their daily lives.

Dénouement of AI-driven systems per sector in our dataset: Finally, we cataloged the eventual actions taken (or lack there of) against the offending AI-driven systems after the negative outcomes from their use were reported, along with their frequency of occurrence, organized by the sector in which they were deployed (see Table 5). *Since this information was often not available in the databases, we had to perform additional searches for 28 of the 79 incidents in our dataset.* Hence, the results reported here describe the state of affairs, identified to the best of our ability, as of early April 2025. According to our findings, in 22 of the 79 incidents, sadly, no action seems to have been taken to update the offending AI-driven system. In 20 of the 79 incidents, the status of the AI-driven system was unclear as to whether anything changed. This group is mostly concentrated in the social media, education proctoring, and various technology sectors. In 13 of the 79 incidents, the AI-driven system was updated. In 13 separate incidents, the AI-driven system was discontinued. In 9 of the 79 incidents, the court cases were still ongoing, meaning that the AI-driven system is likely still operational. We found two miscellaneous incidents, which did not fit the other criteria. In one of these incidents it is not clear whether AI-driven system involved had been updated/reformed or not [110]. The other incident was against the German magazine *Die Aktuelle*, which misused a large language model to generate a fake interview. The magazine was sued because of this faux interview and lost the case [107]. Altogether, we found that a majority (51 of the 79 = ~65%)

Sectors	Ongoing court cases	Misc.	No Action Taken	System discontinued	System updated	Unclear	Total
Welfare and social services	1		5	1	5	1	**13**
Education	1		3	3	1	3	**11**
Social media			1	1	3	4	**9**
Technology: chatbots	2	1	1	1	1	1	**7**
Technology: web	1		2		1	3	**7**
Employment	1	1		1		3	**6**
Healthcare	1			2		1	**4**
Law enforcement			1	1		1	**3**
Technology: NLP						2	**2**
Housing	1		1				**2**
Financial services			2				**2**
Autonomous vehicles			1		1		**2**
Technology: virtual assistant			1				**1**
Politics			1				**1**
Teleconferencing				1			**1**
Delivery service				1			**1**
Technology: Speech-to-text						1	**1**
Retail			1				**1**
Technology: BCI					1		**1**
Health insurance	1						**1**
Technology: robots				1			**1**
Border security			1				**1**
Business/professional services			1				**1**
Total	**9**	**2**	**22**	**13**	**13**	**20**	**79**

Table 5: Distribution of the various sectors where the offending AI-driven systems from our dataset were deployed and a catalog of eventual action taken against these systems, once the negative outcomes were reported

of the offending AI-driven systems remain operational despite the negative outcomes they caused for people with disabilities.

4 Our taxonomy of the negative outcomes produced by AI-driven systems for people with disabilities

When we analyzed the documented incidents of how deployed AI-driven systems have negatively affected people with disabilities, we organized the negative outcomes into nine thematic categories. For each category of negative outcomes, we list the count of the number of incidents we found of that type in our dataset. Table 6 summarizes our taxonomy.

4.1 Denying people with disabilities of vital resources (37 incidents)

One of the most common negative outcomes emanating from the use of AI-driven systems was that their decisions often restricted vital resources (e.g., welfare and social services, health insurance, housing, education, etc.) on which people with disabilities depend.

Denying people with disabilities of welfare and social services (12 incidents): Our dataset included many incidents of social

services being restricted for people with disabilities because of decisions made by AI-driven systems. This included the US state of Idaho's Medicaid[3] disability resource allocation model, which was designed to determine in-home care and service budgets for people with developmental disabilities, was found to be arbitrary in its decisions and lacking transparency, which led to a loss of care services for many [115, 124]. Similar problems were discovered in the US state of Oregon's use of AI for disability resource allocation as well [38]. AI-driven systems deployed to control the provision of Medicaid healthcare services were found to deny coverage for children and adults with disabilities in several US states, including Tennessee [43], Arkansas [79], Texas [113], Missouri [13] and West Virginia [62]. Such restrictions to social services from decisions made by AI-driven systems was not unique to the US. In Serbia, a system deployed to rout out welfare fraud was found to be discriminatory against people with disabilities [78]. In the UK, the benefits fraud detection algorithm used by their Department for Work and Pensions was found to unfairly issue funding cuts for people with disabilities without explanation [115]. The disability insurance system in Australia, which was updated to develop a "personalized

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[3]Medicaid is a federal governmental program in the US that provides health insurance for adults and children with limited income and resources.

Negative outcome category	Subcategory	Example
Denying people with disabilities of vital resources (37 incidents)	Welfare / social services	The US state of Idaho's Medicaid disability resource allocation model was found arbitrary in its decisions and lacking transparency, leading to a loss of care services for people with developmental disabilities [124]
	Technology	A person with ALS found that her Amazon Alexa did not understand her commands because of her dysarthria [29]
	Employment	HireVue's job applicant assessment system was criticized in New Zealand for using facial analysis, tone of voice, etc. to assess job applicants' psychological state and predict employee performance, which screened out candidates with visual and other disabilities [24]
	Health insurance	United Healthcare's nH Predict tool stopped payments for people with disabilities, often against medical expertise [112]
	Education	A system used to predict student exam grades in the UK was found to downgrade the exam results of students with disabilities, which had lasting consequences for them [1].
	Housing	A visually-impaired individual was threatened with eviction after a facial-recognition-based surveillance camera accused her of lending her key fob to an unauthorized person when it was someone she had asked to help by delivering her groceries [76]
Falsely accusing people with disabilities of serious offenses (14 incidents)	Academic dishonesty	Proctorio, an exam proctoring system, repeatedly flagged as suspicious students who self-stimulate or "stim" during exams, which prevented them from taking exams [44]
	Fraud	An insurance company Lemonade misinterpreted the non-verbal cues of individuals with disabilities as signs of fraud [85].
	Being a security threat	Vera-2R, a system designed to predict one's risk of engaging in terrorist activities, identified autism as a risk factor without any evidence for this claim [20]
Disrespecting the privacy of people with disabilities (7 incidents)	-	Austria's public employment system was found to violate the EU's GDPR privacy rules due to its conducting "invasive profiling" of applicants with disabilities [125]
Suppressing the voices of people with disabilities (6 incidents)	Censoring content by people with disabilities	TikTok's AI-based automated content moderation system was abused to intentionally misreport innocuous content from people with disabilities, which removed their content from the app [82]
	Invalidating the votes of people with disabilities	In the US state of Alabama, a signature recognition system failed to recognize the signatures of people with physical and mental disabilities, causing their ballots to be rejected and invalidating their votes [131]
Providing skewed content to people with disabilities (5 incidents)	-	The Character.AI chatbot was criticized for showing text with inappropriate themes, includimg topics such as self harm and incest, to a teenager with autism [36]
Causing distress to people with disabilities (5 incidents)	Physical harm	A smart gate, designed to automatically allow paying customers to leave and block people who are shoplifting, closed on a person in a wheelchair, hurting them and damaging their wheelchair [130]
	Emotional distress	A German magazine published an AI-generated interview with Formula 1 driver Michael Schumacher that included fake quotations and incorrect information about his family life and medical condition, causing considerable distress to the driver and his family [107]
Fostering prejudice about people with disabilities (4 incidents)	Policing disability-oriented language	Google's Perspective tool was found to assign higher "toxicity" scores to statements that involved people with disabilities and other marginalized groups [37]
	Generating offensive statements about disability	The Lee Luda chatbot was found to generate offensive and discriminatory comments about people with disabilities and other marginalized groups [67]
Impersonating people with disabilities (4 incidents)	-	ChatGPT's web crawlers were found to pose as a visually-impaired person and request human help in order to avoid having to deal with CAPTCHAs during their crawl [30].
Limiting access for people with disabilities (2 incidents)	-	People with visual and physical disabilities can find it difficult to board autonomous taxis, as they can no longer rely on social interaction with the driver to help them enter the vehicle [31]

Table 6: An overview of our taxonomy of negative outcomes from the use of AI-driven systems on people with disabilities. The total number of incidents is greater than the number of individual incidents, as some incidents involved multiple categories.

budget" for each applicant, was criticized for prioritizing efficiency in the form of cost cutting rather than providing flexible means of spending one's money [126]. In another incident, the biometric system used in the online system for the US Department of Veterans Affairs failed, causing individuals with Alzheimer's disease to be locked out of the system with no immediate recourse [50].

Denying people with disabilities of technology (10 incidents): In our dataset, we found several incidents where access to technology was restricted for people with disabilities. Most of these incidents involved companies making false claims about the efficacy of their automated tools that ostensibly made websites screen-reader-friendly for blind and low-vision users [11, 61, 73, 119, 121]. Other incidents where access to technology was curtailed for people with disabilities included individuals with speech impairments For example, a person with amyotrophic lateral sclerosis (ALS) found that her Amazon Alexa did not understand her commands [29]. Similarly companies, such as Microsoft and Cisco, have started to implement AI chatbots for customer service. Navigating these chatbots can be especially challenging, if not outright exclusionary, for individuals with disabilities, as this population often encounters accessibility barriers and experiences frustration with such automated systems [97]. Finally, a paralyzed individual from the state of Arizona in the US who had Neuralink brain-computer interface installed could no longer use this device to control his computer after a chip malfunction occurred mere months after its deployment [56].

Denying people with disabilities of employment (10 incidents): Our dataset included numerous incidents of AI-driven systems restricting access to employment for people with disabilities. (1) The company Workday was sued for discriminatory practices by someone with chronic depression because their machine learning tool for screening job applicants allowed its customers to use biased and subjective judgments in reviewing and evaluating employees for hire, which disproportionately affected people with disabilities [25]. (2) A company called Kami, which generated a virtual model that was supposed to look like someone with Down Syndrome, as a purported way to increase diversity in the context of fashion advertising. This effort was, of course, criticized for taking away opportunities from actual people with disabilities [2]. (3) The company HireView was sued for using facial cues to measure job applicants' cognitive ability, emotional intelligence, and social aptitude, which was found to discriminate against people with disabilities [24, 49]. (4) The company Aon's ADEPT-15 personality test, used in hiring, included questions that were found to disproportionately impact autistic people [8]. (5) The parent of a college student with bipolar disorder sued several companies after their son was rejected for multiple jobs by an online personality test developed by Workforce Ready HR that claimed to use AI to map the best person for a given job. This software concluded that this job applicant was likely to ignore his customers if upset [96]. (6) Austria's public employment system was criticized for systematically assigning lower grades to women and people with disabilities [125]. (7) In Poland a system intended to provide personalized support for people who are unemployed by determining the type of assistance they need was found to categorize people with disabilities as lacking health insurance and likely to refuse to cooperate with employment officials [92]. (8) ChatGPT was shown to consistently rank résumés with

disability-related terms lower than résumés without such terms [34]. (9) Regulators found that AI-driven systems being used by employers to screen résumés, in general, were screening out applicants with disabilities [110].

Denying people with disabilities of education (2 incidents): Our dataset included a couple of incidents where AI-driven systems' decisions affected access to education. In the first incident, the US state of Nevada partnered with a company called Infinite Campus to introduce an AI-driven system that used more factors, such as GPA, attendance, household structure, and home language, to predict which students might struggle in school. However the AI-driven system misclassified the number of at-risk students to less than 65,000, which led to budget cuts affecting actual at-risk students, including students with disabilities [26]. In another incident, a system in the UK used to predict student exam scores during the COVID-19 pandemic was found to assign lower grades to the tests of students with disabilities, which had a lasting effect on these students [1].

Denying people with disabilities of housing (2 incidents): We also had a couple of incidents where AI-driven systems affected housing access for people with disabilities. One incident was a situation where a visually-impaired individual was threatened with eviction after a facial-recognition-equipped surveillance camera accused her of allowing an unauthorized guest use her key fob when this person was in fact helping her by delivering her groceries [76]. In another incident, RentSafe, an AI-driven system for rating tenants assigned a low score to a man who was not able to speak, walk, or care for himself and denied him housing because of a prior incident for which the charges had been dropped [41].

Denying people with disabilities of insurance (1 instance): Our dataset includes an instance where an AI-driven system's decision affected health insurance availability for people with disabilities. In this instance, United Healthcare's nH Predict tool which was used to deny payments for continuing treatment for people with disabilities, often against medical opinion. To make matters even worse, this system provided no recourse for the physicians or the patients to question nH Predict's decisions [112].

4.2 Falsely accusing people with disabilities of serious offenses (14 incidents)

The other most common negative outcome from the use of AI-driven systems is people with disabilities being labeled as dishonest, inappropriate, suspicious, or fraudulent for displaying symptoms and behaviors relating to their disability. In our dataset, such incidents of false accusations were of three main types, as described below.

Falsely accusing people with disabilities of academic dishonesty (6 incidents): We had several incidents in our dataset where AI-driven systems often falsely labeled individuals with disabilities of not being truthful in an academic setting. This included online exam proctoring systems like Honorlock, ProctorU, Proctoio, which were found *not* to be able to detect the facial features of students with a variety of disabilities and thus flagging them for cheating due to the AI-driven system's shortcomings. For instance

such systems interpret the following as evidence of cheating: autistic students' fidgeting and stimming; students with physical disabilities having difficulty sitting still for long periods of time; students with impaired eyesight for displaying "atypical" eye movements [44, 95]. In [19], it was reported that proctoring systems negatively affect students with ADHD and dyslexia as well. In other incidents, exam proctoring systems incorrectly identified a student's work as AI-generated and thus accused them of cheating [84, 116]. The ever-increasing use of AI-driven systems, in academia and elsewhere, can sometimes lead to downstream, indirect consequences where human behavior contributes to the negative outcomes for people with disabilities already being generated by the AI-driven systems themselves. For instance, it was reported that a researcher accused their autistic colleague's self-written email as being AI-generated for allegedly "lacking warmth." [104].

Falsely accusing people with disabilities of fraud (4 incidents): There were incidents in our dataset of an AI-driven system identifying people with disabilities as being likely to commit fraud. For instance, a system intended to detect social service fraud in France was found to flag people with disabilities as suspicious for slight changes in behavior, which led to their being subjected to invasive investigations into their personal lives [123]. In the US, a risk modeling tool in the state of Pennsylvania for improving child safety was consistently flagging families with people with disabilities, which led to higher screening rates for them [39]. In the insurance space, an AI-driven system used by the discount insurance company Lemonade, was found to use the non-verbal cues of individuals with disabilities as signs of fraud [85]. Another AI-driven system called DeepScore was found to use facial ticks and anxiety in neurodiverse individuals as indicators of being untrustworthy, when these individuals applied for financial services [42].

Falsely accusing people with disabilities of being a security threat (4 incidents): There were also some examples in our dataset of situations where an AI-driven system designed for screening applications was incorrectly targeting people with disabilities. For instance, a system called Vera-2R, designed to predict future terrorist activities, was shown to consider autism as a risk factor [20]. In a similar incident, body scanners at US airports were disproportionately singling out against people with disabilities, which resulted in invasive screenings and concerns about profiling [117]. In another incident, a system designed to strengthen border security in the EU called iBorderCtrl was found to use facial cues to determine whether people who are attempting to cross the border into the EU were telling the truth. This system was found to profile people with disabilities and those from other marginalized groups [90]. Finally, in the state of Florida in the US, a predictive policing system deployed to identify people who are most likely to commit crime was found to be biased against people with disabilities [14].

4.3 Disrespecting the privacy of people with disabilities (7 incidents)

Another category of negative outcomes for people with disabilities took the form of AI-driven systems gathering excessive information about people with disabilities, often without their consent or knowledge. Several incidents in this category have already been described

above [19, 42, 92]. These systems were further shown to also collect enormous amounts of personal information about people in order to make an assessment, thus affecting the privacy of people with disabilities as well. There were four additional incidents in this category. These included: an Argentine city government deploying a teenage-pregnancy predictive algorithm, built by Microsoft, which was criticized for privacy violation because it used sensitive and potentially irrelevant data about their disability status in its predictions [7]; Facebook's People You May Know feature was found to violate the privacy and confidentiality of the patients at a psychiatrist's office by showing the patients to each other (this involved people with disabilities) [52]; Austria's public employment system violated the EU's General Data Protection Regulation (GDPR) rules in terms of the privacy of potential applicants by conducting "invasive profiling" of people with disabilities [125]; and a research team at Keele University in the UK was found to be unethically using YouTube videos of children to determine if they are autistic or not ,without the consent of the families involved [46].

4.4 Suppressing the voices of people with disabilities (6 incidents)

Another negative outcome from AI-driven systems is that they often end up suppressing the voices and opinions of people with disabilities. We describe these below.

Fostering the censorship of content from people with disabilities or content related to disability (5 incidents): In these incidents, we found AI-driven systems censored or suppressed content from people with disabilities or about disability. This included an incident where TikTok's AI-based automated content moderation system was allegedly abused in order to intentionally have content created by users from marginalized groups, including people with disabilities, mistakenly reported as inappropriate, thus preventing their content from being shown in the app [82]. In another incident, TikTok's moderators had been instructed to tune the content moderation system to prioritize certain types of content over others (in the name of removing inappropriate content), which led to deprioritizing content from people with disabilities [100]. Censorship was also perpetuated when an image-cropping tool from the erstwhile Twitter , which automatically edited photos to focus on people's faces, was found to crop out images of people with disabilities [27]. In another incident, Open AI's Whisper speech-to-text system was found to "hallucinate" violent language and fabricated details, especially when there were pauses in speech, as is common for with people with certain speech impairments [37]. In yet another example, an advertisement from an adaptive clothing company called Mighty Well, which makes clothing for people with disabilities, was removed by Facebook because its automated content analysis system wrongly classified it as a medical device advertisement (which is not allowed on the social media platform). The latter is an example of an AI-driven system "medicalizing" disability when it is not appropriate to do so [45].

Interfering with the voting of people with disabilities (1 incident): We also found an incident where AI-driven systems could prevent people with physical disabilities from making their vote count during an election. In the US, mail-in ballots during elections require a signature verification step before the ballot is

accepted. In the state of Alabama, an automated signature recognition system was determined not to recognize the signatures of people with physical or mental disabilities. As a result, these ballot are rejected and these votes invalidated [131].

4.5 Providing skewed content to people with disabilities (5 incidents)

AI-driven systems also have the issue of producing output that is incorrect, misleading, or even harmful. In our dataset there were several such incidents. In one example, the Character.AI chatbot was criticized for showing text with inappropriate themes, such as self harm and incest, to a teenager with autism [36]. Similarly, the use of the Character.AI chatbot led another 14-year old autistic boy to become dependent on the chatbot's depiction of the character Daenerys Targaryen from the show Game of Thrones, leading him tragically to commit suicide in order to be with the character [91]. A study by Center for Democracy and Technology found that chatbots often provide information about conspiracy theories and arguments for why people with intellectual disabilities should not be allowed to vote [122]. AI-driven systems, other than generative AI, also produce problematic, incorrect output. For example, many teleconferencing apps (e.g., Zoom) try to use facial cues to identify their users' mood. We found a couple of incidents in our dataset where such apps were found to make a lot of errors, demonstrating that such AI-driven systems often have a narrow model of how they expect people to look or act in particular scenarios [105, 120].

4.6 Causing distress to people with disabilities (5 incidents)

Another type of negative outcome from the development and use of AI-driven systems was that they can and do hurt people with disabilities as a result of the decisions they are permitted to make. In our dataset, we found that AI-driven systems are liable to hurt people with disabilities both physically as well as emotionally.

Physical distress (3 incident): Our dataset contains a few incidents where AI-driven systems led to people with disabilities being physically hurt or worse. For example, a self-driving bus designed by Toyota hit a visually impaired athlete crossing the street during the Paralympic games in 2021 [74]. In another incident, a smart-gate designed to automatically open and close, allowing paying customers to leave and blocking people who are presumably attempting to shoplift, closed on a person in a wheelchair. The smart-gate injured this person's arms and damaged their wheelchair [130]. A particularly egregious case in this context was an AI-driven staffing system that was found to regularly allocate fewer workers to a Brookdale senior living center in the state of Florida in the US, which left the facility understaffed. This led to a resident with dementia dying after falling and being left unattended for over two hours, due to a lack of workers at the facility [77].

Emotional distress (2 incidents): In our dataset, we also found a couple of incidents where a decision made by an AI-driven system had severe emotional impact on one or more individuals with disabilities. This included an incident involving a German magazine *Die Aktuelle*, which published an AI-generated interview purportedly with the Formula 1 driver Michael Schumacher - who was

paralyzed due to a traumatic brain injury. The faux interview included fake quotations and incorrect information about his family life and medical condition. This caused considerable controversy and distress to the driver and his family, culminating in a successful lawsuit [107]. Contrary to the examples above, which mostly describe the failures of AI-drive systems, our dataset also includes an incident where an otherwise successful AI-driven system was the cause of emotional distress. A robotics company that made what is considered to be a successful robot companion for autistic children, called Moxie, had to close for financial reasons. As a result, Moxie ceased to function, which caused considerable emotional and psychological distress to its user base (i.e., autistic children) [93].

4.7 Fostering prejudice about people with disabilities (4 incidents)

In this category, we include incidents involving AI-driven systems that essentially produce or promote content that is prejudicial against people with disabilities and their way of life, which we describe below.

Policing disability-oriented language (2 incidents): Our dataset includes some incidents where AI-driven systems assign a negative valance to words associated with disability. In one incident, Google's Perspective tool was found to assign higher "toxicity" scores to a statements that describe a person with a disability [16]. In a similar incident, a study found that statements referring to people with disabilities received significantly more negative and toxic scores from a variety of popular AI-based sentiment analysis tools, such as VADER, TextBlob, DistilBERT, and Toxic-BERT. [9].

Enabling offensive views about disability (2 incidents): Our dataset also captured a couple of incidents where AI-driven systems were shown to make offensive and harmful comments about people with disabilities. An example of this is the Lee Luda chatbot that produced offensive and discriminatory comments about people with disabilities and other marginalized groups [67]. In another example an app called Fable, which tracks books read during the year, developed an AI-driven system to create personalized end-of-year summaries for its users. This system was found to use discriminatory language against disability narratives in its summaries [116].

4.8 Impersonating people with disabilities (4 incidents)

Our dataset includes a few incidents where AI-driven systems were used to impersonate people with disabilities, often for expediency or for committing some form of fraud. Examples of this include the aforementioned AI-driven system used to generate fake images of a person with Down Syndrome in the context of "diversifying" models in advertisements [2]. In other incidents, criminals used AI-generated images of people with disabilities as a way to ask for money from unsuspecting people on social media. The latter was specially common on Facebook and Instagram [66]. Others did the same (i.e., used AI-generated images of people with disabilities) with the goal of increasing engagement with their posts on Facebook [98]. Interestingly, such impersonation has also been done during the training of AI-driven systems. In our dataset there is an incident where ChatGPT's crawlers were found to be posing as a

visually impaired person and requesting human help in order to avoid having to deal with CAPTCHAs during their crawl of various websites [30].

4.9 Limiting access for people with disabilities (2 incidents)

In our dataset there are a couple of incidents where AI-driven systems made it difficult for people with disabilities to access a physical location or move around. In one incident, in Pittsburgh in the US, a delivery robot from a company called Starship, which was used to deliver groceries autonomously, was found to put a disabled person in wheelchair in harm's way by blocking their access to the sidewalk from a busy city street [132]. In another incident, it was found that autonomous taxis are often hard for blind and low vision individuals and those with physical disabilities to use. A chief reason for this difficulty it that such individuals can no longer rely on social interaction with a driver to help them enter the vehicle, which they could otherwise do with a human-driven taxi service [31].

5 Designing AI-driven systems that meet the needs of people with disabilities is a relatively new area of research that merits further exploration

In this paper, we looked at the various ways in which AI-driven systems have been reported to produce negative outcomes for people with disabilities. To this end, we compiled a dataset of negative outcomes affecting people with disabilities from several online AI incident databases. In this section, we describe the implications of our taxonomy by discussing five areas for future research opportunities for the HCI and accessibility communities. These opportunities describe how we should go about designing and deploying AI-driven systems, such that the identified negative outcomes for people with disabilities can be minimized. For each opportunity, we list a few specific research questions that we believe should be tackled.

5.1 Opportunity 1: Provide a seamless means of recourse for decisions made by AI-driven systems

Some of the most common issues that we found in our taxonomy (in Section 4) was AI-driven systems restricting some form of access to resources for people with disabilities, such as welfare and social services, housing, education, or even reputation. If an AI-driven system has to be deployed in a specific situation that affects people with disabilities, it is important that processes are in place that provide some form of recourse for its decisions. Further, the recourse should be seamlessly available and part of the design of the larger ecosystem in which the AI-driven system is deployed rather than as an afterthought. The form this recourse takes has to be something of which people with disabilities can easily avail themselves, despite their disability. For example, if an AI-driven proctoring tool is inaccessible to someone with physical disabilities [44], the educational ecosystem should allow the person in question to take the test in the presence of a human proctor (who may even be remotely located). There is no reason such a system

cannot be made available, given the availability of cheap and reliable teleconferencing tools. A reasonable means of recourse is even more important when the reputation of a person with disability is threatened by an AI-driven system (e.g., being labeled as a potential fraud or a security threat). As the introduction of AI-driven systems is affecting more and more people with disabilities, it behooves the designers of such systems to adapt them to accommodate the needs of the various disability communities rather than asking people with disabilities to deal with the consequences of the output *cum* decisions generated by AI-driven systems. Some research questions in this area include:

- How to design AI-driven system recourse strategies for the needs of people with disabilities, given the diversity of the disability communities and their vastly different needs?
- How to incentivize the development of such recourse strategies so they are considered at design time rather than as a patch - usually post legal remedies or from public pressure?

5.2 Opportunity 2: A "nothing about us without us" mindset to the design and deployment of AI-driven systems

More than a third of the incidents in our dataset (in Section 4) comprise situations where people with disabilities were physically, mentally, or emotionally harmed by the use of AI-driven systems. Such situations can be avoided by including the voices of people with disabilities during the design of the AI-driven systems or the ecosystem within which it will be deployed. A perfect example of an AI-system that would have avoided inherent design flaws if the designers had elicited input from people with disabilities is the delivery robot that prevents wheelchair users from moving out of the busy street to the safety of the sidewalk, as seen in [132]. Such situations can easily be predicted and compensated for by including people with disabilities in the design process. Many disabilities communities have self-advocates who are trained to bring the perspectives of their specific community to outsiders. Such self-advocates can be easily brought in during the design phase of AI-driven systems and their larger deployment ecosystem to identify potential issues. Work like this with self-advocates also organically fulfills one of the fundamental requirements of working with people with disabilities: *nothing about us without us* [53]. Working with disability communities in this manner also has the added advantage of building trust and buy-in around the AI-driven system within such communities. Some research questions in this area include:

- How to incorporate ideas and suggestions from disability self-advocates and self-advocacy groups in the design of AI-driven systems?
- How to build and sustain the relationship and the trust needed between AI-driven system designers and self-advocates throughout this collaborative process?

5.3 Opportunity 3: Creating guidelines for the deployment of AI-driven systems with respect to people with disabilities

Broadly speaking it would be useful to create specific guidelines that designers can follow when *deploying* AI-driven systems that affect people with disabilities. In [28], the authors present a comprehensive set of guidelines for responsible AI use. The resulting guidelines are divided into six broad categories that address various aspects of AI-driven systems, including: intended uses, harm, system, data, oversight, and team. In these incidents the focus of the guidelines is on identifying and focusing on the safety of the eventual users of the AI-driven system. Though not developed specifically for people with disabilities, these guidelines are, in general, a good starting point for thinking about the design of AI-driven systems in terms of people with disabilities. However, to develop the guidelines, more systematic work needs to be done to better understand the views of various disability communities on different AI-driven systems. Some research has already ongoing in space, which in the future can inform the guidelines [22, 22, 47, 48, 59]. Some research questions in this space include:

- What experience have different communities of people with disabilities (e.g., people with vision impairments, intellectual and developmental disabilities, etc.) had with various AI-driven systems? What do they like and what changes do they want?
- What specific criteria (e.g., accountability, privacy, transparency, reliability, etc.) should be considered in the development of these guidelines?
- How to adapt the responsible AI guidelines specifically for individual disability communities based on their experience?

5.4 Opportunity 4: Promoting audits, documentation, and standards to reduce negative outcomes of AI-driven systems for people with disabilities

It is not enough to have guidelines alone. We also have to develop ways to make sure that the AI-driven systems are following the guidelines. A variety of safety-critical systems in other domains, such as medicine, transportation, and finance, often use internal audits and documentation to make sure that the systems are performing as expected [109]. When it comes to checking AI-driven systems' effects on people with disabilities, it is essential that audits of performance be completed from time-to-time and communicated externally in a timely manner. This is especially true when the AI-driven systems are deployed to make public services better (e.g., welfare or employment services, which have had serious downsides of AI-driven systems for people with disabilities, as seen in Section 3.2 above). Further, to enable efficient and standardized audits, we might need to develop appropriate, ecologically valid benchmarks, which would allow end-users to compare the results across AI-driven systems that provide similar services. It is also important to develop standards, such as those developed by IEEE or ISO, around reducing harm specifically for disability communities from AI-driven systems (when applicable).

Finally, we saw in Section 3.2 that, despite the fact that incidents highlighting the negative outcomes of AI-driven systems for people with disabilities are coming to light (being reported and substantiated), in most of the incidents no change was made to the offending system. A lack of consequences is not a tenable situation as more and more AI-driven systems are being deployed around people with disabilities and within society in general. Consequently, it may be necessary to conduct audits and create documentation and certifications around standards, and statuary requirements as much as possible to be performed by specialized auditors, as we do in other crucial industries such as aerospace and financial services [108]. Some research questions in this area include:

- How to design ecological valid benchmarks (and corresponding datasets) with the goal of auditing AI-driven systems with respect to their effects on people with disabilities?
- How to design documentation processes that can support the identification of issues prior to AI deployment?
- What kind of standards and certification regimes can be developed that can ensure that AI-driven systems do not negatively impact the lives of people with disabilities?

5.5 Opportunity 5: Create a reference system for disability-focused negative outcomes

Just as we have developed a common reference method for cybersecurity vulnerabilities, in the form of common vulnerabilities and exposures (CVE) [32], we should endeavor to develop and maintain a reference system for disability-focused (and other marginalized groups) negative outcomes that AI-driven systems produce in the real world. One of the reasons we need this is because we need a systematic way to track the systems that produce such negative outcomes to see if they have been updated over time. As we saw in section 3.2, a vast majority of the AI-driven systems are never updated (sometimes even despite legal challenges). With the rapid deployment of AI-driven systems in society, we need a better way to track the negative outcomes they cause. The taxonomy presented in this paper (along with other studies that have examined the harms and risks of AI [55, 69, 103]) can act as a starting point for categorizing the negative outcomes in the reference system we envision and outline here. Most importantly, such a system also would allow us to put pressure on the developers and deployers of AI-driven systems to better incentivize them to refine or update their system if they are found to affect the disabled, much like CVE does in the cybersecurity realm. Some research questions in this area include:

- How to design a reference system that tracks negative outcomes for people with disabilities from AI-driven systems?
- How to design the operation rules and workflows for a voluntary, international, community-driven effort to identify, define, catalog, and share information about AI-related negative outcomes?
- How to develop the partnerships among the various stakeholders needed to keep up and maintain the effort of tracking the negative outcomes?

6 Limitations

Our study has a few limitations. First, the taxonomy presented in this paper is based on the incidents we found in popular AI incident

databases as of mid March 2025. As newer incidents emerge from the real world, it is possible that they contain situations which do not fit neatly within our taxonomy. Therefore the taxonomy presented here should be seen as a work-in-progress and an evolving categorization that will probably need to be updated from time to time.

Second, each incident in these databases links to multiple major news sources, all of which were checked by us, as part of this work. It is possible that some incidents could have been incorrectly reported but if they were, then we expect that a retraction would be published or the article would be removed from the new source's website (as is common practice in the new industry). We did not find any such issues with the news reports associated with the incidents we covered in this paper. However, it is conceivable that incidents mentioned in the present paper could be retracted or amended in the future.

Third, our dataset is relatively small, as compared to the cumulative size of the databases from which it is compiled. This is because the number of documented incidents involving people with disabilities was small. Even though we tried our best to be comprehensive in our search and use of keywords, it is possible that we may have missed a few incidents in our dataset.

Fourth, there were several incidents in our dataset where the exact description of how the AI-driven system negatively affected a specific community of people with disabilities is described at a very high level without many specifics. Despite this vagueness, we included such cases in the our dataset, analysis, and taxonomy because there was a concrete report that someone with disability was negatively impacted and we felt it was important nonetheless to highlight the issue.

Fifth, even though our taxonomy can describe the type of negative outcome on people with disabilities, it does not help identify the root cause(s) of the problem, based on the description of the incident it captures. This because we are ultimately dependent on the incident databases that collect the public reporting of these negative outcomes, which often do not provide enough information for us to judge the precise cause of the negative outcomes. As a result, our taxonomy should be used as a guide to identify possible problems of which to be cognizant during the design of AI-driven systems that (could) negatively impact people with disabilities.

7   Conclusions

In this paper we presented a taxonomy of negative outcomes from the use of AI-driven systems for people with disabilities. To ground the taxonomy in the real world, we curated a dataset of 79 incidents of negative outcomes affecting people with disabilities from five AI incident databases. We then analyzed the incidents in our dataset and produced a taxonomy of negative outcomes grouped into nine broad categories. These negative outcomes were quite varied, from restricting resources to creating prejudice and causing distress. Based on our taxonomy, we provided five areas for future research that could be undertaken to design AI-driven systems in order to minimize such negative outcomes for people with disabilities going forward.

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Appendix

The list below shows the URLs to the entries in the AI incident databases for the incidents in our dataset. The links are listed in the order in which they appear in our dataset. Some rows have multiple entries (i.e., links) because we found multiple entries in a given incident database for what seemed to be the same incident. These incidents are only counted once in our dataset. As stated before, we also found the several incident listed across multiple incident databases. We have *not* included these in the list below, to maintain clarity.

- [124] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/idaho-medicaid-disability-resource-allocation
- [115] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/dwp-disability-benefits-fraud-algorithm
- [39] –> https://incidentdatabase.ai/cite/502/#r2843
- [126] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/ndis-independent-assessments-robo-planning
- [96] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/kyle-behm-kroger-algorithmic-personality-assessment
- [43] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/tenncare-automated-system-illegally-denies-people-medicaid
- [122] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/research-ai-chatbots-fail-disabled-voters
- [79] –> https://blogs.gwu.edu/law-eti/ai-litigation-database/case-detail-page/?Case_snug=ark-dept-of-human-servs-v-ledgerwood-->pid=15
- [44] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/uiuc-dumps-proctorio-over-significant-accessibility-concerns
- [90] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/mep-files-lawsuit-to-release-iborderctrl-lie-detection-system-documents
- [123] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/cnaf-fraud-detection-algorithm-accused-of-exacerbating-inequality
- [119] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/accessibe-automated-accessibility

- [100] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/tiktok-accused-of-suppressing-ugly-poor-disabled-lbgt-users
- [82] –> https://incidentdatabase.ai/cite/133/#r1468
- [50] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/id-me-facial-recognition-identity-verification
- [92] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/poland-psz-unemployment-scoring-algorithm
- [41] –> https://blogs.gwu.edu/law-eti/ai-litigation-database/case-detail-page/?Case_snug=connecticut-fair-housing-center-et-al-v-corelogic-rental-property-solutions-->pid=109
- [78] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/serbia-social-card-excludes-thousands-of-welfare-beneficiaries
- [49] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/hirevue-recruitment-facial-analysis-screening
- [95] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/university-of-wisconsin-online-proctoring
- [25] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/workday-ai-job-screening-tool
- [42] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/deepscore-trustworthiness-assessments
- [1] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/ofqal-algorithm-skews-student-grade-predictions
- [74] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/toyota-paralympics-self-driving-bus-hits-athlete
- [112] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/navihealth-nh-predict-used-to-deny-medicare-advantage-benefits
- [67] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/lee-luda-chatbot
- [132] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/starship-robots-impede-wheelchair-users
- [121] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/faciliti-automated-accessibility
- [120] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/apple-iphone-depression-detection-study
- [46] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/keele-university-youtube-autism-prediction-study
- [45] –> https://incidentdatabase.ai/cite/142/#r1481
- [19] –> https://incidentdatabase.ai/cite/140/#r1478
- [91] –> https://blogs.gwu.edu/law-eti/ai-litigation-database/case-detail-page/?Case_snug-->pid=260
- [16] –> https://incidentdatabase.ai/cite/13/#r1414

- [37] –> https://incidentdatabase.ai/cite/732/#r3953
- [77] –> https://blogs.gwu.edu/law-eti/ai-litigation-database/case-detail-page/?Case_snug=bright-v-brookdale-senior-living-inc-->pid=172
- [20] –> https://incidentdatabase.ai/cite/588/#r3256
- [30] –> https://incidentdatabase.ai/cite/498/
- [117] –> https://incidentdatabase.ai/cite/531/#r2943
- [14] –> https://incidentdatabase.ai/cite/195/
- [26] –> https://incidentdatabase.ai/cite/808/#r4142
- [7] –> https://incidentdatabase.ai/cite/188/#r1782
- [52] –> https://incidentdatabase.ai/cite/406/
- [11, 73] –> https://incidentdatabase.ai/cite/148/#r1499 [4]
- [131] –> https://venturebeat.com/ai/automatic-signature-verification-software-threatens-to-disenfranchise-u-s-voters/ [5]
- [38] –> https://blogs.gwu.edu/law-eti/ai-litigation-database/case-detail-page/?Case_snug=cs-et-al-v-saiki-->pid=16
- [62] –> https://blogs.gwu.edu/law-eti/ai-litigation-database/case-detail-page/?Case_snug-->pid=267
- [104] –> https://oecd.ai/en/incidents/35189
- [31] –> https://oecd.ai/en/incidents/42781; https://oecd.ai/en/incidents/46186
- [2] –> https://oecd.ai/en/incidents/60488
- [9] –> https://oecd.ai/en/incidents/19203
- [24] –> https://oecd.ai/en/incidents/15272
- [85] –> https://oecd.ai/en/incidents/14679
- [107] –> https://oecd.ai/en/incidents/24554
- [113] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/deloitte-systems-accused-of-making-inaccurate-unreliable-medicaid-eligibil
- [88] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/fable-ai-reader-summary-tells-user-to-read-more-white-authors
- [116] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/ai-detectors-falsely-accuse-students-of-cheating
- [36] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/character-ai-chatbot-suggests-son-kills-his-parents
- [125] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/austria-ams-job-seeker-algorithm; https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/privacy-watchdog-halts-austria-job-seeker-prediction-system
- [93] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/ai-robot-company-closure-leaves-kids-bereft
- [29] –> https://oecd.ai/en/incidents/13898
- [97] –> https://oecd.ai/en/incidents/109925
- [76] –> https://oecd.ai/en/incidents/27703
- [34] –> https://oecd.ai/en/incidents/93872; https://oecd.ai/en/incidents/91370

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[4]A total of four incidents listed in this one entry.
[5]This incident was originally listed on the Where in the World is AI? database, but since it's now offline, we have listed the associated news report instead.

- [8] –> https://oecd.ai/en/incidents/86698; https://oecd.ai/en/incidents/91049
- [84] –> https://oecd.ai/en/incidents/76076
- [13] –> https://oecd.ai/en/incidents/106191
- [130] –> https://oecd.ai/en/incidents/61850
- [56] –> https://oecd.ai/en/incidents/82197
- [27] –> https://incidentdatabase.ai/cite/103/#r2145

- [105] –> https://www.aiaaic.org/aiaaic-repository/ai-algorithmic-and-automation-incidents/zoom-ai-emotion-recognition
- [61] –> https://incidentdatabase.ai/cite/830/
- [98] –> https://oecd.ai/en/incidents/88138
- [17] –> https://incidentdatabase.ai/cite/803/
- [66] –> https://incidentdatabase.ai/cite/700/
- [110] –> https://oecd.ai/en/incidents/29895