Towards an Accessible Inclusive Artificial Intelligence (AI2)

Final Report

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Executive Summary

Background

Artificial intelligence (AI) is a field of study that allows computers to mimic human intelligence and is part of health informatics. Machine learning techniques are a subset of AI techniques that detect patterns in the data to assist users in making decisions. However, AI can also perpetuate biases against certain groups, including people with disabilities. This is because AI software learns from pre-existing data and uses that data to make predictions. AI bias has been reported in many areas, including business, social media, the economy, politics, and healthcare. While researchers started to account for the types of biases built in AI-based software, an assessment of AI biases towards people with disabilities is virtually nonexistent. We must ensure that AI models are built accessibly and inclusively for people with disabilities and other groups.

Objectives

This project assesses AI use for people with disabilities, its current advantages, and challenges. The outcomes will support future research agendas, practices, and policies.

Results

A) AI, Disability, and Accessibility

AI holds the potential to enhance accessibility for individuals with disabilities; however, the prevalent perspective in research has been limited to a medical model. Thus, the need to interrogate AI bias in the context of disability is an increasing necessity as dependence on AI systems becomes more validated in contemporary state-led institutions and services.

Our findings confirm the scarcity of research tackling AI bias, the prevalence of the medical model, and the absence of a disability justice approach. Issues such as data colonialism and medical colonialism are at the center of how AI biases materialize to facilitate the operation, normalization, and exaltation of ableist AI systems that systematically erase disabled people and their experiences. As such, a much-needed disability justice framework to address ableism within or through AI requires attention to data injustice, medical colonialism, and the exclusion, violence, and erasure that shape the everyday experience of people with disabilities.

B) Data Justice co-design

Data justice is rooted in the tensions between development and surveillance studies. To negotiate this conflict, data justice proponent Linnet Taylor proposed three pillars of data justice – visibility, engagement with technology, and non-discrimination. Building on these pillars, the field of data

justice has been increasingly pushed to broaden a Western-centric lens and scope of research, from problems with datafication, informational capitalism, individual privacy and security rights to social justice issues, collective needs, and non-Western framings of data justice.

Co-design is a form of participatory design that involves a larger range of methods to include users in design processes. However, many co-design approaches become extractive by "good" intentions in which designers feel good about including community members in tokenizing and disempowering ways. Design justice is an emerging field of research and practice that draws from participatory design and builds on co-design as a critical principle. Drawing on Black feminism and disability justice, design justice works to challenge white supremacy, heteropatriarchy, capitalism, and settler colonialism in design.

C) Disability Justice Framework for AI

AI systems function in unidirectional ways that leave out accountability issues of these systems to predictable ableist and biased data. A disability justice framework to address ableism and AI begins with decentering medical modalities and moving away from the limited rights-based approaches to disability care. A disability justice framework centers on the interdependent nature of socio-political and economic relationships that shape social interactions, especially in health care and well-being contexts.

Key Messages

- Future research should extend the research to include a social lens of disability and address AI biases. Research and development in AI need to be multi/trans-disciplinary and inclusive of people with disabilities as partners; it cannot be left to engineers. Such an approach aims to foster a more inclusive understanding of AI-driven interventions' health and social advantages for people with disabilities. Moreover, embedding social and ethical components in the engineering and computer science curriculum is imperative.
- Extractive logic always drives data, even when data processes are driven to achieve justice-oriented outcomes. Yet, there remains promise in the role of data in justice. Labour-based and feminist design justice approaches with and for the Global South can support the design and development of more justice-oriented data practices and outcomes.
- To address data colonialism, there is a need to move beyond a one-size-fits-all approach in how social policies and care practices are promoted and valorized in the race for effective AI systems. Nuanced policies governing AI production, use and consumption need to move away from cost-benefit analysis to include a comprehensive account of the socio-political and economic implications of AI use beyond technical terms of efficiency and effectiveness.

Methodology

We've conducted three studies.

Study 1: We conducted two systematic scoping reviews (Result 1). In the first scoping review, we identified and reported about 45 articles from eight online databases (ProQuest, IEEE Xplore, ACM Digital Library, Web of Science, Medline, PubMed, PsycINFO, and CINAHL) to answer the question: how is AI used in the disability domain? In the second scoping review, we identified and reported about 19 articles from four online databases (ProQuest, IEEE PubMed, and PsycINFO) to answer the question: how does AI impact inclusive design for people with disabilities?

Study 2: An integrated rapid literature review (Result 2) was conducted to identify best practices for co-design methods to support data justice and accessible and inclusive AI. An anti-racist, anti-colonial, and disability justice-informed critical appraisal questionnaire was used to identify 33 articles (from n=401 articles) with relevant best practices.

Study 3: A comprehensive literature review (Result 3) addressed the following key questions: What is a disability justice framework for AI? How can such a framework help enhance data justice to support inclusive and accessible AI systems? A total of (n=97) articles were identified using search terms that include the following: disability justice, data colonialism, inclusive AI, accessible AI, data justice, AI and/or disability, disability and/or accessibility, disability rights and *disability and/inclusion. A variation of these keywords was combined in this search using key multidisciplinary academic databases, including Academic Search Complete (EBSCO), ProQuest, Canadian Research Index, and Google Scholar. A disability justice-informed critical approach using anti-ableism, anti-colonial, anti-racist and intersectional analysis allowed for focusing on a total of 31 articles and book chapters were chosen because they center a disability justice framework to address various issues related to AI development and how it can be used to advance disability justice and liberation.

Towards an Accessible Inclusive Artificial Intelligence (AI2)

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Full report

1 Background

Artificial intelligence has become a remarkable feature of our era; it is being deployed in many aspects of our lives without properly considering its impact. Specifically, AI can perpetuate and exacerbate biases. AI bias is a situation where AI algorithms reproduce or exacerbate existing inequities in socioeconomic status, race, ethnic background, religion, gender, disability, or sexual orientation (Panch et al., 2019).

AI-based software group data or make predictions about future occurrences of events (e.g., onset of a disease, likelihood of success of an operation, risk of readmission to a hospital, the song you would like to play next, the likelihood of being a productive employee); AI can also predict numbers (number of people infected with COVID-19). Finally, it can cluster people or events into similar groups and predict to which group a new person/event belongs based on its similarity with existing groups.

To make these predictions, AI-based software uses algorithms that rely on models built based on existing data (e.g., data that represents the past). These models are assumed to represent the real world and are used to make future predictions (Figure 1).

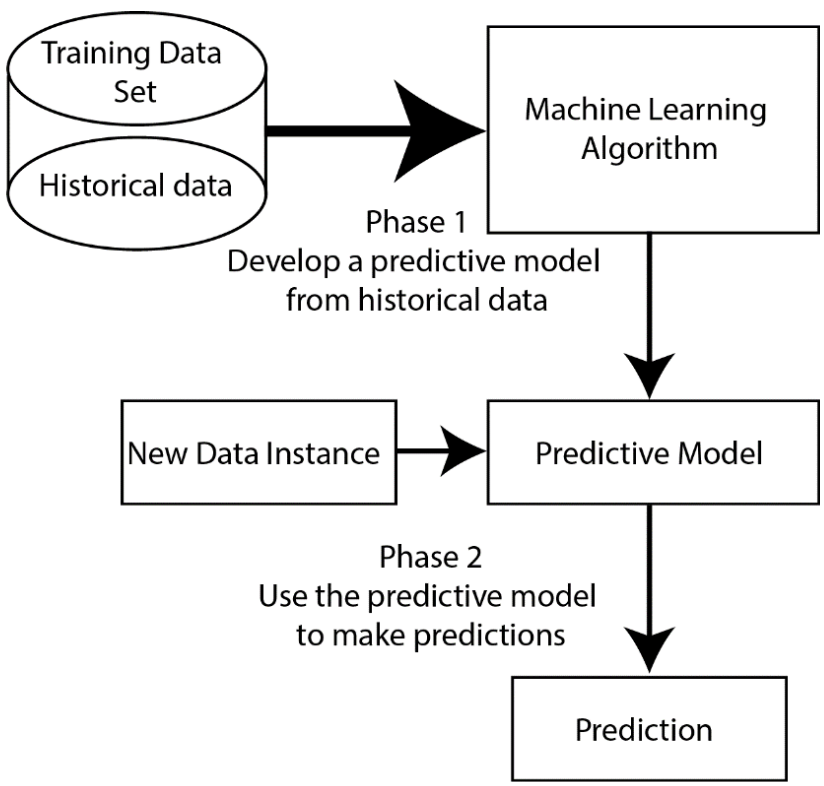

Figure 1: AI: Building and Using a Predictive Model (El Morr & Ali-Hassan, 2019)

AI bias can be introduced or amplified at various points from the initial dataset to the algorithm output. If algorithms use biased data, the results could also be biased (Parikh et al., 2019).

The quality of data used to train the AI algorithm determines the quality of the model and its predictive capacity (Parikh et al., 2019). Data sources like electronic health records (EHRs) and insurance claims generate data as a result of human decisions; if the data represent biases in the current social environment, then AI models that rely on this data will perpetuate and exacerbate those biases (Kundi et al., 2023; Parikh et al., 2019). For example, an AI algorithm that learns from older EHR data may not recommend that older women be tested for cardiac ischemia, resulting in delaying potentially lifesaving treatment and further perpetuating implicit social biases (Parikh et al., 2019).

Furthermore, the person in charge of designing these algorithms can reflect their human judgment and prejudice in the AI models, making them biased (Parikh et al., 2019); for example, specialists charged with building the models can decide to focus on some aspects of the data and ignore others for reasons of availability of some data items and the lack of other ones. This might exacerbate biases against some populations; for example, people from vulnerable populations, including immigrants and those with lower socioeconomic status or mental health issues, are more likely to visit several institutions or healthcare organizations to receive care (Gianfrancesco et al., 2018); these patients may have inadequate or missing information in the electronic health records; any AI decision support tool will lack representativeness of their situation and hence, if used, will exacerbate exclusion (Gianfrancesco et al., 2018). Another example would be an AI model that analyzes clinical trial data in order to determine the best treatment option; such a model would contain inherent racial and gender biases since clinical trial subjects are overwhelmingly male and White, which could potentially result in inappropriate recommendations for other patients (Curran, 2021).

AI bias has been reported in many areas, including business (Manyika, 2019; Manyika et al., 2019), social media (Nouri, 2021), the economy (Omowole, 2021), politics (Kumawat, 2020), and healthcare (Siwicki, 2021). While researchers started to account for the types of biases built in AI-based software, to our knowledge, investigating AI biases towards people with disabilities is virtually nonexistent. A recent scoping review by the applicants that documented AI biases could not find studies related to AI bias in relation to people with disabilities. There are virtually no studies about the subject, while AI is increasingly present daily. We must ensure that AI models are built accessibly and inclusively for people with disabilities and other groups.

AI is gaining ground in daily social lives and is used to assist in decision-making for social and health needs. AI has the potential to benefit people with disabilities if properly designed, implemented, tested, and monitored to make sure that they are accessible by and inclusive of people with disability.

The disability inclusion framework, "Nothing about us without us' needs to extend to new technologies that have the potential to exacerbate inaccessibility and add to exclusion. While literature is starting to address AI biases, no prior work has been done concerning AI and its impact on accessibility and inclusion. As such, ensuring the representation of the disability communities is at the center of this project from its inception to various proposed knowledge-mobilizing activities. Concretely, we will establish an advisory group composed of disability organizations representing the sector, disability advocates, and individuals with disabilities to guide the research process and ensure that the voice and representation of the disability communities are at the heart of this proposal. This will help facilitate our commitments to equity, diversity and inclusion principles and support our accountability to creating an inclusive and accessible AI framework.

Synthesizing knowledge AI accessibility and inclusivity in relation to people with disabilities is paramount. We intend to work with people with disabilities organizations to conclude our knowledge synthesis with the development of a framework that helps building an accessible and inclusive AI for people with disabilities.

In a time where there is much emphasis on equity, diversity and inclusion principles guiding research and knowledge production, it is important to recognize AI biases and eliminate their impacts on the disability communities. As such, we expect this synthesis to open the door for a new field of research and add a much-needed interdisciplinary and transdisciplinary knowledge development that addresses AI biases and their impacts on people with disabilities. Our project seeks to engage graduate students, disability advocates, policymakers, researchers, AI companies, and the public with the aim of transforming AI to be more inclusive by understanding and addressing its biases against people with disabilities.

Yet beyond and through this tangible outcome, we anticipate major impacts on the disability and AI fields. We want to be part of a movement to bring AI to bear on public policy and public good while guarding against corporate rentiership of human and social data and the reproduction of oppression and inequality (Birch & Muniesa, 2020). We hope that by focusing on Accessible and Inclusive AI for people with disabilities, we can develop a preliminary framework for approaching broad and challenging issues related to AI and disability, which are to:

- Identify the type of exclusions and hurdles to accessibility embedded in AI algorithms in relation to people with disabilities.
- Identify preliminary parameters (policies and techniques) required for an accessible, inclusive AI.

2 Objectives

This project is concerned with synthesizing knowledge about AI's impact on people with disabilities and proposing a framework for developing **A**ccessible **I**nclusive **A**rtificial **I**ntelligence (AI^2) for people with disabilities.

3 Methods

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4 Results

4.1 Result 1: AI, Disability, and Inclusive Design

1.1.1 AI and Disability

4.1.1.1 Addressing Disability Justice

Thirty-five articles out of forty-six (76.09%) addressed using AI for disability, and eleven addressed the disadvantages and challenges. Twenty-five articles out of thirty-five (71.43%) were medically focused. In comparison, six articles addressed assistive technologies for people with disabilities (17.14%), and only four articles (11.43%) have addressed disability justice issues and hence focused on the social context of people with disabilities. However, one of the four articles technically focused on AI development (Terziyan & Kaikova, 2021), and two belonged to the same study addressing disability justice (El Morr et al., 2021; Gorman et al., 2021). Hence, we conclude that only two studies out of thirty-five (5.71%) addressed disability justice issues. This reflects a social context where the medical model of disability is prevalent in AI.

There is a lack of use of the social model of disability in AI research. The field of disability research would benefit from involvement in **interdisciplinary research** with AI researchers as it enlarges the vision of disability in the AI field beyond impairment to the social context and reclaims the disability voice in the engineering and computer science fields so that the “nothing about us without us” materializes in those fields. Thus, upholding the "nothing about us without us" principle in these fields is crucial. More concerted interdisciplinary research joining researchers from critical disabilities, social work, and health informatics and more targeted funding would be essential to advance the social agenda related to people with disabilities in AI.

4.1.1.2 Prevalence of the Medical Perspective

This high prevalence of the medical perspective in the use of AI for people with disabilities is reflected by the topics covered by previous studies. A study by Ghafghazi et al. (2021) proposed an AI-based e-health system that simplifies access to outpatient clinics, telehealth platforms, and rural areas for early **detection of autism and intellectual and developmental disabilities** (AUIDD). The proposed AI-augmented learning and applied behaviour analytics (AI-ABA) platform used sensors (e.g., cameras, wearable sensors) and AI algorithms to enhance the quality of personalized treatments and learning plans provided to AUIDD patients. Another study addressed the application of ML techniques in predicting disability progression, which is critical in MS management.

4.1.1.3 Assistive Perspective: Missing the Broader Implications

Previous reviews also covered assistive technologies about life experiences, communication, and the elderly population.

Life experiences**.** A review by Domingo et al. (2021) provided an overview vision of the ways ML can be used for assistive technologies for visually impaired, hard of hearing, and physically impaired people and suggested the use of AI and 5G to support people with disabilities and life experiences while shopping, travelling, working, and at home.

Communication**.** Another review analyzed how AI technologies can be assistive technology for people with disabilities by providing speed and precision in analyzing and decoding complex communication, expression, and visual behaviours, enhancing communication and educational experiences for children with disabilities (Zdravkova et al., 2022). Also, a systematic review reported how AI-based conversational systems, such as chatbots and dialogue agents, can provide accessible and affordable healthcare services to individuals with cognitive disabilities, such as dementia and Parkinson's disease (Huq et al., 2022).

Elderly**.** We found that the elderly population is getting attention in the AI field, consistent with previous research on Assistive technologies for the elderly population, such as health applications, autonomous robots, and intelligent homes that could address the critical challenges of aging and improve the well-being of older adults (Teng & Ren, 2021). AI-based innovative community network platforms combining medical care and elderly care were suggested to help older individuals and those with disabilities, including those with visual, hearing, and intellectual disabilities, receive the necessary support and maintenance and improve their health and well-being (Teng & Ren, 2021).

There is a potential for AI-powered products to cater to elderly and disabled individuals who face more complex healthcare needs, remove psychological barriers, and improve individuals' overall quality of life. Humanoid robots, for instance, can assist older individuals and those with disabilities complete complex tasks and speed up rehabilitation (Teng & Ren, 2021). These robots can perform real-time health monitoring, provide intelligent, emotional interaction, and issue accident warnings (e.g., during a fire) to help the disabled person move to a safe area and act as an escort to provide care and safety (Teng & Ren, 2021). AI also has the potential to address the educational, adaptive, and social skill gaps that occur because of persistent health problems in students with intellectual disabilities, including the elderly population (Kharbat et al., 2020).

However, such use of AI raises serious concerns about data security and individuals' privacy, especially when the individuals concerned by the application are people with intellectual disabilities. **This interplay between intellectual disability and privacy has received little attention in AI and could be a potent future research area.**

4.1.1.4 Disability Risk: A Narrow View

The use of AI to address disability at work was found to be tailored towards managing human resources. This is consistent with previous reviews that covered the use of AI to predict **absenteeism** and **temporary disability** (Montano et al., 2020). Across 58 articles the review covered, the social implications of such human rights approaches were absent. There is a tendency to use AI from a technology perspective to achieve effectiveness and efficiency **without consideration of the broader impacts of the use of technology.**

4.1.1.5 From AI Ableism to Knowledge Creators

Previous research found that disabled people are depicted as AI and ML technology users in various sources, including academic literature, Canadian newspapers, and Twitter tweets with a techno-optimistic tone (Lillywhite & Wolbring, 2020). However, disabled individuals, such as governance and ethics, are not depicted as knowledge producers or influencers in AI/ML discussions. This highlights the need for a more diverse representation of disabled people in AI/ML-related contexts to ensure they become meaningful contributors and beneficiaries in AI/ML discussions (Lillywhite & Wolbring, 2020). **This lack of disability-centeredness and the approach to AI production that excludes people with disabilities as knowledge producers are significant deficits in AI research today.**

4.1.1.6 Bias is off the radar: the absence of Debiasing Strategies.

None of the articles dealing with prediction accounted for bias; none measured bias related to any population (e.g., gender, type of disability). This reflects a situation where the awareness of bias and the need for debiasing strategies is virtually nonexistent in the studies covered in this review. There is a need to emphasize AI risks, including bias and risk mitigation, on the research agenda of AI researchers and in the academic curriculum.

1.1.2 AI and Inclusive Design

The reviewed studies show that AI technology can significantly help people with disabilities. AI was used to improve accessibility in many settings and for several conditions, which resulted in better accessibility at home, in daily activities, or education, employment, and healthcare settings. However, the results of these studies seem to be in their preliminary phases, as testified by the lack of research in AI and accessibility and the small sample sizes of participants. Among the 14 studies that reported their number of participants, 11 had less than 70 participants, two had 145(Rivas-Pérez et al., 2019) and 215(Gupta & Chen, 2022), and the only study that included one thousand participants was in the face of a dataset collected, not an experiment conducted (Namoun et al., 2022).

4.1.1.7 Absence of a co-design approach

Remarkably, two studies had participants with disabilities (Ballenger, 2022; Rocha et al., 2023). This contradicts a long-standing health information systems principle of user-centred design (El Morr, 2023).

Also, researchers in health informatics, computer science, and engineering dealing with systems for living human beings need to understand the domain they are working in from a human perspective. One of the main principles of the disability justice world is “nothing about us without us” (Charlton, 1998; United Nations, 2004); i.e., people with disabilities’ voices should be central to any work, including AI, on disability issues, especially if such work aims to increase accessibility *for* people with disabilities. Researchers can go beyond the co-design principle (David et al., 2013) to engage with design for justice (Costanza-Chock, 2020), particularly design justice AI (Costanza-Chock, 2018).

4.1.1.8 Potential Biases

The effectiveness of data-driven AI models is heavily contingent on how the data was predominantly collected (Wald, 2020). For example, a limited understanding of accents and speech patterns (Ballenger, 2022) or low data quality in low-light areas (Amangeldy et al., 2022) could affect AI models. Also, non-representative data would lead to biased AI models (Kundi et al., 2023) that directly impact equity (Gurevich et al., 2023).

Ethnicity and gender were either not captured or not reported adequately. Age groups were more adequately captured and aligned with the uniqueness of the studies' aims. The inadequacy of the limited (very limited in some cases) sample sizes is another limitation that may lead to biases. A small sample size might be acceptable in a prototyping phase; the confirmation of improvement in accessibility driven by AI needs larger sample sizes and robust intervention designs.

4.1.1.9 **Diversity and Inclusion**

The studies were from different continents, reflecting some global diversity in the population; however, 11 were from Europe and North America. In addition, the participants in only two studies that reported ethnicity and limited diversity were predominantly Caucasian: 100% in a study in North America (Raja Vora et al., 2021) and 75% in a study from Europe (de Saille et al., 2022).

Diversity and inclusion are important to drive social inclusion in an information system (Cushman & McLean, 2008; Trauth, 2017). A diverse and inclusive environment is important for designing AI-based systems and mitigating AI biases.

4.1.1.10 **AI Model's Acceptability**

Also, the model performance needs to be studied well. At what performance level might an AI system become a nuisance?

In the AI field, a model with low performance indicates a poorly working model. Low-performing models might deter engagement, adoption, and use. An AI-based system that provides feedback to users, such as in assisted living, can lead to mistrust and frustration if it provides a lot of false positive alarms (Piau et al., 2019). AI-based systems must guarantee high accuracy and specificity, potentially flagging ordinary situations as hazardous (Guerra et al., 2020). In addition, design issues might be problematic; for instance, fast and loud movements of robotic arms, as observed in cobot applications (Drolshagen et al., 2020), can result in discomfort and stress among users.

However, in the disability field, the high accuracy sometimes indicates a poorly working model. A model that becomes a nuisance is a poorly working one. In one study, the Automatic Speech Recognition software unquestioningly represented every word said, including words that were not meaningful, such as pause (e.g., "like," "um," side comments), which became more distractions (Ballenger, 2022). A high-performing model should consider these pauses like human-provided Speech-to-Text-Services. This new insight must be integrated into AI research for people with disabilities and can benefit any users.

The reviewed studies highlight the many accessibility advantages offered by AI research. It also points to several challenges and future research directions. While AI systems can increase accessibility, the field is a developing field of research. Future studies need to be more rigorous in research design (e.g., gender and ethnically balanced), more inclusive of people with disabilities in the design approach (e.g., co-design, justice design), and be more transparent in reporting (e.g., age groups, gender, ethnicity). The performance measures of AI systems dedicated to people with disabilities could benefit from adding an element that tames the (over)performance of AI models by a usefulness indicator provided by the users.

While AI technologies offer significant benefits, these disadvantages underscore the importance of addressing technical, ethical, and usability challenges to ensure the effective and inclusive implementation of such technologies for individuals with disabilities. The models' bias remains largely unaddressed.

4.2 Data Justice co-design

Co-design is a form of participatory design (PD) that involves a more extensive range of methods than PD to include users in design processes. "Co-design aims to bring people outside formal design and research spaces into the design process. This method pushes for deeper collaboration with designers and non-designers across disciplines and cultures, emphasizing an acknowledgment of lived expertise" (Bray et al., 2022, para 1). However, Costanza-Chock (2020) explains that many PD and co-design approaches remain extractive by design, i.e., when facilitated by multinational corporations with objectives to commodify co-designers' ideas. More often, efforts at PD and co-design become extractive by "good" intentions and effects in which designers feel good about including community members. For example, Till et al. (2022) describe situations in which co-design efforts led by English-speaking Global North researchers alienate Global South community participants because of unaddressed assumptions of the researchers, language barriers between designers and co-designers, and conflicting cultural norms and interests to the detriment of the communities being "served." This can result in PD and co-design processes in which "inclusion without power is tokenism" (Piepzna-Samarasinha, 2021, p.53).

Data justice is rooted in the tensions between development and surveillance studies in the mid-2000s (Taylor, 2019). The onset of mobile phone technology in low-income countries led to the creation of high volumes of data, which development researchers and giant technology corporations were eager to mine and capitalize on (Taylor, 2019). Development practitioners championed the ability to collect data on poverty and inequities, believing that these datasets would also facilitate remedies to these problems. However, surveillance studies cautioned against the uninhibited harvesting of data from low-income counties, with limited attention to power imbalances, data extraction, and exploitation (Dencik et al., 2016; Taylor, 2019). To negotiate the conflict between development and surveillance, Taylor (2017) asked, "How should we address this tension between the right to be seen and counted and the right to be left alone"? In response, Taylor (2017) proposed three pillars of data justice – visibility, engagement with technology, and non-discrimination.

1.1.3 "Best" practices

4.2.1.1 Data Justice

Building on Taylor's pillars, Heeks and Renken (2016) called for the engagement of data justice frameworks with human rights, and Dencik et al. (2016) called for data justice engagements with activists in civil society. Overall, the field of data justice has been increasingly pushed to broaden the Western-centric lens and scope of research, from problems with datafication, informational capitalism, individual privacy and security rights to social justice issues, collective needs, and non-Western framings of data justice (Leslie et al., 2022).

4.2.1.2 Design Justice

Design justice is an emerging field of research which draws from the history of PD and emphasizes co-design as a critical principle. Design justice came out of the work of the Design Justice

Network. During the Allied Media Conferences in 2015, a group of designers, artists, technologists, and community organizers developed 10 principles for design justice, including a commitment to address oppression through participatory design. Since then, leading design justice researchers and practitioners such as Costanza-Chock (2020), drawing on Black feminist theories of intersectionality, the matrix of domination (Collins, 2002), and disability justice, have defined design justice as a theory and practice which works to challenge white supremacy, heteropatriarchy, capitalism, and settler colonialism in design.

1.1.4 Shortcomings of Current Approaches in Data and Design "Justice"

4.2.1.3 <u>Data "Justice"</u>

Vera et al. (2019) argue that extractive logic will always drive data, even when data and data processes are driven to achieve justice-oriented outcomes. According to the authors, "no data practice can fully escape the pull of non-innocent relations – the embeddedness in racial capitalism and colonialism - that shape data" (Vera et al., 2019, p.3). For example, examining the role of datafication in anti-poverty programs, focusing on India's Aadhaar system, Masiero and Das (2019) unveil multiple instances of data injustice experienced by recipients, including issues such as narrow targeting, misalignment of programs with policy principles, and exclusion of entitled individuals. This reveals a tension between the intended benefits of datafication and the actual outcomes for those in need. Based on field narratives, the authors expose problems such as legal, design-related, and informational forms of data injustice that have emerged with the implementation of Aadhaar. This challenges the assumption that datafication alone can seamlessly improve social protection agendas.

4.2.1.4 <u>Design "Justice"</u>

Chinn (2022) critically examines the communication of goals by Design Justice, arguing that their vision of a liberated world, achieved by flattening the hierarchy between designers and non-designers, falls short due to a lack of analysis of the material conditions within which designers operate. The focus on freelancers, design studio owners, and academics as highlighted members excludes a significant portion of designers in typical corporate settings. Chinn suggests addressing design justice should move beyond personal reflections on individual design roles. Instead, the author recommends following scholars advocating a shift away from design as the primary vehicle for liberation, proposing a broader framework of "plain-old liberation." In a similarly critical vein, Poudyal (2023) challenges us to reflect: "What would the journey toward decolonial-feminist computing, hospitable data, and design justice look like in practice when performed from a space which has access to the "innovation" labs, big data extracting tools, technology centers, massive funding, and audiences?" (p.151).

4.3 Disability Justice Framework for AI

A disability justice framework builds on anti-ableist, anti-racist, anti-colonial and decolonial principles to advance a framework that questions the process and technologies that enable ableism and its normalization. It also facilitates a justice framework beyond liberal notions of inclusion and accessibility. A justice framework for AI and disability seeks to liberate disability from the socio-political, economic, and environmental remnants of heteronormativity and coloniality.

1.1.5 Focus on Technicalities while Neglecting Social Realities

Many scholars call out the focus of AI systems on technical aspects of algorithms and machine learning and question the neglect of social factors beyond ethics and morality (De Oliveira et al., 2022; Ostherr, 2022; Tilmes, 2022). Although many publications speak to the ethics of developing and using AI systems, the social aspects and implications of using AI continue to have significant impacts on disabled individuals and groups. A key tension raised here is related to how AI systems rely on the assumption that foster a universality of knowledge, or one size fits all, which has been heavily challenged and rejected by many disability justice scholars (Mekosha, 2011; Oliver, 2013). Social realities are shaped by many nuanced social interactions that have been neglected by AI design systems.

1.1.6 Lack of Protective Legislations

AI technologies have been widely used in many areas that support people with disabilities, such as in medical assessment and diagnosis, assistive devices, and communication technologies. However, many scholars would argue that the benefits that come with AI technological advancements also created significant challenges that need to be mitigated and addressed (Bennet & Keys, 2019; Land, 2023; Liliwhite & Wolbring, 2020; Marjanovic, Cecez-Kecmanovic & Vidgen, 2022). Some of these challenges include loss or lack of privacy (Ritter, 2021), concerns over AI use in health diagnosis (Bennet & Key, 2019; Whittaker et al., 2019), as well as the overall injustices caused by the over-reliance on AI systems in various disciplines and social interactions (Marjanovic, Cecez-Kecmanovic & Vidgen, 2022; Benett, Rosner & Taylor, 2020; Buyl et al., 2022, Lilywhite & Wolbring, 2020). Liliwhite & Wolbring (2020) call out false assumptions that promote “AI for social good” and argue that disabled people are impacted by how these “social goods" are defined and accessed or whether “doing good” also helps in preventing “bad” (p. 5). As such, the focus of many AI-promoting initiatives continues to center on general governance and standardizations while neglecting legislation that protects disabled communities and groups in meaningful and effective ways.

1.1.7 AI Systems and the Maintenance of Dominant Social Norms

Dominant social norms such as ableism, racism, ageism and so forth continue to be prevalent in societies. AI systems and the algorithms that help their decision-making process are inherently biased and are shaped by widespread dominant social norms that do not question systems of oppression and marginalization, such as ableism and ableist assumptions (Egger, 2021; Liliwite & Wolbring, 2020; Packin, 2021; Ostherr, 2022; Ritter, 2021; Tilmes, 2022). The key premise of AI systems and their biases is based on their limited algorithmic abilities to connect the sophisticated social networks that enable people to interact with other individuals and groups and to negotiate their everyday social realities. Peckin (2021) notes that AI algorithms are mainly built on massive data processing to assess individuals, which fosters wide-scale discrimination in ways that maintain the dominant ableist social norms. The author asserts that “ableism and technology are deeply intertwined in any society” and notes that privileges are assigned to certain types of bodies depending on two key issues: the type of technology and how it is used (p. 489). As such, decision-making processes that do not account for questioning and challenging dominant social norms are inherently problematic and feed into creating and maintaining oppressive ableist AI systems. As such, a disability justice framework would help mitigate some of these inherent flows and address the ways AI systems can be used to challenge dominant social systems instead of maintaining their existence and facilitating their operation.

7.3.4 Lack of accountability

One of the key issues that needs to be investigated further in AI systems is their lack of social and legal accountability. An example of AI's lack of accountability and its consequences for people with disabilities can be seen in the widespread use of AI in military-armed technologies, including automated weapons. People with disabilities are subjected to many risks during armed conflicts and operations, and automated weapons further escalate these risks. Further, Meekosha (2011) speaks about the colonial dimensions that facilitate the production of impairment and questions the ways wars and conflicts have played a major role in supporting violent colonial technologies to control resources and minerals to serve the interests of the Global North. As AI technologies continue to be adopted and widely used in various areas, including wars and conflicts, through automated weapon systems, it is important to question how new war technologies have contributed to the lack of accountability and responsibility to those affected by their use. A study by Diaz Figueroa et al. (2022) calls out the use of AI in autonomous weapons and the lack of legislation that controls their accountability suggests that throughout the international debates and UN discussions on AI and its role in autonomous weapon production and utilization, people with disabilities were never included. Their rights have been constantly violated by the use of these systems. The authors assert that AI systems are not developed in a neutral context and emphasize that they result from Global North's dominant social and economic priorities that constantly reproduce "disproportionate negative consequences for marginalized groups, and for the global south in general" (p. 286).

5 Implications

5.1 Implications for AI Researchers

After considering the issues of disability justice, narrow views on disability risk, AI ableism, debiasing strategies, co-design approach, diversity and inclusion, and AI model's acceptability, it is clear that there is a need for more emphasis on these areas in the development and implementation of AI systems. To address these issues, three recommendations are important:

1. AI developers and researchers take a more holistic approach that is centred on understanding the social and medical perspectives of disability.
2. This approach should include diverse perspectives and experiences in designing, developing, and evaluating AI systems.
3. Additionally, it is important to prioritize implementing debiasing strategies to mitigate the risk of AI ableism and address the absence.

5.2 Recommendations for future research and practice

1. Engage data practices against racial capitalism and colonialism. Discussing Environmental Data Justice (EDJ), Vera et al. (2019) argue that "EDJ as a framework still sees promise in data as part of justice." The authors give the example of the Indigenous Data Sovereignty

Network, which stewards data for and about Indigenous Nations and peoples in settler America in the interest of collective and individual Indigenous aspirations and needs.

2. Engage with Chinn's (2022) concept of incorporating labour analysis into the design justice framework, positioning labour unions as conduits for design justice work. This perspective allows for identifying hierarchies within unions, particularly between traditionally recognized designers and non-designers. Chinn argues that stronger unions can be built by addressing these stratifications, which better address the concerns of the most marginalized individuals and contribute to collective liberation.
3. Engage with Poudyal's (2023) feminist design justice approach with and for the Global South. Poudyal (2023) builds on design justice (Costanza-Chock, 2020) to advance a dialogue between design and data, which subverts the "heteropatriarchal, imperialist, capitalist, neoliberal understanding and practice of design and technology" (p. 149).

5.3 Towards a Disability Justice Framework

AI systems function in unidirectional ways that leave out accountability issues of these systems to predictable ableist and biased data. A disability justice framework to address ableism and AI begins with decentering medical modalities and moving away from the universal and limited rights-based approaches to disability care. A disability justice framework centers on the interdependent nature of socio-political and economic relationships that shape social interactions, especially in health care and well-being contexts. As such, key principles to be outlined in a disability justice framework for AI include:

1. Centering the social realities of disabled people during the design, development, and updates of AI systems.
2. The focus needs to center on the interconnectedness of social relationships within and between various social systems affecting the everyday experience of disabled individuals and groups.
3. Paying explicit attention to how AI systems have been actively used in wars and armed conflict in ways that inflict colonial violence and contribute to the production of impairment.
4. There is an urgency to move away from focusing on cost-benefits and one-size-fits-all approaches of AI design, development, and updates to center the socio-political and economic implications of AI use beyond the limited technical priorities of efficiency and effectiveness.

6 Conclusion

- Future research should extend the research to include a social lens of disability and address AI biases. Research and development in AI needs to be multi/trans-disciplinary and inclusive of people with disabilities as partners; it cannot be left to engineers. Such an approach aims to foster a more inclusive understanding of AI-driven interventions' health and social advantages for people with disabilities. Moreover, embedding social and ethical components in the engineering and computer science curriculum is imperative.
- Extractive logic always drives data, even when data processes are driven to achieve justice-oriented outcomes. Yet, there remains promise in the role of data in justice. Labour-based

and feminist design justice approaches with and for the Global South can support the design and development of more justice-oriented data practices and outcomes.

- To address data colonialism, there is a need to move beyond a one-size-fits-all approach in how social policies and care practices are promoted and valorized in the race for effective AI systems. Nuanced policies governing AI production, use and consumption need to move away from cost-benefit analysis to include a comprehensive account of the socio-political and economic implications of AI use beyond technical terms of efficiency and effectiveness.

7 Knowledge Mobilization Activities

The project aims to inaugurate a new multidisciplinary research and partnerships field and develop an inclusive and accessible AI framework. Our comprehensive knowledge mobilization plan aims to address AI biases against people with disabilities. Our knowledge mobilization plan includes academic, community, and government domains.

In the **academic domain**, the project will disseminate its findings through peer-reviewed publications and the development of an inclusive and accessible AI framework. The dissemination will focus on engaging academics and researchers through conference presentations, webinars, and workshops to enhance and fine-tune the framework. Students will also be mentored and supported to participate actively in knowledge creation and dissemination. The project findings will be channelled to disability studies, social work, and AI classrooms to support students' skills and knowledge development.

The **community organization** domain will also participate in the webinars and workshops and be partners in developing the inclusive and accessible AI framework.

In the **government domain**, our team will develop policy briefs and videos targeting policymakers. The policy briefs will inform policymakers on how to navigate AI systems and support the development of programs and services that benefit from inclusive and accessible AI systems.

The knowledge mobilization activities include **publications**, **videos**, **webinars**, **workshops**, student **training**, **teaching**, **supervision**, and **social media communication**. The results of the knowledge synthesis will be published at national and international **conferences** and in high-impact open-access **journals**.

The AI2 framework will be available on the project website for all stakeholders. Workshops, webinars, and videos will raise public awareness and engage researchers, the disability community, and policymakers on AI biases towards people with disabilities and the need for a debiasing framework.

The knowledge created from the project will be used in teaching material in disability studies, AI, and social work. The project will create opportunities for the supervision of graduate students interested in contributing to developing the subject in many directions and developing the AI2 framework.

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