Alternative models: Critical examination of disability definitions in the
development of artificial intelligence technologies

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Abstract
Disabled people are subject to a wide variety of complex decision-making processes in diverse areas such as healthcare, employment, and government policy. These contexts, which are already often opaque to the people they affect and lack adequate representation of disabled perspectives, are rapidly adopting artificial intelligence (AI) technologies for data analytics to inform decision making, creating an increased risk of harm due to inappropriate or inequitable algorithms. This article presents a framework for critically examining AI data analytics technologies through a disability lens and investigates how the definition of disability chosen by the designers of an AI technology affects its impact on disabled subjects of analysis. We consider three conceptual models of disability: the medical model, the social model, and the relational model; and show how AI technologies designed under each of these models differ so significantly as to be incompatible with and contradictory to one another. Through a discussion of common use cases for AI analytics in healthcare and government disability benefits, we illustrate specific considerations and decision points in the technology design process that affect power dynamics and inclusion in these settings and help determine their orientation towards marginalisation or support. The framework we present can serve as a foundation for in-depth critical examination of AI technologies and the development of a design praxis for disability-related AI analytics.

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Introduction

People with disabilities must often rely on a wide range of resources and support systems to meet access needs in their personal goals and daily activities. These resources and systems are managed by a broad network of constituencies, ranging from healthcare and social services to employers, policymakers, and urban planners, each largely disconnected from the others and using a limited subset of information to make decisions that affect the lives of thousands or millions of disabled people. As artificial intelligence (AI) technologies become more widespread and are increasingly used by these different stakeholders to inform decision-making, there is a clear need to understand how the design of AI technologies will affect the disabled people who are the subject of those decisions.

Disabled people already experience significant injustice and ableism in healthcare, the public sphere, and the workplace (Shakespeare et al, 2009; Ross and Taylor, 2017). By drawing on existing (and inequitable) structures of power, algorithmic and AI systems have considerable potential to not only replicate these injustices but even exacerbate them through broader application and the illusion of algorithmic neutrality (Whittaker et al, 2019; Alkhatib, 2021). Entwined with the question of equitability is the complex issue of when it is appropriate to use a technology, and what the risks might be of using it or not using it. This was well-illustrated by the use of algorithmic approaches to automatically expand the list of people recommended to shelter at home in the United Kingdom due to COVID-19 risk: automated identification of vulnerable members of the population offered improved safety with respect to health, but also increased risk of physical and mental harm from isolation and restrictions in opportunities to participate in the workplace (Patel, 2021). Moreover, through perceptions of impartiality, algorithmic tools can offer ostensibly neutral insight while actually reinforcing existing power structures and deflecting attention away from structural injustices, as seen in the focus on self-management over contextual understanding in mental health apps (Weinberg, 2021).

This article investigates a deceptively simple question that is fundamental to the process of developing responsible disability-related AI technologies: What do we mean by disability, and what does that mean for AI development? Our discussion aligns with a critical disability studies perspective (Garland-Thomson, 2013), and examines the AI development process through the lens of crip technoscience, which reflects “the co-production of science, technology, and political life” with regard to disability as an important and desirable part of the world (Hamraie and Fritsch, 2019). Following the goals articulated by Meekosha and Shuttleworth (2009), we present a theoretical framework to illuminate previously-invisible assumptions in the praxis of (disability-related) AI development. We use three common ways of conceiving
disability—the medical model, the social model, and the political/relational model—to illustrate how different definitions of disability can lead to distinct and often incompatible AI technologies, even when they are developed to serve the same overall goal. We show how combined with the lack of disabled people’s input and perspectives in the AI development process, these divergent technological endpoints lead to both representational and allocational harms in social processes that use AI technologies.

The umbrella of “AI technologies” includes both end user-facing technologies for accessibility and more “under the hood” uses of AI for information processing and data analytics, which often occur behind the scenes and may be invisible to end users. The role of AI technologies in accessibility is an active and growing area of study, including developing and improving technologies for accessibility (Raja, 2016; Wu et al, 2020; Zhang et al, 2020), evaluation of existing technologies through an accessibility lens (Kushalnagar et al, 2014; Gleason et al, 2019; Bennett et al, 2021), and critical analysis of the role of technologies in mediating accessibility (Elcressor, 2016; Alper, 2017; Goggin, 2017; Miller, 2017; Shaheen and Lohnes Watulak, 2018).

In this article, we focus on “under-the-hood” use of AI for information processing, particularly AI technologies used to inform decision-making processes in healthcare, employment, and policy. Decision-making is a rapidly growing area of AI application and one with significant risks for inequitable development due to the distance between the AI technologies and the people who are affected by their use. Our work begins to lay a path towards disability-led design of AI technologies for decision-making settings, not only to improve the equitability of these technologies but also to imagine how AI technologies can help to advance inclusion and political power for disabled people.

We structure our discussion using two running examples of use cases for AI-powered data analytics, set in two decision-making contexts that have historically pathologized and marginalised disabled people: healthcare and government benefits. We focus not only on the use of AI technologies to make (or recommend) decisions automatically, but also to inform decisions made by humans, often as one part of complex, pre-existing processes. Our example use cases are:

(1) Facilitating communication of the needs and priorities of disabled people in their healthcare, to inform decisions made by health providers and systems regarding diagnoses, treatments, and allocation of support resources such as assistive devices or home health aides;

(2) Facilitating the process of determining eligibility for and allocating financial benefits to disabled people via social support programs.

These use cases represent common scenarios encountered by disabled people, and key points at which the introduction of AI technologies for information processing and data analytics has the opportunity to both advance equitable decision-making and reinforce existing inequities. We examine how normative assumptions and a lack of disabled inclusion in the AI design process

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can lead to harmful technologies that perpetuate unjust power structures and curative violence in situations like these, and lay out a basis for actively interrogating each step of the design process to critically examine AI technologies through a disability lens. Our discussion thus serves as a first step towards illustrating what a disability-led and anti-ableist design process can look like for AI technologies in decision-making.

**Definitions of Disability**

We frame our discussion through three common conceptual models of disability, each of which presents a different perspective on what disability is, how it may be perceived or measured, and who or what is involved in producing disability identity. In Table 1, we compare and contrast the goals of AI technologies for data analytics that could be developed for our two example use cases under each of these disability models.

The **medical model** views disability as an attribute of a person, typically stemming from a particular health condition or injury. On this view, disability is *diagnosable* and may be clearly defined in terms of specific criteria: e.g., a person with muscular dystrophy or a lower extremity amputation inherently *has a disability*. The medical model thus reduces disability to a specific “problem”; healthcare then aims to “fix” this problem, while social support programs in government or civil society largely aim to provide financial or other resources to people rendered *incapable* by their disability. Medicalization of disability has facilitated significant and consistent harms to disabled people since the Industrial Revolution, from eugenics policies to medical errors and unnecessary interventions (Peña-Guzmán et al, 2019). Despite these issues, the medical model of disability remains the predominant operational definition in disability policy (Smith-Carrier et al, 2017), employment (Barnes and Mercer, 2005), and medical practice (Shakespeare et al, 2009), and therefore often serves as the default understanding of how “disability” is defined in daily life. Under the medical model, AI technologies are thus primarily developed to analyse information related to diagnosis and pathology, and emphasise curative treatments and goals rather than person-centred interventions.

The **social model of disability**, by contrast, conceptualises disability as a phenomenon emerging from the interaction between a person and their environment. On this view, disability is neither static nor internal as in the medical model: rather it is dynamic and external, emerging from situations and environments that contribute to a process of enablement or disablement (Verbrugge and Jette, 1994; Shakespeare, 2006). The social model thus in principle requires measuring and understanding both a person’s capacities and needs (physical, cognitive, and otherwise) with respect to functioning in different activities and social roles, and the facilitators and barriers to that functioning presented by a given environment.
Table 1. Comparison of possible goals for developing AI technologies for data analytics under different definitions of disability, using use cases in healthcare and government benefits.

| Example use case                                                                 | Medical model                                                                 | Social model                                                                 | Political/Relational model                                                                 |
|---------------------------------------------------------------------------------|-------------------------------------------------------------------------------|------------------------------------------------------------------------------|------------------------------------------------------------------------------------------|
| Facilitate the communication of the needs and priorities of disabled people in their healthcare | Capture, monitor, and analyse information on body functions and structures to detect changes in health trajectory | Monitor and analyse physical environments to identify barriers to desired function and suggest appropriate assistive devices and/or accessibility changes | Analyse information about access to healthcare, social support, and government resources to identify gaps in supporting the person’s stated goals and priorities |
|                                                                                 | Prioritise treatment targets and strategies based on patient’s health priorities and provider goals | Prioritise therapeutic interventions based on person’s priorities and barriers in functioning | Help to identify other disabled people with similar goals to connect and grow community and power |
| Facilitate the process of determining and allocating financial benefits to disabled people via social support programs | Analyse medical evidence to assess whether a person meets impairment-based eligibility criteria for benefits | Analyse evidence of functional limitations and functional needs to assess whether benefits are needed/appropriate to cover the gap | Analyse evidence of needs for assistive resources and support structures to identify resource gaps that financial benefits can help allay |
|                                                                                 | Recommend additional medical screening to assess relevant criteria           | Recommend additional self-reported data collection or professional assessment on functional status | Recommend additional programs and services to connect the disabled person to regarding their non-financial needs |
The social model has its roots in sociological research in the mid-20th century (Nagi, 1965) and since its formal articulation in the 1980s (Oliver, 1983) it has become one of the dominant academic perspectives across disability studies, social policy research, and rehabilitation science. The World Health Organization’s International Classification of Functioning, Disability and Health (ICF; World Health Organization, 2001), an internationally-accepted standard for defining and describing disability, draws primarily on the social perspective in its biopsychosocial model of human function, and disability policies in the United Kingdom and in Scandinavian nations draw on the social model’s focus on contextual factors (including physical, social, and cultural environments) (Mercer and Barnes, 2004; Christensen et al, 2008; Lindqvist and Lamichhane, 2019). However, the multidimensional nature of the social model has proven difficult to operationalise in practice, and measurement and decision-making in healthcare, employment policy, and other areas often still rely primarily on medical definitions (Roulstone, 2004; Bingham et al, 2013). The social model has also been criticised for overreliance on environmental factors, leading to de-emphasis and de-valuing of biological and medical factors that affect people’s health and personal experience (Oliver, 2013; Owens, 2015; Shakespeare, 2017). The social model has been used to guide only limited development of AI technologies, but these have focused primarily on information about experienced limitations in function and barriers to function from a whole-person perspective (Agarronik et al, 2020; Newman-Griffis et al, 2021).

A more recently-developed model, the political relational model of disability bridges some aspects of both the social and medical models, but shifts to a more community-level understanding of how disability is produced. Rather than focusing on the source of disability, the relational model emphasises the role of disability identity (whether claimed by oneself or assigned by others) as a site of collective action and a category affecting social relations (Kafer, 2013). The relational model has emerged in part together with the growth of critical disability studies as a field over the last two decades, but is strongly rooted in the history of disability justice and crip activism in the twentieth and twenty-first centuries that has helped build an academic and policy understanding of the intersectionality of disability. On this view, disability is both a shared political experience and a way of categorising and relating to others, whether for community-building, support, and inclusion or for othering, marginalisation, and exclusion. A political relational perspective on disability thus critically extends the social model to account for collective factors of access, support structures, governance, and political power to achieve personal goals and address individual or collective needs. It therefore resists the depoliticization of disability through technology (or other means) by centering the political milieu that technology is necessarily produced in, despite narratives of neutrality and impartiality. This understanding—that because disability is inherently political, so too must be anything that materialises disability, including information technology—is central to our critique of AI development practices. While no AI technologies we are aware of have been developed with an explicit alignment to the relational model, Table 1 imagines possible goals for AI technologies
focusing on information about power and support structures, communal resources, and building interdependent connections.

*Interactions between these definitions*

These and other definitions of disability are neither mutually exclusive nor strictly complementary. Rather, each highlights different aspects of individual experience and health as more or less salient, and prioritises different factors in defining what is and is not disability or being a disabled person. It is in the operationalization of these definitions that they may come into conflict. For example, a person with a medical diagnosis of chronic pain may meet medical criteria of disability, but with access to appropriate medication and support structures may experience minimal disablement from a social model perspective. Similarly, a person with severe arthritis may experience considerable disablement in environments that require high mobility, but may not be diagnosed with a medical condition that meets political/formal definitions of disability and thus lack access to helpful state-provided financial, social, or medical resources. When technology is introduced—whether or not it is explicitly disability-related—the presence and use of the technology affects both behaviour and the production of identity, thus becoming both part of the environmental context of the social model and the personal and political context of the relational model (Forlano, 2017). The development and critique of information technologies, even if conceptualised through one dominant model, must therefore be viewed through multiple lenses to understand their goals and effects.

**The Need to Interrogate Ideology in AI Development**

AI and other information and communication technologies (ICTs) are typically designed in environments and with goals that reflect ableist ideologies that actively harm disabled people. AI technologies are often conceptualised as an intervention-based cure that can “heal” or “erase” disability, thus both stigmatizing disability as “wrong” and in need of fixing and framing analysis in terms of impairments and pathologies rather than the disabled person’s lived experience and participation (Stramondo, 2019; Williams and Gilbert, 2019; Kafer, 2013). Additionally, non-disabled creators and technologists bring top-down assumptions toward creating technology where disabled “stakeholders” are not agentic, but passive users testing out the ideas of designers who are almost always non-disabled (Gardner et al, 2021). Our focus in this article is not on how AI may support access needs or improve quality of life. Rather, we are concerned with the mechanisms through which ableist ideologies are often assumed and rarely interrogated in AI development, and the resulting ways in which AI technologies tend to engage in curative violence and serve to erase disability as a cultural and political identity (Kim, 2017; Williams and Gilbert, 2019).
There are multiple interlocking mechanisms that support ableism in AI development. Disabled people are neither assumed to be nor hired to work as creators and designers of AI technologies, excluding them from having agency in the development and evaluation of AI technologies with direct impact on their lives. Efforts to improve marginalised communities’ “participation” in AI design often fail to make meaningful change in representation and input, as this participation comes in the form of external feedback rather than truly collaborative participatory design (Sloane et al, 2020). This is intertwined with the curative goals that often drive conceptualisation and implementation of health-related AI technologies (i.e., that they will be used to help cure or fix the “harm” of disability), which are often based on normative assumptions of disability as deviation from a desired social norm. By drawing on the crip technoscience perspective articulated by Hamraie and Fritsch (2019), we reject the position that disability needs to be conformed to societal norms and assimilated within a society that tolerates it, and begin to imagine AI development processes that see disability as a desirable part of the world and AI technology as inextricably political in materialising that view.

To inform our analysis, we draw on the robust methods that have been developed by critical digital race studies and Black technoscience scholars who challenge the interlocking networks of racism and other networks of oppression (see Noble, 2018; Benjamin, 2019; Hampton, 2021; McIlwain, 2019). For instance, Chun’s (2011) articulation of race and/as technology interrogates the ways ICTs, such as AI, work both alongside racist ideologies to reinforce racism, and can be used as a tool of racism themselves. Just as ableism is interconnected with racism, so ableism too is reinforced by technology and is used as a design tool (Williams et al, 2021; Spiel et al, 2020; Rauchberg, 2022). Birhane and Guest (2021) interrogate the many pressures, assumptions, and norms throughout the computational science ecosystem that oppress and exclude people of color and queer people; their observations and call for decolonialisation may easily be extended to include the ways in which disabled people are oppressed and excluded in computation (including AI). We do not see ableism as an ideology separate from racism, and the same critical tools that shed light on technological racism can inform our understanding and change of technological ableism.

To develop a praxis for more just development of disability-related AI, it is important to first understand the patterns in how unjust AI harms disabled people. AI technologies can contribute to medical harms (such as unnecessary amputations or overmedication), social and financial harms (such as refusal of benefits or exclusion from the hiring process), and political harms (such as over-policing and disenfranchisement). Ableist approaches to AI development harm are largely rooted in assumptions of compulsory able-bodiedness and -mindness (McRuer, 2006), and often impose additional access-based burdens on disabled people, both as users and as subjects of analysis.

Assistive AI and other technologies, though motivated by principles of universal design, can nonetheless often place more onus on disabled people to generate accessibility, thus reinforcing
ableism, neurotypicality, and audism in technology creation. For example, sign language gloves and translation technologies tend to place the burden of access on deaf people to conform to an ableist assumption of hearing as the norm, rather than shift and challenge communication norms to support multiple modalities (Erard, 2017; Bragg et al, 2019). Computer vision technologies for Blind people often undervalue the non-visual sense making skills of Blind people by relying on visual signal processing exclusively rather than multimodal integration with sound, etc., and can lead to further surveillance and privacy harms (Bennett & Keyes, 2019). Affective/emotional AI technologies for autistic people (particularly autistic children) assume normative expectations and views of emotion, and violently impose these norms on autistic people. As Bennett and Keyes (2019) and Keyes (2020) discuss, the use of AI technologies to automate diagnosis of autism and other labels reinforce the legitimacy of existing power structures that remove the agency of the disabled people who are subjects of analysis. Such top-down and allistic approaches emphasise curative violence that erases autistic and other intellectually/developmentally disabled (I/DD) users and creators (Williams et al, 2021; Rauchberg, 2022). These approaches, which fail to draw on extensive experience in engaging people with disabilities as partners in participatory design (Louw, 2017; Spencer González et al, 2020), wrongfully assume that I/DD people do not have agency in their insights on technology creation or user experiences, and reinforce the ableist idea that only non-disabled people are valued as technologists or users. Similarly, AI-powered hiring algorithms may fail to recognize disabled ways of living and working, furthering the exclusion of disabled people from the workforce (Kelly-Lyth, 2021; Tilmes, 2022; Equal Employment Opportunity Commission, 2022).

The harms cited here have largely occurred in situations where AI technologies are serving as user-oriented tools, rather than data analytics and decision-making. However, the patterns of exclusionary design and the use of technology to exert pressures to conform to societal norms, which underlie these examples, are equally relevant to the use of AI in decision-making contexts, which has not been subject to the same degree of critical analysis. We thus draw on these examples to raise the question: what does more just development of AI technologies look like? More specifically, how do we shift from a disability technoscience—grounded in assimilation, compulsory able-bodiedness, and designing for rather than design with—to a crip and neuroqueer technoscience, rooted in multiplicity, collective access, and friction as technology?

Critical disability approaches to AI programming and research present new possibilities for agency for disabled researchers and users, in which their leadership and expertise are at the core of technological design. As defined by Williams et al (2021), crip human-computer interaction (HCI) “recognizes the researcher as situated, and thus articulated within, the sociotechnical meta-contexts of society, scholarship, research, design inquiry and practice” (p. 28) From the point of view of AI as a tool for information processing, we complement this study of interaction by drawing on Galloway’s (2008) conception of computation as an “unworkable interface” whose very nature is its information loss: AI tools are inherently a palimpsest, erasing the
multidimensionality of the individual person and replacing it with an approximation based on what is deemed “important”. To crip AI development for data analytics (as for user-oriented tools), we must decompose how this information interface is designed, and map alternative paths to representing the real experience of disabled people.

A Framework for Critical Examination of AI Analytics and Disability

While every technology is developed for different purposes and situations, there are common elements to the process of designing AI technologies for data analytics that can guide critical examination. As we show, by identifying fundamental questions in the design process, we can see how the definition(s) used for disability affect every characteristic of an AI technology, and begin to develop a critical framework for analysing the process of technology conceptualisation, implementation, and evaluation.

Data analytics can be broadly thought of as taking some information on a subject—a person, a setting, or some other aspect of the world—and distilling it to some insight, pattern, or subset of information that supports making a decision about that subject. Designing a data analytic technology therefore requires defining (1) what information is needed (or useful) for this process and (2) what might be useful to get out of that information. These criteria often differ significantly for different definitions of disability, meaning that a technology designed using one definition as its premise may be inappropriate and even harmful under another definition.

We consider two aspects of the technology design process, each of which interacts with disability definitions in different ways. The first aspect is the problem formulation that the technology is designed to address, and the second is the operational definition of the technology itself—i.e., how it accomplishes the stated goals of the design. The problem formulation and operational definition can then be examined in terms of a sequence of definitions representing how the technology is intended to operate within its target setting. Figure 1 illustrates the relationship between these components of AI analytics design.

Problem formulation: From broad goals to specific technology needs

Any data analytic technology is designed to meet a specific purpose. This may be a targeted application, such as informing a particular decision-making process (e.g., recommending an at-home exercise regimen), or more general-purpose, such as identifying and summarising key information from a large collection of data (e.g., displaying information about environmental barriers documented in text reports from various sources). Defining a broad need that data analytics can address is the motivation for beginning the technology design process. Considering our example use cases for AI analytics development, we can rearticulate each in terms of specific
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To develop an AI technology to address a broad goal, the first step is to translate that goal into a specific problem formulation that identifies the scope, role, and desired impact of the technology. Importantly, where a broad goal may be generally or loosely defined, a problem formulation is situated in a specific context: for a decision-making case like our examples, this would typically be a specific decision-making process (or more abstracted type of process) that would benefit from technological intervention, and a clear definition of the portion of that process that the technology is intended to facilitate. For our healthcare use case, an example target context could be recommending a home exercise regimen in a primary care setting, with the AI technology being used to analyse information on the person’s functional needs and characteristics of their

Figure 1. Conceptual illustration of the data analytics design process for decision-making applications. Panel (A) illustrates the sequence of moving from an overarching goal to a specific operational definition for a technology. Panel (B) illustrates the components that compose a problem formulation, beginning with the data available to analyse, the elements of the operational definition of the technology, and the role the technology plays in the decision-making process. Key questions for critical examination are provided for each component of the operational definition.

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home to help identify exercises appropriate for the home environment. For our benefits use case, a target context could be review of new applications for disability benefits under a particular government program (e.g., the Social Security Disability Insurance program in the U.S.), with the AI technology being used to help identify information related to functional limitations in the applicant’s medical records.

With a particular target context in mind for analytics, formulating a problem for AI technology development requires understanding the three interconnected elements of data, use, and operational definition. Each of these interacts with definitions of disability in different ways to produce very different technologies for any particular broad goal and target context (Table 2).

**Data: What is available to analyse**

The first component is the data that are collected in the target context, and therefore are available for use in data analytics. Beyond just what is collected–as well as what is not collected but would be informative to know–understanding why and how information is collected is also fundamental to both responsible and effective problem formulation. For example, if information on environmental barriers and accessibility concerns in one’s home neighbourhood is only collected for people who are already receiving disability benefits, then this information would not be available in practice for initial determination of benefits and should therefore not be used in designing data analytics for initial determination (cf. Eubanks, 2018 for a discussion of similar issues in technological systems in welfare contexts). Similarly, if information on a person’s priorities for daily living is only recorded through data entry by healthcare providers asking specific questions, then this information may not be representative of what people would provide for themselves in their own words and less-controlled settings.

Often, research effort in data analytics focuses on developing reusable methodologies which target more abstract types or categories of problems rather than specific contexts, and are thus intentionally underspecified. In such methodology development work, the key data questions are: (1) what kinds of data may reasonably be expected to be available when the technology is implemented and adapted to a specific target context, and (2) what is required to address the overarching goal in terms of the role the technology may be intended to play in a specific application. However, the operating definition of disability remains fundamental in determining what is considered “relevant” data, as well as in the more application-specific challenge of assessing how and why those data were collected. Thus, a method for identifying descriptions of experienced limitations in function may be designed to target free-text clinical data, on the assumption that clinical observations are an important source of information for assessing disability status. This method may then be applied and adapted to work with much more specific data to address a specific technology need, such as, for identifying healthcare-related priorities of people with mobility limitations, analysing both physical therapy notes and self-reported
### Table 2

Two examples of how the same broad goal for a data analytic technology can yield very different problem formulations for analytics when filtered through different definitions of disability. Problem formulations are presented in terms of (1) the data available for analysis; (2) the operational definition of the analytic technology; and (3) the role it is intended to play in decision-making.

| Broad goal                                                                 | Disability definition | Problem formulation                                                                 | Decision-making role                                                                 |
|---------------------------------------------------------------------------|-----------------------|-----------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
| Facilitate the communication of the needs and priorities of disabled people in their healthcare | Medical model         | Medical records, in-home sensors, wearable devices, self-reports of physiological or cognitive conditions | Analyse collected data to identify persistent/severe health conditions and impairments Connect subjective reports to objective evidence of impairment to support treatment and rehabilitation decisions |
|                                                                            | Social model          | Self-reports of experienced limitations and barriers, environmental sensors, images and video, infrastructure and health and safety reports, medical records, in-home sensors, wearable devices | Analyse collected data to identify significant environmental barriers and facilitators to desired functioning Connect personal reports to evidence of specific environmental barriers and facilitators to inform use of assistive devices, pursuit of environmental access improvements |
|                                                                            | Political/relational model | Health services records, social services records, evidence from advocacy organisations, self-reports of available resources and support systems | Analyse collected data to identify specific needs for government, advocacy, or community support Connect person to appropriate services and support systems to address gaps in needed resources |
| Facilitate the process of determining and allocating financial benefits to disabled people via social support programs | Medical model         | Medical records, application forms, commissioned expert assessments               | Analyse collected data to identify evidence of medical impairments Connect medical evidence to regulatory criteria for disability benefits |
|                                                                            | Social model          | Professional assessments of functional activity and participation, in-home and environmental sensors, medical records, self-reports of limitations and barriers | Analyse collected data to identify environmental barriers to work-related/daily life functioning Connect professional reports and objective evidence of functional barriers to needs for functioning in society to inform need for additional benefits |
|                                                                            | Political/relational model | Health services records, social services records, social work assessments, self-reports of available resources and support systems | Analyse collected data to identify available resources and resource needs for work-related/daily life functioning Connect evidence of available resources to resource needs to assess need for additional support through financial benefits |
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descriptions of mobility barriers and facilitators. Thus, both the nature of the analytic method and its materialisation in a specific technology are equally governed by the operating definition of disability that determined the criteria for data “relevance” in initial development.

Use: What role the technology will play

The second component is the use of the technology within the decision-making process. This encompasses a wide range of questions, such as: Who is using the technology to gain insight from information, and who is using that insight to guide decision-making? (These are not necessarily the same person, for example a data analyst may use AI technologies to produce reports that inform the decision made by a benefits program adjudicator.) What other sources of information outside the scope for data analytics (e.g., policy considerations, quotas, limited available resources for allocation, etc.), affect that decision? When (and for whom) is the technology used, and what process, technological, or other controls are in place to govern the use of the technology?

These are complex questions whose answers often change and develop over time, and a complete accounting for them at any single point in time is rarely realistic. Nonetheless, a clear understanding not only of what a data analytic technology is meant to do, but also of how it will (or could) be used is a critical component of both design and evaluation. For example, in the context of developing AI technologies to identify and organise information from medical evidence about experienced functional limitations (under our government benefits use case), technology designers may choose to focus on higher coverage or higher reliability in different situations—a common and frequently unavoidable tradeoff in AI development between precision (the proportion of what the AI system produced that it should have produced) and recall (the proportion of what the AI system should have produced that it in fact did. If the technology is to be used to support human review of benefits claims, designers may focus on higher coverage at the expense of erroneously identifying some information as related to functional limitations, knowing that it is easier for a human reviewer to filter out irrelevant results than to identify missing ones (Newman-Griffis and Fosler-Lussier, 2019). If the technology were to be used for automated cohort identification in population health research, where missing some relevant population members may be preferable to including people outside the target population, technology designers may instead focus on reliability to minimise erroneous inclusion. In an underspecified setting (i.e., development of reusable analytic methods for a category of target contexts), the use of the data analytic technology may be left intentionally nebulous: in these cases, it is important to clearly define and convey what sorts of applications a given technology might or might not be appropriate for based on its underlying assumptions. In all cases, the designer’s operating definition of disability affects the types of target contexts a technology may be appropriate to and what role it can reasonably fulfil within those contexts.
Operational definition: How the technology will work

The third component, and the focus of most design effort in current AI practice, is the operational definition of an analytic technology. The operational definition specifies how a technology will accomplish the use it is designed for: i.e., given the data that are available for analysis, how are those data to be processed to inform the context the technology is situated in? There are three primary elements to this operational definition that inform critical analysis: the input used by the technology, the output it produces for further use, and the process it is designed to execute to get from input to output. Each can vary significantly depending on the overarching model of disability used in the design process.

The analytic input will necessarily be a subset of the available data, but where the critical question from a data perspective is what is available to use, the critical question from an input perspective is what is chosen to actually be used. For example, in our government benefits use case, the same medical records may be available data for an AI technology developed under the social model as under the medical model, but the medical model technology might primarily use information about medical conditions and impairments, while the social model technology might primarily use information about environmental barriers and functional limitations.

The analytic output is the final step in the analysis sequence, but its definition helps to determine the actual analytic process the technology implements. The primary question about output is: what is the technology intended to tell the user about the person or situation being analysed? Again, this is a separate question from the use of the technology within the larger process: where critical examination of use focuses on how the technology is used, the critical question for output is what the technology produces to inform that use. For example, in our healthcare use case, an analytic technology developed to analyse a person under the medical model might produce a set of risk scores indicating degree of deviation from normative expectations of different aspects of health, while a relational model technology might produce an ordered list of people with similar experiences to connect the person who was analysed to for community building.

The actual analytic process, then, is in effect a model of the relationship between the input and the output. The specific architecture of the analytic model used may or may not lend itself to direct interpretation, and model interpretability may be more or less measurable: e.g., a linear regression represents explicit relationships between input and output variables, while a deep learning model represents complex mathematical transformations of input data that may not correlate with human intuition in any traceable way (Rudin, 2019), and causality can be extremely difficult to establish in highly dynamic algorithms drawing on hundreds or thousands of subroutines (Noble, 2018).

However, there are design decisions in terms of the types of analyses used—and the assumptions they make—that lend themselves more directly to critical examination. For example, in our government benefits use case, an analytic technology
developed under the social model might reasonably use a time series analysis to model a person’s trajectory of functional limitations over time, while a relational model technology might be focused on information about access to resources which is not likely to change rapidly, in which case the temporal sequence of the evidence analysed may matter much less. Similarly, when data are likely to be missing in practice (as is common in healthcare), it may be preferable to use models that offer some robustness to missingness such as a neural network over models that require well-defined assumptions for imputing missing data.

Towards a Design Praxis for Disability-Related AI Analytics

Every component of designing data analytics technologies for disability is thus affected by the lens or lenses through which disability is framed. The critical framework we have laid out here provides initial questions and considerations for examining how AI analytics technologies are designed, and a structure to guide efforts to design new technologies with a critical understanding of how they materialise and relate to disability.

Three themes will be key in building on this framework to develop a more robust design praxis for disability-related AI. The first is to dig deeper into the analytic design process, and to connect specific technical decisions back out to their conceptualisation and impact under different models of disability. Implementation details such as preprocessing input data to prepare it for analysis, algorithm and model architecture choices in machine learning, and data structures and representation of outputs serve as concrete ways in which ideologies of disability may be materialised, and these too must be subject to critical examination. Extending our framework for these inquiries will help articulate the connections between critical analysis and technical implementation, and can serve as the basis for developing reporting standards and assessment criteria for design decisions in new technologies. Technical extensions of our framework will further help provide the scaffolding for developing a vision for multidimensional AI analytics for disability that draws on multiple ways of conceiving of, defining, and operationalising disability.

The second theme is one of breadth: improved identification of the sociotechnical aspects of the context surrounding technology use that affect the appropriateness, efficacy, and power dynamics of AI technologies for disability. For example, if the data available for analysis in a particular healthcare context do not include information about occupational health, personal or social environments, or community structures, AI technologies cannot realistically be developed under the social or relational models without first changing the processes by which data are collected. Similarly, there are higher level questions of fit that must be addressed in terms of who is driving the development process and why: for example, if the development of an analytic technology for a government benefits use case is being funded by an agency that subscribes to the medical model, they may be unwilling to accept a technology designed to refute harmful normative assumptions about disabled people. The transparency with which AI technologies will
be implemented and used must also be examined: in many cases, disabled people whose lives are affected by AI systems may be entirely unaware that those systems have been adopted, and may be unable to access information on how they might be impacted by their use.

The final theme is one of outward change of both power and practice in AI development. In addition to a better understanding of the representational and allocational harms that result from under-informed design of AI analytics in the disability context, the fundamental issue must be explored that *not all information about disability is equal*. Information from disabled people, who can speak most directly and accurately to their own lived experience, is often dispreferred or entirely ignored in favour of information from more privileged sources such as healthcare professionals or government staff, who may have little understanding of—or actively pathologize—disabled experience. In investigating how these issues interact with the AI technologies that are used to analyse collected information, it will be particularly useful to draw on the concepts of testimonial and hermeneutical injustice described by Fricker (2007), which reflect on the ethical harms produced when people with marginalised experiences are both devalued and underrepresented in design processes. Such an understanding can further help in assessing and improving access for disabled people to meaningfully contribute to the analytic design and evaluation process.

**Conclusion**

The proliferation of artificial intelligence (AI) technologies as behind the scenes tools to support decision-making processes presents significant risks of harm for disabled people. Even when developing AI technologies to address the same overall goal, different definitions of disability can yield highly distinct analytic technologies that reflect contrasting, frequently incompatible decisions in the information to analyse, what analytic process to use, and what the end product of analysis will be. Here we have presented an initial framework to support critical examination of the design of AI technologies for data analytics in terms of the definitions of disability used in their design and the resulting effects on the technology. Using two use cases in healthcare and government benefits, we have illustrated how technologies developed under the medical, social, or relational models of disability contrast and conflict with one another, creating distinct risks for harm.

Critical examination of disability-related AI technology development is not only crucial in guiding the initial process of developing new analytic technologies, but also in capturing and assessing the range of decisions that affected an existing technology and imagining alternative designs. This article provides both a starting point for that examination and a roadmap to strengthen and expand the critical tools available for understanding the relationship between AI technologies and disability.
Notes

1 We use the identity-focused phrase “disabled people” and the person-centred “people with disabilities” interchangeably throughout this article, to indicate the nature of disability as both a category socially assigned to people and a personal identity expressed by people. For a deeper discussion of person-first and identity-first language, see Dunn and Andrews (2015).

2 We use “ableism” as a blanket term to refer to both discrimination against people perceived or identified as having a disability (referred to in some contexts as “disablism” (Miller et al, 2004; Gappmayer, 2021) and discrimination in favour of people perceived of identified as non-disabled.

3 We here follow McRuer (2006) in using “crip” as a verb in addition to an adjective. “Crip AI” may be thought of as AI that sees disability as a desirable part of the world; “to crip AI” is then making this perspective shift happen within the AI research, development, and application communities. For an introduction to crip AI design beyond the decision-making setting, see Hickman (2021).

4 A discussion of methods to interpret machine learning models (as well as the separate issue of decentralised algorithms) is out of scope for this article, but is a vital area for critical inquiry in AI. For discussions of the complexity of machine learning interpretability, see Lipton (2018) and Krishnan (2020). Note that one of the major lines of research in this area is on “explainable” machine learning, which relies on an entirely different post hoc model to fabricate explanations for system outputs. See Babic et al (2020) for a discussion of risks of these approaches in healthcare; the risks posed to already vulnerable and marginalised disabled populations by such fabricated explanations are significant.

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