The Promise and Peril of AI for Disability Health Equity: A Justice-Centered Analysis

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Background

- 1.3 billion people (≈16% of the world’s population, about 1 in 6) have a disability [1].

- 80% of PwDs live in low- and middle-income countries.

World Health Organization

Global report on health equity for persons with disabilities

Current health inequities for PwDs

- **LeDeR report** published in 2025 by NHS England [2]
  - Adults with learning disabilities **die nearly 20 years earlier** on average than the general population.
  - 46% of these premature deaths were "avoidable" - effective healthcare *should* have prevented them

- **Physical** (inaccessible examination tables, diagnostic equipment, poorly designed clinic spaces) and **digital barriers** (accessing telehealth platforms, public health information) to access care: Accessibility is not a "nice-to-have." It is a civil right.
- Provider bias and **inadequate** training of healthcare professionals
- **Exclusion** from clinical trials and population health datasets: Populations systematically left out of the data, are also left out of the solutions.

Reflecting deeper structural and justice failures, shaping every level of healthcare access, quality, and hence, outcomes.

Disability datasets

- **Fragmented** (different pots of data here and there)
- **Heterogeneous:** differences in how disability is defined and measured across datasets
- **Idiosyncratic:** inconsistent coding practices, such as combining intellectual and developmental disabilities into a single category in one dataset while separating them in another
- **Incomplete:** disability status not recorded in many datasets
- **Non-representative:** large-scale datasets may under-represent people living in institutions, group homes, or those with complex communication needs

Should we wait for the **perfect** data? **NO**, there exists an opportunity cost of doing so.

AI advantages in enhancing health equity

AI models offers unique advantages in:

- Handling unstructured & incomplete data (for instance, disability datasets) [3-4]
- Identifying hidden patterns

Applications: **Personalized care** (Predict disability progression and tailored rehabilitation), **Equitable resource allocation** (Identify underserved regions using **Geospatial tools** like the AI-driven Accessibility Mapping Tool), **Assistive technologies** (machine learning-driven wheelchair systems)

ADVANTAGES only IF designed ethically and inclusively.

Examples from the literature

- In rehabilitation, deep learning pipelines such as **PrimSeq** [5] classify functional movements during stroke recovery, while platforms like **Walk4Me** [6] use smartphone sensors for remote mobility monitoring.

- **ML-driven wheelchair interfaces** now interpret muscle or eye-movement signals with very high accuracy.
  - Kim et al., 2024: **Up to 99% gesture recognition** using sEMG and standard classifiers [7]
  - Dahmani et al., 2020: **99.3% accuracy** using a CNN-based gaze-tracking control system [8]

- **Wearable navigation tools** using RGB-D system for **visually impaired users:** Enabling real-time obstacle detection and safer spatial navigation [9].

- **AI-powered communication** and **cognitive assistive technologies**: **up to 99.8% accuracy**, supporting greater autonomy for people with cognitive disabilities [10].

Recommendations for justice-aligned AI

1. **Invest in disability-inclusive datasets** capturing environment, participation, functioning
2. **Algorithmic fairness**

   Involving PwDs in defining "**success**" and shaping **model goals**

   fairness is measured in terms of equity, inclusion, and their real-world relevance

3. Models validated across diverse populations and real-world contexts, particularly those underrepresented in training data

4. **Enhancing interpretability**
5. **Co-design with PwDs** at every stage

Key limitations of AI models

- *Lack of sufficiently detailed and unbiased disability data:* Studies relying on datasets created for broader purposes, where disability is included only as a secondary measure.

  Models trained on such data risk overlooking their needs

- Poor **generalizability** across contexts: perform well in controlled environments or in specific clinical settings, but their **real-world applicability** is frequently limited

- *Deep conceptual and philosophical ambiguities* in how disability is defined.

  Many applications adopt a purely medical perspective, which shapes data collection (e.g., diagnoses vs. social barriers), outcome definitions (e.g., physical improvement vs. independence), and criteria for "success."

  For example, in a rehabilitation algorithm: **success** as regaining walking ability while **overlooking** whether an individual can return to work, school, or community life

- Lack of interpretability

Ethical risks

- **Privacy:** disability data is sensitive, misuse can expose PwDs to discrimination in employment, education, or insurance.
- **Consent:** often indirect, or missing
  - Standard consent models rarely account for the ways disability-related data is collected and re-used in secondary research.
  - PwDs may have limited control over how their data is used into machine learning models

- **Fairness:** how to measure fairness?

Do machine learning model outcomes align with holistic goals such as independence, participation, and accessibility

Justice requires **empowering**, not merely “fixing,” disabled people.

A Swiss perspective

- Aging population → rising disability [roughly **21-22 % of the total population]**
- Intercultural & linguistic diversity → data complexity
- Push for digital health & AI integration

- Need for inclusive data systems across cantons
- Switzerland must ensure AI tools support **participation, autonomy,** and **equity**.

Conclusion

- AI offers powerful opportunities for **equitable, personalized care**
- But without justice-centered design, AI may **magnify structural inequities**
- Disability health equity requires:
  - Inclusive data
  - Transparency, fairness, and accountability

- AI must **support human dignity**, autonomy, and real freedoms.

Discussion questions

1. How can Switzerland ensure disability data is **ethically collected** and **representative**?
2. What standards should guide **fairness audits** for disability-focused AI?
3. How can health institutions ensure PwDs **co-design-AI-systems**?
4. Should Switzerland adopt **stricter regulatory safeguards** for disability data?
5. How can AI be used to **strengthen**, not **replace** relational care?

Thanks! :)

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