

Karthik Shivashankar, Venkat Bakthavatchaalam

Chapter 2

Education Policies Through Data Driven Decision Making: Accelerating Inclusive Education for People with Disabilities

Abstract: This research explores the development of data-driven management practices and policies to address the educational needs of children with disabilities within an evolving economic landscape. Around 1.3 billion people globally live with disabilities, with 80% in developing nations. The proposed model, targeting these marginalised groups, incorporates a data-driven approach segmented into three levels: school, regional, and national. In this work, initial non-intrusive data collection at the school level identifies students' needs based on demographics and unique requirements. Regional bodies collect similar data from the participating schools to define policies tailored to the particular needs of the demography. Centralised data from various regions informs national-level analysis, allowing for evaluating teaching practices and leading to data-informed policies and procedures. This interconnected system promotes the development of indigenous practices at school, regional, and national levels and ensures adequate documentation and sharing of successful strategies. Integrating AI with wearable technologies, tailored content delivery, virtual classrooms, and empowering educators provides a multifaceted solution. Collaborative efforts between technology companies, educational institutions, and governments are vital for overcoming existing challenges. This research illustrates AI's potential in crafting an inclusive, personalised, and efficient learning environment for children with disabilities, particularly in emerging economies, which would be helpful for special needs school management, policymakers and governmental bodies.

Keywords: Education Policies, Disability, Inclusive Education, Artificial Intelligence, Data Driven Approach, Developing Countries

2.1 Introduction

In the contemporary world, education stands as a universal necessity, playing a critical role in the lives of children, regardless of their abilities (UNICEF, 2017; UNHCR, 2014). The importance of education is magnified for children with disabilities, as it empowers

Karthik Shivashankar, Department of Informatics, University of Oslo, Norway

Venkat Bakthavatchaalam, School of Engineering, Cardiff University, Cardiff, United Kingdom

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them to not only develop essential skills and knowledge but also fosters integration into society. Guided by Sustainable Development Goal 4 (SDG4), the emphasis on inclusivity and justice has never been more vital, resonating with UNESCO's (2017) call for leaving no one behind. Although inclusivity encompasses a wide array of attributes such as gender, age, ethnicity, and financial status (Antoninis et al., 2020), this research narrows its focus on the intersection of children with disabilities, AI technology, and the context of emerging economies to create management practices.

The challenges faced by children with disabilities transcend geographical boundaries, and the situation is even more precarious in developing countries, where issues stem from various social, economic, and cultural barriers (Antoninis et al., 2020). Education offers a path for children with disabilities to overcome these obstacles, nurturing their self-confidence and self-advocacy skills and protecting them from discrimination (Dyssegaard & Larsen, 2013; Hayes & Bulat, 2017; Kuper et al., 2018; Szumski et al., 2017).

Educational management practices and policies rely heavily on fragmented pockets of evidence, needing a centralised repository conducive to developing policies informed by comprehensive, large-scale metadata. This research endeavours to address this gap by delving into the possibilities and barriers surrounding collecting and analysing extensive data on a large scale in an emerging economy. The ultimate goal is to leverage this data to formulate evidence-based policies to enhance educational management practices. The past decade has seen significant strides in adopting inclusive education policies, increased teacher training, and AI-driven solutions to address unique challenges (Dyssegaard & Larsen, 2013; Oh-Young & Filler, 2015). The emergence of data-driven Artificial Intelligence (AI) as an instrumental force in the educational sphere marks an essential shift in tailoring educational experiences. AI's capabilities align with the unique learning needs of children with disabilities, promising a new frontier in personalised, accessible, and quality education. This research explores the innovative ways AI can be harnessed to mitigate the educational disparities that children with disabilities face, particularly in developing countries.

Building upon this technological advancement, the proposed model in this study seeks to offer a comprehensive, data-driven approach that synergises AI, machine learning, and the specific regional context. The model focuses on the non-intrusive collection and analysis of data, the development of adaptive teaching practices, policy formulation, and a cross-collaborative framework that connects schools, regions, and national entities. The subsequent sections will detail the challenges, scenarios, strategies, and potential outcomes of integrating AI within the education sector, spotlighting the proposed model as a beacon for future innovation and inclusivity.

2.2 Background

Disability is a condition that limits a person's ability to perform activities as they would like or what is considered normal (DESA, 2023). This section will initially explore education for disabled children, focusing on developing countries, followed by a few developed models or solutions. According to the WHO (2023), there are many types of disability, including physical, sensory, intellectual, and mental health conditions. For a detailed view of what a disability is and its models, see UNESCO (2022).

The education of disabled children presents a substantial global challenge. Approximately 1.3 billion people, or 16% of the world's population, live with disabilities (DESA, 2023). As the largest minority group globally, the growth of this demographic is propelled by factors such as population growth, medical advancements, and ageing trends (WHO, 2023). Among those with disabilities, most reside in developing nations, drawing attention to the pervasive issue in lower-income contexts.

The WHO (2022) has highlighted that around 80% of individuals with disabilities live in developing countries. Women are particularly impacted within OECD countries, reporting higher disability rates in most OECD nations, indicative of substantial socioeconomic disparities (OECD, 2022). Moreover, the world's poorest populations include nearly 20% of individuals with disabilities (World Bank, 2018). The intersection of gender and disability further compounds these disparities, leaving women more susceptible to marginalisation (Disabled World, 2023). Such inequalities are exemplified by elevated risks of abuse, including domestic violence.

2.3 The Status of Children with Disabilities

The situation concerning children with disabilities is gravely alarming, with UNICEF (2021) reporting that around 30% of street youth have some disability, and mortality rates reaching as high as 80% in certain regions. In the context of developing countries, education for disabled children faces profound challenges. The WHO (2022) notes that only 1 in 5 disabled children have access to education, with UNESCO (2018) emphasising that the education gap is more acute in emerging economies. Alarming, 90% of disabled children in these countries do not attend school, leading to low global literacy rates for adults with disabilities and even lower for women with disabilities (UNICEF, 2018).

Segregation, poverty, discrimination, and lack of access to appropriate educational services exacerbate these issues, often isolating disabled children from their non-disabled peers. The attempts at inclusive education through various approaches, such as curriculum modifications and assistive technology, have yielded mixed results (Shivashankar & Bakthavatchalam, 2019). COVID-19 has intensified the struggles of this vulnerable group, disproportionately affecting their learning, especially during the transition to online education (NCPEDP, 2020). The lack of infrastructure, resour-

ces, affordability, specialised teaching methods, and societal stigma further hindered the path to quality education (Peters & Hehir, 2017). Additionally, the research by the OECD (2022), McLaughlin and Noonan (2017), and Smith et al. (2018) delineate the multitude of challenges faced by children with disabilities.

These barriers extend beyond educational hindrances, impeding social interaction and future community engagement. The lack of suitable accommodations and support mechanisms translates into lower learning outcomes and stifled skill development. Despite global initiatives towards inclusive education, the pursuit of equitable education for disabled children, particularly in developing countries, continues to be a multifaceted and often neglected concern. The alarming statistics and the vast disparities in access to quality education for children with disabilities necessitate a concerted global effort. Policymakers, educational practitioners, and communities must work collaboratively to address these inequalities. Only through targeted interventions, informed policies, and dedicated resources can the educational rights of all children, regardless of ability, be fully realised, thus contributing to a more inclusive and just society.

2.4 AI as a Tool for Inclusion: A Review

Integrating Artificial Intelligence (AI) with wearable technologies revolutionises education, particularly for disabled students in developing countries. A few of the AI-based technologies for people with sensory and intellectual disabilities and research on them are discussed in this section.

Regarding Sensory disabilities, Mukhiddinov & Cho (2021) use smart glasses equipped with Convolutional Neural Networks (CNN) to provide real-time accessibility for visually impaired students. Similarly, Wang et al. (2023), in their study, comment on how AI could be used for obstacle avoidance and assisted reading technology using deep learning techniques. Exploring auditory disability, Lesica et al. (2021) comment on how AI technologies in hearing can improve care for common auditory conditions, foster understanding of complex disorders like tinnitus, and develop artificial auditory systems. Using an in-ear onboard training model, Bhowmik et al. (2021) developed an on-demand edge AI computing solution that enhances speech clarity. Looking at some industry developments, Kesari (2023) comments on Starkey's 'Genesis AI', which uses a Deep Neural Network (DNN) accelerator engine to analyse and optimise sound in real time. This enables hearing aids to function like the human cerebral cortex, enhancing speech, reducing noise, and providing a more personalised auditory experience.

Regarding intellectual and mental health conditions, Megat et al. (2023) looked at using a speed-reading tool powered by AI technologies to assist students with ADHD, dyslexia, or short attention spans. The tool uses the Multilayer Perceptron algorithm for text processing and summarisation, using 'Bionic Reading' principles to enhance read-

ability. For children with autism, Haber et al. (2020) use a wearable device as a social interaction aid. This focuses on addressing deficits in eye contact, facial expression recognition, and social interaction. Similarly, a randomised controlled trial by Fahimi et al. (2019) found that the EEG headband with CNN effectively reduced inattention and hyperactivity symptoms of children and adolescents with ADHD. Crippa et al. (2015) explored using the 'Support Vector Machine' to identify children with Autism Spectrum Disorder by analysing upper-limb movements such as reach, grasp, and drop.

AI's potential to personalise content delivery is unlocking new educational avenues translating and adapting content to local customs, languages, and histories while being aware of possible biases (Kazimzade et al., 2019). Virtual classrooms empowered by AI are breaking linguistic barriers, and AI-driven administrative automation frees educators to focus on teaching, fostering continuous improvement through a self-determination theory design approach (Xia et al., 2022). AI aids in inclusive education, offering tailor-made content formats and real-time adaptation, with emerging technologies monitoring students' emotional states to enhance learning (Balachandran & Rabbiraj, 2023).

Most research in this field has primarily occurred within developed countries, where the socio-economic landscape differs significantly. However, there is a noticeable scarcity of studies addressing developing and implementing management practices and policies for children with disabilities through a data-driven model within evolving economic contexts, particularly in developing nations. This research aims to bridge this critical gap by focusing primarily on developing countries. The study endeavours to design a comprehensive model and thoroughly investigate the numerous prospects and obstacles associated with its implementation within developing country contexts. By doing so, it aspires to contribute significantly to formulating effective management practices and policies tailored to the unique needs and challenges of children with disabilities in these regions.

2.5 Proposed Model

This section focuses on the newly conceived three-tiered data-driven model under development, explicitly aiming to enhance teaching and learning for children with disabilities within the framework of emerging economies. This model is centred around creating a system that integrates management and policy, providing a comprehensive approach to education for those with special needs (Figure 2.1).

The proposed data-driven model, as depicted in Figure 2.1, is segmented into three sections. The initial phase involves the non-intrusive collection of data at the school level from students with disabilities, aiming to pinpoint specific needs based on demography and individual requirements. This data is relayed to regional or governmental bodies in conjunction with similar information gathered from other institutions. The

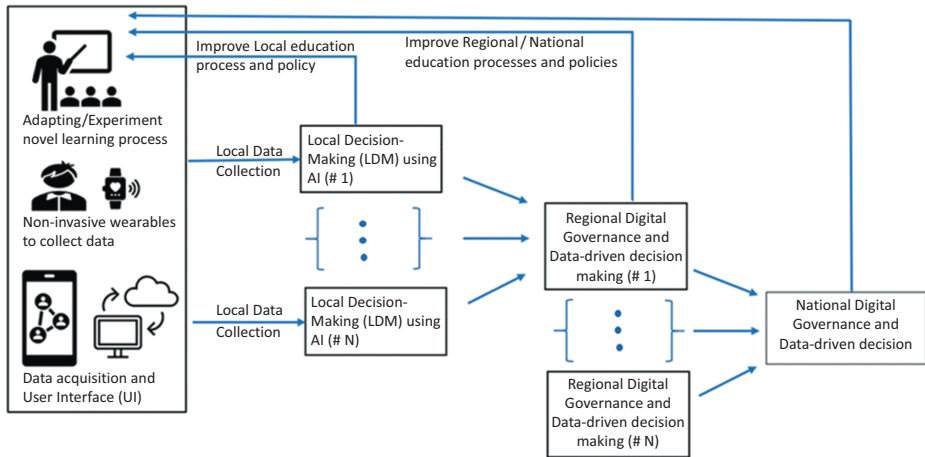


Figure 2.1: Proposed model of the three-tiered data-driven model.

broad spectrum of data thus accumulated enables a thorough analysis, facilitating the creation of policies and regulations tailored to the region's unique characteristics.

Furthermore, the model accommodates data from various regions or states, creating a centralised repository. This aggregation of diverse data concerning teaching methodologies, their effectiveness, and outcomes fosters a detailed examination, culminating in the formulating of informed practices and policies. The interplay between national and regional data contributes to a coherent strategy where national insights inform regional and school-level policies. In contrast, regional policies reciprocate by shaping data-driven practices at the institutional level.

The embodiment of this model not only empowers individual schools and regions to cultivate their distinct practices and policies but also ensures that strategies are recorded and disseminated across the regional and national levels. This collaborative approach, underpinned by the proposed model, is poised to shift the education of children with disabilities, aligning practices and policies with the specific needs and contexts of the children they are designed to support. The following section will look at the model in detail, exploring the various non-intrusive data collection, analysis of the data, the training of the algorithm and how it incorporates feedback mechanisms to iterate the data-driven process within the three-tier model for creating effective education management policies and practices.

2.6 Research Methodology

The research methodology is divided into two main phases: the data collection, which integrates quantitative and qualitative insights, and a comprehensive data analysis phase employing advanced machine learning algorithms.

During the initial phase, data are meticulously collected at individual, regional, and national levels. The method leverages wearables to acquire real-time physiological data and standardised assessments to monitor academic and social progressions at the individual or school level. Furthermore, qualitative feedback is sought from key stakeholders, such as students, parents, and teachers, furnishing a well-rounded view of the educational process. Moving to a broader scope, regional-level data analysis amalgamates information from various schools to discern regional trends, which would be vital in crafting policies that are sensitive to local needs yet have the potential to be scaled nationally. Lastly, a macro-analysis is conducted at the national level, which harnesses the accumulated regional data to foster a unified and data-informed educational strategy.

The second phase delves deep into data analysis and policy formulation. Here, machine learning models, including Decision Trees, Random Forests, and Transformer-based models, are utilised to dissect and comprehend intricate data sets, providing a versatile analytical framework. Subsequently, the policy-making process is facilitated through data-driven dashboards at different administrative levels. These dashboards assist in shaping teaching methodologies at the local level and formulate grounded policy recommendations at the regional level based on a thorough analysis of quantitative and qualitative feedback. At the national spectrum, aggregating and synthesising a vast pool of textual data assist policymakers in identifying broader trends, which in turn help shape nationwide strategies and reforms.

In addition to the methodological aspects, this research accentuates the necessity for open science and adhering to stringent ethical guidelines, promoting transparency and reproducibility in research. This approach envisages fostering multi-disciplinary collaborations for further refinement and longitudinal studies. Moreover, a tiered governance structure is proposed, incorporating local educational bodies, regional departments, and national entities to warrant a coherent and effective strategy implementation backed by multidisciplinary inputs.

2.7 Data Collection

This section discusses the data collection at all the levels based on the model. At the individual or school level, three types of data will be collected:

1. **Quantitative Data from Sensors:** This data, acquired through wearables like heart rate monitors and temperature sensors, will offer insights into the physiological

and emotional states of students, enabling real-time adjustments to lessons and interventions.

2. **Quantitative Scores from Standard Assessments:** These scores and metrics will be derived from standardised assessments designed to address each child's unique social and academic needs.
3. **Qualitative Feedback:** Qualitative feedback will be gathered from children, teachers, parents, and caregivers. This feedback mechanism will complement the quantitative data, ensuring active stakeholder engagement in the educational journey.

The initial phase of our study involves the continuous collection of data from students with disabilities in the classroom. The data can be collected in schools or at home, depending on the child's requirements. Based on the model, data will be collected using a variety of sensors, including heart rate monitors, temperature sensors, and other physiological sensors. At the same time, students are engaged in the learning process. Non-intrusive wearables designed for this research or easily available devices like smartwatches can be used.

In addition to sensor data, quantitative data based on a standardised set of assessments tailored to the unique learning requirements of individual children will be collected. This data will include scores and metrics from standard assessments considering the children's unique social and academic needs. These assessments will encompass functional capabilities, social interactions, and academic achievements. Combining these standardised tests with continuous monitoring through wearables will provide a comprehensive understanding of students' learning abilities, a critical factor in designing personalised interventions.

In addition to the quantitative data, more holistic qualitative feedback will be gathered from children (if appropriate), teachers, parents, and caregivers as required. The qualitative data ensures that every stakeholder remains engaged and actively participates in the educational journey. Qualitative data offers rich, contextual insights that lend depth to the statistical findings, helping researchers understand the 'why' behind the numbers. For example, while test scores (quantitative data) may indicate a decline in performance, interviews with children and teachers (qualitative data) may reveal underlying reasons, such as a specific technological requirement or a lack of sufficient supporting mechanisms.

This qualitative data can be further used to determine the teaching and learning practice's effectiveness, make necessary changes to the curriculum iteratively, and influence the policy on various levels within the three-tiered proposed model. Qualitative feedback from these groups is essential for understanding the lived realities of the educational experience beyond what can be captured through quantitative metrics alone. The three data types will be collected at the individual level within the schools.

Similarly, data will be collected from various participating schools at the regional level, which will then be aggregated to form a regional data repository. Analysing trends at regional levels makes it possible to design interventions sensitive to local needs while

also scaling effective strategies to a national level. This fosters a dynamic, responsive policy environment that is both locally relevant and nationally effective. Regional and national policy evaluation is a scale-up of insights, moving from granular, school-level analyses to broader, systemic evaluations. Data repositories that aggregate information from various regional schools allow researchers and policymakers to identify common trends, challenges, and successes that may be specific to that geographical area.

Once regional data repositories have been analysed, they serve as an empirical basis for designing and implementing region-specific interventions. These interventions can then be piloted on a smaller scale before broader implementation. Such a targeted approach ensures that policies are finely tuned to local needs, sociocultural contexts, and existing infrastructures, thereby enhancing their likelihood of success.

While regional repositories offer insights into local trends, aggregating these repositories at a national level facilitates the formation of overarching educational strategies. A national data repository offers a macroscopic view that captures the educational landscape, including regional disparities or consistencies. National-level analyses can help policymakers to identify commonalities and differences, resource allocation and policy harmonisation. The suggested approach involves identifying common challenges and achievements at a national level while recognising regional variations, which enables the development of a more nuanced policy framework. This, in turn, facilitates informed resource allocation decisions, such as deploying teachers, educational materials, or specialised training programs where they are most needed. Additionally, the proposal advocates establishing national benchmarks or standards grounded in empirical evidence, which can serve as a basis for evaluating regional or local educational performance. Lastly, it emphasises the importance of integrating and harmonising educational policies to achieve a degree of standardisation across regions while accommodating local adaptations.

Incorporating wearable sensors in educational settings offers a granular approach to personalised learning, particularly for students with disabilities. These sensors collect real-time physiological and emotional data, enabling tailored educational experiences. This data is then seamlessly integrated into a mobile-based application connected to nearby edge devices, which aggregate the information from multiple students and schools in the region. Edge computing enhances data processing efficiency and enables quicker decision-making by reducing latency and bandwidth usage, thus making it feasible for real-time interventions or policy adjustments at local, regional, or even national levels. However, the methodology faces challenges, including sensor accuracy, high data volume, untrained usage and ethical considerations like informed consent and prioritising the privacy and anonymity of individuals by subjecting them to masking and homomorphic encryption. Interdisciplinary collaboration and further longitudinal studies could significantly refine this data collection technique.

2.8 Analysis and Policy Making

Quantitative sensor data are used as the features. Features are training example data points such as the data from many sensors used to infer an individual's emotional and physiological state. The data from the standardised assessment scores are used as the ground truth label. With this data in hand, we aim to create a comprehensive dataset. The data collected from the sensors will be the independent variables, whereas the scores from the standardised assessments are the dependent variable quantitatively.

The data can be analysed using various algorithms such as 'Decision Trees', 'Random Forests', and 'Transformer'-based models. Given the complex nature of the data and the tasks, advanced ML models should be considered to enhance the analytical framework. A few algorithms that can be used for analysing the data at different levels include ensemble learning methods such as 'Gradient Boosting Machines' and 'XGBoost', especially for cases with missing data – suited to the current requirement. For analysing the quantitative data, 'Recurrent Neural Networks' and 'Long Short-Term Memory Networks' can offer insights into trends over time in a student's physiological data. In addition, more specific variants like BERT (Bidirectional et al. from Transformers) or GPT (Generative Pre-trained Transformer) can be employed for complex tasks, such as understanding the context in which physiological changes occur in the students based on textual data (e.g., classroom transcripts or notes). These ML models can be selectively deployed depending on the specific data characteristics and the analytical requirements, thereby adding significant robustness and versatility to the analytical framework. Furthermore, considering security and data privacy, we could also employ federated learning models to train on decentralised data across schools while keeping raw data localised. This aligns well with the noted need for localised decision-making in educational interventions.

Qualitative feedback from the school level can be integrated into the dashboard to provide context to the quantitative KPIs. For instance, teacher observations about student behaviour can be juxtaposed with physiological data from wearables to offer a richer understanding of student well-being. Natural Language Processing (NLP) algorithms such as 'Topic Modeling' or 'Sentiment Analysis' can summarise this qualitative feedback, allowing immediate and actionable insights. The dashboard could flag quantitative and qualitative data discrepancies, prompting further investigation. Overall, a web or mobile app dashboard at the local school level will display Key Performance Indicators such as student engagement, stress levels and attendance patterns. A set of metrics around academic performance collected through the app could help teachers tailor their teaching methods.

For regional educational authorities, an advanced dashboard version could aggregate data across multiple schools. KPIs like average student well-being, teacher effectiveness, and resource utilisation could be monitored. Advanced models like Gradient Boosting Machines or Bayesian Models could analyse regional trends, offering policy recommendations such as resource allocation or curricular changes. Regionally, quali-

tative data can provide insights into varying educational methods, resource utilisation, and school stakeholder satisfaction. ML techniques like ‘Latent Dirichlet Allocation’ can cluster similar feedback, helping educational authorities understand common themes or issues in different schools. This will enable them to craft policies for the region-specific challenges.

On a national scale, the dashboard could incorporate broader metrics like literacy rates, regional comparisons, and national test scores. Transformer-based models could synthesise large-scale textual data, such as feedback from educators nationwide, to identify overarching trends and challenges. This would enable policymakers to make data-driven decisions on a grander scale, such as nationwide curricular reforms or targeted teacher training programs. On a national scale, the synthesis of qualitative feedback can inform broader educational strategies. Advanced NLP models, such as Transformer-based algorithms, can process large volumes of text data, identifying overarching trends and needs that may not be apparent through quantitative metrics alone. For instance, widespread concerns about exam stress could lead to policy recommendations about exam reform or mental health support in schools.

In principle, all the non-sensitive data and resource materials would be made publicly available. These include the research designs, draft ethical forms, codes used, schematics and experiments set up and so on for further scrutiny and research purposes. The final AI models, results and policies will also be opened up for reproducibility and adaptation for the community and similar developing countries.

At the local or school level, educational institutions are responsible for the initial data collection, monitored by local education authorities and in consultation with parents and caregivers. Local bodies will thus handle the daily data acquisition, ensuring it aligns with ethical and procedural norms. Moving up to the regional or state level, the State Education Department takes the helm. They are charged with aggregating the collected data into regional repositories and are accountable for its oversight. Regional healthcare institutions and non-governmental organisations (NGOs) play supplementary roles, aiding data interpretation and liaising between the government and the community. The Ministry of Education oversees the entire framework at the national level, including maintaining a national data repository and formulating educational benchmarks and standards. National Data Protection Authorities ensure compliance with data privacy regulations. Ministries of Health, advisory committees, and academic research institutions provide multidisciplinary expertise to inform and evaluate the implemented policies. Together, these entities contribute to a coherent and effective governance structure.

2.9 Barriers to Implementing this Model in Developing Countries

This data-driven model can create a significant impact in the lives of disabled children by offering innovative solutions tailored to their unique needs and challenges. However, implementing this in developing countries is fraught with numerous barriers. In the developing countries, a few of the often-cited barriers include the lack of technology, resources and infrastructure, need for qualified teachers, social stigma (Kuper et al., 2018; Oh-Young & Filler, 2015). The situation is further complicated in countries like India, where the diversity of regional languages presents additional hurdles. Moreover, economic constraints and the lack of established ethical principles and legislation concerning AI (Chatterjee, 2020), particularly in relation to disabled children, exacerbate these difficulties.

This section explores the various themes of barriers: Technological, cultural, economic, administrative and regulatory barriers. Along with identifying the themes, this section also addresses how the interplay of these themes influences the adoption and effective use of the data-driven model.

A prominent obstacle is limited access to technology (Shivashankar & Bakthavatchaalam, 2021), particularly in rural areas of developing countries, where essential infrastructure and equipment for AI-based solutions are often lacking. Moreover, WHO and UNICEF (2022) emphasise the global disparity in the availability of assistive technology in low and middle-income nations. Dias (2015) further highlights technical issues, security concerns (Yathiraju et al., 2022), and a digital divide that limits access to smart devices for children and educators. Schools and governments must ensure equitable access to these devices to mitigate this. Given the increasing affordability of mobile phones in developing countries (IFC, 2020; Silver et al., 2019), the model needed to be developed with easy access through mobile phones, thus increasing accessibility.

Along with this, the lack of access to special schools is another issue. Schools in developing countries are often not accessible to children with disabilities. This may be due to physical barriers, such as lack of wheelchair ramps or accessible toilets, or policy barriers, such as lack of inclusive education policies. (Dyssegaard & Larsen, 2013; Oh-Young & Filler, 2015). In addition, the data collected needs to be harmonised (Mont et al., 2022) for the model both at the statistical analysis system and the administrative system., but this could pose a challenge at a regional and national level. Even though this has been considered in devising this model, it must be carefully implemented.

Digital literacy and expertise gaps, as noted by IFC (2020) and Bapna et al. (2020), are major barriers to implementing this model or similar AI-based solutions in developing countries. The lack of qualified teachers capable of using technology with disabled children is a common theme that is reported by several works, including WHO and UNICEF (2022), IFC (2020), Shalini and Shipra (2020) and Hashemi et al. (2020). The shortage of trained teachers, primarily those proficient in educating children with dis-

abilities and those who can correctly use the wearables and collect proper data, threatens to deprive these children of the support they require for academic and socio-emotional development (Hayes & Bulat, 2017; Kuper et al., 2018; Szumski et al., 2017). So, implementing this model and making a success of it requires investigation. This is noted to be one of the significant barriers, so special needs teaching and the Governments must look at the funding requirements. There is a need to provide more training for teachers on how to work with children with disabilities. This training should cover both the academic and the social-emotional aspects of education.

The cost associated with special education is comparatively higher than that of regular school, making it difficult for middle-class and low-income families to afford (Shalini & Shipra, 2020; Lakshminarayana et al., 2019; Senjam et al., 2021). Many families in developing countries cannot afford to send their children to school, even if the school is free. This is especially true for families with children with disabilities, as they may incur additional costs for special education or assistive devices (UNICEF, 2018; WHO, 2011; World Bank, 2018). Governments need to invest more in education, especially for children with disabilities. This includes providing financial assistance to families, making schools more accessible, and training more teachers (UN, 2019; WHO, 2011).

Additionally, a pervasive social stigma is associated with disability and special schools in developing countries, constituting a substantial barrier (Kuper et al., 2018; Oh-Young & Filler, 2015). Negative attitudes towards disability can lead to discrimination against disabled children within educational institutions and communities. This can make it difficult for children with disabilities to feel welcome and included in school (Kuper et al., 2018; Oh-Young & Filler, 2015). There is a need to change attitudes towards disability in developing countries. This is an essential barrier in implementing this model, as the data collected might need to be revised. To overcome this, concerted efforts are needed to change societal perceptions through awareness campaigns, community leader training, and media initiatives with appropriate cultural sensitivity.

There are also barriers to implementing this model using ML. Even though ML offers significant potential for extracting valuable insights from continuous physiological monitoring in healthcare, as noted by Rush et al. (2019). However, this potential is counterbalanced by regulatory and medico-legal issues, necessitating rigorous evaluation and clear demonstration of value. Simultaneously, the reliance on potentially unreliable datasets can lead to machine bias stemming from errors or incomplete data input. The operationalisation of ML models across various levels in the model also poses a challenge, as it demands substantial capital investment and the presence of adequately trained staff.

Moreover, the often-opaque nature of ML algorithms – the often quoted ‘black box’ factor – makes understanding the underlying rationale for specific conclusions difficult. The introduction of accurate learning ML models further compounds these issues, raising complex questions about decision-making processes and potential adverse outcomes. In this model, not all the measures used are quantitative, with some of them being qualitative, especially the feedback from the children, teachers, pa-

rents, school management and the other stakeholders in terms of their learning and functional skills, the subjective nature of such data could impact the results, all these would have to be carefully considered while training the model.

Finally, the absence of relevant legislation, particularly in AI and data usage with vulnerable populations, represents a critical barrier (Jobin et al., 2019). Governments must adopt inclusive education policies, meaning all children can attend the same schools regardless of their abilities. This will help to break down barriers and create a more inclusive environment for all children (Dyssegaard & Larsen, 2013; Oh-Young & Filler, 2015).

Concluding this section, rather than identifying the barriers in isolation, it is essential to comprehend how they collectively impact individuals with disabilities and their families. This holistic understanding becomes essential for devising and executing efficient interventions to enhance access to primary healthcare. Addressing these barriers requires a multidimensional approach involving governments, international organisations, academia, and the private sector to create inclusive and accessible AI solutions. To provide holistic support for the children, changes need to happen not only in the teaching practice but also in the curriculum design, textbook and online material, teacher education, school facilities, and community inclusion, thus helping form appropriate management practices.

2.10 Future Works

This study encompasses a convergence of four key domains: data-driven computing and AI, experts in the field of disabilities, educators, and policymakers. While it might be easy for future researchers to narrow their focus on the AI aspects of this research, they must approach the children with empathy and adopt a sensitive approach whilst gathering data and formulating policies grounded in the data. Furthermore, given their vulnerable nature, the chapter advocates the presence of either a parent or a trained expert during interactions with children, given their vulnerable nature. This work aims to create a data-driven model for emerging economies where social dynamics differ from those in developed or underdeveloped countries. The framework should not be generalised in emerging economies, as political, geographical, and cultural dimensions vary within regions and countries. As a result, the framework should consider these differences and produce context-specific practices derived from the data.

Future research could consider validating the general framework using quantitative and qualitative data in longitudinal studies. This work focuses on wearables, learning assessment, and a particular type of data analysis. However, AI's swiftly evolving landscape necessitates considering novel data collection and analysis methodologies and the results tested with other AI methods. Future research should also

consider the implications of data collection from disabled children on their long-term development. Additionally, this research should have considered the political will among emerging economies for comprehensive regional and national research initiatives. Future work should investigate this in detail.

2.11 Conclusion

In conclusion, data-driven decision-making can accelerate inclusive education for people with disabilities. By collecting and analysing data on student outcomes, educators can identify areas where improvements are needed and develop targeted interventions. The framework developed can help ensure that all students, regardless of their abilities, have the opportunity to succeed in school. At the same time, the chapter has also identified various challenges in implementing such a system in developing countries. Despite these challenges, data-driven decision-making has the potential to make a significant difference in the lives of students with disabilities. By overcoming or reducing the challenges, educators and policymakers can use data to improve student outcomes and create more inclusive schools for all and overall in achieving SDG 4.

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