Malnutrition Among Children Under Five with Neurodevelopmental Disabilities: Identifying and Managing Risk Using a Multimethod Approach

Riffat Ara Shawon

A dissertation
submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy

University of Washington
2026

Reading Committee:
Judd L Walson, Chair
Arianna Rubin Means
Ali Rowhani-Rahbar

Program Authorized to Offer Degree:
Epidemiology

University of Washington

ABSTRACT

Malnutrition Among Children Under Five with Neurodevelopmental Disabilities: Identifying and Managing Risk Using a Multimethod Approach

Riffat Ara Shawon

Chair of the Supervisory Committee:

Judd L. Walson

Department of Epidemiology and Department of Global Health

Children with neurodevelopmental disabilities (NDD) are at elevated risk of malnutrition compared to children without NDD. Yet they remain notably underrepresented in prevention and intervention research. This dissertation used a multimethod approach to examine malnutrition risk and management among children under five with NDD.

The first study used retrospective longitudinal electronic health record (EHR) data from Seattle Children's Health System to identify baseline factors associated with incident malnutrition outcomes among children under five with NDD. In the primary 12-month wasting outcome cohort, 135 of 2,715 children developed incident wasting following an NDD diagnosis,

corresponding to an incidence rate of 8.49 cases per 100 person-years. Children younger than six months had higher hazard of incident wasting compared with children aged 24 to <48 months (aHR, 3.56; 95% CI, 2.33–5.44). Feeding difficulty was also associated with higher wasting hazard (aHR, 2.00; 95% CI, 1.09–3.65), as was having multiple broad NDD domains compared with social and communication NDDs (aHR, 2.42; 95% CI, 1.11–5.26). Secondary analyses showed that underweight and percentage weight loss captured distinct vulnerability patterns: underweight was associated with younger age, area deprivation index (ADI) rank, perinatal factors, respiratory morbidity, hospitalization, and feeding difficulty, whereas hospitalization was most strongly associated with percentage weight loss from baseline.

The second study shifted from risk-factor association to prognostic prediction. Using the same EHR source, a prototype point-of-care prediction tool was developed and internally validated to estimate the six-month risk of incident wasting among children with NDD. The prediction cohort included 3,480 children aged 54 months or younger at baseline. During six-month follow-up, 97 children developed incident wasting. A compact Cox model including age, broad NDD type, and respiratory morbidity performed similarly to larger clinical and data-driven models. After bootstrap internal validation, the final model had an optimism-corrected C-index of 0.693, calibration slope of 0.947, IPCW (Inverse Probability of Censoring Weighting) AUC of 0.708 at 6 months, and IPCW Brier score of 0.0288. The model stratified children into groups with distinct observed 6-month cumulative incidence of wasting. The final model was translated into a simple bedside prototype lookup table using age, broad NDD type, and respiratory morbidity.

The third study explored health-worker perceptions of the feasibility of implementing a malnutrition risk prediction tool for children with NDD in a Kenyan referral-hospital setting. Sixteen healthcare workers participated in in-depth interviews guided by the Consolidated

Framework for Implementation Research (CFIR 2.0). Participants perceived strong potential value in a tool that could identify children with NDD at elevated malnutrition risk, but emphasized that adoption would depend on simplicity, local validation, integration into existing workflows, availability across multiple service points, and clear guidance on actions after risk identification. Health workers also highlighted major barriers, including staffing shortages, gaps in NDD and malnutrition guidelines, weak referral and follow-up systems, poverty, and stigma related to both disability and malnutrition.

Together, these studies show that children with NDD have heterogeneous malnutrition risk profiles, that short-term wasting risk can be estimated using a small number of routinely available clinical variables, and that implementation of such a tool in a tertiary LMIC clinical setting will require attention to workflow, resources, local context, and proof of efficacy.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

DEDICATION

To Allah, my Creator and my Lord. Indeed, all success comes only through Him. And as He promises:

“So, surely with hardship comes ease. Surely with ˹that˺ hardship comes ˹more˺ ease.”

— Qur’an 94:5–6

ACKNOWLEDGEMENTS

All praise and gratitude are due to Allah, the Most Merciful, the Most Compassionate. May He allow the knowledge produced through this work to benefit His creation in ways that please Him.

I am deeply grateful to my dissertation chair, Dr. Judd L Walson, for his mentorship, guidance, and steady support throughout my doctoral training. I also sincerely thank my dissertation committee members, Drs. Arianna Rubin Means, Ali Rowhani-Rahbar, Grace C. John-Stewart, and Marco Carone, for their thoughtful feedback, careful reading, and generous engagement with this work. Their guidance strengthened this dissertation and helped me grow as a researcher. I am also grateful to my Graduate School Representative, Dr. Ting Ye, for her time, support, and service on my committee.

I would also like to thank the collaborators, research partners, and data teams who made this work possible. I am grateful to the collaborators involved in the Seattle Children's and to the Kenya-based research team. I also extend my sincere thanks to the healthcare workers who generously shared their time, experiences, and perspectives for this research.

I am profoundly grateful to my family. My parents, Nur Jahan and Mohammad Mozibur Rahman, have given me endless love, sacrifice, prayers, and belief. Everything I have been able to pursue has been built on the foundation they gave me. I remember my late grandparents with deep love and gratitude; may Allah have mercy on them. Their prayers, affection, and legacy remain with me, and I carry them with deep gratitude. I am also thankful for my sister, Sharmin, for her steady presence in my life and for the ways her own journey helped show me a path forward.

I am deeply grateful to my husband, Pavel, for his patience, kindness, and unwavering support. He stood beside me through the long, difficult, and uncertain parts of this journey. This path required sacrifices not only from me, but also from him, and I am deeply grateful for the many ways he carried those challenges with me. I am also sincerely grateful to my mother-in-law, Jahanara Parvin, for her exceptional support, patience, and generosity, and to my sister-in-law, Tora, for her kindness, warmth, and encouragement. My absence and the demands of this doctoral journey affected our family in many ways, and I am grateful for the patience and love with which they supported me. I also remember my late father-in-law with respect and prayer; may Allah have mercy on him.

Finally, I am thankful to the faculty, staff, colleagues, neighbors, friends, and mentors at the University of Washington who supported me throughout my doctoral journey. Graduate school was intellectually demanding and personally challenging, but I was sustained by many forms of care, encouragement, practical help, and friendship. I am deeply grateful to everyone who helped me reach this point.

CHAPTER 1 : INTRODUCTION

Malnutrition is a common and serious health problem among children with neurodevelopmental disorders in the world. Nearly 50 million children of age five or below worldwide suffer from acute malnutrition and a similar number from neurodevelopmental disorders (NDD) [1], [2]. Low and middle-income countries (LMICs) bear most of the burden for both conditions [1], [3]. High-income countries (HICs) also have a considerable burden of NDD[4] and malnutrition [5]. Management of both NDD and malnutrition varies significantly between HICs and LMICs due to a myriad of factors, including healthcare infrastructure, accessibility to medical care, and economic resources.

"Neurodevelopmental disorders are a group of heterogeneous conditions characterized by a delay or disturbance in the acquisition of skills in various developmental domains, including motor, social, language, and cognition" [6]. Specific conditions include intellectual disabilities, communication disorders, autism spectrum disorder, attention-deficit/hyperactivity disorder, specific learning disorder, epilepsy, motor disorders, and other/unspecified NDDs.[7], [8] While acute malnutrition is a condition that is most prevalent in children under two years of age[9], [10], most neurological disorders are diagnosed quite later in childhood.[11], [12], [13] However, some neurodevelopmental disorders are apparent, with prominent signs and symptoms from soon after birth [14]. Targeting to prevent acute malnutrition in these children can be a start to fighting malnutrition-related mortality and morbidity in children with NDD. Commonly diagnosed NDDS in children under two years are cerebral palsy and Down's syndrome.[14], [15] A systematic review revealed that the odds of developing undernutrition in children with NDDs can be two to three times more than in children without those disabilities [16]. The co-existence of malnutrition and NDD can lead to serious health risks, leading to further morbidities and

mortality. The Global Nutrition Report reveals negligible progress in achieving the global target to reduce childhood acute malnutrition [17]. Reasons include disparities that run beyond regional and national patterns of malnutrition burden and likely include populations that are not addressed or excluded from programs and interventions; children with NDD, for example. A pressing need for disaggregated health outcome data by population characteristics has been pointed out to identify groups disproportionately affected by malnutrition [18]. Identifying specific risk factors for developing malnutrition among children with NDD is urgent to prioritize interventions in nations with limited resources.

Malnutrition and neurodevelopmental disorders have a complex relationship, and most efforts targeting malnutrition in this group have been narrow in scope.

Nutritional deficiencies can cause delayed developmental growth, contributing to NDDs. However, NDDs can also directly lead to malnutrition by increasing nutrient and caloric expenditure, modifying nutrient loss, and hampering nutritional intake (Figure 1.1) [19], [20]. This bi-directional relationship between malnutrition and NDD complicates management. The relationship also implies that when one condition is observed, vigilant actions are needed to prevent the other condition and the worsening of the primary condition. Several interventions have been tested to improve developmental outcomes in malnourished children, such as providing psychosocial

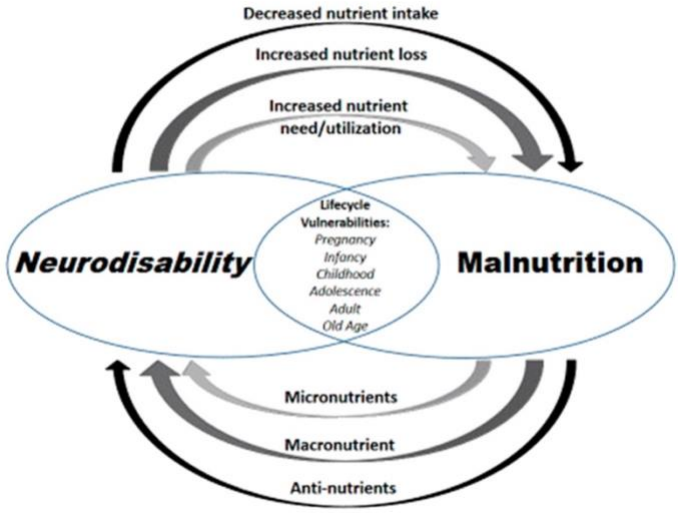

Figure 1.1: Bidirectional relationship between malnutrition and NDD

stimulation, education programs, and micronutrient supplementation[21]. Few interventions have been tested to prevent malnutrition among children with NDD in a holistic way, focusing on barriers unique to NDD conditions, for example, swallowing difficulties in disabilities involving the motor system [22], [23], [24].

Risk factors and management of acute malnutrition specific to children with NDDs remain largely under-researched. Guidelines for acute malnutrition rarely mention specific management for children who have challenges with feeding and digestion, like many children with NDDs [25]. Children with NDDs often have gastrointestinal dysfunction and motor dysfunctions [26]. Thus, impaired routine feeding is common. Hence, general management of malnutrition may not apply to children with NDDs with specific disabilities. Evidence shows that nutritional outcomes do not solely depend on energy consumption in children with disabilities[27]. There is a lack of literature on risk factors for developing acute malnutrition and subsequent poor health outcomes among children with NDDs. Determining risk factors that are highly predictive of malnutrition among children with NDDs will inform prevention strategies.

A significant consideration for advancing this research is the availability of data. While High-Income Countries offer good opportunities to utilize existing data sources like Electronic Medical Records (EMR), such resources are scarce in LMICs. Our exploration to find data sources in LMICs that capture both NDD assessment at a young age and follow-up anthropometry revealed that such data sources may not exist in routine setups where malnutrition in children with NDDs is managed. Utilizing data from HICs could serve as a good initiation to the efforts to identify factors contributing to malnutrition in children with NDDs. This, in turn, will help us advocate for specific data collection endeavors to address the research question in LMIC settings.

It is critical to identify children with NDDs who are at risk of malnutrition and intervene as early as possible to prevent poor outcomes in these children and to reduce the overall burden of childhood acute malnutrition. An opportunity for the early identification of acute malnutrition is when a child with NDD comes in contact with the health system for any service. However, there are many barriers to preventing and managing acute malnutrition in children with NDD. Seeking health services is challenging for caregivers, especially in low-resource settings [28], [29]. Clinical service providers also have minimal support. For example, there is no linkage between guidelines for disabilities and acute malnutrition, adding to the complexity of diagnosis and management [30], [31].

Appropriate management of acute malnutrition depends greatly on timely access to and effective provision of health services. However, several barriers, such as financial constraints, geographical access challenges, inadequate healthcare resources, stigma, and a general lack of awareness, often hinders optimal healthcare utilization for children with NDDs [32]. It's crucial to delve into the specific challenges that physicians face while managing acute malnutrition, as well as the challenges encountered by caregivers of children with NDDs. An in-depth exploration of these challenges is needed to establish and sustain a healthcare system that duly prioritizes the needs of these children. Engaging both healthcare providers and caregivers can help foster a collaborative and inclusive approach toward reducing the adverse impacts of acute malnutrition in children with NDDs.

This dissertation addressed three aims: first, to estimate baseline risk factors associated with incident wasting and related nutritional outcomes among children under five with NDD using longitudinal EHR data; second, to develop and internally validate a prototype 6-month wasting

risk prediction tool for children with NDD; and third, to assess health-worker perceptions of the feasibility of implementing such a tool in a Kenyan referral-hospital setting.

CHAPTER 2 : ASSESSMENT OF RISK FACTORS FOR MALNUTRITION AMONG CHILDREN UNDER FIVE YEARS WITH NEURODEVELOPMENTAL DISABILITIES: A RETROSPECTIVE LONGITUDINAL STUDY

Introduction

Childhood malnutrition remains an important driver of under-five mortality globally[33], [34], affecting approximately 43 million children each year and leading to an estimated 4.9 million deaths annually. [35]. In particular, wasting, measured by a child's weight-for-height (WHZ) z-score less than -2, is associated with extremely high rates of morbidity and mortality[36],[37]. In addition to wasting, underweight, defined by a weight-for-age (WAZ) z-score of less than -2, is also associated with significant morbidity [36]. Despite available evidence-based interventions for the prevention and management of both wasting and underweight, many countries are off track to meet the UN Sustainable Development Goals (SDGs) and World Health Organization (WHO) global nutrition targets for 2030 [38], [39], [40], [41], [42].

Neurodevelopmental disabilities (NDDs), including intellectual disabilities, communication disorders, autism spectrum disorder, specific learning disorders, epilepsy, motor disorders, and others, are common, affecting over 50 million children under five years old globally[43]. Children with NDDs are at high risk of malnutrition, with some studies suggesting that as many as 50% of children with NDDs may have coexisting malnutrition [44], [45] [46]. While most children with NDDs appear at high risk of undernutrition, some NDDs, such as ADHD and autism, may also be linked to overnutrition[47]. Children with NDDs may make up a substantial proportion of children with malnutrition seeking medical care, with as many as one-fifth of

hospitalized children admitted for severe malnutrition may have an underlying disability or NDD[48]. Importantly, the mechanisms underlying malnutrition in children with NDDs may differ substantially from those in other children. For example, motor and psychomotor difficulties, as well as comorbid neurologic and psychiatric conditions, may impact both feeding patterns and energy metabolism[49]. Current guidelines for the prevention and management of malnutrition do not differentiate prevention or treatment approaches based on these differences and may not adequately the pathways and mechanisms driving malnutrition in many children with NDDs.[50], [51], [52].

In order to identify optimal interventional targets to prevent and manage malnutrition in children with NDD, data are needed to determine which children will benefit from such targeted strategies. However, few studies have examined risk factors for malnutrition among this population. In addition, the limited data that are available come primarily from cross-sectional studies, limiting the ability to determine temporal relationships, a core principle in evaluating causality, even when biological pathways from exposure to outcome seem plausible[45], [53], [54]. We used a retrospective longitudinal EHR data source to examine associations between baseline characteristics and incident wasting among children under five years with NDD. Through secondary analyses, we also assessed risk factors for incident underweight and weight loss outcomes.

Methods

Study design

We conducted a retrospective longitudinal cohort study using electronic health record (EHR) data from Seattle Children's Health Systems. The Biostatistics, Epidemiology, and Analytics in Research (BEAR) department at Seattle Children's Institute was provided access to data on

specific preselected variables. The dataset included visit-level records of children from October 2020 through May 2024.

Study setting

Seattle Children's Health Systems serves children from a quarter of the land mass of the United States, including Washington, Wyoming, Alaska, Montana, and Idaho. The health system provides inpatient, outpatient, emergency, surgical, and rehabilitative care across nearly 60 pediatric specialties and subspecialties and includes Seattle Children's Hospital, a tertiary pediatric referral center in Seattle, Washington, with 423 beds.

Study population

The study population consisted of under five children who received care at sites within the Seattle Children's Health System between October 2020 and May 2024 and had received an NDD diagnosis. NDD was identified using ICD-10 diagnosis codes and, when available, clinician-entered problem list information. The eligible NDD diagnoses included cerebral palsy, autism spectrum disorders, intellectual disabilities, developmental speech and language disorders, and congenital malformations of the nervous system. A complete list of ICD-10 codes and related diagnoses is provided in Table A.1. The sequential application of eligibility criteria is shown in Figure 2.1 and summarized in Table 2.1.

Table 2.1: Inclusion and exclusion criteria for the primary outcome (incident wasting within 12 months from baseline) cohort

Inclusion Criteria	Exclusion Criteria
1. Age younger than 48 months at baseline	1. No eligible visit before 48 months of age
2. ICD -10 code available for eligible NDD diagnosis	2. No eligible NDD diagnosis
3. Sex recorded as male or female	3. Sex recorded as clinically undetermined or non-binary
4. Height/length and weight data available for WHZ calculation	4. Height/length or weight value unavailable after applying data-cleaning and completion rules
5. Wasting-free at baseline	5. No wasting-free baseline visit available
6. At least one follow-up WHZ measurement available between 14 days and 12 months after baseline	6. No follow-up WHZ measurement available during the eligible follow-up period

Baseline definition and cohort construction

For each eligible child, the baseline visit for the primary wasting analysis was defined as the earliest visit that met the eligibility criteria, including age younger than 48 months, an eligible NDD diagnosis, a valid WHZ, and no wasting (Table 2.1). Following the same principle, three different cohorts were built: one for wasting, one for underweight, and one for weight loss outcomes. If multiple visits occurred on the same eligible date, the visit with the most complete data was selected.

Follow-up began at baseline and continued until the first observed wasting event, the last available valid WHZ measurement within the 12-month follow-up window, or 12 months after baseline, whichever occurred first. Follow-up duration was calculated in days from the baseline to the outcome or censoring date.

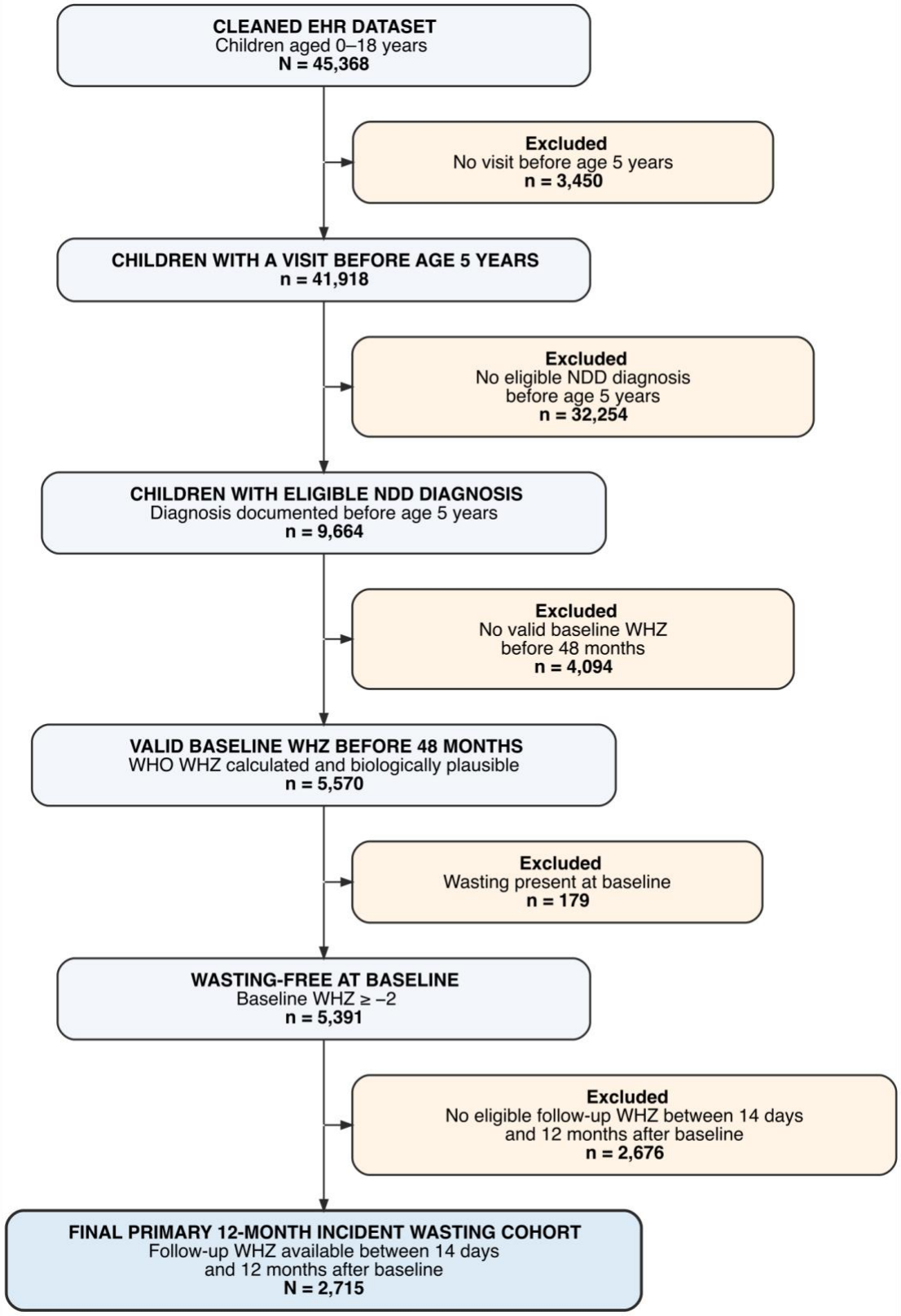

Figure 2.1: Applied steps in wasting cohort construction

Outcome variables

The primary outcome of this study was incident wasting within 12 months after baseline, defined as the first post-baseline visit with WHZ < −2 among children who were free of wasting at baseline. Secondary outcomes defined within the same 12-month follow-up framework included incident underweight, defined as the first post-baseline encounter with WAZ < −2, and first observed weight loss of ≥5% and ≥10% relative to baseline weight. Only the first qualifying event during follow-up was counted, and repeated outcomes were not considered in this study.

Baseline exposures and covariates

Baseline exposures and covariates were selected a priori based on clinical relevance, prior literature, and a directed acyclic graph representing known pathways to malnutrition. Variables included demographic and socioeconomic characteristics, perinatal factors, and clinical comorbidities, including broad NDD type.

Demographic variables included age at baseline, sex, race, and ethnicity. Age was categorized as <6 months, 6 to <24 months, and 24 to <48 months. Race and ethnicity were derived from EHR demographic fields, with race collapsed into mutually exclusive categories of White, Black, or African American, Asian, American Indian, Alaska Native, and non-Hispanic Pacific Islander (AI/AN/NHPI), and a category combining other races, refused to answer, or unknown race. Socioeconomic variables included insurance type, categorized as private and public insurance/self-pay/financial assistance, and Area Deprivation Index (ADI) national rank, categorized into quintiles. ADI is a scale measuring an area's socioeconomic disadvantage, ranging from 1 to 100, with higher values indicating greater disadvantage. Perinatal variables included gestational age, categorized as preterm, early term, full term, and late/post-term, and

birthweight, categorized as extremely low, very low, low, and normal birthweight using standard thresholds.

Several clinical diagnosis variables were derived using information from clinician-entered problem-list text. Free-text problem-list entries were processed in JMP Text Explorer software to identify clinically relevant terms and phrases, which were then manually grouped into prespecified clinical diagnosis indicators. Text-derived indicators included feeding difficulty or tube feeding, respiratory morbidity, congenital heart disease, infectious conditions, and prematurity-related conditions. When information about a clinical variable was available from multiple sources, structured fields and text-derived indicators were combined to improve ascertainment.

Missing data

Height and weight values were first inspected for biological plausibility. Subsequently, missing height or weight data at a visit was completed using the closest non-missing measurement from the same child within a ±7-day window. WHZ and WAZ were then calculated using the WHO child growth standards. Implausible z-score values were set to missing. For other EHR-derived variables, missing values were retained as missing. In case of clinical variables derived from clinician-entered problem-list text, the absence of a specific diagnosis was treated as an absence of documented evidence for that condition. However, this may reflect either true absence or incomplete documentation in EHR.

Statistical analysis

Descriptive statistics were used to summarize demographic, socioeconomic, perinatal, NDD-type, and clinical characteristics of the primary 12-month wasting cohort. Continuous variables

were summarized using medians and interquartile ranges, and categorical variables were summarized using frequencies and percentages.

Kaplan–Meier methods were employed to estimate the cumulative incidence of outcomes descriptively, computed as one minus the Kaplan–Meier survival estimate. The overall cumulative incidence, as well as estimates stratified by broad NDD type, were reported for six and 12 months post-baseline intervals.

Associations between baseline characteristics and first observed incident wasting within 12 months after baseline were estimated using Cox proportional hazards (Cox PH) regression models with robust standard errors based on complete-case observations. Follow-up was administratively censored at 12 months. Time since baseline was treated as the time scale for all analyses. For each baseline exposure, we estimated an unadjusted Cox model for descriptive purposes to assess crude exposure-outcome associations. These unadjusted models did not determine which variables were included in the adjusted models. Instead, adjusted models were specified a priori using a Directed Acyclic Graph (DAG) (Figure 2.2). In this approach, separate models for each exposure were fitted with a minimum required set of confounders (Supplemental Table A.3).

Cox PH model-derived hazard ratios (HRs) and their 95% confidence intervals (CIs) were reported for each exposure relative to a reference group. For all secondary outcomes, the corresponding outcome-specific cohort was used. The rest of the analytic approach was the same as the primary outcome. Results based on sparse events were interpreted cautiously.

As a sensitivity analysis, missing baseline exposures and covariates for the wasting cohort were imputed using multiple imputation by chained equations (MICE) with 50 imputed datasets [55].

The imputation model included baseline demographic, socioeconomic, perinatal, NDD-type, and clinical variables, the outcome indicator, and follow-up time. Incident wasting indicator and observed follow-up time were not imputed in this process. Text data-derived clinical diagnosis variables were also not imputed. Cox PH models were refit within each imputed dataset, and hazard ratio estimates were combined across imputations using Rubin's rules. Results from the imputed analyses were compared with the primary complete-case results. The complete case findings are presented as primary results in this paper.

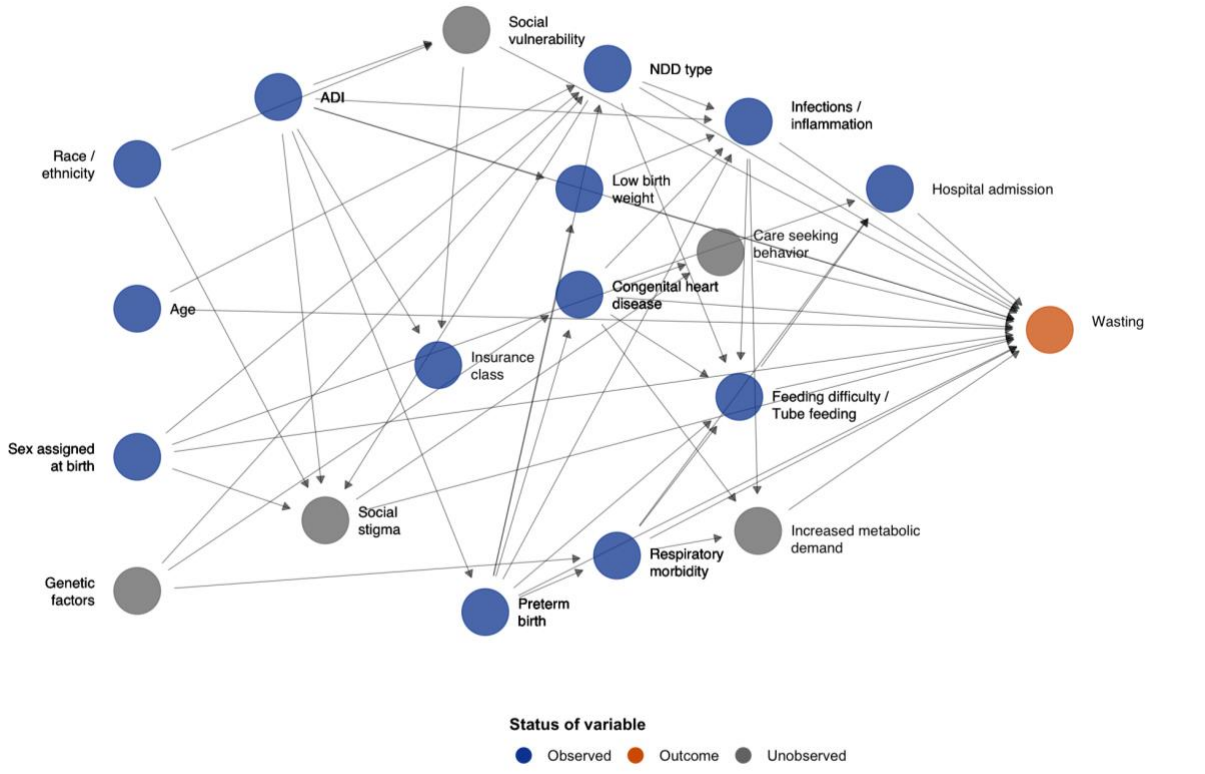

Figure 2.2: Directed Acyclic Graph- Pathways to wasting in children with NDD

Ethical considerations

The study protocol was reviewed by the University of Washington Institutional Review Board and determined to be exempt because the analysis used secondary clinical data and involved no direct participant contact. Data were handled and stored according to institutional requirements for privacy and confidentiality. All analyses were conducted using a deidentified dataset prepared for research use.

Results

After applying the inclusion criteria to the available EHR data, the final analytic cohort for wasting outcome included 2,715 children (Figure 2.1). The median age at baseline was 21.6 months (IQR: 10.0, 33.6); 17% were younger than 6 months, 39% were 6 to <24 months, and 45% were 24 to <48 months (Table 2.2). Overall, 59% children were male. The majority of the children (53%) were White, with 13% Asian, 11% Black or African American, 2% American Indian, Alaska Native, Native Hawaiian, or Pacific Islander, and 21% categorized as other or unknown. One-quarter of children were Hispanic. Less than half (47%) of the children had private insurance and the rest were covered by public insurance, self-pay, or charity care. The median ADI rank score was 23.0 (IQR: 12.0, 37.0).

Gestational age data were only available for 58% children. In the available data, the median gestational age was 38.0 weeks (IQR: 36.0, 39.0); 29% were preterm, 28% were early-term, 38% were full-term, and 6% were late/post-term. Birthweight was available for 50% children. The median birthweight was 3,056 g (IQR: 2,466, 3,487); among children with available birthweight, 5% had extremely low birthweight, 4% very low birthweight, 17% low birthweight, and 74% normal birthweight (Table 2.2).

Physical and motor disabilities were identified in 40% of children, cognitive and learning disabilities in 11%, social and communication disabilities in 32%, and 17% of children were found to have multiple co-occurring broad NDD diagnoses. At baseline, 7% of children had feeding difficulties, 4% had respiratory morbidity, 4% had congenital heart disease, and 21% were hospitalized (Table 2.2).

Table 2.2: Baseline characteristics of children included in the primary 12-month incident wasting analysis (N = 2,715)

Characteristic	Median (Q1, Q3) | N (%)	Characteristic	Median (Q1, Q3) | N (%)
Age at baseline, months	21.6 (10.0, 33.6)	**Insurance type, n = 2,617**	
Age category		Private Insurance	1,226 (47%)
<6 months	457 (17%)	Public Insurance, self-pay, charity	1,391 (53%)
6–<24 months	1,049 (39%)	**Gestational age, weeks, n = 1,574**	38.0 (36.0, 39.0)
24–<48 months	1,209 (45%)	**Gestational age category**	
Sex		Preterm (<37 weeks)	456 (29%)
Male	1,602 (59%)	Early-Term (37–38 weeks)	434 (28%)
Female	1,113 (41%)	Full-Term (39–40 weeks)	590 (38%)
Race category, n = 2,705		Late/post-term (41+ weeks)	94 (6%)
Black or African American	297 (11%)	**Birthweight, grams, n = 1,358**	3,056 (2,466, 3,487)
Asian	338 (13%)	**Birthweight category**	
AI/AN/NHPI	66 (2%)	Extremely low birthweight (<1000 g)	71 (5%)
White	1,443 (53%)	Very low birthweight (1000 to <1500 g)	52 (4%)
Other/Unknown	561 (21%)	Low birthweight (1500 to <2500 g)	231 (17%)
Ethnicity, n = 2,588		Normal birthweight (>=2500 g)	1,004 (74%)
Hispanic	645 (25%)	**Baseline co-morbidities**	
Non-Hispanic	1,943 (75%)	Feeding difficulty	193 (7%)
NDD type		Respiratory morbidity	95 (4%)
Physical & Motor	1,097 (40%)	Congenital heart disease	112 (4%)
Cognitive & Learning	292 (11%)	Current hospitalization	568 (21%)
Social & Communication	859 (32%)	**ADI national rank, n = 2,509**	23.0 (13.0, 37.0)
Multiple broad NDD diagnoses	467 (17%)		

Notes: Percentages are calculated among children with non-missing data for each variable; variables with missing data include the available denominator in the row label.

ADI = Area Deprivation Index; NDD = neurodevelopmental disability.
ADI national rank is a measure of neighborhood disadvantage, with higher values indicating greater deprivation.

For the survival analysis, the median time to incident wasting or censoring was 223 days (IQR: 126, 312 days), contributing 580,766 person-days of time at risk. During the 12-month follow-up period, 135 of 2,715 children developed incident wasting, corresponding to a crude observed event proportion of 5%. The remaining 2,580 children did not have an observed wasting event before censoring. This translates to 8.49 cases of incident wasting per 100 person-years. Among children who developed wasting, the median observed time to incident wasting was 109 days (IQR: 56, 210 days).

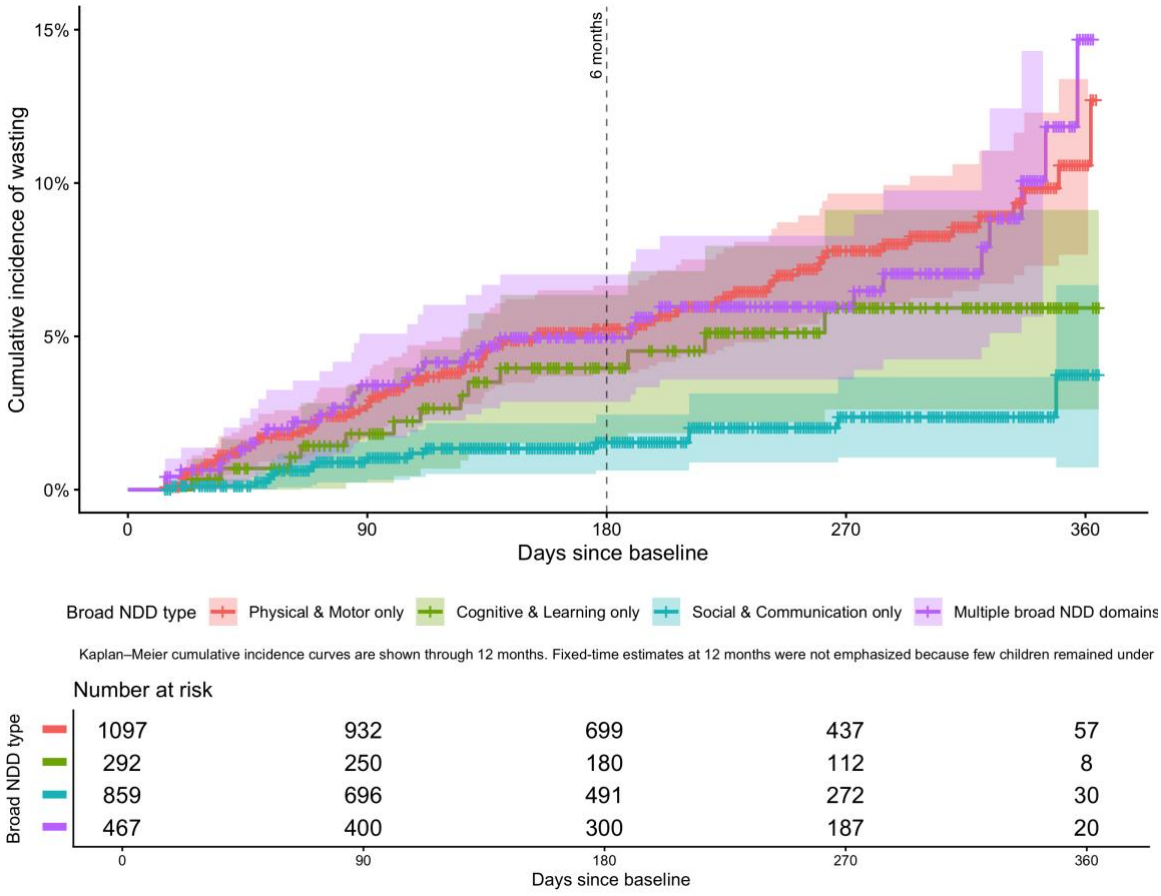

Figure 2.3: Cumulative incidence of wasting by broad NDD types

The Kaplan–Meier estimated cumulative incidence was 3.9% at six months (95% CI: 3.1%–4.7%) (Supplemental Figure A.1). Six-month cumulative incidence varied by broad NDD type. It was highest among children with Physical & Motor NDDs (5.2%; 95% CI: 3.8%–6.7%) and Multiple broad NDD domains (5.0%; 95% CI: 2.9%–7.0%), followed by children with Cognitive & Learning NDDs (4.0%; 95% CI: 1.5%–6.4%) (Figure 2.3). Children with Social & Communication NDDs had the lowest six-month cumulative incidence (1.5%; 95% CI: 0.6%–2.5%). Estimates at 12 months were interpreted cautiously because few children remained under observation near the end of the follow-up window, which made those estimates unstable.

In complete-case DAG-informed Cox models, younger age, broad NDD type and feeding difficulty were associated with incident wasting within 12 months (Table 2.3 and Figure 2.4). Compared with children aged 24 to <48 months, children younger than 6 months had a higher hazard of wasting (adjusted HR [aHR], 3.56; 95% CI, 2.33-5.44). Hazard among children aged 6 to <24 months and 24 to <48 months were not statistically different (aHR 1.49; 95% CI: 0.97, 2.30).

Children with multiple broad NDD domains had a higher hazard of wasting compared with children with Social & Communication NDDs (aHR, 2.42; 95% CI, 1.11–5.26). Estimates for children with Physical & Motor NDDs (aHR, 1.56; 95% CI, 0.71–3.42) and Cognitive & Learning NDDs (aHR, 1.48; 95% CI, 0.56–3.87), were not significant in the complete case adjusted analysis. In addition, feeding difficulty was associated with a higher hazard of incident wasting (aHR, 2.00; 95% CI, 1.09–3.65).

Table 2.3: Baseline Risk Factors for Wasting (WHZ < -2) Among Children Under Five Years Following First Observed NDD Diagnosis

Exposure	Contrast	Unadjusted HR (95% CI)	DAG-adjusted HR (95% CI)	p-value	Reference group events/person-time, days	Comparison group events/ person-time, days
Age category	6–<24 months vs 24–<48 months	1.49 (0.97, 2.30)	1.49 (0.97, 2.30)	0.068	37 / 260,015	47 / 218,618
	<6 months vs 24–<48 months	3.56 (2.33, 5.44)	3.56 (2.33, 5.44)	<0.001	37 / 260,015	51 / 102,133
Sex	Female vs Male	0.82 (0.58, 1.16)	0.82 (0.58, 1.16)	0.266	87 / 342,867	48 / 237,899
Race	Black or African American vs White	1.14 (0.66, 1.95)	1.14 (0.66, 1.95)	0.638	75 / 313,265	16 / 60,229
	Asian vs White	0.90 (0.52, 1.54)	0.90 (0.52, 1.54)	0.695	75 / 313,265	16 / 75,596
	AI/AN/NHPI vs White	0.63 (0.15, 2.56)	0.63 (0.15, 2.56)†	0.515	75 / 313,265	2 / 13,575
	Other/Unknown/Patient Refused vs White	0.96 (0.61, 1.49)	0.96 (0.61, 1.49)	0.844	75 / 313,265	26 / 115,990
Ethnicity	Hispanic vs Non-Hispanic	0.92 (0.61, 1.38)	0.92 (0.61, 1.38)	0.676	99 / 417,274	30 / 138,381
Area deprivation index	Q2 vs Q1 (least deprivation)	1.61 (0.93, 2.77)	1.61 (0.93, 2.77)	0.087	21 / 104,025	34 / 105,533
	Q3 vs Q1 (least deprivation)	0.92 (0.50, 1.69)	0.92 (0.50, 1.69)	0.781	21 / 104,025	20 / 110,165
	Q4 vs Q1 (least deprivation)	1.13 (0.63, 2.02)	1.13 (0.63, 2.02)	0.675	21 / 104,025	25 / 109,615
	Q5 (most deprivation) vs Q1 (least deprivation)	1.23 (0.69, 2.17)	1.23 (0.69, 2.17)	0.485	21 / 104,025	27 / 108,656

Broad NDD type	Physical & Motor only vs Social & Communication only	3.60 (2.07, 6.27)	1.56 (0.71, 3.42)	0.269	9 / 72,960	60 / 174,798
	Cognitive & Learning only vs Social & Communication only	2.36 (1.12, 4.95)	1.48 (0.56, 3.87)	0.426	9 / 72,960	8 / 40,715
	Multiple broad NDD domains vs Social & Communication only	3.61 (1.95, 6.67)	2.42 (1.11, 5.26)	0.026	9 / 72,960	23 / 70,024
Hospital admission at baseline	Yes vs No	1.79 (1.25, 2.57)	1.23 (0.78, 1.95)	0.376	92 / 459,342	43 / 121,424
Gestational age category	Early-Term (37–38 weeks) vs Full-Term (39–40 weeks)	1.59 (0.96, 2.64)	1.48 (0.87, 2.50)	0.147	26 / 121,781	30 / 90,247
	Late/Post-Term (41+ weeks) vs Full-Term (39–40 weeks)	1.99 (0.93, 4.24)	2.15 (1.00, 4.60)	0.050	26 / 121,781	9 / 19,365
	Preterm (<37 weeks) vs Full-Term (39–40 weeks)	1.38 (0.83, 2.32)	1.27 (0.74, 2.17)	0.381	26 / 121,781	28 / 101,309
Birthweight category	Extremely Low Birthweight vs Normal Birthweight	1.40 (0.61, 3.25)	1.83 (0.60, 5.55)	0.285	53 / 198,184	5 / 15,735
	Very Low Birthweight vs Normal Birthweight	1.57 (0.63, 3.91)	2.09 (0.64, 6.89)†	0.225	53 / 198,184	4 / 10,688
	Low Birthweight vs Normal Birthweight	1.47 (0.90, 2.40)	1.70 (0.92, 3.13)	0.088	53 / 198,184	20 / 50,680
Congenital heart disease	Yes vs No	2.21 (1.27, 3.85)	0.95 (0.46, 1.97)	0.884	88 / 333,516	12 / 24,981
Respiratory morbidity	Yes vs No	2.66 (1.53, 4.64)	1.19 (0.58, 2.46)	0.638	87 / 335,991	13 / 22,506

Infections/inflammation	Yes vs No	1.39 (0.34, 5.62)	0.70 (0.09, 5.41)†	0.728	81 / 271,870	1 / 3,417
Feeding difficulty	Yes vs No	2.79 (1.81, 4.28)	2.00 (1.09, 3.65)	0.025	76 / 317,382	24 / 41,115

Note: Hazard ratios were estimated using Cox proportional hazards models. Adjusted models used DAG-informed minimal sufficient adjustment sets. Event counts and person-time are calculated from the same exposure-specific complete-case dataset used for the corresponding DAG-adjusted Cox model. Totals vary across exposures because each exposure had a different DAG-specified adjustment set and because of missing covariate data.
*For exposures with no DAG-specified adjustment variables, the DAG-adjusted model is identical to the exposure-only model.
† Estimate based on fewer than 5 events in the comparison group and should be interpreted cautiously

There was no clear evidence of association between incident wasting and Area Deprivation Index, sex, race, ethnicity, birthweight, gestational age, hospitalization at baseline, congenital heart disease, respiratory morbidity, or infections/inflammation in adjusted models although some of the unadjusted models showed statistically significant. Results for associations between incident wasting and infections/inflammation and AI/AN/NHPI race were based on sparse events and thus should be interpreted cautiously.

Multiple imputation was performed as a sensitivity analysis for the primary wasting models. Results were broadly similar to complete case for most exposures. However, imputed analyses suggested stronger associations for broad NDD type. Compared with children with Social & Communication NDDs, higher hazards of wasting were observed among children with Physical & Motor NDDs (pooled aHR, 2.11; 95% CI, 1.13–3.96), Cognitive & Learning NDDs (pooled aHR, 2.20; 95% CI, 1.04–4.66), and multiple broad NDD domains (pooled aHR, 3.31; 95% CI, 1.78–6.16). Low birthweight was found to be associated with wasting in the imputed analysis (pooled aHR, 1.80; 95% CI, 1.03–3.15).

Secondary outcome analyses showed that the pattern of associated baseline factors differed across nutritional indicators (Supplemental Tables A.5–A.7 and Figure 2.4). For incident underweight, children younger than 6 months had the strongest association (aHR, 7.22; 95% CI, 4.96–10.51). Children aged 6 to <24 months also had a higher hazard compared with those aged 24 to <48 months (aHR, 1.58; 95% CI, 1.04–2.41). Higher area deprivation was associated with underweight for Q4 (aHR, 2.11; 95% CI, 1.19–3.74) and Q5 (aHR, 2.60; 95% CI, 1.50–4.53) compared with Q1. Other factors associated with incident underweight included hospitalization at

baseline (aHR, 1.72; 95% CI, 1.18–2.53), preterm birth (aHR, 1.86; 95% CI, 1.20–2.88), low birthweight (aHR, 2.12; 95% CI, 1.25–3.58), respiratory morbidity (aHR, 1.73; 95% CI, 1.03–2.92), and feeding difficulty (aHR, 3.53; 95% CI, 2.22–5.63). Broad NDD type, congenital heart disease, sex, race, and ethnicity were not clearly associated with underweight after adjustment.

Percentage weight-loss outcomes showed a different pattern. Hospitalization at baseline was the most consistent factor associated with both ≥5% (aHR 3.12; 95% CI: 2.29, 4.26) and ≥10% weight loss from baseline (aHR 5.15; 95% CI: 2.97, 8.94). Children younger than 6 months had a lower hazard of ≥5% weight loss (aHR, 0.24; 95% CI, 0.12–0.50) and ≥10% weight loss (aHR, 0.13; 95% CI, 0.02–0.97). Respiratory morbidity was associated with ≥5% weight loss, but the confidence interval was wide (aHR, 3.87; 95% CI, 1.04–14.39). Estimates for ≥10% weight loss were based on several sparse strata and should be interpreted cautiously.

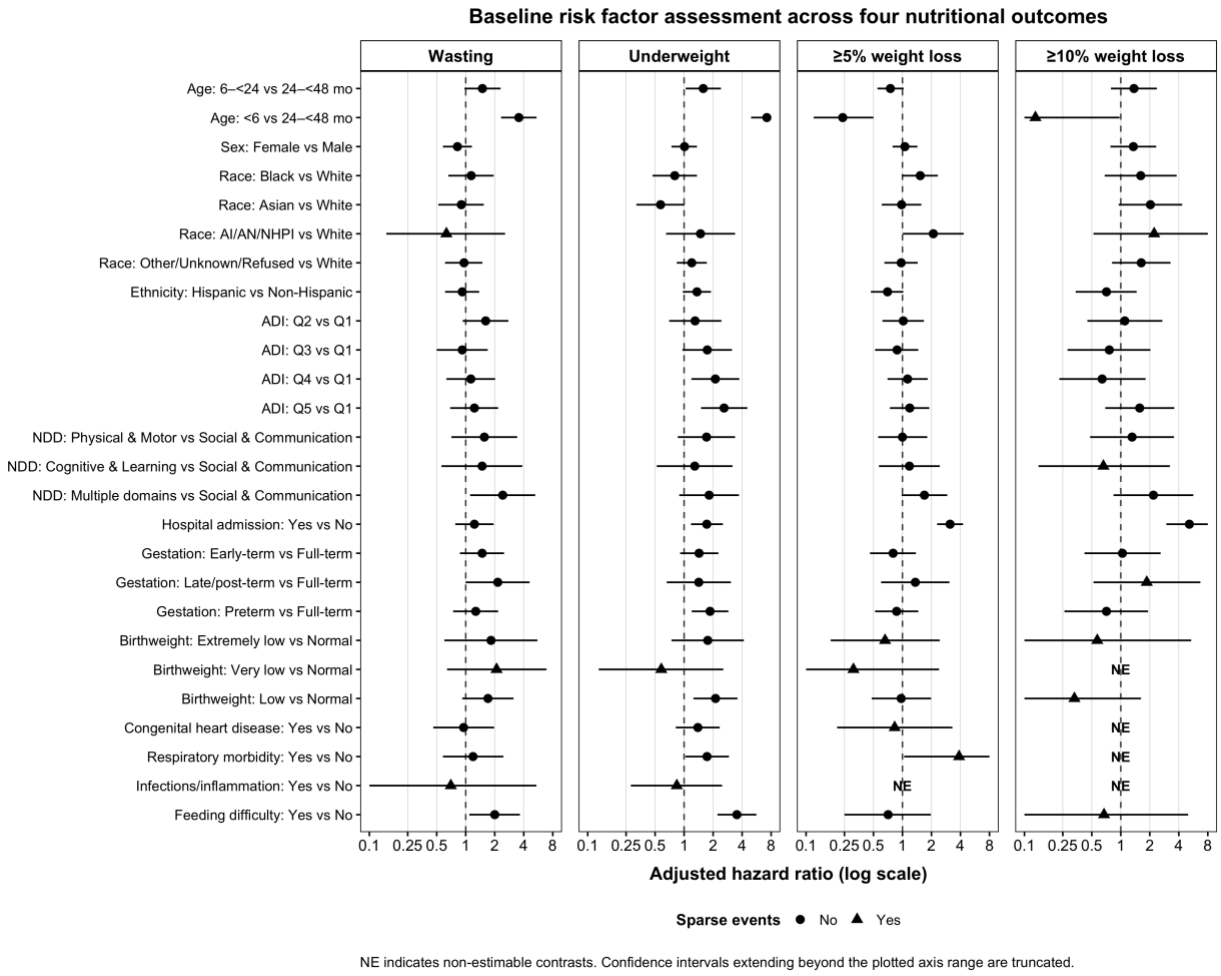

Figure 2.4: Adjusted Hazard Ratios for Baseline Risk Factors Associated with Four Nutritional Outcomes in Children Under Five with NDD

Discussion

Using electronic health records from children under five years of age with neurodevelopmental disabilities, we determined that wasting was relatively common in this population during the 12-month follow-up window, with an observed incidence rate of 8.49 cases per 100 person-years. We were also able to identify baseline factors associated with the onset of wasting, including younger age, feeding difficulty, and broad neurodevelopmental disability classification.

The association between broad NDD type and wasting indicates that nutritional risk varies across children with different neurodevelopmental profiles. Children with multiple co-occurring broad NDD diagnoses exhibited significantly higher risk of wasting compared to children with social and communication type NDDs (e.g., autism) in complete case models. Multiple-imputation sensitivity analyses suggested stronger associations across all non-reference NDD groups including physical and motor type disabilities (e.g., cerebral palsy), cognitive and learning specific NDDs (e.g. intellectual disabilities). This finding well aligns with existing literature describing increased nutritional vulnerability among children with specific NDD conditions, particularly cerebral palsy and other motor disorders, where feeding difficulties, dysphagia, impaired self-feeding, altered energy expenditure, gastrointestinal issues, and recurrent illnesses may contribute to poor growth [56], [57], [58], [59], [60], [61]. Existing studies also demonstrate that feeding difficulties and micronutrient deficiencies are more common in multiple co-occurring NDD diagnoses than in a single NDD diagnosis [62].

Very young infants with NDD may require additional intervention beyond routine care to prevent wasting and underweight conditions. In this study, children under six months at baseline appeared at a higher risk of both wasting and underweight. This may reflect both early-life nutritional demands for rapid growth and the fact that NDDs recognized very early may be more clinically complex affecting feeding, swallowing, gastrointestinal and respiratory health, or overall metabolic demand [63], [64], [65]. However, this age pattern should be interpreted carefully because in this study "baseline" was the point when the child entered our study after NDD was identified in the EHR. Because wasting and underweight can improve and recur over time, the outcomes in this study should be understood as new observed episodes after study entry, rather than first-ever lifetime episodes. Therefore, the lower risk observed among older

children should not be interpreted as evidence that older age is naturally protective. Rather, young age at study entry may identify children with NDD who are clinically complex and need especially close nutritional monitoring.

In contrast, we observed a reversed association between younger age and ≥5% or ≥10% weight-loss risk, which appears counterintuitive and inconsistent with the wasting and underweight results. It is important to note the conceptual difference between these two types of nutritional outcomes: wasting and underweight measures are relative to a standard population, whereas percent weight loss is an absolute measure of weight change. Thus, failure to gain weight can lead to a diagnosis of wasting or underweight, even in the absence of absolute weight loss from baseline, simply because of falling behind in comparison to a standard population.

Proactive monitoring and early intervention for feeding difficulties could play an important role in preventing wasting and underweight in children with NDD. This study found that children with documented feeding difficulties had twice the risk of developing wasting compared to those without, even after accounting for NDD type and related comorbidities. This finding is biologically plausible, as feeding difficulties can restrict oral intake, prolong feeding times, increase caregiver burden, and may be linked with conditions like dysphagia, gastroesophageal reflux, aspiration risk, or altered energy needs in children with NDD. The association between feeding difficulties and incident underweight in secondary analyses further highlights feeding difficulty as a significant factor in nutritional vulnerability in this group.

Secondary outcomes provided further insight, suggesting that nutritional vulnerability may vary by outcome. Incident underweight showed stronger associations with socioeconomic deprivation, preterm birth, low birthweight, respiratory morbidity, and feeding difficulty. Perinatal vulnerability may also contribute to incident wasting, although this pattern was clearer

in sensitivity analysis than in complete-case models. Low birthweight was associated with wasting in multiple-imputation analyses, suggesting that impaired fetal growth may remain relevant to nutritional vulnerability after NDD-related cohort entry. This aligns with prior literature showing that infants born preterm or with low birthweight are more likely to experience feeding and suckling difficulties, lower metabolic reserve, immature oromotor function, and respiratory or infectious morbidity [66] [67], [68]. In contrast, percentage weight-loss outcomes showed a different pattern, including lower observed hazards among younger infants, and higher risk among hospitalized children. These differences underscore that wasting, underweight, and percentage weight loss are related but not interchangeable indicators of nutritional risk. In children with NDD, relying on a single anthropometric definition may miss clinically important patterns, particularly when growth faltering, chronic underweight, and acute weight loss reflect different underlying processes.

It is crucial to identify and address the added stressors that heighten the susceptibility to malnutrition in hospitalized children with NDD. This study shows a strong association between hospitalization and a higher risk of weight loss, aligning with studies indicating that well-nourished children at admission may also face risks. [69]. Metabolic stress, increased energy requirements, poor appetite, and reduced food intake are likely pathways for developing malnutrition in all hospitalized children and these may be further complicated by structural and functional issues due specifically to NDDs [70], [71]. Proactive strategies need to be developed and implemented to support hospitalized children with NDDs. Additionally, some data suggest that anthropometric assessments are often missed during hospital admission, leading to missed early indicators of malnutrition, particularly those that are more acute, such as wasting [72]. Thus, more comprehensive monitoring beyond standard chart records is warranted to ensure

early detection of malnutrition, particularly in high-risk children. The lack of an association between hospitalization and wasting in this study may partly reflect this measurement gap.

A notable strength of this study is its classification of NDDs into broad developmental categories, allowing examination of nutritional differences across neurological dimensions, which is rarely seen in existing literature. Examining multiple nutritional outcomes demonstrated that different outcomes capture distinct patterns of nutritional vulnerability in children with NDD. In addition, the use of longitudinal EHR data allowed us to overcome limitations of cross-sectional data, which can be problematic when the relationship between exposure and outcome is bidirectional, such as is seen with NDDs and nutrition.

Several limitations should be considered when interpreting these findings. A substantial number of otherwise eligible children lacked follow-up WHZ measurements, preventing them from being included in the wasting analysis. Among those included, right censoring was handled using Cox and Kaplan–Meier methods; however, these approaches rely on non-informative censoring assumptions that may be imperfect in EHR data, as follow-up frequency and anthropometric data availability are inherently tied to unmeasured factors such as clinical severity, care-seeking behaviors, and referral patterns. Additionally, the high proportion of missing gestational age and birthweight data requires cautious interpretation of their results. However, our sensitivity analyses utilizing imputed baseline factors support the overall stability of the findings. Furthermore, WHZ and WAZ calculations depend on accurate length and weight measurements, which are uniquely challenging to obtain in pediatric populations with NDDs [73], [74]. Several clinical variables were derived from clinician-entered problem-list text, which may be incomplete, weakening the association results. Residual confounding may persist due to unmeasured disease severity and any ongoing nutritional treatments. Baseline age should be

interpreted carefully because it reflects both developmental age and the timing of NDD recognition and cohort entry. Thus, baseline age influence on incidence is affected by selection bias, partly reflecting differences in who entered the cohort at younger versus older ages, rather than biological age alone. Lastly, because the dataset was derived from a tertiary referral health system for children, the results may not be generalized beyond a similar setting.

Conclusion

Distinct risk profiles for developing malnutrition exist among children with NDDs. Targeted approaches to nutritional monitoring and management among children with NDD may improve outcomes in these high-risk children. In particular, children who are younger, have feeding difficulty, or multiple co-occurring NDD diagnoses appear to be at a higher risk of incident wasting and may benefit from close monitoring and early intervention targeting specific pathways leading to malnutrition in these sub-groups of high-risk children.

CHAPTER 3 : DEVELOPMENT AND INTERNAL VALIDATION OF A PROTOTYPE POINT-OF-CARE PREDICTION TOOL FOR SIX-MONTH WASTING RISK IN CHILDREN UNDER FIVE WITH NEURODEVELOPMENTAL DISABILITIES

Introduction

Globally, more than 50 million children younger than five years are estimated to have neurodevelopmental disabilities (NDDs), including motor, cognitive, learning, and social-communication impairments, intellectual disabilities, communication disorders, autism spectrum disorder, epilepsy, motor disorders, and other developmental conditions [43], [75], [76]. Children with NDD often require complex, multidisciplinary care, as comorbidities, including feeding difficulties, gastrointestinal and respiratory complications and other medical challenges are common in this population [77], [78]. Malnutrition is also common in this population. For example, in children younger than five years with developmental delay, about 24% are wasted, defined as a WHO weight-for-height (WHZ) z-score <-2 [79]. Wasting is a critical concern in children with NDDs due to its association with mortality, long term impairments in growth and development, immune function, overall health, and quality of life [80].

Identifying children at risk for malnutrition early is critical to effective prevention and management [81]. Given the high-risk nature of NDDs for the development of malnutrition, the timing of NDD diagnosis is important. While some NDDs can be identified at birth, such as severe congenital or motor conditions, including cerebral palsy, other NDD diagnoses may present late, such as less pronounced forms of cognitive, learning, or social-communication impairments [82], [83]. As a result, children with NDDs may not be identified until malnutrition or other comorbidities become clinically apparent.

Children with NDD frequently present to healthcare facilities for routine developmental follow-up as well as for respiratory illnesses, infections, seizure management, or other clinical needs [84], [85]. Healthcare encounters provide an important opportunity to identify future nutritional risk among children with NDDs. However, malnutrition risk may be under-appreciated in children with NDDs, particularly when clinical attention is focused on more urgent medical issues or comorbidities [86]. Routine anthropometric monitoring may be inconsistent, and accurate height or length measurement can be particularly challenging in children with motor impairment [87]. These challenges create missed opportunities to identify children at high risk of wasting and other forms of malnutrition.

Screening tools offer an opportunity to identify children who may be at high risk of poor outcomes. Most current nutritional screening tools are primarily designed to identify malnutrition that is already present, which may miss opportunities to prevent malnutrition at those at highest risk [88], [89], [90], [91], [92], [93] [94]. By contrast, screening tools based on prognostic prediction or prognostic screening may offer the opportunity for clinicians to prioritize closer growth surveillance or earlier nutritional referral before physical decline becomes clinically evident [95] [96], [97], [98]. Although prediction tools have been developed to predict weight loss during hospitalization [96], no wasting risk prediction tool has been developed specifically for children with NDD to prevent future wasting events.

To address this gap, we utilized longitudinal electronic health record (EHR) data from a large pediatric health system to develop and internally validate a point-of-care prediction model for incident wasting in children under 5 years with NDD.

Methods

Study setting and data source

We developed and internally validated a survival prediction model using EHR data from the Seattle Children's Health System, which serves children from a quarter of the land mass of the United States, including Washington, Wyoming, Alaska, Montana, and Idaho. The health system provides inpatient, outpatient, emergency, surgical, and rehabilitative care across nearly 60 pediatric specialties and subspecialties and includes Seattle Children's Hospital a tertiary pediatric referral center in Seattle, Washington, with 423 beds. The dataset was obtained from Seattle children's Biostatistics, Epidemiology, and Analytics in Research (BEAR) department. The data included visit-level records from October 2020 through May 2024 with information on demographic status, anthropometric measurements, ICD-10 diagnosis codes for NDD, and selected clinical and socioeconomic characteristics. An analytic dataset was prepared for model development after applying data plausibility checks and data-cleaning rules.

Study population and prediction cohort

The target population for this predictive tool was children under five years of age with an NDD diagnosis. NDD was identified from ICD-10 diagnosis codes and, when available, clinician-entered problem-list information. Eligible NDD conditions were grouped into broad NDD categories, including physical and motor disabilities, cognitive and learning disabilities, and social and communication disabilities (Supplemental Table A.1). Children with evidence of more than one broad domain were classified as having multiple co-occurring NDD diagnoses.

The study eligibility criteria (Table 3.1) were applied to construct the analytic cohort for wasting prediction. Baseline was defined as the earliest eligible wasting-free visit before 54 months of

age, ensuring that children had the opportunity to contribute to 6-month prediction before the fifth birthday.

Table 3.1: Inclusion and exclusion criteria for the primary outcome (incident wasting) cohort

Inclusion Criteria	Exclusion Criteria
1. Age ≤54 months	1. No eligible visit before 54 months
2. ICD -10 code available for eligible NDD diagnosis	2. No eligible NDD diagnosis
3. Sex recorded as male or female	3. Sex recorded as clinically undetermined or non-binary
4. Height/length and weight data available for WHZ calculation	4. Height/length or weight value unavailable after applying data-cleaning and completion rules
5. At least one visit where the child is free of wasting	5. No wasting-free baseline visit available
6. At least one follow-up WHZ measurement available ≥14 days after the wasting-free baseline visit and before the fifth birthday or end of available EHR data	6. No follow-up WHZ measurement available during the eligible follow-up period

The final prediction cohort included under five children with NDD who were free of wasting at baseline and at risk for developing incident wasting during follow-up. Each child contributed one baseline record containing candidate predictors measured at the baseline visit. Subsequent follow-up visit records were used to determine incident wasting development and follow-up time.

Outcome and follow-up

The prediction outcome was the first wasting event (incident wasting) after baseline. Repeated events, although possible during follow-up, were not considered in this study. Wasting was defined as WHZ<-2 and was calculated using height and weight data at baseline and at all subsequent visits. Follow-up began at the baseline visit and continued until the first observed wasting event, the last visit with plausible height and weight data, the child's fifth birthday, or

the end of available EHR data, whichever came first. Six-month predicted risk was estimated at 180 days after baseline.

Candidate predictors

Candidate predictors were selected a priori based on clinical relevance, expected availability at or near the baseline visit, completeness in the electronic health record, interpretability, and feasibility for translation into a simple bedside tool. These variables included age in months, sex, race, ethnicity, insurance type, broad NDD type, feeding difficulty, respiratory morbidity, congenital heart disease, infectious or inflammatory conditions, and hospital admission status at baseline.

Clinical comorbidity predictors were derived from problem-list text, when available (Supplemental Table A.2). The absence of a clinician-entered text derived morbidity indicator was treated as the absence of evidence for that condition.

Missing data

Missingness was preserved except for anthropometric measurements, which were imputed using a predefined completion rule. When height or weight data were missing at a visit, the closest non-missing value for the same child within a ±7-day window was used, if available. Implausible z-score values were set to missing. Missingness was low for most demographic and clinical predictors used in the primary candidate models (Table 3.2) but was substantial for some perinatal variables. Gestational age was available for 1,874 of 3,480 children (54%), and birthweight was available for 1,587 (46%). Therefore, gestational age and birthweight were not included in the primary prediction model comparison despite their clinical relevance. This decision was made to preserve sample size, improve the feasibility of bedside implementation,

and avoid building a tool dependent on information that may be inconsistently available in the EHR or from caregiver report.

Models were evaluated on a sample of children with complete data on the included predictors across the candidate model sets for model comparison. This approach ensured that differences in model performance reflected differences in predictor sets and not differences in the children included in each model.

Candidate model comparisons and final variable selection

We fit Cox proportional hazards models with baseline predictor variables to estimate the time to incident wasting after baseline. Candidate models were specified to represent different levels of model complexity. Three prespecified candidate Cox models used the same modeling framework and differed only in their sets of predictors. A lasso-penalized Cox model was included as a data-driven comparator using a broader candidate predictor set.

First, a 'minimal Cox' model was fit including two variables: age in months and broad NDD type. The second 'clinical Cox' model added baseline respiratory morbidity, feeding difficulty, and hospital admission status to the minimal model. Third, an 'extended clinical Cox' model included additional demographic, socioeconomic, and clinical predictors: age in months, sex, ethnicity, insurance type, broad NDD type, feeding difficulty, respiratory morbidity, congenital heart disease, infectious or inflammatory conditions, and hospital admission status. Finally, a 'lasso-penalized Cox' model was fit to assess whether data-driven variable selection could improve performance compared to the preselected earlier three Cox models. The lasso model included age in months, sex, race, ethnicity, insurance type, Area Deprivation Index (ADI) national rank, feeding difficulty, respiratory morbidity, congenital heart disease, infectious or inflammatory conditions, hospital admission status at baseline, and broad NDD type.

For the first stage of model selection, candidate models were compared using repeated 10-fold cross-validation with 10 repetitions on a common complete-case sample. In each repetition, the data were randomly divided into 10 parts. Models were trained on nine parts and internally validated on the remaining held-out part, rotating the held-out part until each part had served once as the validation set. Performance metrics were averaged across the 10 held-out validation sets and then across the 10 repetitions. For the lasso-penalized Cox model, the penalty parameter was selected using internal 10-fold cross-validation within each training set before the model was evaluated in the corresponding held-out validation set.

Overall model discrimination was assessed using Harrell's concordance index (C-index). The C-index evaluated whether children who developed wasting earlier received higher predicted risk scores than children who remained event-free longer or were censored later. In addition, time-dependent discrimination was assessed using AUC at six months to assess how well the model distinguished children who developed wasting by six months from those who did not. Prediction error was evaluated using Brier scores at six months. Lower Brier scores indicate smaller prediction error. Time-dependent AUC and Brier scores were estimated using inverse probability of censoring weighting (IPCW) to account for right censoring before each time point.

In the second stage of model selection, we examined the contribution of individual predictors within the 'clinical' Cox model by dropping one variable at a time from the model.

In the third stage, additional models were evaluated by adding one clinically accessible predictor (respiratory morbidity, feeding difficulty/tube-feeding, and hospital admission status) at a time to core predictors identified in the second stage (age and NDD type).

Final Model Selection and Performance Assessment

The final model was built using predictors that retained the main predictive information and at the same time, relied on variables that were available at baseline, clinically interpretable, relatively objective, and feasible for translation into a simple tool. Selected variables were then used to fit the final Cox proportional hazards model among all children with complete data for those predictors. Predicted risks at 6 months were calculated from the fitted Cox model by combining the linear predictor with the estimated baseline survival function at 180 days.

Since assessing the final model on the same data used for model fitting could produce overly optimistic performance estimates, final model performance was evaluated using bootstrap internal validation with 500 resamples. In each bootstrap resample, the final Cox model was refit, and performance was estimated in both the bootstrap sample and the original analytic sample to estimate optimism. Optimism-corrected performance was calculated by subtracting the mean optimism from the apparent performance. This procedure was applied to the overall C-index, Cox calibration slope, time-dependent AUC and Brier score at 6 months. For time-dependent AUC and Brier score, metric estimation used inverse probability of censoring weighting with a marginal Kaplan–Meier censoring model.

Time-specific grouped calibration plots were generated by comparing mean predicted risk within deciles of predicted risk against IPCW-estimated observed cumulative incidence at 6 months.

Risk stratification and bedside tool development

Predicted risks from the final model were used to construct risk stratification groups at six months. In the absence of established clinical treatment thresholds for wasting risk in this population, children were categorized into low, intermediate, and high predicted-risk groups

using descriptive tertiles of the estimated predicted risk. These risk groups were further evaluated by plotting the observed cumulative incidence curves over the 6-month prediction window.

To aid practical clinical application, predicted probabilities were framed into bedside lookup tables. These visual tools display predicted risks at 3-month age intervals, using a color-coded heatmap to indicate the corresponding risk tertile (low, intermediate, or high) within the study population. To provide finer age granularity, a detailed supplemental table presents predicted risks stratified at 1-month age intervals.

Software

Text exploration of clinician-entered problem-list data was performed using the Text Explorer module in JMP Student Edition, Version 19.0.5 [99], and derived comorbidity indicators were imported into R to create binary clinical predictor variables. All subsequent statistical analyses, model development, and validation were performed using R V.4.5.3 (R Core Team, Vienna, Austria) through RStudio V.2024.12.1+563 (Posit Software, Boston, MA) [100].

Ethical considerations

This study utilized secondary, de-identified electronic health record data prepared specifically for research use. The study protocol was reviewed by the University of Washington Institutional Review Board and determined to be exempt because the analysis used secondary clinical data and involved no direct participant contact. Data were handled and stored according to institutional requirements for privacy and confidentiality. All analyses were conducted using a deidentified dataset prepared for research use.

Results

The final prediction cohort included 3,480 children with a documented diagnosis of NDD who were ≤54 months of age at baseline, free of wasting at baseline and had sufficient follow-up data to assess incident wasting. During the 6-month follow-up, 97 children developed wasting, corresponding to 2.79% of the cohort, and the incidence rate was 6.29/100 person-years. At baseline, the median age of the cohort was 24.8 months (IQR: 13.0, 38.4), and 60% children were male.

The distribution of broad NDD type included physical and motor disabilities in 1,274 children (37%), cognitive and learning disabilities in 349 children (10%), social and communication disabilities in 1,249 children (36%), and multiple co-occurring broad NDD diagnoses in 608 children (17%). At baseline, 19% of the cohort had been hospitalized. Baseline respiratory morbidity, a predictor used in the final model, was documented in 108 children (3%). All baseline characteristics are presented in Table 3.2.

Table 3.2: Baseline characteristics of children in the primary 6-month wasting prediction cohort (N = 3,480)

Characteristic	Median (Q1, Q3) or N (%)	Characteristic	Median (Q1, Q3) or N (%)
Age at baseline, months	24.8 (13.0, 38.4)	**Insurance type, n = 3,364**	
Age category		Private Insurance	1,557 (46%)
<6 months	482 (14%)	Public Insurance	1,807 (54%)
6–<24 months	1,183 (34%)	**Gestational age category, n = 1,874**	
24–54 months	1,815 (52%)	Preterm (<37 weeks)	547 (29%)
Sex		Early-Term (37–38 weeks)	496 (26%)
Male	2,090 (60%)	Full-Term (39–40 weeks)	706 (38%)
Female	1,390 (40%)	Late/Post-Term (41+ weeks)	125 (7%)
Race category, n = 3,469		**Birthweight category, n = 1,587**	
Black or African American	394 (11%)	Extremely Low Birthweight	82 (5%)
Asian	433 (12%)	Very Low Birthweight	59 (4%)

Characteristic	Median (Q1, Q3) or N (%)	Characteristic	Median (Q1, Q3) or N (%)
AI/AN/NHPI	78 (2%)	Low Birthweight	271 (17%)
White	1,830 (53%)	Normal Birthweight	1,175 (74%)
Other/Unknown/Patient Refused	734 (21%)	**Co-morbidities**	
Ethnicity, n = 3,329		Feeding difficulty	213 (6.1%)
Hispanic	829 (25%)	Respiratory morbidity	108 (3.1%)
Non-Hispanic	2,500 (75%)	Congenital heart disease	123 (3.5%)
Broad NDD type		Hospital admission at baseline	664 (19.1%)
Physical & Motor only	1,274 (37%)	Infections/inflammation	25 (0.7%)
Cognitive & Learning only	349 (10%)	**ADI national rank, n = 3,215**	23.0 (12.0, 37.0)
Social & Communication only	1,249 (36%)		
Multiple broad NDD domains	608 (17%)		

Notes: Percentages are calculated among children with non-missing data for each variable; variables with missing data include the available denominator in the row label.
*AI/AN/NHPI = American Indian, Alaska Native, Native Hawaiian, and Pacific Islander.
ADI = Area Deprivation Index; NDD = neurodevelopmental disability.
ADI national rank is a measure of neighborhood disadvantage, with higher values indicating greater deprivation.

Stage one: Broad model comparisons

Cross-validated performance was similar across all broad candidate models compared in the first step (Table 3.3). The Minimal Cox model had a mean cross-validated C-index of 0.685 and 6-month AUC of 0.696, performing similarly to the larger Clinical Cox model, which had a C-index of 0.681 and 6-month AUC of 0.690. The Extended clinical Cox and Lasso Cox models did not improve predictive performance.

Table 3.3: Broad comparison of candidate prediction models for wasting

Model	Predictors	Mean CV c-index	AUC at 6 months	Brier at 6 months
Minimal Cox	Age, broad NDD type	0.685	0.696	0.0294
Clinical Cox	Age, broad NDD type, respiratory morbidity, admission at baseline, feeding difficulty	0.681	0.690	0.0295
Extended Clinical Cox	Age, sex, ethnicity, insurance type, feeding difficulty, respiratory morbidity, congenital heart disease, infectious conditions, admission at baseline, broad NDD type	0.671	0.682	0.0296
Lasso Cox	Penalized Cox model using candidate baseline predictors	0.662	0.667	0.0296

Note: Models were compared using repeated 10-fold cross-validation on a common complete-case sample. Values represent mean cross-validated performance. AUC and Brier score were estimated at the 6-month prediction horizon using inverse probability of censoring weighting. CV = cross-validation; NDD = neurodevelopmental disability.

Stage two: Drop-One-Variable Analysis

In the second stage, dropping one predictor at a time from the Clinical Cox model showed that age and broad NDD type contributed the most to predictive performance (Table 3.4). Removing age reduced the mean cross-validated C-index from 0.681 to 0.639 and the 6-month AUC from 0.690 to 0.627. Removing broad NDD type reduced the C-index to 0.647. In contrast, removing feeding difficulty, respiratory morbidity, or hospital admission at baseline produced little change in performance.

Table 3.4: Drop-one predictor analysis of the bedside model

Model	Predictors	Mean CV c-index	AUC at 6 months	Brier at 6 months
Clinical Cox model	Age, broad NDD type, respiratory morbidity, admission at baseline, feeding difficulty	0.681	0.690	0.0295
Drop feeding	Age, broad NDD type, respiratory morbidity, admission at baseline	0.684	0.694	0.0295
Drop respiratory	Age, broad NDD type, admission at baseline, feeding difficulty	0.683	0.688	0.0295

Model	Predictors	Mean CV c-index	AUC at 6 months	Brier at 6 months
Drop admission	Age, broad NDD type, respiratory morbidity, feeding difficulty	0.686	0.697	0.0295
Drop broad NDD type	Age, respiratory morbidity, admission at baseline, feeding difficulty	0.647	0.683	0.0296
Drop age	Broad NDD type, respiratory morbidity, admission at baseline, feeding difficulty	0.639	0.627	0.0296

Note: Models were compared using repeated 10-fold cross-validation on a common complete-case sample. Values represent mean cross-validated c-index.

Stage three: Compact Model Performance and Final Selection

Three parsimonious compact models, including age and NDD type (based on the most important predictors detected in stage two) plus one clinical comorbidity variable, achieved cross-validated performance values that were similar to each other and to the Clinical Cox model (Table 3.5). The Compact Respiratory model had the highest mean cross-validated C-index (0.695) and 6-month AUC (0.714).

Given comparable performance across compact models, the Compact Respiratory model was selected as the final prototype because respiratory morbidity was clinically interpretable, relatively objective, and feasible for use in a simple bedside lookup tool. In selecting this model, considerations were made regarding the objectivity of data, including that feeding difficulty may depend on caregiver report and hospital admission status may reflect health-system factors such as bed availability, provider practice, insurance coverage, and care-seeking practices. Respiratory morbidity on the other hand was defined from clinician-entered problem-list terms indicating acute respiratory failure, chronic respiratory disease, bronchopulmonary dysplasia, or respiratory distress syndrome (Supplemental Table A.2). However, the Compact Feeding and Admission models performed similarly and remain clinically plausible alternatives for future external validation and implementation testing.

Table 3.5: Cross-validated performance of compact candidate models used for final model selection

Model	Predictors	Mean CV c-index	AUC at 6 months	Brier at 6 months
Compact respiratory model	Age, broad NDD type, respiratory morbidity	0.695	0.714	0.0287
Compact admission model	Age, broad NDD type, admission at baseline	0.691	0.713	0.0287
Compact feeding model	Age, broad NDD type, feeding difficulty	0.689	0.700	0.0287
Clinical Cox model	Age, broad NDD type, respiratory morbidity, admission at baseline, feeding difficulty	0.689	0.706	0.0288

Note: Models were compared using repeated 10-fold cross-validation on a common complete-case sample. Values represent mean cross-validated c-index.

Final Model Performance

After accounting for model optimism using 500 bootstrap resamples, the final Compact Respiratory Cox model achieved an optimism-corrected C-index of 0.693 (95% CI: 0.659, 0.726) and calibration slope of 0.947 (95% CI: 0.758, 1.164) (Table 3.6). The optimism-corrected IPCW AUC at 6 months was 0.708 (95% CI: 0.666, 0.759), and the optimism-corrected IPCW Brier score was 0.0288 (95% CI: 0.0232, 0.0342).

Table 3.6: Final compact model performance after model selection

Metric	Optimism corrected estimate (95% Bootstrap CI)
C-index	0.693 (0.659, 0.726)
Calibration slope	0.947 (0.758, 1.164)
IPCW AUC at 6 months	0.708 (0.666, 0.759)
IPCW Brier score at 6 months	0.0288 (0.0232, 0.0342)

Note: Values are optimism-corrected estimates from bootstrap internal validation with 500 resamples. Intervals are 95% bootstrap percentile intervals from the distribution of optimism-corrected estimates. Time-dependent AUC and Brier score were estimated using inverse probability of censoring weighting with a marginal Kaplan–Meier censoring model. IPCW = inverse probability of censoring weighting.

Time-specific calibration plots at the six-month (Figure 3.1) showed reasonable alignment between mean predicted risk and IPCW-estimated observed cumulative incidence across predicted-risk deciles. However, some variability was noted in the highest-risk groups.

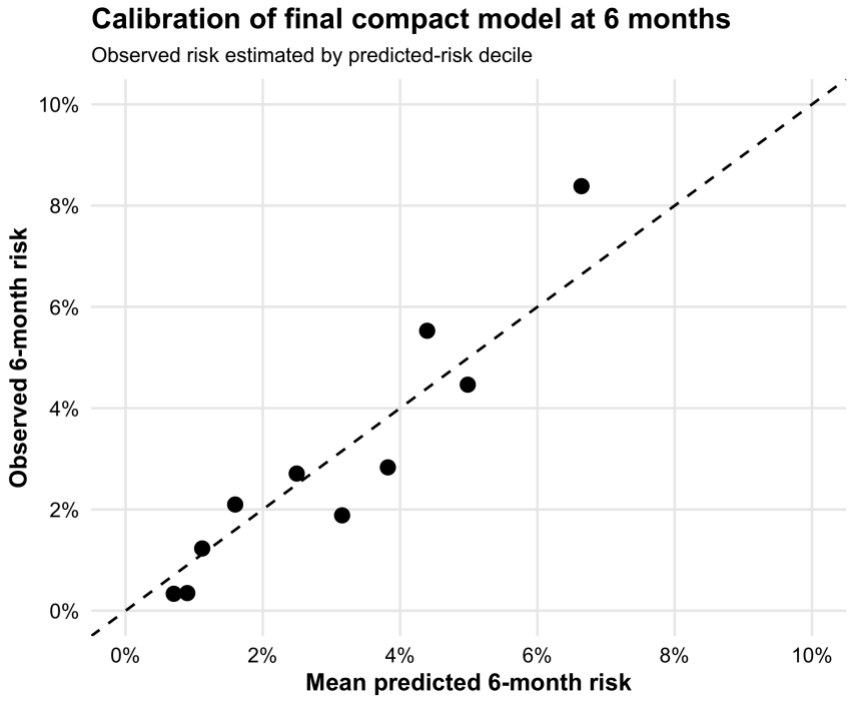

Figure 3.1: Calibration of the final compact model at 6 months

To examine whether the model separated children into groups with different observed cumulative incidence of wasting, children were categorized into low, intermediate, and high predicted-risk tertiles based on the distribution of predicted risks. Kaplan–Meier estimated observed cumulative incidence of wasting increased consistently across these strata (Figure 3.2). Observed 6-month cumulative incidence increased across risk groups: 0.76% in the low-risk tertile, 2.10% in the intermediate tertile, and 6.11% in the high-risk tertile.

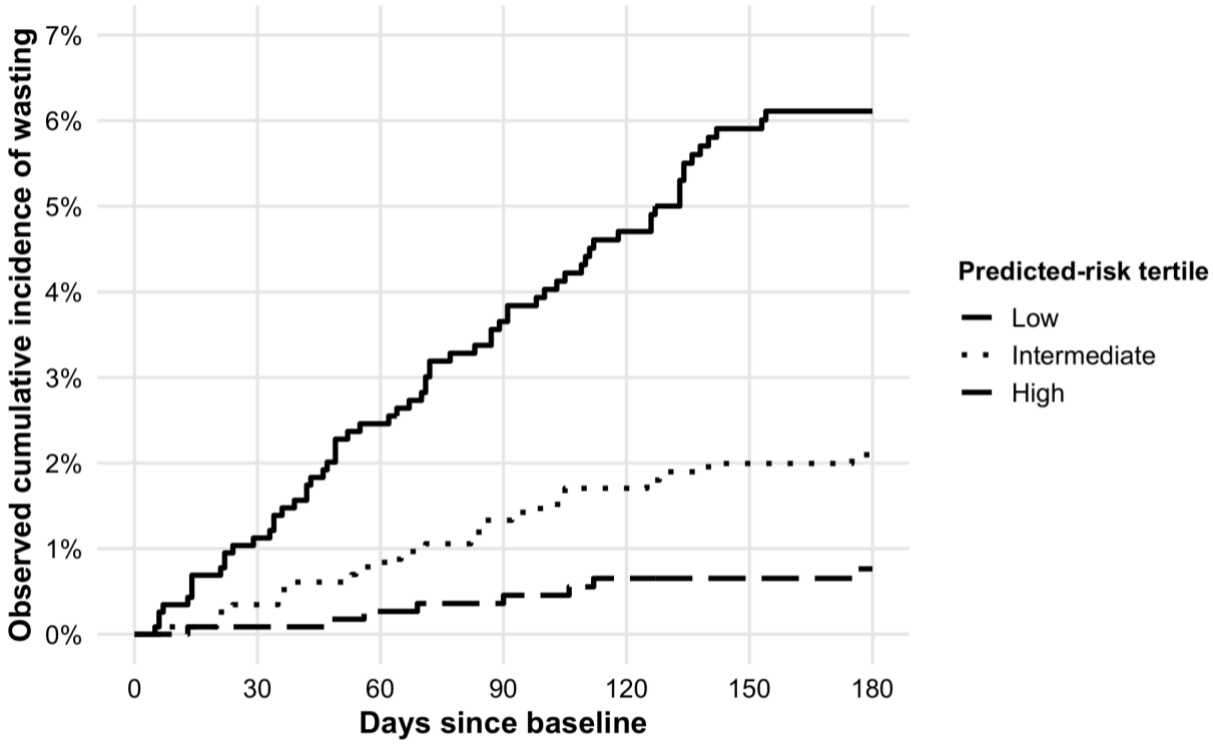

Figure 3.2: Kaplan–Meier estimated cumulative incidence of wasting by predicted-risk tertile over 6 months

The final compact model was translated into a prototype bedside lookup table displaying predicted 6-month wasting risk at 3-month age intervals (Figure 3.3). For each combination of age, broad NDD type, and respiratory morbidity status, the tool provides an estimated probability of incident wasting within 6 months. The supplemental 1-month interval table provides more granular age-specific risk estimates (Supplemental Table A.8).

These risk bands, defined as low, intermediate, and high based on tertiles of predicted risk, are intended only to support model-based risk stratification and visualization in this prototype tool and should not be interpreted as clinical treatment thresholds.

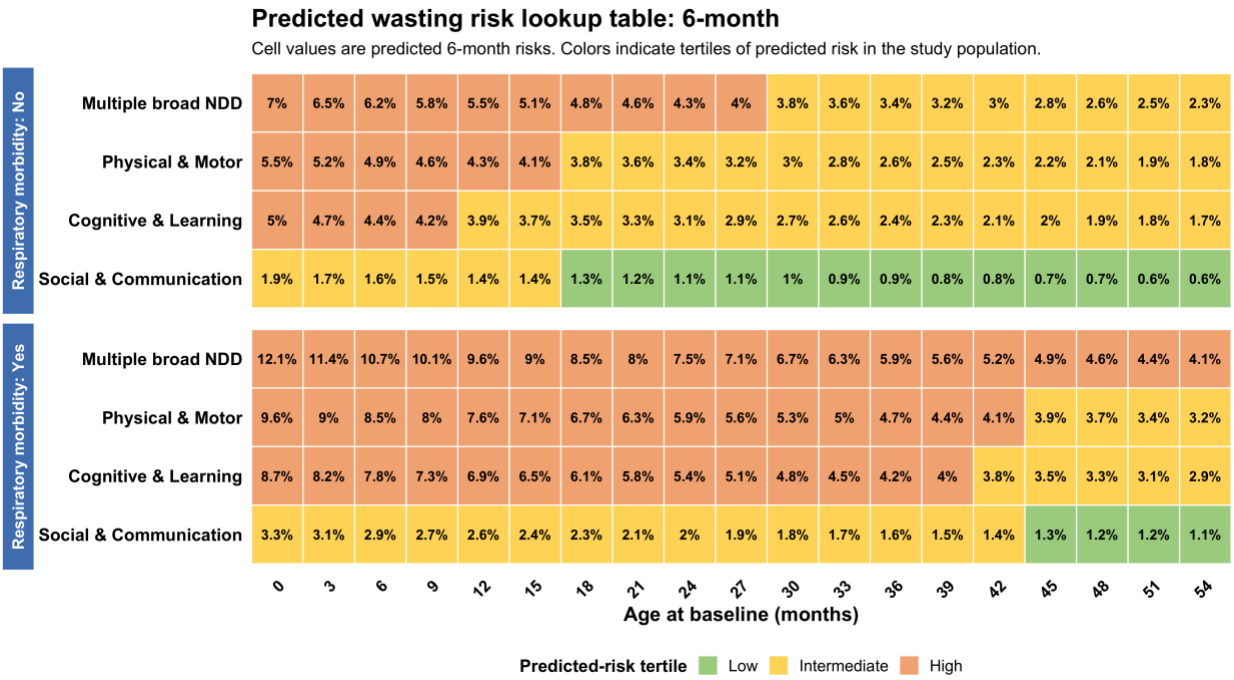

Figure 3.3: Risk stratification chart for 6 months wasting risk prediction in children with NDD

Cell values are predicted risks (%). Colors indicate predicted-risk tertiles: green = low predicted-risk tertile, yellow = intermediate predicted-risk tertile, and orange = high predicted-risk tertile**.**

Discussion

This study demonstrates that short-term wasting risk in children younger than five years with NDDs can be estimated using a small set of baseline clinical variables. A three-variable model, namely age, NDD type, and presence of respiratory morbidity, performed comparably to larger clinical and data-driven models. This suggests that a clinically interpretable risk-stratification tool can be developed without a complex and large predictor set. The prediction model showed moderate discrimination, limited evidence of overfitting, and clear separation of children into groups with different observed cumulative incidence of wasting.

The selected predictors support a clinically justifiable interpretation of wasting risk in routine clinical settings. Age was one of the strongest predictors, likely reflecting a combination

of early life vulnerability, feeding dependence, growth patterns during early childhood, and the timing of cohort entry [101], [102]. The predictor representing the broad NDD types reflects differences in developmental and functional profiles across dimension-specific NDD diagnoses. [45], suggesting children with NDD should not be treated as a single homogeneous nutritional-risk group [103]. Respiratory morbidity was retained among other clinical indicators because it preserved model parsimony while adding a relatively observable marker of clinical complexity.

The model's moderate performance should be interpreted in light of both the complexity of wasting risk in this study population and the tool's possible use. Wasting among children with NDD is influenced by a complex interplay of dynamic feeding difficulty, breastfeeding history, parental education, caregiving patterns, recent illness, severity of NDD-related impairment, food insecurity, prior growth trend, and ongoing treatments [45], [104], [105], [106], [107]. Many of these factors were either unavailable in the EHR data used in this study or not captured in sufficient detail for the current model. Therefore, the modest discrimination achieved by the final model is not surprising. However, the model’s practical value lies in its potential to support clinicians in prioritizing who may need closer monitoring and earlier clinical review [108], [109]. In this context, a simple model that stratifies children into risk groups with different observed cumulative incidence can be useful, particularly when no established NDD-specific wasting prediction tool exists. Nonetheless, the tool should not be seen as a standalone diagnostic or treatment guideline.

In practice, the developed prototype tool could be used during a clinical visit for a child younger than five years with documented NDD who is not currently wasted to support follow-up planning. This visit may occur when NDD is newly recognized or during ongoing care for a child with previously known NDD. The clinician would enter three inputs: age in

months, broad NDD type, and whether respiratory morbidity is documented. The lookup table would then provide the estimated six-month wasting risk for the child. The predicted risk would need to be interpreted alongside any care already ongoing, such as feeding support, respiratory management, or nutrition counseling. Thus, a higher predicted-risk category may not automatically require a specific treatment, especially since such threshold-specific actions are not yet defined. The tool could prompt measures such as earlier monitoring, ensuring accurate anthropometric measurements, scheduling frequent growth reassessments, reviewing feeding and comorbidity issues, asking caregivers about recent feeding changes, or considering a nutrition referral when appropriate [110]. However, these actions would need to be defined and evaluated in future implementation studies followed by guideline generation.

Because this model relies on a small number of broadly interpretable clinical variables, it is expected to be easier to adapt than a more complex tool [111], [112], [113]. The simplicity of the tool would also allow both paper-based and electronic versions of the tool, as preferred by clinical staff in a particular setting. However, differences in NDD diagnosis, respiratory documentation, anthropometric practices, and follow-up patterns in different settings require that external validation and local recalibration are performed [114].

Research on setting-specific action thresholds based on local policies, resources, and acceptable tradeoffs between missed cases and unnecessary referrals is needed [115]. Once a threshold is proposed, the model will need to be validated in different settings. Performance characteristics, including sensitivity, specificity, positive and negative predictive values and decision curves, will need to be calculated. Ultimately, choices regarding the trade-offs between these performance metrics will need to be based on clinical and ethical judgement and incorporated into facility, sub-national, national or global guidance to be scalable for use.

This study possesses several strengths. It introduces a novel, prediction-oriented approach for the assessment of nutritional risk within a vulnerable and understudied pediatric population [50]. The model addresses an important research gap by moving beyond a description of malnutrition burden toward a practical approach for earlier risk recognition and follow-up planning. The study design has distinct methodological strengths. It utilized longitudinal EHR data, allowing for the prediction of incident wasting after baseline. Moreover, the intentional use of baseline-only predictors supports the intended clinical workflow for applying the tool at the point of care when a child with documented NDD is assessed and is not currently wasted. Finally, compiling the final model into a bedside lookup table improves clinical interpretability and provides a concrete prototype for future external validation, threshold development, and implementation research.

The main limitation of this study is that the model was developed within a single tertiary pediatric health system and may not generalize to all children with NDD. Additionally, several EHR-related documentation limitations may introduce measurement error in secondary data-based study. Collecting accurate height, length, and weight measurements can be challenging in young children and especially difficult for children with severe motor or physical impairments. Furthermore, clinical predictors derived from unstructured problem-list text, including respiratory morbidity and feeding difficulty, may be incomplete due to variations in provider documentation practices. Baseline respiratory morbidity was uncommon in the data (3%), which may affect the statistical stability and transportability of its model coefficient. Finally, we did not explicitly model competing risks, such as death occurring before incident wasting. Death before the six-month prediction windows was uncommon in our analytic cohort, suggesting that competing-risk bias is unlikely to be a major driver of these results.

Future research should focus on external validation, threshold development, and implementation work. The model should be externally tested in similar and dissimilar health systems, primary care settings, and lower-resource contexts. Future studies should also examine how clinicians use the tool in real-world workflows, including its practical usability, user acceptability, and whether it changes monitoring or referral behavior. The current model was not validated for repeated application at later visits. If clinicians reapply the lookup table at subsequent visits, the reported calibration and discrimination may no longer hold. Future work should assess dynamic prediction approaches that update wasting risk over time as new anthropometric and clinical information becomes available. Future models may also test whether adding recent changes in growth trend, severity of symptoms, caregiver-reported feeding concerns, household food insecurity, or other granular clinical and socio-demographic information improves predictive performance while also justifying the added data-collection burden.

Conclusion

We developed an internally validated prototype tool for estimating short-term incident wasting risk among children under five years old with NDD using routinely available information in clinical settings. Recognizing that children with NDD are at particularly high risk of wasting and developing tools to identify to prioritize these children for intervention, may be an important step in reducing poor outcomes related to wasting in this high-risk population.

CHAPTER 4 : HEALTH WORKER PERCEPTIONS OF THE FEASIBILITY OF IMPLEMENTING A MALNUTRITION RISK PREDICTION TOOL FOR CHILDREN WITH NEURODEVELOPMENTAL DISABILITIES

Introduction:

Neurodevelopmental disabilities (NDDs), including Autism Spectrum Disorder (ASD), Attention-Deficit/Hyperactivity Disorder (ADHD), cerebral palsy (CP), intellectual disability (ID), communication disorders, and specific learning disorders, affect about 50 million kids under five worldwide [43]. In many African settings, the prevalence of NDDs has been estimated to be considerably higher than the global average [43]. Children with NDDs are more likely to experience acute malnutrition compared to children without NDDs [116]. Behavioral and social factors, such as communication issues and/or specific food preferences, coupled with specific biological factors including inadequate feeding difficulties, abnormal energy expenditure, dysregulated metabolism, and/or increased loss of nutrients, all contribute to this risk [117]. In addition, children with NDDs disproportionately experience a higher burden of poverty, frequent infectious disease episodes, lack of adequate health services, and neglect in low-and middle-income (LMIC) settings and overall are more likely to experience acute malnutrition as compared to children in higher income settings [118], [119], [120].

Because children with NDD are at high risk of developing malnutrition and because the mechanisms that underpin malnutrition in this population differ from the general population, it is important to identify tailored interventions for early detection and management. One potential intervention is predictive risk screening, which can be deployed during routine care visits to identify children at greatest risk of developing malnutrition in the future. Although numerous

tools exist claiming to predict acute or any form of malnutrition, they primarily offer screening results. Screening tools are generally designed to flag children who may already be malnourished or who require further nutritional assessment, diagnostic evaluation, closer monitoring, or referral. This differs from prognostic prediction, which estimates an individual child's probability of developing malnutrition over a specified future time horizon [91], [92], [93] [88], [89], [90]. Only recently, an AI-based tool was developed to predict the future risk of malnutrition in Kenya, combining clinical and satellite crop imagery data for a region up to 6 months in advance, but not the individual risk of acute malnutrition [121]. However, to date, no predictive tools are available for health workers treating children with NDD, despite the fact that risk factors for developing malnutrition in these children may vary [122], [123], [124] [125]. Current efforts are underway to develop predictive screening tools in this context aimed at predicting malnutrition risk at least 6 months in advance.

Availability of predictive tools may not translate to real world benefit. Tools that demonstrate good accuracy (positive predictive value) during development are rarely used if they are not integrated into existing workflows or if they do not meet healthcare workers' perceived needs. New tools may be particularly cumbersome in settings with high patient volumes, staffing shortages, and infrastructural barriers. It is very common for a clinical prediction tool to be developed but not incorporated into practice [126], [127], [128]. It is critical to assess needs and perceived feasibility from the end users' perspective before investing time and resources in developing a new malnutrition prediction tool specifically for children with NDD.

Predictive tools are intended to guide responsive actions. If malnutrition is predicted for a given child with NDD, healthcare workers will need to make decisions regarding the frequency of ongoing monitoring or even preemptive follow-up care, such nutritional supplementation or

social support. As such, the appropriate actions to be indicated and guided by a potential malnutrition screening tool are currently unclear and may present ethical and financial challenges.

This study aims to describe healthcare workers' perceptions of the feasibility of implementing a malnutrition risk prediction tool for children under five with NDD in Kenya and describe the potential implications of deploying such a tool on malnutrition prevention and treatment. In this research, we have utilized the Consolidated Framework for Implementation Research (CFIR 2.0) to systematically explore multilevel factors influencing the successful implementation of the tool.

Methods

To assess healthcare workers' perspectives on technical, operational, economic, and cultural feasibility, and potential for sustainability and adaptability of a tool that predicts the risk of malnutrition among children with neurodevelopmental disability in an LMIC context, we conducted in-depth interviews with healthcare workers at a county referral hospital in Migori, Kenya.

Theoretical framework

We structured our feasibility exploration by using CFIR 2.0 as our guiding conceptual framework to develop qualitative interview questions and a deductive codebook for analyzing the data [129]. CFIR 2.0, or the updated CFIR, is a popular and comprehensive framework that guides the determination of contextual factors influencing implementation outcomes. The framework comprises five main 'domains': Innovation, Inner Setting, Outer Setting, Individuals, and Implementation Process. These serve as overarching categories that organize the factors influencing implementation outcomes and include 48 'constructs' that are listed as actionable

elements within each domain. For instance, the Inner Setting domain includes constructs such as Structural Characteristics and Incentive Systems. Some domains and subdomains also contain subcategories. This user-friendly framework provides detailed definitions and examples of all domains, constructs, and their subcategories. The literature offers numerous examples of how to use this framework to determine implementation outcomes at different stages of an intervention.

Feasibility definition and assessment:

We defined 'feasibility' as assessing whether the future development and application of a specific risk prediction tool 'can and/or should be done', and, if so, 'how it could/should be done' [130].

Sample

We aimed to explore healthcare workers' perceptions from different roles and with varying years of experience involved in caring for children with NDD. We purposively recruited a diverse sample of male and female health workers across multiple experience levels and roles, such as clinical officers, medical officers, residents, staff nurses, senior nurses, nutritionists, physiotherapists, and occupational therapists, to gather a wide range of perspectives. The interviewer, who was familiar to healthcare workers from previous research at the same facility, approached them to obtain consent for participation. A total of 16 healthcare workers were approached face-to-face, and all agreed to take part. The number of interviews was chosen to reasonably represent all roles typically involved in caring for children with NDD at the facility and was based on the resources available for the study. The Kenya-based research team members were key personnel planning the data collection.

Participants were recruited from Migori County Referral Hospital in Western Kenya. The hospital provides both outpatient and 24-hour inpatient care, with a capacity of 100 beds (including 26 beds in the pediatric ward) and 10 cots.

Data collection

A semi-structured interview guide was developed using the CFIR 2.0 framework and tailored to the research objectives. The interview guide was pilot tested with a physician from a different LMIC who volunteered for this purpose.

All participants were required to provide written informed consent before the interviews. Face to face in-depth interviews (IDIs) were led by a trained qualitative researcher and social scientist in Kenya at the Migori County Referral Hospital maintaining adequate privacy. All IDIs were conducted in English and audio-recorded following participant consent. All audio recordings were transcribed verbatim. Transcriptions were also generated by the interviewer. The qualitative study received certification of an exempt status by the University of Washington Human Subjects Division

The primary qualitative data collected, including audio recordings, consent forms, and transcripts, were anonymized to remove identifiable information from the file names and text. Following each interview, the facilitator documented notable contextual information and main takeaway messages within a structured debrief template.

Data analysis

We conducted a mix of inductive and deductive coding. First, we created a deductive codebook drawing upon 33 of 48 total constructs from the CFIR 2.0 framework. One researcher independently coded all transcripts, and another independent code validator reviewed and validated the initial coding. Almost all of the applied codes were used multiple times, and no new codes emerged, indicating data saturation. During validation, the coder and validator met multiple times to resolve disagreements until they reached consensus on all applied codes across all transcripts. Coding and validation were performed using the qualitative data analysis software

Dedoose. The ‘memo’ feature in Dedoose was used for location-specific note keeping and tracking disagreements. Memo documents were generated at multiple stages of the data collection and analysis process. The coder generated thematic memos during coding to document main findings and patterns in each transcript. After the code validation process we completed, final detailed memos were created organized by the CFIR 2.0 constructs. The final coded transcripts and detailed memos were then utilized for thematic analysis. Patterns, repetitions, agreements, and disagreements in perceptions were logged and repeatedly reflected on to generate broad themes, each informed by multiple codes (constructs). Themes were refined by connecting the findings back to the research aims and through discussion between the independent coder and supervisors.

Results

We conducted 16 IDIs between March 6, 2025, and March 13, 2025. Participants included five nurses, four clinical and medical officers, three nutritionists, three physiotherapists and occupational therapists, and one pediatrician (Table 4.1). The duration of interviews ranged from 21 minutes to 56 minutes, with most interviews lasting more than 30 minutes.

Table 4.1: Characteristics of IDI participants (N=16)

Characteristics	N (%)
Cadre	
Clinical and Medical Officers	4 (25)
Nutritionists	3 (18)
Pediatrician	1 (6)
Nurse	5 (31)
Physiotherapist and Occupational therapist	3 (18)
Gender	
Male	8 (50)
Female	8 (50)
Age (years)	
< 30	4 (25)
30-40	6 (38)
40-50	3 (18)
50 <	3 (18)
Years of experience	
< 5	6 (38)
5-10	3 (18)
10 <	7 (44)

We identified five main themes: the perceived benefit of the malnutrition risk prediction tool by the facility clinical staff in their setting, the tool's simplicity as the key feature for successful adoption, uncertainty about who should deploy the tool in children with NDD, gaps in malnutrition management guidelines, and sociocultural stigma impacting follow-up and management after prediction. Themes were disproportionately influenced by the constructs of inner setting and outer setting domains of CFIR 2.0. However, all other domains, namely 'Innovation characteristics', 'Individuals', and the 'Implementation process', also contributed to the generation of themes on factors affecting the tool's feasibility.

While healthcare workers perceive that an effective malnutrition risk-prediction tool will be a "game changer", they need to be convinced of its impact on the target population and its relevance to their practice setting to ensure adherence

(CFIR domains and constructs: Innovation domain: innovation relative advantage, innovation evidence base, innovation adaptability; Implementation Process Domain: implementation need)

Participants of all cadres agreed that there are no pediatric prediction tools available to identify children with NDD who are at risk of developing malnutrition. However, several respondents emphasized the urgent need for a malnutrition prediction tool. Many mentioned that malnutrition is very common among children with NDD, and it is easy to overlook a diagnosis of malnutrition in these children. They stated that such a tool would help identify early cases of malnutrition and prevent poor outcomes, including mortality,

---

"Yeah, the tool, actually, it will be a game changer. Just as I said earlier, we don't have a specific tool that has been developed by the Ministry of Health or by any partner for use. So, that tool, basically, is welcome." (IDI-03, Nutritionist)

Respondents also reported that a prediction tool would provide valuable patient information for follow-ups and help identify the common factors leading to recurrent hospital admissions among these children. Some respondents also recognized that these follow-ups could, in turn, improve developmental outcomes in children.

Staff motivation to use the tool depends on its ability to effectively prevent poor nutrition outcomes and reduce deaths in their local context. Many healthcare workers emphasized that before adopting the prediction tool, they need convincing evidence that it performs as claimed and has been proven to reduce readmissions and improve survival in children with NDD. While

they recognize that new tools can sometimes be viewed as burdensome or adding to their workload, a highly effective tool that benefits young children is likely to be adopted, driven by their passion for children's well-being. Additionally, multiple healthcare workers indicated that if the tool is developed in the Western setting, it must first be tested and adapted to the African context before being suggested for routine use in their setting.

"...when there's a tool, and you made a test on it, and the outcome is good, I think that is the most impressive one, even to make us adapt it, and even to use it like daily. Yes, so the major factor there is the outcome of the test." (IDI-08, Clinical Officer)

"Well, if it's adapted, because what is always the underside of adopting westernized instruments is that they capture westernized style of living. While in Kenya, there are different things…Yeah, like what causes some of these things locally, if we don't do that it won't be able to be effective." (IDI-14, Occupational therapist)

Ease of use and perceived simplicity will be the primary factors influencing the tool's adoption

(**CFIR domains** and constructs: **innovation Domain**: innovation complexity, innovation design)

Nearly all respondents emphasized that a new tool must be simple and easy to use. They mentioned that if healthcare workers see the tool as too complex to understand and apply, they are unlikely to use it regularly. Multiple respondents also pointed out that staffing shortages and

staff rotations across departments could make it difficult to implement a new tool that is not simple to administer.

> *"The factors that could hinder as I said before if the tool is too complex and if there is a limited understanding and it takes a lot of time to apply with lack of resources and things like that but what could be the opposite, if it is simplified enough, people easily understand it and it is easy to apply people will gladly apply it." (IDI-14, Occupational therapist)*

When asked about the preferred format for the tool, most respondents favored a paper-based version that can be hung on a wall for easy reference, as well as chart forms that can be quickly filled out. Ideas included attaching paper tools or checklists to all admission files and the maternal and child booklet to ensure the tool is deployed. However, they did not specify whether it should be limited to the files of children with an NDD diagnosis only. Some also suggested a pocket-sized version of the tool for portability and quick access. Only a few respondents spoke in favor of app-based tools and a hybrid implementation of both digital and paper-based versions of the tool, while multiple respondents highlighted significant infrastructural barriers to such digital tools. They noted that soft copies are unreliable because mobile phones easily run out of battery, and that navigating a digital platform is impractical when a provider is overwhelmed by high patient volumes, particularly in rural settings. Furthermore, they pointed out that not all staff members have access to smartphones to utilize app-based tools. One staff member explained the need for reliable internet infrastructure and the associated cost of a digital tool for routine clinical use.

"I think it should be on a chart like SOP... So, I think if it can be on the wall too maybe MCH, pediatric ward, or malnutrition room, I think it would be a good idea. Then, even if we have a small booklet it can be good that we can move around with." (IDI 09, Nutritionist)

"As per what happens in my department, if it should be in a chart form, it's easier to use it. But also it can be in a booklet, like a pocket booklet for those… if you're somewhere, you can... Sometimes you get calls from our colleagues they want you to assist them in some things, so, if you have it as a pocket booklet, you can also refer. But, you should have a summary in a chart form." (IDI-13, Nurse)

A few respondents recommended incorporating specific variables into the malnutrition risk assessment tool, such as caregiver socioeconomic status, birth weight, prematurity, feeding practices, and other maternal and child medical history. In particular, socioeconomic status heavily influences the development and outcomes of childhood malnutrition from the perspective of healthcare workers. They also emphasized that the tool should consider the child's age, as factors like breastfeeding vary accordingly. An occupational therapist uniquely proposed including both subjective and objective assessments to account for potential withholding of information by caregivers. This concern about the risk of incomplete or inaccurate information from caregivers potentially impacting the prediction tool's performance was echoed by several other respondents.

"When now you bring this tool, I would request if we could include a place whereby we enter this information, the socioeconomic history of the caregiver… At least it will be easy to predict what's next after this." (IDI-04, Clinical officer)

Lack of streamlined services for children with NDD and resource shortages require staff in all departments to be trained on a malnutrition prediction tool

(**CFIR domains** and constructs: **innovation Domain**: innovation deliverers, **Inner Setting domain**: access to knowledge and information, Tension for Change, communication, Relational connections, work infrastructure, materials and equipment; **Implementation Process domain**: teaming, planning, tailoring strategies)

Despite being a referral facility, providing holistic treatment for children with NDD is seen as challenging by many healthcare workers. They note that once NDD and comorbid conditions are identified, NDDs should be managed alongside all relevant conditions, including malnutrition. Additionally, parent counseling and other necessary support need must also be identified and offered. Focusing solely on malnutrition is neither ethical nor practical for this vulnerable group of children.

"In terms of treatment, it is a bit difficult, because one, this patient will require the physio department to take him. This patient will also require a pediatrician or a specialist to be also in. It can be either medical condition or surgical

condition. And also, this patient will also require the psychologist, because their condition is sometimes worrying the child, while worrying the parents. And some of the parents are also hiding them, unless otherwise the health workers come across this patient." (IDI-15, Nurse)

Respondents reported that the facility is understaffed and lacks sufficient infrastructure to implement the tool alongside all necessary child services. Staff shortages can cause missed follow-ups and inadequate multidisciplinary care. Respondents from all roles highlighted staffing as a major issue, noting that one person often handles hundreds of patients alone during a shift. There is no additional time to screen children for malnutrition risk, and systemic infrastructure for effective interdepartmental coordination is absent. Moreover, children with NDD may seek services at different points, such as inpatient, outpatient, physiotherapy, emergency, or other departments, depending on their needs. Applying the prediction tool at any specific service point could result in missed opportunities for implementation. Relying solely on specialized staff, such as nutritionists, is also expressed as problematic not only due to staffing shortages but also due to the unavailability of specialists during nights, weekends, or public holidays. Additionally, some respondents noted a critical shortage of therapeutic feeds necessary for managing malnutrition at the center.

"So how can you take time with the child? If you are here doing work for 12 hours by the 6 hour, you wont even be asking what you are supposed to ask because the numbers are huge and the staff is minimal. So it trickles down to being overwhelmed, patient ratio versus clinician ratio" (IDI 11, Pediatrician)

> *"One, we don't have specialists. We lack specialist nurses and doctors. Two, lack of a nutrition team room, for example, like MCH, it should be next to the clinician so that when they see a case, they refer to (the) nutrition room. But with current practice, they are very far, they are on the other side, so referrals become a problem…inadequate commodities, and also, inadequate test(s) or specialist personnel can also hinder." (IDI-15, Nurse)*

There is no dedicated register or formal place to document children with NDD. Instead, these children are managed and recorded in general pediatric or malnutrition registers. Data collection is not integrated across departments. For example, records in the physiotherapy department do not merge with those in the Mother and Child Health (MCH) clinic, leading to a disconnect between assessment management and follow-up care.

The importance of assessing the child with the tool at initial contact and during all follow-ups was stressed by many respondents. Due to the lack of a specialized system and flow of care for children with NDD, the majority of respondents suggested that CMEs could be provided to all cadres across the facility to introduce the malnutrition prediction tool, and that restricting its use to a single location may not be practical. Patients may "sneak from the hospital without being noticed" if they are asked to move around in the facility to receive different services, especially those from poor families. According to some respondents, a wider range of staff cadres equipped to implement the tool could reduce the load on individual staff. One respondent mentioned that staff across different entry points need to be aware of the tool and communicate to avoid duplication or missed assessments.

"...we do not want to lose the chances we have. Like other people say, opportunity knocks once [laughter]. So in this case, this is an opportunity you are given to meet a certain child in need, and then we do not actually want to miss this. So it would be better to do it at first contact. " (IDI-04, Clinical officer)

"All children who are being admitted with neurodevelopmental disorders and are being managed for other medical conditions other than malnutrition should also be screened at this point. And at every follow-up, of course, this should happen. Whenever they come for clinics, nutritional clinics, or follow-up medical clinic for the condition they are in.." (IDI-06, Medical officer)

"The tool should be in all areas where children are seen, like OPD, MCH, I think, and children's ward" (IDI-16, Nurse)

Gaps in malnutrition treatment guidelines, as well as lack of NDD screening and diagnosis in routine practice make it challenging for prediction tools to have meaningful impact

(**CFIR domains** and constructs: **Outer Setting domain:** Policies and Laws)

Some respondents highlighted the issue of delayed or missing diagnosis of NDD conditions in children, which challenges the use of the malnutrition risk prediction tool. This is because a child must first be identified as having an NDD before they can be assessed with the NDD-specific malnutrition risk prediction tool. The overall lack of standard guidelines for screening and

managing neurodevelopmental disabilities was mentioned as a reason for such delays in diagnosing NDD or for cases where no diagnosis is made at all. Even when NDDs are known, managing malnutrition in these children remains complex, according to the staff. Almost all respondents mentioned that there are no specific national or facility-level guidelines or Standard Operating Procedures (SOPs) for managing malnutrition specifically in children with NDD.

"The guideline has nothing. It doesn't indicate anything on the CP or these other neurodevelopmental disorders." (IDI-09, Nutritionist)

Diagnosing and managing malnourished children with NDD using standard guidelines was expressed to be challenging for healthcare workers. Respondents mentioned that most children with NDD, especially with cerebral palsy, appear to have severe acute malnutrition anytime they present at the facility if general guidelines are followed for diagnosis, since they grow and appear physically significantly different than others. When admitted for malnutrition, these children also often fail to meet the standard discharge criteria outlined in the general guidelines that staff follow.

“So, they are not going to grow just like a normal child …and they'll never get discharged because there's no single day they reach the discharge criteria being used for the children who are normal.” (IDI-03, Nutritionist)

"Same thing with cerebral palsy children who have the pseudobulbar palsy. How they drink the milk is not the same as this other child who is normal. It's just a

matter of misunderstanding. But we still follow that protocol, and we still say, this one has not taken this percentage, so it has failed" (IDI-11, Pediatrician)

The eventual effectiveness of a prediction tool may be tempered by the lack of follow-up visits due to the dual burden of stigma associated with both NDD and malnutrition, widespread lack of awareness in society about these conditions, and poverty

(**CFIR domains** and constructs: **Outer Setting domain:** Local attitude, local conditions; **Individuals domain:** Innovation recipients; **Implementation Process domain**: tailoring strategies)

The dual stigma around both NDD and malnutrition was perceived by most healthcare workers as a major barrier to the successful implementation of the tool and post-prediction care. Caregivers of children with NDDs may delay routine healthcare seeking due to stigma, myths, shame, and neglect. Many in the community associate NDD with witchcraft, curses, taboo, or moral wrongdoing. Similarly, there are community-level stigmas associated with malnutrition. For example, respondents mentioned superstitions that malnutrition may be driven by marital infidelity known as 'Chira' in the community, or the effects of 'poisonous' breast milk. This double burden of stigma related to NDD and malnutrition prevents children suffering from these conditions from accessing the health system. These children are either kept hidden from society, taken to traditional healers, or abandoned entirely by their families.

"That is actually where there's a giant in the, that giant in the room… So some of them will be associated with being… there is an element of witchcraft…they

[do] not go the conventional way, they go the traditional way... some of them may fail to bring up their children. So culture plays a role." (IDI-03, Nutritionist)

"When you have got a child with a disability, the way people see you, and the way people see the child, becomes a taboo. The family did something. That's why I saw the lady dump the child because she doesn't want to be with a disabled child… In fact she wrote a note and dumped her in her neighbor's house and forgot about it, 'Goodbye, my little girl.' " (IDI 15, Nurse)

"Because you know malnutrition, they do associate it with something, 'chira,'…the father has cheated or the mother has cheated, things like that. So when the child starts becoming thin, they say that you hold the baby with dirt from promiscuity." (IDI-02, Clinical officer)

Once at the facility, many respondents did not see a barrier from the caregiver side in applying the tool. However, a few respondents perceived that parents or caregivers may hide information needed to complete the screening tool due to fear of being blamed or being unable to provide accurate information, especially about feeding practices at home.

" ... parents always tend to withhold information. They will tell you a child started feeding when you keep bombarding them with questions. 'Oh, this child doesn't seem... Like, the weight is not growing.' They will be like, 'I feed him and things are not going so well.' Or 'that is because their genes don't get fat.' So,

they will withhold information, and you are forced to go with whatever they say. " (IDI-14, Occupational therapist)

"Actually, if you give them orally and you are not around, there is a possibility that the mother will tell you that she got it, but she didn't get it. Because maybe she knows that if she tells you that she didn't get it, you will blame her somewhere. So, they lie..." (IDI-09, Nutritionist)

"Sometimes a mother can tell you that her child is okay, but after a while, she might not be okay... She hasn't seen it yet, and maybe she can't even see it." (IDI-05, Nurse)

Societal stigma and caregiver lack of awareness are further complicated by widespread poverty in the community, according to many respondents. Families cannot afford medical treatment and often turn to local pharmacists or traditional healers. Even those who get medical help cannot follow the feeding advice at home.

"Mostly they are not successful because what we tell them here, they don't do. Maybe a child needs blended food and the parent cannot afford a blender…She keeps on giving carbohydrates like potatoes and whatever." (IDI-01, Nutritionist)

Several respondents said the tool might be more effective if stigma reduction efforts related to NDD and malnutrition were deployed in the community in tandem. One respondent suggested involving local and religious leaders to increase the impact of such efforts.

> *"..we also need to target, we have the opinion leaders in the community, because they have a say. So when they are doing maybe the radio talk shows, they need to be targeted as well. ...So we have to have a tailor made communication to be able to address those particular opinion leaders." (IDI-03, Nutritionist)*

Discussion

In this study, we examined healthcare workers' perceptions regarding the feasibility of implementing a malnutrition risk prediction tool for children with neurodevelopmental disabilities (NDD) in Kenya. Our findings reveal that while staff perceive the need for such an instrument to reduce malnutrition and associated negative outcomes, its successful implementation depends on addressing significant structural, operational, and sociocultural barriers, as well as certain tool features.

The practical adoption of the malnutrition prediction tool will depend upon its simplicity and seamless integration into existing workflows, especially in high-volume, low-resource settings. Evidence from other settings similarly suggests that prediction tools fail to be adopted when they are not integrated into the clinical workflow [131]. In this study, participants favored paper-based, portable tools or wall charts that can be quickly referenced across departments, given the high patient load, staffing limitations, smartphone availability, and battery and internet data issues. Although current research advocates for the use of app-based clinical decision tools

that enhance patient care, increase efficiency, and boost clinician confidence when they support rather than replacing clinical judgment [132], [133], [134], there is also evidence suggesting that these tools could disrupt workflow, slow down patient care, and demand skills that all clinical staff may lack, even if they initially show interest in using the electronic decision support tool [135], [136], [137]. The literature highlights that usability and early design planning are critical to avoid non-adoption [138]. It also stresses the importance of embedding tools into current workflows and physical environments rather than using separate systems, particularly through a human-centered approach[139]. Resources like the FRESCO framework (Framework for the co-design of clinical practice tools) are available to help develop user-friendly, human-centered tools tailored for clinical use [138]. Most importantly, the study participants mentioned that the tool needs to demonstrate effectiveness in reducing mortality and readmissions so that they can apply the tool on their patients with confidence.

There are perceived gaps in the malnutrition guidelines and resources at the facility level, which could hinder post-prediction management if not addressed before or in tandem with a prediction tool. In this study, staff reported that inadequate interdepartmental coordination, insufficient supply of therapeutic feeds, and severe staffing shortages exist, creating a service gap. The literature also suggests that lack of coordinated care and resource shortages are frequent causes of the failure to implement clinical support tools[140], [141], [142]. Study participants reported that standard malnutrition protocols do not aid with the specialized management needs of children with NDD For example. standard growth charts, which inform routine malnutrition management in the study setting, frequently fail to account for the atypical body composition and physical development common in many NDDs. They also suggested that comprehensive management protocols fail to integrate NDD-specific nutritional care, despite the

common co-occurrence of the two morbidities. These findings suggest that successful implementation of a malnutrition risk prediction tool requires strengthening current institutional capacity and ensuring the availability of guidelines for post-prediction care [143].

Active referral channels, patient data management and use at the facility level, and specific socio-cultural beliefs and practices were identified as factors impacting the overall goal of reducing mortality and morbidity associated with malnutrition in children with NDD. Respondents reported that the absence of an integrated data management system to track these children across departments and for follow-up means that, even when clinical management is initiated, the child may drop out of care. Without strengthening necessary referral pathways and data management and utilization for these children with complex needs who will likely require long-term monitoring, implementing a prediction tool may serve little purpose. Screening and prediction tools are often de-implemented if they do not serve their intended purpose. [144].

The reach and eventual efficacy of a malnutrition prediction tool built for children with NDD is highly likely to be constrained by sociocultural barriers prevalent in our study setting. Participants identified that stigma, cultural myths (such as 'Chira' for malnutrition or witchcraft for NDD), and economic hardship often prevent families from seeking care for these already especially vulnerable children. They expressed worry that when children with NDD are kept hidden or abandoned, they do not present at the facility until their condition becomes severe and complicated, significantly limiting the effectiveness of available interventions. This concern is frequently observed in LMIC contexts where stigma plays a role in care-seeking behaviors [145], [146], [147]. According to the study respondents' suggestions, implementation of the prediction tool must therefore include community-based sensitization efforts involving local opinion leaders and educational systems to ensure that children reach the facility at a stage when predictive tools

can still make a difference. Similar strategies have been applied in LMIC contexts to combat socio-cultural stigma, while also emphasizing that the recipient side (i.e., caregivers or parents in the current study) should be involved in designing such interventions [148].

This study had several strengths. The study was conducted in a county referral hospital fairly representative of similar facilities serving a relatively large catchment area. All healthcare providers working with children with NDD at the center were interviewed to assess the feasibility of malnutrition prediction tools in this context. To reduce bias and increase acceptability, interviews were carried out by a local social scientist who was independent of the researchers involved in developing the predictive tool. The assessment was based on a theoretical framework, enhancing its rigor, depth, and potential for future comparison with similar studies elsewhere. This research highlighted key factors to consider during the development of the prediction tool and at both local (such as improving services for children with NDD and addressing resource shortages) and systemic levels (including gaps in malnutrition management guidelines and local attitudes).

However, the study also had several limitations. The study was conducted at a single referral hospital in Kenya. The center may not fully represent the infrastructure or cultural attitudes of other regions, especially concerning NDD and malnutrition. However, we believe these findings could be relevant to similar health facilities in LMICs. There is a chance that healthcare workers might have over-reported the tool's usefulness to appear supportive of the innovation, even if they found it burdensome, due to social desirability bias. While the study focuses on healthcare workers' perceptions, parents and caregivers were not included. An additional study exploring recipients' views on factors affecting the tool's feasibility would give a more complete picture, especially regarding follow-up procedures when the tool flags at-risk children. The study

evaluated the feasibility of a tool that is still in development. Perceptions of feasibility may change once the tool is available. This pre-design assessment of healthcare workers' perceptions led to some confusion at times during the interviews about the distinction between a screening tool assessing current risk and a prediction tool predicting future risk. Use of such prediction tools, while common in developed settings, is not as widely utilized in low-resource settings [149], [150], [151]. Furthermore, due to the complexity of screening and diagnosing NDD conditions in children, responses suggested that staff struggled to identify the intended target for the tool's implementation, as well as the suitable department or personnel for deployment. However, this study includes user feedback during the development stage, which is important in deciding whether investing in a malnutrition prediction tool for children with NDD is justified before conducting costly large-scale trials [152].

Conclusion

Children with NDD are at disproportionate risk of malnutrition and are not effectively identified or managed within existing programs. There is a clear need for tools to better identify this high-risk group in low and middle-income settings. Healthcare workers expressed strong interest in the development of such a tool but noted that the feasibility of such a tool depends on designing it to be simple and well integrated into the existing workflow of staff without overburdening them. They also emphasized that evidence is needed that the tool accurately identifies children at elevated risk or malnutrition and supports actions to reduce adverse outcomes. Healthcare workers also noted the importance of developing and promoting malnutrition guidelines that include guidance for children with NDDs. Community-based efforts targeting poverty, lack of awareness, and stigma will be essential for maximizing the impact of the tool and ultimately improving the lives of children affected by both NDD and malnutrition, as well as their families.

CHAPTER 5 : CONCLUSION

Children with neurodevelopmental disabilities have substantial malnutrition risk, yet their needs are often insufficiently addressed in nutrition research, clinical systems, and guidelines. This dissertation examined malnutrition risk among children under five with NDD with three related questions: which children are at most risk, whether short-term future risk can be estimated using routinely available information in hospital settings, and whether it would be feasible for such risk identification strategy to be implemented in a real LMIC clinical setting.

The findings show that malnutrition risk in children with NDD is not uniform. In the longitudinal risk-factor analysis, younger age, feeding difficulty, and broad NDD type were associated with incident wasting. Underweight was associated with a broader set of demographic, perinatal, socioeconomic, and clinical factors. Finally, percentage weight loss from baseline was most strongly linked to hospitalization.

Building on this risk-factor analysis, the prediction study demonstrated that six-month wasting risk at baseline can be estimated using a parsimonious set of variables. A compact model including age, broad NDD type, and respiratory morbidity performed similarly to larger clinical and data-driven models and was translated into a simple prototype risk lookup tool. The tool was not designed to provide individual-level predictions or treatment decisions. Rather, its value lies in showing that routinely available clinical information can help identify groups of children who may benefit from earlier interventions and closer monitoring.

The qualitative study showed that predictive performance of a tool alone is not enough for it's feasible implementation in clinical settings. Healthcare workers in Kenya saw potential value in a tool to identify children with NDD at elevated risk of malnutrition, but they emphasized that such a tool would be useful only if it was proven to be effective in preventing adverse outcome,

simple, locally validated, and integrated into existing workflows. They also described broader barriers, including staffing shortages, gaps in NDD and malnutrition guidelines, weak referral and follow-up systems, poverty, and stigma related to both disability and malnutrition. These findings highlight that malnutrition risk prediction in children with NDD must be embedded within a health system that is capable of responding to identified risk.

The overall contribution of this dissertation is to connect risk identification, prediction, and implementation feasibility as linked steps toward earlier and effective nutritional care for children with NDD.

BIBLIOGRAPHY

[1] United Nations Children's Fund (UNICEF) World Health Organization & International Bank for Reconstruction and Development/The World Bank, "Levels and trends in child malnutrition: key findings of the 2021 edition of the joint child malnutrition estimates.," 2021.

[2] C. V. Kramer, "Malnutrition in developing countries," *Paediatr. Child Health*, vol. 25, no. 9, pp. 422–427, 2015, doi: 10.1016/j.paed.2015.04.002.

[3] B. O. Olusanya *et al.*, "Developmental disabilities among children younger than 5 years in 195 countries and territories, 1990–2016: a systematic analysis for the Global Burden of Disease Study 2016," *Lancet Glob. Health*, vol. 6, no. 10, pp. e1100–e1121, 2018, doi: 10.1016/S2214-109X(18)30309-7.

[4] B. O. Olusanya, V. Kancherla, A. Shaheen, F. A. Ogbo, and A. C. Davis, "Global and regional prevalence of disabilities among children and adolescents: Analysis of findings from global health databases," *Front. Public Health*, vol. 10, 2022, doi: 10.3389/fpubh.2022.977453.

[5] S. Das, M. Z. Hossain, and M. K. Nesa, "Levels and trends in child malnutrition in Bangladesh," *Asia-Pac. Popul. J.*, vol. 24, no. 2, pp. 51–78, 2009, doi: 10.18356/6ef1e09a-en.

[6] S. S. Jeste, J. Frohlich, and S. K. Loo, "Electrophysiological biomarkers of diagnosis and outcome in neurodevelopmental disorders," *Curr. Opin. Neurol.*, vol. 28, no. 2, pp. 110–116, Apr. 2015, doi: 10.1097/WCO.0000000000000181.

[7] American Psychiatric Association, *American Psychiatric Association; Diagnostic and statistical manual of mental disorders: DSM-5*. Washington, D.C: American Psychiatric Association, 2013.

[8] U. S. Epa, "America's Children and the Environment: Neurodevelopmental Disorders," no. October, pp. 1–32, 2015.

[9] S. Awasthi, T. Verma, T. Sanghvi, and E. A. Frongillo, "Path to severe acute malnutrition in children below 2 years of age: Findings of qualitative research in Uttar Pradesh, North India," *Clin. Epidemiol. Glob. Health*, vol. 7, no. 2, pp. 246–252, 2019, doi: 10.1016/j.cegh.2018.11.001.

[10] K. Raj, "Severe acute malnutrition in children," *Public Health Nutr. Dev. Ctries. Part-I*, pp. 310–340, 2015, doi: 10.1533/9780857093905.310.

[11] S. Macleod and R. E. Appleton, "Neurological disorders presenting mainly in adolescence," *Arch. Dis. Child.*, vol. 92, no. 2, pp. 170–175, 2007, doi: 10.1136/adc.2005.088070.

[12] N. Marlow, D. Wolke, M. Bracewell, and S. Muthanna, "Neurologic and Developmental Disability at Six Years of Age after Extremely Preterm Birth," *N. Engl. J. Med.*, vol. 355, pp. 11–20, 2006.

[13] I. N. Mohamed, M. A. Elseed, and A. A. Hamed, "Clinical Profile of Pediatric Neurological Disorders," *Child Neurol. Open*, vol. 3, p. 2329048X1562354, 2016, doi: 10.1177/2329048x15623548.

[14] M. Hadders-Algra, "Early diagnostics and early intervention in neurodevelopmental disorders—age-dependent challenges and opportunities," *J. Clin. Med.*, vol. 10, no. 4, pp. 1–24, 2021, doi: 10.3390/jcm10040861.

[15] F. A. S. R. A. Bokhari., *Down Syndrome*. 2023.

[16] M. Hume-Nixon and H. Kuper, “The association between malnutrition and childhood disability in low- and middle- income countries: systematic review and meta-analysis of observational studies,” *Trop. Med. Int. Health*, vol. 23, no. 11, pp. 1158–1175, 2018, doi: 10.1111/tmi.13139.
[17] The Global Nutrition Report’s Independent Expert Group, “Global Nutrition Report,” 2020.
[18] N. Nisbett, J. Harris, K. Backholer, P. Baker, V. B. B. Jernigan, and S. Friel, “Holding no-one back: The Nutrition Equity Framework in theory and practice,” *Glob. Food Secur.*, vol. 32, p. 100605, 2022, doi: 10.1016/j.gfs.2021.100605.
[19] M. Bitta, S. M. Kariuki, A. Abubakar, and C. R. J. C. Newton, “Burden of neurodevelopmental disorders in low and middle-income countries: A systematic review and meta-analysis,” *Wellcome Open Res.*, vol. 2, p. 121, 2017, doi: 10.12688/wellcomeopenres.13540.1.
[20] M. Kerac *et al.*, “The interaction of malnutrition and neurologic disability in Africa,” *Semin. Pediatr. Neurol.*, vol. 21, no. 1, pp. 42–49, 2014, doi: 10.1016/j.spen.2014.01.003.
[21] S. Dulal, A. Prost, S. Karki, N. Saville, and D. Merom, “Characteristics and effects of integrated nutrition and stimulation interventions to improve the nutritional status and development of children under 5 years of age: A systematic review and meta-analysis,” *BMJ Glob. Health*, vol. 6, no. 7, pp. 1–16, 2021, doi: 10.1136/bmjgh-2020-003872.
[22] N. Groce *et al.*, “Malnutrition and disability: Unexplored opportunities for collaboration,” *Paediatr. Int. Child Health*, vol. 34, no. 4, pp. 308–314, 2014, doi: 10.1179/2046905514Y.0000000156.
[23] T. Vaivada, M. F. Gaffey, and Z. A. Bhutta, “Promoting early child development with interventions in health and nutrition: A systematic review,” *Pediatrics*, vol. 140, no. 2, 2017, doi: 10.1542/peds.2016-4308.
[24] S. M. Grantham-Mcgregor, L. C. H. Fernald, R. M. C. Kagawa, and S. Walker, “Effects of integrated child development and nutrition interventions on child development and nutritional status,” *Ann. N. Y. Acad. Sci.*, vol. 1308, no. 1, pp. 11–32, 2014, doi: 10.1111/nyas.12284.
[25] M. Engl *et al.*, “Children living with disabilities are absent from severe malnutrition guidelines,” *medRxiv*, p. 2021.09.24.21264078, 2021.
[26] P. B. Sullivan, “Gastrointestinal disorders in children with neurodevelopmental disabilities,” *Dev. Disabil. Res. Rev.*, vol. 14, no. 2, pp. 128–136, 2008, doi: 10.1002/ddrr.18.
[27] E. A. C. Calis, R. Veugelers, R. Rieken, D. Tibboel, H. M. Evenhuis, and C. Penning, “Energy intake does not correlate with nutritional state in children with severe generalized cerebral palsy and intellectual disability.,” *Clin. Nutr. Edinb. Scotl.*, vol. 29, no. 5, pp. 617–621, Oct. 2010, doi: 10.1016/j.clnu.2010.02.006.
[28] E. A. Lungu, R. Biesma, M. Chirwa, and C. Darker, “Healthcare seeking practices and barriers to accessing under-five child health services in urban slums in Malawi: A qualitative study,” *BMC Health Serv. Res.*, vol. 16, no. 1, pp. 1–11, 2016, doi: 10.1186/s12913-016-1678-x.
[29] M. J. Pajuelo *et al.*, “Delays in seeking and receiving health care services for pneumonia in children under five in the Peruvian Amazon: a mixed- methods,” pp. 1–11, 2018.
[30] M. Engl, P. Binns, I. Trehan, N. Lelijveld, and C. Angood, “Children Living with Disabilities Are Absent From Severe Malnutrition Guidelines,” pp. 1–19.
[31] M. Gladstone *et al.*, “Assessment of neurodisability and malnutrition in children in Africa,” *Semin. Pediatr. Neurol.*, vol. 21, no. 1, pp. 50–57, 2014, doi: 10.1016/j.spen.2014.01.002.

[32] J. A. Abuga, L. W. Mwangi, E. Cottrell, S. M. Kariuki, S. M. Kinyanjui, and C. R. J. C. Newton, “Barriers to access and utilization of healthcare by children with neurological impairments and disability in low-and middle-income countries: A systematic review,” *Wellcome Open Res.*, vol. 6, pp. 1–21, 2022, doi: 10.12688/wellcomeopenres.16593.2.
[33] R. Liu, L. Pi, F. Leng, and Q. Shen, “Global disability-adjusted life years and deaths attributable to child and maternal malnutrition from 1990 to 2019,” *Front. Public Health*, vol. 12, p. 1323263, Jan. 2024, doi: 10.3389/fpubh.2024.1323263.
[34] Z. J. Madewell *et al.*, “Contribution of malnutrition to infant and child deaths in Sub-Saharan Africa and South Asia,” *BMJ Glob. Health*, vol. 9, no. 12, p. e017262, Dec. 2024, doi: 10.1136/bmjgh-2024-017262.
[35] “United Nations Inter-Agency Group for Child Mortality Estimation (UN IGME), Report 2025,” UNICEF, Mar. 2026. [Online]. Available: https://data.unicef.org/resources/levels-and-trends-in-child-mortality-2025/
[36] World Health Organization, “Malnutrition.” [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/malnutrition
[37] World Health Organization, “Child malnutrition: Wasting among children under 5 years of age,” The Global Health Observatory. [Online]. Available: https://www.who.int/data/gho/indicator-metadata-registry/imr-details/302
[38] Dr Mariachiara Di Cesare, Dr Shibani Ghosh, Dr Saskia Osendarp, Dr Dariush Mozaffarian, “A world free from malnutrition: An assessment of progress towards the global nutrition targets,” 2026. [Online]. Available: https://globalnutritionreport.org/1e3f75
[39] Z. S. Lassi *et al.*, “Community-Based Child Food Interventions/Supplements for the Prevention of Wasting in Children Up to 5 Years at Risk of Wasting and Nutritional Oedema: A Systematic Review and Meta-Analysis,” *Nutr. Rev.*, vol. 83, no. 8, pp. 1402–1424, Aug. 2025, doi: 10.1093/nutrit/nuaf041.
[40] E. C. Keats *et al.*, “Effective interventions to address maternal and child malnutrition: an update of the evidence,” *Lancet Child Adolesc. Health*, vol. 5, no. 5, pp. 367–384, May 2021, doi: 10.1016/S2352-4642(20)30274-1.
[41] R. A. Heidkamp *et al.*, “Mobilising evidence, data, and resources to achieve global maternal and child undernutrition targets and the Sustainable Development Goals: an agenda for action,” *The Lancet*, vol. 397, no. 10282, pp. 1400–1418, Apr. 2021, doi: 10.1016/S0140-6736(21)00568-7.
[42] C. G. Victora, P. Christian, L. P. Vidaletti, G. Gatica-Domínguez, P. Menon, and R. E. Black, “Revisiting maternal and child undernutrition in low-income and middle-income countries: variable progress towards an unfinished agenda,” *The Lancet*, vol. 397, no. 10282, pp. 1388–1399, Apr. 2021, doi: 10.1016/S0140-6736(21)00394-9.
[43] “Global report on children with developmental disabilities: from the margins to the mainstream,” World Health Organization and the United Nations Children’s Fund (UNICEF), Geneva, 2023.
[44] L. A. Almousa, N. M. Alshwaiyat, J. Z. ALTamimi, R. I. Alagal, M. A. Alsemari, and N. A. AlFaris, “Prevalence of Malnutrition Among School-Aged Children With and Without Intellectual and Developmental Disabilities in Saudi Arabia: A Cross-Sectional Study,” *Food Sci. Nutr.*, vol. 14, no. 5, p. e71816, May 2026, doi: 10.1002/fsn3.71816.
[45] R. Khatun *et al.*, “Nutritional status of children with neurodevelopmental disorders: a cross-sectional study at a tertiary-level hospital in northern Bangladesh,” *BMC Nutr.*, vol. 10, no. 1, p. 61, Apr. 2024, doi: 10.1186/s40795-024-00863-9.

[46] E. Emerson, A. Savage, and G. Llewellyn, “Prevalence of underweight, wasting and stunting among young children with a significant cognitive delay in 47 low-income and middle-income countries,” *J. Intellect. Disabil. Res.*, vol. 64, no. 2, pp. 93–102, Feb. 2020, doi: 10.1111/jir.12698.
[47] Y. Zhu, N.-N. Wang, D. Pan, and S. Wang, “Risk of Overweight and Obesity in Children and Adolescents With Attention-Deficit/Hyperactivity Disorder: A Systematic Review and Meta-Analysis,” *Child. Obes.*, vol. 20, no. 2, pp. 119–127, Mar. 2024, doi: 10.1089/chi.2022.0230.
[48] A. McCarthy *et al.*, “Prevalence of Malnutrition in Pediatric Hospitals in Developed and In-Transition Countries: The Impact of Hospital Practices,” *Nutrients*, vol. 11, no. 2, p. 236, Jan. 2019, doi: 10.3390/nu11020236.
[49] “Nutrition in neurologically impaired children,” *Paediatr. Child Health*, vol. 14, no. 6, pp. 395–401, Jul. 2009.
[50] N. Groce *et al.*, “Malnutrition and disability: unexplored opportunities for collaboration,” *Paediatr. Int. Child Health*, vol. 34, no. 4, pp. 308–314, Nov. 2014, doi: 10.1179/2046905514Y.0000000156.
[51] United Nations Children’s Fund, *Nutrition Guidance including children with disabilities in humanitarian action*. UNICEF, 2018.
[52] A. Klein, M. Uyehara, A. Cunningham, M. Olomi, K. Cashin, and C. M. Kirk, “Nutritional care for children with feeding difficulties and disabilities: A scoping review,” *PLOS Glob. Public Health*, vol. 3, no. 3, p. e0001130, 2023, doi: 10.1371/journal.pgph.0001130.
[53] R. Z. Pancheva-Dimitrova, A. Toneva, M. Georgieva, D. Konstantinova, and S. Petrova, “Nutritional status, macro- and micronutrient deficiency in children with neurodevelopmental disorders,” *Scr. Sci. Salut. Publicae*, vol. 4, no. 0, p. 7, Jun. 2018, doi: 10.14748/sssp.v4i0.4104.
[54] T. Mutsindashyaka *et al.*, “High Burden of Undernutrition among At-Risk Children in Neonatal Follow-Up Clinic in Rwanda,” *Ann. Glob. Health*, vol. 86, no. 1, p. 125, Oct. 2020, doi: 10.5334/aogh.2636.
[55] M. J. Azur, E. A. Stuart, C. Frangakis, and P. J. Leaf, “Multiple imputation by chained equations: what is it and how does it work?,” *Int. J. Methods Psychiatr. Res.*, vol. 20, no. 1, pp. 40–49, Mar. 2011, doi: 10.1002/mpr.329.
[56] D. C. G. Da Silva, M. De Sá Barreto Da Cunha, A. De Oliveira Santana, A. M. Dos Santos Alves, and M. Pereira Santos, “Malnutrition and nutritional deficiencies in children with cerebral palsy: a systematic review and meta-analysis,” *Public Health*, vol. 205, pp. 192–201, Apr. 2022, doi: 10.1016/j.puhe.2022.01.024.
[57] M. N. Kuperminc and R. D. Stevenson, “Growth and nutrition disorders in children with cerebral palsy,” *Dev. Disabil. Res. Rev.*, vol. 14, no. 2, pp. 137–146, Jan. 2008, doi: 10.1002/ddrr.14.
[58] S. Boudokhane, H. Migaou, A. Kalai, A. Dhahri, A. Jellad, and Z. Ben Salah Frih, “Feeding problems and malnutrition associated factors in a North African sample of multidisabled children with cerebral palsy,” *Res. Dev. Disabil.*, vol. 118, p. 104084, Nov. 2021, doi: 10.1016/j.ridd.2021.104084.
[59] D. C. O. Caramico-Favero, Z. C. F. Guedes, and M. B. D. Morais, “FOOD INTAKE, NUTRITIONAL STATUS AND GASTROINTESTINAL SYMPTOMS IN CHILDREN WITH CEREBRAL PALSY,” *Arq. Gastroenterol.*, vol. 55, no. 4, pp. 352–357, Dec. 2018, doi: 10.1590/s0004-2803.201800000-78.

[60] F. Penagini, C. Mameli, V. Fabiano, D. Brunetti, D. Dilillo, and G. Zuccotti, “Dietary Intakes and Nutritional Issues in Neurologically Impaired Children,” *Nutrients*, vol. 7, no. 11, pp. 9400–9415, Nov. 2015, doi: 10.3390/nu7115469.
[61] V. K. Kavitha, K. G. Singh, and D. Chandraiah, “Nutritional assessment in developmentally retarded children of 3-10 years age group,” *Int. J. Contemp. Pediatr.*, vol. 6, no. 1, p. 77, Dec. 2018, doi: 10.18203/2349-3291.ijcp20185087.
[62] Z. Matthews, D. Pigden-Bennett, T. Tavassoli, and S. Snuggs, “Comparing eating and mealtime experiences in families of children with autism, attention deficit hyperactivity disorder and dual diagnosis,” *Autism*, vol. 29, no. 2, pp. 518–535, Feb. 2025, doi: 10.1177/13623613241277605.
[63] R. Rana, M. McGrath, P. Gupta, E. Thakur, and M. Kerac, “Feeding Interventions for Infants with Growth Failure in the First Six Months of Life: A Systematic Review,” *Nutrients*, vol. 12, no. 7, p. 2044, Jul. 2020, doi: 10.3390/nu12072044.
[64] J. M. Bracken, L. Pappas, J. Wilkins, K. Tracy, T. R. Al-Rajabi, and R. A. Abdelhadi, “Measuring growth in critically ill neonates and children,” *Nutr. Clin. Pract.*, vol. 38, no. S2, Oct. 2023, doi: 10.1002/ncp.11057.
[65] A. Mertens *et al.*, “Child wasting and concurrent stunting in low- and middle-income countries,” *Nature*, vol. 621, no. 7979, pp. 558–567, Sep. 2023, doi: 10.1038/s41586-023-06480-z.
[66] S. Sengupta *et al.*, “Adverse Neonatal Outcomes Associated With Early-Term Birth,” *JAMA Pediatr.*, vol. 167, no. 11, p. 1053, Nov. 2013, doi: 10.1001/jamapediatrics.2013.2581.
[67] A. Bukhari, Z. Dawoud, S. Tang, M. Matthews, K. Yusuf, and S. U. Hasan, “Respiratory insufficiency, feeding issues and length of stay in 33–36 weeks post-menstrual age infants,” *Pediatr. Res.*, vol. 99, no. 4, pp. 1504–1516, Mar. 2026, doi: 10.1038/s41390-025-04411-4.
[68] R. Kamity, P. K. Kapavarapu, and A. Chandel, “Feeding Problems and Long-Term Outcomes in Preterm Infants-A Systematic Approach to Evaluation and Management,” *Children*, vol. 8, no. 12, p. 1158, Dec. 2021, doi: 10.3390/children8121158.
[69] G. A. Rocha, E. J. M. Rocha, and C. V. Martins, “The effects of hospitalization on the nutritional status of children,” *J. Pediatr. (Rio J.)*, vol. 82, no. 1, pp. 70–74, 2006, doi: 10.2223/JPED.1440.
[70] V. Groleau, M. Thibault, M. Doyon, E.-E. Brochu, C. C. Roy, and C. Babakissa, “Malnutrition in hospitalized children: prevalence, impact, and management,” *Can. J. Diet. Pract. Res. Publ. Dietit. Can. Rev. Can. Prat. Rech. En Diet. Une Publ. Diet. Can.*, vol. 75, no. 1, pp. 29–34, 2014, doi: 10.3148/75.1.2014.29.
[71] S. Saengnipanthkul *et al.*, “Development and Validation of a Pediatric Hospital-Acquired Malnutrition (PHaM) Risk Score to Predict Nutritional Deterioration in Hospitalized Pediatric Patients: A Secondary Analysis Based on a Multicenter Prospective Cohort Study,” *Nutrients*, vol. 16, no. 17, p. 2898, Aug. 2024, doi: 10.3390/nu16172898.
[72] S. Persaud *et al.*, “Improving anthropometric measurements in hospitalized children: A quality-improvement project,” *Nutr. Clin. Pract.*, vol. 39, no. 3, pp. 685–695, Jun. 2024, doi: 10.1002/ncp.11112.
[73] J. Hardy, H. Kuter, M. Campbell, and D. Canoy, “Reliability of anthropometric measurements in children with special needs,” *Arch. Dis. Child.*, vol. 103, no. 8, pp. 757–762, Aug. 2018, doi: 10.1136/archdischild-2017-314243.

[74] R. D. Stevenson, “Weight and alternative measures for nutrition assessment in children with cerebral palsy,” *Dev. Med. Child Neurol.*, vol. 63, no. 7, pp. 768–768, Jul. 2021, doi: 10.1111/dmcn.14909.
[75] M. K. Dulcan, R. R. Ballard, P. Jha, and J. M. Sadhu, Eds., *Concise Guide to Child and Adolescent Psychiatry*, Fifth Edition. American Psychiatric Association Publishing, 2017. doi: 10.1176/appi.books.9781615371457.
[76] D. J. Morris-Rosendahl and M.-A. Crocq, “Neurodevelopmental disorders—the history and future of a diagnosticconcept,” *Dialogues Clin. Neurosci.*, vol. 22, no. 1, pp. 65–72, Mar. 2020, doi: 10.31887/DCNS.2020.22.1/macrocq.
[77] V. Dipasquale, F. Gottrand, P. B. Sullivan, and C. Romano, “Top-ten tips for managing nutritional issues and gastrointestinal symptoms in children with neurological impairment,” *Ital. J. Pediatr.*, vol. 46, no. 1, p. 35, Mar. 2020, doi: 10.1186/s13052-020-0800-1.
[78] J. Pruccoli, G. Guardi, A. La Tempa, B. Valeriani, F. Chiavarino, and A. Parmeggiani, “Food and Development: Children and Adolescents with Neurodevelopmental and Comorbid Eating Disorders—A Case Series,” *Behav. Sci.*, vol. 13, no. 6, p. 499, Jun. 2023, doi: 10.3390/bs13060499.
[79] A. T. Wondemagegn and A. Mulu, “Effects of Nutritional Status on Neurodevelopment of Children Aged Under Five Years in East Gojjam, Northwest Ethiopia, 2021: A Community-Based Study,” *Int. J. Gen. Med.*, vol. Volume 15, pp. 5533–5545, Jun. 2022, doi: 10.2147/IJGM.S369408.
[80] “Malnutrition in children,” World Health Organization, 2026. [Online]. Available: https://www.who.int/data/nutrition/nlis/info/malnutrition-in-children
[81] R. D. Murray, K. W. Kerr, C. Brunton, J. A. Williams, T. DeWitt, and K. L. Wulf, “A First Step Towards Eliminating Malnutrition: A Proposal for Universal Nutrition Screening in Pediatric Practice,” *Nutr. Diet. Suppl.*, vol. Volume 13, pp. 17–24, Feb. 2021, doi: 10.2147/NDS.S287981.
[82] I. Novak *et al.*, “Early, Accurate Diagnosis and Early Intervention in Cerebral Palsy: Advances in Diagnosis and Treatment,” *JAMA Pediatr.*, vol. 171, no. 9, p. 897, Sep. 2017, doi: 10.1001/jamapediatrics.2017.1689.
[83] L. A. D. Araújo, “Warning signs for identifying neurodevelopmental disorders: a systematic literature review,” *J. Pediatr. (Rio J.)*, vol. 102, p. 101478, Mar. 2026, doi: 10.1016/j.jped.2025.101478.
[84] R. G. Arim, A. R. Miller, A. Guèvremont, L. M. Lach, J. C. Brehaut, and D. E. Kohen, “Children with neurodevelopmental disorders and disabilities: a population-based study of healthcare service utilization using administrative data,” *Dev. Med. Child Neurol.*, vol. 59, no. 12, pp. 1284–1290, Dec. 2017, doi: 10.1111/dmcn.13557.
[85] L. Li, H. Bhurawala, and A. Liu, “Impact of COVID -19 on Hospital Admissions for Children With Developmental Disadvantages: A Western Sydney Metropolitan Hospital Experience on Health Inequity,” *J. Paediatr. Child Health*, vol. 61, no. 5, pp. 714–720, May 2025, doi: 10.1111/jpc.16798.
[86] R. Z. Pancheva-Dimitrova, A. Toneva, M. Georgieva, D. Konstantinova, and S. Petrova, “Nutritional status, macro- and micronutrient deficiency in children with neurodevelopmental disorders,” *Scr. Sci. Salut. Publicae*, vol. 4, no. 0, p. 7, Jun. 2018, doi: 10.14748/sssp.v4i0.4104.
[87] V. Marchand, K. J. Motil, and NASPGHAN Committee on Nutrition, “Nutrition Support for Neurologically Impaired Children: A Clinical Report of the North American Society for

Pediatric Gastroenterology, Hepatology, and Nutrition," *J. Pediatr. Gastroenterol. Nutr.*, vol. 43, no. 1, pp. 123–135, Jul. 2006, doi: 10.1097/01.mpg.0000228124.93841.ea.
[88] S. Aanjankumar *et al.*, "Prediction of malnutrition in kids by integrating ResNet-50-based deep learning technique using facial images," *Sci. Rep.*, vol. 15, no. 1, p. 7871, Mar. 2025, doi: 10.1038/s41598-025-91825-z.
[89] H. M. C. Nirmani and U. P. Kudagamage, "Ensemble Approach for Early Prediction of Malnutrition Level of Children: A Case Study on Children Under Five Years Old," in *2024 4th International Conference on Advanced Research in Computing (ICARC)*, Belihuloya, Sri Lanka: IEEE, Feb. 2024, pp. 91–96. doi: 10.1109/ICARC61713.2024.10499742.
[90] L. Sha *et al.*, "Implementation of STRONGkids for identifying nutritional risk in outpatients of child health care clinics: Results of a multicentre study," *Clin. Nutr.*, vol. 42, no. 11, pp. 2207–2213, Nov. 2023, doi: 10.1016/j.clnu.2023.09.020.
[91] O. Mukuku *et al.*, "Predictive Model for the Risk of Severe Acute Malnutrition in Children," *J. Nutr. Metab.*, vol. 2019, pp. 1–7, Jul. 2019, doi: 10.1155/2019/4740825.
[92] S. M. Janssen, Y. Bouzembrak, and B. Tekinerdogan, "Artificial Intelligence in Malnutrition: A Systematic Literature Review," *Adv. Nutr.*, vol. 15, no. 9, p. 100264, Sep. 2024, doi: 10.1016/j.advnut.2024.100264.
[93] S. Aanjankumar *et al.*, "Prediction of malnutrition in kids by integrating ResNet-50-based deep learning technique using facial images," *Sci. Rep.*, vol. 15, no. 1, p. 7871, Mar. 2025, doi: 10.1038/s41598-025-91825-z.
[94] N. R. Cook, "Statistical Evaluation of Prognostic versus Diagnostic Models: Beyond the ROC Curve," *Clin. Chem.*, vol. 54, no. 1, pp. 17–23, Jan. 2008, doi: 10.1373/clinchem.2007.096529.
[95] D. Feller and A. Chiarotto, "When Is a Prognostic Prediction Model Ready for Clinical Use? A Primer for Clinicians," *J. Orthop. Sports Phys. Ther.*, vol. 56, no. 4, pp. 227–234, Apr. 2026, doi: 10.2519/jospt.2026.13868.
[96] I. Sermet-Gaudelus *et al.*, "Simple pediatric nutritional risk score to identify children at risk of malnutrition," *Am. J. Clin. Nutr.*, vol. 72, no. 1, pp. 64–70, Jul. 2000, doi: 10.1093/ajcn/72.1.64.
[97] Y. Fu *et al.*, "Prognostic ability of the sTarT back screening tool for disability and pain intensity outcomes in older adults with low back pain seeking chiropractic care: a multi-national external validation study," *Chiropr. Man. Ther.*, vol. 33, no. 1, p. 30, Jul. 2025, doi: 10.1186/s12998-025-00592-1.
[98] A. Bustamante-Fermosel *et al.*, "Screening Tools for the Early Identification of Palliative Care Needs in Patients with Advanced Chronic Conditions: An Updated Systematic Review," *J. Clin. Med.*, vol. 15, no. 3, p. 919, Jan. 2026, doi: 10.3390/jcm15030919.
[99] JMP Statistical Discovery LLC, *JMP Student Edition*. (2026). Cary, NC.
[100] R Core Team, *R: A Language and Environment for Statistical Computing. Vienna, Austria: R Foundation for Statistical Computing*. (2026). [Online]. Available: https://www.R-project.org/
[101] K. G. Dewey, "The challenge of meeting nutrient needs of infants and young children during the period of complementary feeding: an evolutionary perspective," *J. Nutr.*, vol. 143, no. 12, pp. 2050–2054, Dec. 2013, doi: 10.3945/jn.113.182527.
[102] D. W. Abdulghani, "The impact of early nutritional interventions on growth and development in infants- Meta-analysis," *Int. J. Innov. Res. Sci. Stud.*, vol. 8, no. 3, pp. 4888–4899, Jun. 2025, doi: 10.53894/ijirss.v8i3.7636.

[103] A. R. Miller, L. C. Mâsse, J. Shen, V. Schiariti, and L. Roxborough, “Diagnostic status, functional status and complexity among Canadian children with neurodevelopmental disorders and disabilities: a population-based study,” *Disabil. Rehabil.*, vol. 35, no. 6, pp. 468–478, Mar. 2013, doi: 10.3109/09638288.2012.699580.
[104] T. S. H. Lim *et al.*, “Diet, growth, nutritional status and predictors of severity of feeding difficulties in autistic children with co-occurring pediatric feeding disorder,” *Early Hum. Dev.*, vol. 199, p. 106137, Dec. 2024, doi: 10.1016/j.earlhumdev.2024.106137.
[105] A. Anato, “Predictors of wasting among children under-five years in largely food insecure area of north Wollo, Ethiopia: a cross-sectional study,” *J. Nutr. Sci.*, vol. 11, p. e8, 2022, doi: 10.1017/jns.2022.8.
[106] H. M. Babikako *et al.*, “Neurodevelopment and Recovery From Wasting,” *Pediatrics*, vol. 150, no. 5, p. e2021055615, Nov. 2022, doi: 10.1542/peds.2021-055615.
[107] H. A. Asebe *et al.*, “The level of wasting and associated factors among children aged 6–59 months in sub-Saharan African countries: multilevel ordinal logistic regression analysis,” *Front. Nutr.*, vol. 11, p. 1336864, Jun. 2024, doi: 10.3389/fnut.2024.1336864.
[108] S. Lawanaskol, J. Patumanond, P. Phinyo, N. Ratchapakdee, P. Kulseth, and A. Tantraworasin, “Prediction model to prioritize colorectal cancer screening with visual colonoscopy,” *J. Med. Screen.*, p. 09691413261449113, May 2026, doi: 10.1177/09691413261449113.
[109] T. Anothaisintawee *et al.*, “Development and Validation of a Breast Cancer Risk Prediction Model for Thai Women: A Cross-Sectional Study,” *Asian Pac. J. Cancer Prev.*, vol. 15, no. 16, pp. 6811–6817, Aug. 2014, doi: 10.7314/APJCP.2014.15.16.6811.
[110] “Nutritional Interventions for Children and Youth with Special Health Care Need,” Washington State Department of Health, 2025. [Online]. Available: https://doh.wa.gov/sites/default/files/legacy/Documents/8100/961-158-CSHCN-NI-en-L.pdf
[111]S. M. Shortreed *et al.*, “Complex modeling with detailed temporal predictors does not improve health records-based suicide risk prediction,” *Npj Digit. Med.*, vol. 6, no. 1, p. 47, Mar. 2023, doi: 10.1038/s41746-023-00772-4.
[112] D. Shamsutdinova, D. Stamate, and D. Stahl, “Balancing accuracy and Interpretability: An R package assessing complex relationships beyond the Cox model and applications to clinical prediction,” *Int. J. Med. Inf.*, vol. 194, p. 105700, Feb. 2025, doi: 10.1016/j.ijmedinf.2024.105700.
[113] L. N. Sanchez-Pinto, L. R. Venable, J. Fahrenbach, and M. M. Churpek, “Comparison of variable selection methods for clinical predictive modeling,” *Int. J. Med. Inf.*, vol. 116, pp. 10–17, Aug. 2018, doi: 10.1016/j.ijmedinf.2018.05.006.
[114] G. S. Collins *et al.*, “Evaluation of clinical prediction models (part 1): from development to external validation,” *BMJ*, vol. 384, p. e074819, Jan. 2024, doi: 10.1136/bmj-2023-074819.
[115] L. Wynants, D. J. McLernon, D. Timmerman, E. W. Steyerberg, and B. Van Calster, “Three myths about risk thresholds for prediction models,” *BMC Med.*, vol. 17, no. 1, p. 192, Dec. 2019, doi: 10.1186/s12916-019-1425-3.
[116] D. C. G. Da Silva, M. De Sá Barreto Da Cunha, A. De Oliveira Santana, A. M. Dos Santos Alves, and M. Pereira Santos, “Malnutrition and nutritional deficiencies in children with cerebral palsy: a systematic review and meta-analysis,” *Public Health*, vol. 205, pp. 192–201, Apr. 2022, doi: 10.1016/j.puhe.2022.01.024.

[117] "Nutrition in neurologically impaired children," *Paediatr. Child Health*, vol. 14, no. 6, pp. 395–401, Jul. 2009.
[118] R. Khatun *et al.*, "Nutritional status of children with neurodevelopmental disorders: a cross-sectional study at a tertiary-level hospital in northern Bangladesh," *BMC Nutr.*, vol. 10, no. 1, p. 61, Apr. 2024, doi: 10.1186/s40795-024-00863-9.
[119] H. Kuper *et al.*, "Malnutrition and Childhood Disability in Turkana, Kenya: Results from a Case-Control Study," *PloS One*, vol. 10, no. 12, p. e0144926, 2015, doi: 10.1371/journal.pone.0144926.
[120] E. S. Chanie *et al.*, "Estimate the burden of malnutrition among children with cerebral palsy in Sub-Saharan Africa: a systematic review with meta-analysis," *Sci. Rep.*, vol. 14, no. 1, p. 6494, Mar. 2024, doi: 10.1038/s41598-024-55730-1.
[121] G. A. Tadesse *et al.*, "Forecasting acute childhood malnutrition in Kenya using machine learning and diverse sets of indicators," *PLOS One*, vol. 20, no. 5, p. e0322959, May 2025, doi: 10.1371/journal.pone.0322959.
[122] A. Batra and R. M. Beattie, "Recognising malnutrition in children with neurodisability," *Clin. Nutr.*, vol. 39, no. 2, pp. 327–330, Feb. 2020, doi: 10.1016/j.clnu.2019.08.011.
[123] R. Khatun *et al.*, "Nutritional status of children with neurodevelopmental disorders: a cross-sectional study at a tertiary-level hospital in northern Bangladesh," *BMC Nutr.*, vol. 10, no. 1, p. 61, Apr. 2024, doi: 10.1186/s40795-024-00863-9.
[124] F. Penagini, C. Mameli, V. Fabiano, D. Brunetti, D. Dilillo, and G. Zuccotti, "Dietary Intakes and Nutritional Issues in Neurologically Impaired Children," *Nutrients*, vol. 7, no. 11, pp. 9400–9415, Nov. 2015, doi: 10.3390/nu7115469.
[125] J. Zhao, Y. Qiu, and H. Wang, "Nutritional risk screening and nutritional assessment for children with cerebral palsy: A review of the current research status and future directions," *Clin. Nutr. ESPEN*, vol. 65, pp. 382–389, Feb. 2025, doi: 10.1016/j.clnesp.2024.12.018.
[126] B. Arshi, L. Wynants, E. Rijnhart, K. Reeve, L. E. Cowley, and L. J. Smits, "What proportion of clinical prediction models make it to clinical practice? Protocol for a two-track follow-up study of prediction model development publications," *BMJ Open*, vol. 13, no. 5, p. e073174, May 2023, doi: 10.1136/bmjopen-2023-073174.
[127] V. Sharma, I. Ali, S. Van Der Veer, G. Martin, J. Ainsworth, and T. Augustine, "Adoption of clinical risk prediction tools is limited by a lack of integration with electronic health records," *BMJ Health Care Inform.*, vol. 28, no. 1, p. e100253, Feb. 2021, doi: 10.1136/bmjhci-2020-100253.
[128] F. Markowetz, "All models are wrong and yours are useless: making clinical prediction models impactful for patients," *Npj Precis. Oncol.*, vol. 8, no. 1, p. 54, Feb. 2024, doi: 10.1038/s41698-024-00553-6.
[129] L. J. Damschroder, C. M. Reardon, M. A. O. Widerquist, and J. Lowery, "The updated Consolidated Framework for Implementation Research based on user feedback," *Implement. Sci.*, vol. 17, no. 1, p. 75, Oct. 2022, doi: 10.1186/s13012-022-01245-0.
[130] Y. C. Learmonth and R. W. Motl, "Important considerations for feasibility studies in physical activity research involving persons with multiple sclerosis: a scoping systematic review and case study," *Pilot Feasibility Stud.*, vol. 4, no. 1, p. 1, Dec. 2018, doi: 10.1186/s40814-017-0145-8.
[131] J. A. Balch and T. J. Loftus, "Actionable artificial intelligence: Overcoming barriers to adoption of prediction tools," *Surgery*, vol. 174, no. 3, pp. 730–732, Sep. 2023, doi: 10.1016/j.surg.2023.03.019.

[132] M. C. Politi, P. Adsul, M. D. Kuzemchak, R. Zeuner, and D. L. Frosch, “Clinicians’ perceptions of digital vs. paper-based decision support interventions,” *J. Eval. Clin. Pract.*, vol. 21, no. 2, pp. 175–179, Apr. 2015, doi: 10.1111/jep.12269.
[133] R. K. Rosen *et al.*, “Designing a Novel Clinician Decision Support Tool for the Management of Acute Diarrhea in Bangladesh: Formative Qualitative Study,” *JMIR Hum. Factors*, vol. 9, no. 1, p. e33325, Mar. 2022, doi: 10.2196/33325.
[134] B. Lefchak, K. R. Bergmann, S. Lammers, and G. Z. Hester, “Piloting a Mobile Clinical Decision Support Application for Pediatric Clinical Guidelines,” *Clin. Pediatr. (Phila.)*, vol. 63, no. 6, pp. 822–830, Jun. 2024, doi: 10.1177/00099228231197078.
[135] C. Horwood *et al.*, “Challenges of using e-health technologies to support clinical care in rural Africa: a longitudinal mixed methods study exploring primary health care nurses’ experiences of using an electronic clinical decision support system (CDSS) in South Africa,” *BMC Health Serv. Res.*, vol. 23, no. 1, p. 30, Jan. 2023, doi: 10.1186/s12913-022-09001-2.
[136] Y. O’ Connor *et al.*, “Stakeholders perspectives on paper-based and electronic clinical decision support systems in Malawi Africa,” *J. Decis. Syst.*, vol. 25, no. sup1, pp. 410–420, Jun. 2016, doi: 10.1080/12460125.2016.1187400.
[137] H. Wisniewski and J. Torous, “Digital navigators to implement smartphone and digital tools in care,” *Acta Psychiatr. Scand.*, vol. 141, no. 4, pp. 350–355, Apr. 2020, doi: 10.1111/acps.13149.
[138] M. Woodward *et al.*, “How to co-design a prototype of a clinical practice tool: a framework with practical guidance and a case study,” *BMJ Qual. Saf.*, vol. 33, no. 4, pp. 258–270, Apr. 2024, doi: 10.1136/bmjqs-2023-016196.
[139] J. N. Babione *et al.*, “Human-centred design processes for clinical decision support: A pulmonary embolism case study,” *Int. J. Med. Inf.*, vol. 142, p. 104196, Oct. 2020, doi: 10.1016/j.ijmedinf.2020.104196.
[140] L. Samal *et al.*, “Care coordination gaps due to lack of interoperability in the United States: a qualitative study and literature review,” *BMC Health Serv. Res.*, vol. 16, no. 1, p. 143, Dec. 2016, doi: 10.1186/s12913-016-1373-y.
[141] M. Molloy, P. Hagedorn, and M. Dewan, “Why Does Current Clinical Decision Support Frequently Fail to Support Clinical Decisions?*,” *Pediatr. Crit. Care Med.*, vol. 23, no. 8, pp. 670–672, Aug. 2022, doi: 10.1097/PCC.0000000000003000.
[142] T. Oluoch *et al.*, “The effect of electronic medical record-based clinical decision support on HIV care in resource-constrained settings: A systematic review,” *Int. J. Med. Inf.*, vol. 81, no. 10, pp. e83–e92, Oct. 2012, doi: 10.1016/j.ijmedinf.2012.07.010.
[143] T. H. Kappen *et al.*, “Barriers and facilitators perceived by physicians when using prediction models in practice,” *J. Clin. Epidemiol.*, vol. 70, pp. 136–145, Feb. 2016, doi: 10.1016/j.jclinepi.2015.09.008.
[144] J. H. LeLaurin, K. Pluta, W. E. Norton, R. G. Salloum, and N. Singh Ospina, “Time to de-implementation of low-value cancer screening practices: a narrative review,” *BMJ Qual. Saf.*, vol. 34, no. 8, pp. 547–555, Aug. 2025, doi: 10.1136/bmjqs-2025-018558.
[145] T. Brown *et al.*, “Caring for children with SAM: Intersectional stories of shame, blame and stigmatisation in Zimbabwe, Zambia and Kenya,” *Glob. Public Health*, vol. 20, no. 1, p. 2439883, Dec. 2025, doi: 10.1080/17441692.2024.2439883.
[146] N. Imran, S. M. Tahir, M. Ayub, and A. Nazeer, “Neurodevelopmental disabilities among children and adolescents: perspectives and priorities in low- and middle-income countries,”

Curr. Opin. Psychiatry, vol. 39, no. 2, pp. 103–108, Mar. 2026, doi: 10.1097/YCO.0000000000001064.
[147] D. Tilahun, C. Hanlon, A. Fekadu, B. Tekola, Y. Baheretibeb, and R. A. Hoekstra, "Stigma, explanatory models and unmet needs of caregivers of children with developmental disorders in a low-income African country: a cross-sectional facility-based survey," *BMC Health Serv. Res.*, vol. 16, no. 1, p. 152, Dec. 2016, doi: 10.1186/s12913-016-1383-9.
[148] T. Smythe, J. D. Adelson, and S. Polack, "Systematic review of interventions for reducing stigma experienced by children with disabilities and their families in low- and middle-income countries: state of the evidence," *Trop. Med. Int. Health*, vol. 25, no. 5, pp. 508–524, May 2020, doi: 10.1111/tmi.13388.
[149] S. R. Neal *et al.*, "Clinical prediction models to diagnose neonatal sepsis in low-income and middle-income countries: a scoping review," *BMJ Glob. Health*, vol. 10, no. 4, p. e017582, Apr. 2025, doi: 10.1136/bmjgh-2024-017582.
[150] N. Peiffer-Smadja *et al.*, "Machine learning for clinical decision support in infectious diseases: a narrative review of current applications," *Clin. Microbiol. Infect.*, vol. 26, no. 5, pp. 584–595, May 2020, doi: 10.1016/j.cmi.2019.09.009.
[151] R. Haniffa, I. Isaam, A. P. De Silva, A. M. Dondorp, and N. F. De Keizer, "Performance of critical care prognostic scoring systems in low and middle-income countries: a systematic review," *Crit. Care*, vol. 22, no. 1, p. 18, Dec. 2018, doi: 10.1186/s13054-017-1930-8.
[152] X. Liu *et al.*, "The Necessity and Feasibility Assessment Tool of the Clinical Prediction Model for Individual Prognosis Before Its Startup: A Multi-Sectoral Delphi Consensus Study," *J. Evid.-Based Med.*, p. e70106, Dec. 2025, doi: 10.1111/jebm.70106.

APPENDIX A: SUPPLEMENTAL TABLES AND FIGURES

Table A.1: ICD-10 codes and assigned NDD diagnoses

Broad NDD diagnosis	NDD diagnosis	What each included ICD-10 code indicates
Cognitive & Learning disability	Intellectual disabilities (F70–F79); Other/unspecified disorders of psychological development (F88–F89)	F70 = Mild intellectual disabilities; F71 = Moderate intellectual disabilities; F72 = Severe intellectual disabilities; F73 = Profound intellectual disabilities; F78 = Other intellectual disabilities; F78.A1 = SYNGAP1-related intellectual disability; F78.A9 = Other genetic related intellectual disability; F79 = Unspecified intellectual disabilities; F88 = Other disorders of psychological development; F89 = Unspecified disorder of psychological development
Social & Communication disabilities	Specific developmental disorders of speech and language (F80); Pervasive developmental disorders / autism-related disorders (F84)	F80.0 = Specific speech articulation disorder; F80.1 = Expressive language disorder; F80.2 = Mixed receptive-expressive language disorder; F80.4 = Speech and language development delay due to hearing loss; F80.81 = Childhood onset fluency disorder; F80.82 = Social pragmatic communication disorder; F80.89 = Other developmental disorders of speech and language; F80.9 = Developmental disorder of speech and language, unspecified; F84.0 = Autistic disorder; F84.2 = Rett syndrome; F84.3 = Other childhood disintegrative disorder; F84.5 = Asperger's syndrome; F84.8 = Other pervasive developmental disorders; F84.9 = Pervasive developmental disorder, unspecified
Physical, Motor and Congenital malformation of the nervous system	Specific developmental disorder of motor function (F82); Cerebral palsy (G80); Congenital malformations of the nervous system (Q00–Q07)	F82 = Specific developmental disorder of motor function; G80.0 = Spastic quadriplegic cerebral palsy; G80.1 = Spastic diplegic cerebral palsy; G80.2 = Spastic hemiplegic cerebral palsy; G80.3 = Dyskinetic cerebral palsy; G80.4 = Ataxic cerebral palsy; G80.8 = Other cerebral palsy; G80.9 = Cerebral palsy, unspecified; Q00.0 = Anencephaly; Q01.1 = Nasofrontal encephalocele; Q01.2 = Occipital encephalocele; Q01.8 = Encephalocele of other sites; Q01.9 = Encephalocele, unspecified; Q02 = Microcephaly; Q03.0 = Malformations of aqueduct of Sylvius; Q03.1 = Atresia of foramina of Magendie and Luschka; Q03.8 = Other congenital hydrocephalus; Q03.9 = Congenital hydrocephalus, unspecified; Q04.0 = Congenital malformations of corpus callosum; Q04.2 = Holoprosencephaly; Q04.3 = Other reduction deformities of brain; Q04.4 = Septo-optic dysplasia; Q04.5 = Megalencephaly; Q04.6 = Congenital cerebral cysts; Q04.8 = Other specified congenital malformations of brain; Q04.9 = Congenital malformation of brain, unspecified; Q05.1 = Thoracic spina bifida with hydrocephalus; Q05.2 = Lumbar spina bifida with hydrocephalus; Q05.3 = Sacral spina bifida with hydrocephalus; Q05.4 = Unspecified spina bifida

Broad NDD diagnosis	NDD diagnosis	What each included ICD-10 code indicates
		with hydrocephalus; Q05.5 = Cervical spina bifida without hydrocephalus; Q05.6 = Thoracic spina bifida without hydrocephalus; Q05.7 = Lumbar spina bifida without hydrocephalus; Q05.8 = Sacral spina bifida without hydrocephalus; Q05.9 = Spina bifida, unspecified; Q06.1 = Hypoplasia and dysplasia of spinal cord; Q06.2 = Diastematomyelia; Q06.4 = Hydromyelia; Q06.8 = Other specified congenital malformations of spinal cord; Q06.9 = Congenital malformation of spinal cord, unspecified; Q07.00 = Arnold-Chiari syndrome without spina bifida or hydrocephalus; Q07.01 = Arnold-Chiari syndrome with spina bifida; Q07.02 = Arnold-Chiari syndrome with hydrocephalus; Q07.03 = Arnold-Chiari syndrome with spina bifida and hydrocephalus; Q07.8 = Other specified congenital malformations of nervous system; Q07.9 = Congenital malformation of nervous system, unspecified

Table A.2: Variable extraction from EHR free-text through natural language processing

Grouped variable	Clinician's note-derived indicators
Cerebral palsy	Cerebral palsy
Developmental delay	Developmental delay, global developmental delay
Speech/language-related conditions	Expressive language disorder, speech and language disorders, speech delay
Autism	Autism spectrum disorder
Feeding difficulty or tube-feeding	Feeding difficulty, feeding intolerance, gastrostomy tube (G-tube) dependence, nasogastric tube (NG-tube) dependence, tube-fed newborn, failure to thrive, risk for alteration of nutrition in newborn
Prematurity-related conditions	Anemia of prematurity, apnea of prematurity, premature infant, preterm newborn
Breech birth	Breech birth
Diabetic mother	Infant of diabetic mother
Neonatal hyperbilirubinemia	Neonatal hyperbilirubinemia
Newborn at risk of sepsis	suspected sepsis in newborn
Congenital heart disease	Congenital heart disease, septal defect (atrial, ventricular, or atrioventricular canal), aortic arch anomaly, aortic valve stenosis, bicuspid aortic valve, coarctation of the aorta, patent ductus arteriosus (PDA), patent foramen ovale (PFO), pulmonary artery stenosis, pulmonary valve stenosis, hypoplastic left heart syndrome, tetralogy of Fallot, transposition of the great arteries
Respiratory morbidity	Acute respiratory failure, chronic respiratory disease, bronchopulmonary dysplasia (BPD), respiratory distress syndrome
Infectious conditions	COVID-19, methicillin-resistant Staphylococcus aureus (MRSA) infection, urinary tract infection
Renal morbidity	Acute kidney injury
Cleft palate	Cleft lip and palate
Current hospitalization	Current hospitalization

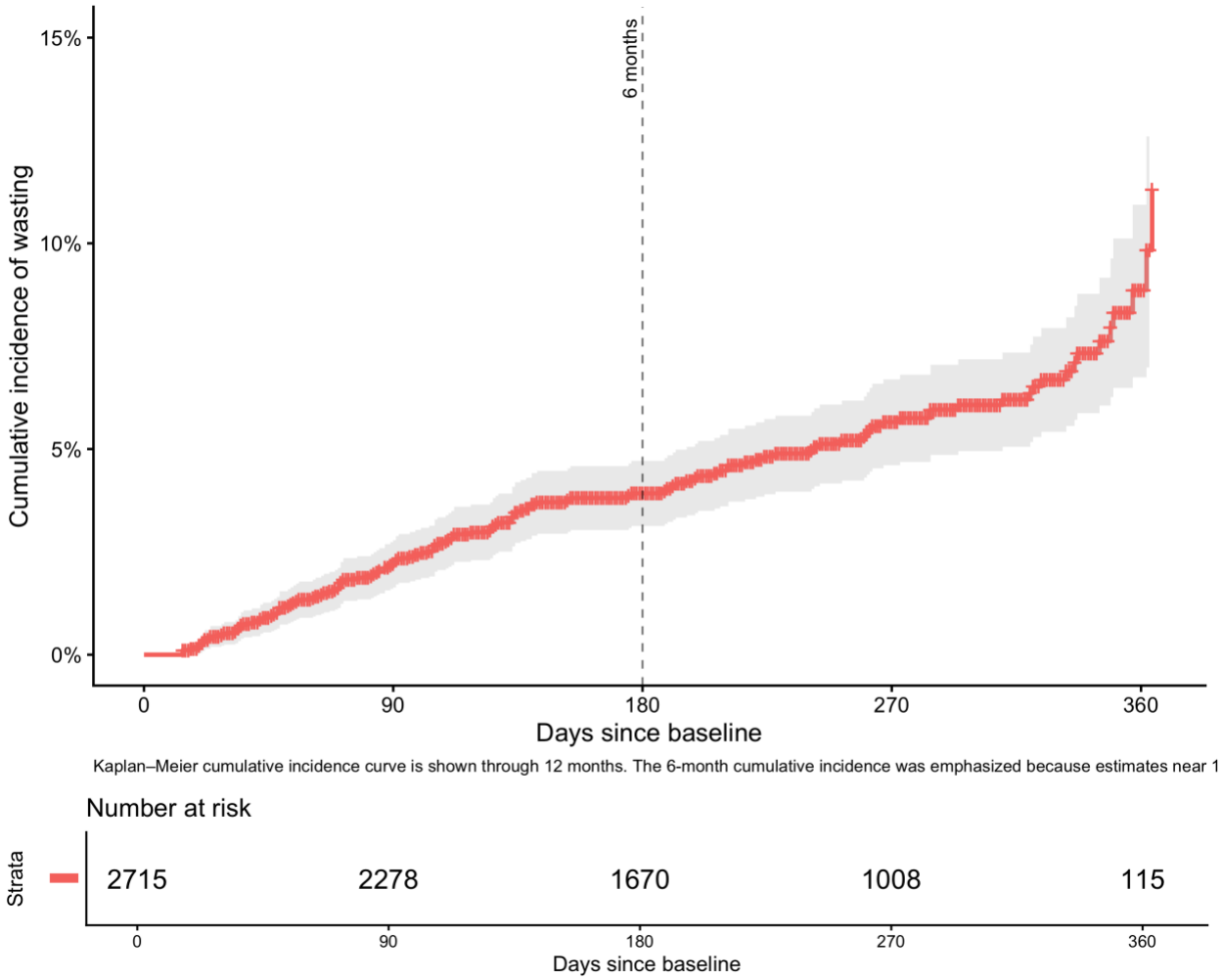

Figure A. 1: Overall cumulative incidence of wasting

Table A.3: DAG-informed exposure-specific adjustment sets

Exposure (risk factor)	Minimum adjustment set
Age	None
Sex	None
Ethnicity	None
Race	None
ADI	None
Preterm birth	Area deprivation index
Low birth weight	Area deprivation index, Preterm birth
NDD type	Age, Congenital heart disease, Preterm birth, Respiratory morbidity, Sex assigned at birth
Congenital heart disease	Age, NDD type, Preterm birth, Respiratory morbidity, Sex assigned at birth
Respiratory morbidity	Age, Congenital heart disease, NDD type, Preterm birth, Sex assigned at birth
Infections/inflammation	Area deprivation index, Congenital heart disease, Low birth weight, NDD type, Preterm birth
Feeding difficulty / tube feeding	Congenital heart disease, Infections/inflammation, NDD type, Preterm birth, Respiratory morbidity
Admitted at hospital	Congenital heart disease, Feeding difficulty /tube feeding, Respiratory morbidity

Table A.4: Baseline Risk Factors for Wasting (WHZ < -2) Among Children Under 5 Years Following First Observed NDD Diagnosis Using Multiply Imputed Baseline Variables

Exposure	Contrast	Pooled DAG-adjusted HR (95% CI)	p-value
Age category	6–<24 months vs 24–<48 months	1.49 (0.97, 2.30)	0.068
	<6 months vs 24–<48 months	3.56 (2.33, 5.44)	<0.001
Sex	Female vs Male	0.82 (0.58, 1.16)	0.266
Race	Black or African American vs White	1.14 (0.66, 1.95)	0.642
	Asian vs White	0.90 (0.52, 1.54)	0.693
	AI/AN/NHPI vs White	0.63 (0.15, 2.56)	0.516
	Other/Unknown/Patient Refused vs White	0.96 (0.61, 1.50)	0.852
Ethnicity	Hispanic vs Non-Hispanic	0.94 (0.63, 1.39)	0.743
Area deprivation index	Q2 vs Q1 (least deprivation)	1.61 (0.94, 2.78)	0.084
	Q3 vs Q1 (least deprivation)	0.92 (0.50, 1.69)	0.784
	Q4 vs Q1 (least deprivation)	1.13 (0.63, 2.01)	0.681
	Q5 (most deprivation) vs Q1 (least deprivation)	1.24 (0.70, 2.19)	0.455
Broad NDD type	Physical & Motor only vs Social & Communication only	2.11 (1.13, 3.96)	0.020
	Cognitive & Learning only vs Social & Communication only	2.20 (1.04, 4.66)	0.040
	Multiple broad NDD domains vs Social & Communication only	3.31 (1.78, 6.16)	<0.001
Hospital admission at baseline	Yes vs No	1.23 (0.78, 1.95)	0.376
Gestational age category	Early-Term (37–38 weeks) vs Full-Term (39–40 weeks)	1.60 (1.00, 2.56)	0.051
	Late/Post-Term (41+ weeks) vs Full-Term (39–40 weeks)	2.02 (0.98, 4.14)	0.056
	Preterm (<37 weeks) vs Full-Term (39–40 weeks)	1.39 (0.85, 2.26)	0.190
Birthweight category	Extremely Low Birthweight vs Normal Birthweight	2.17 (0.86, 5.47)	0.100
	Very Low Birthweight vs Normal Birthweight	2.29 (0.82, 6.37)	0.112
	Low Birthweight vs Normal Birthweight	1.80 (1.03, 3.15)	0.040

Congenital heart disease	Yes vs No	1.06 (0.54, 2.09)	0.861
Respiratory morbidity	Yes vs No	1.23 (0.62, 2.46)	0.558
Infections/inflammation	Yes vs No	0.87 (0.20, 3.74)	0.852
Feeding difficulty	Yes vs No	1.93 (1.10, 3.38)	0.021

Note: Hazard ratios were estimated using Cox proportional hazards models. Adjusted models used DAG-informed minimal sufficient adjustment sets. Estimates were pooled across 50 imputed datasets using Rubin's rules.

Table A.5: Baseline Risk Factors for Incident Underweight (WAZ < −2) Among Children Under 5 Years Following First Observed NDD Diagnosis

Exposure	Contrast	Unadjusted HR (95% CI)	DAG-adjusted HR (95% CI)	p-value	Reference group events/person-time, days	Comparison group events/ person-time, days
Age category	6–<24 months vs 24–<48 months	1.58 (1.04, 2.41)	1.58 (1.04, 2.41)	0.032	40 / 301,983	48 / 227,691
	<6 months vs 24–<48 months	7.22 (4.96, 10.51)	7.22 (4.96, 10.51)	<0.001	40 / 301,983	85 / 88,475
Sex	Female vs Male	1.01 (0.74, 1.36)	1.01 (0.74, 1.36)	0.966	103 / 368,010	70 / 250,139
Race	Black or African American vs White	0.80 (0.47, 1.36)	0.80 (0.47, 1.36)	0.417	95 / 329,563	16 / 69,150
	Asian vs White	0.57 (0.32, 1.01)	0.57 (0.32, 1.01)	0.055	95 / 329,563	13 / 80,025
	AI/AN/NHPI vs White	1.48 (0.65, 3.38)	1.48 (0.65, 3.38)	0.349	95 / 329,563	6 / 13,967
	Other/Unknown/Patient Refused vs White	1.20 (0.84, 1.72)	1.20 (0.84, 1.72)	0.319	95 / 329,563	43 / 123,665
Ethnicity	Hispanic vs Non-Hispanic	1.36 (0.97, 1.90)	1.36 (0.97, 1.90)	0.074	112 / 447,199	49 / 143,126
Area deprivation index	Q2 vs Q1 (least deprivation)	1.30 (0.70, 2.44)	1.30 (0.70, 2.44)	0.407	17 / 109,443	23 / 114,108
	Q3 vs Q1 (least deprivation)	1.74 (0.96, 3.14)	1.74 (0.96, 3.14)	0.067	17 / 109,443	31 / 114,484
	Q4 vs Q1 (least deprivation)	2.11 (1.19, 3.74)	2.11 (1.19, 3.74)	0.010	17 / 109,443	38 / 115,313

	Q5 (most deprivation) vs Q1 (least deprivation)	2.60 (1.50, 4.53)	2.60 (1.50, 4.53)	<0.001	17 / 109,443	48 / 118,545
Broad NDD type	Physical & Motor only vs Social & Communication only	7.38 (4.30, 12.65)	1.71 (0.86, 3.38)	0.126	12 / 84,252	99 / 160,519
	Cognitive & Learning only vs Social & Communication only	3.92 (1.96, 7.86)	1.29 (0.52, 3.18)	0.582	12 / 84,252	8 / 39,566
	Multiple broad NDD domains vs Social & Communication only	4.12 (2.21, 7.69)	1.82 (0.89, 3.71)	0.102	12 / 84,252	21 / 71,197
Hospital admission at baseline	Yes vs No	3.44 (2.55, 4.63)	1.72 (1.18, 2.53)	0.005	88 / 482,951	85 / 135,198
Gestational age category	Early-Term (37–38 weeks) vs Full-Term (39–40 weeks)	1.64 (1.06, 2.53)	1.43 (0.91, 2.27)	0.124	37 / 133,823	36 / 88,920
	Late/Post-Term (41+ weeks) vs Full-Term (39–40 weeks)	1.32 (0.62, 2.82)	1.42 (0.66, 3.06)	0.368	37 / 133,823	8 / 20,699
	Preterm (<37 weeks) vs Full-Term (39–40 weeks)	2.02 (1.33, 3.07)	1.86 (1.20, 2.88)	0.005	37 / 133,823	45 / 86,087
Birthweight category	Extremely Low Birthweight vs Normal Birthweight	2.29 (1.15, 4.58)	1.76 (0.74, 4.17)	0.201	65 / 210,074	8 / 11,690
	Very Low Birthweight vs Normal Birthweight	1.08 (0.34, 3.43)	0.58 (0.13, 2.55)†	0.469	65 / 210,074	2 / 7,956
	Low Birthweight vs Normal Birthweight	2.63 (1.77, 3.89)	2.12 (1.25, 3.58)	0.005	65 / 210,074	34 / 40,939

Congenital heart disease	Yes vs No	5.83 (3.95, 8.61)	1.39 (0.82, 2.34)	0.219	111 / 336,749	29 / 18,785
Respiratory morbidity	Yes vs No	7.32 (5.01, 10.70)	1.73 (1.03, 2.92)	0.039	107 / 338,210	33 / 17,324
Infections/inflammation	Yes vs No	4.77 (2.11, 10.77)	0.84 (0.28, 2.48)†	0.750	105 / 267,700	4 / 2,959
Feeding difficulty	Yes vs No	7.16 (5.21, 9.85)	3.53 (2.22, 5.63)	<0.001	85 / 322,200	55 / 33,334

Note: Hazard ratios were estimated using Cox proportional hazards models. Adjusted models used DAG-informed minimal sufficient adjustment sets. Event counts and person-time are calculated from the same exposure-specific complete-case dataset used for the corresponding DAG-adjusted Cox model. Totals vary across exposures because each exposure had a different DAG-specified adjustment set and because of missing covariate data. For exposures with no DAG-specified adjustment variables, the DAG-adjusted model is identical to the exposure-only model. NE = not estimable because of zero or very sparse events, or model non-convergence. †Estimate based on fewer than 5 events in the comparison group and should be interpreted cautiously.

Table A.6: Baseline Risk Factors for ≥5% Weight Loss from Baseline Among Children Under Five Years Following First Observed NDD Diagnosis

Exposure	Contrast	Unadjusted HR (95% CI)	DAG-adjusted HR (95% CI)	p-value	Reference group events/person-time, days	Comparison group events/ person-time, days
Age category	6–<24 months vs 24–<48 months	0.75 (0.55, 1.03)	0.75 (0.55, 1.03)	0.078	111 / 525,304	60 / 369,511
	<6 months vs 24–<48 months	0.24 (0.12, 0.50)	0.24 (0.12, 0.50)	<0.001	111 / 525,304	8 / 158,553
Sex	Female vs Male	1.06 (0.79, 1.43)	1.06 (0.79, 1.43)	0.703	107 / 647,822	72 / 405,545
Race	Black or African American vs White	1.53 (1.00, 2.33)	1.53 (1.00, 2.33)	0.047	87 / 553,454	29 / 118,599
	Asian vs White	0.98 (0.61, 1.57)	0.98 (0.61, 1.57)	0.923	87 / 553,454	21 / 136,720
	AI/AN/NHPI vs White	2.09 (1.01, 4.32)	2.09 (1.01, 4.32)	0.046	87 / 553,454	8 / 23,910
	Other/Unknown/Patient Refused vs White	0.97 (0.65, 1.44)	0.97 (0.65, 1.44)	0.869	87 / 553,454	34 / 218,175
Ethnicity	Hispanic vs Non-Hispanic	0.70 (0.47, 1.02)	0.70 (0.47, 1.02)	0.066	139 / 758,755	32 / 249,413
Area deprivation index	Q2 vs Q1 (least deprivation)	1.02 (0.62, 1.67)	1.02 (0.62, 1.67)	0.940	31 / 190,181	32 / 193,356
	Q3 vs Q1 (least deprivation)	0.88 (0.52, 1.46)	0.88 (0.52, 1.46)	0.609	31 / 190,181	28 / 196,278
	Q4 vs Q1 (least deprivation)	1.13 (0.70, 1.83)	1.13 (0.70, 1.83)	0.616	31 / 190,181	36 / 195,423

	Q5 (most deprivation) vs Q1 (least deprivation)	1.19 (0.74, 1.90)	1.19 (0.74, 1.90)	0.478	31 / 190,181	39 / 202,941
Broad NDD type	Physical & Motor only vs Social & Communication only	0.67 (0.46, 0.97)	1.00 (0.56, 1.81)	0.992	24 / 142,774	27 / 273,894
	Cognitive & Learning only vs Social & Communication only	1.01 (0.61, 1.68)	1.18 (0.57, 2.44)	0.649	24 / 142,774	11 / 63,718
	Multiple broad NDD domains vs Social & Communication only	1.35 (0.93, 1.98)	1.69 (0.98, 2.92)	0.058	24 / 142,774	30 / 112,114
Hospital admission at baseline	Yes vs No	2.57 (1.91, 3.47)	3.12 (2.29, 4.26)	<0.001	107 / 839,285	72 / 214,082
Gestational age category	Early-Term (37–38 weeks) vs Full-Term (39–40 weeks)	0.72 (0.42, 1.24)	0.80 (0.46, 1.38)	0.417	35 / 207,804	20 / 148,341
	Late/Post-Term (41+ weeks) vs Full-Term (39–40 weeks)	1.20 (0.54, 2.69)	1.36 (0.60, 3.07)	0.459	35 / 207,804	7 / 29,576
	Preterm (<37 weeks) vs Full-Term (39–40 weeks)	0.90 (0.55, 1.48)	0.87 (0.52, 1.46)	0.589	35 / 207,804	24 / 163,442
Birthweight category	Extremely Low Birthweight vs Normal Birthweight	0.67 (0.21, 2.12)	0.66 (0.18, 2.44)†	0.534	53 / 319,557	3 / 24,000
	Very Low Birthweight vs Normal Birthweight	0.30 (0.04, 2.13)	0.31 (0.04, 2.40)†	0.260	53 / 319,557	1 / 17,590
	Low Birthweight vs Normal Birthweight	0.95 (0.54, 1.66)	0.97 (0.48, 1.98)	0.941	53 / 319,557	14 / 84,728

Congenital heart disease	Yes vs No	0.57 (0.21, 1.53)	0.83 (0.21, 3.30)†	0.796	89 / 556,425	3 / 36,075
Respiratory morbidity	Yes vs No	1.31 (0.61, 2.79)	3.87 (1.04, 14.39)†	0.043	88 / 562,040	4 / 30,460
Infections/inflammation	Yes vs No	NE	NE	0.995	71 / 441,412	0 / 4,464
Feeding difficulty	Yes vs No	0.69 (0.34, 1.40)	0.71 (0.25, 1.97)	0.507	86 / 531,469	6 / 61,031

Note: Hazard ratios were estimated using Cox proportional hazards models. Adjusted models used DAG-informed minimal sufficient adjustment sets. Event counts and person-time are calculated from the same exposure-specific complete-case dataset used for the corresponding DAG-adjusted Cox model. Totals vary across exposures because each exposure had a different DAG-specified adjustment set and because of missing covariate data. For exposures with no DAG-specified adjustment variables, the DAG-adjusted model is identical to the exposure-only model. NE = not estimable because of zero or very sparse events, or model non-convergence. †Estimate based on fewer than 5 events in the comparison group and should be interpreted cautiously.

Table A.7: Baseline Risk Factors for ≥10% Weight Loss from Baseline Among Children Under 5 Years Following First Observed NDD Diagnosis

Exposure	Contrast	Unadjusted HR (95% CI)	DAG-adjusted HR (95% CI)	p-value	Reference group events/person-time, days	Comparison group events/ person-time, days
Age category	6–<24 months vs 24–<48 months	1.37 (0.79, 2.37)	1.37 (0.79, 2.37)	0.265	26 / 543,639	25 / 376,286
	<6 months vs 24–<48 months	0.13 (0.02, 0.97)	0.13 (0.02, 0.97)†	0.046	26 / 543,639	1 / 160,375
Sex	Female vs Male	1.35 (0.78, 2.33)	1.35 (0.78, 2.33)	0.278	28 / 663,482	24 / 416,818
Race	Black or African American vs White	1.61 (0.68, 3.80)	1.61 (0.68, 3.80)	0.281	20 / 568,099	7 / 122,492
	Asian vs White	2.03 (0.95, 4.34)	2.03 (0.95, 4.34)	0.067	20 / 568,099	10 / 139,447
	AI/AN/NHPI vs White	2.22 (0.52, 9.49)	2.22 (0.52, 9.49)†	0.283	20 / 568,099	2 / 25,258
	Other/Unknown/Patient Refused vs White	1.63 (0.81, 3.28)	1.63 (0.81, 3.28)	0.169	20 / 568,099	13 / 222,495
Ethnicity	Hispanic vs Non-Hispanic	0.71 (0.34, 1.46)	0.71 (0.34, 1.46)	0.347	39 / 779,966	9 / 254,132
Area deprivation index	Q2 vs Q1 (least deprivation)	1.10 (0.45, 2.70)	1.10 (0.45, 2.70)	0.842	9 / 194,731	10 / 198,545
	Q3 vs Q1 (least deprivation)	0.76 (0.28, 2.03)	0.76 (0.28, 2.03)	0.579	9 / 194,731	7 / 200,408
	Q4 vs Q1 (least deprivation)	0.64 (0.23, 1.81)	0.64 (0.23, 1.81)	0.405	9 / 194,731	6 / 201,614
	Q5 (most deprivation) vs Q1 (least deprivation)	1.57 (0.69, 3.59)	1.57 (0.69, 3.59)	0.285	9 / 194,731	15 / 208,180

Broad NDD type	Physical & Motor only vs Social & Communication only	0.97 (0.50, 1.87)	1.31 (0.48, 3.56)	0.595	7 / 146,562	10 / 278,306
	Cognitive & Learning only vs Social & Communication only	0.42 (0.10, 1.79)	0.66 (0.14, 3.23)†	0.609	7 / 146,562	2 / 65,526
	Multiple broad NDD domains vs Social & Communication only	1.83 (0.92, 3.62)	2.18 (0.84, 5.66)	0.109	7 / 146,562	11 / 116,347
Hospital admission at baseline	Yes vs No	3.80 (2.20, 6.54)	5.15 (2.97, 8.94)	<0.001	26 / 856,834	26 / 223,466
Gestational age category	Early-Term (37–38 weeks) vs Full-Term (39–40 weeks)	0.85 (0.35, 2.05)	1.04 (0.42, 2.59)	0.928	11 / 213,926	8 / 150,546
	Late/Post-Term (41+ weeks) vs Full-Term (39–40 weeks)	1.51 (0.43, 5.31)	1.86 (0.52, 6.70)†	0.343	11 / 213,926	3 / 30,449
	Preterm (<37 weeks) vs Full-Term (39–40 weeks)	0.59 (0.22, 1.55)	0.71 (0.26, 1.92)	0.496	11 / 213,926	6 / 167,738
Birthweight category	Extremely Low Birthweight vs Normal Birthweight	0.59 (0.08, 4.38)	0.57 (0.06, 5.38)†	0.622	22 / 326,996	1 / 24,537
	Very Low Birthweight vs Normal Birthweight	0.00 (0.00, Inf)	0.00 (0.00, Inf)†	0.996	22 / 326,996	0 / 17,942
	Low Birthweight vs Normal Birthweight	0.33 (0.08, 1.40)	0.33 (0.07, 1.62)†	0.173	22 / 326,996	2 / 87,266
Congenital heart disease	Yes vs No	0.48 (0.07, 3.50)	0.00 (0.00, Inf)†	0.998	30 / 570,064	0 / 36,676

Respiratory morbidity	Yes vs No	NE	NE	0.999	30 / 575,452	0 / 31,289
Infections/inflammation	Yes vs No	NE	NE	0.999	25 / 452,277	0 / 4,464
Feeding difficulty	Yes vs No	0.29 (0.04, 2.07)	0.67 (0.09, 5.00)†	0.696	29 / 544,444	1 / 62,297

Note: Hazard ratios were estimated using Cox proportional hazards models. Adjusted models used DAG-informed minimal sufficient adjustment sets. Event counts and person-time are calculated from the same exposure-specific complete-case dataset used for the corresponding DAG-adjusted Cox model. Totals vary across exposures because each exposure had a different DAG-specified adjustment set and because of missing covariate data. For exposures with no DAG-specified adjustment variables, the DAG-adjusted model is identical to the exposure-only model. NE = not estimable because of zero or very sparse events, or model non-convergence. †Estimate based on fewer than 5 events in the comparison group and should be interpreted cautiously

Table A.8: Supplemental full risk estimation tables for wasting at 1 month age interval

Age at baseline (months)	Broad NDD type	Respiratory morbidity	Predicted 6-month risk (%)	6-month tertile band
0	Multiple broad NDD domains	No	7	High
0	Multiple broad NDD domains	Yes	12.1	High
0	Physical & Motor only	No	5.5	High
0	Physical & Motor only	Yes	9.6	High
0	Cognitive & Learning only	No	5	High
0	Cognitive & Learning only	Yes	8.7	High
0	Social & Communication only	No	1.9	Intermediate
0	Social & Communication only	Yes	3.3	Intermediate
1	Multiple broad NDD domains	No	6.8	High
1	Multiple broad NDD domains	Yes	11.8	High
1	Physical & Motor only	No	5.4	High
1	Physical & Motor only	Yes	9.4	High
1	Cognitive & Learning only	No	4.9	High
1	Cognitive & Learning only	Yes	8.6	High
1	Social & Communication only	No	1.8	Intermediate
1	Social & Communication only	Yes	3.2	Intermediate
2	Multiple broad NDD domains	No	6.7	High
2	Multiple broad NDD domains	Yes	11.6	High
2	Physical & Motor only	No	5.3	High
2	Physical & Motor only	Yes	9.2	High
2	Cognitive & Learning only	No	4.8	High
2	Cognitive & Learning only	Yes	8.4	High
2	Social & Communication only	No	1.8	Intermediate
2	Social & Communication only	Yes	3.2	Intermediate
3	Multiple broad NDD domains	No	6.5	High
3	Multiple broad NDD domains	Yes	11.4	High
3	Physical & Motor only	No	5.2	High
3	Physical & Motor only	Yes	9	High
3	Cognitive & Learning only	No	4.7	High

3	Cognitive & Learning only	Yes	8.2	High
3	Social & Communication only	No	1.7	Intermediate
3	Social & Communication only	Yes	3.1	Intermediate
4	Multiple broad NDD domains	No	6.4	High
4	Multiple broad NDD domains	Yes	11.2	High
4	Physical & Motor only	No	5.1	High
4	Physical & Motor only	Yes	8.9	High
4	Cognitive & Learning only	No	4.6	High
4	Cognitive & Learning only	Yes	8.1	High
4	Social & Communication only	No	1.7	Intermediate
4	Social & Communication only	Yes	3	Intermediate
5	Multiple broad NDD domains	No	6.3	High
5	Multiple broad NDD domains	Yes	11	High
5	Physical & Motor only	No	5	High
5	Physical & Motor only	Yes	8.7	High
5	Cognitive & Learning only	No	4.5	High
5	Cognitive & Learning only	Yes	7.9	High
5	Social & Communication only	No	1.7	Intermediate
5	Social & Communication only	Yes	3	Intermediate
6	Multiple broad NDD domains	No	6.2	High
6	Multiple broad NDD domains	Yes	10.7	High
6	Physical & Motor only	No	4.9	High
6	Physical & Motor only	Yes	8.5	High
6	Cognitive & Learning only	No	4.4	High
6	Cognitive & Learning only	Yes	7.8	High
6	Social & Communication only	No	1.6	Intermediate
6	Social & Communication only	Yes	2.9	Intermediate
7	Multiple broad NDD domains	No	6	High
7	Multiple broad NDD domains	Yes	10.5	High
7	Physical & Motor only	No	4.8	High
7	Physical & Motor only	Yes	8.4	High
7	Cognitive & Learning only	No	4.3	High
7	Cognitive & Learning only	Yes	7.6	High

7	Social & Communication only	No	1.6	Intermediate
7	Social & Communication only	Yes	2.9	Intermediate
8	Multiple broad NDD domains	No	5.9	High
8	Multiple broad NDD domains	Yes	10.3	High
8	Physical & Motor only	No	4.7	High
8	Physical & Motor only	Yes	8.2	High
8	Cognitive & Learning only	No	4.2	High
8	Cognitive & Learning only	Yes	7.5	High
8	Social & Communication only	No	1.6	Intermediate
8	Social & Communication only	Yes	2.8	Intermediate
9	Multiple broad NDD domains	No	5.8	High
9	Multiple broad NDD domains	Yes	10.1	High
9	Physical & Motor only	No	4.6	High
9	Physical & Motor only	Yes	8	High
9	Cognitive & Learning only	No	4.2	High
9	Cognitive & Learning only	Yes	7.3	High
9	Social & Communication only	No	1.5	Intermediate
9	Social & Communication only	Yes	2.7	Intermediate
10	Multiple broad NDD domains	No	5.7	High
10	Multiple broad NDD domains	Yes	9.9	High
10	Physical & Motor only	No	4.5	High
10	Physical & Motor only	Yes	7.9	High
10	Cognitive & Learning only	No	4.1	High
10	Cognitive & Learning only	Yes	7.2	High
10	Social & Communication only	No	1.5	Intermediate
10	Social & Communication only	Yes	2.7	Intermediate
11	Multiple broad NDD domains	No	5.6	High
11	Multiple broad NDD domains	Yes	9.7	High
11	Physical & Motor only	No	4.4	High
11	Physical & Motor only	Yes	7.7	High
11	Cognitive & Learning only	No	4	High
11	Cognitive & Learning only	Yes	7	High
11	Social & Communication only	No	1.5	Intermediate

11	Social & Communication only	Yes	2.6	Intermediate
12	Multiple broad NDD domains	No	5.5	High
12	Multiple broad NDD domains	Yes	9.6	High
12	Physical & Motor only	No	4.3	High
12	Physical & Motor only	Yes	7.6	High
12	Cognitive & Learning only	No	3.9	Intermediate
12	Cognitive & Learning only	Yes	6.9	High
12	Social & Communication only	No	1.4	Intermediate
12	Social & Communication only	Yes	2.6	Intermediate
13	Multiple broad NDD domains	No	5.4	High
13	Multiple broad NDD domains	Yes	9.4	High
13	Physical & Motor only	No	4.2	High
13	Physical & Motor only	Yes	7.4	High
13	Cognitive & Learning only	No	3.8	Intermediate
13	Cognitive & Learning only	Yes	6.8	High
13	Social & Communication only	No	1.4	Intermediate
13	Social & Communication only	Yes	2.5	Intermediate
14	Multiple broad NDD domains	No	5.2	High
14	Multiple broad NDD domains	Yes	9.2	High
14	Physical & Motor only	No	4.1	High
14	Physical & Motor only	Yes	7.3	High
14	Cognitive & Learning only	No	3.8	Intermediate
14	Cognitive & Learning only	Yes	6.6	High
14	Social & Communication only	No	1.4	Intermediate
14	Social & Communication only	Yes	2.5	Intermediate
15	Multiple broad NDD domains	No	5.1	High
15	Multiple broad NDD domains	Yes	9	High
15	Physical & Motor only	No	4.1	High
15	Physical & Motor only	Yes	7.1	High
15	Cognitive & Learning only	No	3.7	Intermediate
15	Cognitive & Learning only	Yes	6.5	High
15	Social & Communication only	No	1.4	Intermediate
15	Social & Communication only	Yes	2.4	Intermediate

16	Multiple broad NDD domains	No	5	High
16	Multiple broad NDD domains	Yes	8.8	High
16	Physical & Motor only	No	4	High
16	Physical & Motor only	Yes	7	High
16	Cognitive & Learning only	No	3.6	Intermediate
16	Cognitive & Learning only	Yes	6.4	High
16	Social & Communication only	No	1.3	Intermediate
16	Social & Communication only	Yes	2.4	Intermediate
17	Multiple broad NDD domains	No	4.9	High
17	Multiple broad NDD domains	Yes	8.7	High
17	Physical & Motor only	No	3.9	Intermediate
17	Physical & Motor only	Yes	6.8	High
17	Cognitive & Learning only	No	3.5	Intermediate
17	Cognitive & Learning only	Yes	6.2	High
17	Social & Communication only	No	1.3	Low
17	Social & Communication only	Yes	2.3	Intermediate
18	Multiple broad NDD domains	No	4.8	High
18	Multiple broad NDD domains	Yes	8.5	High
18	Physical & Motor only	No	3.8	Intermediate
18	Physical & Motor only	Yes	6.7	High
18	Cognitive & Learning only	No	3.5	Intermediate
18	Cognitive & Learning only	Yes	6.1	High
18	Social & Communication only	No	1.3	Low
18	Social & Communication only	Yes	2.3	Intermediate
19	Multiple broad NDD domains	No	4.7	High
19	Multiple broad NDD domains	Yes	8.3	High
19	Physical & Motor only	No	3.7	Intermediate
19	Physical & Motor only	Yes	6.6	High
19	Cognitive & Learning only	No	3.4	Intermediate
19	Cognitive & Learning only	Yes	6	High
19	Social & Communication only	No	1.3	Low
19	Social & Communication only	Yes	2.2	Intermediate
20	Multiple broad NDD domains	No	4.7	High

20	Multiple broad NDD domains	Yes	8.2	High
20	Physical & Motor only	No	3.7	Intermediate
20	Physical & Motor only	Yes	6.4	High
20	Cognitive & Learning only	No	3.3	Intermediate
20	Cognitive & Learning only	Yes	5.9	High
20	Social & Communication only	No	1.2	Low
20	Social & Communication only	Yes	2.2	Intermediate
21	Multiple broad NDD domains	No	4.6	High
21	Multiple broad NDD domains	Yes	8	High
21	Physical & Motor only	No	3.6	Intermediate
21	Physical & Motor only	Yes	6.3	High
21	Cognitive & Learning only	No	3.3	Intermediate
21	Cognitive & Learning only	Yes	5.8	High
21	Social & Communication only	No	1.2	Low
21	Social & Communication only	Yes	2.1	Intermediate
22	Multiple broad NDD domains	No	4.5	High
22	Multiple broad NDD domains	Yes	7.8	High
22	Physical & Motor only	No	3.5	Intermediate
22	Physical & Motor only	Yes	6.2	High
22	Cognitive & Learning only	No	3.2	Intermediate
22	Cognitive & Learning only	Yes	5.6	High
22	Social & Communication only	No	1.2	Low
22	Social & Communication only	Yes	2.1	Intermediate
23	Multiple broad NDD domains	No	4.4	High
23	Multiple broad NDD domains	Yes	7.7	High
23	Physical & Motor only	No	3.4	Intermediate
23	Physical & Motor only	Yes	6.1	High
23	Cognitive & Learning only	No	3.1	Intermediate
23	Cognitive & Learning only	Yes	5.5	High
23	Social & Communication only	No	1.2	Low
23	Social & Communication only	Yes	2.1	Intermediate
24	Multiple broad NDD domains	No	4.3	High
24	Multiple broad NDD domains	Yes	7.5	High

24	Physical & Motor only	No	3.4	Intermediate
24	Physical & Motor only	Yes	5.9	High
24	Cognitive & Learning only	No	3.1	Intermediate
24	Cognitive & Learning only	Yes	5.4	High
24	Social & Communication only	No	1.1	Low
24	Social & Communication only	Yes	2	Intermediate
25	Multiple broad NDD domains	No	4.2	High
25	Multiple broad NDD domains	Yes	7.4	High
25	Physical & Motor only	No	3.3	Intermediate
25	Physical & Motor only	Yes	5.8	High
25	Cognitive & Learning only	No	3	Intermediate
25	Cognitive & Learning only	Yes	5.3	High
25	Social & Communication only	No	1.1	Low
25	Social & Communication only	Yes	2	Intermediate
26	Multiple broad NDD domains	No	4.1	High
26	Multiple broad NDD domains	Yes	7.2	High
26	Physical & Motor only	No	3.2	Intermediate
26	Physical & Motor only	Yes	5.7	High
26	Cognitive & Learning only	No	2.9	Intermediate
26	Cognitive & Learning only	Yes	5.2	High
26	Social & Communication only	No	1.1	Low
26	Social & Communication only	Yes	1.9	Intermediate
27	Multiple broad NDD domains	No	4	High
27	Multiple broad NDD domains	Yes	7.1	High
27	Physical & Motor only	No	3.2	Intermediate
27	Physical & Motor only	Yes	5.6	High
27	Cognitive & Learning only	No	2.9	Intermediate
27	Cognitive & Learning only	Yes	5.1	High
27	Social & Communication only	No	1.1	Low
27	Social & Communication only	Yes	1.9	Intermediate
28	Multiple broad NDD domains	No	4	High
28	Multiple broad NDD domains	Yes	7	High
28	Physical & Motor only	No	3.1	Intermediate

28	Physical & Motor only	Yes	5.5	High
28	Cognitive & Learning only	No	2.8	Intermediate
28	Cognitive & Learning only	Yes	5	High
28	Social & Communication only	No	1	Low
28	Social & Communication only	Yes	1.9	Intermediate
29	Multiple broad NDD domains	No	3.9	Intermediate
29	Multiple broad NDD domains	Yes	6.8	High
29	Physical & Motor only	No	3	Intermediate
29	Physical & Motor only	Yes	5.4	High
29	Cognitive & Learning only	No	2.8	Intermediate
29	Cognitive & Learning only	Yes	4.9	High
29	Social & Communication only	No	1	Low
29	Social & Communication only	Yes	1.8	Intermediate
30	Multiple broad NDD domains	No	3.8	Intermediate
30	Multiple broad NDD domains	Yes	6.7	High
30	Physical & Motor only	No	3	Intermediate
30	Physical & Motor only	Yes	5.3	High
30	Cognitive & Learning only	No	2.7	Intermediate
30	Cognitive & Learning only	Yes	4.8	High
30	Social & Communication only	No	1	Low
30	Social & Communication only	Yes	1.8	Intermediate
31	Multiple broad NDD domains	No	3.7	Intermediate
31	Multiple broad NDD domains	Yes	6.5	High
31	Physical & Motor only	No	2.9	Intermediate
31	Physical & Motor only	Yes	5.2	High
31	Cognitive & Learning only	No	2.7	Intermediate
31	Cognitive & Learning only	Yes	4.7	High
31	Social & Communication only	No	1	Low
31	Social & Communication only	Yes	1.7	Intermediate
32	Multiple broad NDD domains	No	3.6	Intermediate
32	Multiple broad NDD domains	Yes	6.4	High
32	Physical & Motor only	No	2.9	Intermediate
32	Physical & Motor only	Yes	5.1	High

32	Cognitive & Learning only	No	2.6	Intermediate
32	Cognitive & Learning only	Yes	4.6	High
32	Social & Communication only	No	1	Low
32	Social & Communication only	Yes	1.7	Intermediate
33	Multiple broad NDD domains	No	3.6	Intermediate
33	Multiple broad NDD domains	Yes	6.3	High
33	Physical & Motor only	No	2.8	Intermediate
33	Physical & Motor only	Yes	5	High
33	Cognitive & Learning only	No	2.6	Intermediate
33	Cognitive & Learning only	Yes	4.5	High
33	Social & Communication only	No	0.9	Low
33	Social & Communication only	Yes	1.7	Intermediate
34	Multiple broad NDD domains	No	3.5	Intermediate
34	Multiple broad NDD domains	Yes	6.2	High
34	Physical & Motor only	No	2.8	Intermediate
34	Physical & Motor only	Yes	4.9	High
34	Cognitive & Learning only	No	2.5	Intermediate
34	Cognitive & Learning only	Yes	4.4	High
34	Social & Communication only	No	0.9	Low
34	Social & Communication only	Yes	1.6	Intermediate
35	Multiple broad NDD domains	No	3.4	Intermediate
35	Multiple broad NDD domains	Yes	6	High
35	Physical & Motor only	No	2.7	Intermediate
35	Physical & Motor only	Yes	4.8	High
35	Cognitive & Learning only	No	2.4	Intermediate
35	Cognitive & Learning only	Yes	4.3	High
35	Social & Communication only	No	0.9	Low
35	Social & Communication only	Yes	1.6	Intermediate
36	Multiple broad NDD domains	No	3.4	Intermediate
36	Multiple broad NDD domains	Yes	5.9	High
36	Physical & Motor only	No	2.6	Intermediate
36	Physical & Motor only	Yes	4.7	High
36	Cognitive & Learning only	No	2.4	Intermediate

36	Cognitive & Learning only	Yes	4.2	High
36	Social & Communication only	No	0.9	Low
36	Social & Communication only	Yes	1.6	Intermediate
37	Multiple broad NDD domains	No	3.3	Intermediate
37	Multiple broad NDD domains	Yes	5.8	High
37	Physical & Motor only	No	2.6	Intermediate
37	Physical & Motor only	Yes	4.6	High
37	Cognitive & Learning only	No	2.4	Intermediate
37	Cognitive & Learning only	Yes	4.2	High
37	Social & Communication only	No	0.9	Low
37	Social & Communication only	Yes	1.5	Intermediate
38	Multiple broad NDD domains	No	3.2	Intermediate
38	Multiple broad NDD domains	Yes	5.7	High
38	Physical & Motor only	No	2.5	Intermediate
38	Physical & Motor only	Yes	4.5	High
38	Cognitive & Learning only	No	2.3	Intermediate
38	Cognitive & Learning only	Yes	4.1	High
38	Social & Communication only	No	0.8	Low
38	Social & Communication only	Yes	1.5	Intermediate
39	Multiple broad NDD domains	No	3.2	Intermediate
39	Multiple broad NDD domains	Yes	5.6	High
39	Physical & Motor only	No	2.5	Intermediate
39	Physical & Motor only	Yes	4.4	High
39	Cognitive & Learning only	No	2.3	Intermediate
39	Cognitive & Learning only	Yes	4	High
39	Social & Communication only	No	0.8	Low
39	Social & Communication only	Yes	1.5	Intermediate
40	Multiple broad NDD domains	No	3.1	Intermediate
40	Multiple broad NDD domains	Yes	5.5	High
40	Physical & Motor only	No	2.4	Intermediate
40	Physical & Motor only	Yes	4.3	High
40	Cognitive & Learning only	No	2.2	Intermediate
40	Cognitive & Learning only	Yes	3.9	Intermediate

40	Social & Communication only	No	0.8	Low
40	Social & Communication only	Yes	1.4	Intermediate
41	Multiple broad NDD domains	No	3	Intermediate
41	Multiple broad NDD domains	Yes	5.4	High
41	Physical & Motor only	No	2.4	Intermediate
41	Physical & Motor only	Yes	4.2	High
41	Cognitive & Learning only	No	2.2	Intermediate
41	Cognitive & Learning only	Yes	3.8	Intermediate
41	Social & Communication only	No	0.8	Low
41	Social & Communication only	Yes	1.4	Intermediate
42	Multiple broad NDD domains	No	3	Intermediate
42	Multiple broad NDD domains	Yes	5.2	High
42	Physical & Motor only	No	2.3	Intermediate
42	Physical & Motor only	Yes	4.1	High
42	Cognitive & Learning only	No	2.1	Intermediate
42	Cognitive & Learning only	Yes	3.8	Intermediate
42	Social & Communication only	No	0.8	Low
42	Social & Communication only	Yes	1.4	Intermediate
43	Multiple broad NDD domains	No	2.9	Intermediate
43	Multiple broad NDD domains	Yes	5.1	High
43	Physical & Motor only	No	2.3	Intermediate
43	Physical & Motor only	Yes	4.1	High
43	Cognitive & Learning only	No	2.1	Intermediate
43	Cognitive & Learning only	Yes	3.7	Intermediate
43	Social & Communication only	No	0.8	Low
43	Social & Communication only	Yes	1.4	Intermediate
44	Multiple broad NDD domains	No	2.9	Intermediate
44	Multiple broad NDD domains	Yes	5	High
44	Physical & Motor only	No	2.2	Intermediate
44	Physical & Motor only	Yes	4	High
44	Cognitive & Learning only	No	2	Intermediate
44	Cognitive & Learning only	Yes	3.6	Intermediate
44	Social & Communication only	No	0.7	Low

44	Social & Communication only	Yes	1.3	Intermediate
45	Multiple broad NDD domains	No	2.8	Intermediate
45	Multiple broad NDD domains	Yes	4.9	High
45	Physical & Motor only	No	2.2	Intermediate
45	Physical & Motor only	Yes	3.9	Intermediate
45	Cognitive & Learning only	No	2	Intermediate
45	Cognitive & Learning only	Yes	3.5	Intermediate
45	Social & Communication only	No	0.7	Low
45	Social & Communication only	Yes	1.3	Low
46	Multiple broad NDD domains	No	2.7	Intermediate
46	Multiple broad NDD domains	Yes	4.8	High
46	Physical & Motor only	No	2.2	Intermediate
46	Physical & Motor only	Yes	3.8	Intermediate
46	Cognitive & Learning only	No	2	Intermediate
46	Cognitive & Learning only	Yes	3.5	Intermediate
46	Social & Communication only	No	0.7	Low
46	Social & Communication only	Yes	1.3	Low
47	Multiple broad NDD domains	No	2.7	Intermediate
47	Multiple broad NDD domains	Yes	4.7	High
47	Physical & Motor only	No	2.1	Intermediate
47	Physical & Motor only	Yes	3.7	Intermediate
47	Cognitive & Learning only	No	1.9	Intermediate
47	Cognitive & Learning only	Yes	3.4	Intermediate
47	Social & Communication only	No	0.7	Low
47	Social & Communication only	Yes	1.3	Low
48	Multiple broad NDD domains	No	2.6	Intermediate
48	Multiple broad NDD domains	Yes	4.6	High
48	Physical & Motor only	No	2.1	Intermediate
48	Physical & Motor only	Yes	3.7	Intermediate
48	Cognitive & Learning only	No	1.9	Intermediate
48	Cognitive & Learning only	Yes	3.3	Intermediate
48	Social & Communication only	No	0.7	Low
48	Social & Communication only	Yes	1.2	Low

49	Multiple broad NDD domains	No	2.6	Intermediate
49	Multiple broad NDD domains	Yes	4.6	High
49	Physical & Motor only	No	2	Intermediate
49	Physical & Motor only	Yes	3.6	Intermediate
49	Cognitive & Learning only	No	1.8	Intermediate
49	Cognitive & Learning only	Yes	3.3	Intermediate
49	Social & Communication only	No	0.7	Low
49	Social & Communication only	Yes	1.2	Low
50	Multiple broad NDD domains	No	2.5	Intermediate
50	Multiple broad NDD domains	Yes	4.5	High
50	Physical & Motor only	No	2	Intermediate
50	Physical & Motor only	Yes	3.5	Intermediate
50	Cognitive & Learning only	No	1.8	Intermediate
50	Cognitive & Learning only	Yes	3.2	Intermediate
50	Social & Communication only	No	0.7	Low
50	Social & Communication only	Yes	1.2	Low
51	Multiple broad NDD domains	No	2.5	Intermediate
51	Multiple broad NDD domains	Yes	4.4	High
51	Physical & Motor only	No	1.9	Intermediate
51	Physical & Motor only	Yes	3.4	Intermediate
51	Cognitive & Learning only	No	1.8	Intermediate
51	Cognitive & Learning only	Yes	3.1	Intermediate
51	Social & Communication only	No	0.6	Low
51	Social & Communication only	Yes	1.2	Low
52	Multiple broad NDD domains	No	2.4	Intermediate
52	Multiple broad NDD domains	Yes	4.3	High
52	Physical & Motor only	No	1.9	Intermediate
52	Physical & Motor only	Yes	3.4	Intermediate
52	Cognitive & Learning only	No	1.7	Intermediate
52	Cognitive & Learning only	Yes	3.1	Intermediate
52	Social & Communication only	No	0.6	Low
52	Social & Communication only	Yes	1.1	Low
53	Multiple broad NDD domains	No	2.4	Intermediate

53	Multiple broad NDD domains	Yes	4.2	High
53	Physical & Motor only	No	1.9	Intermediate
53	Physical & Motor only	Yes	3.3	Intermediate
53	Cognitive & Learning only	No	1.7	Intermediate
53	Cognitive & Learning only	Yes	3	Intermediate
53	Social & Communication only	No	0.6	Low
53	Social & Communication only	Yes	1.1	Low
54	Multiple broad NDD domains	No	2.3	Intermediate
54	Multiple broad NDD domains	Yes	4.1	High
54	Physical & Motor only	No	1.8	Intermediate
54	Physical & Motor only	Yes	3.2	Intermediate
54	Cognitive & Learning only	No	1.7	Intermediate
54	Cognitive & Learning only	Yes	2.9	Intermediate
54	Social & Communication only	No	0.6	Low
54	Social & Communication only	Yes	1.1	Low