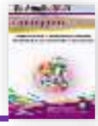

Predictive Models and Tools for Early Detection of Stunting in Children: A Systematic Review

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Abstract

Child stunting remains a critical public health challenge globally, with early detection essential for preventing irreversible developmental consequences. This review uniquely synthesizes predictive and measurement tools for early stunting detection across multiple low- and middle-income countries, addressing the gap in systematic evaluation of their diagnostic performance. Following PRISMA 2020 guidelines, we systematically searched PubMed, ProQuest, Emerald, and Springer databases for studies published between 2019-2024. We used the SPIDER method to define this study's inclusion, and eligible studies included those developing or validating predictive models and diagnostic tools for stunting detection in children aged 0-19 years. The articles included in this assessment use different methodologies conduct a critical appraisal to determine the quality of the articles using the instrument tool from Joana Briggs Institute (JBI). Thirteen studies met the inclusion criteria, identifying four primary tool categories clinical scoring systems, omposite anthropometric indices, diagnostic charts and machine learning models. The MEIRU chart demonstrated superior diagnostic accuracy (sensitivity 97.6%, specificity 96.3%, kappa 0.93) compared to traditional WHO methods. Clinical scores exhibited moderate performance with sensitivity ranging from 61.9% to 90.0%. Common predictors across models included maternal education, birth weight, child age, gender, and socioeconomic status. Predictive models and measurement tools are valuable for the early detection of stunting, enabling timely and targeted interventions to reduce its long-term impact on child health and development.

Keywords: Anthropometry, Diagnostic accuracy, Early detection, Prediction models, Risk factors

INTRODUCTION

Stunting is one of the major health issues drawing global concern because it affects children's growth and development. It occurs when poor nutrition slows a child's growth, often making them shorter than their peers (Simbolon et al., 2019; UNICEF et al., 2023; Yani et al., 2023). Beyond height, stunting has serious long-term consequences (Aychiluhm et al., 2021; Yani et al., 2023). It can lead to complications that impact not only the child's future but also the next generation if it isn't identified and prevented early.

Stunting remains one of the most pressing global health challenges, with the highest prevalence found in Southern Asia, affecting around 78.6 million children. In Africa, the number of stunted children rose slightly from 61.3 million in 2012 to 63.1 million in 2022 (UNICEF et al., 2023). In Indonesia, the prevalence in 2024 was 30.5%, showing a decrease from 34.6% in 2023 (WHO, 2025). Stunting is primarily linked to poor nutrition, but it is also shaped by a range of family, child, and environmental factors (Afework et al., 2021; Chapagain et al., 2023; Huriah & Nurjannah, 2020).

Family influences are especially critical during the first 1,000 days of life, when nutrition plays a decisive role. A mother's and family's knowledge about infant nutrition strongly affects outcomes (Bantie et al., 2021; Tamrat et al., 2024). Maternal education (Suratri et al., 2023) is another key factor. Children of mothers with lower education levels face a 1.6 times higher risk of stunting compared to those whose mothers are more educated.

Child-related factors also matter, including gender, medical history, age, birth weight, and milk consumption (Kebede et al., 2021; Mkungudza et al., 2024). Suratri et al., (2023) highlight that children aged 24–35 months, those with less educated mothers, and those living in rural areas are particularly vulnerable. Environmental conditions further contribute, such as access to clean water, which influences food hygiene and overall health (Bazie et al., 2021; Mengesha et al., 2021). Economic status, family size, and comorbid diseases are also frequently cited as contributing factors (Muche et al., 2021; Tamrat et al., 2024).

Many of the factors that contribute to stunting are already well understood. To assess its occurrence and underlying causes, researchers typically rely on anthropometric tools and questionnaires. Anthropometric indices help measure physical growth and body weight, including weight-for-age, height/length-for-age, weight-for-height/length, and BMI-for-age. These indicators are applied across different age groups, preschool children (under 5 years), school-aged children (5–11 years), and adolescents (12–18 years) (Marume et al., 2022). Each index is expressed as a z-score, calculated according to WHO standards.

Yisak et al., (2021) used anthropometric instruments to assess body mass index (BMI). Their measurements included a wooden length board, a vertical wooden height board with a sliding headpiece, and a tape measure for upper arm circumference. For children under two years old, body length was measured barefoot using a horizontal wooden board while the baby lay supine. In another study, Bazie et al., (2021) employed the SECA digital measuring instrument from Germany. Each child was examined under strict conditions—without shoes, wearing minimal clothing, with empty pockets, and no earrings. Measurements were taken twice, and the average weight or height was recorded under close supervision. Beyond anthropometry, Chanyarungrojn et al., (2023) used additional tools to detect stunting, including the MEIRU chart, WHO lookup tables, and WHO Growth Charts.

Identifying the risk factors for stunting is the first step toward designing effective interventions (Suratri et al., 2023). In 2025, Permatasari et al., 2025 developed and evaluated a stunting risk detection application based on nutrition and sanitation indicators for children under five. The tool demonstrated strong accuracy, allowing for rapid assessment and timely recommendations to prevent stunting. Similarly, Sk et al., (2021) examined nutritional status and stunting risk factors among preschool children aged 36–59 months in Malda, analyzing data across different disaggregate levels. Assessment systems play a crucial role in classifying stunting risk. By determining key variables, these systems can distinguish between high-risk and low-risk groups, enabling earlier identification and intervention. However, while many risk factors are well-documented, there remains a gap: a systematic synthesis of validated predictive models and tools for early stunting detection across diverse populations is still lacking.

This knowledge gap highlights the need for systematic investigation to guide evidence-based screening strategies. Although risk factors for stunting are well-documented, there is still no comprehensive synthesis of validated predictive models and diagnostic tools for early detection across diverse low- and middle-income country populations. Such a synthesis is crucial for public health programming, as it would help resource-constrained health systems prioritize tools that balance diagnostic accuracy, implementation feasibility, and contextual relevance.

Accordingly, this systematic review set out to identify and describe predictive models and measurement tools developed for early stunting detection in children. It aimed to evaluate the diagnostic performance of these instruments through systematic appraisal of sensitivity and specificity, assess methodological quality and risk of bias across included studies, and determine implementation readiness and external validation needs. Particular emphasis was placed on applications in low- and middle-income country settings, with a focus on the Indonesian context.

METHODS

Protocol Registration and Reporting Guidelines

This study employs a systematic review approach, guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). No meta-analysis was conducted. The review protocol was not prospectively registered in PROSPERO, and this limitation is acknowledged and discussed in the limitations section. The purpose of this systematic review is to identify and synthesize all relevant studies that examine prediction tools used to determine the prevalence and associated factors of stunting in children.

Eligibility Criteria

This study applied the SPIDER method to define inclusion and exclusion criteria. The research sample consisted of infants, toddlers, children, and adolescents. Inclusion criteria covered studies reporting stunting prevalence, risk factors, and measurement tools. Eligible tools included: (1) clinical scoring systems that incorporate weighted risk factors; (2) composite anthropometric indices combining multiple nutritional indicators; (3) visual assessment charts or lookup tables; and (4) statistical or machine learning prediction algorithms.

Studies that used the WHO Child Growth Standards specifically height/length-for-age z-scores below−2 SD as the diagnostic criterion for stunting were included. In addition, only studies reporting at least one diagnostic performance metric (such as sensitivity, specificity, area under the receiver operating characteristic curve [AUC], predictive values, likelihood ratios, calibration statistics, or agreement measures) were considered eligible. This review included cross-sectional studies, case-control designs, cohort studies involving prediction model development or validation, and diagnostic accuracy studies. In contrast, systematic reviews, meta-analyses, intervention trials, qualitative studies, case reports, editorials, and commentaries were excluded. Only studies published in English between January 2019 and November 2024 were considered, to ensure the evidence reflects recent methodological advances in predictive modeling. Studies that reported stunting prevalence or risk factor associations without developing or validating prediction tools were classified as supporting evidence and excluded from the primary synthesis.

Information Sources and Search Strategy

Systematic literature searches were conducted across four electronic databases: PubMed, ProQuest, Emerald, and Springer Link. The initial search took place on November 15, 2024, with no subsequent updates. Search terms included Toddlers OR Children AND Predictive Model and Tools OR Prediction AND Stunting OR Growth Disorder. The search was refined using the predefined inclusion criteria, focusing on studies published within the last five years (2019–2024).

Study Selection Process

References identified through database searches were imported into the Mendeley application. Deduplication was performed using Mendeley's automatic duplicate detection algorithm, supplemented by manual verification of ambiguous cases based on title, author list, and publication year. Two independent reviewers (initials masked for peer review) screened titles and abstracts against predefined eligibility criteria using a piloted standardized screening form. Full-text articles deemed potentially eligible were then retrieved and independently assessed by both reviewers.

Given the methodological diversity of the included studies, a critical appraisal was conducted using the Joanna Briggs Institute (JBI) Critical Appraisal Tool to evaluate study quality. Thirteen articles were rated as high quality and were identified as relevant to the review's focus on stunting prediction tools. Data synthesis was organized into tables categorizing prevalence of stunting, risk factors, and measurement tools. Studies that did not meet the inclusion criteria were excluded, with reasons systematically documented. The overall study selection process is illustrated in the PRISMA 2020 flow diagram (Figure 1).

Data Extraction

Data extraction was conducted independently by two reviewers. The following variables were collected:

1) Study Characteristics: first author, publication year, country/region, study design, setting, sample size, participant age range, and stunting prevalence.
2) Prediction Model/Tool Characteristics: tool name/type, intended use (development or validation), predictor variables included, method of predictor selection (e.g., univariable screening, multivariable analysis, machine learning algorithms), and validation approach (apparent validation, internal validation via bootstrapping or cross-validation, or external validation).
3) Reference Standard: details of anthropometric measurements, equipment specifications, measurer training procedures, and diagnostic criteria for stunting.
4) Performance Metrics: discrimination measures (AUC/c-statistic, sensitivity, specificity) with 95% confidence intervals where available; calibration metrics (calibration slope, intercept, Hosmer–Lemeshow statistic); classification accuracy (overall agreement, kappa coefficient); and predictive values.

Data Synthesis

Because of substantial heterogeneity in prediction tool types, target populations, predictor variables, outcome definitions, and performance metrics, a meta-analysis was not feasible. Instead, evidence was synthesized using a framework approach, with findings organized by: (1) tool typology (clinical scoring systems, composite indices, visual charts, machine learning models); (2) target age groups; (3) geographic settings; and (4) validation status. Within each category, studies were compared in terms of predictor variables used, discrimination performance (AUC, sensitivity, specificity), calibration adequacy, and implementation feasibility.

The synthesis emphasized identifying patterns across studies, explaining heterogeneity in performance metrics through methodological or contextual differences, and assessing implementation readiness for primary healthcare settings in low- and middle-income countries. Results are presented in summary tables, supported by narrative interpretation that highlights key findings, methodological strengths and limitations, and knowledge gaps. Vote counting based on direction of effect was not employed, and statistical synthesis methods (e.g., random-effects meta-analysis) were deemed inappropriate given the qualitative nature of the evidence integration.

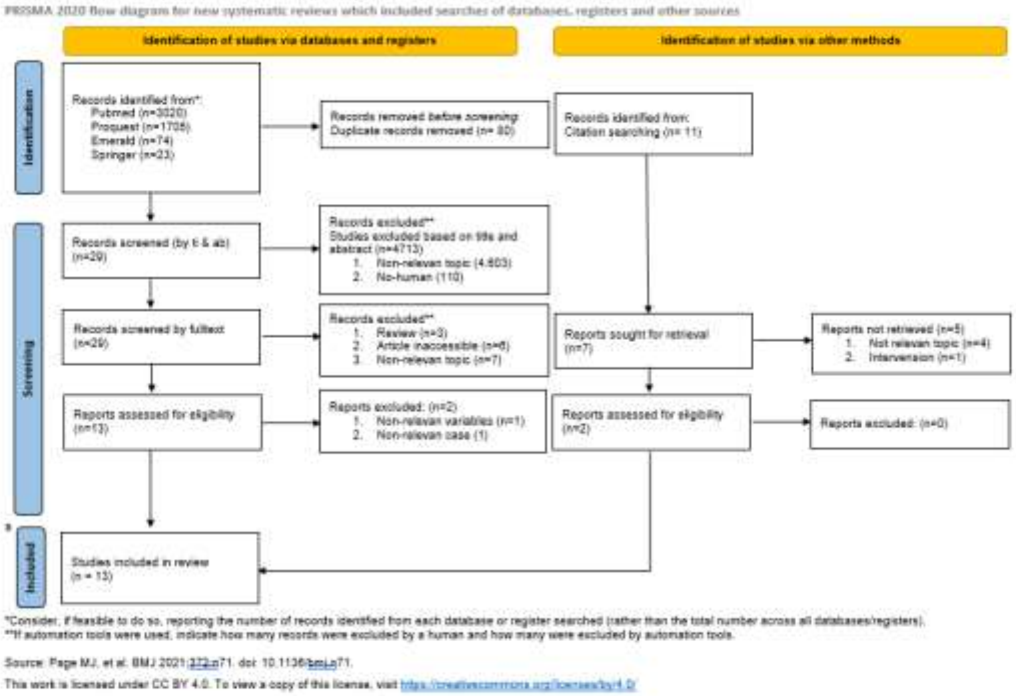

Figure 1. PRISMA 2020 flow diagram

RESULT

Study Selection and characteristic

This systematic review adhered to PRISMA 2020 guidelines to ensure transparent reporting. Database searches conducted on November 15, 2024, identified 4,822 records using the selected keywords: PubMed (n = 1,245), ProQuest (n = 1,876), Emerald (n = 892), and Springer Link (n = 809). After removing 80 duplicates, 4,742 unique records were screened by title and abstract. Of these, 4,713 were excluded for reasons including irrelevant topics (n = 3,821), non-human studies (n = 456), inappropriate study designs (n = 298), and other reasons (n = 138). Twenty-nine full-text articles were assessed for eligibility, with 16 excluded: 8 were review articles, 5 lacked full-text availability, and 3 examined irrelevant variables. Ultimately, 13 studies met all inclusion criteria and were synthesized narratively.

Table 1. Summary of Review Articles

No	Authors/ Year	Design	Setting/Country	Sample Size & Age	Key Predictive Tool	Main Findings
1	(Simbolon, 2019)	Cross-Sectional	The study setting is based on the IFLS 2007 research location, Indonesia	3596 toddlers 1-5 years old	Scoring system with eight weighted predictors: birth weight, number of children, gender, birth age, maternal height, immunization status, maternal education, family residence, Fe tablet use.	a. Prevalence was higher in 12-23 months and 24-35 months of age. b. The scoring obtained cut-off point >13.5 as a detection of stunting risk with a sensitivity of 61.9%, spesificity of 60.9%, value of area under the curve 65.5.
2	(Masrul & Usman, 2020)	Case-control	West Sumatera Province, Indonesian	40 children (case group stunting) and 40 children (non-stunting)	Scoring system with five predictors: maternal education, birth weight, exclusive breastfeeding, child appetite, parenting style	a. The cut-off point in grouping high risk of stunting and low risk of stunting is based on a total score of ≥ 4 (high risk of stunting) and < 4 (low risk of stunting) b. The accurasy of scoring system in prediction of stunting risk among children with a sensitivity of 70.0% and specificity of 90.0%.
3	(Muche et al., 2021)	Cross-Sectional	Community Based/Ethiopia	8117 Children Age 6-59 months	Composite Index of Anthropometric Failure (CIAF) and Bayesian multilevel analysis	a. Prevalence of stunting (41.20%), Moderate stunting (22.41%), Severe stunting (18.79%) b. Predictors of stunting: Sex of child, Child age, Type of birth, Anemia status of the child, History of fever in the last 2 weeks, Education level of mother, Maternal BMI, Maternal height, Birth interval, Family wealth.
4	(Yisak et al., 2021)	Cross-Sectional	Elementary school of South Gondar Zone/Ethiopia	300 children Aged 6-12 years	Standard anthropometry (Weights were taken using a	a. The prevalence of stunting, wasting, and underweight was 11%, 6.3% and

No	Authors/ Year	Design	Setting/Country	Sample Size & Age	Key Predictive Tool	Main Findings
					digital portable weighing calibrated SECA the height was measured by using a length board to the nears 0.1 cm in Frankfurt position).	11.4%, respectively. b. Factors associated with stunting: milk comsumption habit, how often you use soap during hand washing and Occasionally
5	(Mengesha et al., 2021)	Cross-Sectional	A community-based in Wonago district, Gedeo zone, Southern Ethiopia	660 Children Children under five years of age	Standard anthropometry and structured questionnaire	a. Prevalence of stunting among children under five years of age was 37.7% b. Predictors of stunting Family size less than five, Age less than 11 months, Rich wealth status, Drinking water like river water, Presence of two or more under five children in the household, Undiversified diet, Household food insecurity
6	(Bazie et al., 2021)	Cross-Sectional	A school-based Kutaber district, Northeast Ethiopia	341 Children primary school children Living at least for 6 months prior to the study in the district	Standard anthropometry (SECA digital measuring instrument)	a. Prevalence of stunting was found to be 14.1% b. Predictors of stunting: family size, washing hands less frequently before eating, Intestinal parasitic infection.
7	(Kebede et al., 2021)	Cross-Sectional	A school-based in Finote Selam Town, Northwest Ethiopia	Adolescents Aged 10-19	Standard anthropometry and structured questionnaire	a. Prevalence Stunting (21.8%), Thinness (16.9%) b. Factors Associated with stunting: Sex, Place of residence, Family monthly income, Dietary diversity
8	(Chapagain et al., 2023)	Cross-Sectional	Kanti Children's Hospital (KCH) in Nepal.	Children and adolescents aged 0–15 years visiting	Standard anthropometry (WHO standards) and sociodemograp	a. The prevalence: Stunting (25.9%), Wasting (17.3% and 24.0%) b. Predictors of nutritional status:

No	Authors/ Year	Design	Setting/Country	Sample Size & Age	Key Predictive Tool	Main Findings
				either the inpatient or outpatient	hic questionnaire	Food insecurity (wasting and stunting), Chronic medical conditions (wasting and stunting), Wealth Index (stunting), Ethnicity (wasting).
9	(Tamrat et al., 2024)	Cross-Sectional	Community Based, was conducted in the Rural Kersa district, Jimma zone, Southwest Ethiopia	Mother–child pairs aged 6–23 months who were residents in theselected kebeles for more than 6 months	Composite Index of Anthropometric Failure (CIAF)	a. Prevalence of undernutrition was 57.3% among children aged 6-23 months b. Factors aasociated: Child sex, Mother education, Birth order, Family Size, Comorbidity
10	(Mkungudza et al., 2024)	Cross-Sectional	Sab-Saharan Africa, specifically in Malawi	Children aged 0-59 months	Machine learning variable selection models (multiple algorithms compared)	Risk factors selected by all the variable selection models include household wealth index, age of the child, household size, type of birth (singleton/multiple births), and birth weight.
11	(Chanyarungrojn et al., 2023)	Cross-Sectional	A periurban area, with low and middle-income countries, Malawi, Afrika	244 participants Aged 8-19 years (children and adolescents)	Diagnostic accuracy comparison: (1) MEIRU chart, (2) WHO lookup tables, (3) WHO growth charts	a. Diagnostic accuracy of each test method around HAZ-2 (stunting) b. Sensitivity (MEIRU 97,6; WHO lookup table 98,8; WHO growth chart 69,7). Specificity (MEIRU 96,3; WHO lookup table 61,7; WHO growth chart 71,2) c. Agreement (MEIRU 98,7; WHO lookup table 99,0; WHO growth chart 81,1), Kappa (MEIRU 0,93; WHO lookup table 0,51; WHO growth chart 0,39)
12	(Budiailmiawan, Aryati, Kadir, & Yusuf, 2024)	Cross-Sectional	Public Health Centres in the Sukabumi Regency area, North Maluku, and Teruwai Village, Central West Nusa Tenggara Regency, West	210 children were confirmed to be stunted, aged 1 – 24 months	Standard anthropometry (Endo Anthropometric Kit) and biochemical/hematology tests	Two hundred and ten stunted children were identified with various anaemias and comorbidities

No	Authors/ Year	Design	Setting/Country	Sample Size & Age	Key Predictive Tool	Main Findings
			Nusa Tenggara, Indonesia			
13	(Mhamad et al., 2024)	Cross-Sectional	The urban areas in Halabja Governorate of the Kurdistan Region, Iraq	646 Children Aged 4 to 5 years old	Standard anthropometry and structured questionnaire	The prevalence of stunting was 7.9%

DISCUSSION

Summary of key findings

This systematic review identified and evaluated 13 studies that reported predictive models, diagnostic tools, or measurement instruments for stunting detection across diverse low- and middle-income country settings. Four main categories of tools emerged:

(1) Clinical scoring systems incorporating weighted risk factors,

(2) Composite anthropometric indices combining multiple nutritional indicators,

(3) Visual assessment charts designed for field application, and

(4) Machine learning–based variable selection models.

Reported diagnostic accuracy varied considerably across tool types, with sensitivity ranging from 61.9% to 98.8% and specificity from 60.9% to 96.3%. Visual assessment tools, particularly the MEIRU chart, demonstrated superior performance (sensitivity 97.6%, specificity 96.3%, kappa = 0.93) compared to clinical scoring systems (sensitivity 61.9–70.0%, specificity 60.9–90.0%) and traditional WHO growth charts (sensitivity 69.7%, specificity 71.2%, kappa = 0.39).

However, external validation remains limited. Only one study Chanyarungrojn et al., (2023) directly compared tools within the same population, restricting the ability to draw definitive conclusions about optimal instrument selection across diverse implementation contexts.

Comparative performance of predictive tools

The performance disparities observed across tool categories highlight fundamental trade-offs between diagnostic accuracy, implementation feasibility, and resource requirements. Visual assessment charts, such as the MEIRU wallchart, demonstrated the highest diagnostic accuracy (kappa = 0.93). Their design innovations, most notably the color-coded, age-stratified format, address common challenges in field assessments by eliminating the complex calculations required for z-score computation. This simplification reduces assessment time and minimizes training demands for community health workers with diverse educational backgrounds (Chanyarungrojn et al., 2023). By contrast, WHO growth charts showed the lowest agreement (kappa = 0.39) despite their widespread use. Their reliance on precise height-for-age plotting and z-score interpolation introduces interpretation complexity, requiring sustained training and quality assurance mechanisms that are often unavailable in resource-constrained settings. Clinical scoring systems occupy an intermediate position, offering enhanced predictive capacity but at the cost of reduced diagnostic accuracy.

Unlike anthropometric tools that detect stunting retrospectively, weighted scoring systems stratify future risk prospectively by integrating accessible demographic and socioeconomic predictors. Simbolon et al., (2019), developed an eight-variable model that achieved modest discrimination (AUC = 0.655), suggesting greater utility for population-level screening than for individual diagnosis. Its sensitivity–specificity balance (61.9%/60.9%) implies that approximately 40% of at-risk children would be misclassified, an acceptable trade-off for low-cost community screening when followed by confirmatory anthropometric assessment. Masrul et al.'s refined five-variable system demonstrated improved specificity (90.0%), thereby reducing false positives, though at the expense of lower sensitivity (70.0%). This trade-off may be more appropriate for targeted intervention allocation in resource-limited contexts, where false positives carry significant opportunity costs.

However, the limited reporting of discrimination metrics for composite indices such as the Composite Index of Anthropometric Failure (CIAF) and for machine learning models prevents definitive performance comparisons. While CIAF offers a nuanced classification of malnutrition by capturing concurrent wasting and stunting, its value for early detection remains uncertain without prospective validation demonstrating predictive superiority over simpler anthropometric indicators.

Measurement tools of stunting

Literature consistently highlights the use of anthropometry as the primary tool for assessing children's height and weight (Bazie et al., 2021; Budiailmiawan, Aryati, Kadir, Yusuf, et al., 2024; Chapagain et al., 2023; Kebede et al., 2021; Mengesha et al., 2021; Mhamad et al., 2024; Muche et al., 2021; Simbolon et al., 2019; Yisak et al., 2021). In addition to anthropometric measures, other tools have been employed, including the Composite Index of Anthropometric Failure (CIAF), the MEIRU Chart, WHO lookup tables, WHO Growth Charts, and biochemical or hematological tests to assess anemia in children. To capture demographic and contextual factors, such as gestational age, types of food provided, maternal education, household size, and socio-economic status, researchers also utilized questionnaires, both validated instruments and newly developed forms.

Anthropometric measurements are numerical assessments of body size and proportions that can be performed without invasive procedures. According to the World Health Organization (WHO) and the Centers for Disease Control and Prevention (CDC), these measurements provide valid indicators of nutritional status from childhood through adulthood (Casadei & Kiel, 2022). Common anthropometric indicators include height, weight, body mass index (BMI), and age-specific z-scores for BMI, weight, and height. Results often vary across studies, depending on the standards applied for assessment (Santra et al., 2023). In Indonesia, stunting research frequently relies on anthropometry as the primary measurement tool. For example, Aryanti et al. assessed the nutritional status of girls aged 13–15 years in Galesong District, South Sulawesi, and reported a stunting prevalence of 25.1% (Aryanti et al., 2024). Similarly, Budiailmiawan et al. (2024) conducted anthropometric measurements on stunted children and their parents, recording both weight and height. These measurements were performed by professional healthcare personnel Budiailmiawan, et al., (2024) using the Endo Anthropometric Kit 10 (Endo International plc, Dublin, Ireland).

Stunting research is also widely conducted in Ethiopia. In addition to conventional anthropometric indices, studies frequently apply the Composite Index of Anthropometric Failure (CIAF), which integrates three measures, weight-for-age (WAZ), height/length-for-age (LAZ), and weight-for-height/length (WHZ), to assess the nutritional status of children under five. CIAF provides a single, comprehensive estimate of overall malnutrition prevalence among children aged 6–23 months. Malnutrition classification within CIAF is divided into seven groups Tamrat et al., (2024): Group A (no failure), Group B (only thin), Group C (thin and underweight), Group D (short, thin, and underweight), Group E (short and underweight), Group F (only short), and Group Y (only underweight).

In Malawi, a study was conducted to evaluate the accuracy of stunting diagnostic tools, specifically the MEIRU wallchart, traditional lookup tables, and WHO growth charts. The MEIRU wallchart is a wall-mounted board with age-specific graphs (8–19 years), each color-coded to indicate stature categories: orange for very short stature (HAZ -4 to < -3), yellow for short stature (HAZ -3 to < -2), and green for normal stature (HAZ ≥ -2). Diagnostic accuracy estimates showed that the MEIRU wallchart achieved an overall agreement rate of 95.5%, compared to 59.4% for WHO lookup tables and 61.9% for WHO growth charts. Both participants and healthcare workers expressed a strong preference for the MEIRU chart (Chanyarungrojn et al., 2023) over traditional methods, citing its simplicity and ease of use.

CONCLUSION

This systematic review synthesized evidence from 13 studies evaluating predictive models and diagnostic tools for early stunting detection across low- and middle-income countries. The review successfully achieved its primary objectives: characterization of available tools, evaluation of diagnostic accuracy, assessment of methodological quality, and identification of implementation considerations for resource-constrained settings, with particular emphasis on Indonesia.

Multisite external validation studies assessing MEIRU chart performance across Indonesia's diverse geographic and ethnic contexts would be critical to determine implementation readiness for national screening programs. Public health systems in low- and middle-income countries should consider piloting MEIRU-style visual charts for community-based screening, while simultaneously investing in local validation and calibration studies to optimize tool performance for specific population contexts.

Clinical scoring systems provide complementary utility for prospective risk stratification, offering moderate discrimination with the advantage of identifying risk before anthropometric stunting becomes evident. However, several critical implementation gaps remain: the absence of external validation studies in Indonesian populations, limited prospective cohort designs to confirm true early detection capacity, and minimal reporting of calibration statistics essential for individual-level risk communication.

Future implementation science research should examine the real-world effectiveness, cost-effectiveness, and integration barriers of simplified screening tools when deployed through community health worker platforms. Such evidence would inform scalable delivery strategies and strengthen national stunting prevention programs.

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