

Original Article

From Paper to Precision: A Systematic Review on Digital Technologies for Improving the Quality of Childhood Growth Monitoring

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Abstract:

Background: Childhood growth monitoring is essential for detecting malnutrition and growth disorders. However, traditional paper-based methods are prone to errors, incompleteness, and fragmentation. Digital technologies have emerged as potential tools to enhance efficiency of growth monitoring. This systematic review aims to synthesize evidence on the benefits and challenges of implementing digital technologies for growth monitoring in children.

Methods: A systematic review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. A comprehensive literature search was conducted across multiple databases. Eligible studies evaluated digital interventions such as mobile health applications with automated anthropometric calculations, computer-based growth monitoring integrated into the electronic health record, and chatbot-based reporting systems. Data were extracted on study design, population, technology features, and outcomes related to data and implementation.

Result: Seven studies were analyzed, representing over 50,000 child growth assessments and involving approximately 400 frontline health workers. Digital technologies improved the completeness, accuracy, and timeliness of data collection. Automation reduced human error, supporting more consistent interpretation of nutritional status, earlier detection and reporting of inadequate growth, along with improved nutritional outcomes. These technologies were highly accepted by frontline health workers for their ability to simplify complex tasks. However, most challenges arose from constraints in digital infrastructure and uneven technology implementation across healthcare facilities.

Conclusion: Digital technologies can transform growth monitoring from a manual, error-prone process into a precise and scalable system for early detection of malnutrition. Addressing challenges is essential for successful implementation and scale-up in health systems.

Keywords: anthropometry, child growth, health information systems, mobile health, pediatric growth assessment

Introduction

Optimal growth monitoring in childhood is a cornerstone of pediatric nutrition and essential for the early detection of malnutrition and weight faltering.¹ In 2024, an estimated 150.2 million (23.2%) children under five globally were stunted and 42.8 million were wasted; in Indonesia, the national stunting prevalence remained high at 19.8%.^{2,3} Accurate anthropometric assessment enables timely nutritional interventions and prevents long-term adverse outcomes, including impaired cognitive development, increased morbidity, and mortality.¹

However, child growth extends beyond nutritional status alone and reflects a complex interplay of biological and environmental factors, including genetic potential, fetal health, endocrine regulation, chronic infection, physical activity, and broader influences such as socioeconomic conditions and family environment.^{4,7} The Infant–Childhood–Puberty model further illustrates this complexity by describing growth as overlapping phases, each governed by different biological mechanisms. Growth during infancy is primarily influenced by nutritional factors, whereas growth hormone becomes a major regulator during childhood, followed by the synergistic effects of sex steroids and growth hormone during puberty.^{5,8} These concepts highlight that growth is not solely determined by nutrition.

In practice, this complexity requires accurate and consistent growth monitoring across different healthcare settings. In Indonesia, growth monitoring is routinely conducted in primary health care and community-based settings. However, in routine field practice, despite the availability of comprehensive tools such as the Maternal and Child Health (KIA) Handbook, community health workers and healthcare providers frequently encounter difficulties in accurately plotting and interpreting growth charts, particularly in the context of high service workloads. Additionally, caregivers often fail to bring the KIA handbook during health visits, resulting in incomplete documentation and limited accessibility of longitudinal growth data. In parallel with these challenges, digital health technologies for child growth monitoring have rapidly evolved in recent years to support more accurate and continuous growth monitoring.⁹

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Although evidence on digital growth monitoring is expanding, existing studies differ widely in terms of platforms, settings, and reported outcomes. A comprehensive synthesis of the benefits and challenges relevant to routine child health care, including growth monitoring, is therefore needed. This systematic review aims to summarize the advantages and limitations of digital growth monitoring technologies in early childhood to inform their integration into pediatric growth monitoring programs.

Method

Data Sources and Search Strategy

This systematic review was conducted following PRISMA guidelines. A comprehensive search was independently performed by two reviewers using PubMed, Scopus, and Google Scholar databases, without restrictions on publication year up to 7 August 2025. The search strategy applied to these databases was as follows: (“Electronic Health Records”[MeSH] OR “EHR”[tiab] OR “Digital Record”[tiab] OR “eHealth”[tiab] OR “mHealth”[tiab]) AND (“Manual”[tiab] OR “Paper”[tiab] OR “Paper Based”[tiab]) AND (“Anthropometry”[MeSH] OR “Growth Measurement”[tiab] OR “Stunting”[tiab] OR “Failure to Thrive”[tiab] OR “Malnutrition”[tiab]) AND (“Infant”[MeSH] OR “Child”[tiab] OR “Toddler”[tiab]).

Inclusion and Exclusion Criteria

The inclusion criteria were as follows: (1) studies involving children undergoing growth monitoring, (2) studies evaluating digital growth monitoring technologies, and (3) studies reporting outcomes related to growth monitoring. Only original primary studies with full-text articles published in English or Indonesian were included.

The exclusion criteria were: (1) non-original publications, including reviews, editorials, protocols, and conference abstracts without primary data, (2) studies that evaluated nutrition-only interventions, and (3) studies involving digital tools not used for child growth monitoring or describing digital growth monitoring tools without empirical evaluation or outcome data.

Eligibility Criteria

All records were managed in Mendeley, with duplicates removed automatically and manually. Two reviewers independently screened titles, abstracts, and full texts, resolving any discrepancies by consensus.

Data Extraction

Data were extracted using a standardized form and organized in a spreadsheet. Extracted variables included author, publication year, country, study design, population and sample size, clinical setting, type of digital growth monitoring intervention, and comparator where applicable. Outcomes related to data quality (accuracy, completeness, timeliness), usability and acceptability, and operational challenges were also collected.

Quality

Methodological quality was assessed using the cohort version of the Newcastle–Ottawa Scale (NOS). NOS was selected because the primary comparison across studies was based on exposure to digital growth monitoring systems. The NOS is flexible and widely applied to non-randomized observational designs, including

implementation studies, allowing an appropriate assessment of selection, comparability, and outcome domains.

Result

The Study Selection

A total of 147 studies were identified. After removing 37 duplicates, 110 studies were screened, with 65 excluded. Forty full-text articles were assessed, and 33 were excluded for ineligible study types or interventions. Seven studies met the inclusion criteria and were included in the final review (**Figure 1**).

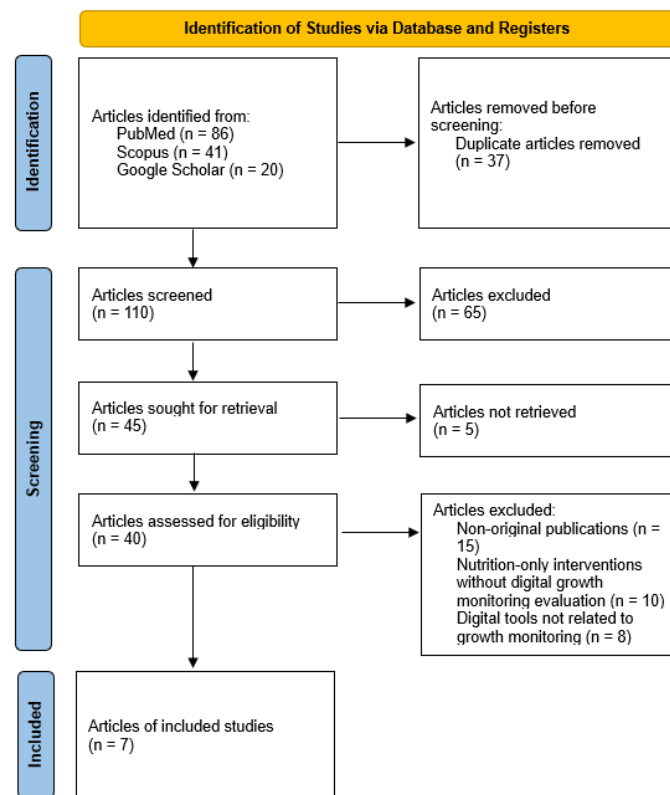


Figure 1. PRISMA flowchart

Quality Assessment

Risk of bias was assessed using NOS, and all included studies demonstrated good methodological quality, with scores ranging from 7 to 9 stars (**Table 1**).

Study Characteristics

The characteristics of the included studies are summarized in **Table 2**. The seven studies were conducted across diverse settings, including community-based, primary care, and hospital contexts in low-, middle-, and high-income countries. Sample sizes varied from small community implementations to large population-based cohorts.

Table 1. Newcastle-Ottawa Scale risk of bias for cross-sectional study

Study	Selection	Comparability	Outcome	Score NOS	Standard AHRQ
Aisyah et al., 2025 ⁹	★★★	★★	★★	7	Good Quality
Al Rahmad et al., 2024 ¹⁰	★★★	★★	★★	7	Good Quality
Nemerimana et al., 2021 ¹¹	★★★★	★★	★★	8	Good Quality
Kana et al., 2020 ¹²	★★★★	★★	★★	8	Good Quality
Dainty et al., 2018 ¹³	★★★	★★	★★★	8	Good Quality
Chanani et al., 2016 ¹⁴	★★★★	★★	★★★	9	Good Quality
Sankilampi et al., 2013 ¹⁵	★★★★	★★	★★★	9	Good Quality

Table 2. Characteristics of included studies

Author, Year	Country – Setting	Study Design	Sample Size	Intervention	Control	Result
Aisyah et al., 2025 ⁹	Indonesia Posyandu—community health posts	Prospective observational descriptive	282 cadres; 4,571 children	WhatsApp-based chatbot for growth data entry	No comparison group	<p>Completeness: WhatsApp-based reporting covered 76–90% of children measured at Posyandu, increased over time.</p> <p>Usability: Most users reported good usability, with the system perceived as easy to use, variables and data entry flow easy to understand, improved data reporting quality, and adequate user proficiency, including the ability to train peers.</p> <p>Challenge: Internet dependence, coverage varied across sites.</p>
Al Rahmad et al., 2024 ¹⁰	Indonesia Posyandu	Prospective before–and–after quasi-experimental	123 nutritionists	Mobile-based application for growth monitoring	Month 1 (baseline) measurement with the same digital application	Significant improvements ($p < 0.05$) were observed in completeness (59.8% → 93.8%), timeliness (62.1% → 86.6%), accuracy (73.9% → 94.1%), and usefulness (85.0% → 95.9%).

Author, Year	Country – Setting	Study Design	Sample Size	Intervention	Control	Result
Nemerimana et al., 2021 ¹¹	Rwanda Primary health care	Quasi-experimental	880 infants	Mobile-based application for growth monitoring	Manual growth monitoring is recorded on paper	<p>Challenge: Implementation required additional training and adaptation for consistent use.</p> <p>Completeness: Higher completeness of growth monitoring in intervention clinics compared with controls for length-for-age (82% vs 57%), weight-for-age (93% vs 67%), and weight-for-length (90% vs 59%) (all $p \leq 0.001$).</p> <p>Nutritional outcomes: Inadequate growth decreased in intervention clinics (59% → 26%) but increased in controls (52% → 56%) ($p < 0.001$); underweight prevalence decreased in intervention clinics (47% → 33%) and increased in controls (30% → 53%) ($p = 0.014$); stunting prevalence decreased in intervention clinics (59% → 44%) and increased in controls (48% → 58%) ($p = 0.041$).</p> <p>Challenge: Colour-coded displays without numeric z-scores caused misclassification in borderline cases, resulting in no significant improvement in accuracy.</p>
Kana et al., 2020 ¹²	Nigeria Tertiary teaching hospital	Prospective observational cohort	3,152 infant records	Computer-based growth monitoring	No comparison group	<p>Completeness: Overall data completeness was high (88.5%).</p> <p>Continuity: Follow-up attendance declined with age (91.5% at 6 weeks; 77.2% at 10 weeks; 57.8% at 14 weeks; 31.7% at 24 weeks; 22.3% at 36 weeks). Higher maternal education</p>

Author, Year	Country – Setting	Study Design	Sample Size	Intervention	Control	Result
						was associated with increased likelihood of follow-up (OR 1.33, 95% CI 1.06–1.51). Challenge: Power outages required backup electricity.
Dainty et al., 2018 ¹³	New Zealand Secondary health care district hospitals	Retrospective observational cohort	8,551 children	Computer-based growth monitoring integrated into the electronic health record	No comparison group	Completeness: Entries increased over time (1,962 to 8,407 records); weight was recorded in 98.2%, height in 82.6%, and BMI in 81.5%. Accuracy: Very low error rate (0.2%). Challenge: Lower uptake in inpatient settings (18.4%) compared with outpatient care (67%), reflecting limited routine inpatient growth measurement.
Chanani et al., 2016 ¹⁴	India Community-based home visit	Quasi-experimental crossover	14 frontline health workers; 1,120 child growth assessments	Mobile-based application for growth monitoring	Manual growth monitoring was recorded on paper	Accuracy: Error rate reduced from 5.5% (paper-based) to 0.7% (mobile-based) ($p < 0.001$); interrater reliability improved (Cohen's κ 0.79 \rightarrow 0.97); sensitivity increased (0.79 \rightarrow 1.00; $p = 0.014$); specificity increased (0.97 \rightarrow 1.00; $p = 0.002$). Challenge: Human errors arising from manual grade selection following automated calculation.
Sankilampi et al., 2013 ¹⁵	Finland Primary health care	Quasi-experimental with historical control	32,404 children	Computer-based automated growth monitoring integrated into the electronic health record	Standardized growth monitoring recorded in the electronic health record	Accuracy: Higher detection of new growth disorders in the intervention year (0.9 vs 0.1 per 1,000 children; $p < 0.001$); specialist referrals increased (72.7 to 209 annually; $p < 0.001$). Timeliness: Reduced diagnostic delay, with earlier

Author, Year	Country – Setting	Study Design	Sample Size	Intervention	Control	Result
						identification of abnormal height measurements (median delay 1.79 years). Challenge: Increased specialist workload and associated costs due to higher diagnostic yield.

BMI = Body mass index

Discussion

This systematic review summarizes the evidence on digital growth monitoring in childhood and its role in strengthening routine child health care. Digital tools including mobile applications, computer-based records, and WhatsApp-based chatbots were associated with improved growth data recording.⁹⁻¹⁵

In Indonesia, a WhatsApp-based chatbot evaluated by Aisyah et al. simplified data submission by leveraging a platform already familiar to community health cadres, facilitating consistent recording and improving completeness.⁹ In Rwanda, Nemerimana et al. demonstrated that mHealth tools with automated growth calculations supported clinical decision-making, which encouraged health workers to complete all required fields so that automated nutritional status interpretations could be generated.¹¹ Similar patterns were observed in higher-resource settings. In New Zealand, Dainty et al. reported a gradual increase in documentation completeness following the introduction of a digital growth monitoring system that was initially implemented without enforced adoption, allowing health workers to familiarize themselves with its ease of use before routine uptake.¹³

These findings align with broader evidence, a longitudinal German hospital study showing improved documentation completeness across clinical settings after electronic medical record implementation.¹⁶ In line with this, the United Nations Children's Fund and the World Health Organization emphasize the role of digital and mobile health technologies in improving the accuracy, timeliness, and completeness of routine pediatric health data, including growth monitoring.¹⁷

Beyond data completeness, several studies reported improved measurement accuracy through automated anthropometric calculations and standardized digital plotting. In higher-resource settings, Dainty et al. reported a low error rate in growth assessment using electronic growth charts, supporting more accurate interpretation in routine clinical practice.¹³ Sankilampi et al. also reported increased identification of growth disorders and higher referral rates following the implementation of electronic growth charts, highlighting the clinical relevance of improved data precision.¹⁵

Accurate assessment of child growth requires objective and standardized measures, such as z-scores, which express growth relative to a reference population in standard deviation units.¹⁸ In lower-resource and community-based settings, Chanani et al. demonstrated that mobile-based growth monitoring reduced recording errors during community home visits and minimized variability in performance among community health workers.¹⁴ However, in a low-resource setting, Nemerimana et al. found that nutritional status was initially determined using color-coded visual displays without numeric z-scores, leading to misclassification in borderline cases. Diagnostic accuracy improved only after numeric z-scores were incorporated, underscoring the importance of combining visual aids with precise numerical indicators in digital growth monitoring systems.¹¹ In addition to underdiagnosis, reliance on imprecise visual tools may also increase the risk of overdiagnosis, as color-coded classifications may not adequately capture individual growth patterns. This is particularly relevant in children older than two years, where normal growth channeling and genetic potential play an important role in growth interpretation, as most children follow a stable growth channel consistent with their genetic potential, termed canalization.¹⁹

Broader implementation evidence also indicates that mobile applications improve the accuracy of child growth monitoring by automating growth calculations, standardizing chart interpretation, and reducing manual plotting errors. These tools streamline data entry, reduce workload, and enhance the accuracy and reliability of routine growth assessment.²⁰

In addition to improvements in completeness and accuracy, several studies reported benefits related to timeliness. Al Rahmad et al. found that digital growth monitoring improved the timeliness of data recording, while Sankilampi et al. showed that electronic growth charts supported earlier detection of growth disorders by reducing diagnostic delays commonly seen with manual systems.^{10, 15} Real-time data availability supports faster and more informed clinical decision-making, particularly for time-sensitive conditions.^{20, 21} Timely access to growth data enables early detection of weight faltering and timely nutritional intervention during the first 1,000 days of life, which is critical for preventing stunting and supporting optimal growth and cognitive development.²²

Several studies suggested that ease of use and practicality of digital tools supported their implementation in routine growth monitoring. Digital tools were generally perceived as easier to use than manual growth charts, particularly when calculations and growth interpretation were automated. In community settings, the use of familiar platforms such as WhatsApp-based systems in Indonesia lowered barriers to adoption and supported more consistent data recording.⁹ In primary care settings, Al Rahmad et al. described digital growth monitoring as practical for routine anthropometric recording.¹⁰ In community-based settings, where frontline community volunteers with

limited formal health training play a central role in growth monitoring, user-friendly digital tools are essential to support accurate and consistent practice.²³

Direct nutritional outcomes were assessed by Nemerimana et al., showing that mHealth-supported growth monitoring in rural pediatric clinics was associated with significant reductions in inadequate growth, underweight, and stunting, whereas these indicators increased in control clinics using paper-based monitoring.¹¹ These findings suggest that digital growth monitoring, when combined with automated growth assessment and decision support, may strengthen the management of weight faltering and contribute to improved nutritional outcomes. Nonetheless, further studies are needed to confirm these effects across settings.

Kana et al. identified limitations in the continuity of growth monitoring despite the use of a digital anthropometric data system, with follow-up attendance declining as children aged. Maternal education was associated with better follow-up, indicating that caregiver-related factors influence continued engagement.¹² Although digital growth monitoring can address practical barriers such as caregivers forgetting to bring paper-based growth records, these findings highlight the need to complement digital systems with caregiver education and supportive strategies to sustain engagement. Qualitative evidence further indicates that caregivers who recognize the importance of growth monitoring and believe it benefits their children are more likely to attend sessions.²⁴

Digital records facilitate longitudinal growth assessment through continuous tracking of individual growth trajectories. Long-term evidence links sustained early childhood growth monitoring with improved health, cognitive, and educational outcomes, as well as continued engagement with health services.²⁵ Beyond individual outcomes, centralized and integrated digital records may strengthen system-level functions by improving data accessibility and supervisory oversight, enabling timely review of data completeness, trend identification, and feedback to health workers.²⁶

However, several challenges were identified across studies. Dependence on stable internet connectivity and recurrent power outages disrupted system functionality in some low-resource contexts, requiring additional infrastructure such as backup electricity solutions.^{9, 12} Implementation also required training and adaptation, as some health workers needed additional support to use digital systems correctly and consistently.^{10, 14} Adoption varied across service settings, reflecting gaps in routine measurement workflows.^{9, 13} In addition, higher diagnostic yield in some settings was accompanied by increased specialist workload and additional costs, highlighting the need for adequate system planning to support sustainable scale-up.¹⁵ Taken together, these findings emphasize that successful integration of digital growth monitoring tools requires not only technological readiness but also supportive infrastructure, adequate

workforce capacity, and alignment with existing health system workflows to ensure effective and sustainable use.²⁷

Conclusion

Digital growth monitoring shows clear potential to improve the completeness, accuracy, and timeliness of child growth data, thereby strengthening routine child health care. Automated calculations and standardized digital records reduce documentation errors and support more consistent growth assessment across settings. However, implementation challenges related to infrastructure, workforce capacity, workflow integration, and uneven adoption remain. Addressing these system-level constraints is essential to enable effective implementation and sustainable scale-up.

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Conflict of Interest

The authors declare no conflict of interest.

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