Review Article

Artificial Intelligence in Pediatric Healthcare - Part II: AI in Ambulatory Preventive Pediatrics

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ABSTRACT

Artificial intelligence (AI) is increasingly being incorporated into ambulatory and preventive pediatric practice through advances in machine learning, deep learning, computer vision, natural language processing, and mobile health technologies. The growing availability of electronic health records, wearable devices, telemedicine platforms, and digital health applications has created new opportunities for AI-assisted screening, risk prediction, preventive care, and outpatient clinical decision support. In pediatric healthcare, AI has emerging applications in developmental and autism screening, vision and hearing assessment, growth and nutrition monitoring, vaccination programs, infectious disease surveillance, symptom triage, prescribing support, remote patient monitoring, and parent-facing digital health tools. These technologies have the potential to improve early diagnosis, enhance preventive interventions, expand access to care, and support more personalized management of pediatric patients in outpatient settings. However, significant challenges remain, including limited pediatric-specific validation, algorithmic bias, data privacy concerns, regulatory uncertainties, workflow integration barriers, and the need to maintain trust among clinicians and caregivers. This narrative review summarizes current evidence regarding AI applications in ambulatory pediatrics, preventive pediatrics, and pediatric outpatient care, highlighting their clinical utility, limitations, implementation challenges, and future directions. This article is the second in a four-part series on AI in pediatrics; subsequent articles will discuss AI applications in pediatric inpatient and critical care settings, as well as the ethical, regulatory, and future implications of AI in child healthcare

Key words : Artificial Intelligence, Ambulatory Pediatrics, Preventive Pediatrics, Pediatric Outpatient Care, Clinical Decision Support, Telemedicine

The trajectory of artificial intelligence (AI) in healthcare has moved from rule-based expert systems of the 1970s and 1980s toward statistical machine learning (ML) and, more recently, deep learning (DL) and large language model (LLM) architectures capable of processing unstructured clinical text, images, and physiological signals [1]. Although early clinical AI research concentrated heavily on adult medicine, radiology, and inpatient critical care, the past decade has seen a marked expansion of AI research directed at pediatric populations, with published output in pediatric ML research said to have crossed several hundred original studies annually by the mid-2020s [2]. This growth reflects both the broader digitalization of pediatric services, including electronic health records (EHRs), mobile health applications, and remote monitoring platforms, and an increasing recognition that children represent a population with distinct physiological, developmental, and ethical considerations that cannot be addressed simply by extrapolating adult-derived algorithms [3].

Ambulatory and preventive pediatrics constitute the setting in which most child health contact occurs: well-child visits, immunization encounters, developmental surveillance, and outpatient department consultations for acute and chronic complaints collectively dwarf the volume of pediatric inpatient or intensive care encounters. Yet much of the existing AI-in-pediatrics literature has concentrated on neonatal intensive care, pediatric critical care, and diagnostic imaging, leaving a comparatively underexamined evidence base for the ambulatory, preventive, and outpatient department context [4].

The role of AI in primary and ambulatory pediatric care is increasingly framed not as a replacement for clinical judgment but as an augmentative layer integrated into existing workflows,

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ranging from automated interpretation of growth and developmental screening data to AI-supported triage and antimicrobial stewardship decision support [5]. The European Confederation of Primary Care Pediatricians has explicitly called for structured engagement with digital health and AI in pediatric primary care, noting both substantial opportunity and the need for caution given the heterogeneity of pediatric populations and the paucity of pediatric-specific validation data [5]. Simultaneously, professional bodies such as the American Academy of Pediatrics have begun issuing guidance that addresses both the equity-promoting potential of AI and its capacity, if implemented carelessly, to exacerbate existing health disparities affecting children [6].

This review builds on the first article in this four-part series, which introduced the fundamental concepts of AI in pediatric healthcare, including its evolution, core methodologies, data sources, and model development [7]. Building on this foundation, the present review summarizes the current evidence on the clinical applications of AI in ambulatory pediatrics, preventive pediatrics, and pediatric outpatient care. It discusses the use of AI in screening, early diagnosis, growth and nutrition monitoring, preventive care, clinical decision support, mobile health applications, and telemedicine, while also highlighting the challenges and future directions for implementing these technologies in pediatric practice.

2. AI in Pediatric Screening and Early Diagnosis

Developmental screening tools:

Developmental surveillance traditionally relies on structured parent-report instruments such as the Ages and Stages Questionnaire and the Parents' Evaluation of Developmental Status, administered during well-child visits [8]. More recently, ML approaches have been used to augment these tools and develop predictive models from routinely collected clinical data. Models based on EHRs, developmental milestones, and parent-reported information have demonstrated promising performance for developmental risk stratification (AUCs: 0.70-0.86) [9,10]. Key predictors include feeding status, follow-up patterns, developmental milestones, growth parameters, and birth characteristics [9,10].

Other studies have used gradient boosting and related ensemble methods to improve developmental delay detection, reporting better accuracy than conventional screening approaches [11]. However, most models have been developed and tested in single-center or registry-based cohorts, limiting their generalizability. These tools are primarily intended for risk stratification rather than diagnosis, and strong performance in retrospective studies does not necessarily translate into improved clinical outcomes. A systematic review of AI applications in child health found that few developmental screening models have undergone prospective external validation, highlighting an important gap between model development and routine clinical implementation [4]. This limitation remains a common challenge across pediatric AI research [2].

Early detection of autism and neurodevelopmental disorders:

Artificial intelligence approaches for autism spectrum disorder (ASD) screening have expanded rapidly and include behavioral video analysis, eye-tracking, speech and language analysis, neuroimaging, and multimodal data integration. A systematic review found that AI-based screening tools show promise for ASD identification, although further improvement in model accuracy and multimodal integration is needed before routine clinical implementation [12]. A scoping review reported that multimodal DL models combining voice and behavioral data achieved the highest accuracies, often exceeding 90%, although most studies were based on curated research datasets rather than real-world clinical populations [13].

Computer vision techniques analyzing facial expressions and joint attention have demonstrated value in ASD assessment, with systematic reviews showing that facial information extracted during social interactions can improve diagnostic accuracy [14]. Some DL models have also been used to assess symptom severity in addition to screening [14]. Eye-tracking and neuroimaging-based approaches have shown promising results, with multiple studies using eye-tracking data, magnetic resonance imaging (MRI), functional MRI, and electroencephalography (EEG) to detect ASD. However, methodological heterogeneity and small sample sizes continue to limit clinical translation [15].

A systematic review of 25 studies on AI-driven ASD diagnostic approaches concluded that AI tools improved diagnostic accuracy, reduced assessment time, and enhanced prediction across behavioral, visual, motor, microbiome, genetic, and neuroimaging modalities [16]. However, integration into routine clinical pathways remains limited. Another review focusing on children aged 0–7 years found substantial variation in study design and sample size, ranging from small case-control studies to large administrative datasets [16]. A recurring limitation across the literature is the predominance of male participants in training datasets, raising concerns about reduced performance in girls and other underrepresented populations [17,18].

AI-based vision and hearing screening:

AI-assisted vision screening has advanced significantly with the development of smartphone-based photoscreening and image-analysis systems. DL-models using facial photographs, eye-tracking data, fixation eye movement analysis, and AI-based stereovision testing have demonstrated promising performance for detecting amblyopia and related visual disorders [19–22]. In addition, mobile image-based DL systems have shown high accuracy for identifying myopia, strabismus, and ptosis, highlighting their potential for community and primary-care screening, where access to specialized equipment and trained personnel may be limited [23,24].

AI applications in hearing screening have evolved from automated auditory brainstem response (AABR) systems, which achieve sensitivities exceeding 99.9% and form the basis of many universal newborn hearing screening programs, to newer approaches incorporating ML and computer vision [25,26]. Recent studies have explored AI-based analysis of infant facial, eye, and body movements in response to auditory stimuli, offering a potential adjunct to conventional behavioral audiometry [27].

ML-enhanced AABR systems have also been developed for use in resource-limited settings, while generative AI has been applied to automate the classification of pediatric audiology reports and reduce administrative workload [28,29]. Overall, AI-based vision and hearing screening technologies demonstrate strong technical performance and the potential to expand screening access. However, challenges related to implementation, referral pathways, over-referral, and integration into existing screening programs remain insufficiently studied [24].

3. AI in Growth and Nutrition Monitoring

Automated growth monitoring :

Electronic growth charts have long been integrated into EHR systems, and the addition of ML techniques has expanded their role from descriptive monitoring to risk prediction [30]. Interest in AI-based growth monitoring has increased rapidly, with growing research focused on predicting growth-related disorders, analyzing growth trajectories, and identifying children at risk of stunting or abnormal growth patterns [31]. Studies using anthropometric, demographic, and socio-environmental data have demonstrated the feasibility of predicting growth-related risks, although this field remains less developed than other pediatric AI applications [31].

Growth faltering is a particularly promising target for ML models because of the longitudinal nature of growth data routinely collected during well-child visits. However, compared with obesity prediction, relatively few studies have focused on detecting growth faltering, and most existing models primarily address excessive rather than inadequate growth [31]. Integration of predictive algorithms into EHR systems offers the advantage of using routinely collected clinical data without increasing the burden of data collection for families or healthcare providers [32].

Detection of undernutrition and obesity risk :

Childhood obesity prediction is one of the most extensively studied applications of ML in ambulatory pediatrics, supported by the availability of large EHR datasets. Early studies demonstrated that routinely collected clinical data from the first two years of life could predict obesity at age five (AUC: 81.7% for girls and 76.1% for boys), identifying weight-for-length z-scores and BMI measurements as key predictors [32]. Subsequent studies using longitudinal EHR data and advanced ML approaches, including recurrent neural networks and XGBoost models, reported improved predictive performance (AUC: $\geq$0.8) [33,34]. These models have also identified additional predictors, such as head circumference and physiological measurements, that may not be readily recognized in routine clinical assessment [34].

Large multicenter studies have further shown that reliable obesity prediction can be achieved using routinely collected EHR data alone, without the need for additional research-specific information, improving the feasibility of real-world implementation [34]. Reviews of this literature conclude that ML and DL models generally outperform traditional statistical approaches for obesity risk prediction and may improve early identification of at-risk children [35,36]. However, important challenges remain, including limited model interpretability, the need for validation across diverse populations, and insufficient evidence that early risk prediction leads to effective preventive interventions or improved clinical outcomes [35,36]. Although these models may support population-level risk stratification and targeted preventive counseling, further research is needed to determine their impact in routine pediatric practice[35,37].

4. AI for Preventive Pediatrics

Vaccination tracking and predictive coverage models:

Artificial intelligence has been applied to both individual-level prediction of vaccine hesitancy and population-level forecasting of immunization coverage. ML models using demographic and geographic data have identified communities at increased risk of vaccine hesitancy, providing a useful approach when individual-level data are incomplete or unavailable [38]. A separate cross-national study surveying adults across five countries found that a parsimonious ML model using 12 variables could identify vaccine hesitancy with 82% sensitivity and 79 to 82% specificity, with vaccination conspiracy beliefs, pandemic-related anxiety, and perceived social rank emerging as the most informative predictors [39].

More advanced approaches, including graph-based DL models, have been developed to predict the spatial and temporal distribution of vaccine hesitancy and identify under-immunized populations for targeted interventions [40]. AI has also been used to support vaccination programs through chatbot-based delivery of personalized vaccine information and natural language processing of social media data to identify misinformation hotspots and public concerns related to vaccination [41]. In addition, AI-based forecasting models have been applied to predict outbreak hotspots and optimize resource allocation for immunization campaigns. However, evidence regarding the long-term impact of AI-driven interventions on vaccine uptake remains limited [41].

Early detection of infectious disease outbreaks:

Machine-learning approaches are increasingly being integrated into syndromic surveillance systems to improve the early detection of infectious disease outbreaks. These methods can identify unusual patterns in clinical encounters and support pre-syndromic surveillance by detecting emerging disease clusters before they meet established case definitions [42]. A combined unsupervised ML and dynamical systems approach, evaluated using primary healthcare encounter data from 27 Brazilian health regions spanning 2017 to 2023, demonstrated the capacity to detect anomalous increases in encounter volume that could indicate emerging respiratory disease activity, validated against established syndromic surveillance methods, including the Early Aberration Reporting System [43].

Pediatric populations have historically served as particularly sensitive sentinels for outbreak detection; early work on influenza syndromic surveillance demonstrated that children and infants presenting to pediatric emergency departments (PED) with respiratory syndromes provided an early indicator of impending influenza morbidity, in some analyses preceding signals from EDs serving predominantly adult populations by as much as three weeks [44]. More recently, AI-based early warning systems combining epidemiological data with Google search trends have achieved high accuracy in detecting respiratory disease outbreaks and peaks, providing two to five weeks of warning [45]. At the individual patient level, ML models using symptom data have also been developed to support early identification of respiratory syncytial virus (RSV) infection in children, particularly in settings where diagnostic confirmation may be delayed [46].

AI for injury risk prediction :

The application of AI to pediatric injury prevention remains comparatively underdeveloped compared with the screening and surveillance domains, with the most rigorous peer-reviewed evidence concentrated in sports medicine rather than in home injury or general accident prevention contexts. A narrative review of AI and wearable sensors in sports injury risk prediction concluded that AI-enabled analysis of wearable sensor data is increasingly reshaping injury risk assessment by enabling continuous, individualized, and data-driven monitoring, with bidirectional long short-term memory architectures applied to inertial measurement unit-derived angular velocity and acceleration data during jump-landing movements demonstrating superior temporal modeling of biomechanical instability compared to support vector machine and random forest baselines, including in cohorts of youth athletes [47]. The same review noted that commercial wearable devices have become increasingly accessible to youth and amateur athletes, supporting individualized training load management and proactive injury prevention strategies, while cautioning that practical challenges, including device adherence, comfort, and data integrity, continue to constrain real-world deployment in younger populations [47].

Table 1. AI Technologies Used in Preventive Pediatrics

Preventive Domain	AI Technology	Public Health / Clinical Function
Immunization	ML hesitancy-prediction models; graph-based spatio-temporal deep learning; NLP-based social media monitoring	Identifying under-immunized populations and individuals at risk of missed vaccination; informing targeted outreach
Outbreak surveillance	Syndromic surveillance anomaly detection; transfer-learning early warning systems	Early detection of respiratory and vaccine-preventable disease outbreaks at the community and population levels
Infection prediction	Patient-reported symptom ML classifiers	Supporting earlier identification of RSV and other common pediatric infections in ambulatory settings
Injury prevention	Wearable IMU-based deep learning (Bi-LSTM); computer-vision hazard detection	Predicting biomechanical injury risk in youth athletes: emerging home-safety hazard monitoring
Obesity/ growth risk	Logistic regression and ensemble models on anthropometric and EHR data	Population-level risk stratification to prioritize preventive nutritional intervention

A separate analysis applying DL models to sports injury prediction reported accuracy of 92%, sensitivity of 89%, and specificity of 94% using an integrated prediction-enhanced DL architecture, outperforming traditional ML approaches, although the populations studied in this and related work skew toward adolescent and young adult athletes in organized sport settings rather than younger children or unstructured play contexts [48]. Computer vision-based hazard detection technologies, increasingly deployed in industrial and occupational safety contexts to identify unsafe behaviors and environmental hazards in real time, have begun to be adapted toward child-specific applications including pool area monitoring, detection of children entering restricted or hazardous zones, and smart crib monitoring systems capable of alerting caregivers to unusual movement patterns such as a child attempting to climb out of a crib [49]. However, peer-reviewed clinical evaluation of these consumer-oriented child safety computer vision systems remains sparse, and most available evidence derives from industry sources rather than controlled pediatric injury prevention research, representing a notable gap between technological capability and clinical evidence in this particular subdomain of preventive pediatrics (Table 1) (Figure 1).

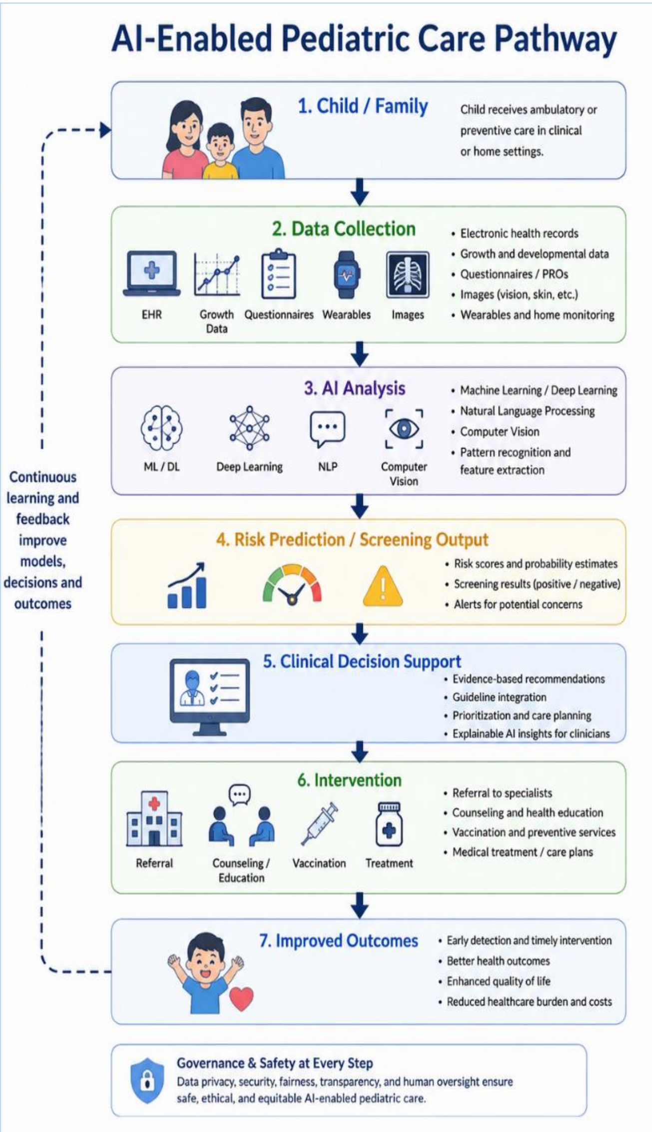

Figure 1. AI-Enabled Pediatric Care Pathway

5. AI in Pediatric Outpatient Clinical Decision Support

Symptom checker systems :

AI-powered symptom checkers and triage chatbots have proliferated as a mechanism for guiding parents toward appropriate levels of care without requiring direct clinician contact for every concern. A pediatric medical chatbot deployed at a Singapore children's hospital, developed through collaboration between clinical staff and an AI vendor, recorded 57,302 chat sessions between January 2022 and December 2024, of which 14,289 sessions reached a completed disposition recommendation; among these, 90.5% of users were advised to continue monitoring at home, 7.7% were directed to primary care, and only 1.8% were advised to seek emergency care, suggesting substantial potential for triage chatbots to reduce low-acuity ED utilization when appropriately designed and clinically supervised [50]. Other reports have suggested that symptom checkers may reduce unnecessary healthcare utilization through triage of common pediatric complaints such as fever, cough, and rash, although much of this evidence is based on vendor-reported data and should be interpreted cautiously [51].

Independent evaluations have generally reported more variable performance. Studies comparing symptom checkers with physician assessment found that diagnostic and triage accuracy remains lower than clinician performance and varies considerably between platforms [52]. However, AI-based systems have often outperformed traditional rule-based tools, suggesting continued improvement as the technology evolves [53]. A broader review concluded that symptom checkers are most useful for triage and health education rather than definitive diagnosis, with performance improving when patient history and contextual information are incorporated [51]. Patient safety remains an important consideration. Although LLM–based chatbots can provide rapid guidance and may occasionally offer recommendations comparable to clinicians, inappropriate reliance on unsupervised AI tools during pediatric emergencies could delay access to urgent medical care [54]. Balancing improved accessibility with patient safety is therefore a key challenge for the use of symptom checkers in pediatric practice.

Risk stratification tools :

Machine-learning models have been developed to support risk stratification in children by predicting clinical deterioration, hospitalization, ICU transfer, and sepsis. A scoping review of pediatric sepsis prediction studies identified 27 eligible investigations (AUC: 0.56-0.99), although most studies were single-center and showed substantial variation in methodology, outcome definitions, and reporting standards [55]. These findings highlight both the potential of AI-based risk prediction and the need for greater standardization and validation.

Several studies have demonstrated that ML models can outperform conventional pediatric early warning scores in identifying children at risk of clinical deterioration or transfer to the ICU [56]. In 2024, the Phoenix Sepsis Score criteria were developed using EHR data from 63,875 PICU encounters across two institutions, comparing four ML architectures for daily sepsis-onset prediction using readily available vital-sign, laboratory, demographic, medication, and organ-dysfunction data [57]. A separate model, applying extreme gradient boosting and gated recurrent unit (GRU) architectures to a combined cohort from a Chinese PED and the external MIMIC-III critical care database, achieved real-time sepsis prediction by integrating both static and dynamic EHR features over a 12-hour prediction window before clinical diagnosis [58]. AI-based risk prediction has also been extended beyond ICU settings through tools designed to detect deterioration early across multiple hospital units and clinical workflows [59].

Despite promising performance, implementation in routine practice remains limited. Common barriers include insufficient external validation, high false-alarm rates that may contribute to alarm fatigue, and limited evaluation of model performance across diverse patient populations. [60]. These challenges may be particularly important in ambulatory and outpatient settings, where most existing prediction models have not yet been extensively tested.

AI-assisted prescribing:

Artificial intelligence is increasingly being applied to pediatric prescribing through medication recommendation systems, dosing support, therapeutic drug monitoring, error detection, and antimicrobial stewardship. These applications are particularly relevant in pediatrics because of frequent off-label medication use and substantial age-related variability in drug metabolism, which complicate prescribing decisions [61]. A scoping review found that AI-based tools have the potential to improve dosing precision and medication safety, although most studies remain focused on model development rather than clinical implementation [61].

AI has also been used to improve medication-related clinical decision support by reducing alert fatigue, identifying atypical prescribing patterns, and optimizing alert generation through ML approaches [62]. In antimicrobial stewardship, proposed applications include clinical decision support, risk stratification, surveillance, and antimicrobial drug discovery. Although early studies suggest that ML models may assist in distinguishing bacterial from non-bacterial illness, most evidence is derived from retrospective single-center datasets and lacks external validation [63]. A usability study of an AI-supported decision support tool for antibiotic prescribing in PED demonstrated improved user satisfaction, fewer decision-making errors, and better adherence to clinical guidelines compared with standard order sets [64]. However, important challenges remain, including limited real-world validation and unresolved ethical and legal issues related to liability, clinician oversight, and communication with families when AI tools influence prescribing decisions [61,63] (Table 2).

6. AI-enabled Mobile Health Applications for Parents

Parenting support tools:

AI-powered chatbots and digital parenting assistants are increasingly being used to provide health education and behavioral guidance outside routine clinical encounters. Studies suggest that families managing chronic pediatric conditions value the continuous availability of chatbot-based support, particularly for issues such as symptom management, medication adherence, and disease flares occurring outside normal healthcare service hours. However, concerns remain about the accuracy and appropriateness of AI-generated responses in complex, individualized clinical situations [65].

Table 2. Benefits, Challenges, and Future Directions of AI in Pediatric OPD Practice

Domain	Benefits	Challenges and Future Directions
Diagnostic and screening accuracy	High discriminative performance (AUC >0.8) for ASD, amblyopia, obesity, and sepsis risk	Predominantly single-center derivation; limited external and prospective validation
Workflow and access	Reduced low-acuity ED utilization via triage chatbots; expanded access in rural/underserved areas	Alert fatigue; integration burden on time-limited ambulatory workflows; infrastructure cost
Equity and representation	Potential to identify at-risk populations for targeted preventive outreach	Underrepresentation of children in training data; algorithmic bias; only 17% of FDA-approved AI devices are pediatric-labeled
Trust and governance	Favorable parental engagement with developmental and growth-tracking tools	Limited explainability; unclear liability; parental trust contingent on regulatory transparency & clinician oversight
Regulatory landscape	Emerging FDA and EU AI Act attention to bias and transparency	Absence of mandatory pediatric-specific subgroup validation requirements in most jurisdictions

A cross-sectional survey study of 185 family members of children receiving hospital care examined parental understanding of and attitudes toward AI applications in pediatric healthcare, finding that most respondents' direct experience with AI was through general-purpose LLM chatbots rather than purpose-built pediatric health applications [66]. Evaluations of popular AI chatbots have shown considerable variation in the quality and consistency of responses to pediatric health-related questions, raising concerns about their reliability as independent sources of medical guidance [67].

Potential benefits of AI-enabled parenting support include continuous access to information, reduced demand on telephone triage services, and scalable delivery of personalized health education. However, important risks include inaccurate or inappropriate advice, delayed medical consultation due to overreliance on chatbots, and the propagation of biases present in training data [68]. The AAP has emphasized that guidance regarding AI use should be tailored to developmental stage, recognizing the differing needs of children and adolescents across the pediatric age spectrum [69].

Developmental monitoring apps :

Digital developmental monitoring applications extend traditional parent-report developmental surveillance tools into mobile and web-based formats. The Centers for Disease Control and Prevention's Milestone Tracker app illustrates how AI and digital technologies can support both developmental monitoring and parental engagement [70]. Other applications use age-specific questionnaires covering developmental, cognitive, behavioral, and sensory domains, combined with algorithm-based alert systems to identify children who may require further evaluation [71]. Studies evaluating these tools have reported generally favorable engagement and usability. However, concerns remain regarding the accuracy of parent-entered data and the possibility that families may place excessive emphasis on growth or developmental metrics without appropriate clinical interpretation [72,73].

Home hazard detection systems :

Computer vision applications for home hazard detection have begun to be adapted toward child-specific applications. Patent and industry literature describes AI engines trained to recognize and score hazards, including poor lighting, clutter, and trip hazards, from photographs or video of a household environment, intended to support both injury prevention and caregiver education regarding household risk factors [74]. Object detection-based child safety systems have been described for applications including pool area monitoring, detection of children entering restricted or hazardous zones such as workshops containing dangerous tools, traffic safety monitoring near driveways, and smart crib systems capable of detecting unusual movement patterns such as a child attempting to climb out of a crib, with corresponding real-time alerts directed to caregivers [7]. Practical implementation challenges for these systems include the computational and connectivity infrastructure required for continuous video processing in the home environment, the privacy implications, the risk of false alarms that generate caregiver fatigue, and the relative scarcity of peer-reviewed injury-prevention outcome data [7,74].

7. Telemedicine and Remote Pediatric Monitoring

AI-enhanced telemedicine platforms have expanded substantially in pediatric care, accelerated by the operational necessity of remote care delivery during the COVID-19 pandemic and sustained subsequently by demonstrated value in extending specialist and primary care access [75]. The European Confederation of Primary Care Pediatricians has noted that telemedicine facilitates both mental health assessment and chronic illness management in pediatric primary care, with digital health technologies, including wearable devices, EHR, and mobile health applications, collectively improving care coordination, health education, and remote monitoring capability [75]. AI applications within these platforms include individualized treatment planning support, automated triage prior to clinician contact, and therapeutic decision support integrated into the telemedicine workflow itself [75].

A systematic review of digital and remote health interventions in pediatric populations from underserved or rural areas, encompassing 11 RCTs evaluating telehealth, telemental health, and mobile health interventions for conditions including obesity, asthma, attention-deficit/ hyperactivity disorder, diabetes, oral health, and neonatal care, found that telehealth interventions improved behavioral and biometric outcomes [76]. Remote developmental surveillance, conducted through video-based assessment or parent-reported digital instruments administered via telemedicine platforms, offers a mechanism for extending developmental screening capacity into communities lacking access to in-person developmental specialist services [71,72]. Chronic disease management applications, including diabetes, asthma, and rheumatological condition monitoring, supported by AI-enhanced telemedicine platforms and chatbot-based support tools, represent a further extension of remote monitoring capability [65,76].

Reported patient satisfaction with AI-supported telehealth has been favorable in broader health system analyses, with one industry analysis reporting that over 90% of telehealth users found that the service adequately addressed their health concerns [77]. Limitations of current pediatric telemedicine and remote monitoring evidence include the predominance of single-condition rather than comprehensive primary health evaluation, limited pediatric-specific wearable device validation, persistent digital divide barriers, including unreliable broadband access in precisely the rural and underserved communities [75,76]. Future opportunities include integration of wearable physiological monitoring with AI-based early warning capability adapted specifically for ambulatory pediatric chronic disease populations, and expansion of rigorously evaluated telehealth models [77].

8. Implementation Challenges in Ambulatory Settings

Despite promising advances, translating pediatric AI tools into routine ambulatory practice faces several important challenges. Data privacy and security are major concerns because children cannot provide independent consent, pediatric health information may have lifelong implications, and many home-based monitoring technologies require continuous collection of sensitive personal data [74].

Ethical concerns extend beyond privacy to include questions regarding clinical responsibility and decision-making when AI-assisted prescribing or risk prediction tools influence care [61,63]. Algorithmic bias is a particularly important issue in pediatric AI because children remain underrepresented in many training datasets. A recent analysis found that only 17% of US FDA-approved AI devices are labeled for pediatric use, reflecting a significant pediatric data gap [78]. Furthermore, participant age was not reported for most approved AI devices, making it difficult to determine whether adequate pediatric validation had been performed.

The AAP has highlighted how algorithmic bias can worsen existing health disparities when training data or model design reflects inequities in healthcare access [6]. Missing data may further amplify bias if not handled appropriately [6]. Bias can arise throughout the AI development process, including data collection, feature selection, model training, and validation. Proposed mitigation strategies include bias-aware model development, use of representative datasets, and federated learning approaches that enable multi-institutional collaboration while preserving privacy [79].

Lack of transparency and explainability presents an additional challenge. Many high-performing ML models function as “black boxes,” making it difficult for clinicians, families, and regulators to understand how decisions are generated or to identify potential errors and biases [79,80]. Regulatory frameworks for pediatric AI also remain underdeveloped. Although recent regulatory guidance has emphasized transparency and bias assessment, pediatric-specific requirements for validation and age-specific labeling are still limited [3,81]. The European Union AI Act's requirements for representative training datasets and bias mitigation in high-risk clinical applications offer a potential model for more explicit pediatric data representation requirements, though the practical implementation and enforcement of such requirements specifically for pediatric AI applications remain to be demonstrated [81].

Practical implementation is further constrained by cost, infrastructure requirements, and workflow integration challenges, particularly in ambulatory and primary care settings with limited technological resources. Successful adoption depends not only on technical performance but also on clinician acceptance, ease of use, and preservation of clinical autonomy [82]. Clinician acceptance of AI tools in pediatric practice depends substantially on perceived reliability, workflow integration, and preservation of clinical autonomy. Parent trust and acceptance represent an equally important and increasingly studied dimension of implementation readiness. A national survey examining parental and carer views on AI use in pediatric imaging found that stakeholder engagement regarding parental acceptance has historically been poor, despite the increasing deployment of AI tools in pediatric clinical contexts [83].

Equity remains a major concern. Algorithmic bias, limited pediatric validation, and unequal access to digital infrastructure risk widening existing healthcare disparities, particularly among rural, low-income, and historically underserved populations [6,78]. Future priorities include mandatory pediatric-specific validation, development of diverse pediatric datasets, improved explainability standards, and active involvement of clinicians, parents, and children in the design and governance of AI systems intended for pediatric care [6,83].

CONCLUSION

Artificial intelligence is increasingly influencing ambulatory and preventive pediatric care through applications in developmental screening, autism detection, vision and hearing assessment, growth and nutrition monitoring, immunization programs, infectious disease surveillance, clinical decision support, parent-facing digital tools, and telemedicine. Current evidence suggests that AI can improve risk stratification, enhance screening efficiency, support clinical decision-making, and expand access to pediatric services,

particularly when integrated with routinely collected health data. However, most studies remain at the stage of model development or retrospective validation, with limited evidence demonstrating sustained clinical benefit in real-world practice. Rather than replacing clinical judgment, AI is most likely to serve as a complementary tool that supports pediatricians, caregivers, and health systems in delivering more proactive, personalized, and efficient care.

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