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Artificial intelligence in child development monitoring: A systematic review on usage, outcomes and acceptance

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A R T I C L E I N F O

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A B S T R A C T

Objectives: Recent advances in Artificial Intelligence (AI) offer promising opportunities for its use in pediatric healthcare. This is especially true for early identification of developmental problems where timely intervention is essential, but developmental assessments are resource-intensive. AI carries potential as a valuable tool in the early detection of such developmental issues. In this systematic review, we aim to synthesize and evaluate the current literature on AI-usage in monitoring child development, including possible clinical outcomes, and acceptability of such technologies by different stakeholders.
Material and methods: The systematic review is based on a literature search comprising the databases PubMed, Cochrane Library, Scopus, Web of Science, Science Direct, PsycInfo, ACM and Google Scholar (time interval 1996–2022). All articles addressing AI-usage in monitoring child development or describing respective clinical outcomes and opinions were included.
Results: Out of 2814 identified articles, finally 71 were included. 70 reported on AI usage and one study dealt with users' acceptance of AI. No article reported on potential clinical outcomes of AI applications. Articles showed a peak from 2020 to 2022. The majority of studies were from the US, China and India (n = 45) and mostly used pre-existing datasets such as electronic health records or speech and video recordings. The most used AI methods were support vector machines and deep learning.
Conclusion: A few well-proven AI applications in developmental monitoring exist. However, the majority has not been evaluated in clinical practice. The subdomains of cognitive, social and language development are particularly well-represented. Another focus is on early detection of autism. Potential clinical outcomes of AI usage and user's acceptance have rarely been considered yet. While the increase of publications in recent years suggests an increasing interest in AI implementation in child development monitoring, future research should focus on clinical practice application and stakeholder's needs.

1. Introduction

Recent advances in Artificial Intelligence (AI) offer promising opportunities for clinical applications in healthcare, a sector with a massive volume of data [1]. By effectively processing big data with AI, quality and efficiency of patient care could be improved [1]. Personalized preventive healthcare is an area to which AI could make an impactful contribution because it might provide more accurate, faster

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diagnoses or predict disease risks beyond human capacities [1,2].

Preventive approaches are especially important in the monitoring of child development as delayed detection of congenital or acquired diseases is often associated with aggravated developmental issues. Early detection of such developmental delays is crucial for timely intervention and attenuation of negative outcomes [3]. However, frequent developmental assessments in different age groups of children are resource-intensive [4]. Although regular screening is recommended for all age groups, many developmentally delayed children still remain unidentified [5]. Inconsistent use of standardized screening tools and a significant delay from parents' first concern to medical consultation lead to substantial delays in correct diagnosis [6,7]. In low and middle-income countries, limited access to developmental assessments aggravates this burden [8,9]. With increasing digitalization of the healthcare sector, AI technologies might provide an accessible solution for monitoring child development [4]. Increasing digitalization however might also widen the gap between developed and underdeveloped countries due to limited technology access. In order to prevent this a global collaboration for equal distribution of resources is necessary [10].

Evidence of AI use in pediatrics is still limited. A recent review examining machine learning in pediatrics identified the subspecialties of neonatology, mental health, and neurology as the main research interests [11]. The detection of autism spectrum disorder (ASD) is a main focus of existing studies [12]. Several studies have shown high accuracy and specificity for diagnosing ASD [12]. However, these reviews agree that there is a lack of real-world clinical and large-scale evaluations of AI [11–13]. One study identified some examples of AI use in different pediatric fields including autism screening, speech analysis, sepsis prediction and preterm care [13]. Even though autism screening has attracted particular attention, other applications in child development monitoring are rarely mentioned.

A possible challenge for successful AI implementation in development monitoring is the broad spectrum of "normal" development in children [14]. A wide range of developmental varieties is considered physiological and the definition of pathological development is often based on longitudinal data and expert knowledge [15].

Another challenge is the acceptance of all involved stakeholders. Even though parents considered digital information as a useful information resource for their child's development, they expressed concerns regarding reliability and preferred consultation of a physician [16]. Physicians and medical staff claimed a lack of practical experience and knowledge and thus had mixed opinions on AI applications [17]. The inclusion of medical staff's experience and opinion remains scarce, especially in the pediatric sector.

In this systematic review, we aimed to summarize and evaluate the current literature on the use of AI in monitoring child development, including beneficial and detrimental outcomes, acceptability as well as opinion on AI applications of all stakeholders.

2. Materials and methods

This systematic review was conducted following the PRISMA guidelines for systematic reviews [18,19] (Fig. 1).

2.1. Search strategy

Studies were obtained from seven electronic databases (PubMed, The Cochrane Library, Scopus, Web of Science, Science Direct, PsycInfo, ACM) using the keywords "artificial intelligence", "machine learning", "deep learning" or "neural networks'' and "child development", "adolescent development" or "child health", "adolescent health". The broader terms of "child and adolescent health" were used to avoid the risk of excluding important papers that may not be mentioned under the specific term "development". Mesh terms and truncations were used to ensure inclusion of all relevant articles. This search was complemented by searching Google Scholar for additional grey literature (n = 980) and manual screening of reference lists. Searches were restricted to 0–18-year-olds and German or English language. All searches were conducted from November 28, 2022 to December 2, 2022. The detailed search strategy can be found in the appendix (Supplementary Information 1).

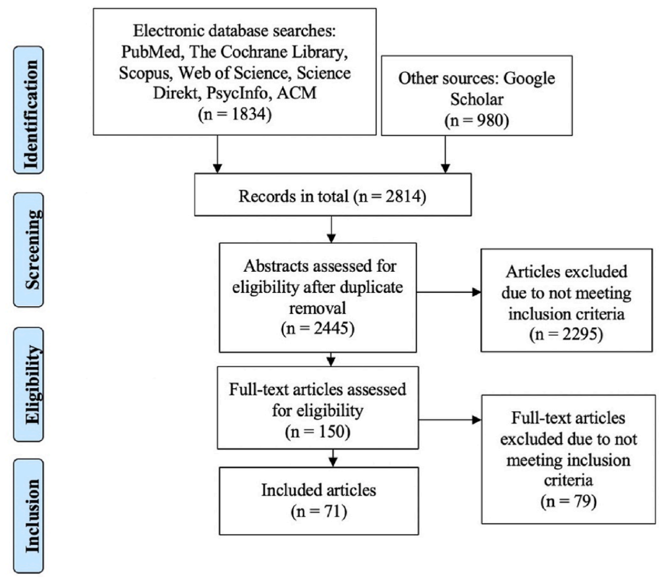

Fig. 1. PRISMA-Flowchart – Screening process of literature research
n = number of articles.

2.2. Study selection

2.2.1. Inclusion and exclusion criteria

All original studies focusing on child development monitoring available until December 2, 2022 were included. Records including participants with a pre-diagnosed disease were included if used to create an AI tool to detect the respective disease. Books, book chapters, editorials, letters, commentaries, workshops, discussions, theses, or reviews were excluded. Articles were excluded if they only included adults, fetuses, did not include child development, contained image analysis via fMRI or EEG but did not address child development, or no AI method was used. Studies with participants with a diagnosed disease were only included if children with a disease were compared to healthy controls or used to create an AI tool which could detect the respective disease.

2.3. Data charting

All records were collected using EndNote X9 (Clarivate Analytics). After duplicate removal two researchers (AB, LR) jointly piloted the screening procedure and clarified the specification of inclusion and exclusion criteria for ten records. Subsequently, they screened titles and abstracts independently and excluded all articles not meeting the inclusion criteria. If information in the title or abstract was not sufficient or agreement was not reached, full texts were assessed. Full texts were electronically retrieved and screened for eligibility. Any disagreements were resolved by discussion with two other researchers (JK, MH).

2.4. Data extraction

Data extraction was performed independently by two researchers (AB, LR). Author, year of publication, country of study implementation, title, category (monitoring, opinion, outcome), child development category, AI technology and task, study design, dataset, sample and size, short description and outcome or accuracy were extracted. The studies were further reviewed for possible risks of bias. Ten full texts were used for piloting and discussion of content, which led to refinements of

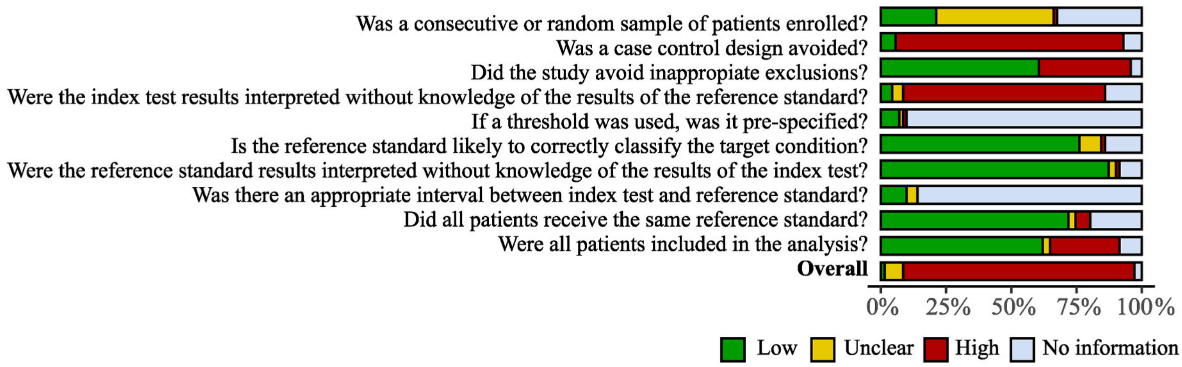

Fig. 2. Risk of bias assessment (summary of all studies).
Percentage represents percentage of all included studies. Color represents respective judgment of risk of bias.

categories and documentation. After completion of the table, the articles for which there was disagreement were jointly reviewed for inclusion criteria, and then accepted or rejected. The articles were categorized among the sub-areas of child development including cognitive, language, social, emotional, physical, and motor development according to the WHO definition [20]. Additionally, autism spectrum disorder (ASD) was added as a separate clinical picture – which contained more than one sub-area of development – due to frequent mention.

2.5. Risk of bias assessment

Based on the Joanna Briggs Institute's checklist for critical appraisal, we performed a risk of bias assessment [21]). The risk of bias was assessed by one researcher (LR), uncertainties were resolved by consultation of a second researcher (AB). Articles were not excluded based on the assessment but provided an overview of potential bias for the evaluation of the study results. Figures were created using the *robvis* tool, Adobe Inc. Adobe Illustrator CC 2019, and Google Documents [22].

3. Results

Of a total number of 2814 identified articles, 2445 titles and abstracts were assessed for eligibility after duplicate removal. A number of 150 full texts were screened, and finally 71 studies were included in this review (Fig. 1). Of those, 70 reported on AI-usage in developmental monitoring, one study dealt with users' acceptance of AI. No article reported on long-term clinical outcomes of AI so far.

About half of the studies were cross-sectional (n = 34, 48 %). 27 articles (38 %) were theoretical studies testing the accuracy of an AI method. Ten studies had a longitudinal study design (14 %). Articles were published between 1996 and 2022, with a peak from 2020 to 2022. Most studies were conducted in the USA (n = 27), China (n = 9) and India (n = 9). Detailed information on the included studies can be found in the data extraction table (Supplementary Information 2).

The risk of bias assessment revealed an intermediate to high risk of bias in most of the studies (including selection, performance, detection, attrition, and reporting bias) (Fig. 2, Supplementary Information 3 for assessment by study). Most studies did not describe the recruitment of patients or sample characteristics, whereas the described AI method mostly reevaluated the results already collected by a reference standard to verify measurement accuracy

3.1. Datasets

The included studies dealt with groups of various sizes (n = 5–242,673) with participants mainly being in the infant or toddler age. Most used previously publicly available datasets, e.g., electronic health records, speech, or video recordings. Data was collected from electronic health records, school records, web games and app data, social media, or home environment recordings [23–27].

3.2. AI tasks and methods

AI was applied in various areas and tasks such as computer vision (n = 17) by obtaining information from digital image sources, disease recognition using information from speech, motion, or sensor data (n = 31), survey analysis (n = 13), predictive models (n = 12), and recommendation systems (n = 2). The most used AI methods included support vector machines (n = 25) used for predictive modeling and diagnosis, random forests (n = 24) and deep learning techniues (n=22) (Fig. 3).

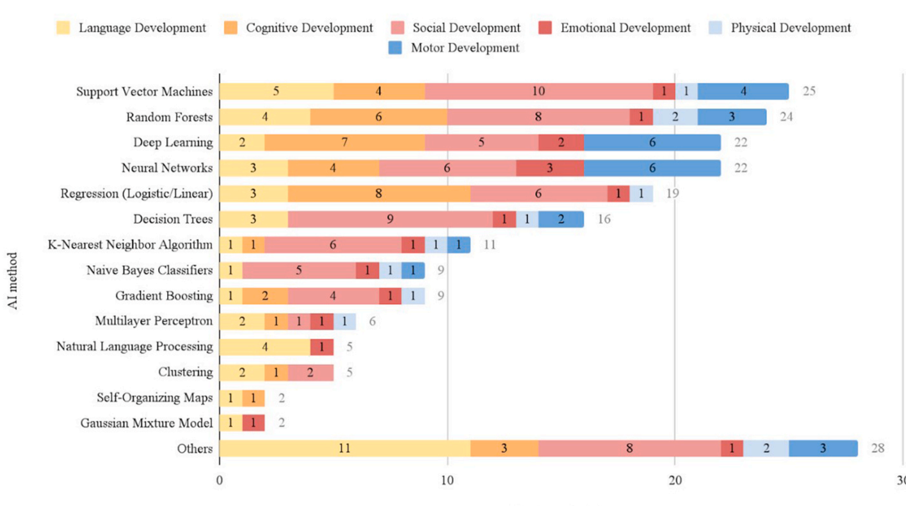

Fig. 3. Distribution of AI methods among categories of child development.

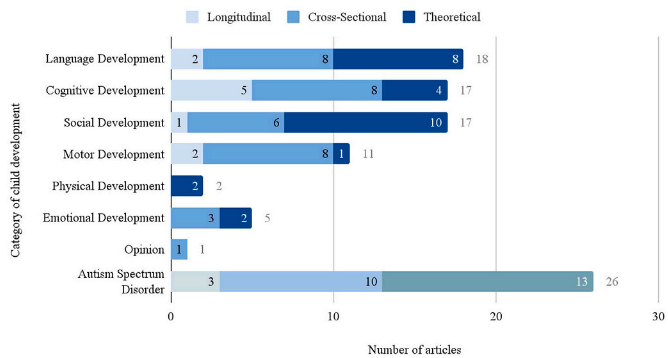

Fig. 4. Categorization of different study types among areas of child development.
Classification into WHO child development and opinion on AI usage categories. The superordinate category of autism spectrum disorder was added due to frequent mention.

3.2.1. *AI usage by development category*

Most articles dealt with language and cognitive development with 26 articles (36 %) focusing on ASD (Fig. 4).

3.2.2. *Language development*

Language development was covered in 18 articles (25 %). Most studies aimed to predict language acquisition delays and disorders (e.g., dyslexia), or to interpret infant cry signals. Dyslexia was often detected via speech samples, e.g., collected through a web game [28], texts [29] or speech recordings [30]. Speech captured by smart devices in the home environment, automatic language environment analysis systems, medical records, or social media posts was used for ASD diagnosis or disease progression detection [24,31–33]. Studies analyzing infant cries collected audio files through an app or a recorder and aimed at distinguishing the needs of babies [23,34–36]. One study aimed at measuring delayed or typical auditory feedback to detect hearing-impaired infants by analyzing auditory evoked potentials [37]. Three studies created a predictive model using language to infer development or vocalization age. One article created a decision support system for pediatricians to detect delayed language acquisition.

3.2.3. *Cognitive development*

In summary, 17 articles (24 %) dealt with the measurement of cognitive development. While four studies sought to detect ASD through analysis of questionnaire data, child-play data or electronic medical records, others focused on predicting neurodevelopmental disorders or cognitive abilities using electronic games, questionnaires, or interviews [4,8,38–45]. Other studies analyzed images of hand gestures to diagnose various neurodevelopmental diseases [46,47] or to infer cognitive processes from visual focus [48]. An ongoing study is examining the effects of environmental factors on cognitive development and mental health using data from several school studies [25].

3.2.4. *Social development*

17 articles (24 %) focused on social development. 13 studies aimed to identify ASD. Several studies used image analysis to infer ASD from facial images or home videos [27,49,50]. Another common data source were questionnaire data provided by parents [51–57]. Three studies focused on the interaction of children with adults to infer social development by analyzing either facial expressions of babies or engagement levels of children during interactions [58–60]. Furthermore, ASD was determined from either electroretinograms, signals from the electrooculography data, or eye movement data [61–63]. Other studies aimed to identify attention deficit hyperactivity disorder from pupillometric biomarkers, or to analyze facial expressions via images [49,64].

3.2.5. *Motor development*

A wide range of motor aspects was covered to predict motor developmental delay in 11 studies. Including the interpretation of drawings about cognitive developmental levels, assessment of coordination patterns or spontaneous movements, using wearable devices to characterize circadian rhythm, analyze day-long-motion recordings to determine health status, a pathological gait-recognition system, and analyzing kinematic data during videogame play to detect autism [14,26,65–72]. Another study aimed at recognizing the visual focus and acuity of children [73].

3.2.6. *Physical development*

Two articles were identified evaluating AI methods to infer child growth, or detecting physical properties from electronic health records to diagnose ASD [74,75].

3.2.7. *Emotional development*

Five articles on monitoring emotional development were found. Three studies analyzed facial expressions, audio files, or EEG data to detect ASD or empathic abilities. One study used audio files to detect stress burden and to infer the children's developmental stage [76–79]. Another study analyzed behavior assessments conducted by teachers to screen children for emotional and behavioral risk [80].

3.2.8. *Clinical outcomes and acceptance*

No articles were found on possible clinical outcomes of AI use in developmental monitoring. The most common primary endpoint was measurement accuracy compared with standard diagnostics. One article addressed acceptability of AI in pediatric healthcare showing a moderate openness of parents towards AI use due to ethical and practical concerns [81]. Parents were worried about data privacy of personal information, loss of control in the process of shared decision making, AI's accuracy and trustworthiness, costs, social justice, dependance on technologies, and loss of reflection from doctors. The study revealed that the severity of a child's disease, educational background as well as affinity for technology influenced the openness towards AI.

4. Discussion

In this review, we provide a systematic summary of AI-usage in monitoring child development. The linguistic, social, and cognitive subareas were particularly well covered. However, the most common application of AI was in autism detection. Almost all articles examined disease or abnormality recognition methods by comparing the accuracy of a new method compared to standard references. These methods used sensory, motion or visual information or aimed at recognizing patterns in electronic health data. Only one study addressed acceptability of AI by pediatricians, parents, or adolescents. None of the articles thematized long-term clinical outcomes of AI use. Only few longitudinal studies exist so far, and most studies have not been tested in clinical settings.

Various approaches of AI in developmental monitoring were identified with a great variation in datasets and sample characteristics. Even though some studies reported a similar or better performance than the reference standard (mostly ASD diagnostic instruments), the transferability to large and heterogenous real-world data and settings should be subject to critical scrutiny and be tested in clinical studies [56,75]. Most studies used cleaned datasets and excluded data that were misleading for the AI algorithm. Yapanel et al. [79] discovered a misinterpretation of their data when including children's data to an adult-trained algorithm emphasizing the importance of data transferability. The estimation of a consistently medium to high risk of bias illustrates the various challenges of AI method implementation and transferability. The identified challenges included methodological limitations in study design and analysis, reporting bias as well as data quality issues which highlights the multifaceted nature of application difficulties. To apply trustworthy AI in clinical practice and meet users' and governmental requirements, such as the European Union ethical requirements, these issues have to be addressed first [82].

4.1. AI methods

Major focus of AI applications in this review has been on detection or prediction of specific diseases and abnormalities that occur during child development. Support vector machines were most frequently applied for collecting data and generating predictions. In general, there has been a great variety of applied methods showing the number of possibilities for AI in the analysis of healthcare data. The heterogeneity of methods highlights the need for further research to identify the most suitable application. Ideally, an AI-based preventive early detection system would be able to cover a wide range of aspects of child development and be adaptable to the different age groups.

4.2. AI usage for development categories

The assessment of language development represented the largest area of this review and can be attributed in part to the simplicity of data collection (e.g., speech recordings). Similarly, there are large datasets on neurodevelopmental monitoring e.g., video recordings, facilitating the analysis of cognitive development. Many studies addressed the fact that diagnosing ASD is complex and requires detailed examination and high levels of expertise. AI driven approaches showed great potential to optimize these procedures [11,12,31,83], revealing a tremendous need for improved autism diagnostic tools. AI-use has shown positive results not only in predicting developmental abnormalities but also in early diagnosis of ASD [11,12,83] and provides affordable access to screening tools for non-specialists in various settings [4].

Promising developments are already evident in several domainssuch as the early identification of dyslexia, delayed language acquisition or the detection of autism. These areas have already showcased remarkable outcomes, achieving measurement accuracy aof approximately 90 %. In contrast, speech detection presents a persistent challenge, with accuracies mainly around 60 % for diagnosing pathological conditions. The assessment of language proficiencyis greatly influenced by diverse linguistic and regional characteristics, adding complexity to the development of broadly applicable AI technologies [28,30]. While one study asserts language independence through the creation of cross-language content and assessment in German- and Spanish-speaking children [28], the transferability of these findings to other languages remains open.

Due to great variability in physiological child development, classifications need to be adjusted accordingly to avoid misjudgment. Children's physical and mental development proceeds at different speeds, which makes it difficult to detect serious abnormalities. Late language acquisition, for example, does not necessarily predict future language skills [84]. Long observation periods are needed to assess the usefulness of AI systems and produce meaningful estimates. The few existing longitudinal studies cover ASD detection, identification of high capabilities as well as mental health, achieving varying degrees of accuracy. Many studies analyzed just one parameter for the respective diagnosis which might perform worse than the standard diagnosis approach by physicians.

Those studies dealing with children's motor and physical development acquire information from various data sources e.g., video recordings, drawings, and motion sensors showing great potential for data collection in home environments. Even though most studies reported good accuracies above 80 %, however, the small number of cases might have led to an overfitting of the model or data leakage. Thus, evaluation with larger datasets is needed for further assessment [60,61].

In most studies where sensory attention was measured in the context of social development, a multitude of devices such as electrooculography data or electroretinography was used [61,62]. This imposes huge barriers to an application in home environments, by non-specialists, or in low- and middle-income countries. Furthermore, interpretation of the respective device results such as electroencephalography is often restricted to specialists and not applicable for broader use. Assessment of social development based on eye movement resulted in moderate accuracies ranging at about 70 % [63].

For the monitoring of emotional development, the capabilities of AI methods are still very limited. Assessment of facial expressions resulted in different accuracies (ranging from 63 to 94 %) depending on the intensity and variation of facial expressions [17,59]. Speech emotion recognition by analyzing audio streams for ASD detection seemed promising so far [77]. Measuring emotions in real time yielded a relatively low accuracy of 63 % [78], showing that AI cannot adapt as well as humans when the scenario is not exactly as trained.

Most studies monitoring social development focused on ASD detection. Other applications remain scarce. ASD detection is usually based on teacher or parental questionnaire data which places great emphasis on the correct assessment of these supervisors. While ASD can be accurately identified based on AI's analysis of questionnaire data, the distinction between abnormal (showing atypical behavior) and delayed (not reaching milestones due to age-incongruent behavior) development was less successful. The assessment of social development may be influenced by various factors, e.g., a familiar or unfamiliar test environment or character traits [60], complicating analyses by AI algorithms.

4.3. Acceptability of AI

The development of AI applications should be accompanied by an analysis of the acceptability of pediatricians, parents as well as children to develop targeted AI applications that can be used in clinical practice. We identified only one article on acceptability of AI in pediatric healthcare. Although this article did not explicitly address child development monitoring, aspects are likely transferable.

Ramgopal et al. [85] reported parents' perception towards AI in emergency departments showing similar benefits and concerns. Obtaining rapid diagnosis and reducing human errors were considered beneficial. Similarly, parents were concerned about diagnostic errors. One bias may be that this survey only targeted parents with healthy children, thus ignoring the perspective of parents with seriously ill children.

Overall, the stakeholders' perspective on AI use in pediatrics has been largely disregarded. Especially in the field of pediatrics, where patient autonomy is limited, the integration of all relevant stakeholders is essential for high acceptability.

4.4. Clinical outcomes of AI

No article focusing on possible beneficial or detrimental clinical outcomes of AI usage has been identified in this review. Now, the focus of research is on the feasibility of using different AI methods. Thus, to identify the effects of AI applications in the clinical context remains an important direction for future research.

4.5. Limitations and strengths

The review systematically searched articles published in selected major databases. Related articles published in other databases may be missing, as well as articles published in other languages than German and English. Articles that were published later than December 2, 2022 were not included in this review. Articles that did not include the terms "artificial intelligence", "machine learning", "deep learning", or "neural networks" and "child/adolescent development" or "child/adolescent health" in title or abstract but addressed specific aspects of development or diseases were not covered in the search. Another limitation might be that applications presented without scientific evaluation, e.g., in app stores, were not included. By omitting the rapidly developing industrial domain, the publications included may not capture the entire picture of the true AI landscape at this time. A major strength of this systematic review is that it addresses the potential of AI in monitoring child development and collects the current literature on the use of AI in child and adolescent development. It mapped all areas of child development and evaluated the acceptance of AI in development monitoring. By including all studies regardless of their risk of bias, we obtained a comprehensive overview of the existing literature.

5. Conclusion

Numerous studies using a wide variety of health data and AI methods seem promising regarding the future use of AI in monitoring child development. Especially the domains of linguistic, social, and cognitive development are well represented. Many approaches aim to identify ASD.

However, the application of AI models in clinical pediatric practice and with real-world data needs further investigation. Most models are tested on small populations, thus complicating transferability. Because of infrequent use in clinical settings, no clinical outcomes of AI-usage have yet been described.

By providing a cross-sectional view of the state of AI methods for child development monitoring in the academic literature, this review reveals the currently existing limitations across multiple studies. Future research should prioritize the assessment of acceptability, involving stakeholder's perspectives at an early stage and the evaluation of long-term outcomes in clinical trials. The implementation and transferability of AI methods remain challenging, requiring future studies to enhance the practical application of AI in child development monitoring.

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Role of the funder

The BMBF had no role in design or conduct of the study.

Availability of data

All identified studies are enclosed in the appendix.

Author contributions

TM, LR, AB, JK and MH conceptualized the study idea and developed an analysis plan. LR and AB developed the inclusion criteria. LR and AB analyzed the data, performed the study selection and screening.

LR and AB drafted the manuscript and created all tables and figures. All authors contributed to the interpretation of data, writing as well as critical revision of the paper and approved the final manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Not applicable.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ibmed.2024.100134.

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