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Applications of artificial intelligence in emotion recognition in pediatrics health care: Scoping review

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ABSTRACT

Background: The use of artificial intelligence in healthcare is growing rapidly. In pediatrics, artificial intelligence technologies have been applied to early diagnosis, treatment, increased precision in care, and recognition of emotions. This will provide new opportunities to overcome the difficulties that may have developed in children's ability to express emotions due to cognitive, physical, or emotional reasons.

Aim: To review the existing literature on the application of artificial intelligence to emotion recognition in children and adolescents, and to evaluate its applicability in clinical settings.

Methods: A scoping review was conducted using the Joanna Briggs Institute methodology. Searches were conducted in PubMed, Scopus, CINAHL Ultimate, MEDLINE Ultimate, IEEE Xplore and Wiley Online Library. A total of 136 records were initially identified, and 23 studies met the inclusion criteria. Data were analyzed and summarized narratively.

Results: The studies varied in methodology and scope, and included the use of artificial intelligence for facial, voice, and drawing-based emotion recognition, with applications in various domains. Artificial intelligence-based tools showed promising levels of accuracy, particularly in improving emotion identification, supporting early diagnosis, and informing clinical decision-making.

Conclusion: Artificial intelligence has the potential to transform pediatric healthcare by improving the identification and management of emotional states, particularly in vulnerable populations. Despite challenges, integrating technology into clinical practice is a promising strategy to promote personalized and emotional care.

Implications: By recognizing and responding to emotional needs, artificial intelligence in pediatric nursing practice can enhance the personalization of care and create therapeutic environments that are emotionally sensitive, promoting the humanization and effectiveness of interventions.

Scoping review registration: doi:10.17605/OSF.IO/NXMH7.

Introduction

Recently, the use of Artificial Intelligence (AI) in healthcare contexts has become an area of growing interest and research. According to the literature, AI is a subfield of computer science dedicated to developing systems capable of performing tasks that typically require human intelligence, such as pattern recognition, decision making, and interpretation of complex data (Berghea et al., 2024). In healthcare, the application of AI capabilities is to improve diagnostic accuracy for personalized treatments that promote efficiency in healthcare. This is particularly relevant in the pediatric context (Berghea et al., 2024).

The use of AI in pediatrics has been gaining increasing relevance, in parallel with the digital transformation of healthcare. The earliest records of AI application in pediatrics date back to 1984, with the development of the SHELP system, designed to support the diagnosis of rare metabolic disorders (Kokol et al., 2017). Since then, the field has gradually evolved until the early 2000s, when a phase of expansion began, driven by the digitalization of clinical data and the development of algorithms capable of learning from large volumes of information. According to Ganatra (2025), this evolution marked a transition from rule-based models to more flexible and autonomous approaches, such as machine learning, which enables computer systems to recognize patterns and make decisions based on previous data. In pediatric contexts, these technologies have been applied, for instance, in the early detection of diseases, the analysis of medical images, and the support of triage processes in emergency settings.

More recent developments have focused on making these technologies safer and more reliable, particularly in sensitive areas such as pediatrics, where trust in digital tools is essential to ensure ethical and responsible clinical care (Ganatra, 2025). This trajectory underpins the

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growing integration of AI into clinical practices. Recent literature illustrates the use of AI for neonatal monitoring, early diagnosis of various diseases, and optimization of pediatric treatment plans, which help reduce clinical errors and speed up the delivery of care with greater precision (Berghea et al., 2024; Li et al., 2020). An example of the application of AI in emotion recognition is the use of advanced tools to identify infant crying, which provides great benefits in understanding the emotional and physical needs of newborns. Recognition systems can analyze the sound of the cry and identify whether the baby is hungry, in pain, or scared, based on specific sound frequencies for each emotion. These tools allow parents and caregivers to respond quickly and accurately, reducing guesswork and making it easier to understand babies' signals. This increases the efficiency of care and contributes significantly to the well-being of newborns (Yasin et al., 2022).

The application of AI to emotion recognition also presented new opportunities for early intervention in pediatric healthcare. Emotional regulation is central to a child's ability to interact with others and their environment, which aligns with evolving nursing perspectives, where emotion plays a crucial role in caregiving (Souza et al., 2021). Nurses operate from an emotional standpoint, recognizing the importance of children developing tools to express and regulate emotions. This is essential in the context of care, especially during hospitalization, where nurses can support a more positive experience for children (Diogo et al., 2021).

Facial recognition algorithms, for example, help identify expressions that support the interpretation of emotions. Interactive games powered by AI can help children build emotional skills and improve self-control during hospitalization. Nonetheless, the presence and emotional support of parents remain irreplaceable in the healthy development of a child (Diogo et al., 2021). Since Florence Nightingale's time, the therapeutic role of emotions has been integral to pediatric care. Initially grounded in charity and compassion, this emotional dimension evolved into a recognized professional competency, particularly in pediatric nursing (Diogo et al., 2021). Understanding the feelings of children and families is key to creating a safe and therapeutic environment. Today, emotional care remains a core element of holistic pediatric nursing, helping promote recovery and enhance the healthcare experience (Diogo et al., 2021).

Children and adolescents may not be able to express their emotions due to cognitive, physical, or emotional limitations, which hinders their healthy development and makes it difficult to identify emotion-related problems early (Tanabe et al., 2024). Recognizing and understanding emotions is a critical nursing intervention, as it affects the balance of mind, body, and spirit (Diogo et al., 2021; Watson, 2018). Here, AI fills these gaps by providing the ability to analyze large amounts of emotional data, as the extraction of such complex emotional patterns may not be as easily captured by the naked human eye. Analyzing children's drawings is one of the most promising uses of AI in pediatric care to monitor their emotional states. For example, an AI-based mobile app was created to interpret children's emotional states through a drawing test from parents and teachers. The accuracy was around 55–79 % in recognizing emotions (Ali et al., 2022). This is one of the most valuable applications that can help in a much better recognition of emotional states to better intervene according to the child's needs.

Another important development in the application of AI in pediatric contexts is the identification of emotions in children with severe and multiple intellectual disabilities, who have difficulty expressing their feelings, making it difficult to communicate and interact with caregivers (Tanabe et al., 2024). An AI system using physiological and motion signals was able to achieve a recognition rate of 70.4 % for “negative emotions” and “non-negative emotions,” significantly higher than the rate of 48.5 % achieved by human observers (Tanabe et al., 2024). These results suggest that AI can make a valuable contribution to improving the communication and care situation of the most severely disabled children.

In addition to the above, AI has also been used to recognize emotions in children with autism spectrum disorder. AI, specifically Convolutional Neural Networks (CNN), which are systems that learn to recognize patterns in images like facial expressions, enables emotion recognition and responds to the difficulty many children have in expressing their feelings (Tanabe et al., 2024). This technology has significant benefits in therapeutic contexts, allowing for earlier and more effective interventions for children who struggle with emotional expression (Tanabe et al., 2024). In addition, AI's ability to process and analyze complex emotional data that may not be immediately apparent to healthcare professionals makes it a valuable tool for early identification of emotional and developmental challenges. Through AI-based emotion recognition, healthcare providers can increase diagnostic accuracy and provide tailored interventions, thereby improving mental health outcomes for children and adolescents (Pavez et al., 2023). These findings highlight the transformative potential of AI to reshape pediatric healthcare by improving early detection and intervention strategies (Pavez et al., 2023).

Looking ahead, AI is expected to continue expanding significantly in healthcare, particularly in pediatrics. The use of machine learning algorithms is likely to become increasingly common in areas such as personalized treatment, early clinical event prediction, and real-time triage support (Ganatra, 2025). The integration of data from multiple sources, such as medical imaging, electronic health records, and physiological signals, is also expected to enable the development of more comprehensive and accurate systems. According to Ganatra (2025), combining different types of clinical data and improving interoperability across systems may support the adoption of AI tools capable of assisting with complex clinical decisions, which is particularly relevant in pediatric contexts where emotional and subjective evaluation plays a key role.

Studies in the field of nursing (with a focus on child and adolescent care) are mostly scarce. Nevertheless, there is evidence in this field, namely in the application of AI in primary health care as a distraction strategy during vaccination (Beran et al., 2015), in the identification of emotions through the analysis of drawings (Ali et al., 2022), and in the concomitant intervention in the face of painful procedures such as blood sampling or venipuncture (Farrier et al., 2020).

In light of the above, this research question arises: “What AI technologies are currently being used for emotion recognition in pediatric contexts?”. This review aims to map the existing literature on AI applications in emotion recognition in pediatrics and to assess their applicability in clinical practice.

This review is essential to consolidate existing knowledge on this emerging topic, identify the most relevant technologies, and highlight current gaps to inform evidence-based pediatric clinical practices. Given the innovative nature of this field and the variability in study designs, technologies, and outcomes, a scoping review was selected as the most appropriate methodology. According to the Joanna Briggs Institute, this type of review is particularly suitable for mapping evidence in new and complex areas where systematic reviews may not yet be feasible (Tricco et al., 2018).

By synthesizing available evidence on AI applications in pediatric emotion recognition, this review aims to inform nursing practice. It does so by supporting the development of emotionally responsive and child-centered care strategies, guiding ethical use of AI tools, and promoting the integration of innovative technologies into everyday clinical practice.

Materials and methods

This review was developed in accordance with the Joanna Briggs Institute (JBI) methodological guidelines for scoping reviews (Tricco et al., 2018). The review included the following stages: 1) identification of the research question, 2) identification of relevant studies, 3) selection of studies, 4) data extraction, and 5) synthesis and presentation of results. The protocol was registered on the Open Science Framework platform with the registration number doi:10.17605/OSF.IO/NXMH7.

Inclusion criteria

Population: Studies involving children and adolescents (0–18 years) will be considered.

Concept: Studies that explore the application of AI for emotion recognition, including face analysis, voice recognition, text and drawing analysis, and physiological data will be considered.

Context: Studies conducted exclusively in therapeutic settings for children and adolescents will be included.

Types of studies

Primary quantitative and qualitative studies, mixed-methods studies, and gray literature (e.g., theses and dissertations) were included. Out-of-scope studies, duplicate publications, letters, editorials, and opinion pieces were excluded. No time restrictions were applied, as the aim was to cover all available evidence on the topic. The languages of inclusion were Portuguese, English, and Spanish, to ensure reliability of interpretation and analysis.

Research strategy

The research strategy was developed according to JBI guidelines, using the PCC (Population, Concept, Context) mnemonics to ensure a comprehensive and systematic search of the existing literature. The framework components and the full strategy were detailed to allow replication of the process, as shown in Tables 1 and 2.

The search was conducted in the following databases: PubMed, Scopus, CINAHL Ultimate, MEDLINE Ultimate, IEEE Xplore and Wiley Online Library using the following Boolean expression: ('artificial intelligence' OR 'AI' OR 'machine learning') AND ('emotion recognition' OR 'emotion detection' OR 'emotion analysis' OR 'emotion') AND ('pediatric' OR 'children' OR 'adolescents' OR 'youth') AND ('healthcare' OR 'health care' OR 'clinical care' OR 'health services' OR 'patient care'). The search strategy also included gray literature, conducted via Google Scholar using the same Boolean search strings and eligibility criteria applied to the indexed databases.

The preliminary search of the above databases in August 2024 did not identify any scoping reviews on the topic. The final search, conducted in July 2025, yielded a total of 136 results, using the search strategy described in Table 2.

Study selection

The selection of studies was carried out by two independent reviewers using the Rayyan platform, a dedicated online tool for screening systematic reviews. Initially, titles and abstracts were screened, followed by a full-text reading of studies considered potentially relevant to confirm their eligibility. Disagreements between reviewers were resolved by consensus or by a third reviewer. The selection of studies was presented visually using a PRISMA flowchart (Fig. 1), which is the recommended standard for reporting systematic and scoping reviews (Moher et al., 2009; Page et al., 2021).

Table 1
Framework component.

Framework Component	Criteria
Population	"pediatric" OR "children" OR "adolescents" OR "youth"
Concept	"artificial intelligence" OR "AI" OR "machine learning" AND ("emotion recognition" OR "emotional detection" OR "emotion analysis" OR "emotion")
Context	"healthcare" OR "health care" OR "clinical care" OR "health services" OR "patient care"

Table 2
Research strategy.

Database	Research strategy	Results
PubMed	("Artificial Intelligence" OR "AI" OR "Machine Learning") AND ("emotion recognition" OR "emotional detection" OR "emotion analysis" OR "emotion") AND ("pediatric" OR "children" OR "adolescents" OR "youth") AND ("healthcare" OR "health care" OR "clinical care" OR "health services" OR "patient care")	30
Scopus	ABS (("Artificial Intelligence" OR "AI" OR "Machine Learning") AND ("emotion recognition" OR "emotional detection" OR "emotion analysis" OR "emotion") AND ("pediatric" OR "children" OR "adolescents" OR "youth") AND ("healthcare" OR "health care" OR "clinical care" OR "health services" OR "patient care"))	33
IEEE Xplore	("Artificial Intelligence" OR "AI" OR "Machine Learning") AND ("emotion recognition" OR "emotional detection" OR "emotion analysis" OR "emotion") AND ("pediatric" OR "children" OR "adolescents" OR "youth") AND ("healthcare" OR "health care" OR "clinical care" OR "health services" OR "patient care")	37
Medline Ultimate	AB (("Artificial Intelligence" OR "AI" OR "Machine Learning") AND ("emotion recognition" OR "emotional detection" OR "emotion analysis" OR "emotion") AND ("pediatric" OR "children" OR "adolescents" OR "youth")) AND TX (("healthcare" OR "health care" OR "clinical care" OR "health services" OR "patient care"))	31
CINAHL Ultimate	("Artificial Intelligence" OR "AI" OR "Machine Learning") AND ("emotion recognition" OR "emotional detection" OR "emotion analysis" OR "emotion") AND ("pediatric" OR "children" OR "adolescents" OR "youth") AND ("healthcare" OR "health care" OR "clinical care" OR "health services" OR "patient care")	2
Wiley Online Library	("Artificial Intelligence" OR "AI" OR "Machine Learning") AND ("emotion recognition" OR "emotional detection" OR "emotion analysis" OR "emotion") AND ("pediatric" OR "children" OR "adolescents" OR "youth") AND ("healthcare" OR "health care" OR "clinical care" OR "health services" OR "patient care")	2

Data extraction

Data were extracted using an instrument developed following the guidelines established by JBI to ensure consistency and completeness of information (Supplementary File 1). The tool was pre-tested on a number of articles to assess its usefulness within the JBI recommended data charting approach. Data were extracted on the basis of author, year of publication, country, aim of the study, type of design, target population, type of intervention, comparator used, intervention period, evaluation method, main results and conclusions. Data were extracted independently by two reviewers. Disagreements on data selection between the two reviewers were resolved by the involvement of a third reviewer to ensure the reliability of the extracted data. This approach ensured that all relevant information was systematically and transparently analyzed in accordance with best methodological practices (Tricco et al., 2018).

Results

This review mapped the applications of AI in emotion recognition in pediatric contexts, considering 23 articles that investigated different approaches, study populations, and clinical implications (Table 3). The studies analyzed examined the use of AI in mental health assessment, interventions for children with autism spectrum disorder (ASD) and children with hearing impairments, and support strategies for emotional well-being. We conducted a synthesis of the results found, which were divided into sections (see Table 4).

AI in pediatric mental health assessment

The study by Alemu et al. (2023) used advanced AI approaches to detect the risk of suicidal ideation through a structured study protocol.

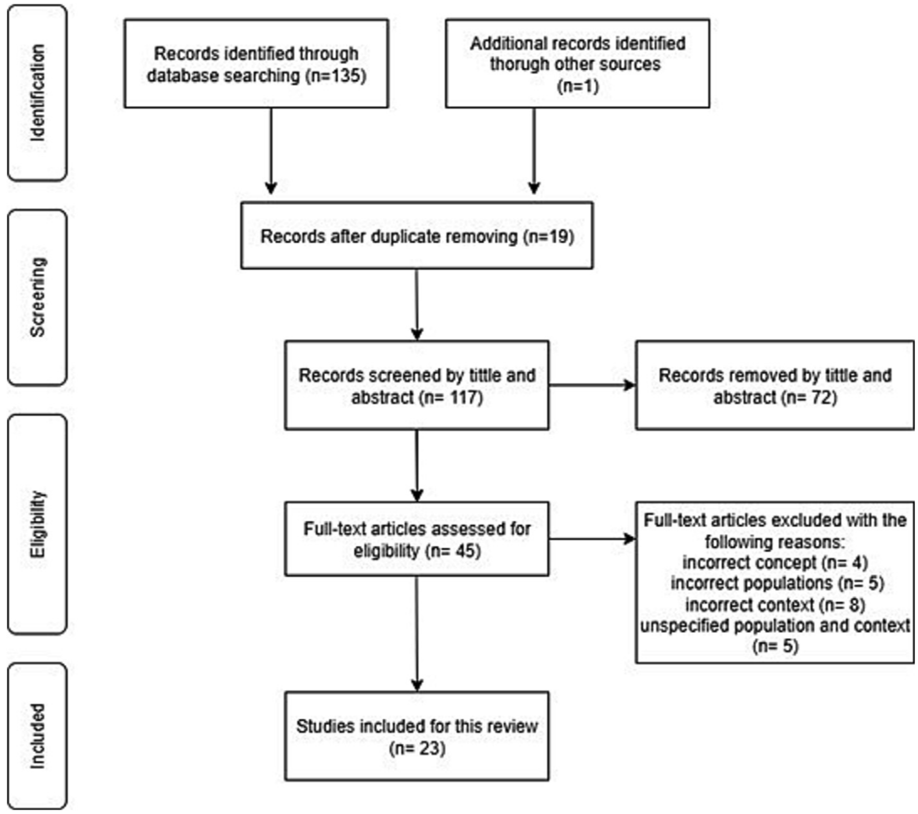

Fig. 1. PRISMA flowchart.

A probabilistic model algorithm was used to classify speech and predict the speaker's emotions. These findings underscore the importance of AI applications in clinical practice, particularly in identifying emotional distress in children and adolescents. The findings will contribute to the ongoing transformation of digital health and the advancement of collaborative mental health care practices. The algorithm has the potential to improve therapeutic outcomes by helping children and adolescents navigate the Internet digitally (Alemu et al., 2023).

Caulley et al. (2023) evaluated the use of AI to objectively quantify psychiatric severity in children and adolescents through audio analysis of therapy sessions. Deep learning models, including CNN and transform-based models, were used to detect emotions such as anger, fear, sadness, and happiness. The transform-based model achieved the best precision (86 %) and recall (79 %), suggesting that AI can be a useful tool to complement clinical assessment. This study aimed to develop and test a speech analysis algorithm to detect clinically relevant emotional distress and functional impairment in children and adolescents with diagnosable mental disorders. The protocol aimed to develop speech-emotion recognition algorithms using AI or ML that can link trauma, stress, and voice type, including disruptive speech-based features, and detect clinically relevant emotional distress and functional impairment in children and adolescents. However, challenges such as variability in therapist emotion labeling and audio data quality have been identified as limitations (Caulley et al., 2023).

Another study by Vahdati et al. (2022) reflects how, by using a supervised machine learning (ML) algorithm with a social media data network platform, they were able to identify symptoms of depression (such as sadness, moodiness, frustration, emptiness, and anxiety) in adolescents aged 12–17 years. In this study, several depression detection methods were identified, including multimodal approaches, which combine data from different sources, such as text, audio, and images, to form a more complete understanding of emotional states. Other methods include Depression Dictionary Learning, which uses predefined emotional keywords to recognize depressive expressions in text, naive bayesian learning, a simple and fast probabilistic model that estimates the likelihood of depression based on word patterns, and multiple social network learning, which analyzes behavior across different social media platforms to detect emotional changes. Additionally, techniques such as Wasserstein dictionary learning help decompose complex emotional signals into simpler components to aid analysis, Random Forest, an ensemble method that uses multiple decision trees to improve the accuracy of predictions, and Support Vector Machines (SVM), which identify patterns in data to distinguish between depressive and non-depressive content.

The authors of this review concluded that ML algorithms show potential in detecting depression through analysis of text and images from social media, although further research is still needed in this field (Vahdati et al., 2022).

The study by Hatano and Inoue (2022) investigated the use of AI to recognize children's emotions from speech in a daycare setting. CNN algorithms were applied to the analysis of audio spectrograms to identify emotions such as happiness, anger, and a neutral state in children aged 5 to 6 years. The results showed an accuracy between 40 % and 60 %, with the model performing better in classifying positive and neutral emotions, but having difficulty in detecting negative emotions such as anger (Hatano & Inoue, 2022).

In addition to being used to recognize children's emotions, AI is also being applied to their caregivers to assess the emotional impact of interactions and predict potential risks to children's mental health. Mirheidari et al. (2024) explored the use of ML algorithms to classify the level of emotional "warmth" expressed by caregivers in five-minute speech samples. The analysis used automatic speech recognition (ASR) techniques, acoustic and textual feature extraction, and models such as logistic regression, support vector machine, random forest, and multilayer perceptron. This study demonstrated the potential of AI to indirectly assess children's emotional states by analyzing

Table 3
Data synthesis.

Title	Autor	Study Design	AI modality	Population	Reported performance metrics
A machine learning-based depression detection on social media platforms for adolescents: A work in progress narrative review	Farahnaz Vahdati, Amara Atif, Morteza Saberi	This is a Narrative Review	Machine learning algorithms, such as logistic regression model, k-means model, multimodal depressive dictionary learning, Random Forest, Naive Bayesian learning, Multiple social networking learning, and Wasserstein dictionary learning and text data from social media (Facebook, Instagram, Twitter and Yotube)	1500 adolescents particularly active on social media platforms, and more than 300.000 posts	F1-scores reached up to 85 % with multimodal approaches on Twitter data. Random Forest models using Instagram features achieved an F1 of 0.647, while logistic regression on survey data yielded 72.3 % accuracy. Ensemble methods and boosting algorithms attained accuracies up to 87 %
Affect-Learn: An IoT-based Affective Learning Framework for Special Education	Ghazal Yadav, Prabha Sundaravadivel, Lokeshwar Kesavan	This is a proof-of-concept experimental study	Mobile application that uses a facial emotion recognition system; Affective computing (also known as artificial emotional intelligence) It is also used the apliccation of the Internet of Things affective framework and support vector machine-based models to check the vitals	Children diagnosed with ADHD, initial validation conducted with 3 volunteers.	The Support Vector Machine model achieved 90.23 % accuracy when matching user input with its predictions
AI-Based Communication Tool for High-Functioning Autistic Children	Farah Ossama, Fatmah Issam, Menna Hesham, Menna Kamel, Yumna Hamdy, Merna Bibars, Ibrahim Sadek	This is a quantitative study based of a prototype technological intervention	Facial Emotional Recognition system within a mobile gaming App. They used other framework for the app (Google speech recognition, Google cloud)	The study target high-functioning autistic children, specifically Arabic speakers, although it is does not report a formal clinical trial	The autors experimented with several pretrained models. The MobileNetV2 had the best results (an accuracy of 83.97 % and a precision of 80.40 %)
Artificial Intelligence-Based Mobile Application for Sensing Children EmotionThrough Drawings	Nashva Ali, Alaa Abd-Alrazaq, Zubair Shah, Mohannad Alajlani,Tanvir Alam, Mowafa Househ	This is a proof-of-concept in applied artificial intelligence, quantitative study	For the development of an AI based Emotion Sensing Recognition App it was used three pre-trained models (ResNet18, ResNet34, and ResNet50) in the four experiments. The application included image augmentation (rotation, flipping, zooming, etc.) and heatmap visualization of layer activations	623 drawings were analyzed: 102 drawings collected from a local school in Doha, and 521 drawings collected online from Google and Instagram	The ResNet50 convolutional neural network model had the best results for accuracy (79 %), sensitivity (86 %) and precision (74 %)
Automatic detection of expressed emotion from Five-Minute Speech Samples: Challenges and opportunities	Bahman Mirheidari; André Bittar; Nicholas Cummins; Johnny Downs; Helen L. Fisher; Heidi Christensen	This is a cohort study	Four machine learning classifiers were tested: Logistic Regression, Support Vector Machine, Random Forest, and Multi-Layer Perceptron. It was also used a Speech Emotion Recognition (SER) combining acoustic features (via openSMILE) and text features	52 audio recordings from 1116 families with 5 years old twins were selected for this study	The best performance was achieved using Random Forest with the acoustic-only IS13-CPE features, reaching an F1-score of 64.3 %. For text-only features, the highest F1-score of 60.4 % was obtained using SVM with BERT embeddings.
Child Facial Recognition Technology in Early Assist and Intervention in Hospital Outpatient Clinics	Li Na; Yihan Wang; Li Xinying	This is na experimental study conducted in a pediatric outpatient clinic.	Child Facial Expression Recognition and Facial Recognition using Artificial Intelligence with Convolutional Neural Networks and Recurrent Neural Networks.	50 children, treated in a hospital in F Province, China, between February and June 2023.	High accuracy in detecting facial expressions associated with health conditions (specific percentages not reported)
Childcare Emotion Recognition Support Solved by Machine Learning	Masaki Hatano, Shota Fuji, Hayato Fujita, Yu Hagiwara, Yutarou Tsubaki, Kokoro Maekawa, Kanata Ito, Kiyomasa Okuda, Masato Nishiyama, Supervisor Kiyomi Asai	This is na experimental study involving the development and testing of a machine learning model in a real-world daycare setting	Speech Emotion Recognition using Convolutional Neural Networksto analyze audio spectrograms. Combined with deep learning techniques for feature extraction and emotion classification.	17 children aged 5 to 6 years, enrolled in a daycare center in Kanagawa Prefecture, Japan	Accuracy ranged from 40 % to 60 %, depending on the emotion detected The best performance was for joy and neutral states with a sruggled with detecting anger, likely due to dataset imbalance.
Computer Vision for detection of body expressions of children with cerebral palsy	Cristhian Rosales, Luis Jácome, Jorge Carrión, Carlos Jaramillo, Mario Palma	This is a quantitative case study	The machine learning techniques used was the AdaBoost boosting algorithm with Haar cascade classifier. The prototype system used OpenCV (version 3.0.0) in Python (v2.7.11).	1 child, 8 years old with ataxic cerebral palsy	These results suggest the particularly effectiveness for detecting fear (88 % accuracy, 97 % precision) and hunger (82 % accuracy, 90 % sensitivity).

(continued on next page)

Table 3 (*continued*)

Title	Autor	Study Design	AI modality	Population	Reported performance metrics
Detecting Clinically Relevant Emotional Distress and Functional Impairment in Children and Adolescents: Protocol for an Automated Speech Analysis Algorithm Development Study	Yared Alemu; Hua Chen; Chenghao Duan; Desmond Caulley; Rosa I Arriaga; Emre Sezgin	This is a quantitative experimental study, specifically designed as a prospective protocol	Machine Learning Models utilized by the authors: Gaussian Mixture Model and Recurrent Neural Network and Long Short-Term Memory.	Children aged 5–18 years	Both machine learning are evenly matched, with na accuracy of 79,15 % from Gaussian Mixture Model and 79,6 % from Recurrent Neural Network and Long Short-Term Memory.
Improved Digital Therapy for Developmental Pediatrics Using Domain-Specific Artificial Intelligence: Machine Learning Study	Peter Washington; Haik Kalantarian; John Kent; Arman Husic; Aaron Kline; Emilie Leblanc; Cathy Hou; Onur Cezmi Mutlu; Kaitlyn Dunlap; Yordan Penev; Maya Varma; Nate Tyler Stockham; Brianna Chrisman; Kelley Paskov; Min Woo Sun; Jae-Yoon Jung; Catalin Voss; Nick Haber; Dennis Paul Wall	This is a quantitative experimental study	The machine learning that were used are: Child Affective Facial Expression, convolutional neural network (ResNet-152) It was also used a learning algorithm on a rating platform named HollywoodSquares.	456 unique children, who contributed to the dataset by playing a therapeutic mobile game called *GuessWhat*	The Child Affective Facial Expression had a 66.9 % balanced accuracy and 67.4 % F1-score
Designing a Smart Virtual Environment for Autism Spectrum Disorder Detection	Estephanos Mekbib, Yan Huang, Chao Mei, and Yi (Joy) Li	This is a quantitative study	Smart Virtual reality environment gaming system with affective computing - motion recognition models based on physiological signals and in-game performance	In the preliminary phase, there were 3 individual (one autistic individual and two neurotypical individuals (control).	Unspecified, although the study suggests that the results via preliminary surveys justified that their objetive were accomplished.
Effect of wearable digital intervention for improving socialization in children with autism spectrum disorder a randomized clinical trial	Catalin Voss, Jessey Schwartz, Jena Daniels, Aaron Kline, Nick Haber, Peter Washington, Qandeel Tariq, Thomas N. Robinson, Manisha Desai, Jennifer M. Phillips, Carl Feinstein, Terry Winograd, and Dennis P. Wall.	This is a randomized controlled trial (RCT) design with participants assigned to treatment and control groups to evaluate the efficacy of a wearable digital intervention.	The Superpower Glass is a wearable device (Google Glass) which employs machine learning algorithms for real-time emotion recognition with the help of a smarthphone app.	71 children (6–12 years old) diagnosed with Autism Spectrum Disorder, with 40 children randomized to the treatment group	Children who received the intervention demonstrated statistically significant gains on the Vineland Adaptive Behavior Scales socialization subscale compared to the treatment-as-usual control group, with a mean treatment effect of 4.58 ($SD = 1.62$); $P = .005$. Although positive mean effects were also observed across the three other primary outcome measures, these did not reach the adjusted significance threshold of $P = .0125$
Experience with an Affective Robot Assistant for Children with Hearing Disabilities	Pinar Uluer, Hatice Kose, Elif Gumuslu, Duygun Erol Barkana	This is na experimental, within-subject user study combining quantitative and qualitative methods.	Machine learning systems: Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest (RF) and Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks with gamified setups.	16 children with 5–8 years old, diagnosed with hearing disabilities and using either cochlear implants ($n = 10$) or hearing aids ($n = 6$)	Accuracy reached up to 99.5 % for distinguishing robot versus tablet and robot versus conventional setups. In multi-class classification tasks the models achieved up to 85.7 % accuracy, though with slightly reduced F1-scores due to class imbalance. In the robot condition, binary classification of pleasant vs unpleasant emotions reached an accuracy of 79.2 %, while neutral vs unpleasant achieved 68.2 %.
Objectively Quantifying Pediatric Psychiatric Severity Using Artificial Intelligence, Voice Recognition Technology, and Universal Emotions: Pilot Study for Artificial Intelligence-Enabled Innovation to Address Youth Mental Health Crisis	Desmond Caulley; Yared Alemu; Sedara Burson; Elizabeth Cárdenas Bautista; Girmaw Abebe Tadesse; Christopher Kottmyer; Laurent Aeschbach; Bryan Cheungvivatpant; Emre Sezgin	This is a multisite pilot study employing a data-driven experimental design	Convolutional Neural Networks for the prediction of emotional intensity and transformer-based models (such as Wav2Vec 2.0 and Speechbrain) for detecting specific emotions. Data were collected via a mobile app during therapeutic sessions, with over 1000 voice samples annotated by four expert therapists.	Children and adolescents (5 to 18 years old) recruited from 3 mental health care centers	The best-performing transformer-based emotion-specific model achieved a test-set precision of 86 % and recall of 79 % for binary emotional intensity classification. The generalized CNN model achieved 83 % precision and recall across all emotions

Table 3 (*continued*)

Title	Autor	Study Design	AI modality	Population	Reported performance metrics
Robot-Based Intervention for Children With Autism Spectrum Disorder: A Systematic Literature Review	Katrin D. Bartl-Pokorny, Małgorzata Pykała, Pinar Uluer, Duygun Erol Barkana, Alice Baird, Hatice Kose, Tatjana Zorcec, Ben Robins, Björn W. Schuller, and Agnieszka Landowska	This is a Systematic Literature Review conducted according to PRISMA guidelines	The studies reviewed employed a range of AI modalities integrated into robotic platforms. These included automated emotion recognition systems, affective loop mechanisms, and behavioral adaptation models. Robots such as NAO, ZECA, Darwin-Mini, and others used preprogrammed affective behaviors or multimodal sensor data to recognize or express emotions. While the AI methods varied across studies, key techniques involved machine learning-driven emotion classification, gesture recognition, and engagement tracking, occasionally supported by RGB-D sensors and wearable physiological sensors.	The review included 50 original articles with 892 participants. Of those, 570 were children with Autism Spectrum Disorder and 322 were typically developing participants.	Robots such as NAO and ZECA were the most commonly used platforms due to their expressive and humanoid features. The most trained skill was recognition of basic emotions, addressed in 19 studies and commonly targeted emotions included happiness, sadness, fear, and anger.
The ASC-Inclusion Perceptual Serious Gaming Platform for Autistic Children	Erik Marchi, Bj¨orn Schuller, Alice Baird, Simon Baron-Cohen, Amandine Lassalle, Helen O'Reilly, Delia Pigat, Peter Robinson, Ian Davies, Tadas Baltru˘saitis, Andra Adams, Marwa Mahmoud, Ofer Golan, Shimrit Fridenson-Hayo, Shahar Tal, Shai Newman, Noga Meir-Goren, Antonio Camurri, Stefano Piana, Sven B¨olte, Metin Sezgin, Nese Alyuz, Agnieszka Rynkiewicz, and Aurelie Baranger	This is na intervention study with quasi-experimental elements, combining quantitative and qualitative (mixed) methods	Facial expression recognition using the OpenFace toolkit, Voice emotion analysis using openSMILE and Support Vector Machines and Body gesture analysis based on 3D skeleton data and biomechanical descriptors, also using Support Vector Machines	The review included 99 children with Autism Spectrum Condition, aged 5 to 10 years	The study demonstrated high efficacy and accuracy in enhancing emotion recognition in children with ASC. Significant improvements were observed post-intervention, with large effect sizes for body gestures ($\eta^2 = 0.51$), and moderate for voice ($\eta^2 = 0.26$) and face ($\eta^2 = 0.24$). A strong correlation ($r = 0.64$) was found between in-game performance and TEC scores. Vocal feedback reached 65 % accuracy overall, with pitch-related feedback achieving up to 70 %
Toward Collective Intelligence for Fighting Obesity	Ivor D. Addo, Sheikh I. Ahamed, William C. Chu	This is a exploratory, developmental prototype, proof-of-concept study	Supervised learning machines(Naïve Bayes classification, Spoken Language Understanding for real-time interpretation of user intent during child-robot dialogue and Multimodal emotion recognition, combining facial expressions, voice tone, and gestures to enhance human-robot interaction. It was also used de NAO humanoid robot, a Kinnect a computer, an Ipad Smart Refrigerator. The user was connected to a prototype wrist band and na mobile app.	15 children (8 boys, 7 girls) aged between 3 and 19	Preliminary results show that 60 % of participants would accept robot interaction at home, and 80 % would be willing to use it in a lab setting. The childrenshowed higher engagement when the robot expressed social cues and believable behavior
Video-based Continuous Affect Recognition of Children with Autism Spectrum Disorder Using Deep Learning	Mamadou Dia, Ghazaleh Khodabandelou, Aznul Qalid Md Sabri, and Alice Othmani	This is na observational, data-driven study with computational modeling experimental study	Video Affect Recognition, Convolutional neural networks and transformer-based architectures, particularly a custom version of the Perceiver model, a CNN-Wasserstein GAN, and Inception V3. Various dataset including the SSBD dataset (video clips of children with ASD exhibiting self-stimulatory behaviors),	Children diagnosed with Autism Spectrum Disorder.	Ther Perceiver model achieved an accuracy of approximately 74.5 %, with F1-scores and recall around 73 %. In lab-controlled datasets, models such as Inception V3 and WGAN reached high levels of classification and regression performance, with F1-scores up to 97.7 % and CCC (concordance correlation coefficient) values between 0.357 and 0.448 for affect

(continued on next page)

Table 3 (*continued*)

Title	Autor	Study Design	AI modality	Population	Reported performance metrics
			AffectNet, IEMOCAP, and CK +. Facial images were pre-processed using Haar-cascade filters.		prediction. In uncontrolled, real-world conditions, performance decreased moderately, with CCC values peaking at 0.661 for valence and 0.513 for arousal, reflecting the challenge of generalization in less structured environments.
Automated Speech Recognition System to Detect Babies' Feelings through Feature Analysis	Sana Yasin, Umar Draz, Tariq Ali, Kashaf Shahid, Amna Abid, Rukhsana Bibi, Muhammad Irfan, Mohammed A. Huneif, Sultan A. Almedhesh, Seham M. Alqahtani, Alqahtani Abdulwahab, Mohammed Jamaan Alzahrani, Dhafer Batti Alshehri, Alshehri Ali Abdullah and Saifur Rahman	This is a quantitative study using a supervised machine learning experimental design	Automatic speech recognition (ASR) combined with Audio-based emotion recognition using machine learning. The system extracted acoustic features (e.g., Mel-Frequency Cepstral Coefficients, pitch, energy) from baby cries and applied classifiers to detect emotional states.	Infants up to 6 months old.	Accuracy rates by emotional category: Hunger – 98 %, Pain – 70 %, Fear – 75 %, Happiness – 85 %.
Identifying Children With Autism Spectrum Disorder via Transformer-Based Representation Learning From Dynamic Facial Cues	Chen Xia; Hexu Chen; Junwei Han; Dingwen Zhang; Kuan Li	This is a quantitative experimental study	Leveraging advanced deep learning techniques such as the Vision Transformer and the Longformer, the model extracts global facial features from individual video frames and analyzes temporal correlations across sequences to detect atypical patterns associated with Autism Spectrum Disorder	Children aged 2 to 8 years	Results demonstrated high accuracy in distinguishing between Autism Spectrum Disorder and typically developing children using only short facial videos recorded in naturalistic settings, but not specified
AI-Powered Autism Detection in Children from Images Beyond Human Perception	Harish M; A. Devi; Divya M; Shanmugalakshmi M	This is a quantitative experimental study	Convolutional Neural Networks to analyze micro-expressions, eye gaze, and facial asymmetry that may be imperceptible to the human eye.	Children with Autism Spectrum Disorder and neurotypical children	The new system demonstrates a notable improvement over its predecessor, achieving high scores in various performance metrics: a 94 % recall rate, 91 % precision, 92 % F1-score, and 92 % accuracy.
Enhancing ADHD Diagnostic Assessments with Virtual Reality integrated with Biofeedback and Artificial Intelligence	Anmol Garg, Sayed Mohsin Reza, Dara Babinski	This is a quantitative experimental study	Virtual Reality, biofeedback, and Artificial Intelligence; Convolutional Neural Networks and Large Language Models	Target population: children and adolescents with ADHD.	Preliminary results show significant physiological changes during anxiety-inducing tasks, reinforcing the applicability of biofeedback in identifying emotional states associated with attention-deficit/hyperactivity disorder. Sensitivity 0.80, Specificity 1.00; strong correlation with rating scales
Facial Emotion Detection in Autistic Children: A Deep Learning Approach	Madhusoodanan, D., Sagar, N., Vismaya, R., Santhosh, H., Palaniswamy, S.	This is a quantitative experimental study	Internet of Things cloud pipeline for real-time facial emotion detection - Convolutional Neural Networks, MobileNetV2, Inception-ResNetV2, U-Net autoencoder, Xception baseline	Autistic children	While showed promising results with moderate overall accuracy (61 %) in detecting emotions like “joy” (F1-score = 0.79), it underperformed in recognizing subtler expressions such as “anger” and “fear” due to class imbalance.

Many of the included studies exhibit substantial statistical limitations. Small sample sizes limit statistical power and undermine the generalizability of findings. Furthermore, several studies did not incorporate validation cohorts or external datasets, raising concerns about overfitting and model robustness. While cross-validation techniques were employed, these were not always clearly described or adequately controlled for variance. In addition, class imbalance in training data was frequently observed but inconsistently addressed through appropriate correction methods such as resampling or cost-sensitive algorithms.

caregivers' speech, suggesting new approaches for early detection of risk factors for pediatric mental disorders. However, the authors highlight challenges such as variability in recording quality and class imbalance in emotional distributions, indicating the need for model refinement and expansion of the datasets used (Mirheidari et al., 2024).

AI in school and community emotion recognition

The study by Yadav et al. (2020) focused on improving the learning outcomes of students with special educational needs (such as attention deficit hyperactivity disorder or anxiety) through the application of an

Table 4
Application matrix of AI tools in pediatric emotion recognition.

	Emotional Assessment	Therapeutic Intervention	Clinical Decision Support	Communication Support
Facial Recognition	✓		✓	
Voice Recognition	✓		✓	
Drawing Analysis	✓		✓	
Social Robots		✓		✓
Mobile Apps	✓	✓		✓
Serious Games		✓		
Virtual Environments	✓	✓		
Gesture Recognition (Sensors)		✓		✓

Internet of Things-based affective learning framework. An affective computing system is an artificial emotional intelligence that can help detect, interpret, and stimulate emotions. By analyzing sensors in the children's wearables, it was possible to monitor vital signs and biometric data. Later, with the interpretation of an AI and the construction of an SVM network, they will be able to understand the emotional state and customize an intervention plan. The study does not provide direct, clear results in emotion recognition. However, the indirect results refer to the recognition of happiness, relaxation, peace, calm, fatigue, laziness, sadness, fear, anger, tension, alertness, and excitement (Yadav et al., 2020).

A recent study proposed an innovative system to enhance the diagnosis of Attention-Deficit/Hyperactivity Disorder (ADHD) through the integration of virtual reality, biofeedback, and AI. The immersive virtual environment simulates controlled scenarios (such as classrooms) and collects real-time behavioral, physiological, and emotional data using sensors. Utilizing Convolutional Neural Networks and Large Language Models, the system analyzes the captured signals and generates personalized reports on attention and impulsivity patterns. The authors highlight the potential of this approach to offer more objective, personalized, and ecologically valid assessments, especially in pediatric populations. Preliminary results show significant physiological changes during anxiety-inducing tasks, reinforcing the applicability of biofeedback in identifying emotional states associated with ADHD. This model represents a promising advancement in the development of more sensitive and behaviorally adapted diagnostic tools for children (Garg et al., 2025).

AI in behavioral interventions

Addo et al. (2013) explored the use of a humanoid robot as a health coach for childhood obesity interventions. Using ML and human-robot interaction, the intervention aimed to modify behaviors related to diet and physical activity. Preliminary results showed that 60 % of children would accept interacting with the robot at home and 80 % would accept using it in the laboratory, suggesting that the technology can be well received as a support for behavior change (Addo et al., 2013).

The application of AI for facial recognition in pediatrics has shown significant progress in the early detection of disease, as demonstrated by Na et al. (2024). However, the authors highlight that the variability in the quality of facial images and the need for a more representative database are challenges in ensuring the reliability of the models. In addition, the heterogeneity of facial expressions across age groups and cultures may affect the accuracy of the analysis. These findings highlight the importance of investing in improving algorithms and expanding the database so that the technology can be effectively integrated into clinical settings. Future research should consider adapting the models to different populations and validating the technology in different pediatric care scenarios (Na et al., 2024).

The study by Yasin et al. (2022) proposed an ASR system aimed at identifying the emotional states of infants through acoustic analysis of their cries. Recognizing that newborns and infants up to 6 months of age lack verbal means of communication. The study addresses a critical gap in non-clinical methods for interpreting audio signals associated with physiological and emotional states such as pain, hunger, fear, and contentment. The system demonstrated encouraging levels of accuracy in detecting various emotional responses, achieving 98 % accuracy for hunger, 85 % for happiness, 75 % for fear, and 70 % for pain. The developed application is capable of real-time analysis of infant cries and outputs the most likely emotional cause in textual format. Statistical analyses of the extracted acoustic features support the robustness and reliability of the classification, reinforcing the validity of the frequency-based differentiation of emotional states. The authors conclude that the proposed system represents a noteworthy innovation at the intersection of AI and neonatal care, providing an objective and accessible tool for interpreting infant vocal expressions. The findings highlight the potential of machine learning technologies to enhance nonverbal communication, with significant implications for both clinical settings and home care (Yasin et al., 2022).

Social robots for children with ASD

The review by Bartl-Pokorny et al. (2021) identified 50 studies on the use of robots to promote social interaction and emotion recognition in children with ASD. The most commonly used robots were NAO and ZECA - Zeno Engaging Children with Autism - which were used to train skills such as emotion recognition, social interaction, and emotional control. The studies showed that children with ASD improved their ability to recognize basic emotions (happiness, sadness, fear and anger) and developed greater social engagement. However, challenges such as the lack of standardization in the assessments and the predominance of male participants have been identified as limitations (Bartl-Pokorny et al., 2021).Thus, the ability of technological systems such as robots is essential for socialization.

In the study conducted by Voss et al. (2019) at Stanford University Medical School, the efficacy of Superpower Glass, an AI driven wearable behavioral intervention, was evaluated to improve social outcomes in children aged 6 to 12 years with a diagnosis of ASD. This study was the first randomized clinical trial to demonstrate the efficacy of a wearable digital intervention for improving social behavior in children with ASD. It highlights the potential of digital in-home therapy to improve upon the current standard of care (Voss et al., 2019).

AI for emotion recognition in ASD

The study by Dia et al. (2024) developed a platform for continuous monitoring of affect in children with ASD, using deep learning to classify levels of excitement (arousal) and pleasantness of emotions (valence) in videos. The Inception v3 model, specifically tuned for ASD data, performed best at predicting emotion. The research highlighted that models trained only on data from neurotypical children showed lower accuracy, highlighting the importance of specialized databases to advance emotion recognition in children with ASD (Dia et al., 2024).

In another study, Ossama et al. (2023) presented a possible solution for children with ASD to improve their interaction within their family and community. They proposed a high-functioning Arabic-speaking AI-based communication tool based on facial emotional recognition system and a mobile serious game to communicate, understand and express emotions. This game app was developed in collaboration with Google's free cloud platform and Google speech recognition. The app offered four games based on therapeutic techniques selected by therapists in consultation with ASD specialists: "audio stories", the child listens to a story and rearranges the sequence of actions from the story heard; "act out the emotion", the child spins a wheel of emotions and has to imitate the selected emotion; "match emotion with related objects", the child has to match a color and a photo with an emotion; and "what are you feeling?", the child is presented with a scene in which he has to choose the right answer of what he is supposed to feel. The following emotions are present in the data: neutral, anger, disgust, fear, happiness, sadness, surprise, and contempt. The game system achieved significant accuracy in emotion recognition, and the games developed were designed to help practice social scenarios with a focus on promoting community interaction. The authors also reported the development of a dashboard designed to allow healthcare professionals and therapists to individually monitor children with ASD (Ossama et al., 2023).

The study by Xia et al. (2025) presented an innovative model for detecting emotional and behavioral markers of ASD in children using dynamic facial video analysis. Leveraging advanced deep learning techniques such as the Vision Transformer and the Longformer, the model extracts global facial features from individual video frames and analyzes temporal correlations across sequences to detect atypical patterns associated with ASD. The research included 146 children aged 2 to 8 in computer-based eye-tracking experiments and 76 additional children in smartphone-based tests. Results demonstrated high accuracy in distinguishing between ASD and typically developing children using only short facial videos recorded in naturalistic settings. This approach highlights the potential of AI in facial-based emotion recognition and supports the development of accessible, non-invasive, and scalable tools for early ASD screening, particularly valuable in low-resource clinical settings (Xia et al., 2025).

Harish et al. (2025) introduced a deep learning model for the early detection of ASD through static facial image analysis. Unlike traditional diagnostic methods that rely on behavioral observation and clinical expertise, which are often subjective and time-consuming, this model employs CNNs to analyze micro-expressions, eye gaze, and facial asymmetry that may be imperceptible to the human eye. The system achieved impressive performance, with 92 % accuracy, 94 % recall, and 91 % precision, outperforming traditional tools in both speed and accuracy. The study highlights the model's robustness across different demographics and its potential for scalability in community settings such as schools and primary healthcare. It supports automated, objective, and cost-effective screening, offering a promising complement to existing clinical methods for earlier and more reliable ASD intervention (Harish et al., 2025).

The study by Madhusoodanan et al. (2025) also proposed a lightweight deep learning model, based on the MobileNetV2 architecture, for real-time facial emotion recognition in autistic children. Trained on a dataset specifically curated for this population, the model classified six basic emotions (joy, sadness, surprise, anger, fear, and neutral). Despite achieving a moderate overall accuracy (61 %), performance varied significantly across categories: the model performed well in detecting "joy" (F1-score = 0.79), but showed poor accuracy for "anger" and "fear" (F1-score = 0.00), primarily due to class imbalance and subjectivity in emotion labeling. The macro F1-score (0.26) reflects the limited generalizability across emotional states. Still, the authors highlight the model's feasibility for use in assistive, emotion-aware technologies aimed at improving socio-emotional interaction in autistic children.

Virtual environments and drawings in emotion recognition

In a 2021 study, the research topic in human-computer interaction was the ability of machines to recognize certain emotional patterns in humans. ASD is a developmental disorder that affects communication and behavior. Symptoms of ASD include difficulties with social communication and interaction. The environment includes any single or combined methods such as visual exposure, such as pictures, video, 3-D, or virtual reality (VR), and audio exposure (affective sounds or music) to induce the user's emotions. In this study, Mekbib et al. (2021) proposed a VR game system that uses response, stressor mini-game to detect different emotional reactivity patterns and dynamically change the game according to the current emotional state. The goal is to develop a VR system with real-time feedback to support early screening and diagnosis of ASD, using a virtual environment in the treatment of mental disorders. Research on mental disorders and the use of VR to induce emotional responses: technologies for ASD, emotion recognition for ASD detection, affective games using VR. AI technologies applied to emotion recognition in pediatrics allow for the understanding of the child's emotional experience, the interpretation of their emotions, and the perception of the therapeutic environment (Mekbib et al., 2021).

Ali et al. (2022) studied the use of AI to assess children's emotions through drawings. The authors had two data sources: a primary one, where they collected 102 drawings from a school in Doha; the second was online, where they collected 521 drawings through Google and Instagram. The analysis started with the help of an art therapist, who suggested having only two emotional classifications: the positive emotions and the negative emotions. The positive emotions included happiness, hope, joy, excitement, and "energy," while the negative emotions included anger, sadness, fear, abuse, hate, and disappointment. The authors developed an AI-based emotion recognition application to help parents and teachers understand children's emotions by analyzing their drawings, and thereby develop strategies to promote mentoring and guidance according to their emotions. The deep learning model classifies the drawings into positive or negative emotions. Despite the accuracy in experiments ranging from 55 % to 79 % and the potential to identify emotions in children, the Emotion Sensing Recognition App and the underlying algorithm need to improve their accuracy through training (Ali et al., 2022).

Serious games for emotional development

The Autism Spectrum Condition (ASC) Inclusion platform evaluated by Marchi et al. (2019) used serious games to help children with ASD recognize and express emotions through facial expressions, voice, and body gestures. The study, which was conducted in a variety of ways, showed significant improvements in emotion recognition, particularly in body language. Controlled trials in Sweden and Israel showed that children who used the platform had better outcomes than those who received conventional therapy. These findings reinforce the potential of AI in neurodevelopmental rehabilitation (Marchi et al., 2019).

A study by Rosales et al. (2017) explored the use of computer vision and machine learning to detect body expressions in children with cerebral palsy, with the goal of facilitating communication with caregivers and medical professionals. The system used cameras to capture body patterns and a mobile application to alert caregivers to specific needs such as headaches, happiness, hunger, fear, and recreation. The prototype demonstrated high accuracy in detecting emotional and physiological states, with success rates ranging from 75 % to 88 %. The research suggests that this technology could improve the care and quality of life for children with motor and communication difficulties by promoting a more responsive and personalized approach to child care. However, the authors emphasize that the study was conducted with only one participant, highlighting the need to expand the sample and optimize the algorithms to increase the generalizability of the results (Rosales et al., 2017).

In another study, Washington et al. (2022) aimed to improve the accuracy of emotion classification in children, especially those with developmental disorders such as autism. To accomplish this, the researchers developed a strategy to optimize the coding and labeling of children's emotional images to make recognition models more effective for this population. The research involved the development of a mobile game (Guesswhat) designed to gamify the collection of videos of children expressing emotion, and a neural labeling interface (HollywoodSquares) used to more accurately score and classify these expressions. This resulted in the creation of a database. The classifier achieved 66.9 % balanced accuracy and 67.4 % F1 on the entire Child Affective Facial Expression (CAFE), as well as 79.1 % balanced accuracy and 78 % F1 on CAFE Subset A, a subset containing at least 60 % human agreement on emotion labels. With this dramatically expanded pediatric emotion-centric database, we trained a computer vision CNN classifier on happy, sad, surprised, fearful, angry, disgusted, and neutral expressions produced by children (Washington et al., 2022).

Affective robots for hearing-impaired children

A study by Uluer et al. (2023) demonstrated an enhanced robotic system that demonstrated emotional recognition capabilities in individuals with hearing impairments. It is observed that positive and negative emotions in children are more distinguishable when interacting with a robot than in other settings. The results show that the signals collected during the tests can be successfully separated, and the positive and negative emotions of children can be better distinguished when they interact with the robot than in the other two setups. The robot can stimulate emotions in children, leading to differences in their physiological signals and learning process. Through this application, children's emotions during interaction with the robot can be understood. It is also observed that children enjoy interacting with the robot and perceive it as intelligent and funny. Roborehad is an assistive robotic system with an affective module for children with hearing impairments. The system has been designed and developed for audiometric testing and rehabilitation of children in clinical settings. It includes the social robot Pepper, a tablet, a specially designed interface for children's verbal and non-verbal interaction with the robot gamification of the tests, a sensory set, and an emotion recognition module based on machine learning (Uluer et al., 2023).

Summary of applications

To visually synthesize the findings of this scoping review, we developed a graphical summary in the form of an application matrix. This matrix maps the primary functions of each AI tool identified across the included studies, distributed across four domains: *Emotional Assessment*, *Therapeutic Intervention*, *Clinical Decision Support*, and *Communication Support*.

This matrix illustrates the breadth and variability of AI applications, highlighting the multifunctionality of some technologies, such as mobile apps and serious games, as well as the predominant use of tools like facial and voice recognition for emotional assessment. This graphical summary facilitates a clearer understanding of the practical relevance of AI tools in clinical pediatric settings.

Discussion

AI-powered devices and platforms are increasingly present in healthcare, and pediatrics is no exception. This review shows that AI tools are being applied across multiple domains, including emotional assessment, therapeutic intervention, clinical decision support, and communication support. Particularly in pediatric mental health, multimodal approaches have proven essential to capturing children's emotional experiences. Facial and voice analysis are widely explored for detecting distress (Alemu et al., 2023; Caulley et al., 2023), but broader cues remain critical: combining facial and postural information improves recognition of emotions such as fear and anger (Filntisis et al., 2019), while developmental variability and cultural factors limit generalizability (Hatano & Inoue, 2022; Na et al., 2024). These findings highlighted the need for models that are both multimodal and developmentally sensitive, ensuring nuanced recognition of psychological distress.

Applications in neurodevelopmental contexts illustrate both the promise and challenges of AI. Interventions using wearables and socially assistive robots have been shown to foster emotion recognition, engagement, and physiological awareness (Uluer et al., 2023; Voss et al., 2019), yet difficulties in detecting negative emotions such as anger persisted due to class imbalance in datasets (Hatano & Inoue, 2022). Similarly, digitally enhanced environments enable children with ASD to recognize and express emotions over time (Washington et al., 2022), while fusion-based wearable platforms extend communication possibilities for nonverbal children (Ullah et al., 2023). Collectively, these approaches demonstrate the capacity of AI to support children with ASD and other developmental conditions, but also underscore the need for more robust and representative data.

In parallel, AI has been integrated into interactive and playful contexts, making therapeutic processes more engaging and inclusive. Serious games and mobile applications have improved children's ability to recognize and express emotions while creating less intimidating therapeutic environments (Kalantarian et al., 2019; Marchi et al., 2019). Humanoid robots have shown potential as health coaches to influence lifestyle behaviors (Addo et al., 2013), and emotion detection through children's drawings provides accessible alternatives for those with limited verbal communication (Ali et al., 2022). Socially assistive robots have also been effective in enhancing emotional expression among children with hearing impairments (Uluer et al., 2023). More advanced methods, such as hybrid neural models, further improve facial emotion recognition in child–robot interactions, though they stress the importance of contextual validation and participatory system design (Zimmer et al., 2023).

Beyond these interventions, the scope of AI in pediatric care continues to diversify. Advances in deep learning have been applied to ASD detection through facial videos and static images (Harish et al., 2025; Xia et al., 2025), lightweight models allow real-time emotion recognition tailored to autistic children (Madhusoodanan et al., 2025), and VR-integrated systems show potential in ADHD assessment by combining biofeedback and behavioral monitoring (Garg et al., 2025). At the same time, computational agents such as EMMA and SERMO chatbots demonstrate how natural language processing can promote self-awareness and emotional support through just-in-time interventions (Saha et al., 2022). While most of these systems were designed for adults and adolescents, their architectures and evaluation metrics are highly relevant to pediatrics, provided appropriate adaptation and validation.

Recent advances in the application of AI in pediatric nursing demonstrate significant potential to improve care quality, particularly through the early identification and management of children's emotions. Evidence suggests that AI can support nurses in clinical decision-making and continuous monitoring, enabling more timely and personalized interventions (Rony et al., 2024). Moreover, the automation of administrative tasks may free up time for professionals to focus on child-centered care, promoting more meaningful interactions and enhancing emotional sensitivity in practice (Bende, 2024). Within this review, applications in contexts such as ASD, emotional disorders, and communication limitations further illustrate how AI-based tools, whether grounded in facial, vocal, or drawing analysis, can enrich the interpretation of children's emotional states. These findings not only highlight the diagnostic value of AI but also align with the humanistic tradition of pediatric nursing, where attention to the child's emotional dimension has long been central (Bende, 2024).

Despite the promising applications of AI in pediatric care, its potential risks must be critically considered. One of the most pressing concerns is the reliance on algorithms trained with biased or incomplete datasets, which can compromise clinical safety and equity in care delivery. Equally important are issues of privacy and confidentiality, given the continuous collection and processing of sensitive health data by intelligent systems (Organisation for Economic Co-operation and Development, 2024; World Health Organization, 2024). Overreliance on these technologies may also risk reducing humanization in healthcare, as excessive automation can undermine empathy and the quality of professional–patient relationships. To mitigate these risks, international frameworks emphasize anticipatory governance, adaptable regulation, and stakeholder engagement (Organisation for Economic Co-operation and Development, 2024; World Health Organization, 2024). Yet, pediatric-specific ethical guidelines remain scarce. Classical bioethical principles such as beneficence, non-maleficence, justice, and autonomy require careful adaptation to children's developmental vulnerabilities (Chng et al., 2025), and governance should align with the UN Convention on the Rights of the Child to safeguard participation, privacy, and equity (Third et al., 2021).

Ultimately, AI should be understood as a complementary resource that strengthens evidence-based practice rather than replacing the empathic presence of nurses. Its integration must be guided by digital literacy, interdisciplinarity, and ethical safeguards to ensure that technological innovation supports, rather than substitutes, the relational dimension of pediatric care.

Conclusion

This scoping review provided a comprehensive synthesis of the current landscape regarding the use of AI for emotion recognition in pediatric contexts. It identified a wide array of tools, including facial and voice recognition systems, serious games, mobile applications, and wearable sensors, which are being applied to support emotional assessment and therapeutic responses in children and adolescents. The findings highlight how AI is beginning to play a meaningful role in pediatric healthcare, particularly in helping vulnerable populations such as children with autism spectrum disorder, hearing impairments, or severe disabilities, by enabling early detection of emotional distress, promoting personalized interventions, and improving the emotional experience of care. Therefore, this review offers a valuable foundation for future investigations, encouraging the development of culturally sensitive, ethically grounded, and clinically validated AI tools that can be safely integrated into pediatric nursing practice. Future research should focus on rigorous clinical trials, culturally diverse datasets, and interdisciplinary collaboration that includes the perspectives of nurses, children, and families to ensure that AI technologies are aligned with real needs. Ultimately, AI should not be seen as a substitute for human relationships in care, but as a complementary instrument with the potential to strengthen child-centered, ethical, and evidence-based pediatric practice.

Strengths and limitations of the study

This scoping review represents a relevant and innovative contribution to mapping the use of AI in emotion recognition in pediatric contexts. Among its main strengths are the breadth of the literature search, conducted across multidisciplinary databases, and the inclusion of different types of studies and pediatric populations, which allowed for a comprehensive and integrative perspective of the phenomenon. In addition, the rigorous application of the JBI methodology strengthens the transparency, replicability, and methodological quality of the review, ensuring that the synthesis followed internationally recognized standards.

Despite these strengths, several limitations should be acknowledged. The studies included were highly heterogeneous in their methodological designs, which makes direct comparison challenging and limits the generalizability of the results. Many were based on small, homogeneous, or non-representative samples, and few controlled clinical trials or longitudinal studies were identified, which restricts the ability to evaluate the long-term effectiveness and real clinical impact of AI technologies. In most cases, the tools analyzed had only been tested in experimental or pilot contexts, with limited integration into routine pediatric care.

Furthermore, the search strategy, although broad, was restricted to three languages (Portuguese, English, and Spanish), which may have led to the omission of relevant studies published in other languages. Another limitation is that no formal risk of bias or structured quality appraisal was carried out, as this is not mandatory in scoping reviews. However, the variability in the rigor of the included studies may have influenced the robustness of the conclusions. These factors should be taken into account when interpreting the findings and in planning future research.

Implications for nursing practice

The findings of this review highlight the transformative potential of AI in pediatric nursing practice, particularly in identifying and responding to the emotional needs of children and adolescents. AI-based tools, such as facial recognition systems, voice analysis, and interpretation of children's drawings, can serve as valuable allies for nurses in the early detection of emotional changes-especially in populations with communication difficulties, such as children with autism spectrum disorders, multiple disabilities, or cognitive impairments. This ability can enhance the personalization of care and contribute to the creation of therapeutic environments that are more sensitive to the child's emotions, promoting both humanization and effectiveness of interventions. Nursing, as a profession centered on relationships and holistic care, can benefit from the ethical and critical integration of these technologies, provided it is accompanied by specific training, contextualized validation, and the preservation of clinical judgment.

Checklists

The PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation-PubMed (nih.gov) was used in this scoping review.

CRediT authorship contribution statement

Ana Rita Figueiredo: Conceptualization, Methodology, Writing – review & editing. **António Pereira:** Methodology, Writing – review & editing. **Francisca Frias:** Methodology, Writing – review & editing. **Luíza Moura Dias Rodrigues:** Writing – review & editing. **Paula Diogo:** Writing – review & editing.

Informed consent statement

Not applicable.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this manuscript, the authors used Grammarly, QuillBot, and DeepL to improve the language, clarity, and readability. After using these tools, the authors thoroughly reviewed and edited the content and take full responsibility for the final version of the manuscript.

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Declaration of competing interest

The authors declare no conflicts of interest.

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Appendix A. Supplementary data

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