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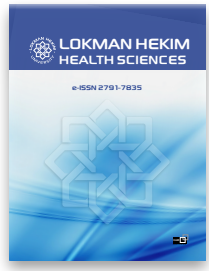

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SYSTEMATIC REVIEW

Mapping Artificial Intelligence-based Assessment Domains in Pediatric Occupational Therapy: A Scoping Review

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Abstract

Introduction: Although artificial intelligence (AI) has increasingly been integrated into health and rehabilitation sciences, the assessment domains in which AI-based approaches are applied in pediatric occupational therapy have not yet been comprehensively mapped in the literature. The aim of this study was to systematically identify the assessment domains in which AI-based approaches have been applied in pediatric occupational therapy and to describe how these applications have been reported in the existing literature.

Methods: A scoping review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews. Searches were performed in CINAHL, OTseeker, PubMed/MEDLINE, Scopus, and Web of Science for English-language, peer-reviewed studies published between 2015 and 2025. Empirical studies reporting the use of AI-based approaches for assessment purposes in pediatric occupational therapy were included. Data were charted and synthesized descriptively to provide an overview of research characteristics and thematic patterns.

Results: Sixteen studies met the inclusion criteria. Most studies employed observational or validation-based designs and primarily utilized machine learning approaches, including deep learning and computer vision techniques. AI-based assessment applications were predominantly focused on motor and sensory-perceptual domains. Fewer studies addressed cognitive functioning and activities of daily living, while no studies explicitly examined psychosocial, environmental, or participation-related assessment domains. Image- and video-based data were the most frequently used modalities.

Discussion and Conclusion: The findings indicate that AI-based assessment research in pediatric occupational therapy has largely concentrated on performance-oriented domains, particularly motor and sensory-perceptual functioning. Important occupational therapy domains, such as participation, environmental context, and psychosocial functioning, remain underrepresented. This scoping review provides an overview of current research trends and highlights key gaps, offering a foundation to guide future interdisciplinary research and the development of more holistic, occupation-centered AI-based assessment approaches within health sciences.

Keywords: Artificial intelligence; Machine learning; Occupational therapy; Outcome assessment; Pediatrics

Artificial intelligence (AI) refers to a broad class of technological systems that enable machines to perform tasks typically requiring human intelligence, such as learning from data, recognizing complex patterns, and making decisions. Over the past decade, AI has driven substantial advances in both basic and clinical research across multiple fields related to human health and behavior, including medicine, psychology, and education.[1,2] In the

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fields of health and rehabilitation, AI plays an innovative role in enhancing the quality of healthcare services through applications such as clinical decision support systems, the development of intervention strategies, improved accuracy and efficiency of assessments, and more precise data analysis.[3,4] Although AI is used for various purposes across multiple fields, evidence from the literature indicates that its application in occupational therapy has primarily focused on functional assessments, personalized rehabilitation programs, and intervention planning.[4,5]

In pediatric occupational therapy, assessment is a fundamental process that enables the holistic identification of the physical, cognitive, sensory-perceptual, and psychosocial challenges children encounter during activities of daily living (ADL).[6] Through this comprehensive assessment process, occupational therapists are able to support goal setting and the structuring of interventions by simultaneously considering the child's individual needs, environmental factors, and activity demands.[5] Occupational therapy assessments largely rely on therapists' clinical experience and observational judgment, which may lead to inconsistencies among evaluators.[7] In addition, the time-consuming nature of the assessment process may increase therapists' workload while causing fatigue and reduced motivation in children, thereby negatively affecting assessment accuracy.[8]

In recent years, AI-based assessment approaches have increasingly been adopted to address the limitations and challenges of conventional evaluation methods.[9] These approaches offer therapists objective, standardized, and data-driven information to enhance the assessment process and can automate data analysis, reducing the time and effort required for manual evaluation and interpretation.[4,8] In this context, despite the growing number of AI-driven applications in the health sciences, studies that systematically and comprehensively examine the assessment domains in which these technologies are applied in pediatric occupational therapy, as well as the types of data and AI approaches employed, remain limited.[5,9] Therefore, a scoping review was deemed necessary to comprehensively map the existing literature. This scoping review aims to elucidate how AI-based applications are positioned across assessment domains in pediatric occupational therapy, including sensory-perceptual, motor, cognitive, psychosocial, environmental, ADL, and participation domains; to classify the technologies and AI methods utilized; and to identify gaps in the current literature, thereby providing a guiding framework for future research.

Materials and Methods

Study Design

This study was conducted as a scoping review with the aim of systematically identifying the assessment domains in which AI has been used in pediatric occupational therapy and describing how these applications have been reported in the literature. The methodology and reporting of the review were guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) guidelines. The methodological framework for this scoping review was developed before the initiation of the literature search and made available on the Open Science Framework to enhance transparency. The procedures defined in the protocol were followed throughout the review process.

Identifying the Research Questions

The following research questions guided the review:

RQ1. In which assessment domains of pediatric occupational therapy have AI-based approaches been applied?

RQ2. What types of AI methods have been used across these assessment domains in pediatric occupational therapy?

RQ3. How have the outcomes and contributions of AI-based assessment applications been reported in the existing literature?

RQ4. Which pediatric populations have been represented in studies using AI-based assessment approaches in pediatric occupational therapy?

Search Strategy

A comprehensive literature search was conducted to identify studies examining the use of AI-based approaches for assessment purposes in pediatric occupational therapy. The following electronic databases were searched: CINAHL (through EBSCOhost), OTseeker, PubMed/MEDLINE, Scopus, and Web of Science.

The search strategy combined relevant keywords and, where applicable, controlled vocabulary terms related to AI, assessment, pediatric populations, and occupational therapy. Search terms included combinations of "artificial intelligence," "machine learning," "deep learning," "computer vision,""algorithm,""pattern recognition,""intelligent systems," "assessment," "evaluation," "measurement," "screening," "functional assessment," "functional analysis," "performance-based assessment," "occupational therapy," "pediatric," "child," "infant," and "adolescent." Boolean operators (AND/OR) were

used to combine search terms appropriately. The search strategy was adapted for each database to account for differences in indexing and search functionalities.

No restrictions were applied regarding geographical location. The search was filtered to English peer-reviewed articles published between 2015 and 2025. In addition to electronic database searching, the reference lists of included studies were manually screened to identify additional relevant publications.

The search strategy was reviewed and refined by the research team before implementation to ensure adequate coverage and relevance. All records retrieved from the database searches were imported into EndNote, a reference management software, which was used to organize citations and identify and remove duplicate records before the screening process.

Study Selection

Study selection was conducted in two stages, beginning with title and abstract screening, followed by full-text review. Three researchers independently screened the titles and abstracts of all retrieved records to assess relevance based on the predefined inclusion and exclusion criteria. Studies were considered eligible if they reported empirical research examining AI-based approaches used for assessment purposes in pediatric occupational therapy. Eligible studies included qualitative, quantitative, and mixed-methods research, published in English in peer-reviewed journals between 2015 and 2025. Studies were excluded if they focused on AI in health care without direct relevance to occupational therapy; did not address assessment processes; were systematic reviews, scoping reviews, or narrative reviews; did not involve human participants; examined assistive technologies without an AI component; or consisted of opinion pieces, editorials, or conceptual papers lacking empirical data. Full-text versions of studies deemed potentially eligible were retrieved and independently assessed by the same researchers for final inclusion. The reference lists of all included articles were also screened for additional eligible studies not captured in the primary database search. Any discrepancies in screening decisions were resolved through discussion until consensus was achieved. The study selection process is summarized in a PRISMA-ScR flow diagram (Fig. 1), detailing the number of records identified, screened, included, and excluded at each stage.

Data Charting

A standardized data charting form was developed to systematically extract relevant information from the included studies. The data charting framework was designed to align with the objectives of the scoping review and the predefined research questions. Before full data charting, the form was reviewed by the research team to ensure clarity and consistency. For each included study, the following information was charted: Publication characteristics (author(s), year of publication, and country), study design, participant characteristics (age range and pediatric population when reported), type of AI method used, assessment domain(s) addressed within pediatric occupational therapy, purpose of the AI-based assessment application, and how assessment-related outcomes were reported in the literature.

Assessment domains were defined a priori to support systematic mapping and included sensory-perceptual, motor, cognitive, psychosocial, environmental, ADL, and participation-related domains, consistent with occupational therapy assessment frameworks.[10] Studies could be assigned to more than one assessment domain where applicable.

Data charting was performed independently by three researchers. Any discrepancies in the charted data were discussed and resolved through consensus to ensure accuracy and consistency. The extracted data were subsequently used to support descriptive synthesis and mapping of assessment domains, AI methods, and pediatric populations addressed in the included studies.

Data Synthesis and Analysis

Data synthesis was performed using a descriptive and narrative approach, in accordance with the objectives and methodological guidance of the PRISMA-ScR. The purpose of the synthesis was to map the breadth, characteristics, and distribution of existing evidence, rather than to evaluate effectiveness or conduct quantitative pooling of results. Following data charting, the extracted data were organized and summarized to address the predefined research questions. Studies were grouped according to assessment domains in pediatric occupational therapy, types of AI approaches, data modalities, reported outcome measures, and pediatric populations represented. Assessment domains were categorized a priori (sensory-perceptual, motor, cognitive, psychosocial, environmental, ADL, and participation), and studies addressing multiple domains were classified under all relevant categories.

AI approaches were descriptively classified (e.g., machine learning, deep learning, computer vision, hybrid methods), and their distribution across assessment domains was

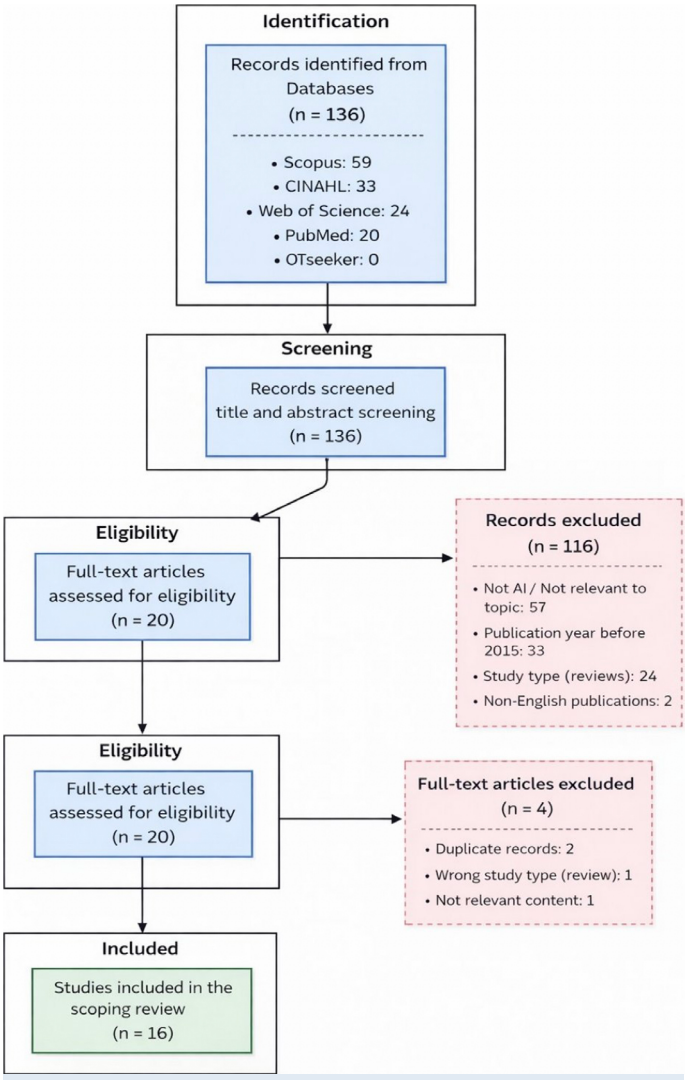

Figure 1. Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews flow diagram illustrating the study selection process.

examined. Data synthesis was supported by tabular and visual representations, including summary tables and a heatmap illustrating the relationship between AI techniques and assessment domains. The findings were synthesized narratively, with an emphasis on overall patterns, trends, and gaps in the literature, consistent with the exploratory aims of a scoping review.

Results

An initial search identified 136 articles. After removing duplicates and conducting detailed screening, 20 studies were deemed potentially relevant. Applying the inclusion criteria narrowed this down to 16 articles included in the qualitative synthesis. The screening process is outlined in Figure 1, following PRISMA-ScR guidelines.

The characteristics of the included studies are summarized in Table 1, providing an overview of study designs, AI techniques, data modalities, assessment domains, outcome measures, and population characteristics.

Study Design

Most included studies employed observational designs and primarily focused on validation and measurement purposes (Table 1). Cross-sectional approaches were commonly reported, whereas longitudinal and experimental designs were less frequently observed.

AI Type

Machine learning emerged as the predominant AI approach across the included studies (Table 1). Deep learning and computer vision techniques were also frequently applied, while hybrid methods and rule-based systems were used only in a limited number of studies. No studies reported the use of natural language processing techniques.

Data Modality

A wide range of data modalities was used across studies, with image- and video-based data being most common (Table 1). Clinical records, questionnaire-based data, and wearable sensors were also utilized, whereas depth cameras, audio data, and multimodal data integration were relatively uncommon.

Outcome Measures

Accuracy emerged as the most frequently reported outcome measure across the included studies, followed by validity or correlation metrics and clinician agreement (Table 1). Sensitivity, specificity, and area under the curve were also commonly used performance indicators, whereas F1-score and precision/recall metrics were reported less frequently. Reliability indices, such as intraclass correlation coefficients, were included in a limited number of studies, and measures related to time efficiency were reported only occasionally. Other advanced performance indicators, including mean absolute error, root mean squared error, and R^2, were rarely reported.

Population Characteristics

The included studies predominantly involved general pediatric populations and children with neurological or developmental conditions, particularly cerebral palsy (Table 1). A smaller number of studies focused on children with developmental coordination disorder, brain tumor survivors, and specific learning disorders, while a limited number included mixed clinical populations or children with idiopathic toe walking.

Table 1. Characteristics of included studies (n=16)

	n	%
Study design		
Observational	15	93.8
Experimental (RCT)	1	6.3
Validation/measurement	13	81.3
Feasibility/pilot	1	6.3
Cross-sectional	11	68.8
Longitudinal	4	25.0
AI type		
Machine learning	14	87.5
Deep learning	6	37.5
Computer vision	6	37.5
Hybrid	3	18.8
Rule-based/expert system	1	6.3
Data modality		
Video	5	31.3
Image/photo	7	43.8
Wearable sensors (IMU)	4	25.0
Depth camera (Kinect)	1	6.3
Audio	1	6.3
EHR/clinical records	5	31.3
Questionnaire/scale	5	31.3
Multi-modal	2	12.5
Other	1	6.3
Assessment domain		
Motor	14	87.5
Sensory-perceptual	9	56.2
Cognitive	2	12.5
ADL	2	12.5
Outcome type		
Accuracy	13	81.3
Sensitivity	6	37.5
Specificity	6	37.5
AUC	6	37.5
F1-score	3	18.8
Precision/recall	2	12.5
Validity/correlation	10	62.5
Reliability (ICC)	3	18.8
Agreement (clinician)	8	50.0
Time/efficiency	4	25.0
Other (MAE, RMSE, R^2)	1	6.3
Population group		
Cerebral palsy	5	31.25
Developmental coordination disorder	1	6.3
Brain tumor survivors	1	6.3
General pediatric	6	37.5
Specific learning disorders	1	6.3
Other (mixed, ITW, etc.)	2	12.5

AUC: Area under the curve; EHR: Electronic health records; IMU: Inertial measurement unit; RCT: Randomized controlled trials; AI: Artificial intelligence; ADL: Activities of daily living; MAE: Mean absolute error; RMSE: Root mean squared error; ICC: Intraclass correlation coefficient. Categories are not mutually exclusive; therefore, percentages may exceed 100%.

Assessment Domains and AI Techniques

Figure 2 illustrates the distribution of AI types across assessment domains. Most studies primarily focused on motor functioning (n=14/16, 87.5%), followed by sensory-perceptual processes (n=9/16, 56.2%). Machine learning was predominantly applied in motor-related assessments and, to a lesser extent, in sensory-perceptual evaluations. Deep learning and computer vision methods were also mainly used in these two domains. Only a limited number of studies addressed cognitive functioning and ADL (each 12.5%). Notably, none of the included studies evaluated psychosocial, environmental, or participation-related domains. Several studies employed multiple AI techniques and addressed more than one assessment domain. Therefore, these studies were classified under all relevant categories in the heatmap analysis.

Detailed characteristics of individual studies, including AI methods, assessment tools, and outcome measures, are provided in Appendix 1.

Discussion

The findings of this scoping review provide a comprehensive synthesis of how AI-based assessment approaches have been applied within pediatric occupational therapy. The existing literature demonstrates a clear concentration of AI applications within motor and sensory-perceptual assessment domains, while cognitive and ADL-related assessments remain comparatively underrepresented. Notably, no studies were identified that explicitly addressed psychosocial, environmental, or participation-related domains. From an occupational therapy perspective, these findings highlight a critical imbalance between performance-based and occupation-centered assessment approaches. According to the occupational therapy practice framework-4, assessment should encompass not only performance skills (e.g., motor and process skills) but also participation, contextual factors, and environmental influences. However, the current distribution of AI-based applications appears to be heavily skewed toward observable motor performance components, with limited attention to broader occupational engagement and real-life participation contexts.

In line with this perspective, two key findings emerged from this review. First, AI-based assessment applications in pediatric occupational therapy are predominantly concentrated in motor and sensory-perceptual domains, which are more easily quantifiable through image- and sensor-based data. Second, there is a notable absence of

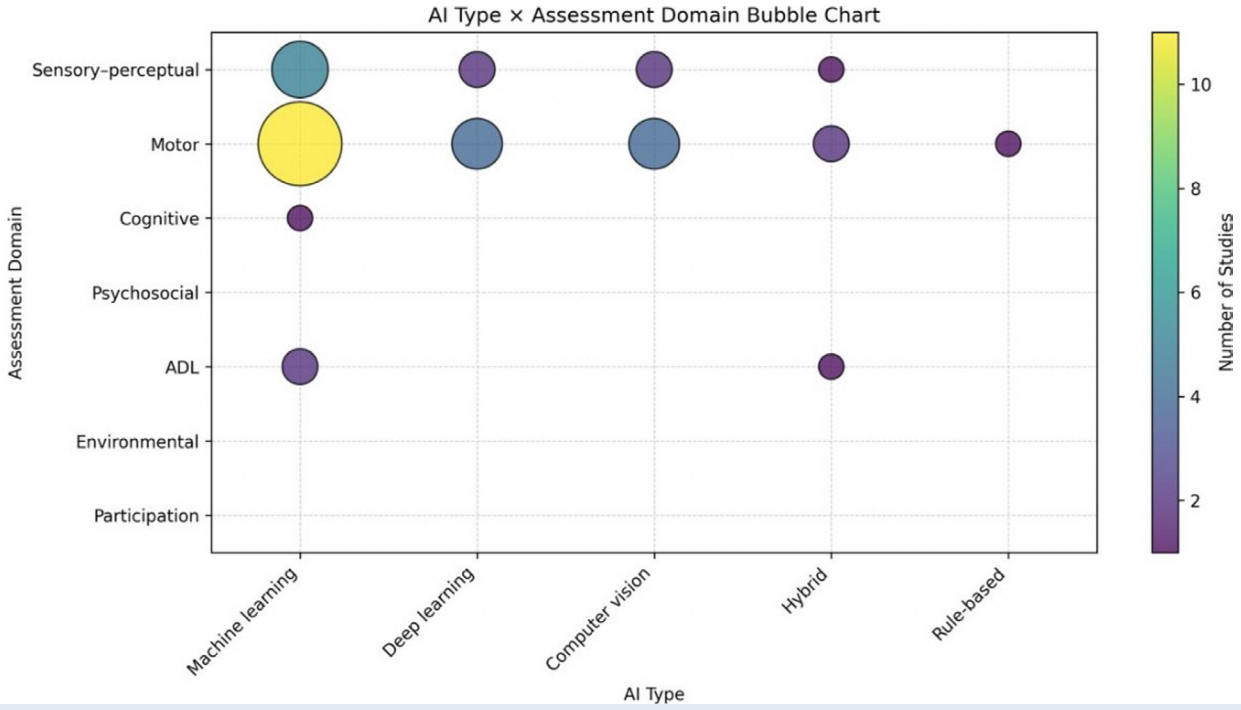

Figure 2. Distribution of artificial intelligence types across assessment domains.

AI applications targeting psychosocial, environmental, and participation-related domains, despite their central importance in occupational therapy practice. These findings are consistent with existing literature on AI applications in rehabilitation, which similarly emphasizes the predominance of performance-based approaches and the early-stage integration of AI into clinical practice.[11,12] Previous reviews have also highlighted limitations in methodological rigor and validation processes, including the limited use of multimodal data and external validation strategies.[13] In this context, the present study extends the literature by specifically mapping these patterns within pediatric occupational therapy and identifying critical gaps in participation and environmental domains.

The predominance of observational and validation-focused study designs further indicates that AI technologies in this field are primarily positioned as measurement-enhancement tools, rather than as fully integrated components of routine clinical assessment and decision-making. This methodological pattern aligns with trends reported in broader pediatric health and rehabilitation research, where exploratory and validation-oriented designs are commonly adopted during the early phases of technological implementation.[14,15] While such approaches are valuable for establishing feasibility, proof of concept, and clinical relevance, they inherently limit causal inference and the generalizability of findings.

The limited representation of experimental randomized controlled trials (RCTs) identified in this review highlights a critical methodological gap. As RCTs are widely regarded as providing higher levels of evidence through controlled and structured designs, their underrepresentation raises concerns regarding potential bias and the robustness of current findings.[16] Consistent with previous critiques in the literature, there is a clear need for more rigorously designed experimental studies to systematically evaluate the efficacy, safety, and clinical impact of AI-based assessment approaches in pediatric occupational therapy.[15,17] Addressing this gap may strengthen evidence-based integration and more effectively inform clinical decision-making processes.

The dominance of machine learning techniques, including deep learning and computer vision-based methods, observed in this review is consistent with broader trends in AI-driven health research. These approaches are particularly well-suited for tasks such as image classification, pattern recognition, and movement analysis, which are central to motor and sensory-perceptual assessments commonly employed in pediatric populations.[14,18–20] The use of hybrid models further reflects an emerging tendency to integrate multiple AI techniques to improve model performance, adaptability, and applicability across diverse assessment contexts.[21,22]

In parallel, the strong reliance on image- and photo-based data underscores a broader shift toward visually driven assessment approaches in pediatric rehabilitation settings.

This trend is supported by evidence demonstrating that computer vision-based techniques can enhance objectivity and precision in the evaluation of motor performance and developmental outcomes in children.[14,15,23] Nevertheless, the comparatively limited use of wearable sensors and the infrequent implementation of multimodal data integration highlight significant opportunities for methodological advancement. Emerging research suggests that combining visual data with physiological and kinematic information may yield more comprehensive and ecologically valid assessments, thereby improving predictive accuracy and clinical relevance.[24–27]

While the emphasis on motor functioning reflects clinical priorities, it also reveals a notable imbalance in the literature.[15,28] Specifically, limited attention has been given to cognitive functioning and ADL, alongside a conspicuous absence of AI-based assessment approaches targeting participation and environmental domains. This gap is particularly salient given that participation and person-environment interactions constitute foundational constructs within pediatric occupational therapy practice. This imbalance may be explained by the inherent complexity of participation and psychosocial constructs, which are context-dependent, subjective, and difficult to operationalize using current AI methodologies. In contrast, motor performance can be more readily captured through structured, quantifiable data such as movement kinematics or visual recordings. This technological bias may inadvertently reinforce a reductionist perspective, limiting the ability of AI systems to reflect the holistic and occupation-centered nature of pediatric occupational therapy. These applications remain largely confined to performance-level indicators, with broader, contextually embedded aspects of occupational engagement remaining underrepresented. Expanding AI-based assessment approaches to encompass participation and environmental factors may therefore support more holistic, occupation-centered, and family-centered evaluations.[29,30] From a clinical perspective, the current emphasis on performance-level indicators raises concerns regarding the alignment of AI-based assessments with the core principles of occupational therapy, which prioritize participation, context, and meaningful engagement in daily life. This limitation may reduce the ecological validity of assessments and their relevance for clinical decision-making. Furthermore, although accuracy was the most frequently reported outcome measure, the limited use of reliability indices and advanced performance metrics constrains the clinical interpretability of existing tools. Broader outcome reporting, combined with assessments that capture participation and environmental context, may enhance the robustness and ecological validity of AI-based assessment systems.[22,24,25] In practical terms, current AI-based approaches may support clinicians in tasks such as objective motor performance analysis, early screening, and progress monitoring. For example, computer vision-based systems can assist in quantifying movement patterns, while wearable sensor-based approaches may provide continuous data on functional performance. However, expanding these applications toward real-world contexts and participation-based outcomes is essential to better support occupation-centered clinical decision-making.

Another important issue identified in this review relates to the limited transparency and variability in reporting AI model development processes across the included studies. In several cases, insufficient detail was provided regarding model architecture, training procedures, parameter selection, and validation strategies, which may hinder reproducibility and critical appraisal. Furthermore, although performance metrics such as accuracy were frequently reported, their clinical relevance and interpretability in occupational therapy contexts were often unclear.

Finally, the predominant focus on general pediatric populations and conditions such as cerebral palsy mirrors prevailing priorities in pediatric rehabilitation research, where these groups are frequently targeted due to their prevalence and clinical significance. However, expanding future research to include more diverse and mixed clinical populations may enhance the generalizability and applicability of AI-based assessment approaches across a wider range of pediatric profiles.[23,31] Such diversification holds the potential to support more personalized assessment strategies and contribute to improved outcomes for currently underrepresented pediatric populations.[14,29]

In addition to these considerations, ethical aspects should also be acknowledged in the use of AI in pediatric populations. Ethical considerations are important in the use of AI in pediatric populations, particularly regarding data privacy, informed consent, and the protection of sensitive child data. Transparency and explainability are also essential to ensure trust in clinical practice. AI should be considered as a decision-support tool that complements, rather than replaces, clinical judgment.

This review has several strengths. It provides a comprehensive and systematic mapping of AI-based assessment approaches across multiple domains in pediatric occupational therapy. In addition, the use of a structured framework to categorize assessment domains allows for a clearer identification of trends and gaps in the literature.

Study Limitations

Despite these contributions, several limitations should be considered. Although a comprehensive and systematically developed search strategy was implemented across multiple major databases, relevant studies may not have been identified due to variations in terminology, indexing practices, or publication in sources not covered by the selected databases. The restriction to English-language, peer-reviewed publications may have resulted in the exclusion of relevant studies published in other languages or disseminated through gray literature, potentially limiting the global representation of AI-based assessment practices. In addition, the review was confined to studies that explicitly reported AI-based approaches within pediatric occupational therapy contexts; therefore, relevant assessment applications described in adjacent disciplines but not clearly framed within occupational therapy may not have been captured. In addition, variability and limited transparency in reporting AI methodologies across the included studies may have constrained the depth of analysis.

Conclusion

This scoping review reveals a clear imbalance in the current use of AI-based assessment approaches within pediatric occupational therapy. Existing applications are largely concentrated in performance-oriented domains, particularly motor and sensory-perceptual functions, while key occupational therapy domains such as participation, psychosocial functioning, and environmental context remain largely unexplored.

This imbalance highlights a critical gap between the capabilities of current AI technologies and the holistic, occupation-centered perspective that underpins pediatric occupational therapy practice. As a result, the clinical relevance and ecological validity of existing AI-based assessment tools may be limited.

Future research should focus on developing AI-based assessment approaches that extend beyond performance-level indicators to incorporate participation, contextual, and environmental factors. Integrating multimodal data sources and adopting more rigorous and transparent methodological practices – including detailed reporting of training, validation (e.g., cross-validation or external validation), and testing procedures – may enhance both the clinical relevance and reliability of these systems. Advancing AI applications toward more comprehensive and contextually grounded frameworks may better support clinical decision-making and promote more client-centered pediatric occupational therapy practice.

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Appendix 1. Detailed characteristics of included studies

Author(s), year	Title	Journal	Country/ region	Study design	Setting/context	Age range	Pediatric population/ condition	Sample size (n)	Study objective/aim	AI method type	AI model/algorithm	Data modality	Assessment domain(s)	Assessment tool/ measure	Purpose in assessment	Clinical application/intended Use	Reported outcomes/metrics	Key findings (assessment)	Reported limitations
Fair-Field and Modayur[32]	Clinical validation of an abridged AIMS: Streamlining motor screening in the 1st-year infant	Early Human Development	USA	Observational, validation	Clinical and telehealth video-based screening	0–12 months	Typically developing and at-risk infants	123 (102 training, 21 validation)	To validate a shortened version of the AIMS using ML for early motor screening	ML	SVR	Video	Motor	AIMS	Early identification of motor delay	Screening and early detection	Accuracy, sensitivity, specificity, ICC, correlation, time efficiency	The abridged 15-item AIMS showed excellent agreement with the full scale (r=0.99), high sensitivity (1.00), and reduced assessment time	Small validation sample, limited generalizability, reliance on video recordings
Lin and Kuo[33]	Ensemble learning-based functional independence ability estimator for pediatric brain tumor survivors	Health Informatics Journal	Taiwan	Observational, Validation	Rehabilitation clinic/ Secondary dataset	6–18 years	Pediatric brain tumor survivors	73	To predict functional independence (WeeFIM) scores using ensemble ML models	ML (Ensemble)	RF, MLP, AdaBoost, SVR, DT, k-NNR	EHR/Clinical records, Questionnaire/ Scale	ADL, Motor	WeeFIM, WISC-IV	Estimation and prediction of functional independence scores	Prognosis and rehabilitation planning	MAE, RMSE, R2	Ensemble models demonstrated superior predictive performance compared with single ML models and accurately estimated WeeFIM total, cognition, mobility, and self-care scores	Secondary dataset use, limited sample size, lack of external validation, and limited generalizability
Philip et al.[34]	Motor Assessment with the STEGA iPad App to Measure Handwriting in Children	American Journal of Occupational Therapy	USA	Observational, Validation	School and clinical settings	6–11 years	Typically developing children and children with handwriting difficulties	57	To evaluate the validity of the STEGA iPad app for handwriting assessment	ML	SVR	Image/Tablet input	Motor, Sensory–perceptual	STEGA iPad App, DASH	Objective measurement of handwriting performance	Screening and progress monitoring	Accuracy, validity coefficients, and agreement	The STEGA app demonstrated strong validity and reliability for assessing handwriting speed, pressure, and legibility	Limited sample size, restricted age range, use of tablet-based writing only
Khaksar et al.[35]	Application of inertial measurement units and ML classification in cerebral palsy: Randomized controlled trial	JMIR Rehabilitation and Assistive Technologies	Australia	RCT, observational	Multicenter clinical rehabilitation settings	5–15 years	Children with and without cerebral palsy	190	To develop and evaluate an IMU-based system using ML to classify wrist movement patterns in children with cerebral palsy	ML	RF, C4.5, SVM, KNN, MLP, Naïve Bayes, Logistic Regression	Wearable sensors (IMU - Accelerometer and Gyroscope)	Motor, Sensory–perceptual	Custom IMU system, Goniometer, Vicon	Objective measurement of active wrist range of motion and movement classification	Therapy evaluation and long-term monitoring	Accuracy, AUC, ROC, classification rate	RF and C4.5 achieved high classification accuracy (up to 89.39%) in distinguishing cerebral palsy and typical movement patterns	Sensor drift, data noise, technical issues, limited comfort, potential data loss, and restricted ecological validity
Li et al.[36]	Automated fine motor evaluation for developmental coordination disorder	IEEE Transactions on Neural Systems and Rehabilitation Engineering	Hong Kong/ China	Observational, validation	Laboratory and clinical assessment setting	6–10 years	Children with DCD and TD	40 (20 DCD, 20 TD)	To develop an automated system for assessing fine motor performance in children with DCD	ML	CNN-based temporal filtering, image processing	Motion capture/ digital pen, depth camera (e.g., Kinect)	Motor, Sensory–perceptual	Based on MABC-2 tasks (drawing trail, Threading lace, Posting coins)	Automated scoring to replace subjective observational analysis	Screening and diagnostic support	Accuracy, sensitivity, specificity, classification rate	The automated system successfully differentiated children with DCD from controls with high classification accuracy	Small sample size, controlled laboratory setting, limited ecological validity
Duran et al.[37]	Artificial intelligence to improve the efficiency of the administration of gross motor function assessment in children with cerebral palsy	Developmental Medicine and Child Neurology	Germany, Turkey	Retrospective, observational, validation	Single-center rehabilitation program ("Auf die Beine")	<18 years (mean age 8 years 10 months)	Children with cerebral palsy	1217 unique assessments (validation set: 187 assessments)	To create a reduced version of the GMFM-66 (rGMFM-66) to improve clinical efficiency	ML	RF, SVM, feed-forward neural network	Clinical assessment records, Questionnaire/ Scale	Motor	GMFM-66, rGMFM-66, GMFCS	Predicting the total score from a subset of items to save time	Outcome monitoring and therapy evaluation	ICC, MAE, Bland–Altman, sensitivity, specificity	The rGMFM-66 showed excellent agreement with the full GMFM-66 (ICC>0.99) and significantly reduced assessment time	Retrospective design, selection bias, limited representation of GMFCS I and V, lack of prospective validation
Hagihara et al.[7]	CV-based approach for quantifying occupational therapists' qualitative evaluations of postural control	Occupational Therapy International	Japan	Observational, validation	Nursery schools	3–6 years	Typically developing preschool children	34	To develop and validate a CV–based method for quantifying postural control based on therapists' qualitative evaluations	Deep learning/CV	Pose estimation–based CV (OpenPose)	Video	Motor, Sensory–perceptual	JPAN (One Arm and One Leg Balance task), TQCE	Quantification of postural control performance	Screening and detailed motor assessment	Spearman correlation, regression coefficients, ICC	CV-based indices (SPB, AG) showed significant correlations with therapists' evaluations and outperformed conventional duration-based measures	Small sample size, typically developing sample only, limited clinical diversity, single-task assessment
Syafrudin et al.[38]	A self-care prediction model for children with disabilities based on a genetic algorithm and extreme gradient boosting	Mathematics	South Korea, Brunei, Malaysia, Indonesia	Observational, validation	Secondary dataset analysis (SCADI, ICF-CY)	6–18 years	Children with various disabilities	70	To develop a hybrid prediction model (GA-XGBoost) for classifying self-care activity levels	ML (hybrid feature selection)	Genetic algorithm+XGBoost	EHR/ questionnaire-based dataset	ADL	ICF-CY	Automated classification of self-care difficulties	Diagnostic support and rehabilitation planning	Accuracy, precision, recall, F1-score, AUC	GA-XGBoost outperformed other ML models, achieving up to 98.57% accuracy in binary classification and 90% in multi-class tasks	Use of secondary dataset, small sample size, lack of real-time clinical validation, and limited ecological validity
Soangra et al.[39]	Classifying Toe Walking Gait Patterns Among Children Diagnosed With Idiopathic Toe Walking Using Wearable Sensors and Machine Learning Algorithms	IEEE Access	USA	Observational, Validation	Laboratory and outpatient gait analysis setting	4–12 years	Children with idiopathic toe walking (ITW)	35 (17 ITW, 18 Typically Developing)	To identify and classify toe-walking steps from typical gait using wearable inertial sensors and ML.	Machine Learning	Random Forest, SVM, KNN, Decision Tree	Wearable sensors (IMU)	Motor, Sensory–perceptual	Custom IMU system, gait analysis protocol	Automated detection of abnormal gait cycles (toe-walking steps)	Clinical decision support, monitoring treatment (e.g., botox, casting) and intervention planning.	Accuracy, precision, recall, F1-score	ML models achieved high accuracy (>90%) in distinguishing ITW from typical gait patterns	Small sample size, controlled environment, limited generalizability, short recording duration
Yiwen & Yonghui[40]	Development and Validation of a Prognostic Model for Independent Walking in Children With Cerebral Palsy Based on Machine Learning	Archives of Physical Medicine and Rehabilitation	China	Retrospective cohort, Observational, Validation	National CP registry and telephone follow-up	Birth–6 years (followed up to 6 years)	Children with cerebral palsy	807	To develop and validate prognostic models for predicting independent walking ability before age 6.	Machine Learning	Logistic Regression, XGBoost, MLP, RF, GBM, SVM, KNN, Naïve Bayes	EHR / Registry data, Questionnaire	Motor	GMFCS, GMFM-88, structured interview	Prediction of future walking ability	Prognosis and individualized rehabilitation planning	AUC, sensitivity, specificity, PPV, NPV, C-index	ML models showed excellent predictive performance (AUC up to 0.947) and accurately predicted independent walking outcomes	Lack of external validation, overestimation in ages 5–6, possible misclassification bias, usability not evaluated
Tsai, Lee & Huang[8]	Research on Applying Deep Learning to Visual–Motor Integration Assessment Systems in Pediatric Rehabilitation Medicine	Algorithms	Taiwan	Observational, Validation	University OT department / laboratory setting	3–6 years	Typically developing preschool children	8610 images (from multiple children)	To develop and optimize a deep learning–based automated scoring system for VMI assessment	Deep Learning / Computer Vision	Improved DenseNet201 (CNN)	Scanned drawings (Image)	Motor, Sensory–perceptual,	Beery–Buktenica VMI	Automated scoring of visual–motor integration performance	Large-scale screening and clinical assessment support	Accuracy, training time, validation loss	The improved DenseNet model achieved up to 95.13% accuracy (6 items) and 89.84% (12 items), outperforming previous CNN-based methods	Imbalanced dataset, limited real-world testing, lack of external validation, dependence on high-quality scanned images
Hegde et al.[41]	The Pediatric SmartShoe: Wearable Sensor System for Ambulatory Monitoring of Physical Activity and Gait	IEEE Transactions on Neural Systems and Rehabilitation Engineering	USA	Observational, Feasibility	Community and laboratory environment	5–15 years	Typically developing children and children with cerebral palsy	21 (10 CP, 11 TD)	To develop and test a wearable shoe-based sensor system for monitoring gait and physical activity in children	Machine Learning	SVM, Random Forest, Naïve Bayes (leave-one-out cross-validation, activity classification)	Wearable sensors (pressure sensors, accelerometers)	Motor, Sensory–perceptual	SmartShoe system, gait protocol	Continuous monitoring of gait and activity patterns	Long-term monitoring and functional assessment	Accuracy, step detection rate, activity classification rate	The SmartShoe system reliably detected walking, running, and activity levels in natural environments	Small sample size, early prototype limitations, limited battery life, outdated hardware
Rico-Olarte et al.[42]	Towards Classifying Cognitive Performance by Sensing Electrodermal Activity in Children With Specific Learning Disorders	IEEE Access	Colombia, Germany	Quasi-experimental, Observational, Validation	Clinical rehabilitation center using HapHop-Physio	7–11 years	Children with specific learning disorders (SLD)	14 children (945 data samples from 130 sessions)	To classify cognitive performance using electrodermal activity signals collected during rehabilitation therapy	Machine Learning	Random Forest, MLP, SVM, KNN, J48, Naïve Bayes, Boosting, Bagging	Wearable sensors (EDA – E4 wristband), Audio recordings	Cognitive	ENI battery, HapHop-Physio performance scores	Objective monitoring of cognitive performance during therapy	Progress monitoring and rehabilitation support	Accuracy, recall, AUC, Kappa	The Random Forest model achieved the best performance with 79.95% accuracy and substantial agreement (κ = 0.698), demonstrating feasibility for cognitive monitoring	Small sample size, subject-dependent models, signal noise, lack of independent validation
Schafmeyer et al.[43]	Using artificial intelligence-based technologies to detect clinically relevant changes of gross motor function in children with cerebral palsy	Developmental Medicine & Child Neurology	Germany	Retrospective cohort, Observational, Validation	Single-center rehabilitation program ("Auf die Beine")	<18 years (mean age 6 years 4 months)	Children with cerebral palsy	1352 paired assessments	To compare GMFM-66 and rGMFM-66 for detecting clinically relevant changes in gross motor function	Machine Learning	Random Forest, Feedforward Neural Network, SVM	Clinical assessment records	Motor	GMFM-66, rGMFM-66, GMFCS	Detection of meaningful change in motor function	Outcome monitoring and therapy evaluation	AUC, sensitivity, specificity, PPV, NPV, correlation	rGMFM-66 showed high agreement with GMFM-66 (r = 0.99) and excellent accuracy for detecting improvement and deterioration	Retrospective design, underrepresentation of GMFCS I and V, lack of prospective validation
Ienaga et al.[44]	Development and Verification of Postural Control Assessment Using Deep-Learning-Based Pose Estimators: Towards Clinical Applications	Occupational Therapy International	Japan	Observational, Validation	Laboratory and preschool settings	3–6 years (children); 19–35 years (adults)	Typically developing children and adults	57 (34 children, 23 adults)	To compare pose estimation algorithms and develop quantitative indices reflecting OT evaluations of postural control	Deep Learning / Computer Vision	MediaPipe Pose, OpenPose, AlphaPose (CNN-based pose estimators)	Video	Motor, Sensory–perceptual	JPAN "One Arm and One Leg Balance" task, Likert OT ratings	Automated quantification of postural control	Clinical screening and detailed motor assessment	AIC, adjusted R^2, regression coefficients, processing time, estimation error	MediaPipe Pose showed optimal balance of accuracy and speed; SPB1, SPB3, and AG2 best reflected therapists' evaluations	Limited clinical populations, inclusion of adults, task-specific validation, lack of large clinical samples
Villegas-Ch et al.[45]	Detection of Abnormal Patterns in Children's Handwriting by Using an Artificial-Intelligence-Based Method	Informatics	Ecuador	Observational, Validation	Primary school classrooms	7–11 years	Typically developing school-aged children	71 children (210 samples)	To develop and evaluate an AI system for detecting abnormal handwriting patterns	Machine Learning / Computer Vision	DTW (PyDTW), Feature-based classifiers, OpenCV processing	Video, Image, Tablet data	Motor, sensory-perceptual	Camera-based handwriting analysis system, digital tablet	Early detection of handwriting difficulties	Screening and referral support for OT and special education	Accuracy, sensitivity, specificity, F1-score, AUC, PPV, NPV	The system achieved 92% accuracy and 95% detection agreement with camera data; 36 children were referred for intervention and showed 30% improvement	Limited sample size, indirect measurement of muscle tension, sensitivity to environmental factors, lack of standardized validation

AIMS: Alberta Infant Motor Scale; AI: Artificial intelligence; SVR: Support vector regression; ICC: Intraclass correlation coefficient; EHR: Electronic health records; ADL: Activities of daily living; MAE: Mean absolute error; RMSE: Root mean squared error; ML: Machine learning; RCT: Randomized controlled trial; DCD: Developmental coordination disorder; TD: Typically developing; CNN: Convolutional neural networks; MLP: Multilayer perceptron; SVM: Support vector machine; KNN: K-Nearest neighbors; PPV: Positive predictive value; NPV: Negative predictive value; AUC: Area under the curve; ROC: Receiver operating characteristic; RF: Random forest; ITW: Idiopathic toe walking; SLD: Specific learning disorders; OT: Occupational therapy; K-NNR: K-Nearest neighbors regression; IMU: Inertial measurement unit; GBM: Gradient boosting machine; GMFCS: Gross motor function classification system; GMFM-66: Gross motor function measure-66; CV: Computer vision.