International Journal of Medical Informatics 188 (2024) 105479

Contents lists available at ScienceDirect

International Journal of Medical Informatics

journal homepage: www.elsevier.com/locate/ijmedinf

Review article

A review of information sources and analysis methods for data driven decision aids in child and adolescent mental health services

Kaban Koochakpour [a,*], Øystein Nytrø [a,b], Bennett L. Leventhal [c], Odd Sverre Westbye [d,e], Thomas Brox Røst [f], Roman Koposov [g], Thomas Frodl [h], Carolyn Clausen [d], Line Stien [d], Norbert Skokauskas [d]

[a] Department of Computer Science, Norwegian University of Science and Technology (NTNU), Trondheim, Norway
[b] Department of Computer Science, The Arctic University of Norway (UiT), Tromsø, Norway
[c] The University of Chicago, Chicago, IL, USA
[d] Regional Centre for Child and Youth Mental Health and Child Welfare (RKBU Central Norway), Department of Mental Health, Faculty of Medicine and Health Sciences, Norwegian University of Science and Technology (NTNU), Trondheim, Norway
[e] Department of Child and Adolescent Psychiatry, St. Olav's University Hospital, Trondheim, Norway
[f] Vivit AS, Trondheim, Norway
[g] Regional Centre for Child and Youth Mental Health and Child Welfare (RKBU), The Arctic University of Norway (UiT), Tromsø, Norway
[h] Department of Psychiatry, Psychotherapy and Psychosomatics, RWTH Aachen University, Aachen, Germany

ARTICLE INFO

Keywords:
Data analysis
Decision support system
Data driven
Mental health
Mental disorder
Child and adolescent
Machine learning

ABSTRACT

Objective: Clinical data analysis relies on effective methods and appropriate data. Recognizing distinctive clinical services and service functions may lead to improved decision-making. Our first objective is to categorize analytical methods, data sources, and algorithms used in current research on information analysis and decision support in child and adolescent mental health services (CAMHS). Our secondary objective is to identify the potential for data analysis in different clinical services and functions in which data-driven decision aids can be useful.

Materials and methods: We searched related studies in Science Direct and PubMed from 2018 to 2023(Jun), and also in ACM (Association for Computing Machinery) Digital Library, DBLP (Database systems and Logic Programming), and Google Scholar from 2018 to 2021. We have reviewed 39 studies and extracted types of analytical methods, information content, and information sources for decision-making.

Results: In order to compare studies, we developed a framework for characterizing health services, functions, and data features. Most data sets in reviewed studies were small, with a median of 1,550 patients and 46,503 record entries. Structured data was used for all studies except two that used textual clinical notes. Most studies used supervised classification and regression. Service and situation-specific data analysis dominated among the studies, only two studies used temporal, or process features from the patient data. This paper presents and summarizes the utility, but not quality, of the studies according to the care situations and care providers to identify service functions where data-driven decision aids may be relevant.

Conclusions: Frameworks identifying services, functions, and care processes are necessary for characterizing and comparing electronic health record (EHR) data analysis studies. The majority of studies use features related to diagnosis and assessment and correspondingly have utility for intervention planning and follow-up. Profiling the disease severity of referred patients is also an important application area.

* Corresponding Author.
E-mail address: kaban.koochakpour@ntnu.no (K. Koochakpour).

https://doi.org/10.1016/j.ijmedinf.2024.105479
Received 3 March 2023; Received in revised form 16 June 2023; Accepted 8 May 2024
Available online 13 May 2024

1. Introduction

Mental disorders often start developing in childhood and adolescence and can cause long-term, negative impacts on individuals, communities, and society [1]. In Norway, the prevalence of at least one mental health problem in children is 20 % [2,3]. It is estimated that 25 % of all children will experience a mental disorder during their life, with nearly 50 % of all mental health problems developing before age 14 [4]. A standard assessment in CAMHS starts with an intake assessment, gathering relevant information from the patient and caregivers through interviews with potentially additional tests required to exclude or include other disorders. In this procedure, it is crucial that services take local resources into account and that precise, evidence- and practice-based care is given early enough to achieve positive outcomes and prevent long-term negative effects [1].

The services and functions within CAMHS are significantly different from adult mental health services (AMHS). The CAMH services collaborate with families, caretakers, social services, schools, childcare, child protection agencies, community health services, family doctors, and leisure activities. CAMHS and AMHS have different jurisdictions and are handled by different branches of specialist healthcare. Most importantly, CAMHS and AMHS have different long- and short-term objectives for different patient groups.

1.1. Research objectives

This article aims to find potential clinical services and functions that can benefit from data analyses in CAMHS. To achieve this, we reviewed studies to find services, service providers, their roles, and functions, and most importantly, the contribution of the individual studies.

1.2. Research questions

In the growing research on decision support and data analysis methods in CAMHS, we want to uncover: What are the main characteristics of research contributions? What is the potential clinical utility[1] of this research? How can this contribute to individualized decision aids that enable local, early, and precise care?

2. Methodology

We searched and reviewed existing studies conducted between 2018 and 2023. The objective was to explore these studies' characteristics to enhance understanding of employed variables and methods and gain insight into the actual experiences of those involved in CAMHS. Additionally, expert clinicians were consulted to interpret the categorized data, ultimately developing a framework highlighting the essential services and functions within CAMHS. Further elaboration on these methods is provided below.

2.1. Searching articles and data exploration

The first step was to explore pertinent databases for target articles. We used Science Direct and PubMed (2018–2023), ACM Digital Library, DBLP, and Google Scholar (2018–2021). The following search terms were used, but the actual search procedure varied with different database search capabilities. Where applicable, the terms were searched for in all fields (e.g., Title, abstract, keywords, mesh-terms). We did not add specific diagnoses and CAMHS-specific problems in the initial search.

- Topic: Data analysis OR Data-driven OR Decision support
- Domain: (Mental OR Psychiatric) AND (Health OR Disorder)
- Population: Child OR Adolescent OR Juvenile
- Publication year: 2018, 2019, 2020, 2021, 2022, 2023(Jun)

A total of 434 articles met the inclusion criteria and were screened based on the pertinence of the title and the abstract. As a result of title and abstract screening, 282 articles were excluded. Eight additional articles that were not initially included due to falling outside of the narrow publication period were acquired and were found by snowballing and included at this stage. The remaining 160 articles underwent screening for inclusion based on the article type, accessibility, and content relevance and resulting in the exclusion of 110 articles. All articles that met one of the following exclusion criteria were excluded from the current review: Books, book chapters, *meta*-analyses, review articles, studies based on/for COVID-19, studies with very few variables, studies with specific applied methodology (i.e., questionnaires or qualitative based inquiry). A total of 50 articles were found to be eligible for full-text screening. In the end, from the full-text articles included, eleven were excluded as the predetermined required study characteristics were not present, resulting in a final total 39 articles to form the basis of the review (Fig. 1) [5].

2.2. Studies' characteristics

The included studies varied in the specific objective of the data analysis, and utilized different analytical methods to detect, diagnose, or predict the onset, progress, or prognosis of the mental disorders. For this review, materials and methods of each study was characterized by the following:

- Data source type
- Input variables[2]
- Analytical methods (Machine learning algorithms and statistics)
- Evaluation metrics and methods

This allows us to understand and compare different aspects of previous studies and identify similarities, differences, and deficiencies more easily.

2.3. Data interpretation and framework development

We are studying CAMHS decision support [6–8]. In particular, we are researching data-driven decision aids, utilizing a comprehensive and complete CAMHS-specific EHR database with rich, well-structured data [1]. This EHR system supported detailed process and role documentation, which helped us characterize data and identify processes, services, roles, situations, and service functions where data analysis and corresponding data-driven aid would be helpful. Fig. 2 presents how we used our EHR data to bootstrap our first data characterization and process framework versions. The figure also depicts how the literature search and selected studies were used to extend and refine the data characterization and process framework. Our research team comprises senior clinical psychiatrists, psychologists, and clinic managers having practiced or practicing in many different countries. None of the clinicians had used the EHR system that was used to bootstrap the process. This domain specialist team was used to validate data characterization and process framework. We had more than eight workgroup meetings or individual interviews, which led to a redesign of either data characterization or process framework. As seen in the figure, we refined the characterization and framework iteratively after specialist validation. In the early iterations, the computer scientists doing the EHR data exploration wanted to maintain a detailed patient perspective on data and

[1] A utility is a term considered by the authors to describe their perceptions of the outcomes the reviewed studies had targeted to provide as achievements for society.

[2] "Variable" refers to the term used for each individual data included in the clinical data sheet/set.

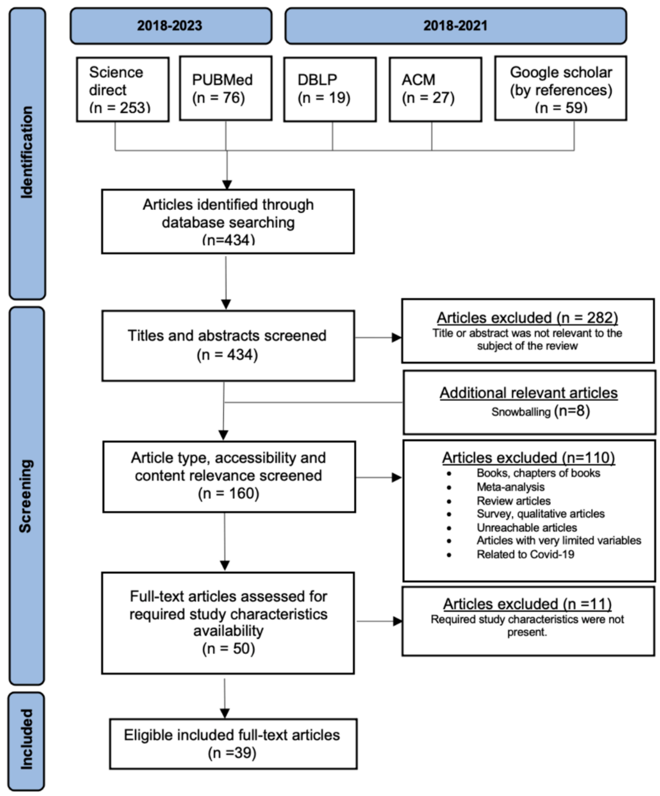

Fig. 1. Article selection flowchart.

processes. However, the international team of clinical specialists quickly reduced the initial particularities of Norwegian CAMHS and EHR-specific details. As a last step of simplification, we purged and combined data and process elements if they were representative for less than three studies.

3. Results

This section describes the characteristics of studies we used, our developed framework of child and adolescent mental health services, and finally, the potential utilities of the different studies.

3.1. Characteristics of studies

Gathered Information from the included 39 studies is organized into the following outputs and categories:

3.1.1. Data source categories

The studies used different data sources. We arrived at five categories as shown in Table 1.

3.1.2. Input variable categories

The input variables vary in their type and their intended use and function. We have categorized the variables used as inputs in different

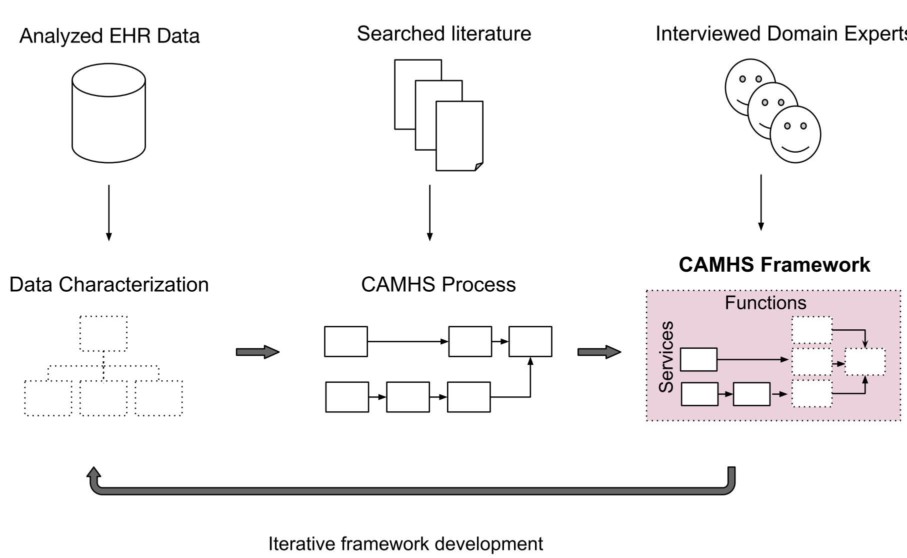

Fig. 2. CAMHS framework development.

Table 1
Data sources categories.

Data source Type	Provenance	Cohort details (Period if reported[a])
Administrative registers	National Death Index data	139 694 participants [23]
	National Health Insurance Research Database	125,940 visits [18]
Healthcare records	Referral records	46,503 referrals (2010–2014) [17]
	(Mental) electronic health record (containing Text, notes, …)	57,687 admissions (2008–2009) [22], 2,483 participants [25], 1,825 referrals [21], 638 participants [45]
	Semi-structured clinician-patient medical interviews	18 participants [13], 1078 participants [49], 1176 Participants (3 time points during 7 years) [54]
	Behavioral health rehabilitation services (BHRS)	3,385 participants (2013–2019) [15]
	Primary care records	11,807 participants [19]
	Child and Adolescent Mental Health Service (CAMHS)	476 referrals [24]
Individual records	Self/Parent-report	9,553 participants [26], 3,492 participants [20], 1,384 participants [16], 1,660 participants [48], 1,078 participants [49], 140 participants (January 2015-April 2021 in five time points) [53]
Research registers	Interaction of patients with smartphones – voice and text	33 participants (everyday life for up to 15 months) [37]
	ADHD-200	The length of data coverage for the ADHD-200 dataset depends on the specific data contributed by each site ([36,28,30,31]).
	Antipsychotic Trials of Intervention Effectiveness (CATIE) dataset	1,049 participants [33]
	Data collection with interviews by Child Protection Services (CPS) agency	8.46 million case records [27]
	Data collection in EDs, hospitals or mental health centers – Phenotypic, cognitive, genetic, eye tracking and MRI study (EEG and NeuroIMAGE study)	1,167 participants [55], 120 recruited participants [59] 686 participants [29], 6905 participants [58], 32 participants [57], 4136 participants [56], 133 participants [52], 1,112 participants [51], 2,368 participants [50]
	Manual collected/recorded data	14,901 participants [19], 5,210 participants (2 years) [14], 129 participants [32], 61 participants [34], 14 participants ([11,12])1,176 Participants (2010–2017 in 3 time points) [54]
School/social records	School records	249 participants [35]

[a] The length of data coverage was not generally possible to uncover.

studies based on their types and their specific respective applications (Table 2).

3.1.3. Categorizing analytical methods (Machine learning and statistics)

Multiple analytical methods were found in the studies, including both machine learning techniques and statistical methods.[3] We have divided the description of results into four phases: Data pre-processing, feature selection, classification and prediction, and evaluation.

Data pre-processing: It is the first and one of the most important phases in data analysis. It usually consists of data manipulation and dropping to ensure optimal quality analysis [10]. Methods utilized in some studies (e.g., [11–13]) also referred to this phase as missing data removal, noisy data removal, inconsistent data removal, co-registration, realignment, normalization, smoothing, slice time correction, and linear discriminant analysis (LDA). In addition, studies in the scope of Neuroimaging, EEG, and eye tracking (e.g., [57–59]) usually have specific steps as pre-processing that were significantly clearer described compared to the papers in other scopes. Most of the studies did not describe the details of the methods they used in this phase.

Feature selection: This is the process of determining the independence and causality of the variables, and ultimately which are most important for developing a (predictive) model and which can be removed from the analysis. We found correlation-based feature selection, mean, standard deviation, rolling mean, seed-based correlation, feature selection genetic algorithm (FSGA), ReliefF, and information gain measures. Support Vector Machine (SVM) was used in several studies as the feature selection method.

Classification and prediction: The algorithms used for classification and prediction in the reviewed articles are gathered in Table 3. All studies were supervised, except two [37,42], which were not supervised.

[3] "Statistics draws population inferences from a sample, machine learning finds generalizable predictive patterns" [9].

Table 2
Input variables' categories.

Category	Input variable types and examples
Demographics	**Family situation:** Members, social, economic, educational **Living status:** Location, urbanization **Personal attributes:** Age, gender, marital state
Diagnosis	Psychiatric diagnoses, somatic diagnoses, mental disorders, general symptoms
Assessment	**Biological:** Sex, somatic health, genetic variant, IQ, electrodermal activity, brain activity, emotional parameter **Phenotype:** Disabilities (conduct/functional, vocal/speech, thinking, concentrating, cooperation, psychomotor retardation, facial/behavioral responses) **Specific symptoms and severity:** Emotional symptoms (mood, anxiety, worry, feeling guilty)Pscho symptoms (destruction, lose/misplace, excessive talking, stealing, deceit, truancy)Somatic symptoms (sleep difficulty, weight and appetite change, drug abuse, restlessness, biting nails) **Psychological:** Mental health, cognitive ability, maltreatment, psycho measurement score **Environmental:** Social, financial, safety, living status, schooling, patient preferences, hospital, and physician **History/exposure:** Family history (drug abuse, crime, disorders) Personal health status history (general, mental, somatic, behavioral, criminal) Personal experience history (emergency admission, referral, discharge, assessment)Service history (protective, deprivation index) **General:** Patient concerns, protective and risk factors **Family:** – **Social:** –
Treatment evaluation & follow-up	**Biological:** Medication (Prescription, dose level, dose change, stopping reason) **Psychotherapy:** Type, level, interest, referral, stopping reason Environmental: Hospitalization and Length/number of stays **Social:** Service and receivers' characteristic **Follow-up:** Treatment-seeking, patient preference, intervention planning, treatment dropout/stability) **Treatment history:** Medication, psychotherapy, treatment and intervention, number of consultations/visits

The learned model types of the algorithms are in the second column of the table. While many studies have used only machine learning algorithms for classification and prediction, some used some statistical models too. The statistical methods used included the chi-squared test, univariate analyses, *t*-test, pairwise *t*-test, and Bayesian network. Other tests included two-sided, Kolmogorov-Smirnov, Mann-Whitney U, Analysis of Variance (ANOVA), the partial eta squared measure, and analysis like post-hoc pairwise comparisons analysis, timeline analysis,

Table 3
Machine learning algorithm categories.

Algorithm	Learned/Output model Type	Study(s)
Latent Growth curve modeling	Structural Equational Modeling (SEM)	[14,15,16]
Logistic regression model	Regression	[17,18,19,20,21,22,23,24,25,56,48]
McFadden's R2	Regression	[20]
Linear regression model	Regression	[24,20,26,27,16,18,53,57]
Random forest/ extremely randomized trees	Classification	[17,18,12,28,29,27,25,52,56,55,54,48]
Naive Bayes	Classification	[18,12,52]
Gaussian Naive Bayes (GNB)	Classification	[27]
Decision tree	Classification	[18,12,13,27,30,31,52]
Classification and regression tree (CART) – Decision tree	Classification	[18]
Support Vector Machine	Classification	[32,33,52,59,54,48]
Gradient boosting classifier	Boosting and Classification	[15]
XGBoost (eXtreme Gradient Boosting)	Boosting and Classification	[17]
AdaBoost (Adoptive Boosting) – Decision tree	Boosting and Classification	[12]
Decision Stump – Decision tree	Boosting and Classification	[12]
Bagging (Bootstrap aggregation)	Boosting and Classification	[12]
Artificial neural network (ANN)	Regression	[27,58]
Convolutional neural network (CNN)	Regression	[34,51]
Radial basis function – Neural Network	Classification	[35]
Multilayer perceptron (MLP) – Neural Network	Classification and Regression	[35]
Extreme learning machine (ELM) – Neural Network	Classification	[36]
Feed-forward Neural Network (FNN)	Classification	[50]
Random Tree – Decision tree	Classification	[12]
Hoeffding Tree – Decision tree	Classification	[12]
J48 – Decision tree	Classification	[12]
REP Tree – Decision tree	Classification	[12]
Partial decision tree (PART) – Decision tree	Classification	[12]
JRip (RIPPER: Repeated Incremental Pruning to Produce Error Reduction) – Rule induction	Classification	[12,11]
Multi-Output Classifiers (MOC)	Classification	[56]
DISSFCM (Dynamic Incremental Semi-Supervised Fuzzy C-Means)	Clustering	[37]
Agglomerative hierarchical clustering	Clustering	[42]
K-Nearest Neighbor (KNN)	Classification	[13,27]
Poisson regression	Regression	[23]
Cox regression	Regression	[45]
Logistic cross-validation lasso prediction models	Regression	[19,58,48]
Natural language processing (NLP)	Classification	[25,45]

Table 4
Evaluation metrics or methods

(a) Evaluation metric	Number of studies
Sensitivity or Recall	16
Accuracy	15
Specificity	8
Area under the ROC Curve (AUC)	6
Precision	6
False Positive Rate (FPR)	3
F-score	5
G-mean score	2
Z-score	3
False Omission Rate (FOR)	1
Beta coefficient (standard error)	1
t score	1
McFadden's R2	1
Cohen's Kappa	1
Error rate	1
Area Under the Precision-Recall Curve (AUPRC)	1
Matthew Correlation Coefficient (MCC)	1
(b) Evaluation method	**Number of studies**
Cross-validation	6
Chi-square test	2
Expert validation	1
Receiver Operating characteristic curve (ROC) model	1
Field-testing by practitioners	1
Continual testing by practitioners	1
Confusion matrix	1
Sensitivity analyses	1

and measures like un-adjusted and adjusted odds ratios (AORs), N (%), mean, standard deviation (SD) and median which were used for some analyzes.

Evaluation: The included studies used a variety of evaluation metrics and/or methods. Some studies used metrics for evaluations, whereas others used methods and models (Table 4).

Recall and Accuracy, for example, were used in several studies, while others (e.g., FOR, Confusion matrix) were applied in only one study.

3.2. A framework for services and functions

In order to understand and sort roles and actors and areas for application of technology, we needed to refine the framework already outlined in Fig. 3. The studies and iterative consultation with clinicians and managers helped us identify the most important services, organizational units, their roles, and functions. The framework in Fig. 3 is the result of refining and generalizing CAMH activities from a service point of view. It tries to represent the most important services, service functions and service providers in a wide CAMHS context, emphasizing roles or responsibility in decision-making. Originally, we wanted to take a patient perspective, but this did not fit naturally with the perspective of the studies. It would indeed be worthwhile to look at the utility of research from a patient point of view.

3.3. Interpretation of studies' results: Intended utilities

Expert clinicians were crucial in interpreting the studies and their intended utility in particular services (Services were introduced in the framework (Fig. 3)). Table 5 shows the utility of studies according to services and their different functions.

4. Discussion

Other review articles in this domain [38–41], do not distinguish between services. Our framework is specific to CAMHS, designed to serve this review's purpose, and is not intended as a general mental health service model. The long-term service framework eDESDE-LTC aims to organize and standardize health services and procedures [47]. It could potentially enable broader and more general comparisons of research results and relevance beyond our CAMHS-specific framework.

The relatively small scope and limited time interval is the shortcoming of this study. While the applied categorization system meets the study's objectives, this presents a potential bias based on over-fitting. Despite this limitation, there is potential for adaptation of the categories for future research. However, future CAMHS data analytical research, having been informed from previous analyses, has the potential to be approached from a broader scope, thus making our framework and categories too narrow in scope and thus no longer applicable. Future studies should first revise, evaluate and validate the framework in line with the study's specific objectives and search criteria. We present and discuss the rest of our findings in the following sections:

4.1. Context of care

While all studies seem to acknowledge more or less that clinical information is directly related to the patient and the care process, no study included a coherent framework to describe those care processes. This motivated us to develop a framework to precisely describe the patient's situations in mental health services.

4.2. Clinical data as input

Data structure All but two studies use only structured variables. The two studies employed NLP-techniques for analysis of clinical EHR text to identify symptoms and disease onsets [25,45]. Clinical text interpretation is a rapidly expanding field of research [60]. We believe that text interpretation using NLP combined with deep learning methodology on structured and unstructured EHR content may revolutionize mental healthcare in general [46].

Data size Study data size was given either as the number of record entries or patients. The median number of patients was 1,550, and the median number of record entries was 46,503. Only two outlier studies had data volumes (576,000 patients and 8,460,000 records) to potentially support unsupervised learning. The range of data set sizes found is not surprising, considering that we did not explicitly search for "machine learning".

Data content With regards to the data content, only one study used "school records" [35]. Additionally, the input variable subcategory of "assessment" did not contain any input variables that were classified directly in the "social" or "family" subcategories. It could be interpreted as a potential lack of interest or inaccessibility to activities at home, studies, or (pre)school (which can have more effects on early recognition) before the patient meets with the community healthcare provider. It is based on our limited observation and may not be correct in general [42].

Among the articles reviewed, ADHD emerged as the most extensively studied disorder, with a total of 11 articles dedicated to it [11,12,16,28,29,30,31,34,35,36,57]. Following closely, depression was examined in four articles [13,14,20,26]. Other disorders such as autism, schizophrenia, conduct disorder, bipolar disorder, suicide, substance use, hypersomnolence, body dysmorphic disorder and common mental disorders (including anxiety), were the subject of other studies.

Many articles focused on predicting risks and other aspects of care rather than on specific disorders. These contributions encompassed topics such as maltreatment [17], juvenile delinquency [32], readmission [22], return visits [18], referral patterns [21], timely services [23], referral and waiting time [24], disorder onset [25,45], child treatment recurrence [27], prediction of outcomes [54] and effectiveness of treatments [53].

It is worth mentioning, half of the articles were included in the period 2022–2023, working on brain activities and neuroimages.

Data As a crucial factor in determining research areas and choosing of targeted data sources, can be considered from two aspects: data does not exist, and data exists but is not publicly available. The first aspect

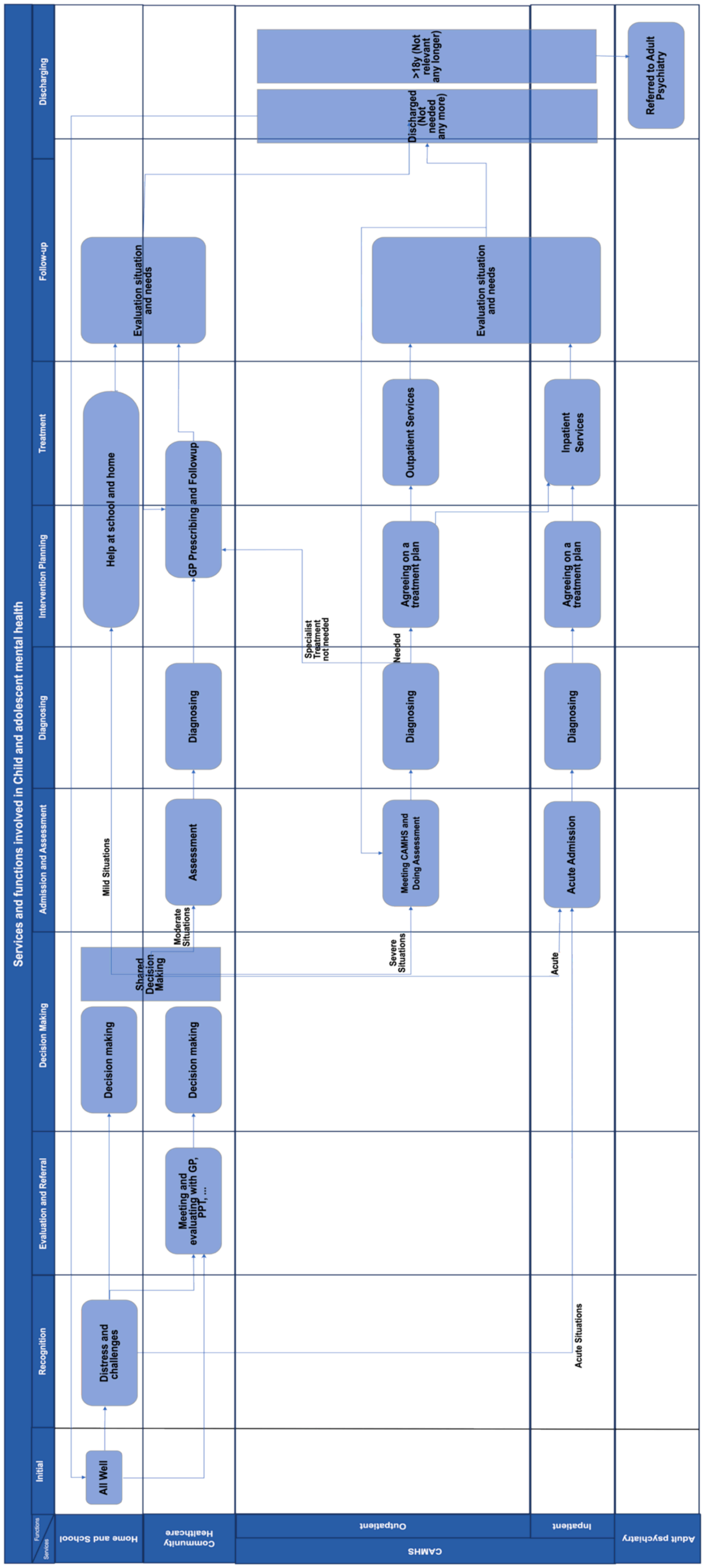

Fig. 3. Services and functions involved in Child and adolescent mental health.

Table 5
The utility of studies for different services and service functions.

Services	Functions	Utilities
Home and School	Recognition	Detect early [34,13,35,19,45]; Prevent early [20,32]; Increase accuracy by including novel information [13,54].
Community Care	Evaluation and Referral	Precise referral admission [21,24]; Reduce waiting time for referral [24].
Home and School; Community Care	Decision making	Predict and reduce health risk [17,52,48]; Predict recurrence [27];
Community Care; CAMHS	Admission and Assessment	Reduce wrong referral rejections [21]; Reduce undue admission delays [24]; Optimize service selection [21].
Community Care; CAMHS	Diagnosing	Increase explainability [30,12]; Increase accuracy [30,31,12,11,28,59]; Increase precision [30,31,36,35]; Predict disorder [37,19,50,51,56,59,55]; Predict symptoms [58]; Improve differentiation of disorder severity [13], symptoms [33,57] and patient subgroups [49]; Increase accuracy by including novel information [29,11]; Reduce diagnosis delay [11].
Home and School; Community Care; CAMHS	Intervention Planning	Enable shared decision-making [20]; Reduce symptoms [14]; Predict outcomes [14,19,26,16]; Design interventions [14,16].
Home and School; Community Care; CAMHS	Treatment and Follow-up	Monitor drop-out [20], Monitor guideline appropriateness [15]; Assess duration [20]; Assess treatment effectiveness [53]; Monitor treatment response [33]; Monitor symptom control [25]; Identify follow-up timeliness indicators and increase timeliness [23].
CAMHS	Discharging	Reduce re-referrals [21]; Predict re-referral [22]; Identify re-referral risk indicators [22,18]; Increase accuracy in re- referral [18].

highlights the comparatively lower level of documentation in child and adolescent mental health services compared to other specialized pediatric services. The second aspect reflects that more obstacles exist for accessing due to the sensitivity of this field.

4.3. Pre-processing and feature selection

While data pre-processing is a mandatory and inseparable part of all data analysis, that can widely affect the quality, validity, and precision of results. Only two studies have described this phase of the research process. Most studies did not describe the details of the methods they used. Not considering the neuroimaging studies, feature selection was only introduced in 8 out of 39 studies. Half of them (4 studies) used Support vector machine as their only feature selection methodology. For the remaining studies, feature selection was not explicit about the method or criteria.

4.4. Learning methodology

While the mental health field is complex and the knowledge about possible clusters is limited, it appears that semi-supervised and unsupervised learning algorithms can be beneficial. However, the minimal use of algorithms limits the strength of the results. The extensive usage of the Logistic and Linear regression models, random forest, and general decision trees are understandable based on the simplicity of use and the ability to interpret the results. It is worth mentioning that most classifications were binary and not multi-class, which shows the intent to classify a set of elements into two classes based on one classification rule. Overall, however, despite the phase of the study or the methods applied, commonly, there was no justification/explanation for the choice of the specific method applied and why it might be most advantageous to analyze that particular type of data.

4.5. Evaluation methods

Regarding to evaluation aspect, the utilization of evaluation metrics and methods in studies reveals inconsistencies and a lack of justification. While some metrics are commonly used, others are rarely employed. Moreover, authors often fail to explain why they chose specific methods and metrics, leaving uncertainty regarding their suitability for evaluating the study results.

4.6. Application and Utilities

Ultimately interpreting the results and developing the framework built a basis for seeing what could be derived from the categorized information, which areas of data are most applicable, and still left untouched with the potential for further assessment. It illustrates many exciting possibilities for looking at data and data analysis, such as referral, referred patient severity profiling, and admission. In addition, data analysis was used significantly for topics such as accurate and early diagnoses, intervention planning, the effectiveness of treatment as well as follow-up care which are still interesting and worthwhile to investigate further using similar analyses on available data sets. Nevertheless, medication, prescriptions, discharges, return visits, re-referrals, and also care trajectory mining have the potential for more work.

4.7. Enhancing CAMHS with Temporal Analysis and Machine Learning

One important feature of CAMHS is that the patient is undergoing rapid mental and physical development. This accentuates that continuous EHR information and comprehensive patient trajectories that integrate all aspects of care for children and adolescents are vital to providing the best possible health service to this fragile group of patients. However, this calls for temporal analyses capturing individual development, disease progression, and underlying processes. Machine learning in temporal domains with sparse and contextual, and complex information is a field in rapid development that may bring fundamentally new insights to CAMHS.

5. Conclusion

This review presents an overview of clinical services and stages of care involved in CAMHS, which can help identify future opportunities for providing more comprehensive CAMHS using EHR data analyses within that landscape. However, there can be areas such as early diagnosis, comorbidities, changes in general functioning, referral, and re-referral processes, disease severity stratification, intervention planning, and the general efficacy of these cases.

Most studies focused on situation data, and 2 of 39 used temporal and process features. Disease progression and multi-episodic care are particularly important at a young age since social and individual development are so dynamic. Trajectory and process modeling may be important areas of further research. The studies were seldom explicit about the context and perspective of services providing care and recording information. Study comparison would be more reliable if actor- and perspective features were available. Natural Language Processing of unstructured clinical text can classify and identify conditions, events, and onsets not otherwise available as structured data. There is reason to believe that the combined use of NLP and structured data can increase the quality of results compared to using only structured data [43]. When analyzing mental health data in the presence of potential comorbidities and other complex health issues, semi-supervised and supervised learning algorithms can provide more accurate results with fewer data than unsupervised methods [44].

While this review is specific to CAMHS, we believe that the framework detailing situations and care processes is important for characterizing EHR secondary usage and data analysis.

Declaration of competing interest

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

Acknowledgements

The IDDEAS project is funded by The Research Council of Norway (grant no. 269117) and the Norwegian University of Science and Technology (NTNU). The project has received clearance from the regional ethical oversight committee and approval from the health service for this research on an anonymized extract of the health record.

References

[1] T.B. Røst, C.E. Clausen, Ø. Nytrø, R.A. Koposov, B.L. Leventhal, O.S. Westbye, V. Bakken, L.H. Knudsen Flygel, K. Koochakpour, N. Skokauskas, Local, early, and precise: Designing a clinical decision support system for child and adolescent mental health services, Frontiers, Psychiatry 11 (2020), https://doi.org/10.3389/fpsyt.2020.564205.
[2] Institute of Public Health, Quality of life and mental health among children and adolescents in Norway. https://www.fhi.no/en/op/hin/mental-health/mental-health-children-adolescents/, 2019 (updated 8 August 2023).
[3] Folkehelsemeldingen: Mestring og muligheter. (2014-2015). https://www.regjeringen.no/no/dokumenter/meld.-st.-19-2014-2015/id2402807/, 2015 (approved 27 March 2015).
[4] N. Skokauskas, D. Eckert, G. Busch, J.K.L. Andrade, T.M. Park, A.P.S. Guerrero, Sustainable child and adolescent psychiatry, Int. Rev. Psychiatry 34 (2022), https://doi.org/10.1080/09540261.2022.2082163.
[5] M.J. Page, J.E. McKenzie, P.M. Bossuyt, I. Boutron, T.C. Hoffmann, C.D. Mulrow, et al., The prisma 2020 statement: an updated guideline for reporting systematic reviews, 372, British Publisher of Medical Journals, 2021, https://doi.org/10.1136/bmj.n71.
[6] K. Koochakpour, Ø. Nytrø, O.S. Westbye, B. Leventhal, R. Koposov, V. Bakken, C. Clausen, T.B. Røst, N. Skokauskas, Success factors of an early EHR system for child and adolescent mental health: Lessons learned for future practice data-driven decision aids, Stud. Health Technol. Inf. 290 (2022) 182–186, https://doi.org/10.3233/SHTI220057.
[7] C.E. Clausen, B.L. Leventhal, Ø. Nytrø, R. Koposov, O.S. Westbye, T.B. Røst, V. Bakken, K. Koochakpour, K. Thorvik, N. Skokauskas, Testing an individualized digital decision as- sist system for the diagnosis and management of mental and behavior disorders in children and adolescents, BMC Med. Inf. Decis. Making 20 (2020), https://doi.org/10.1186/s12911-020-01239-2.
[8] C.E. Clausen, B.L. Leventhal, Ø. Nytrø, R. Koposov, O.S. Westbye, T.B. Røst, V. Bakken, K. Koochakpour, K. Thorvik, N. Skokauskas, Clinical decision support systems: An inno- vative approach to enhancing child and adolescent mental health services, Journal of the American Academy of Child and Adolescent Psychiatry 60 (2020), https://doi.org/10.1016/j.jaac.2020.09.018.
[9] D. Bzdok, N. Altman, M. Krzywinski, Statistics versus machine learning, Nat. Methods 15 (2018) 233–234, https://doi.org/10.1038/nmeth.4642.
[10] A.O. Alzahrani, M.J.F. Alenazi, Ml-idsdn: Machine learning based intrusion detection system for software-defined network, Concurrency and Computation, Pract. Exper. 35 (2023), https://doi.org/10.1002/cpe.7438.
[11] S. De Silva, S. Dayarathna, G. Ariyarathne, D. Meedeniya, S. Jayarathna, A. M. Michalek, Computational decision support system for adhd identification, Int. J. Autom. Comput. 18 (2) (2021) 233–255, https://doi.org/10.1007/s11633-020-1252-1.
[12] S. De Silva, S. Dayarathna, G. Ariyarathne, D. Meedeniya, S. Jayarathna, A. M. Michalek, G. Jayawardena. A rule-based system for adhd identification using eye movement data, IEEE, 2019, pp. 538–543, https://doi.org/10.1109/MERCon.2019.8818865.
[13] M. Muszynski, J. Zelazny, J.M. Girard, L.-P. Morency, Depression severity assessment for adolescents at high risk of mental disorders, in: in: Proceedings of the 2020 International Conference on Multimodal Interaction, 2020, pp. 70–78, https://doi.org/10.1007/s11633-020-1252-1.
[14] C.H. Brown, A. Brincks, S. Huang, T. Perrino, G. Cruden, H. Pantin, G. Howe, J. F. Young, W. Beardslee, S. Montag, et al., Two-year impact of prevention programs on adolescent depression: An integrative data analysis approach, Prev. Sci. 19 (1) (2018) 74–94, https://doi.org/10.1007/s11121-016-0737-1.
[15] J.D. Troy, R.M. Torrie, D.N. Warner, A machine learning approach for identifying predictors of success in a medicaid-funded, community-based behavioral health program using the child and adolescent needs and strengths (cans), Children and Youth, Services Review 126 (2021), https://doi.org/10.1016/j.childyouth.2021.106010.
[16] A. Wüstner, C. Otto, R. Schlack, H. Hölling, F. Klasen, U. Ravens-Sieberer, Risk and protective factors for the development of adhd symptoms in children and adolescents: Results of the longitudinal BELLA study, PloS one 14 (3) (2019), https://doi.org/10.1371/journal.pone.0214412.
[17] A. Chouldechova, D. Benavides-Prado, O. Fialko, R. Vaithianathan, A case study of algorithm-assisted decision making in child maltreatment hotline screening decisions, in: Conference on Fairness, Accountability and Transparency, PMLR (2018) 134–148.
[18] Y.-H. Hu, C.-T. Tai, S.C.-C. Chen, H.-W. Lee, S.-F. Sung, Predicting return visits to the emergency department for pediatric patients: applying supervised learning techniques to the taiwan national health insurance research database, Comput. Methods Programs Biomed. 144 (2017) 105–112, https://doi.org/10.1016/j.cmpb.2017.03.022.
[19] D. Smith, K. Willan, S.L. Prady, J. Dickerson, G. Santorelli, K. Tilling, R.P. Cornish, Assessing and predicting adolescent and early adulthood common mental disorders in the alspac cohort using electronic primary care data, medRxiv (2021), https://doi.org/10.1101/2021.05.14.21255910.
[20] C. Otto, F. Reiss, C. Voss, A. Wüstner, A.-K. Meyrose, H. Hölling, U. Ravens-Sieberer, Mental health and well-being from childhood to adulthood: design, methods and results of the 11-year follow-up of the BELLA study, European child & adolescent psychiatry 30 (10) (2021) 1559–1577, https://doi.org/10.1007/s00787-020-01630-4.
[21] A.S. Hansen, C.H. Christoffersen, G.K. Telléus, M.B. Lauritsen, Referral patterns to outpatient child and adolescent mental health services and factors associated with referrals being rejected. a cross-sectional observational study, BMC Health Services Research 21 (1) (2021) 1–12, https://doi.org/10.1186/s12913-021-07114-8.
[22] J. Billings, I. Blunt, A. Steventon, T. Georghiou, G. Lewis, M. Bardsley, Development of a predictive model to identify inpatients at risk of re-admission within 30 days of discharge (parr-30), BMJ open 2 (4) (2012), https://doi.org/10.1136/bmjopen-2012-001667.
[23] C.A. Fontanella, L.A. Warner, D.L. Steelesmith, G. Brock, J.A. Bridge, J.V. Campo, Association of timely outpatient mental health services for youths after psychiatric hos- pitalization with risk of death by suicide, JAMA Netw. Open 3 (8) (2020), https://doi.org/10.1001/jamanetworkopen.2020.12887.
[24] J. Smith, R.G. Kyle, B. Daniel, G. Hubbard, Patterns of referral and waiting times for specialist child and adolescent mental health services, Child and Adolescent Mental Health 23 (1) (2018) 41–49, https://doi.org/10.1111/camh.12207c.
[25] N. Viani, R. Botelle, J. Kerwin, L. Yin, R. Patel, R. Stewart, S. Velupillai, A natural lan- guage processing approach for identifying temporal disease onset information from mental healthcare text, Sci. Rep. 11 (2021), https://doi.org/10.1038/s41598-020-80457-0.
[26] P. Patalay, E. Fitzsimons, Development and predictors of mental ill-health and wellbeing from childhood to adolescence, Social psychiatry and psychiatric epidemiology 53 (12) (2018) 1311–1323, https://doi.org/10.1007/s00127-018-1604-0.
[27] Y. Han, M. Modaresnezhad, H. Nemati, An adaptive machine learning system for predict- ing recurrence of child maltreatment: A routine activity theory perspective, Knowledge-Based Syst. 227 (2021), https://doi.org/10.1016/j.knosys.2021.107164.
[28] E. Olivetti, S. Greiner, P. Avesani, Adhd diagnosis from multiple data sources with batch effects, Front. Syst. Neurosci. 6 (2012) 70, https://doi.org/10.3389/fnsys.2012.00070.
[29] D. Meer, P. Hoekstra, M. Donkelaar, J. Bralten, J. Oosterlaan, D. Heslenfeld, S. Faraone, B. Franke, J. Buitelaar, C. Hartman, Predicting attention-deficit/hyperactivity disorder severity from psychosocial stress and stress-response genes: A random forest regression approach, Transl. Psychiatry 7 (2017), https://doi.org/10.1038/tp.2017.114.
[30] S. Itani, M. Rossignol, F. Lecron, P. Fortemps, Towards interpretable machine learning models for diagnosis aid: a case study on attention deficit/hyperactivity disorder, PloS one 14 (4) (2019), https://doi.org/10.1371/journal.pone.0215720.
[31] S. Itani, F. Lecron, P. Fortemps, A multi-level classification framework for multi-site medical data: Application to the adhd-200 collection, Expert Syst. Appl. 91 (2018) 36–45, https://doi.org/10.1016/j.eswa.2017.08.044.
[32] I. Ucuz, A.U. Ciçek, A. Ari, O.O. Ozcan, S.A. Sari, Determining the probability of juvenile delinquency by using support vector machines and designing a clinical decision support system, Med. Hypotheses 143 (2020), https://doi.org/10.1016/j.mehy.2020.110118.

[33] F.Z. Esfahlani, K. Visser, G.P. Strauss, H. Sayama, A network-based classification frame- work for predicting treatment response of schizophrenia patients, Expert Syst. Appl. 109 (2018) 152–161, https://doi.org/10.1016/j.eswa.2018.05.005.
[34] M. Moghaddari, M.Z. Lighvan, S. Danishvar, Diagnose adhd disorder in children using convolutional neural network based on continuous mental task eeg, Comput. Methods Programs Biomed. 197 (2020), https://doi.org/10.1016/j.cmpb.2020.105738.
[35] M. Delavarian, F. Towhidkhah, P. Dibajnia, S. Gharibzadeh, Designing a decision support system for distinguishing adhd from similar children behavioral disorders, Journal of medical systems 36 (3) (2012) 1335–1343, https://doi.org/10.1007/s10916-010-9594-9.
[36] V. Sachnev, S. Suresh, N. Sundararajan, B.S. Mahanand, M.W. Azeem, S. Saraswathi, Multi-region risk-sensitive cognitive ensembler for accurate detection of attention- deficit/hyperactivity disorder, Cognit. Comput. 11 (4) (2019) 545–559, https://doi.org/10.1007/s12559-019-09636-0.
[37] G. Casalino, G. Castellano, F. Galetta, K. Kaczmarek-Majer, Dynamic Incremental Semi- supervised Fuzzy Clustering for Bipolar Disorder Episode Prediction (2020) 79–93, https://doi.org/10.1007/978-3-030-61527-76.
[38] R. Koposov, S. Fossum, T. Frodl, Ø. Nytrø, B. Leventhal, A. Sourander, S. Quaglini, M. Molteni, M.d.l. Iglesia Vaýa, H.-U. Prokosch, N. Barbarini, M.P. Milham, F. X. Castellanos, N. Skokauskas, Clinical decision support systems in child and adolescent psy- chiatry: a systematic review, European Child Adolescent Psychiatry 26 (2017), https://doi.org/10.1007/s00787-017-0992-0.
[39] L.F. Ramos-Limaa, V. Waikamp, T. Antonelli-Salgado, I. Cavalcante Passos, L. H. Machado Freitas, The use of machine learning techniques in trauma-related disorders: a systematic review, Journal of Psychiatric Research 121 (2020), https://doi.org/10.1016/j.jpsychires.2019.12.001.
[40] D. Librenza-Garcia, B. Jaskulski Kotzian, J. Yang, B. Mwangi, B. Cao, L.N. Pereira Lima, M. Bagatin Bermudez, M. Vianna Boeira, F. Kapczinski, I. Cavalcante Passos, The impact of machine learning techniques in the study of bipolar disorder: A systematic review, Neurosci. Biobehav. Rev. 80 (2017), https://doi.org/10.1016/j.neubiorev.2017.07.004.
[41] D. Saxena, K. Badillo-Urquiola, P.J. Wisniewski, S. Guha, A human-centered review of the algorithms used within the u.s. child welfare system. in: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, 2020, pp. 1–15, https://doi.org/10.1145/3313831.3376229.
[42] J. Stuart Ward, A. Barker, Undefined by data: A survey of big data definitions. https://doi.org/10.48550/arXiv.1309.5821, 2013.
[43] M. Yan, L. Tuset Gustad, Ø. Nytrø, Sepsis prediction, early detection, and identification using clinical text for machine learning: a systematic review, J. Am. Med. Inf. Assoc. 29 (2022) 559–575, https://doi.org/10.1093/jamia/ocab236.
[44] N. Al-Azzam, I. Shatnawi, Comparing supervised and semi-supervised machine learning models on diagnosing breast cancer, annals of medicine and surgery, Annals of Medicine and Surgery 62 (2021) 53–64, https://doi.org/10.1016/j.amsu.2020.12.043.
[45] J. Downs, H. Dean, S. Lechler, N. Sears, R. Patel, H. Shetty, M. Hotopf, T. Ford, M. Kyriakopoulos, C.M. Diaz-Caneja, C. Arango, J.H. MacCabe, R.D. Hayes, L. Pina-Camacho, Negative Symptoms in Early-Onset Psychosis and Their Association With Antipsychotic Treatment Failure, Schizophrenia Bulletin 45 (1) (2019) 69–79, https://doi.org/10.1093/schbul/sbx197.
[46] R. Patel, S.N. Wee, R. Ramaswamy, S. Thadani, J. Tandi, R. Garg, N. Calvanese, M. Valko, A.J. Rush, M.E. Rentería, J. Sarkar, NeuroBlu, an electronic health record (EHR) trusted research environment (TRE) to support mental healthcare analytics with real-world data, BMJ Open (2022), https://doi.org/10.1136/bmjopen-2021-057227.
[47] L. Salvador-Carulla, J. Alvarez-Gálvez, C. Romero, M.R. Gutiérrez-Colosía, G. Weber, D. McDaid, H. Dimitrov, L. Sprah, B. Kalseth, G. Tibaldi, J.A. Salinas-Perez, C. Lagares-Franco, M.T. Romá-Ferri, S. Johnson, Evaluation of an integrated system for classification, assessment, and comparison of services for long-term care in Europe: the eDESDE-LTC study, BMC Health Serv. Res. (2013), https://doi.org/10.1186/1472-6963-13-218.
[48] S. Adhikari, S. You, A. Chen, S. Cheng, K.Y. Huang, Applied machine learning to identify differential risk groups underlying externalizing and internalizing problem behaviors trajectories: A case study using a cohort of Asian American children, Plos one 18 (3) (2023), https://doi.org/10.1371/journal.pone.0282235.
[49] J.K. Gool, Z. Zhang, M.S. Oei, S. Mathias, Y. Dauvilliers, G. Mayer, G. Plazzi, R. del Rio-Villegas, J.S. Cano, K. Šonka, M. Partinen, Data-driven phenotyping of central disorders of hypersomnolence with unsupervised clustering, Neurology 98 (23) (2022) 2387–2400, https://doi.org/10.1212/WNL.0000000000200519.
[50] L. Chan, C. Simmons, S. Tillem, M. Conley, I.A. Brazil, A. Baskin-Sommers, Classifying conduct disorder using a biopsychosocial model and machine learning method, Biol. Psychiatry: Cognit. Neurosci. Neuroimaging (2022), https://doi.org/10.1016/j.bpsc.2022.02.004.
[51] R. Kashef, ECNN: Enhanced convolutional neural network for efficient diagnosis of autism spectrum disorder, Cognit. Syst. Res. 71 (2022) 41–49, https://doi.org/10.1016/j.cogsys.2021.10.002.
[52] S. Ozdemir, I. Akin-Bulbul, I. Kok, S. Ozdemir, Development of a visual attention based decision support system for autism spectrum disorder screening, International Journal of Psychophysiology 173 (2022) 69–81, https://doi.org/10.1016/j.ijpsycho.2022.01.004.
[53] D. Rautio, M. Gumpert, A. Jassi, G. Krebs, O. Flygare, P. Andrén, B. Monzani, L. Peile, M. Jansson-Fröjmark, T. Lundgren, M. Hillborg, Effectiveness of multimodal treatment for young people with body dysmorphic disorder in two specialist clinics, Behavior Therapy 53 (5) (2022) 1037–1049, https://doi.org/10.1016/j.beth.2022.04.010.
[54] W.A. Rothenberg, A. Bizzego, G. Esposito, Jennifer E. Lansford, S.M. Al-Hassan, D. Bacchini, M.H. Bornstein, L. Chang, K. Deater-Deckard, D. Giunta, K.A. Dodge, S. Gurdal, Q. Liu, Q. Long, P. Oburu, C. Pastorelli, A.T. Skinner, E. Sorbring, S. Tapanya, L. Steinberg, L.M. Uribe Tirado, S. Yotanyamaneewong, L.P. Alampay, Predicting Adolescent Mental Health Outcomes Across Cultures: A Machine Learning Approach, J Youth Adolescence (2023), https://doi.org/10.1007/s10964-023-01767-w.
[55] J. Zhang, S. Sami, R. Meiser-Stedman, Acute stress and PTSD among trauma-exposed children and adolescents: computational prediction and interpretation, Journal of anxiety disorders 92 (2022) 102642, https://doi.org/10.1016/j.janxdis.2022.102642.
[56] N. Langer, M.B. Plomecka, M. Tröndle, A. Negi, T. Popov, M. Milham, S. Haufe, A benchmark for prediction of psychiatric multimorbidity from resting EEG data in a large pediatric sample, NeuroImage 258 (2022) 119348, https://doi.org/10.1016/j.neuroimage.2022.119348.
[57] U. Kumar, A. Arya, V. Agarwal, Altered functional connectivity in children with ADHD while performing cognitive control task, Psychiatry Research: Neuroimaging 326 (2022) 111531, https://doi.org/10.1016/j.pscychresns.2022.111531.
[58] J. Hong, J. Hwang, J.H. Lee, General psychopathology factor (p-factor) prediction using resting-state functional connectivity and a scanner-generalization neural network, Journal of Psychiatric Research 158 (2023) 114–125, https://doi.org/10.1016/j.jpsychires.2022.12.037.
[59] Q. Zhang, B. Li, S. Jin, W. Liu, J. Liu, S. Xie, L. Zhang, Y. Kang, Y. Ding, X. Zhang, W. Cheng, Comparing the Effectiveness of Brain Structural Imaging, Resting-state fMRI, and Naturalistic fMRI in Recognizing Social Anxiety Disorder in Children and Adolescents, Psychiatry Research: Neuroimaging 323 (2022), https://doi.org/10.1016/j.pscychresns.2022.111485.
[60] M. Filannino, Ö. Uzuner, Advancing the State of the Art in Clinical Natural Language Processing through Shared Tasks, Yearb. Med. Inform. (2018) 184–192, https://doi.org/10.1055/s-0038-1667079.