Artificial Intelligence in Pediatric Surgery:

A Systematic Review

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Abstract

Background

Amidst considerable enthusiasm surrounding the integration of artificial intelligence (AI) across various sectors, meaningful roles for AI in multifaceted healthcare ecosystems remain unclear. Initial efforts were centered on simple rule-based systems and data storage tools. Progress in the field led to the development of advanced medical imaging tools and decision-support systems that focused on rule-based reasoning. Despite their limitations, these precursors set the stage for subsequent advancements in machine learning algorithms, which have found applications from medical imaging to drug discovery and precision medicine. In pediatric surgery, AI has begun to show promise in surgical planning and patient care. This thesis aims to investigate the current applications of AI in pediatric surgery

Objective

To investigate the use of AI in pediatric surgery.

Methods

A PRISMA-compliant systematic review to appraise the evidence on machine learning models that address a pediatric surgery need.

Results

A review of nine medical databases identified a total of 8,178 unique records, from which 112 studies were eligible for inclusion in the present study. Those studies reported on 155 models that were trained on data from 430,654 children and adolescents. Half of the models (n=78; 50%) were predictive (for adverse events [n=41; 26%], surgical outcomes [n=26; 17%] and survival [n=11; 7%]), followed by diagnostic (n=43; 28%) and decision support models (n=34; 22%). Neural networks (n=57; 37%) and ensemble learners (n=73; 47%) were the most commonly used AI methods across application domains. The main pediatric surgical subspecialties represented across all models were general surgery (n=72; 46%) cardiac surgery (n=26; 17%), and neurosurgery (n=24; 15%). Overall mean accuracy was 0.86 ± 0.10. Forty-one percent (n=46) of models had a high risk of bias, and concerns over applicability were identified in 7% (n=8). Forty-eight percent of models were interpretable (n=74), and five (3%) were both interpretable and externally validated. However, no evidence suggests that any of those models were adopted in clinical practice.

Conclusions

While AI has wide clinical applications in pediatric surgery, models remain in-silico proofs of concept with no regulatory clearance or integration in clinical workflows. Few of the studied AI models were externally validated, interpretable, and not biased. Diverse, interdisciplinary collaboration is required for prospective external validation, removal of bias through equitable representation of minority classes, building interpretability in model architecture, and integration of AI models in clinical workflows.

Résumé

Contexte

Au milieu d'un enthousiasme considérable entourant l'intégration de l'intelligence artificielle (IA) dans divers secteurs, les rôles significatifs de l'IA dans les écosystèmes de soins de santé multifacettes restent flous. Les premiers efforts étaient axés sur des systèmes simples basés sur des règles et des outils de stockage de données. Les progrès dans le domaine ont conduit au développement d'outils avancés d'imagerie médicale et de systèmes de soutien à la décision axés sur le raisonnement basé sur des règles. Malgré leurs limitations, ces précurseurs ont préparé le terrain pour des avancées ultérieures dans les algorithmes d'apprentissage automatique, qui ont trouvé des applications de l'imagerie médicale à la découverte de médicaments et à la médecine de précision. En chirurgie pédiatrique, l'IA a commencé à montrer des promesses en matière de planification chirurgicale et de soins aux patients. Cette thèse vise à enquêter sur les applications actuelles de l'IA en chirurgie pédiatrique.

Objectif

Investiguer l'utilisation de l'IA en chirurgie pédiatrique.

Méthodes

Une revue systématique conforme à la méthodologie PRISMA pour évaluer les preuves sur les modèles d'apprentissage automatique qui répondent à un besoin en chirurgie pédiatrique.

Résultats

Une revue de neuf bases de données médicales a identifié un total de 8 178 références uniques, parmi lesquelles 112 études étaient éligibles pour inclusion dans la présente étude. Ces études ont porté sur 155 modèles formés à partir de données de 430 654 enfants et adolescents. La moitié des études (50 %) ont rapporté des modèles prédictifs (pour les événements indésirables [25 %], les résultats chirurgicaux [16 %] et la survie [9 %]), suivis de modèles diagnostiques (29 %) et de modèles de soutien à la décision (21 %). Les réseaux neuronaux (44 %) et les modèles d'apprentissage en ensemble (36 %) étaient les méthodes d'IA les plus couramment utilisées dans tous les domaines d'application. Les principales sous-spécialités de chirurgie pédiatrique représentées dans tous les modèles étaient la chirurgie générale (31 %) et la neurochirurgie (25 %). La précision moyenne globale était de 0,86 ± 0,10. Quarante pour cent des modèles présentaient un risque élevé de biais, et des préoccupations concernant l'applicabilité ont été identifiées dans 7 % des cas. Quarante-quatre pour cent des modèles étaient interprétables, et 6 % étaient à la fois interprétables et validés de manière externe. Cependant, aucune preuve ne suggère que l'un de ces modèles ait été adopté dans la pratique clinique.

Conclusions

Bien que l'IA ait de larges applications cliniques en chirurgie pédiatrique, les modèles restent des preuves de concept in-silico sans autorisation réglementaire ni intégration dans les flux de travail cliniques. Peu des modèles d'IA étudiés étaient validés de manière externe, interprétables et non biaisés. Une collaboration interdisciplinaire et diversifiée est nécessaire pour la validation externe prospective, l'élimination des biais grâce à une représentation équitable des classes minoritaires, la construction de l'interprétabilité dans l'architecture des modèles et l'intégration des modèles d'IA dans les flux de travail cliniques.

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Disclosures

Mohamed Elahmedi has no conflicts of interest to disclose.

Author Contribution

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Supervision: Poenaru D.

Abbreviations

Abbreviation	Term
ACTA	Automatic Computerized Transverse Axial scanner
AI	Artificial Intelligence
AKI	Acute Kidney Injury
ANOVA	Analysis of Variance
AUC	Area Under the Curve
CINAHL	Cumulative Index to Nursing and Allied Health Literature
COSTAR	Computer Stored Ambulatory Record
CSF	Cerebrospinal fluid
CT	Computerized Tomography
EHR	Electronic Health Record
FDA	Food and Drug Administration
FNR	False Negative Rate
FPR	False Positive Rate
GAN	Generative Adversarial Network
GMLP	Good Machine Learning Practices
GPT-3	Generative Pre-trained Transformer 3
MAR	Missing At Random
MCAR	Missing Completely At Random
ML	Machine learning
MNAR	Missing Not At Random
MRI	Magnetic Resonance Imaging
MYCIN	Not an acronym
NLP	Natural language processing
NSQIP	National Surgical Quality Improvement Program
OHNS	Otolaryngology–Head and Neck Surgery
OSF	Open Science Framework
PCA	Pricinpal Component Analysis
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PROBAST	Prediction model Risk Of Bias ASsessment Tool
QUADAS-2	Quality Assessment of Diagnostic Accuracy Studies-2
SaMD	Software as a Medical Device
SHAP	Shapley Additive Explanations
SMOTE	Synthetic Minority Oversampling Technique
SVM	Support Vector Machine
VAE	Variable Autoencoder
WHO	World Health Organization

Chapter 1: Introduction

1.1. Rationale

Intelligence is defined as the ability to solve problems [1], and healthcare, far from being an exact science [2], is characterized by complex challenges and uncertainties in diagnosis, decision planning, and treatment response [3,4]. While physician experience and use of available tools do reduce uncertainty, a need for advanced tools and methodologies that support precise, personalized care remains [5].

The advent of AI in healthcare marked a significant shift towards precision medicine [6], offering solutions to some of the most complex challenges in clinical practice. Pediatric surgery, which is distinguished from other clinical disciplines by unique complexities, stands on the cusp of transformation through AI integration. Pediatric surgeons treat heterogeneous patients with diverse ages, developmental stages, and needs, each presenting distinct surgical challenges [7,8]. This variability underscores the necessity for tools that offer personalized and precise care.

This present work provides a systematic review of AI's evolving role in pediatric surgery. It delves into the specific challenges within pediatric surgery that AI aims to address, such as diagnostic uncertainty, surgical planning, adverse event mitigation, and precision care through AI-powered patient selection, prediction of surgical outcomes, and accurate, timely diagnosis of surgical conditions. By way of a thorough examination of the use of AI in this field, the present thesis seeks to guide pediatric surgeons through pathways for improving for our youngest, most vulnerable patient population.

Furthermore, this work explores how AI is not a magic bullet but rather a tool in the pediatric surgeon's armamentarium - a tool that cannot be employed without careful analysis of safety, efficacy, and applicability. In this regard, the thesis also provides pediatric surgeons with a guide on how to critically review an AI model.

1.2. Literature Review

Since the inception of computer technology, its integration into healthcare has led to a transformation in medical practice and patient care. The early days of computing in medicine were marked by the utilization of data storage tools and basic algorithms. As early as the 1960s, computerized systems such as the Massachusetts General Hospital's Computer Stored Ambulatory Record (COSTAR) were being developed to manage patient records, centralizing information and improving administrative efficiency. Within the first 2 years, the system had records for more than 20,000 patients [9]. This laid the groundwork for what would eventually evolve into today's Electronic Health Records (EHR), a vital component of modern healthcare [10].

By the 1970s, advanced software was being developed to analyze medical images and support clinical decisions. The creation of the Automatic Computerized Transverse Axial (ACTA) scanner in 1972 marked a significant advancement in computed tomography (CT) [11], which revolutionized the field of radiology. The 1970s also saw the introduction of Mycin, a rule-based decision-support system designed to assist physicians in diagnosing bacterial infections and recommending antibiotics [12].

1.2.1. Evolution from Rule-Based Systems to Supervised Learning

The development of Mycin and other computer-aided decision tools in the 1970s was an indicator of significant interest in applying rule-based systems and pattern recognition in medicine [13]. These rule-based systems were constructed on the hypothesis that expert knowledge could be simulated through chains of deduction ("if elseif chains"), while matching strategies aimed to align patients' clinical characteristics with stored profiles [14]. However, these approaches faced challenges and did not yield the success that was initially anticipated. The key deficiencies stemmed from their lack of pathophysiological knowledge, and the process proved to be impractical for clinical application [15].

Despite these early setbacks, advances in computer technology led to the evolution from rule-based systems to machine learning algorithms [16] , which were originally classified as supervised vs unsupervised learning algorithms. Supervision refers to whether training the algorithm involves showing it the right answers paired with variables in a dataset - in other words, labeled training data. Training involves learning a model that can accurately map inputs to correct outputs. For example, a supervised learning algorithm might be trained with a dataset of medical images, each labeled with the correct diagnosis. The algorithm learns to recognize patterns associated with various diagnoses and can then apply this learned model to new, unseen images to predict their diagnoses [17].

Decision trees are a type of supervised machine learning algorithm that offers a more flexible and interpretable way of modeling complex relationships. Decision trees split data into branches based on variable values and generate a prediction at the end of each path [18]. Decision trees were inspired by rule-based systems, and they subsequently evolved into random forests, which consist of an ensemble of decision trees. The ensemblement brings further prediction robustness and reduces overfitting, which occurs when the model's rules become too specific to noise and random fluctuations in training data, leading to poor generalizability and limited external validity [19]. Many other ensemble learning techniques allow for the fusion of diverse models to improve prediction accuracy, generalizability, and robustness [20]. Support vector machines (SVMs) emerged as another powerful supervised learning technique, especially for classification tasks. By finding the optimal decision boundary that best separates classes in the data, SVMs provide a solid mathematical framework for complex classification problems, for example, deciding whether a tumor is benign or malignant [21].

1.2.2. Unsupervised Learning in Healthcare

Unsupervised learning is when the algorithm seeks to identify patterns or structures within the data on its own. For instance, it could cluster similar patient data together without prior knowledge of the categories. In the context of pediatric surgery, unsupervised learning might be used to group similar case profiles. Unsupervised learning has steadily gained prominence in healthcare by offering a way to analyze and derive insights from unlabeled data [22]. For example, K-nearest neighbors (K-NN) algorithm is an unsupervised learning technique that classifies a new example based on the majority class of its 'K' closest examples in the training data [23]. This approach has been effectively employed in various healthcare applications, such as predicting disease outbreaks and patient risk assessment. Its simplicity and ease of interpretation make K-NN a valuable tool for clinicians and researchers [24].

Clustering and Principal Component Analysis (PCA) are two other key methods in unsupervised learning. Clustering helps group data in a way that shows how different patient groups are related to each other. For example, it can arrange patients into clusters based on similar symptoms or genetic factors, making it easier to understand patient similarities and differences [25]. On the other hand, PCA is a method often used in analyzing complex data like genetic information and medical images. It simplifies large datasets by creating composite variables. The resultant dataset retains the same information but in a lower number of variables, which simplifies analysis and model training. [26]. PCA often serves as a preprocessing step in pipelines that employ multiple algorithms. Data preprocessing is an important step in AI algorithm design and it will be explored later in this thesis.

1.2.3. Ensemble Learning

Ensemble methods combine the results of multiple (usually supervised) machine learning algorithms into one. For example, a random forest is an ensemble of decision trees. Each individual decision tree gives a prediction (a classification), and the prediction that achieves majority is selected as the random forest's output.

While an ensemble learner is usually a combination of one type of algorithm, for example logistic regression models trained on different subsets of the data, some authors experimented with ensembling different algorithms [27].

An ensemble learner can also be built by combining neural networks. However in practice, neural networks are not improved with ensemble methods, since neural networks themselves are often learning complex patterns in the data. Additionally, training multiple neural networks for an ensemble can be computationally expensive and time-consuming.

1.2.4. Deep Learning

The advent of neural networks marked a significant milestone in AI's capabilities. Inspired by the structure of the human brain, neural networks consist of interconnected nodes or "neurons" that can learn complex nonlinear relationships. These networks learn from data by adjusting the connections between neurons [28]. Neural network-based algorithms like autoencoders, which are designed to learn the most important features in a dataset by compressing the data and then reconstructing it, serve multiple unsupervised learning purposes like dimensionality reduction and feature learning [29]. Autoencoders are a form of Principal Component Analysis that can retain non-linear relationships in composite variables [30]. Autoencoders have been useful in anomaly detection in healthcare settings, which includes identifying outliers in medical images or ECG signals [31].

Advances in neural network theory and design led to the development of several specialized neural network architectures. For example, recurrent neural networks (RNN) which are optimized for sequential processing, are useful for time series (follow-up) data. Convolutional neural networks (CNN), optimized for grid-like image data, have a role in image analysis. Recurrent convolutional neural networks (RCNNs), as the name implies, are useful in analyzing time series image data - videos.

1.2.5. Transformers and Generative Models

Introduced in 2017, transformers have revolutionized natural language processing (NLP) but also have applications in vision. Unlike RNNs, transformers can process all parts of an input sequence simultaneously rather than sequentially, making them highly parallelizable. Central to transformers is the attention mechanism, which selectively focuses on different parts of the input, assigning more weight to the most relevant information for the task at hand. In healthcare, including pediatric surgery, transformers can be used in tasks like automated medical transcription, drug interaction prediction, personalized surgical plans, surgical video analysis, and surgical training. [32] Large language models are essentially generative transformers [33].

Generative Adversarial Network (GAN) is another type of neural network that consists of a generator that synthesizes data that is similar to the input data, and a discriminator that attempts to tell real from generated data. Through this adversarial process, the network becomes increasingly better at synthesizing increasingly realistic data [34]. Variational Autoencoders on the other hand use a probabilistic autoencoder to generate images. The probabilistic process lets the autoencoder generate new data that is similar but not identical to original data. [35]. For instance, MDClone ® (Beer Sheba, Israel) is a platform that generates synthetic medical data for research purposes [36]. Since data availability is frequently a bottleneck that hinders research progress, MDClone and other synthetic data repositories accelerate research especially in pediatric surgery where patient data is often limited due to smaller population sizes and ethical considerations around data privacy. The ability of generative adversarial networks and variational autoencoders to generate synthetic but realistic data can be invaluable in these scenarios. It allows for the creation of large, diverse datasets that can be used to train machine learning models, test hypotheses, or simulate patient outcomes without compromising patient privacy [37,38].

1.2.6. Transfer Learning

This involves taking a model that was pre-trained on a large dataset and tailoring (or fine-tuning) it with a new, usually smaller, dataset specific to a target problem [39]. This approach is particularly useful in situations where the available data for the new task is limited. Transfer learning is effective because it leverages the knowledge gained by training from a large, non-domain specific dataset and applies it to a different but related problem, thereby improving learning efficiency and performance. Convolutional neural networks originally trained on a broad range of images have been fine-tuned to identify specific abnormalities in CT scans or MRIs, making this approach especially useful in pediatric surgery where small sample sizes are often encountered [40] . Similarly, pre-trained large language models like GPT-3 have been fine-tuned for improved biomedical inference [41].

In pediatric surgery, the unique challenges associated with treating children, such as diverse developmental stages, varying anatomical structures, and specific physiological needs, require highly specialized care (6). AI's significance in pediatric surgery arises from the unique challenges associated with treating children, who often cannot articulate their symptoms as clearly as adults, have limitations in undergoing investigations and especially radiologic testing due to radiation exposure concerns, and exhibit significant physiological differences from adults. Additionally, the continuous growth and development of children's bodies necessitate adaptable care approaches. AI tools and techniques are invaluable in this context as they offer advanced capabilities for personalized care, adapting to the evolving needs of pediatric patients and assisting in complex decision-making where traditional methods might be less effective. AI's ability to analyze vast amounts of data, recognize complex patterns, and adapt to individual patient profiles has facilitated advancements in surgical planning, intraoperative guidance, postoperative care, and patient monitoring.

1.3. Research Question

How has AI been applied in the surgical care of children and adolescents?

1.4. Hypothesis

AI models that are developed to address pediatric surgery needs demonstrate varying levels of performance, validation, bias, and interpretability across different pediatric surgery subspecialties

1.5. Objectives

The first objective of this project was to identify studies that reported on AI models that address a pediatric surgical need. The second objective was to analyze use case, performance, validation, bias, applicability and interpretability across all pediatric surgery subspecialties.

To our knowledge, this is the first systematic review that examines the use of AI in pediatric surgery. This work is presently under review with the Canadian Association of Pediatric Surgeons for publication in the Journal of Pediatric Surgery.

Chapter 2: Published Article (Manuscript-based Thesis)

The State of Artificial Intelligence in Pediatric Surgery: A Systematic Review

Mohamed Elahmedi, Riya Sawhney, Elena Guadagno, Fabio Botelho, Dan Poenaru

2.1. Article information

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Highlights

What is currently known about this topic?

Artificial intelligence has significant potential to transform child and adolescent health

What new information is contained in this article?

More than 100 predictive, diagnostic, and decision support AI models have been developed to assist in the care of children undergoing surgery.

The present study is the first comprehensive review that details the use of artificial intelligence in pediatric surgery

External validation, interpretability, and performance vary across models, and only few models were externally validated and interpretable.

2.2. Abstract

Background

Artificial intelligence (AI) has been recently shown to improve clinical workflows and outcomes - yet its potential in pediatric surgery remains largely unexplored. This systematic review details the use of AI in pediatric surgery.

Methods

Nine medical databases were searched from inception until January 2023, identifying articles focused on AI in pediatric surgery. Two authors reviewed full texts of eligible articles. Studies were included if they were original investigations on the development, validation, or clinical application of AI models for pediatric health conditions primarily managed surgically. Studies were excluded if they were not peer-reviewed, were review articles, editorials, commentaries, or case reports, did not focus on pediatric surgical conditions, or did not employ at least one AI model. Extracted data included study characteristics, clinical specialty, AI method and algorithm type, AI model (algorithm) role and performance metrics, key results, interpretability, validation, and risk of bias using PROBAST and QUADAS-2.

Results

Authors screened 8,178 articles and included 112. Half of the studies (50%) reported predictive models (for adverse events [25%], surgical outcomes [16%] and survival [9%]), followed by diagnostic (29%) and decision support models (21%). Neural networks (44%) and ensemble learners (36%) were the most commonly used AI methods across application domains. The main pediatric surgical subspecialties represented across all models were general surgery (31%) and neurosurgery (25%). Forty-four percent of models were interpretable, and 6% were both interpretable and externally

validated. Forty percent of models had a high risk of bias, and concerns over applicability were identified in 7%.

Conclusions

While AI has wide potential clinical applications in pediatric surgery, very few published AI algorithms were externally validated, interpretable, and unbiased. Future research needs to focus on developing AI models which are prospectively validated and ultimately integrated into clinical workflows.

Keywords: machine learning, computer vision, predictive, diagnostic, decision support, children and adolescents

Level of evidence: 2A

2.3. Introduction

Artificial intelligence (AI) models designed to mimic human cognitive functions encompass a variety of statistical techniques and algorithms that allow devices to learn from and respond to their environments [42]. Artificial intelligence includes several fields, such as computer vision (encompasses algorithms and systems for analyzing digital images and videos), natural language processing (NLP; algorithms that can appropriately interpret and generate meaningful human language), robotics, omics, and machine learning (ML) [43].

ML is a subset of AI wherein algorithms ("models") learn patterns from data, and use this knowledge to predict outcomes, infer states, and suggest decisions [44]. ML models have the ability to discover complex nonlinear relationships from large volumes of data. They can therefore be trained to perform tasks that typically involve human intelligence, and have entered routine use in various sectors of society.

AI has demonstrated significant utility in healthcare. Computer vision models have shown accuracy that is comparable to consultant specialists, such as radiologists [45] and pathologists [46]. Neural networks (algorithms of interconnected nodes or "neurons" that can learn complex linear and non-linear relationships) are increasingly being used to predict cardiovascular events [47] and accelerate drug discovery and development [48]. Nevertheless, adoption of ML in healthcare is rate-limited by several factors such as data missingness, bias, applicability, explainability (understandability of the rationale behind the model's output), and privacy and ethical concerns [49]. These factors must be adequately addressed in each model before any clinical use.

The scope of artificial intelligence applications holds substantial potential to revolutionize child and adolescent health. The unique challenges associated with this demographic, encompassing distinct developmental and physiological needs, diverse cognitive abilities, and inherent communication difficulties, underscore the transformative potential of AI in this field. [50]. For children undergoing surgery, accurate diagnosis, timely predictions, and treatment decisions can be significantly bolstered by the integration of AI in clinical workflows [51]. As AI continues to advance, data on the utility of ML, computer vision, and natural language processing accumulate. However, algorithms do not possess uniform designs; models vary in terms of the quality of the data on which they were trained, performance, validation, and interpretability. Thus, evidence remains fragmented, and clinical adoption is limited. For children undergoing surgery, AI is still in its infancy.

In this systematic review, we explore the use of AI in the care of children and adolescents with surgical conditions. We examine model structure, use case, performance, validation, and explainability of models that were tested in a pediatric surgical context. This review informs pediatric surgeons of mature models that can be integrated in the care process, and identifies opportunities to validate and deploy existing models.

2.4. Methods

This work followed the 2020 Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [52]. The research design, methodology, and analysis plan were registered on the Open Science Framework (OSF). The registration can be accessed publicly at https://osf.io/jvz29/.

A senior medical librarian (EG) searched the following electronic databases from inception until January 24, 2023: Medline (Ovid), Embase (Ovid), CINAHL (Ebsco) Cochrane (Wiley), Global Health (Ovid), Web of Science (Clarivate Analytics), Africa Wide Information (Ebsco), Proquest Central and Global Index Medicus (WHO). The search strategy used variations in text words found in the title, abstract or keyword fields, and relevant subject headings to retrieve articles looking at artificial intelligence, machine learning, natural language processing and related concepts in the domain of pediatric surgery or surgical conditions, without language restrictions. The full search strategy and the PRISMA checklist can be found in the Supplementary material. The PRISMA-S extension was used (**Supplementary Table 1**).

References were imported into EndNote X9, where duplicates were removed. Records were then uploaded to Rayyan.ai [53] where two independent reviewers (ME, RS) manually screened titles and abstracts. An arbitrator (DP) resolved conflicts. Inter-rater reliability was measured using the first 50 articles, for which the kappa rate was found to be 68%. Aiming for a kappa score above 80%, the independent reviewers met with the arbitrator who provided guidance. The kappa score for the second set of 50 articles was 84%, and the final kappa score was 86%.

Studies were included if they met the following criteria: (1) original investigations reporting on development, validation, or clinical application of AI models in health conditions that are primarily managed surgically, and (2) pediatric patients (0-18 years). Studies were excluded if they were (1) not peer-reviewed, (2) review articles, editorials, commentaries, or case reports, (3) not focused on pediatric surgical conditions, or (4) not utilizing at least one AI model.

After selecting studies, data was extracted from full texts using a standardized data extraction form (supplementary table 2) that included study metadata, characteristics, patient sample demographics, study characteristics, AI algorithm, outcomes, limitations, risk of bias, and applicability.

Models were classified by their purpose into predictive, diagnostic, or decision support systems. Predictive models were further subdivided into those that predicted surgical outcomes (related to success or effectiveness of surgery), adverse events (negative sequelae, procedural failures, complications) [54], and survival or mortality.. If a diagnostic model involved the use of computer vision, it was labeled as such. In terms of technique, AI models were divided into supervised, unsupervised, or deep learning algorithms. Supervised learning algorithms were further divided into ensemble learners (combination of several models to make a final prediction) [55] which included boosting algorithms, decision trees and random forests, and support vector machines and regression algorithms. Deep learning models use neural networks in a supervised, semi-supervised, or unsupervised environment. In regard to validation status, models were cross-validated, internally validated, externally validated, or not validated. In terms of interpretability, a model was considered interpretable if its authors incorporated mechanisms such as feature importance scores, decision paths, human-readable rules, nomograms (a diagram that allows graphical computation of a mathematical function), or advanced techniques such as attention maps, LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations). These mechanisms should facilitate clear insights into the model's decision-making process, either by local interpretability for individual predictions or global measures. Models were also classified by primary surgical specialty into general surgery, cardiovascular surgery, neurosurgery, orthopedic surgery, ophthalmology, urology, and otolaryngology / head and neck surgery.

Model performance metrics encountered included Area Under Receiver Operating Curve (AUROC), accuracy, specificity, precision, F-score, and positive and negative predictive values.

A narrative synthesis was conducted to summarize findings. All included studies are referenced in the **Supplementary Table 3** and cited in the text by their study ID. Missing performance metrics were imputed using a random forest model, which iteratively predicts and fills in missing values in a dataset, and is capable of handling both numerical and categorical data effectively. Mean age, number of patients, and sex distribution were calculated for each group, performance metrics were pooled. Welch's Analysis of Variance (ANOVA) was used to test for differences in mean accuracy across different specialties, purposes, and techniques. Welch's ANOVA was used because Levene's test indicated that variances were not equal. All statistical analyses were performed using R (Version 2022.07.1+554, R Core Team). Results were visualized using Tableau (Salesforce, CA, USA), for which age and number of patients were normalized in order to limit the effect of outliers on data visualization.

Risk of bias was evaluated using Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2) for diagnostic models [56], and Prediction Model Risk of Bias Assessment Tool (PROBAST) for predictive and decision support models [57]. Both assessment methods start with formulating the review question and tailoring signaling questions, and the first domain of both methods relates to study participants. PROBAST domains measure biases related to predictors, outcome, and analysis, while QUADAS-2 measures biases related to index and reference tests, and timing of the index test in relation to the outcome or the reference test. *Study applicability* in terms of patient selection, index test, and reference standard was assessed for diagnostic models, and in terms of participants, predictors and outcome for predictive and decision support models was assessed against the review question.

2.5. Results

The initial literature search identified 9,179 potentially eligible studies (**Figure 1**). After removing 1,163 duplicates, 8,178 titles and abstracts were manually screened. A total of 154 studies reached the final full-text data extraction stage. Finally, 112 studies that reported on 155 models which were trained on a total of 430,654 children and adolescents were included. The weighted proportion of females was 42.4 (95% confidence interval [95% CI]: 42.2-42.5)%. Excluding conditions that have an unequal gender predisposition yielded a female proportion of 43.1 (95% CI: 43.0-43.3)% (Supplementary Table 3).

Included studies varied in terms of purpose, technique, validation, explainability, and specialty. Most studies were conducted in the United States (n=33; 29%) and China (n=22; 20%), while six studies (5%) were multinational (Figure 2). The earliest study was published in 1998 (Bagli, 1998; Figure 3).

In terms of applied AI models, half of the models (n=78; 50%) reported predictive models, including models for adverse events (n=41; 26%), other surgical outcomes (n=26; 17%) and survival/mortality (n=11; 7%). The next most commonly encountered models were diagnostic (n=43; 28%) and decision support models (n=34; 22%). Neural networks (n=57; 37%), and ensemble learners (n=73; 47%) were the most commonly used AI techniques across subspecialties (**Table 1**).

2.5.1. Mortality Prediction

Eleven models predicted mortality from 50,547 patient records with a mean age of 7.2 ± 7.0 years. This included five that estimated 30-day mortality, with the remaining five predicting mortality after one (one study), four (one study), five (2 studies), and ten (one study) years (**Supplementary Table 3**).

Among all mortality prediction models, only two were interpretable, applicable, and with a low risk of bias. The first was an externally validated neural network that predicted 10-year neuroblastoma survival (Feng, 2021). The second was an internally validated ensemble learner that predicted in-hospital mortality after cardiac surgery (Du, 2022).

2.5.2. Surgical Outcomes Prediction

Twenty-six models predicted surgical outcomes from 9,214 patient records with a mean age of 5.5 ± 6.2 years, with the majority being neural networks and ensemble learners. Neural networks were used to predict outcomes in neurosurgery, such as resolution of medial temporal lobe epilepsy after anterior temporal lobectomy (Shih, 2022), outcomes after CSF shunt placement (Hale, 2021), and endoscopic third ventriculostomy success (Masoudi, 2022). They were also used in general surgery to predict liver (Jung, 2022) and renal transplant outcomes (Santori, 2007; Killian, 2021), and in orthopedic surgery for predicting progression of adolescent idiopathic scoliosis (Peng, 2020; Yahara, 2022). Ensemble learners (combining multiple machine learning models such as decision trees into random forests in one workflow to improve overall prediction accuracy and robustness) were used in cardiovascular and general surgery to predict systemic-pulmonary shunt outcomes (Moein, 2015), liver transplant outcomes (Wadhwani, 2019), and the recurrence of intussusception (Guo, 2022). Furthermore, they were applied in orthopedic surgery to predict the outcomes of posterior spinal fusion surgery in patients with adolescent idiopathic scoliosis (Pasha, 2021). The use of support vector machines was also encountered in neurosurgery for predicting surgical epilepsy outcomes (Tomlinson, 2017), and in otolaryngology for predicting persistent hearing impairment after cochlear implantation (Lu, 2022) (**Supplementary Table 3**).

Only three outcome prediction models were interpretable, applicable, and with a low risk of bias. Two predicted outcomes after liver transplant and one predicted progression of adolescent idiopathic scoliosis (Jung, 2022; Wadhwani, 2019; Yahara, 2022). However, none of the three models were externally validated.

2.5.3. Adverse Event Prediction

Forty-one models predicted postoperative adverse events from 843,819 patient records, with a mean age of 4.4 ± 6.2 years. Twenty-one of those models predicted adverse events after cardiac surgery. Ten predicted adverse events associated with general pediatric surgery, such as necrotizing enterocolitis and intestinal perforation (Son, 2022; Cho, 2022; Irles, 2018), while the remaining studies predicted postoperative pain (Salekin, 2022), surgical site infection (Bartz, 2018), and adverse events after appendectomy (Al, 2019), pyeloplasty (Drysdale, 2022), posterior urethral valve repair (Kwong, 2022), intraocular lens implantation (Zhang, 2019), ventriculoperitoneal shunt insertion (Habibi, 2016), craniofacial surgery (Jalali, 2021), and posterior fossa tumor resection (Sidpra, 2022). (**Supplementary Table 3**).

Six adverse event prediction models were externally validated, interpretable, applicable, and with a low risk of bias. Three predicted adverse events after cardiac surgery - including risk assessment of postoperative pulmonary vein obstruction in children with total anomalous pulmonary venous connection (Pei, 2022) and adverse events after cardiac surgery (Bertsimas, 2022; Luo, 2023; Shi, 2022). The last three models in this series were all ensemble learners from a single study that predicted adverse events after posterior urethral valve repair (Kwong, 2022).

2.5.4. Diagnostic Models

A total of 43 models were primarily diagnostic, trained on data from 53,723 patients with a mean age of 7.5 ± 5.8 years. Twenty-three models employed computer vision models, including 21 that analyzed radiology images, one that diagnosed retinoblastoma from fundus photographs, and one that identified hypospadias from penis photography. In terms of interpretability, six computer vision models used class activation mapping, which is a deep learning method to visualize parts of pictures that play an important role in the algorithm's output. Among the remaining 20 diagnostic non-computer vision models, seven diagnosed appendicitis (Akgul, 2021; Aydin, 2020; Hayashi, 2021; Hsieh, 2011; Sakai, 2007; Norman, 2017; Reismann, 2019) (**Supplementary Table 3**).

Six diagnostic models were interpretable, applicable, and with a low risk of bias. Five of those were computer vision models. Three models classified pectus excavatum (Lai, 2020), one diagnosed craniosynostosis (You, 2022), respectively, and one diagnosed posterior fossa tumors (Zhang, 2021). The last model in this group was an ensemble learner that diagnosed appendicitis (Aydin, 2020). None of these models was externally validated (Supplementary Table 3).

2.5.5. Decision Support Models

We identified 34 models designed to support treatment decision-making in pediatric surgery. Those models were trained on 167,874 patient records with a mean age of 6.1 ± 5.8 years. Neural networks were used in cardiovascular and general surgery for risk stratification in congenital heart surgery (Ruiz, 2016), patient selection for laparotomy for bowel obstruction (Qiu, 2021), prosthesis modeling for pectus excavatum (Rodrigues, 2014), assessing abdominal pain (Mantzaris, 2007), and neuroblastoma prognosis (Jabarkheel, 2022). In neurosurgery, they assisted in the segmentation of CSF fluid in hydrocephalus (Cherukuri, 2018). Ensemble learners were utilized for patient selection in neonatal necrotizing enterocolitis (Qi, 2022), for estimating optimal endotracheal tube depth (Shim, 2021), and selecting thyroid nodules that warrant biopsy (Radebe, 2021). They were also used to identify candidates for ventriculoperitoneal shunt placement (Saez, 2022), and epilepsy surgery (Wissel, 2021). Unsupervised clustering models were used in patient selection for adenotonsillectomy (Liu, 2022), and cochlear implantation in otolaryngology (Abousetta, 2023). In urology, ensemble learners and neural networks were employed to determine the need for orchiectomy in those with testicular torsion (Eksi, 2022) and selection of candidates for vesicoureteral reflux repair (Seckiner, 2008), respectively. In surgical systems, models predicted bed occupancy (Barak, 2022) and surgery cancellations (Liu, 2019).

Six decision support models were interpretable, applicable, and with a low risk of bias: An ensemble learner that generated recommendations regarding epilepsy surgery (Wissel, 2021), orthognathic surgery (Lin, 2021), and thyroid nodules (Radebe, 2021: Biopsy and Radebe, 2021: Likelihood of benign lesion), and a neural network that estimated the likelihood of necrosis and the need for a laparotomy in children with intestinal obstruction (Qiu, 2021). No decision support algorithm was externally validated.

2.5.6. Accuracy

Pooled mean accuracy as reported and imputed across all models was 0.86 ± 0.10. Accuracy of diagnostic, decision support, and adverse event, survival/mortality, and surgical outcomes prediction algorithms was 0.91 ± 0.05, 0.82 ± 0.12, 0.85 ± 0.09, 0.90 ± 0.07, and 0.80 ± 0.10, respectively (**Figure 4**). Accuracy varied by technique, purpose, and specialty (Welch ANOVA: <0.0006, <0.001, and <0.001, respectively).

2.5.7. Validation

Twelve models were externally validated (including nine which were interpretable), 65 were internally validated, 70 were cross-validated, and 8 were not validated (**Figure 5**).

2.5.8. Interpretability

Seventy-four models were interpretable. Interpretability tools included feature importance analysis (ranking the contribution of each variable in the model) in 23 studies, Shapley additive explanation (SHAP; a method that treats each variable in the dataset as a "player" in a cooperative game. The algorithm's prediction is the total "payout". SHAP calculates the extent of contribution of each variable to the payout) in seven studies, and class activation maps (computer vision application) in six (**Figure 6**; **Table 2**).

2.5.9. Risk of Bias

Analysis showed that while 98 studies (88%) were applicable to the review question, 45 studies (40%) had a high risk of bias. The most commonly observed reasons for bias were participant heterogeneity, class imbalance (under-representation), inappropriate (or lack of) missing data management, and inadequate performance evaluation. While most studies lacked external validation, we chose not to include validation signaling questions and analyze validation separately (**Supplementary Table 4**).

2.6. Discussion

The present systematic review identified 112 relevant studies on AI in pediatric surgery representing 155 models. While this suggests that AI has significant application in the care of children and adolescents undergoing surgery, it is worth noting that only six studies were externally validated, interpretable, and bias-free. The vast majority of models were not validated, and less than half were interpretable.

The mean *survival/mortality* prediction algorithm accuracy was 0.92. While this suggests that AI models have a better discriminative ability compared to conventional methods, no model was actually clinically adopted - unlike several other specialties having incorporated survival prediction algorithms in clinical workflows [58–60]. For instance, prediction of cardiovascular events relies on an algorithm with an AUC of 0.71 [61], much lower than what was typically observed from survival algorithms in the present review, yet the former is widely used based on having undergone rigorous external validation. Reliance on AUC for model performance is standard in the AI community. However, for these models to be effectively integrated into clinical practice, a comprehensive suite of performance metrics, including optimum thresholds, sensitivity, specificity, positive predictive value, and negative predictive value, must be considered. These metrics provide a more nuanced view of a model's performance and can help clinicians better understand and trust the model's outputs.

When it comes to *diagnostics*, a common dilemma faced in the reviewed AI models is the balance between sensitivity and specificity. For instance, models predicting adverse events or diagnosing cancer need to heavily penalize false negatives to minimize the risk of missed diagnoses, especially in high-stakes scenarios. Radebe et al. employed a random forest for recommending a biopsy in children with thyroid nodules. To decrease the risk of missing a malignant lesion, authors used false negative

(FNR) and false positive (FPR) rates as metrics of feature importance. For the random forest model, they selected only the features that resulted in the lowest FNR [62].

The fact that appendicitis was the most commonly *diagnosed* general pediatric surgery condition using an AI model reflects disease incidence [63]. Nevertheless, none of the appendicitis diagnosis or decision support models found by the present review were externally validated or adopted in routine use. Instead, surgeons typically rely on conventional ultrasound with human review, which is sensitive to multiple subjective biases. On the other hand, Aydin's decision tree algorithm, trained on more than 7000 patients, reported an accuracy of 0.95. If reproducible and externally validated, such an algorithm has the potential to improve appendicitis outcomes by ensuring accurate and timely diagnosis [64].

Four studies - including six models - were multi-site. Multi-site *validation* not only serves to ensure reliable outputs across heterogenous populations, but also assists in reducing bias within models. The majority of biased models in the present review had concerns with patient selection, potentially resulting in underestimating morbidity risks in marginalized or under-represented patients [65]. During the validation of an ensemble learner that predicted neonatal postoperative mortality based on National Surgical Quality Improvement Program (NSQIP) data, authors noticed that the model overestimated mortality risk among low-risk patients and underestimated it among patients at the highest risk [27].

The v*alidation* process is fundamental in establishing the credibility of AI models, ensuring their accuracy and utility in the actual clinical setting [66]. This review revealed that most of the models identified have not undergone external validation, therefore severely limiting their utility beyond the research arena. Rigorous, prospective studies are needed to validate these models across different healthcare systems and populations [67]. Without this step, AI models, while performing well within the training dataset, may exhibit poor performance when faced with unseen data, due to variations in patient profiles or clinical practices.

Another key finding from our review is the lack of *interpretability* of many models, rendering them "black box algorithms". This is concerning for clinicians, who need to be able to trust the decision-making mechanisms of these models. Gaining this trust requires a model to be able to explain its predictions, especially when employed in high-stakes medical scenarios where a model's interpretability becomes paramount. Thus, the development of AI models providing comprehensible and transparent predictions must be emphasized [68].

A contributing factor to interpretability is the model's ability to identify and communicate important features that influence its decision-making process. Almost 80% of the adverse event prediction models reviewed were interpretable. Ensemble learners offer methods to perform feature importance analysis, which allows users to understand factors that affect the model's output. Other methods that allow interpretability include SHAP, fuzzy logic, and nomograms [69]. Guo, et al. trained an ensemble learner to predict the recurrence of intussusception after air enema or surgery, and designed a nomogram (a diagram that allows graphical computation of a mathematical function) to visually represent it [70]. While Guo's study was interpretable, it had a significant risk of bias due to patient selection and follow-up, and lacked external validation.

In terms of *data integrity*, we noted that bias was often introduced due to the mishandling of missing data or other improper data preprocessing. AI models are only as good as the data they are trained on, so any bias or error in the data can negatively impact the model's effectiveness and precision. This highlights the importance of thorough data preprocessing, upsampling minority classes (increasing the number of samples from under-represented classes to balance distribution and improve performance), effective management of missing data, and ensuring that the dataset is as comprehensive and representative as possible.

Training neural network models often demands large annotated datasets, which are typically not readily available in healthcare studies due to the prohibitive costs of manual feature labeling. The processing power, memory resources, and time required to train neural networks from scratch on smaller datasets are substantial. To mitigate these challenges, researchers often resort to "transfer learning" strategies, which involve training of neural networks that have already been trained on large public datasets [71]. One such example is a study which used a pre-trained neural network to classify developmental hip dysplasia x-rays [40].

The future vision of AI is not in replacing surgeons, but rather augmenting their abilities. AI's potential in pediatric surgery lies in its ability to offer quantifiable improvements in quality of care, thus facilitating a shift towards value-based healthcare. AI models show promise in reducing hospital stays by accurately predicting adverse events, allowing for timely interventions. For instance, models predicting postoperative complications like the ensemble learner of Bertsimas, 2021 can alert cardiovascular surgeons to potential risks, ensuring prompt and targeted care.

AI models can rapidly diagnose conditions through computer vision and other methods, which significantly reduces emergency room stay durations. For instance, the neural network reported by Hayashi, 2021 has been employed to diagnose appendicitis from ultrasound. If externally validated, such algorithms could revolutionize timely diagnosis and intervention, a critical factor in emergency care.

AI-enabled medical devices can significantly improve patient follow-up and home healthcare. Personalized follow-up timelines and remote monitoring tools ensure continual care outside hospital settings, reducing the need for frequent hospital visits.

In surgical education, AI can provide realistic and varied surgical scenarios, AI models can greatly enhance the learning curve of surgical trainees, leading to improved surgical outcomes [72].

By providing data-driven insights and analyses, AI algorithms can contribute significantly to the decision-making process in complex cases, especially in multidisciplinary team and mortality/morbidity meetings, and tumor board deliberations. The deep learning model in Feng, 2021 was able to predict long-term neuroblastoma survival with an accuracy of 0.97.

Despite the promise of AI, the transition from in-silico models to clinical tools is challenging. The present study highlighted the need for rigorous external validation, post-deployment monitoring, and comprehensive performance metrics for effective clinical integration of AI models.

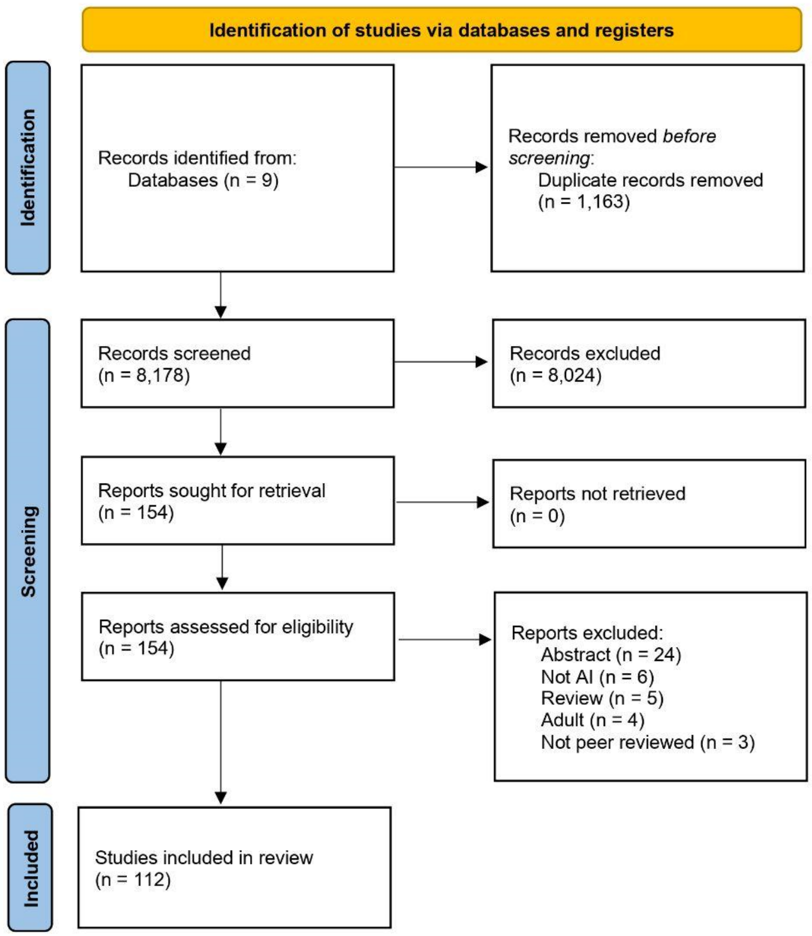
This systematic review has several limitations. First, the included studies varied in terms of AI techniques used, surgical conditions addressed, and outcomes predicted. This made it difficult to conduct any meta-analysis. Second, the overall accuracy of models may be overestimated since models with poor accuracy are less likely to be published. Third, reporting of performance metrics was not uniform across studies, and analyses methods varied across studies. Fourth, clinical heterogeneity in terms of disease and outcome definition were noted. Fifth, most studies were published in high-income countries, which might limit generalizability to patient populations in low- and middle-income countries. Sixth, publication bias cannot be ruled out, since it is known that poor studies with poor results are less likely to be published.

2.7. Conclusion

The present review identified several diagnostic, predictive, and decision support models in pediatric general surgery and surgical subspecialties that could be incorporated into clinical workflows based on their performance. However, such clinical application will require concerted efforts to remove all sources of algorithmic bias, broadening their applicability through prospective external validation, incorporating interpretability methods in models, and designing post-deployment performance surveillance systems.

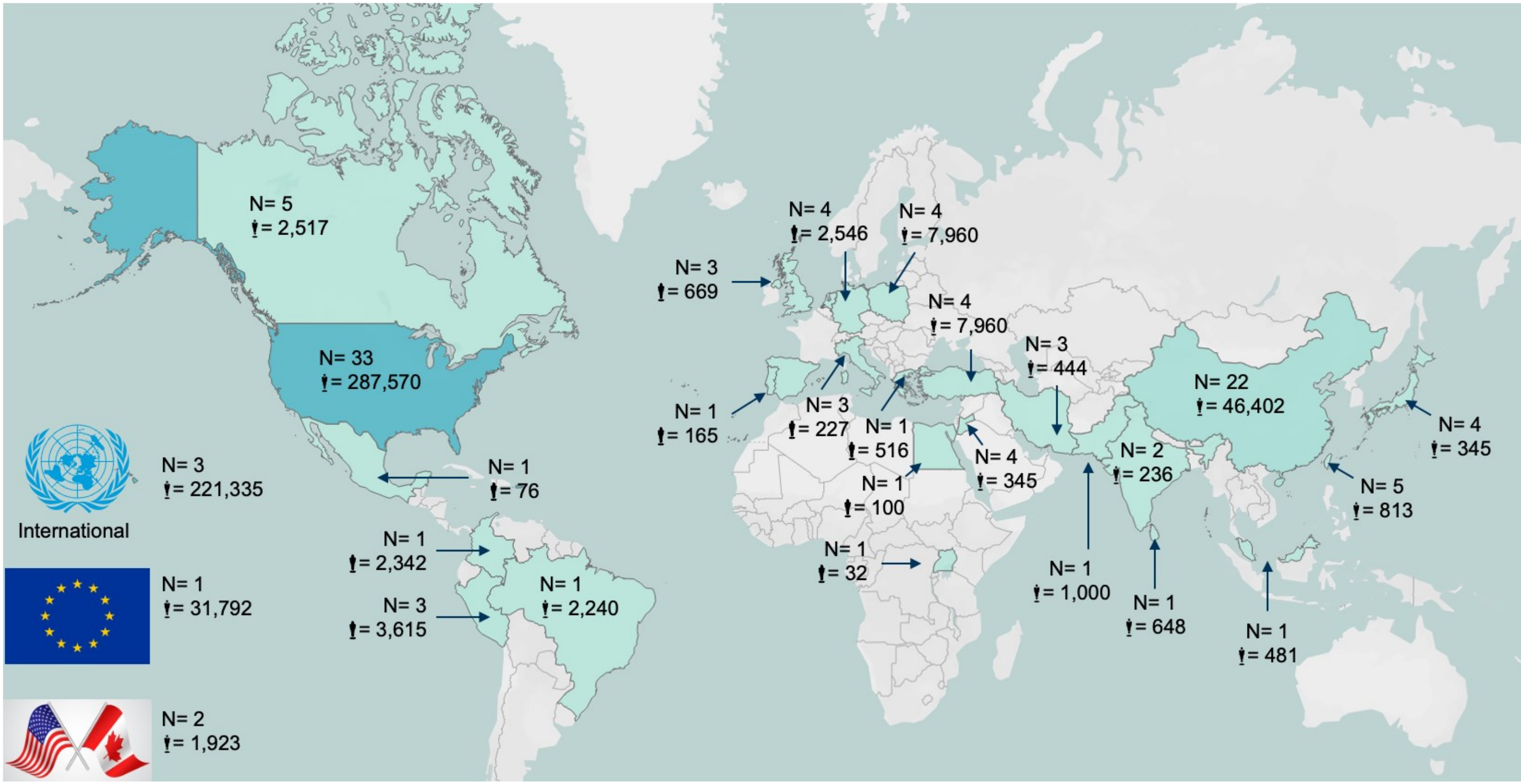
2.8. Figures

2.8.1. Figure 1. PRISMA flow diagram for a systematic review on AI in pediatric surgery

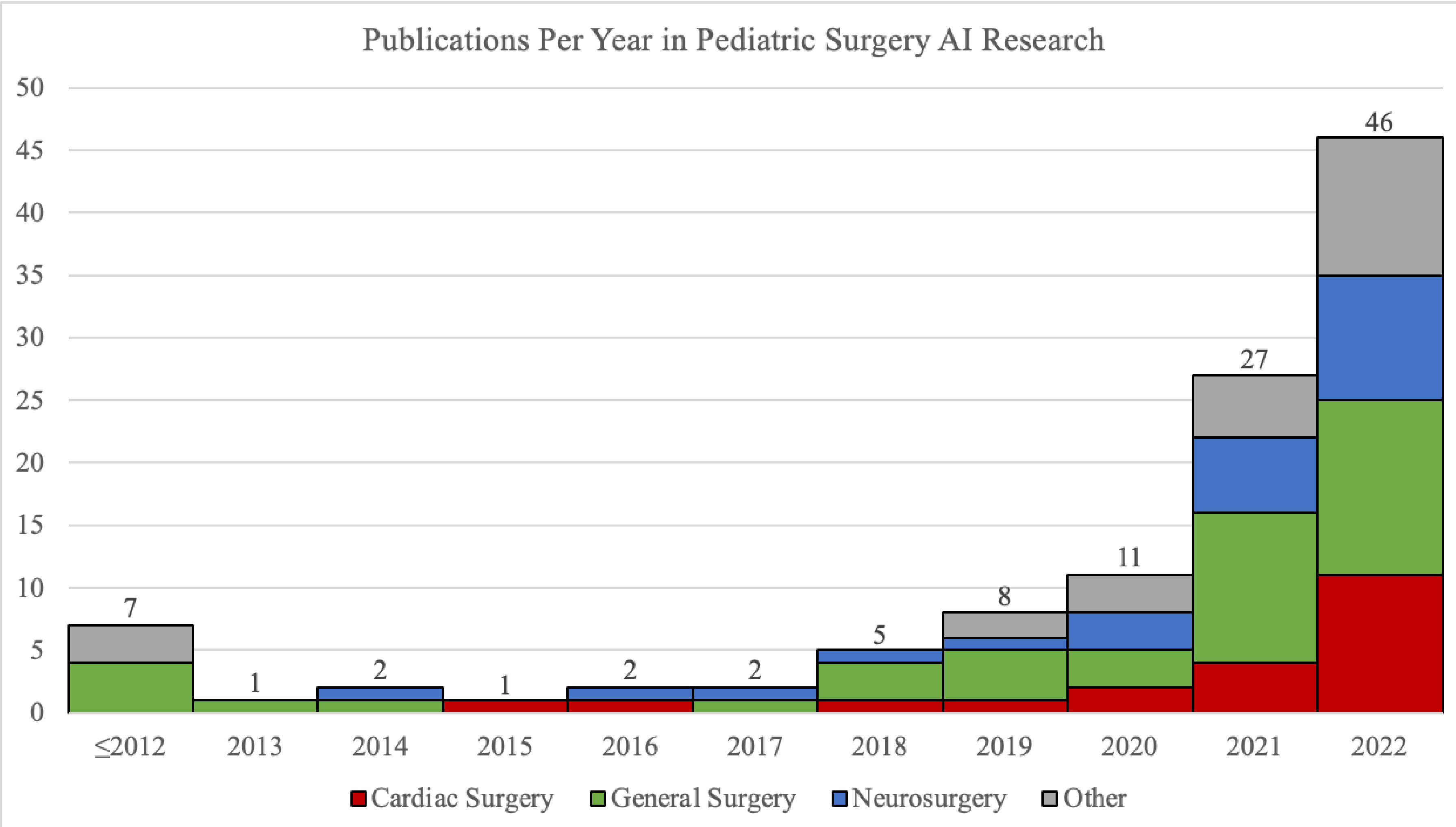


From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71

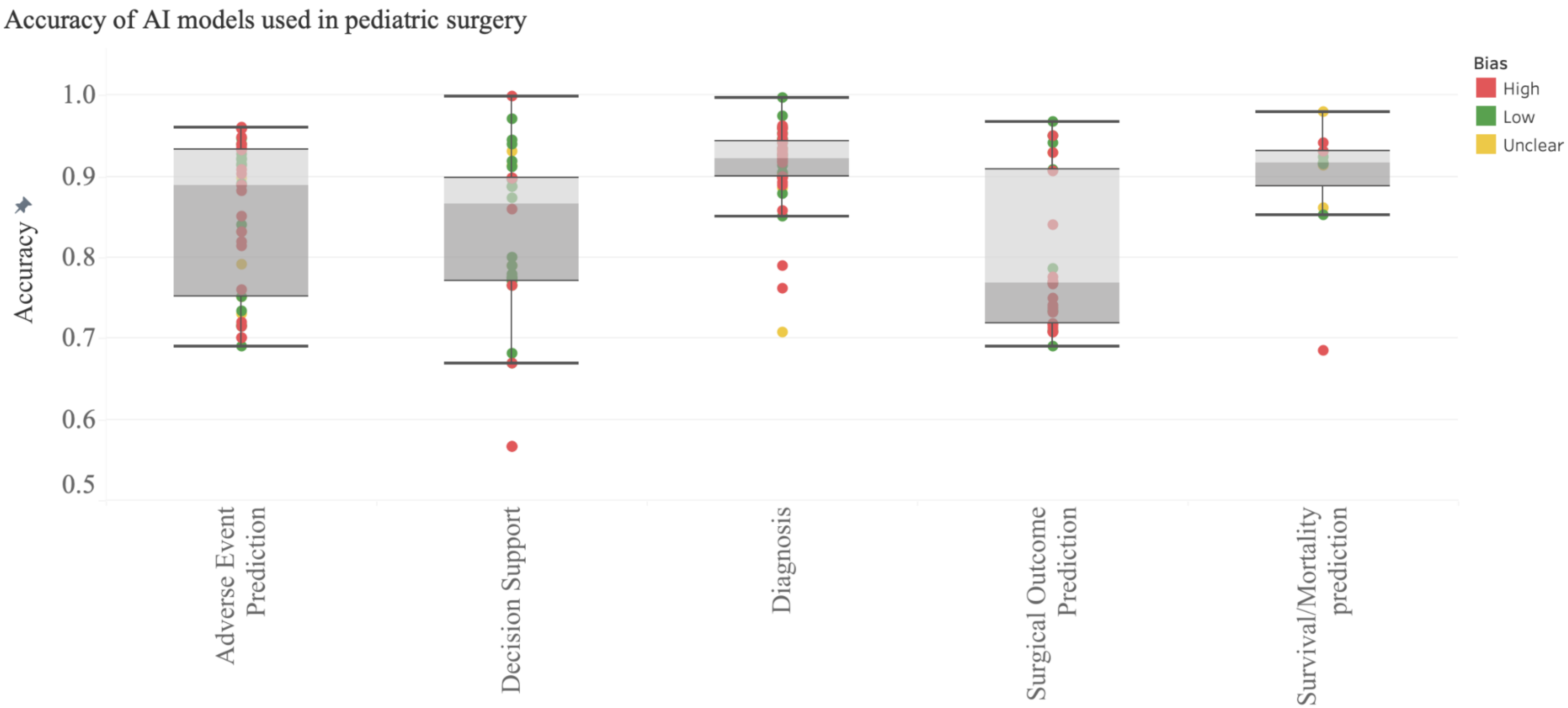
2.8.2. Figure 2. Geographic distribution of included studies



2.8.3. Figure 3. Publications per year in pediatric surgery AI research



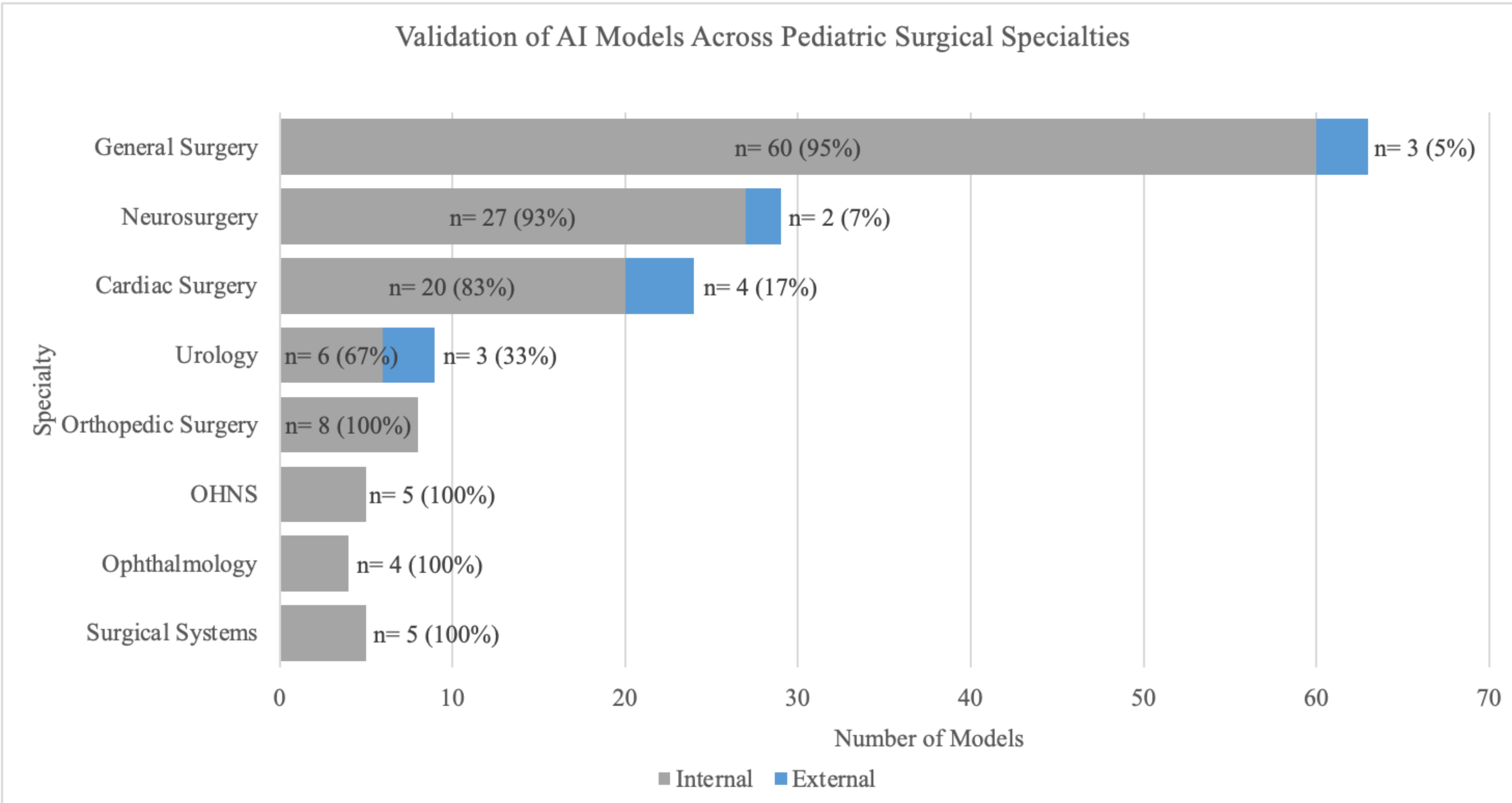
2.8.4. Figure 4. Box and whisker plot showing model accuracy across different use cases



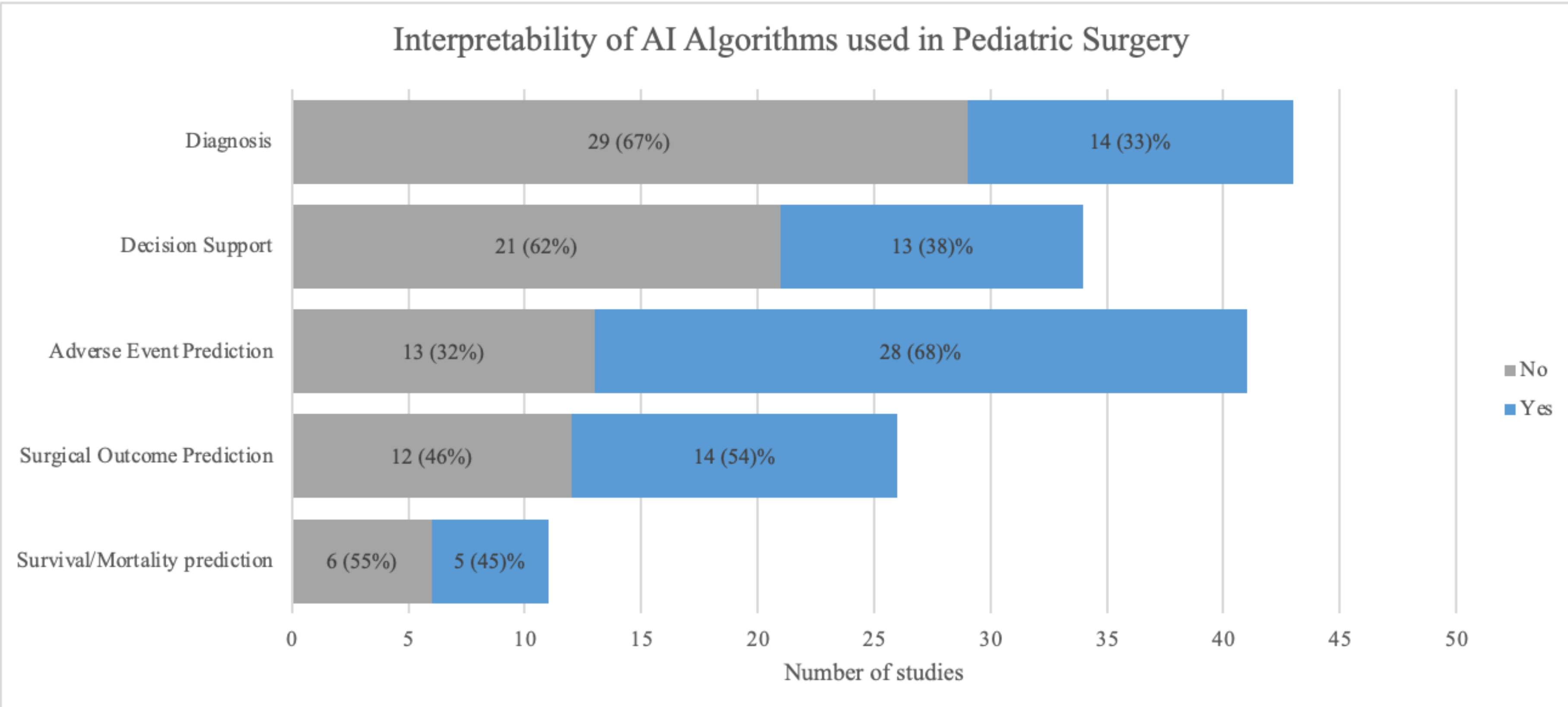
The interactive version of this figure can be found at:

https://public.tableau.com/app/profile/mohamed.elahmedi/viz/Boxplots_16892219737600/Accuracy?publish=yes

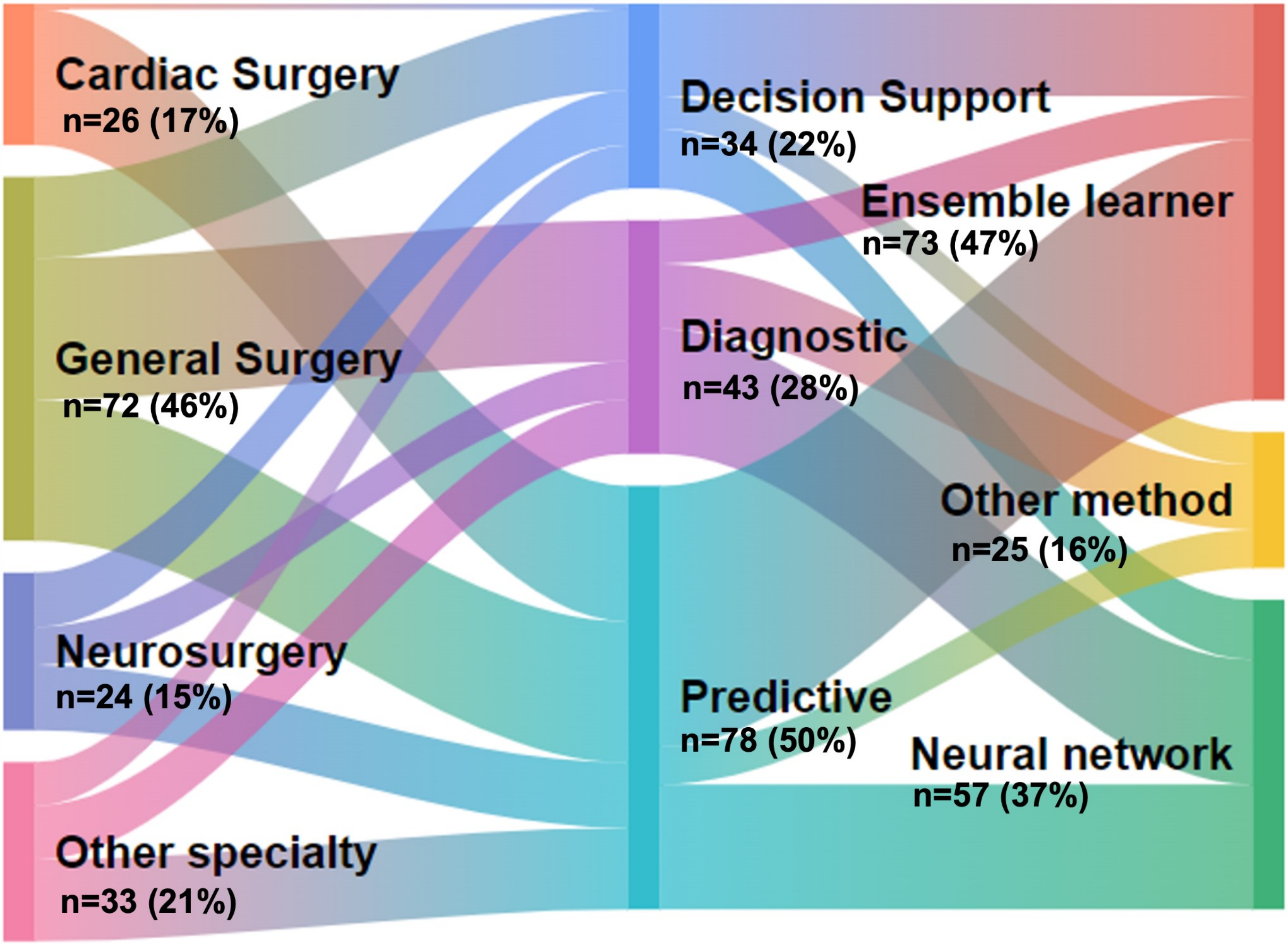
2.8.5. Figure 5. Validation status of AI models across pediatric surgical specialties



2.8.6. Figure 6. Interpretability among AI algorithms used in pediatric surgery



2.8.7. Figure 7. Sankey diagram showing relationship between model specialty, role, and AI architecture



2.9. Tables

2.9.1. Supplementary Table 1. PRISMA-S Checklist

Section/topic	#	Checklist item	Location(s) Reported
INFORMATION SOURCES AND METHODS			
Database name	1	Name each individual database searched, stating the platform for each.	p. 5 & Included in Supplementary Material
Multi-database searching	2	If databases were searched simultaneously on a single platform, state the name of the platform, listing all of the databases searched.	p. 5 & Included in Supplementary Material
Study registries	3	List any study registries searched.	N/A
Online resources and browsing	4	Describe any online or print source purposefully searched or browsed (e.g., tables of contents, print conference proceedings, web sites), and how this was done.	Conference proceedings included primarily within Embase (Ovid) as well as other databases. ProQuest Dissertations & Theses also included.
Citation searching	5	Indicate whether cited references or citing references were examined, and describe any methods used for locating cited/citing references (e.g., browsing reference lists, using a citation index, setting up email alerts for references citing included studies).	N/A
Contacts	6	Indicate whether additional studies or data were sought by contacting authors, experts, manufacturers, or others.	N/A
Other methods	7	Describe any additional information sources or search methods used.	N/A
SEARCH STRATEGIES			
Full search strategies	8	Include the search strategies for each database and information source, copied and pasted exactly as run.	Included in Supplementary Material

Limits and restrictions	9	Specify that no limits were used, or describe any limits or restrictions applied to a search (e.g., date or time period, language, study design) and provide justification for their use.	Pg. 5 Included in Supplementary Material
Search filters	10	Indicate whether published search filters were used (as originally designed or modified), and if so, cite the filter(s) used.	MUHC Pediatric filter used
Prior work	11	Indicate when search strategies from other literature reviews were adapted or reused for a substantive part or all of the search, citing the previous review(s).	Portions of the search were adapted from Antel, R., Abbasgholizadeh-Rahimi, S., Guadagno, E., Harley, J. M., & Poenaru, D. (2022). The use of artificial intelligence and virtual reality in doctor-patient risk communication: A scoping review. Patient education and counseling, 105(10), 3038–3050. https://doi-org.proxy3.library.mcgill.ca/10.1016/j.pec.2022.06.006
Updates	12	Report the methods used to update the search(es) (e.g., rerunning searches, email alerts).	N/A
Dates of searches	13	For each search strategy, provide the date when the last search occurred.	p. 5
PEER REVIEW			
Peer review	14	Describe any search peer review process.	Used PRESS (McGowan J, Sampson M, Salzwedel DM, Cogo E, Foerster V, Lefebvre C. PRESS Peer Review of Electronic Search Strategies: 2015 Guideline Statement. J Clin Epidemiol. 2016 Jul;75:40-6. doi: 10.1016/j.jclinepi.2016.01.021). Peer review provided with the assistance of the MUHC McConnell Resource Centre.
MANAGING RECORDS			
Total Records	15	Document the total number of records identified from each database and other information sources.	Included in PRISMA

Deduplication	16	Describe the processes and any software used to deduplicate records from multiple database searches and other information sources.	Initial deduplication done via Endnote X9.3.3 using modified version of Bramer WM, Giustini D, de Jonge GB, Holland L, Bekhuis T. De-duplication of database search results for systematic reviews in EndNote. Journal of the Medical Library Association : JMLA. 2016;104(3):240-243. doi:10.3163/1536-5050.104.3.014 (see McGill KS guide). Further deduplication manually performed in EndNote then in Rayyan online software.

PRISMA-S: An Extension to the PRISMA Statement for Reporting Literature Searches in Systematic Reviews

Rethlefsen ML, Kirtley S, Waffenschmidt S, Ayala AP, Moher D, Page MJ, Koffel JB, PRISMA-S Group.

Last updated February 27, 2020.

2.9.2. Supplementary Table 2. Variables in the data abstraction form to collect data from eligible studies on AI in Pediatric Surgery

Author	Study Design	Use case	Recall	RMSE
Year	DOI	n	Specificity	Other performance (specify)
Title	Author email	AgeYearMean	Precision	Validation
Abstract	Algorithm	AgeYearSD	Sensitivity	Interpretability
Journal	Architecture	Female	PPV	Risk of Bias
Country	Purpose	AUC	NPV	Applicability
Setting	Specialty	Accuracy	F1-Score	Model link

2.9.3. Supplementary Table 3. Characteristics of studies that were included in a systematic review of AI in pediatric surgery

Speciality	Purpose	Authors	Use	Technique	Interpretability	n
Cardiac Surgery						
	Adverse Event Prediction					
		Bertsimas, 2022	Predicting AE after congenital heart surgery	Ensemble learner	Feature importance	31,792

	Ekhomu, 2022	Predicting right atrial function after TOF repair	Ensemble learner	Feature importance	153
	Faerber, 2021	Predicting AE after TOF repair	Ensemble learner	Feature importance	162
	Samad, 2018	Predicting ventricular deterioration after TOF repair	SVM	Other	153
	Luo, 2023	Predicting AKI after cardiac surgery with cardiopulmonary bypass	Ensemble learner	SHAP	3,863
	Hayward, 2022	Predicting AKI after cardiac surgery with cardiopulmonary bypass	Ensemble learner	Feature importance	396
	Zeng, 2022	Predicting AKI from perioperative time series data	Neural network	SHAP	3,386
	Li, 2022	Predicting duration of mechanical ventilation after cardiac surgery	Ensemble learner	Feature importance	60
	Bertsimas, 2021	Predicting mortality, mechanical ventilatory support, and length of stay after congenital heart surgery	Ensemble learner	Feature importance	221,335
	Jalali, 2020	Predicting one-year postoperative mortality or cardiac transplantation and prolonged length of hospital stay	Neural network	Not interpretable	549
	Gupta, 2022	Predicting prolonged hospital stay after heart transplant	Regression	Regression coefficients	4,414
	Guo, 2021	Predicting postoperative abnormal blood coagulation in children with CHD	Ensemble learner	Feature importance	1,690

	Pei, 2022	Predicting pulmonary vein obstruction after total anomalous pulmonary venous connection repair	Multiple	Feature importance	68
	Shi, 2022	Predicting malnutrition after cardiac surgery for various CHDs	Ensemble learner	SHAP	536
	Sughimoto, 2022	Predicting postoperative lactate levels in children with CHD	Ensemble learner	Not interpretable	48
	Zeng, 2021	Predicting postoperative lung, cardiac, rhythm, or infectious complications in children with CHD	Ensemble learner	SHAP	1,964
Decision Support					
	Ruiz, 2016	Risk stratification in congenital heart surgery	Neural network	Not interpretable	2,432
Surgical Outcome Prediction					
	Moein, 2015	Predicting systemic-pulmonary shunt outcomes	Ensemble learner	Not interpretable	1,036
Survival/Mortality prediction					
	Chang, 2020	Predicting 30-day mortality after cardiac surgery	Ensemble learner	Feature importance	2,240
	Du, 2022	Predicting 30-day mortality after cardiac surgery	Ensemble learner	Feature importance	24,685
	Hu, 2021	Predicting 30-day mortality after cardiac surgery	Ensemble learner	SHAP	1,481
	Miller, 2019	Predicting 1-year mortality after heart transplant	Ensemble learner	Feature importance	3,180

General Surgery						
	Adverse Event Prediction					
		Al, 2019	Predict likelihood of intra-abdominal abscess after appendectomy	Neural network	Feature importance	1,574
		Son, 2022	Predicting intestinal perforation	Neural network	Not interpretable	12,555
		Bartz, 2018	Predict surgical site infection	Ensemble learner	Not interpretable	16,842
		Cho, 2022	Predicting NEC and SIP	Ensemble learner	Feature importance	10,353
		Irles, 2018	Predicting NEC and SIP	Neural network	Other	76
		Salekin, 2022	Estimating postoperative neonatal pain	Neural network	Not interpretable	45
	Decision Support					
		Liu, 2022	Neuroblastoma prognosis	Neural network	Not interpretable	65
		Wei, 2004	Predicting neuroblastoma prognosis from gene expression data	Neural network	Not interpretable	49
		Liu, 2022	Patient selection for adenotonsillectomy	KNN	Not interpretable	323
		Marcinkevics, 2021	Patient selection for appendicectomy	Ensemble learner	Feature importance	430
		Mantzaris, 2007	Estimating abdominal pain	Neural network	Not interpretable	516
		Qi, 2022	Patient selection for surgical treatment of NEC	Ensemble learner	Feature importance	45

	Qiu, 2021	Patient selection for laparotomy after intestinal obstruction	Neural network	Gini impurity	536
	Radebe, 2021	Diagnosing malignant thyroid nodules	Ensemble learner	Feature importance	198
	Rodrigues, 2014	Prosthesis modeling for pectus excavatum	Neural network	Not interpretable	165
	Shim, 2021	Estimating optimal endotracheal tube depth	Ensemble learner	Not interpretable	834
Diagnosis					
	Lure, 2021	Diagnosing NEC vs SIP	Regression	Gini impurity	40
	Akgul, 2021	Diagnosing appendicitis	Neural network	Not interpretable	320
	Aydin, 2020	Diagnosing appendicitis	Ensemble learner	Feature importance	7,244
	Hayashi, 2021	Diagnosing appendicitis	Neural network	Not interpretable	70
	Hsieh, 2011	Diagnosing appendicitis	Ensemble learner	Not interpretable	180
	Sakai, 2007	Diagnosing appendicitis	Neural network	Not interpretable	169
	Norman, 2017	Diagnosing appendicitis	SVM	Regression coefficients	
	Reismann, 2019	Diagnosing appendicitis and differentiating between complicated and uncomplicated appendicitis	Regression	Not interpretable	590
	Reismann, 2021	Classifying appendicitis using gene expression data	KNN	Not interpretable	29

	Bakhuis, 2023	Segmenting congenital lung lesions	Neural network	Not interpretable	5
	Fang, 2022	Diagnosing biliary atresia from US images	Neural network	Not interpretable	180
	Kwon, 2020	Diagnose intussusception from AXR images	Neural network	Class activation map	5,707
	Lai, 2020	Classifying pectus excavatum as normal, mild or severe and visualizing defect in CT images	Neural network	Class activation map	42
	Ma, 2022	Staging nephroblastoma	SVM	Not interpretable	118
	Qian, 2023	Diagnosing neuroblastoma from CT images	Regression	Not interpretable	75
	Zhang, 2022	Diagnosing retinoblastoma from funduscopy images	Neural network	Class activation map	713
	Zhang, 2022	Diagnosing mucoepidermoid tumors	SVM	Not interpretable	16
Surgical Outcome Prediction					
	Guo, 2022	Predicting recurrence of intussusception	Ensemble learner	SHAP	2,469
	Jung, 2022	Predicting liver transplant failure	Regression	Regression coefficients	87
	Wadhwani, 2019	Predicting 3-year liver transplant outcomes	Ensemble learner	Feature importance	887
	Killian, 2021	Predict 1-, 3-, and 5-year post-transplant hospitalization	Ensemble learner	SHAP	814
	Santori, 2007	Predict outcomes of kidney transplant	Neural network	Not interpretable	148

	Survival/Mortality prediction					
		Feng, 2021	Predicting 10-year neuroblastoma survival using gene expression analysis	Neural network	Other	955
		Akbilgic, 2019	Predicting 30-day mortality	Neural network	Not interpretable	6,497
		Cooper, 2018	Predicting 30-day mortality	Multiple	Not interpretable	6,499
Neurosurgery						
	Adverse Event Prediction					
		Habibi, 2016	Predicting VP shunt infection	Neural network	Other	148
		Jalali, 2021	Predicting blood transfusion during craniofacial surgery	Ensemble learner	Feature importance	2,143
		Sidpra, 2022	Predicting cerebellar mutism syndrome after posterior fossa tumor excision	Neural network	Regression coefficients	204
	Decision Support					
		Cherukuri, 2018	Segmentation of CSF fluid in patients with hydrocephalus	Neural network	Not interpretable	32
		Jabarkheel, 2022	Differentiate tumor vs non-tumor tissue	Regression	Not interpretable	29
		Jin, 2022	IVH prognosis	Ensemble learner	Not interpretable	5,926
		Saez, 2022	Patient selection for VP shunt	KNN	Not interpretable	43
		Mesin, 2022	Patient selection for Chiari I Malformation	SVM	Not interpretable	58

	Wissel, 2021	Patient selection for epilepsy surgery	Ensemble learner	Feature importance	5,880
Diagnosis					
	Attallah, 2021	Diagnosis and classification of medulloblastoma from H&E-stained pathology slides	Neural network	Not interpretable	204
	Bhalodia, 2020	Diagnosing metopic craniosynostosis	Ensemble learner	Not interpretable	82
	Grimm, 2020	Segmenting CSF fluid and brain volume in hydrocephalus	Neural network	Not interpretable	47
	Klimont, 2019	CSF segmentation	Neural network	Not interpretable	63
	Quon, 2020	Segmenting cerebral arteries on MRI	Neural network	Not interpretable	48
	You, 2022	Diagnosing craniosynostosis from CT images	Neural network	Class activation map	180
	Zhang, 2021	Diagnosing brain tumors	Regression	Regression coefficients	535
Surgical Outcome Prediction					
	Azimi, 2014	Predicting outcomes of endoscopic third ventriculostomy	Neural network	Not interpretable	168
	Hale, 2021	Outcome prediction after CSF shunt placement	Neural network	Not interpretable	1,036
	Masoudi, 2022	Predicting outcomes of endoscopic third ventriculostomy	Neural network	Not interpretable	128
	Pepi, 2023	Predicting resolution of epilepsy after hemispherotomy	Neural network	Not interpretable	21

		Shih, 2022	Predicting postoperative resolution of medial temporal lobe epilepsy after anterior temporal lobectomy or selective amygdalohippocampectomy	Neural network	Not interpretable	93
		Tomlinson, 2017	Predicting surgical epilepsy outcomes	SVM	Not interpretable	17
		Wang, 2022	Predicting postoperative seizure recurrence	Ensemble learner	Not interpretable	39
	Survival/Mortality prediction					
		Grist, 2021	Predicting 4-year survival in brain tumors	Neural network	Not interpretable	69
OHNS						
	Decision Support					
		Abousetta, 2023	Patient selection for cochlear implant	KNN	Feature importance	100
		Lin, 2021	Patient selection for orthognathic surgery	Ensemble learner	Feature importance	56
	Diagnosis					
		Shafi, 2020	Prenatal prediction of cleft lip and cleft palate	Neural network	Not interpretable	1,000
	Surgical Outcome Prediction					
		Lu, 2022	Predicting persistent hearing impairment after cochlear implantation	SVM	Not interpretable	70

Ophthalmology						
	Adverse Event Prediction					
		Zhang, 2019	Predicting adverse events after intraocular lens implantation	Ensemble learner	Not interpretable	321
	Diagnosis					
		Nalepa, 2022	Segmenting gliomas from MRI	Neural network	Not interpretable	567
Orthopedic Surgery						
	Diagnosis					
		Fraiwan, 2022	Diagnosing developmental dysplasia of the hip	Neural network	Not interpretable	354
		Makhdoomi, 2022	Classifying scoliosis severity	Neural network	Not interpretable	481
		Ratnayake, 2012	Diagnosing supracondylar fracture	Neural network	Not interpretable	
		Sikidar, 2022	Classifying AIS using gait data	KNN	Not interpretable	32
	Surgical Outcome Prediction					
		Pasha, 2021	Predicting the outcome of posterior spinal fusion surgery	Ensemble learner	Feature importance	371
		Peng, 2020	Surgical outcome prediction in AIS patients	Ensemble learner	Not interpretable	44
		Yahara, 2022	Predicting progression of adolescent idiopathic scoliosis	Neural network	Class activation map	58
	Survival/Mortality prediction					
		Chen, 2021	Prognosis of Ewing Sarcoma	Ensemble learner	Not interpretable	2,332

Surgical Systems						
	Decision Support					
		Barak, 2022	Predicting bed occupancy	Neural network	Not interpretable	19,642
		Liu, 2019	Predicting cancellation of surgery	Ensemble learner	Not interpretable	125,693
	Diagnosis					
		Avila, 2021	Predict discharge status (healthy, deceased, unhealthy) from admission records	Ensemble learner	Not interpretable	1,205
Urology						
	Adverse Event Prediction					
		Drysdale, 2022	Predicting recurrence and re-intervention in ureteropelvic junction obstruction	Regression	Other	543
		Kwong, 2022	Outcome prediction after PUV repair	Ensemble learner	Gini impurity	103
	Decision Support					
		Eksi, 2022	Testicular torsion patient selection for orchiectomy	Ensemble learner	Not interpretable	300
		Seckiner, 2008	Patient selection for VUR repair	Neural network	Not interpretable	96
	Diagnosis					
		Fernandez, 2021	Diagnosing hypospadias	Neural network	Not interpretable	1,169
		Yin, 2020	Diagnosing PUV from USG	Neural network	Class activation map	157

Surgical Outcome Prediction					
	Bagli, 1998	Surgical Outcome Prediction	Neural network	Not interpretable	100
Survival/Mortality prediction					
	Bhambhvani, 2021	Survival/Mortality prediction	Neural network	Not interpretable	277

OHNS: Otolaryngology head and neck surgery; AE: Adverse event; TOF: Tetralogy of fallot; AKI: Acute kidney injury; SHAP: Shapley additive explanations; SVM: Support vector machine; NEC: Necrotizing enterocolitis; SIP: Spontaneous intestinal perforation; KNN: K-nearest neighbors; AXR: Abdominal x-ray; CT: Computerized tomography; US: Ultrasound; VP: Ventriculoperitoneal; CSF: Cerebrospinal fluid; IVH: Intraventricular hemorrhage; H&E: Hematoxylin-Eosin; MRI: Magnetic resonance imaging; AIS: Adolescent idiopathic scoliosis; PUV: Posterior urethral valve; VUR: Vesicoureteric reflux; USG: Ultrasound; CHD: Congenital Heart Disease

2.9.4. Table 1. AI techniques used by purpose in surgical children and adolescents. N (%)

Purpose	Neural network	Ensemble learner	Regression	SVM	Unsupervised clustering	Multiple	Grand Total
Diagnosis	20 (60.6)	4 (12.1)	4 (12.1)	3 (9.1)	2 (6.1)	0 (0)	33 (29.5)
Decision Support	9 (39.1)	9 (39.1)	1 (4.3)	1 (4.3)	3 (13)	0 (0)	23 (20.5)
Adverse Event	8 (28.6)	15 (53.6)	3 (10.7)	1 (3.6)	0 (0)	1 (3.6)	28 (25)
Surgical Outcomes	8 (44.4)	7 (38.9)	1 (5.6)	2 (11.1)	(0)	0 (0)	18 (16.1)
Survival	4 (40)	5 (50)	0 (0)	0 (0)	0 (0)	1 (10)	10 (8.9)
Grand Total	**49 (43.8)**	**40 (35.7)**	**9 (8.0)**	**7 (6.3)**	**5 (4.5)**	**2 (1.8)**	**112 (100)**

SVM: Support vector machine

2.9.5. Table 2. Low bias, externally validated, interpretable AI models in pediatric surgery

Authors	Specialty	Purpose	Use	Main Model	Number of patients
Luo, 2023	Cardiovascular	Adverse Event	Predicting AKI after cardiac surgery	Ensemble learner	3,863
Shi, 2022	Cardiovascular	Adverse Event	Predicting major weight loss after cardiac surgery	Ensemble learner	536
Pei, 2022	Cardiovascular	Adverse Event	Predicting pulmonary vein obstruction after total anomalous pulmonary venous connection repair	Multiple	68
Kwong, 2022	Urology	Adverse Event	Outcome prediction after PUV repair	Ensemble learner	103
Feng, 2021	Neurosurgery	Survival	Predicting 10-year neuroblastoma survival using gene expression analysis	Neural network	955

AKI: Acute kidney injury; SHAP: Shapley additive explanation; AXR: Abdominal x-ray

2.9.6. Supplementary Table 4. Risk of bias assessment for studies on AI in pediatric surgery

Author, year	Risk of Bias				Applicability				
PROBAST	**Participants**	**Predictors**	**Outcome**	**Analysis**	**Participants**	**Predictors**	**Outcome**	**Overall ROB**	**Overall Applicability**
Adverse Events									
Bertsimas, 2022									
Ekhomu, 2022									
Faerber, 2021									
Samad, 2018									
Luo, 2023									
Hayward, 2022									
Zeng, 2022									
Li, 2022									
Bertsimas, 2021									
Jalali, 2020									
Gupta, 2022									
Guo, 2021									
Pei, 2022									
Shi, 2022									
Sughimoto, 2022									
Zeng, 2021									
Al, 2019									
Son, 2022									
Bartz, 2018									
Cho, 2022									
Irles, 2018									
Salekin, 2022									
Habibi, 2016									
Jalali, 2021									
Sidpra, 2022									
Zhang, 2019									

Drysdale, 2022									
Kwong, 2022									
Surgical Outcomes									
Moein, 2015									
Guo, 2022									
Jung, 2022									
Wadhwani, 2019									
Killian, 2021									
Santori, 2007									
Azimi, 2014									
Hale, 2021									
Masoudi, 2022									
Pepi, 2023									
Shih, 2022									
Tomlinson, 2017									
Wang, 2022									
Lu, 2022									
Pasha, 2021									
Peng, 2020									
Yahara, 2022									
Bagli, 1998									
Survival/ Mortality									
Chang, 2020									
Du, 2022									
Hu, 2021									
Miller, 2019									
Akbilgic, 2019									
Cooper, 2018									
Feng, 2021									
Grist, 2021									
Chen, 2021									
Bhambhvani, 2021									

QUADAS-2			
Diagnostic			
Lure, 2021			
Akgul, 2021			
Aydin, 2020			
Hayashi, 2021			
Hsieh, 2011			
Sakai, 2007			
Norman, 2017			
Reismann, 2019			
Reismann, 2021			
Bakhuis, 2023			
Fang, 2022			
Kwon, 2020			
Lai, 2020			
Ma, 2022			
Qian, 2023			
Zhang, 2022			
Zhang, 2022			
Attallah, 2021			
Bhalodia, 2020			
Grimm, 2020			
Klimont, 2019			
Quon, 2020			
You, 2022			
Zhang, 2021			
Shafi, 2020			
Nalepa, 2022			
Fraiwan, 2022			
Makhdoomi, 2022			
Ratnayake, 2012			
Sikidar, 2022			
Avila, 2021			

Fernandez, 2021									
Yin, 2020									
Decision Support									
Ruiz, 2016									
Liu, 2022									
Liu, 2022									
Marcinkevics, 2021									
Mantzaris, 2007									
Qi, 2022									
Qiu, 2021									
Radebe, 2021									
Rodrigues, 2014									
Shim, 2021									
Cherukuri, 2018									
Jabarkheel, 2022									
Jin, 2022									
Mesin, 2022									
Saez, 2022									
Wei, 2004									
Wissel, 2021									
Abousetta, 2023									
Lin, 2021									
Barak, 2022									
Liu, 2019									
Eksi, 2022									
Seckiner, 2008									

Green = Low risk of bias or good applicability; Yellow = unclear or moderate risk of bias or applicability; Red = High risk of bias or poor applicability

ROB = Risk of bias; PROBAST = Prediction model risk of bias assessment tool; QUADAS-2 = Quality assessment of diagnostic accuracy studies-2

Legend:

High risk of bias or concern regarding applicability

Unclear risk of bias or concern regarding applicability
Low risk of bias or concern regarding applicability

Chapter 3: Discussion

The systematic review conducted in earlier chapters has not only highlighted diverse AI models addressing various pediatric surgical needs, but also revealed insights regarding their use and performance across different subspecialties. In this discussion, we delve into the implications of our findings on the application of AI in pediatric surgery. We also analyze the various components of AI application in pediatric surgery as reviewed in our study. This includes a focus on good machine learning practices, the role of data pre-processing, the value of feature engineering, and the specifics of algorithm selection and training across different pediatric surgery subspecialties. We also examine the importance of validation and clearance, the challenges of post-deployment data drift, and the complexities of downstream integration in health systems. Additionally, ethical considerations and potential limitations of AI in this field will be explored. This comprehensive discussion aims to offer a holistic view beyond theoretical application to practical, real-world implications and future prospects.

AI is increasingly being applied to tackle some of the most challenging problems in pediatric surgery. These include predicting postoperative adverse events and mortality in children with congenital heart disease (Bertsimas, 2022; Ekhomu, 2022; Faerber, 2021; Samad, 2018; Luo, 2023; Hayward, 2022; Zeng, 2022; Li, 2022; Bertsimas, 2021; Jalali, 2020; Gupta, 2022; Guo, 2021; Pei, 2022; Shi, 2022; Sughimoto, 2022; Zeng, 2021), diagnosing urological emergencies (Eksi, 2022), and organ and tissue segmentation for surgical planning (Cherukuri, 2018; Grimm, 2020; Klimont, 2019; Quon, 2020; Nalepa, 2022). Additionally, AI is being utilized in predicting postoperative remission or adverse events in children with epilepsy (Pepi; 2023, Shih, 2022; Tomlinson, 2017; Wang, 2022), cancer (Liu, 2022; Wei, 2004; Radebe, 2021; Ma, 2022; Qian, 2023; Zhang, 2022; Feng, 2021; Grist, 2021; Chen, 2021) or after organ transplants (Jung, 2022; Wadhwani, 2019; Killian, 2021; Santori, 2007; Jalali, 2020; Gupta, 2022; Miller, 2019) including assessment of survival probabilities. In diagnosing and grading pediatric appendicitis, AI tools are proving invaluable. Moreover, AI is aiding in differentiating spontaneous intestinal perforation from necrotizing enterocolitis, a critical distinction for appropriate treatment planning (Irles, 2018; Lure, 2021; Qi, 2022; Cho, 2022).

The deployment of AI algorithms in pediatric healthcare is a complex, multidisciplinary endeavor that goes beyond the development of the machine learning model itself [73]. This process necessitates robust data pipelines that can efficiently and reliably handle the data needs of the algorithm. Model development and evaluation should adhere to Good Machine Learning Practices, which ensure the development of reliable machine learning models. This is achieved by robust data collection and preprocessing techniques, model selection, and rigorous, reproducible performance evaluation. The following sections explore Good Machine Learning Practices in greater detail [74].

3.1. Data pre-processing

At this step, data is prepared in a way that ensures its suitability and optimizes its potential for yielding accurate and reliable results in model training and analysis [75]. This includes ensuring data quality, addressing inconsistencies, and formatting the data to align with the requirements of the AI models being used. Standard data cleaning practices are performed [76], and special attention is given to the following steps.

3.1.1. Handling Missing Data

Missing data are excluded via complete case analysis, or imputed using one or more of several techniques [77]. Simple (mean) and multiple imputation were superseded by machine learning algorithms that can impute based on relationships between variables [78]. Machine learning imputation is more likely to result in robust estimates when data is Missing Completely At Random (MCAR;

missing data is independent of any other variable in the dataset) or Missing At Random (MAR; missingness is conditional on other observed variables but not on the missing variable itself) [79].

Identification of the pattern in which data is missing plays a significant role in the added value of the dataset, and has long challenged data scientists. While some statistical techniques such as Little's MCAR test do exist [80], manual expert-based reasoning is often required to identify the pattern of missingness, especially in ruling out Missing Not At Random (MNAR; missing data is related to the missing value itself) suspicion, which is a significant source of bias [81]. In pediatric surgery, where data might be MNAR due to reasons like selective reporting or differential data recording practices, it is important to approach imputation cautiously and consider the potential biases that may impact the validity and reliability of the model's outputs. In such cases, balancing may be considered to mitigate algorithmic bias.

3.1.2. ***Balancing***

Training models often involves down-weighting of outlier data [82]. While this process can enhance model performance in majority cases, it might inadvertently sideline information pertaining to minority or under-represented classes. In pediatric surgery, outlier data could include rare surgical conditions, anatomical anomalies, or specific ethnic, socio-economic, or gender minorities [83]. This form of algorithmic bias not only reinforces existing health disparities but may also lead to inadequate or erroneous clinical recommendations, thereby adversely affecting patient experiences and surgical outcomes [84].

Within the scope of existing literature reviewed, Synthetic Minority Oversampling Technique (SMOTE) has been frequently utilized as a countermeasure to ensure that minority classes are adequately represented in the training dataset. However, it is essential to acknowledge that bias mitigation is a complex, ongoing process that requires rigorous validation procedures.

3.1.3. Feature Engineering

Feature engineering involves transforming data, creating new or composite variables from existing ones, or selecting only those variables which are most relevant for the task. Variables can be normalized or standardized as necessary. This process ensures that each variable has a 'manageable' distribution or scale.

Dimensionality reduction techniques like PCA (Principal Component Analysis) have been used to reduce high-dimensional data (data that has a large number of variables) such as medical images, which is a form of tabulated high-dimensional data. Features can also be encoded or transformed as necessary [85].

3.3. Algorithm Selection and Training

Selection of a suitable algorithm depends on the nature of the addressed need and the associated data structure. The following section reviews how algorithms were used in each subspecialty.

3.3.1. General Surgery

In pediatric general surgery, various types of AI models were employed to address different clinical challenges. Neural Networks, especially CNNs were often utilized for complex diagnostic tasks involving image data. For example, a 2023 study by Bakhuis used a CNN for the diagnosis of congenital lung lesions, and another 2022 study by Zhang applied a CNN for diagnosing Retinoblastoma using fundoscopy images. These models were effective in handling high-dimensional and complex image data, but challenges in interpretability remain. To overcome this challenge, Gradient-weighted Class Activation Mapping technique has been developed to visualize what areas of the image are being focused on for classification or diagnosis. This technique overlays a heatmap on the original image to indicate regions of interest, thereby offering some degree of insight into the decision-making process of the CNN [86].

Ensemble methods were mostly used for event prediction and decision support. For instance, random forests were used by Cho in 2022 to predict necrotizing enterocolitis, and Killian (2021) used it to predict outcomes after organ transplant.

Overall, the choice of AI model in pediatric general surgery was determined by the specific requirements of the clinical scenario. Ensemble methods were versatile and robust, making them suitable for a wide range of applications. Neural Networks were effective for image-based diagnostics, although their complexity led to challenges in model interpretability. Simpler models like Regression and SVM were most appropriately used in scenarios requiring straightforward interpretative outcomes.

3.3.2. Cardiac Surgery

Ensemble Learning techniques were notably prevalent. Studies like that by Luo et al. (2023) used ensemble learning to predict acute kidney injury, while Sughimoto et al. employed a random forest to anticipate hemodynamic instability after cardiac surgery. Ensemble methods were especially well-suited for these complex scenarios due to their ability to capture non-linear relationships and provide robust predictions.

Neural Networks also had a significant presence; for example, the study by Zeng et al. (2022) used RNNs on time-series data for predicting acute kidney injury. Use of a RNN in this context can aid in real-time postoperative care planning. Neural networks were adept at handling the complex, high-dimensional, temporal data from cardiac patients, although they present challenges in interpretability that could be critical in clinical decision-making.

Regression models and SVMs were less commonly used but still had specific applications. Gupta et al. used stepwise logistic regression to predict prolonged hospital stays following heart transplant, and Samad et al. employed a SVM to predict ventricular deterioration after Tetralogy of Fallot repair. While these simpler models offered the advantage of interpretability, they may be less capable of capturing complex interactions among variables compared to ensemble learners and neural networks.

3.3.3. Neurosurgery

In neurosurgery, neural networks emerged as the most frequently used AI models, and they were predominantly utilized for both diagnostic and outcome prediction tasks. For example, a study by Sidpra in 2022 used a neural network for predicting cerebellar mutism syndrome after surgical resection of posterior fossa tumors, while another by Pepi in 2023 employed such a model for predicting epilepsy resolution after hemispherotomy.

Less commonly, simpler models like KNN and SVM were employed for narrower use-cases such as patient selection. A study by Saez in 2022 used KNN for selecting patients to undergo Ommaya reservoir conversion to ventriculoperitoneal shunt, and another by Mesin in 2022 utilized a SVM for optimizing surgical technique in children with Chiari I malformation.

Lastly, Regression was used in only one study that used Raman spectroscopy for distinguishing between tumor and non-tumor tissue (Jabarkheel, 2022).

3.3.4. Urology

In pediatric urology, ensemble learners were frequently employed for event prediction and decision support. A study by Kwong in 2022 utilized a random survival forest for predicting progression of chronic kidney disease in children with posterior urethral valves, and Eksi used a random forest to predict the need for orchiectomy in children with testicular torsion.

Neural Networks were applied for survival and surgical outcome prediction as well as diagnosis and decision support. Bhambhvani in 2021 utilized a neural network to predict 5-year overall survival in pediatric patients with genitourinary rhabdomyosarcoma. Another study by Yin in 2020 fine-tuned a pre-trained computer vision neural network called VGG16 to diagnose posterior urethral valve based on ultrasound images.

3.3.5. Ophthalmology

There were only two pediatric ophthalmology studies. The first was Zhang 2019 which developed three random forest models that predicted adverse events after intraocular lens implantation in children. One predicted severe lens proliferation into the visual axis, the second predicted abnormal high intraocular pressure, and third predicted any complication. Notably, Zhang used SMOTE to pre-process the data and oversample minority classes. The second study was that of Nalepa, who used a neural network to detect and segment optic pathway glioma.

3.3.6. Orthopedic Surgery

In pediatric orthopedic surgery, both neural networks and ensemble learners were applied for diagnosis, surgical outcome prediction, and survival prediction. For instance, a study by Yahara in 2022 utilized transfer learning with a pre-trained CNN to predict progression of adolescent idiopathic scoliosis from x-ray images. Ratnayake's 2012 study also used a CNN on x-ray images; the objective of this model was to diagnose supracondylar fracture of the humerus and measure the angle of the fracture.

Ensemble learners, particularly random forest models, were also used in orthopedic surgery. For example, a study by Pasha in 2021 employed a random forest for predicting outcomes after posterior spinal fusion surgery. Another study by Chen in 2021 predicted cancer-specific survival and overall survival for Ewing sarcoma using random forest models.

Lastly, KNN was also used in orthopedic surgery. A study by Sikidar in 2022 used KNN for diagnosing AIS based on gait data.

3.3.7. Otolaryngology-Head and Neck Surgery

In pediatric otolaryngology-head and neck surgery, a variety of AI models were employed for decision support, surgical outcome prediction, and diagnosis. Abousetta tested KNN against AdaBoost (an ensemble learner) and logistic regression in a decision support algorithm that recommended cochlear implantation. This condition was also the subject of Lu's 2022 study, which utilized a SVM to predict persistent postoperative hearing impairment.

Shafi's 2020 study tested random forest, k-nearest neighbor, decision tree, support vector machine, and neural network algorithms for prenatal diagnosis of orofacial clefts (cleft lip or palate) based on questionnaire data. They found that the neural network model had the highest accuracy. Lastly, Lin used an ensemble learning method to select patients for orthognathic surgery.

3.3.8. Surgical Systems

In the area of pediatric surgical systems, ensemble learners were predominantly used for decision support and diagnosis. For instance, a study by Barak in 2022 utilized a random forest to predict bed occupancy in surgical wards. Another study by Avila in 2021 employed an ensemble learner for diagnosing discharge statuses, categorizing them into deceased, unhealthy, and healthy. Additionally, Liu in 2019 used a Gradient-boosted Logistic Regression model for decision support to predict surgery cancellations.

The use of AI models in various pediatric surgical specialties is determined by the specific requirements of clinical scenarios. Neural networks, particularly CNNs, are often employed for complex diagnostic tasks involving image data, although they present challenges in interpretability. Techniques like Gradient-weighted Class Activation Mapping have been developed to address this. Ensemble methods like random forests are versatile and robust, making them suitable for event prediction and decision support in various surgical disciplines. They are especially beneficial in handling complex, non-linear relationships. Simpler models like Regression and SVMs are less commonly used but offer advantages in interpretability and are deployed in scenarios requiring straightforward outcomes. In summary, the landscape of AI in pediatric surgery is varied, with each algorithm offering a unique set of advantages and limitations tailored to the specific clinical questions at hand.

3.4. Validation and Clearance

For most models, the journey ended with local validation followed by a report in a peer-reviewed journal. However, once a model has been developed and internally validated, prospective external validation followed by regulatory clearance must take place before pediatric surgeons can start to use the model in a clinical context. In the United States, clearance is handled by the US Food and Drug Administration, which classifies AI models as Software as a Medical Device [87]. The recent spread of transfer learning strategies present an opportunity to fine-tune pediatric surgery neural network models during external validation. Radiologists have successfully fine-tuned pre-trained computer vision neural networks for several ultrasound, CT, and MRI applications [88]. Several cardiologists have deployed AI-assisted cardiovascular imaging algorithms to select patients for aortic aneurysm repair [89]

3.5. Post-Deployment Data Drift

Upon deployment into a clinical setting, continual validation of AI models is imperative. Ground truth analysis (Post-hoc comparison of the predictions or outputs of a model with the actual, real-world outcomes or facts to ensure that the model remains reliable over time) should be conducted to compare the model's output with actual outcomes. Performance changes should be rigorously monitored, and mechanisms to mitigate the risks associated with dataset drift should be actively implemented.

Dataset drift refers to the phenomenon where the statistical properties of patient features evolve over time, causing the new data encountered by the model to diverge substantially from the original training data (53). This divergence can compromise the model's predictive accuracy and clinical relevance (54). Periodic ground truth analysis (post-hoc comparison of model predictions with true outcomes) mitigates dataset drift by ensuring that deployed AI models maintain their reliability profiles over time.

3.6. Downstream Integration

Downstream integration of the AI model into the existing healthcare system is an additional challenge that necessitates coordinated, multidisciplinary care. Integration should be designed to facilitate communication and decision-making among all stakeholders, including end-users like pediatric surgeons, nurses, and hospitalists. Additionally, involvement of internal stakeholders responsible for the design and technical requirements (computer scientists, network security engineers, data scientists, database developers, systems administrators) should align with the goals of the model. This enables the delivery of high-quality, timely healthcare by ensuring that all team members understand the need for the model and the insights provided by it.

3.7. Ethics

While the integration of AI algorithms into healthcare systems offers substantial advancements in efficiency and patient care, it's crucial to acknowledge that these algorithms can perpetuate existing societal biases and inequalities, as they are trained on data reflective of society [84]. This concern is accentuated in the realm of pediatric surgical healthcare.

Pediatric surgical needs are not static but evolve in accordance with various developmental stages. Moreover, there are significant physiological, anatomical, and cognitive differences between pediatric and adult populations. These distinctions influence the incidence, prevalence, presentation, outcome, and prognosis of diseases across different age groups. Unadjusted analysis from our study that more males were recruited to pediatric surgery AI algorithm studies than females. Given the age-related, intellectual, and developmental heterogeneity present within pediatric populations, amalgamating pediatric and adult data—or even pooling data from different developmental stages within the pediatric spectrum—may introduce significant distortions or biases into machine learning models. These distortions could potentially compromise the accuracy and reliability of diagnostic and predicting algorithms, thereby affecting clinical decision-making and patient outcomes [73].

3.8. Final Notes on Implementation of AI in Pediatric Surgery

An implementation gap exists in healthcare AI stemming from several challenges, including:

1. Framework challenge: Absence of a framework for integrating AI in complex health systems
2. Human resource challenge: Scarcity of diverse, interdisciplinary subject matter expert teams that represent all stakeholders and provide overall direction.
3. Scalable sustainability challenge: The computational demands associated with machine learning algorithms present a substantial obstacle to the scalable and sustainable deployment of AI in healthcare settings. Resorting to external computational resources for mitigating this challenge introduces significant risks concerning the safeguarding of patient confidentiality. Consequently, healthcare AI ecosystems necessitate robust on-premise infrastructure investments to both meet computational requirements and uphold stringent data privacy standards.

The complexity of deploying AI in pediatric healthcare thus extends from ethical decision-making and model development all the way through to downstream integration and ongoing monitoring. Each of these steps requires the collaboration of experts from various domains, from data science and medicine to ethics and healthcare administration. By approaching this as a coordinated, multidisciplinary task, we can ensure not just the scientific rigor but also the ethical integrity and practical efficacy of AI applications in pediatric surgery.

3.9. Limitations

This systematic review has several limitations. The first stems from the fact that AI techniques are rapidly evolving, and recently developed techniques are likely to expand on the utility of AI in pediatric surgery. However, for an AI model to enter routine clinical use, it must be cleared by Health Canada (or the FDA in the US) since AI is software as a medical device (SaMD) [90]. While this is an important safety check against the use of unreliable and unsafe models, it delays model deployment by approximately one year. In the current rapidly evolving environment of AI innovation, one year may be all there is between state-of-the-art and obsolete. This is especially important to take into consideration while Canada participates in the AI race - a race that is currently dominated by China, where relatively lax regulation facilitates rapid iteration [91]. This may explain why close to 15% of all pediatric surgery AI models were trained in China.

Chapter 4. Final Conclusion and Summary

The present review of AI applications in pediatric surgery revealed a landscape replete with both potential and challenges. Various AI algorithms have found utility across different subspecialties, with neural networks excelling in complex diagnostic tasks involving image data, and ensemble methods proving to be versatile and robust for event prediction and decision support (Figure 7). However, those AI models have not undergone clinical integration, largely remaining as in-silico proof of concepts. The challenges hindering integration are multi-faceted:

- Data Pre-processing: the industry has yet to standardize methods for mitigating algorithmic bias, particularly in underrepresented classes
- Algorithm Complexity and Interpretability: While neural networks excel in handling high-dimensional and complex data, their black-box nature poses significant interpretability challenges that hinder clinical acceptability. Although complete transparency, where each model output is accompanied by a detailed rationale, is ideal, it may not always be feasible in

complex AI systems. Instead, providing explanations at the model level, such as the significance and impact of various variables on the model's outputs, can be a viable alternative.

- Regulatory: Models seeking approval in the US and Canada must navigate the stringent regulatory landscape for Software as a Medical Device (SaMD).
- Post-Deployment Issues: Dataset drift, which can compromise the efficacy of deployed models, further underscores the need for ongoing surveillance mechanisms.
- Operational Challenges: The absence of a cohesive framework for AI integration, limited interdisciplinary expertise, and computational constraints further exacerbate the implementation gap in healthcare settings.
- Human Resource challenge: Scarcity of clinical AI experts leads engineers to prioritize technical feats over practical utility [92]. Consequently, this misalignment results in innovations that, while technically advanced, do not present an answer to a real-world problem in pediatric surgery. Shim’s 2021 paper is a prime example of a technically advanced feat that does not solve a pediatric surgery problem; an ensemble learner was trained on data from 834 patients to predict optimal endotracheal tube depth. In practice, optimal depth is verified by listening for breath sounds bilaterally. To ensure purpose-driven innovation in pediatric surgery AI, it is imperative to bridge this gap by training clinicians who possess expertise in AI and can steer engineers towards value-adding ventures.
- Ethics Alignment challenge: The integration of AI in pediatric surgery raises significant concerns about privacy and confidentiality. For instance, large language models have been shown to leak training data [93]. Moreover, it remains unclear how AI algorithms that are trained on patient data can fully comply with Quebec Law 25, including the right to be forgotten [94].

- Impact on insurability: The use of generative AI in healthcare, particularly in the development of synthetic medical data, can indirectly affect insurability. For example, synthetic medical images can potentially be used in insurance scams. Generative AI can be leveraged to modify radiographic images to suit a certain diagnosis.
- Patient acceptance: Potential biases in AI decision support can lead to skepticism and reluctance among patients and families. The ethical concerns, such as the lack of transparency and accountability can hinder the acceptance of these technologies. There's a need for a systematic assessment of ethical considerations, which involves disclosing the benefits, limitations, and potential risks of AI tools. By doing so, healthcare providers and AI developers can work towards gaining the trust and acceptance of patients and their families. ACCEPT-AI is a framework that promotes safe inclusion of pediatric data in AI research. ACCEPT-AI incorporates age, consent and assent, communication, equity, and data protection principles to guide stakeholders [73].

In summary, while the field of AI in pediatric surgery is burgeoning with innovation, the practical integration of these models into healthcare systems remains nascent. The industry must focus on overcoming existing hurdles, particularly those related to data integrity, interpretability, regulation, and real-world implementation. It is crucial that future research and development not only aim to improve algorithmic performance but also address systemic issues, biases, and uphold ethics principles to close the implementation gap and leverage AI's full potential in pediatric surgical care.

Chapter 5. Appendix A: Full Search Strategy

Databases Searched

Africa-Wide Information [EBSCO] (January 24, 2023)

#	Query	Results
S45	S44 AND S21	41
S44	S43 OR S42 OR S41 OR S40 OR S39 OR S38 OR S37 OR S36 OR S35 OR S34 OR S33 OR S32 OR S31 OR S29 OR S30 OR S28 OR S27 OR S26 OR S25 OR S24 OR S23 OR S22	250,627
S43	TI((pectus or chest) N1 (funnel or sunken or excavatum or carinatum)) OR AB((pectus or chest) N1 (funnel or sunken or excavatum or carinatum))	51
S42	TI(congenital* and hernia* and diaphragm*) OR AB(congenital* and hernia* and diaphragm*)	157
S41	TI((congenital* or neonat* or neo-nat* or newborn* or new-born* or birth* or maternal* or fetal or fetus* or fetu or feto or foet* or prenatal* or pre-natal* or antenatal* or ante-natal* or trimester* or pregnan* or uter* or preterm* or pre-term* or premature* or pre-mature* or preemie*) N2 diaphragm* N2 (hernia* or defect*)) OR AB((congenital* or neonat* or neo-nat* or newborn* or new-born* or birth* or maternal* or fetal or fetus* or fetu or feto or foet* or prenatal* or pre-natal* or antenatal* or ante-natal* or trimester* or pregnan* or uter* or preterm* or pre-term* or premature* or pre-mature* or preemie*) N2 diaphragm* N2 (hernia* or defect*))	149
S40	TI((congenital* or neonat* or neo-nat* or newborn* or new-born* or birth* or maternal* or fetal or fetus* or fetu or feto or foet* or prenatal* or pre-natal* or antenatal* or ante-natal* or trimester* or pregnan* or uter* or preterm* or pre-term* or premature* or pre-mature* or preemie*) N5 (posterolateral* or substernal*) N2 hernia*) OR AB((congenital* or neonat* or neo-nat* or newborn* or new-born* or birth* or maternal* or fetal or fetus* or fetu or feto or foet* or prenatal* or pre-natal* or antenatal* or ante-natal* or trimester* or pregnan* or uter* or preterm* or pre-term* or premature* or pre-mature* or preemie*) N5 (posterolateral* or substernal*) N2 hernia*)	5
S39	TI((bochdalek* or morgagni*) N2 (hernia* or defect*)) OR AB((bochdalek* or morgagni*) N2 (hernia* or defect*))	43
S38	TI(agene* N2 (hemidiaphragm* or diaphragm* or ((unilat* or hern*) N1 diaphragm*))) OR AB(agene* N2 (hemidiaphragm* or diaphragm* or ((unilat* or hern*) N1 diaphragm*)))	5
S37	TI(hirschsprung* or ((megacolon or colon* or rectosigmoid or intestin*) N3 (congenital* or aganglion*))) OR AB(hirschsprung* or ((megacolon or colon* or rectosigmoid or intestin*) N3 (congenital* or aganglion*)))	345
S36	TI((anal or anus or anorect* or rectal) N3 (artificial* or malformat* or mal-format* or anomal* or abnormal* or ectopic or stenosis or atres* or atroph* or imperforat* or inperforat* or praet* or pret* or fistula*)) OR AB((anal or anus or anorect* or rectal) N3 (artificial* or malformat* or mal-format* or anomal* or abnormal* or ectopic or stenosis or atres* or atroph* or imperforat* or inperforat* or praet* or pret* or fistula*))	538
S35	TI((esophag* or oesophag* or endoesophag* or intraesophag* or tracheoesophag*) N3 (atres* or atretic* or atroph*)) OR AB((esophag* or oesophag* or endoesophag* or intraesophag* or tracheoesophag*) N3 (atres* or atretic* or atroph*))	167
S34	TI((lung or lungs or pulmon* or wedge or trauma* or postrauma* or posttrauma* or neurotrauma* or fracture*) N3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative*	5,871

	or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)) OR AB((lung or lungs or pulmon* or wedge or trauma* or postrauma* or posttrauma* or neurotrauma* or fracture*) N3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*))	
S33	TI(thoracoscop* or thoracotom* or pleurectom* or pleuroscop* or pleuracotom* or pleurotom* or (pleura* N3 (endoscop* or incision*))) OR AB(thoracoscop* or thoracotom* or pleurectom* or pleuroscop* or pleuracotom* or pleurotom* or (pleura* N3 (endoscop* or incision*)))	1,425
S32	TI ((liver or hepatic or lung or lungs or pulmon* or kidney) N3 (transplant* or graft*)) OR AB((liver or hepatic or lung or lungs or pulmon* or kidney) N3 (transplant* or graft*))	3,319
S31	TI ((hernia* or extraperitoneal or preperitoneal or peritoneal or TEP or TAPP or umbilic* or inguinal or omphalocele* or exomphalos) N3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)) OR AB((hernia* or extraperitoneal or preperitoneal or peritoneal or TEP or TAPP or umbilic* or inguinal or omphalocele* or exomphalos) N3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*))	1,188
S30	TI (fundoplicat* or ((nissen* or toupet or dor) N3 (operat* or procedur* or surger* or surgical*))) OR AB(fundoplicat* or ((nissen* or toupet or dor) N3 (operat* or procedur* or surger* or surgical*)))	120
S29	TI ((cancer or neoplas* or tumor* or tumour* or carcinom* or sarcoma*) N3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or biopsy or biopsie* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*))OR AB((cancer or neoplas* or tumor* or tumour* or carcinom* or sarcoma*) N3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or biopsy or biopsie* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*))	5,164
S28	TI(escharotom* or ((skin or derm*) N2 (graft* or transplant*))) OR AB(escharotom* or ((skin or derm*) N2 (graft* or transplant*)))	703
S27	TI((abdomen or abdominal or intestin* or bowel* or gastrointestin*) N3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)) OR AB((abdomen or abdominal or intestin* or bowel* or gastrointestin*) N3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*))	2,843
S26	TI((tooth or teeth or dental or abcess) N2 (extract* or drain*)) OR AB((tooth or teeth or dental or abcess) N2 (extract* or drain*))	710
S25	TI((perforation* or incision* or laceration*) N3 (repair* or drain* or closure*)) OR AB((perforation* or incision* or laceration*) N3 (repair* or drain* or closure*))	491
S24	TI((opthalmolog* or eye* or vision or ocular or retina* or retinopath*) N5 (operat* or procedur* or surger* or surgical*)) OR AB((opthalmolog* or eye* or vision or ocular or retina* or retinopath*) N5 (operat* or procedur* or surger* or surgical*))	1,449
S23	TI(adenoidectom* or laryngectom* or laryngoplast* or laryngoscop* or pharygectom* or tonsillectom* or tympanoplast* or tracheostom* or tracheotom* or orchidopex* or orchiopex* or orchiectom* or orchidectom* or herniorrhaph* or hernioplast* or	12,854

	herniaplast* or herni* N0 plast* or herniotom* or circumcis* or gastrostom or ileostom* or colostom* or enterostom* or portoenterostom or "roux-en-y" or kasai or pyloromyotom* or piloromyotom* or pyloromiotom* or piloromiotom* or diverticulectom* or diverticulotom* or cholecystectom* or cholangiopancreatograph* or cholangio-pancreatograph* or choledoduodenostom* or choledo-duodenostom or appendicectom* or appendectom* or splenectom* or pneumonectom* or amputation* or amputate* or craniotom* or craniostom* or hydrocelectom* or thoracostom* or fasciotom*) OR AB(adenoidectom* or laryngectom* or laryngoplast* or laryngoscop* or pharygectom* or tonsillectom* or tympanoplast* or tracheostom* or tracheotom* or orchidopex* or orchiopex* or orchiectom* or orchidectom* or herniorrhaph* or hernioplast* or herniaplast* or herni* N0 plast* or herniotom* or circumcis* or gastrostom or ileostom* or colostom* or enterostom* or portoenterostom or "roux-en-y" or kasai or pyloromyotom* or piloromyotom* or pyloromiotom* or piloromiotom* or diverticulectom* or diverticulotom* or cholecystectom* or cholangiopancreatograph* or cholangio-pancreatograph* or choledoduodenostom* or choledo-duodenostom or appendicectom* or appendectom* or splenectom* or pneumonectom* or amputation* or amputate* or craniotom* or craniostom* or hydrocelectom* or thoracostom* or fasciotom*)	
S22	TI(surger* or surgic* or surgeon* or operati* or reoperat* or bypass* or by-pass* or resect* or re-sect* or transplant* or procedure* or debridement* or laparoscop* or laparotom* or postop*) OR AB(surger* or surgic* or surgeon* or operati* or reoperat* or bypass* or by-pass* or resect* or re-sect* or transplant* or procedure* or debridement* or laparoscop* or laparotom* or postop*)	241,165
S21	S19 AND S20	414
S20	TI(newborn* or new-born* or neonat* or neo-nat* or infan* or child* or adolesc* or paediatr* or pediatr* or baby* or babies* or toddler* or kid or kids or boy* or girl* or juvenile* or teen* or youth* or pubescen* or preadolesc* or prepubesc* or preteen*) OR AB(newborn* or new-born* or neonat* or neo-nat* or infan* or child* or adolesc* or paediatr* or pediatr* or baby* or babies* or toddler* or kid or kids or boy* or girl* or juvenile* or teen* or youth* or pubescen* or preadolesc* or prepubesc* or preteen*) OR SO(pediatr* or paediatr*)	284,953
S19	S1 OR S2 OR S3 OR S4 OR S5 OR S6 OR S7 OR S8 OR S9 OR S10 OR S11 OR S12 OR S13 OR S14 OR S15 OR S16 OR S17 OR S18	6,795
S18	TI(multifactor* N1 dimension* N1 reduction*) OR AB(multifactor* N1 dimension* N1 reduction*)	33
S17	TI((latent or structural or equation?) N1 (class or variable* or probabilistic) N1 (analys* or model*)) OR AB((latent or structural or equation?) N1 (class or variable* or probabilistic) N1 (analys* or model*))	363
S16	TI((sentiment N1 (analys* or classif*)) or opinion mining) OR AB((sentiment N1 (analys* or classif*)) or opinion mining)	16
S15	TI(learning N1 (transfer* or hierarchical)) OR AB(learning N1 (transfer* or hierarchical))	78
S14	TI((pattern* or document) N1 classif*) OR AB((pattern* or document) N1 classif*)	108
S13	TI((sentiment N1 (analys* or classification*)) or opinion mining) OR AB((sentiment N1 (analys* or classification*)) or opinion mining)	15
S12	TI((genetic or bio-inspired or learning or clustering) N1 algorithm*) OR AB((genetic or bio-inspired or learning or clustering) N1 algorithm*)	777
S11	TI((case-based or approximate* or automated) N1 reasoning*) OR AB((case-based or approximate* or automated) N1 reasoning*)	43
S10	TI(random* N2 forest*) OR AB(random* N2 forest*)	342
S9	TI(natural language processing* or autoencoder* or metaheuristic* or support vector* or expert system* or markov model* or computer vision system*) OR AB(natural language processing* or autoencoder* or metaheuristic* or support vector* or expert system* or markov model* or computer vision system*)	1,463

S8	TI(knowledge* N1 (acquisition* or representation*)) OR AB(knowledge* N1 (acquisition* or representation*))	310
S7	TI(fuzzy N1 (logic or cognit* or inference* or classific* or rule* or system* or control*)) OR AB(fuzzy N1 (logic or cognit* or inference* or classific* or rule* or system* or control*))	397
S6	TI((data or text) N1 mining)OR AB((data or text) N1 mining)	495
S5	TI(comput* N1 (heuristic or reasoning or soft or evolutionary)) OR AB(comput* N1 (heuristic or reasoning or soft or evolutionary))	59
S4	TI((bayes* or neural or deep or echo or generative or adversarial) N1 (network* or naive* or learning* or reservois*)) OR AB((bayes* or neural or deep or echo or generative or adversarial) N1 (network* or naive* or learning* or reservois*))	1,899
S3	TI(natural-language or chat-bot? or chatbot? or convers* N0 agent?) OR AB(natural-language or chat-bot? or chatbot? or convers* N0 agent?)	209
S2	TI(computer* N1 media* N1 communicat*) OR AB(computer* N1 media* N1 communicat*)	58
S1	TI((artificial* or computat* or machine* or deep or supervi* or unsupervi* or semisupervi* or shallow* or competitive) N1 (intelligen* or learn*)) OR AB((artificial* or computat* or machine* or deep or supervi* or unsupervi* or semisupervi* or shallow* or competitive) N1 (intelligen* or learn*))	1,654

CINAHL Plus [EBSCO] (January 24, 2023)

#	Query	Results
S46	S44 AND S21	560
S45	S44 AND S21	560
S44	S43 OR S42 OR S41 OR S40 OR S39 OR S38 OR S37 OR S36 OR S35 OR S34 OR S33 OR S32 OR S31 OR S29 OR S30 OR S28 OR S27 OR S26 OR S25 OR S24 OR S23 OR S22	966,829
S43	TI((pectus or chest) N1 (funnel or sunken or excavatum or carinatum)) OR AB((pectus or chest) N1 (funnel or sunken or excavatum or carinatum))	490
S42	TI(congenital* and hernia* and diaphragm*) OR AB(congenital* and hernia* and diaphragm*)	1,720
S41	TI((congenital* or neonat* or neo-nat* or newborn* or new-born* or birth* or maternal* or fetal or fetus* or fetu or feto or foet* or prenatal* or pre-natal* or antenatal* or ante-natal* or trimester* or pregnan* or uter* or preterm* or pre-term* or premature* or pre-mature* or preemie*) N2 diaphragm* N2 (hernia* or defect*)) OR AB((congenital* or neonat* or neo-nat* or newborn* or new-born* or birth* or maternal* or fetal or fetus* or fetu or feto or foet* or prenatal* or pre-natal* or antenatal* or ante-natal* or trimester* or pregnan* or uter* or preterm* or pre-term* or premature* or pre-mature* or preemie*) N2 diaphragm* N2 (hernia* or defect*))	1,683
S40	TI((congenital* or neonat* or neo-nat* or newborn* or new-born* or birth* or maternal* or fetal or fetus* or fetu or feto or foet* or prenatal* or pre-natal* or antenatal* or ante-natal* or trimester* or pregnan* or uter* or preterm* or pre-term* or premature* or pre-mature* or preemie*) N5 (posterolateral* or substernal*) N2 hernia*) OR AB((congenital* or neonat* or neo-nat* or newborn* or new-born* or birth* or maternal* or fetal or fetus* or fetu or feto or foet* or prenatal* or pre-natal* or antenatal* or ante-natal* or trimester* or pregnan* or uter* or preterm* or pre-term* or premature* or pre-mature* or preemie*) N5 (posterolateral* or substernal*) N2 hernia*)	8
S39	TI((bochdalek* or morgagni*) N2 (hernia* or defect*)) OR AB((bochdalek* or morgagni*) N2 (hernia* or defect*))	254
S38	TI(agene* N2 (hemidiaphragm* or diaphragm* or ((unilat* or hern*) N1 diaphragm*))) OR AB(agene* N2 (hemidiaphragm* or diaphragm* or ((unilat* or hern*) N1 diaphragm*)))	13

S37	TI(hirschsprung* or ((megacolon or colon* or rectosigmoid or intestin*) N3 (congenital* or aganglion*))) OR AB(hirschsprung* or ((megacolon or colon* or rectosigmoid or intestin*) N3 (congenital* or aganglion*)))	1,069
S36	TI((anal or anus or anorect* or rectal) N3 (artificial* or malformat* or mal-format* or anomal* or abnormal* or ectopic or stenosis or atres* or atroph* or imperforat* or inperforat* or praet* or pret* or fistula*)) OR AB((anal or anus or anorect* or rectal) N3 (artificial* or malformat* or mal-format* or anomal* or abnormal* or ectopic or stenosis or atres* or atroph* or imperforat* or inperforat* or praet* or pret* or fistula*))	1,618
S35	TI((esophag* or oesophag* or endoesophag* or intraesophag* or tracheoesophag*) N3 (atres* or atretic* or atroph*)) OR AB((esophag* or oesophag* or endoesophag* or intraesophag* or tracheoesophag*) N3 (atres* or atretic* or atroph*))	915
S34	TI((lung or lungs or pulmon* or wedge or trauma* or postrauma* or posttrauma* or neurotrauma* or fracture*) N3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)) OR AB((lung or lungs or pulmon* or wedge or trauma* or postrauma* or posttrauma* or neurotrauma* or fracture*) N3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*))	31,100
S33	TI(thoracoscop* or thoracotom* or pleurectom* or pleuroscop* or pleuracotom* or pleurotom* or (pleura* N3 (endoscop* or incision*))) OR AB(thoracoscop* or thoracotom* or pleurectom* or pleuroscop* or pleuracotom* or pleurotom* or (pleura* N3 (endoscop* or incision*)))	6,603
S32	TI ((liver or hepatic or lung or lungs or pulmon* or kidney) N3 (transplant* or graft*)) OR AB((liver or hepatic or lung or lungs or pulmon* or kidney) N3 (transplant* or graft*))	21,236
S31	TI ((hernia* or extraperitoneal or preperitoneal or peritoneal or TEP or TAPP or umbilic* or inguinal or omphalocele* or exomphalos) N3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)) OR AB((hernia* or extraperitoneal or preperitoneal or peritoneal or TEP or TAPP or umbilic* or inguinal or omphalocele* or exomphalos) N3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*))	8,791
S30	TI (fundoplicat* or ((nissen* or toupet or dor) N3 (operat* or procedur* or surger* or surgical*))) OR AB(fundoplicat* or ((nissen* or toupet or dor) N3 (operat* or procedur* or surger* or surgical*)))	1,406
S29	TI ((cancer or neoplas* or tumor* or tumour* or carcinom* or sarcoma*) N3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or biopsy or biopsie* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*))OR AB((cancer or neoplas* or tumor* or tumour* or carcinom* or sarcoma*) N3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or biopsy or biopsie* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*))	49,325
S28	TI(escharotom* or ((skin or derm*) N2 (graft* or transplant*))) OR AB(escharotom* or ((skin or derm*) N2 (graft* or transplant*)))	3,664
S27	TI((abdomen or abdominal or intestin* or bowel* or gastrointestin*) N3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)) OR AB((abdomen or	17,163

	abdominal or intestin* or bowel* or gastrointestin*) N3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*))	
S26	TI((tooth or teeth or dental or abcess) N2 (extract* or drain*)) OR AB((tooth or teeth or dental or abcess) N2 (extract* or drain*))	3,733
S25	TI((perforation* or incision* or laceration*) N3 (repair* or drain* or closure*)) OR AB((perforation* or incision* or laceration*) N3 (repair* or drain* or closure*))	3,031
S24	TI((opthalmolog* or eye* or vision or ocular or retina* or retinopath*) N5 (operat* or procedur* or surger* or surgical*)) OR AB((opthalmolog* or eye* or vision or ocular or retina* or retinopath*) N5 (operat* or procedur* or surger* or surgical*))	6,165
S23	TI(adenoidectom* or laryngectom* or laryngoplast* or laryngoscop* or pharygectom* or tonsillectom* or tympanoplast* or tracheostom* or tracheotom* or orchidopex* or orchiopex* or orchiectom* or orchidectom* or herniorrhaph* or hernioplast* or herniaplast* or herni* N0 plast* or herniotom* or circumcis* or gastrostom or ileostom* or colostom* or enterostom* or portoenterostom or "roux-en-y" or kasai or pyloromyotom* or piloromyotom* or pyloromiotom* or piloromiotom* or diverticulectom* or diverticulotom* or cholecystectom* or cholangiopancreatograph* or cholangio-pancreatograph* or choledoduodenostom* or choledo-duodenostom or appendicectom* or appendectom* or splenectom* or pneumonectom* or amputation* or amputate* or craniotom* or craniostom* or hydrocelectom* or thoracostom* or fasciotom*) OR AB(adenoidectom* or laryngectom* or laryngoplast* or laryngoscop* or pharygectom* or tonsillectom* or tympanoplast* or tracheostom* or tracheotom* or orchidopex* or orchiopex* or orchiectom* or orchidectom* or herniorrhaph* or hernioplast* or herniaplast* or herni* N0 plast* or herniotom* or circumcis* or gastrostom or ileostom* or colostom* or enterostom* or portoenterostom or "roux-en-y" or kasai or pyloromyotom* or piloromyotom* or pyloromiotom* or piloromiotom* or diverticulectom* or diverticulotom* or cholecystectom* or cholangiopancreatograph* or cholangio-pancreatograph* or choledoduodenostom* or choledo-duodenostom or appendicectom* or appendectom* or splenectom* or pneumonectom* or amputation* or amputate* or craniotom* or craniostom* or hydrocelectom* or thoracostom* or fasciotom*)	58,958
S22	TI(surger* or surgic* or surgeon* or operati* or reoperat* or bypass* or by-pass* or resect* or re-sect* or transplant* or procedure* or debridement* or laparoscop* or laparotom* or postop*) OR AB(surger* or surgic* or surgeon* or operati* or reoperat* or bypass* or by-pass* or resect* or re-sect* or transplant* or procedure* or debridement* or laparoscop* or laparotom* or postop*)	919,543
S21	S19 AND S20	4,939
S20	TI(newborn* or new-born* or neonat* or neo-nat* or infan* or child* or adolesc* or paediatr* or pediatr* or baby* or babies* or toddler* or kid or kids or boy* or girl* or juvenile* or teen* or youth* or pubescen* or preadolesc* or prepubesc* or preteen*) OR AB(newborn* or new-born* or neonat* or neo-nat* or infan* or child* or adolesc* or paediatr* or pediatr* or baby* or babies* or toddler* or kid or kids or boy* or girl* or juvenile* or teen* or youth* or pubescen* or preadolesc* or prepubesc* or preteen*) OR SO(pediatr* or paediatr*)	1,047,921
S19	S1 OR S2 OR S3 OR S4 OR S5 OR S6 OR S7 OR S8 OR S9 OR S10 OR S11 OR S12 OR S13 OR S14 OR S15 OR S16 OR S17 OR S18	48,256
S18	TI(multifactor* N1 dimension* N1 reduction*) OR AB(multifactor* N1 dimension* N1 reduction*)	183
S17	TI((latent or structural or equation?) N1 (class or variable* or probabilistic) N1 (analys* or model*)) OR AB((latent or structural or equation?) N1 (class or variable* or probabilistic) N1 (analys* or model*))	5,252
S16	TI((sentiment N1 (analys* or classif*)) or opinion mining) OR AB((sentiment N1 (analys* or classif*)) or opinion mining)	359

S15	TI(learning N1 (transfer* or hierarchical)) OR AB(learning N1 (transfer* or hierarchical))	977
S14	TI((pattern* or document) N1 classif*) OR AB((pattern* or document) N1 classif*)	803
S13	TI((sentiment N1 (analys* or classification*)) or opinion mining) OR AB((sentiment N1 (analys* or classification*)) or opinion mining)	356
S12	TI((genetic or bio-inspired or learning or clustering) N1 algorithm*) OR AB((genetic or bio-inspired or learning or clustering) N1 algorithm*)	3,968
S11	TI((case-based or approximate* or automated) N1 reasoning*) OR AB((case-based or approximate* or automated) N1 reasoning*)	121
S10	TI(random* N2 forest*) OR AB(random* N2 forest*)	2,941
S9	TI(natural language processing* or autoencoder* or metaheuristic* or support vector* or expert system* or markov model* or computer vision system*) OR AB(natural language processing* or autoencoder* or metaheuristic* or support vector* or expert system* or markov model* or computer vision system*)	8,485
S8	TI(knowledge* N1 (acquisition* or representation*)) OR AB(knowledge* N1 (acquisition* or representation*))	1,739
S7	TI(fuzzy N1 (logic or cognit* or inference* or classific* or rule* or system* or control*)) OR AB(fuzzy N1 (logic or cognit* or inference* or classific* or rule* or system* or control*))	544
S6	TI((data or text) N1 mining)OR AB((data or text) N1 mining)	2,937
S5	TI(comput* N1 (heuristic or reasoning or soft or evolutionary)) OR AB(comput* N1 (heuristic or reasoning or soft or evolutionary))	121
S4	TI((bayes* or neural or deep or echo or generative or adversarial) N1 (network* or naive* or learning* or reservois*)) OR AB((bayes* or neural or deep or echo or generative or adversarial) N1 (network* or naive* or learning* or reservois*))	12,198
S3	TI(natural-language or chat-bot? or chatbot? or convers* N0 agent?) OR AB(natural-language or chat-bot? or chatbot? or convers* N0 agent?)	2,933
S2	TI(computer* N1 media* N1 communicat*) OR AB(computer* N1 media* N1 communicat*)	269
S1	TI((artificial* or computat* or machine* or deep or supervi* or unsupervi* or semisupervi* or shallow* or competitive) N1 (intelligen* or learn*)) OR AB((artificial* or computat* or machine* or deep or supervi* or unsupervi* or semisupervi* or shallow* or competitive) N1 (intelligen* or learn*))	22,211

Cochrane [Wiley] (January 24, 2023)

#1	((artificial* or computat* or machine* or deep or supervi* or unsupervi* or semisupervi* or shallow* or competitive) NEAR/1 (intelligen* or learn*)):ti,ab,kw	3893
#2	(computer* NEAR/1 media* NEAR/1 communicat*):ti,ab,kw	16
#3	(natural-language or chat-bot? or chatbot? or convers* NEAR/0 agent?):ti,ab,kw	395
#4	((bayes* or neural or deep or echo state* or generative adversarial) NEAR/1 (network* or naive* or learning* or reservois*)):ti,ab,kw	2753
#5	(comput* NEAR/1 (heuristic or reasoning or soft or evolutionary)):ti,ab,kw	16
#6	((data or text) NEAR/1 mining):ti,ab,kw	196
#7	(fuzzy NEAR/1 (logic or cognit* or inference* or classific* or rule* or system* or control*)):ti,ab,kw	87
#8	(knowledge* NEAR/1 (acquisition* or representation*)):ti,ab,kw	344
#9	(natural language processing* or autoencoder* or metaheuristic* or support vector* or expert system* or markov model* or computer vision system*):ti,ab,kw	5555
#10	(random* NEAR/2 forest*):ti,ab,kw	695
#11	((case-based or approximate* or automated) NEAR/1 reasoning*):ti,ab,kw	14
#12	((genetic or bio-inspired or learning or clustering) NEAR/1 algorithm*):ti,ab,kw	738
#13	((sentiment NEAR/1 (analys* or classification*)) or opinion mining):ti,ab,kw	16
#14	((pattern* or document) NEAR/1 classif*):ti,ab,kw	64
#15	(learning NEAR/1 (transfer* or hierarchical)):ti,ab,kw	121
#16	((sentiment NEAR/1 (analys* or classif*)) or opinion mining):ti,ab,kw	16
#17	((latent or structural equation?) NEAR/1 (class or variable* or probabilistic) NEAR/1 (analys* or model*)):ti,ab,kw	409
#18	(multifactor* NEAR/1 dimension* NEAR/1 reduction*):ti,ab,kw	11
#19	#1 OR #2 OR #3 OR #4 OR #5 OR #6 OR #7 OR #8 OR #9 OR #10 OR #11 OR #12 OR #13 OR #15 OR #16 OR #17 OR #18	11995
#20	(newborn* or new-born* or neonat* or neo-nat* or infan* or child* or adolesc* or paediatr* or pediatr* or baby* or babies* or toddler* or kid or kids or boy* or girl* or juvenile* or teen* or youth* or pubescen* or preadolesc* or prepubesc* or preteen*):ti,ab,kw	337076
#21	(pediatr* or paediatr*):so	35747
#22	#20 OR #21	340715
#23	#19 AND #22	1714
#24	(surger* or surgic* or surgeon* or operati* or reoperat* or bypass* or by-pass* or resect* or re-sect* or transplant* or procedure* or debridement* or laparoscop* or laparotom* or postop*):ti,ab,kw	570481
#25	(adenoidectom* or laryngectom* or laryngoplast* or laryngoscop* or pharygectom* or tonsillectom* or tympanoplast* or tracheostom* or tracheotom* or orchidopex* or orchiopex* or orchiectom* or orchidectom* or herniorrhaph* or hernioplast* or herniaplast* or herni* NEAR/0 plast* or herniotom* or circumcis* or gastrostom or ileostom* or colostom* or enterostom* or portoenterostom or "roux-en-y" or kasai or pyloromyotom* or piloromyotom* or pyloromiotom* or piloromiotom* or diverticulectom* or diverticulotom* or cholecystectom* or cholangiopancreatograph* or cholangio-pancreatograph* or choledoduodenostom* or choledo-duodenostom or appendicectom* or appendectom* or splenectom* or pneumonectom* or amputation* or amputate* or craniotom* or craniostom* or hydrocelectom* or thoracostom* or fasciotom*):ti,ab,kw	34582
#26	((opthalmolog* or eye* or vision or ocular or retina* or retinopath*) NEAR/5 (operat* or procedur* or surger* or surgical*)):ti,ab,kw	8612
#27	((perforation* or incision* or laceration*) NEAR/3 (repair* or drain* or closure*)):ti,ab,kw	1709
#28	((tooth or teeth or dental or abcess) NEAR/2 (extract* or drain*)):ti,ab,kw	4424

#29	((abdomen or abdominal or intestin* or bowel* or gastrointestin*) NEAR/3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)):ti,ab,kw	16636
#30	(escharotom* or ((skin or derm*) NEAR/2 (graft* or transplant*))):ti,ab,kw	1777
#31	((cancer or neoplas* or tumor* or tumour* or carcinom* or sarcoma*) NEAR/3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or biopsy or biopsie* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)):ti,ab,kw	43220
#32	(fundoplicat* or ((nissen* or toupet or dor) NEAR/3 (operat* or procedur* or surger* or surgical*))):ti,ab,kw	794
#33	((hernia* or extraperitoneal or preperitoneal or peritoneal or TEP or TAPP or umbilic* or inguinal or omphalocele* or exomphalos) NEAR/3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)):ti,ab,kw	6290
#34	((liver or hepatic or lung or lungs or pulmon* or kidney) NEAR/3 (transplant* or graft*)):ti,ab,kw	15506
#35	(thoracoscop* or thoracotom* or pleurectom* or pleuroscop* or pleuracotom* or pleurotom* or (pleura* NEAR/3 (endoscop* or incision*))):ti,ab,kw	4347
#36	((lung or lungs or pulmon* or wedge or trauma* or postrauma* or posttrauma* or neurotrauma* or fracture*) NEAR/3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)):ti,ab,kw	16812
#37	((esophag* or oesophag* or endoesophag* or intraesophag* or tracheoesophag*) NEAR/3 (atres* or atretic* or atroph*)):ti,ab,kw	108
#38	((anal or anus or anorect* or rectal) NEAR/3 (artificial* or malformat* or mal-format* or anomal* or abnormal* or ectopic or stenosis or atres* or atroph* or imperforat* or inperforat* or praet* or pret* or fistula*)):ti,ab,kw	987
#39	(hirschsprung* or ((megacolon or colon* or rectosigmoid or intestin*) NEAR/3 (congenital* or aganglion*))):ti,ab,kw	140
#40	(agene* NEAR/2 (hemidiaphragm* or diaphragm* or ((unilat* or hern*) NEAR/1 diaphragm*))):ti,ab,kw [Line kept to maintain consistency between searches]	0
#41	((bochdalek* or morgagni*) NEAR/2 (hernia* or defect*)):ti,ab,kw [Line kept to maintain consistency between searches]	0
#42	((congenital* or neonat* or neo-nat* or newborn* or new-born* or birth* or maternal* or fetal or fetus* or fetu or feto or foet* or prenatal* or pre-natal* or antenatal* or ante-natal* or trimester* or pregnan* or uter* or preterm* or pre-term* or premature* or pre-mature* or preemie*) NEAR/5 (posterolateral* or substernal*) NEAR/2 hernia*):ti,ab,kw [Line kept to maintain consistency between searches]	0
#43	((congenital* or neonat* or neo-nat* or newborn* or new-born* or birth* or maternal* or fetal or fetus* or fetu or feto or foet* or prenatal* or pre-natal* or antenatal* or ante-natal* or trimester* or pregnan* or uter* or preterm* or pre-term* or premature* or pre-mature* or preemie*) NEAR/2 diaphragm* NEAR/2 (hernia* or defect*)):ti,ab,kw	223
#44	(congenital* and hernia* and diaphragm*):ti,ab,kw	233
#45	((pectus or chest) NEAR/1 (funnel or sunken or excavatum or carinatum)):ti,ab,kw	107
#46	#24 OR #25 OR #26 OR # 27 OR #28 OR #29 OR #30 OR #31 OR #32 OR #33 OR #34 OR #35 OR #36 OR #37 OR #38 OR #39 OR #40 OR #41 OR #42 OR #43 OR #44 OR #45	679754
#47	#23 AND #46	720

Embase [Ovid] (January 24, 2023)

Embase Classic+Embase 1947 to 2023 January 23

1	exp artificial intelligence/	71907
2	data mining/	17419
3	big data/	5772
4	*software/	14369
5	computer interface/	34869
6	exp machine learning/	362606
7	natural language processing/	9209
8	expert system/	5716
9	fuzzy logic/ or fuzzy system/	8764
10	((artificial* or computat* or machine* or deep or supervi* or unsupervi* or semisupervi* or shallow* or competitive) adj1 (intelligen* or learn*)).tw,kf.	159412
11	(computer* adj1 media* adj1 communicat*).tw,kf.	353
12	(natural-language or chat-bot? or chatbot? or convers*-agent?).tw,kf.	11044
13	((bayes* or neural or deep or echo state* or generative adversarial) adj1 (network* or naive* or learning* or reservois*)).tw,kf.	143266
14	(comput* adj1 (heuristic or reasoning or soft or evolutionary)).tw,kf.	1388
15	((data or text) adj1 mining).tw,kf.	21077
16	(fuzzy adj1 (logic or cognit* or inference* or classific* or rule* or system* or control*)).tw,kf.	6158
17	(knowledge* adj1 (acquisition* or representation*)).tw,kf.	4176
18	(natural language processing* or autoencoder* or metaheuristic* or support vector* or expert system* or markov model* or computer vision system*).tw,kf.	67122
19	(random* adj2 forest*).tw,kf.	24783
20	((case-based or approximate* or automated) adj1 reasoning*).tw,kf.	618
21	((genetic or bio-inspired or learning or clustering) adj1 algorithm*).tw,kf.	40395
22	((sentiment adj1 (analys* or classification*)) or opinion mining).tw,kf.	1344
23	((pattern* or document) adj1 classif*).tw,kf.	3241
24	(learning adj (transfer* or hierarchical)).tw,kf.	420
25	((sentiment adj1 (analys* or classif*)) or opinion mining).tw,kf.	1348
26	((latent or structural equation?) adj1 (class or variable* or probabilistic) adj1 (analys* or model*)).tw,kf.	10291
27	(multifactor* adj1 dimension* adj1 reduction*).tw,kf.	1471
28	or/1-27	559707
29	exp pediatrics/ or exp child/ or exp adolescent/	4375229
30	(newborn* or new-born* or neonat* or neo-nat* or infan* or child* or adolesc* or paediatr* or pediatr* or baby* or babies* or toddler* or kid or kids or boy* or girl* or juvenile* or teen* or youth* or pubescen* or preadolesc* or prepubesc* or preteen*).tw,kf.	3832842
31	(pediatr* or paediatr*).jx.	846671

32	or/29-31	5541254
33	28 and 32	32404
34	exp *surgery/	2880318
35	exp *surgeon/	45879
36	(surger* or surgic* or surgeon* or procedure* or operation? or laparoscop* or postop*).ti,kf. or (surger* or surgic* or surgeon* or procedure* or operation? or laparoscop* or postop*).ab. /freq=3	2368234
37	or/34-36	4087096
38	exp newborn disease/	1963108
39	exp digestive system disease/	3943636
40	exp urogenital tract disease/	3094216
41	exp hernia/	145501
42	exp musculoskeletal system malformation/ or exp musculoskeletal disease/	2872955
43	exp neoplasm/	5805068
44	exp respiratory tract malformation/	38396
45	exp torsion/ or torticollis/	25126
46	exp ear nose throat disease/	597882
47	exp eye disease/	1185516
48	exp osteomyelitis/	52865
49	brachial plexus neuropathy/	2628
50	exp brain disease/	2570179
51	exp infectious arthritis/	27033
52	(cochlear or adenoid* or otorhinol* or pharyngeal* or laryngeal* or laryngo* or ear or ear or nose or otitis or tonsil* or epistaxis or rhinorrhea* or rhinitis or otolog* or rhinootol* or head or neck or croup* or supraglott* or glottis or glottis or subglott* or trachea* or snoring or snore* or apnea or apnoea or sleep obstruct* or mastoiditis* or sinusitis or trichiasis or cataract* or hydrocephal* or cerebral palsy or muscular dystroph* or syndactyly* or radial club or amniotic band* or septic arthritis or osteomyelitis or flexor tenosynovitis or clubfoot or clubfeet or club-foot* or club-feet* or craniofacial* or cranio-facial* or frontoethmoidal meningoenceph* or hemorrhage* or hematoma* or spina bifida* or resuscitation* or schistosomias* or trachoma* or mediastinitis or buruli ulcer* or choledochal cyst* or cyst* echinococcosis or ilopsoas or epileps* or burr hole* or burn or burns or burned or scald* or burnt or thermal injur*).tw,kf.	2386430
53	(hypospadia* or epispadi* or cloaca* or cryptorchidism* or prolapse or phymosis or paraphymosis or hydrometrocolpos or (bladder adj2 exstroph*) or (undescen* adj2 test?s) or (buried adj1 penis) or (urinary adj2 (retention or lithiasis))).tw,kf.	104689
54	(hirschsprung* or ((megacolon or colon* or rectosigmoid or intestin*) adj4 (congenital or aganglion*)) or ((anal or anus or anorect* or rectal) adj3 (artificial* or malformation or anomal* or abnormal* or ectopic or stenosis or atres* or atroph* or imperforat* or inperforat* or praet* or pret*))).tw,kf.	19675
55	((pierre-robin or apert*) adj2 (syndrome* or disease* or sequenc*)).tw,kf.	3358
56	(cleft adj2 (lip* or palate*)).tw,kf.	31598
57	(coarctation or (septal adj2 defect*) or (tetralogy adj2 fallot)).tw,kf.	66047

58	(brachial plexus adj2 (palsy or neuropath*)).tw,kf.	2041
59	((arthriti* or rheumat*) adj2 infect*).tw,kf.	5054
60	or/38-59	16051486
61	exp surgery/	6054008
62	su.fs.	2397376
63	(surger* or surgical* or operati* or reoperat* or bypass* or by-pass* or resect* or re-sect* or transplant* or procedure or procedures or debridement* or laparoscop* or laparotom*).tw,kf.	6189721
64	or/61-63	8850815
65	60 and 64	5292593
66	(adenoidectom* or adenotonsil* or laryngectom* or laryngoplast* or laryngoscop* or pharygectom* or tonsillectom* or tympanoplast* or tracheostom* or tracheotom* or orchidopex* or orchiopex* or orchiectom* or orchidectom* or herniorrhaph* or hernioplast* or herniaplast* or herni*-plast* or herniotom* or circumcis* or gastrostom* or ileostom* or colostom* or enterostom* or portoenterostom* or roux-en-y or kasai or pyloromyotom* or piloromyotom* or pyloromiotom* or piloromiotom* or diverticulectom* or diverticulotom* or cholecystectom* or cholangiopancreatograph* or cholangio-pancreatograph* or choledoduodenostom* or choledo-duodenostom* or appendicectom* or appendectom* or splenectom* or pneumonectom* or amputation* or amputate* or craniotom* or craniostom* or hydrocelectom* or thoracostom* or fasciotom*).tw,kf.	434269
67	((opthalmolog* or eye* or vision or ocular or retina* or retinopath* or cataract*) adj2 (operat* or procedur* or surger* or surgical*)).tw,kf.	51459
68	((perforation* or incision* or laceration*) adj2 (repair* or drain* or closure*)).tw,kf.	11067
69	((tooth or teeth or dental or abscess* or abcess*) adj2 (extract* or drain* or excision*)).tw,kf.	24123
70	((abdomen or abdominal or intestin* or bowel* or gastrointestin*) adj2 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)).tw,kf.	88556
71	(escharotom* or ((skin or derm*) adj2 (graft* or transplant*))).tw,kf.	35600
72	((cancer or neoplas* or tumor* or tumour* or carcinom*) adj2 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or biopsy or biopsie* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)).tw,kf.	217595
73	(fundoplicat* or ((nissen* or toupet or dor) adj3 (operat* or procedur* or surger* or surgical*))).tw,kf.	11144
74	((hernia* or extraperitoneal or preperitoneal or peritoneal or TEP or TAPP or umbilic* or inguinal or omphalocele* or exomphalos) adj2 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)).tw,kf.	37118
75	((liver or hepatic or lung or lungs or pulmon* or kidney) adj2 (transplant* or graft*)).tw,kf.	258378
76	(thoracoscop* or thoracotom* or pleurectom* or pleuroscop* or pleuracotom* or pleurotom* or (pleura* adj3 (endoscop* or incision*))).tw,kf.	62317
77	((lung or lungs or pulmon* or wedge or trauma* or postrauma* or neurotrauma* or fracture*) adj2 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or	117765

	surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)).tw,kf.	
78	or/66-77	1248064
79	esophagus atresia/	7269
80	((esophag* or oesophag* or endoesophag* or intraesophag* or tracheoesophag*) adj3 (atres* or atretic* or atroph*)).tw,kf.	6929
81	anus atresia/	4732
82	((anal or anus or anorect* or rectal) adj3 (artificial* or malformat* or mal-format* or anomal* or abnormal* or ectopic or stenosis or atres* or atroph* or imperforat* or inperforat* or praet* or pret* or fistula*)).tw,kf.	16397
83	colorectal surgery/	17615
84	rectum disease/ or exp *rectum disease/	304407
85	Hirschsprung disease/	8911
86	(hirschsprung* or ((megacolon or colon* or rectosigmoid or intestin*) adj3 (congenital* or aganglion*))).tw,kf.	9530
87	congenital diaphragm hernia/	7175
88	(agene* adj2 (hemidiaphragm* or diaphragm* or ((unilat* or hern*) adj1 diaphragm*))).tw,kf.	129
89	((bochdalek* or morgagni*) adj2 (hernia* or defect*)).tw,kf.	1790
90	((congenital* or neonat* or neo-nat* or newborn* or new-born* or birth* or maternal* or fetal or fetus* or fetu or feto or foet* or prenatal* or pre-natal* or antenatal* or ante-natal* or trimester* or pregnan* or uter* or preterm* or pre-term* or premature* or pre-mature* or preemie*) adj5 (posterolateral* or substernal*) adj2 hernia*).tw,kf.	109
91	(congenital* and hernia* and diaphragm*).tw,kf.	8724
92	musculoskeletal system malformation/	1142
93	funnel chest/	4965
94	pigeon thorax/	1505
95	((pectus or chest) adj1 (funnel or sunken or excavatum or carinatum)).tw,kf.	4551
96	or/79-95	364791
97	37 or 65 or 78 or 96	7258642
98	33 and 97	3954
99	remove duplicates from 98	3822
100	("36604997" or "36174997" or "36635361" or "36588202" or "36039686" or "36259549" or "36627375" or "36472344" or "36104471" or "36603200" or "36285894" or "36302236" or "35665923" or "35579701" or "35868419" or "36603886" or "36633874" or "35749544" or "36272116" or "36645240" or "36631859" or "36323158" or "34542691" or "35549552" or "35717252" or "35392047" or "36068489" or "36274161" or "35088473" or "36572436" or "35440941" or "35169696" or "36541546" or "35390316" or "35191259" or "36502451" or "35438562" or "35727579" or "35655845" or "36124028" or "35727419" or "36304779" or "36287639" or "35588049" or "35713054" or "35661152" or "35877053" or "36471390" or "35449839" or "35317638" or "34999533" or "34979624" or "35044492" or "35759887" or "35921280" or "35751051" or "35347337" or "36036211" or "35783299" or "36244075" or "34982398" or "35533878" or "35708686" or "35726168" or "35608929" or "35102217" or "35680048" or "35667473" or "35997920" or "35053710" or "35072742" or 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Global Health [Ovid] (January 24, 2023)

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1	((artificial* or computat* or machine* or deep or supervi* or unsupervi* or semisupervi* or shallow* or competitive) adj1 (intelligen* or learn*)).ti,ab,id.	6544
2	(computer* adj1 media* adj1 communicat*).ti,ab,id.	18
3	(natural-language or chat-bot? or chatbot? or convers*-agent?).ti,ab,id.	349
4	((bayes* or neural or deep or echo state* or generative adversarial) adj1 (network* or naive* or learning* or reservois*)).ti,ab,id.	5824
5	(comput* adj1 (heuristic or reasoning or soft or evolutionary)).ti,ab,id.	72
6	((data or text) adj1 mining).ti,ab,id.	1902
7	(fuzzy adj1 (logic or cognit* or inference* or classific* or rule* or system* or control*)).ti,ab,id.	690
8	(knowledge* adj1 (acquisition* or representation*)).ti,ab,id.	261
9	(natural language processing* or autoencoder* or metaheuristic* or support vector* or expert system* or markov model* or computer vision system*).ti,ab,id.	4346
10	(random* adj2 forest*).ti,ab,id.	1943
11	((case-based or approximate* or automated) adj1 reasoning*).ti,ab,id.	22

12	((genetic or bio-inspired or learning or clustering) adj1 algorithm*).ti,ab,id.	2252
13	((sentiment adj1 (analys* or classification*)) or opinion mining).ti,ab,id.	153
14	((pattern* or document) adj1 classif*).ti,ab,id.	89
15	(learning adj (transfer* or hierarchical)).ti,ab,id.	12
16	((sentiment adj1 (analys* or classif*)) or opinion mining).ti,ab,id.	154
17	((latent or structural equation?) adj1 (class or variable* or probabilistic) adj1 (analys* or model*)).ti,ab,id.	2108
18	(multifactor* adj1 dimension* adj1 reduction*).ti,ab,id.	436
19	or/1-18	20724
20	paediatrics/ or exp children/ or exp infants/ or exp adolescents/	540794
21	(newborn* or new-born* or neonat* or neo-nat* or infan* or child* or adolesc* or paediatr* or pediatr* or baby* or babies* or toddler* or kid or kids or boy* or girl* or juvenile* or teen* or youth* or pubescen* or preadolesc* or prepubesc* or preteen*).ti,ab,id.	678741
22	(pediatr* or paediatr*).jw.	95579
23	or/20-22	707043
24	19 and 23	2230
25	(surger* or surgic* or surgeon* or operati* or reoperat* or bypass* or by-pass* or resect* or re-sect* or transplant* or procedure* or debridement* or laparoscop* or laparotom* or postop*).ti,ab,id.	365228
26	(adenoidectom* or laryngectom* or laryngoplast* or laryngoscop* or pharygectom* or tonsillectom* or tympanoplast* or tracheostom* or tracheotom* or orchidopex* or orchiopex* or orchiectom* or orchidectom* or herniorrhaph* or hernioplast* or herniaplast* or herni*-plast* or herniotom* or circumcis* or gastrostom or ileostom* or colostom* or enterostom* or portoenterostom or roux-en-y or kasai or pyloromyotom* or piloromyotom* or pyloromiotom* or piloromiotom* or diverticulectom* or diverticulotom* or cholecystectom* or cholangiopancreatograph* or cholangio-pancreatograph* or choledoduodenostom* or choledo-duodenostom or appendicectom* or appendectom* or splenectom* or pneumonectom* or amputation* or amputate* or craniotom* or craniostom* or hydrocelectom* or thoracostom* or fasciotom*).ti,ab,id.	21074
27	((opthalmolog* or eye* or vision or ocular or retina* or retinopath*) adj5 (operat* or procedur* or surger* or surgical*)).ti,ab,id.	1821
28	((perforation* or incision* or laceration*) adj3 (repair* or drain* or closure*)).ti,ab,id.	924
29	((tooth or teeth or dental or abcess) adj2 (extract* or drain*)).ti,ab,id.	1217
30	((abdomen or abdominal or intestin* or bowel* or gastrointestin*) adj3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)).ti,ab,id.	6349
31	(escharotom* or ((skin or derm*) adj2 (graft* or transplant*))).ti,ab,id.	966
32	((cancer or neoplas* or tumor* or tumour* or carcinom* or sarcoma*) adj3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or biopsy or biopsie* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)).ti,ab,id.	7033
33	(fundoplicat* or ((nissen* or toupet or dor) adj3 (operat* or procedur* or surger* or surgical*))).ti,ab,id.	145

34	((hernia* or extraperitoneal or preperitoneal or peritoneal or TEP or TAPP or umbilic* or inguinal or omphalocele* or exomphalos) adj3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)).ti,ab,id.	1048
35	((liver or hepatic or lung or lungs or pulmon* or kidney) adj3 (transplant* or graft*)).ti,ab,id.	13788
36	(thoracoscop* or thoracotom* or pleurectom* or pleuroscop* or pleuracotom* or pleurotom* or (pleura* adj3 (endoscop* or incision*))).ti,ab,id.	1387
37	((lung or lungs or pulmon* or wedge or trauma* or postrauma* or posttrauma* or neurotrauma* or fracture*) adj3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)).ti,ab,id.	5075
38	((esophag* or oesophag* or endoesophag* or intraesophag* or tracheoesophag*) adj3 (atres* or atretic* or atroph*)).ti,ab,id.	202
39	((anal or anus or anorect* or rectal) adj3 (artificial* or malformat* or mal-format* or anomal* or abnormal* or ectopic or stenosis or atres* or atroph* or imperforat* or inperforat* or praet* or pret* or fistula*)).ti,ab,id.	752
40	(hirschsprung* or ((megacolon or colon* or rectosigmoid or intestin*) adj3 (congenital* or aganglion*))).ti,ab,id.	398
41	(agene* adj2 (hemidiaphragm* or diaphragm* or ((unilat* or hern*) adj1 diaphragm*))).ti,ab,id. [Line kept to maintain consistency between searches]	0
42	((bochdalek* or morgagni*) adj2 (hernia* or defect*)).ti,ab,id.	19
43	((congenital* or neonat* or neo-nat* or newborn* or new-born* or birth* or maternal* or fetal or fetus* or fetu or feto or foet* or prenatal* or pre-natal* or antenatal* or ante-natal* or trimester* or pregnan* or uter* or preterm* or pre-term* or premature* or pre-mature* or preemie*) adj5 (posterolateral* or substernal*) adj2 hernia*).ti,ab,id. [Line kept to maintain consistency between searches]	0
44	((congenital* or neonat* or neo-nat* or newborn* or new-born* or birth* or maternal* or fetal or fetus* or fetu or feto or foet* or prenatal* or pre-natal* or antenatal* or ante-natal* or trimester* or pregnan* or uter* or preterm* or pre-term* or premature* or pre-mature* or preemie*) adj2 diaphragm* adj2 (hernia* or defect*)).ti,ab,id.	157
45	(congenital* and hernia* and diaphragm*).ti,ab,id.	212
46	((pectus or chest) adj1 (funnel or sunken or excavatum or carinatum)).ti,ab,id.	55
47	or/25-46	380392
48	24 and 47	174
49	remove duplicates from 48	174

Global Index Medicus [WHO] (January 24, 2023)

1	(tw:(artificial intelligence or machine learning)) AND (tw:(newborn* OR new-born* OR neonat* OR neo-nat* OR infan* OR child* OR adolesc* OR paediatr* OR pediatr* OR baby* OR babies* OR toddler* OR kid OR kids OR boy* OR girl* OR juvenile* OR teen* OR youth* OR pubescen* OR preadolesc* OR prepubesc* OR preteen*)) AND (tw:(surger* or surgic* or surgeon* or procedure* or operation? or laparoscop* or postop*))	**11**

Hôpital de Montréal pour enfants
Centre universitaire de santé McGill
Montreal Children's Hospital
McGill University Health Centre

Medline [Ovid] (January 24, 2023)

Ovid MEDLINE(R) and Epub Ahead of Print, In-Process & Other Non-Indexed Citations and Daily <1946 to January 20, 2023>

1	exp artificial intelligence/	164454
2	data mining/	10609
3	big data/	2623
4	*Software/	49625
5	exp user-computer interface/	39309
6	((artificial* or computat* or machine* or deep or supervi* or unsupervi* or semisupervi* or shallow* or competitive) adj1 (intelligen* or learn*)).tw,kf.	134589
7	(computer* adj1 media* adj1 communicat*).tw,kf.	317
8	(natural-language or chat-bot? or chatbot? or convers*-agent?).tw,kf.	9517
9	((bayes* or neural or deep or echo state* or generative adversarial) adj1 (network* or naive* or learning* or reservois*)).tw,kf.	119968
10	(comput* adj1 (heuristic or reasoning or soft or evolutionary)).tw,kf.	1049
11	((data or text) adj1 mining).tw,kf.	17035
12	(fuzzy adj1 (logic or cognit* or inference* or classific* or rule* or system* or control*)).tw,kf.	5023
13	(knowledge* adj1 (acquisition* or representation*)).tw,kf.	3443
14	(natural language processing* or autoencoder* or metaheuristic* or support vector* or expert system* or markov model* or computer vision system*).tw,kf.	52187
15	(random* adj2 forest*).tw,kf.	19844
16	((case-based or approximate* or automated) adj1 reasoning*).tw,kf.	501
17	((genetic or bio-inspired or learning or clustering) adj1 algorithm*).tw,kf.	33621
18	((sentiment adj1 (analys* or classification*)) or opinion mining).tw,kf.	1440
19	((pattern* or document) adj1 classif*).tw,kf.	2469
20	(learning adj (transfer* or hierarchical)).tw,kf.	398
21	((sentiment adj1 (analys* or classif*)) or opinion mining).tw,kf.	1445
22	((latent or structural equation?) adj1 (class or variable* or probabilistic) adj1 (analys* or model*)).tw,kf.	8824
23	(multifactor* adj1 dimension* adj1 reduction*).tw,kf.	1238
24	or/1-23 [AI]	425465
25	exp pediatrics/ or exp child/ or exp infant/ or adolescent/	3937240
26	(newborn* or new-born* or neonat* or neo-nat* or infan* or child* or adolesc* or paediatr* or pediatr* or baby* or babies* or toddler* or kid or kids or boy* or girl* or juvenile* or teen* or youth* or pubescen* or preadolesc* or prepubesc* or preteen*).tw,kf.	2838492
27	(paediatr* or pediatr*).jw.	630288
28	or/25-27	4846454
29	24 and 28	27919
30	exp *Specialties, Surgical/	171793
31	exp *Surgical Procedures, Operative/	2241079
32	exp *Surgeons/	12620

33	(surger* or surgic* or surgeon* or procedure* or operation? or laparoscop* or postop*).ti,kf. or (surger* or surgic* or surgeon* or procedure* or operation? or laparoscop* or postop*).ab. /freq=3	1733773
34	or/30-33 [Gen Surg]	3287960
35	exp "Congenital, Hereditary, and Neonatal Diseases and Abnormalities"/	1348116
36	exp Digestive system diseases/	1925059
37	exp Urologic Diseases/ or exp Male urogenital diseases/ or exp Female urogenital diseases/ or exp Prolapse/	1539107
38	exp Hernia/	82676
39	exp Musculoskeletal Abnormalities/ or exp Musculoskeletal Diseases/	1193042
40	exp Neoplasms/	3782670
41	exp Respiratory System Abnormalities/	12250
42	exp Torsion Abnormality/ or Torticollis/	13874
43	exp Otorhinolaryngologic Diseases/	403860
44	exp Eye Diseases/	627375
45	exp Osteomyelitis/	24353
46	exp Brachial Plexus Neuropathies/	4223
47	exp Hemorrhage/	359111
48	exp Brain Diseases/	1380192
49	exp Arthritis, Infectious/	15739
50	(cochlear or adenoid* or otorhinol* or pharyngeal* or laryngeal* or laryngo* or ear or ear or nose or otitis or tonsil* or epistaxis or rhinorrhea* or rhinitis or otolog* or rhinootol* or head or neck or croup* or supraglott* or glottis or glottis or subglott* or trachea* or snoring or snore* or apnea or apnoea or sleep obstruct* or mastoiditis* or sinusitis or trichiasis or cataract* or hydrocephal* or cerebral palsy or muscular dystroph* or syndactyly* or radial club or amniotic band* or septic arthritis or osteomyelitis or flexor tenosynovitis or clubfoot or clubfeet or club-foot* or club-feet* or craniofacial* or cranio-facial* or frontoethmoidal meningoenceph* or hemorrhage* or hematoma* or spina bifida* or resuscitation* or schistosomias* or trachoma* or mediastinitis or buruli ulcer* or choledochal cyst* or cyst* echinococcosis or ilopsoas or epileps* or burr hole* or burn or burns or burned or scald* or burnt or thermal injur*).tw,kf.	1691117
51	(hypospadia* or epispadi* or cloaca* or cryptorchidism* or prolapse or phymosis or paraphymosis or hydrometrocolpos or (bladder adj2 exstroph*) or (undescen* adj2 test?s) or (buried adj1 penis) or (urinary adj2 (retention or lithiasis))).tw,kf.	67461
52	(hirschsprung* or ((megacolon or colon* or rectosigmoid or intestin*) adj4 (congenital or aganglion*)) or ((anal or anus or anorect* or rectal) adj3 (artificial* or malformation or anomal* or abnormal* or ectopic or stenosis or atres* or atroph* or imperforat* or inperforat* or praet* or pret*))).tw,kf.	14482
53	((pierre-robin or apert*) adj2 (syndrome* or disease* or sequenc*)).tw,kf.	2469
54	(cleft adj2 (lip* or palate*)).tw,kf.	24960
55	(coarctation or (septal adj2 defect*) or (tetralogy adj2 fallot)).tw,kf.	45441
56	(brachial plexus adj2 (palsy or neuropath*)).tw,kf.	1623
57	((arthriti* or rheumat*) adj2 infect*).tw,kf.	2954
58	or/35-57	10109340

59	exp Specialties, Surgical/	216984
60	exp Surgical Procedures, Operative/	3492388
61	su.fs.	2219302
62	(surger* or surgical* or operati* or reoperat* or bypass* or by-pass* or resect* or re-sect* or transplant* or procedure or procedures or debridement* or laparoscop* or laparotom*).tw,kf.	4360058
63	or/59-62	6390771
64	58 and 63 [Specialized surg]	3146072
65	(adenoidectom* or laryngectom* or laryngoplast* or laryngoscop* or pharygectom* or tonsillectom* or tympanoplast* or tracheostom* or tracheotom* or orchidopex* or orchiopex* or orchiectom* or orchidectom* or herniorrhaph* or hernioplast* or herniaplast* or herni*-plast* or herniotom* or circumcis* or gastrostom or ileostom* or colostom* or enterostom* or portoenterostom or roux-en-y or kasai or pyloromyotom* or piloromyotom* or pyloromiotom* or piloromiotom* or diverticulectom* or diverticulotom* or cholecystectom* or cholangiopancreatograph* or cholangio-pancreatograph* or choledoduodenostom* or choledo-duodenostom or appendicectom* or appendectom* or splenectom* or pneumonectom* or amputation* or amputate* or craniotom* or craniostom* or hydrocelectom* or thoracostom* or fasciotom*).tw,kf.	284401
66	((opthalmolog* or eye* or vision or ocular or retina* or retinopath*) adj5 (operat* or procedur* or surger* or surgical*)).tw,kf.	40368
67	((perforation* or incision* or laceration*) adj3 (repair* or drain* or closure*)).tw,kf.	10326
68	((tooth or teeth or dental or abcess) adj2 (extract* or drain*)).tw,kf.	16928
69	((abdomen or abdominal or intestin* or bowel* or gastrointestin*) adj3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)).tw,kf.	79832
70	(escharotom* or ((skin or derm*) adj2 (graft* or transplant*))).tw,kf.	27442
71	((cancer or neoplas* or tumor* or tumour* or carcinom* or sarcoma*) adj3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or biopsy or biopsie* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)).tw,kf.	236712
72	(fundoplicat* or ((nissen* or toupet or dor) adj3 (operat* or procedur* or surger* or surgical*))).tw,kf.	7028
73	((hernia* or extraperitoneal or preperitoneal or peritoneal or TEP or TAPP or umbilic* or inguinal or omphalocele* or exomphalos) adj3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)).tw,kf.	32587
74	((liver or hepatic or lung or lungs or pulmon* or kidney) adj3 (transplant* or graft*)).tw,kf.	154297
75	(thoracoscop* or thoracotom* or pleurectom* or pleuroscop* or pleuracotom* or pleurotom* or (pleura* adj3 (endoscop* or incision*))).tw,kf.	41667
76	((lung or lungs or pulmon* or wedge or trauma* or postrauma* or posttrauma* or neurotrauma* or fracture*) adj3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)).tw,kf.	116091
77	or/65-76	957944

78	Esophageal Atresia/	3966
79	((esophag* or oesophag* or endoesophag* or intraesophag* or tracheoesophag*) adj3 (atres* or atretic* or atroph*)).tw,kf.	5035
80	anus, imperforate/	2585
81	((anal or anus or anorect* or rectal) adj3 (artificial* or malformat* or mal-format* or anomal* or abnormal* or ectopic or stenosis or atres* or atroph* or imperforat* or inperforat* or praet* or pret* or fistula*)).tw,kf.	11133
82	Colorectal Surgery/	4284
83	Rectal Diseases/ or exp *Rectal Diseases/	174009
84	hirschsprung disease/	4912
85	(hirschsprung* or ((megacolon or colon* or rectosigmoid or intestin*) adj3 (congenital* or aganglion*))).tw,kf.	7270
86	Hernias, Diaphragmatic, Congenital/	5444
87	(agene* adj2 (hemidiaphragm* or diaphragm* or ((unilat* or hern*) adj1 diaphragm*))).tw,kf.	87
88	((bochdalek* or morgagni*) adj2 (hernia* or defect*)).tw,kf.	1353
89	((congenital* or neonat* or neo-nat* or newborn* or new-born* or birth* or maternal* or fetal or fetus* or fetu or feto or foet* or prenatal* or pre-natal* or antenatal* or ante-natal* or trimester* or pregnan* or uter* or preterm* or pre-term* or premature* or pre-mature* or preemie*) adj5 (posterolateral* or substernal*) adj2 hernia*).tw,kf.	78
90	((congenital* or neonat* or neo-nat* or newborn* or new-born* or birth* or maternal* or fetal or fetus* or fetu or feto or foet* or prenatal* or pre-natal* or antenatal* or ante-natal* or trimester* or pregnan* or uter* or preterm* or pre-term* or premature* or pre-mature* or preemie*) adj2 diaphragm* adj2 (hernia* or defect*)).tw,kf.	5839
91	(congenital* and hernia* and diaphragm*).tw,kf.	6408
92	musculoskeletal abnormalities/	1689
93	funnel chest/	2679
94	pectus carinatum/	140
95	((pectus or chest) adj1 (funnel or sunken or excavatum or carinatum)).tw,kf.	3407
96	or/78-95 [Specific surg cond]	210095
97	34 or 64 or 77 or 96	5066254
98	29 and 97	3640
99	remove duplicates from 98	3633

Hôpital de Montréal pour enfants
Centre universitaire de santé McGill

Montreal Children's Hospital
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ProQuest Central & (January 24, 2023)

Included databases: *ABI/INFORM Collectioninformation, Accounting, Tax & Banking Collectioninformation, Advanced Technologies & Aerospace Databaseinformation, Agriculture Science Databaseinformation, Arts & Humanities Databaseinformation, Asian & European Business Collectioninformation, Australia & New Zealand Databaseinformation, Biological Science Databaseinformation, Business Market Research Collectioninformation, Canadian Business & Current Affairs Databaseinformation, Canadian Newsstreaminformation, Career & Technical Education Databaseinformation, Computer Science Databaseinformation, Consumer Health Databaseinformation, Continental Europe Databaseinformation, Criminal Justice Databaseinformation, Earth, Atmospheric & Aquatic Science Databaseinformation, East & South Asia Databaseinformation, East Europe, Central Europe Databaseinformation, Education Databaseinformation, Engineering Databaseinformation, Environmental Science Databaseinformation, Global Breaking Newswiresinformation, Health & Medical Collectioninformation, Healthcare Administration Databaseinformation*
India Databaseinformation, International Newsstreaminformation, Latin America & Iberia Databaseinformation, Library Science Databaseinformation
Linguistics Databaseinformation, Materials Science Databaseinformation, Middle East & Africa Databaseinformation, Military Databaseinformation
Nursing & Allied Health Databaseinformation, Political Science Databaseinformation, Psychology Databaseinformation, Public Health Databaseinformation, Publicly Available Content Databaseinformation, Religion Databaseinformation, Research Libraryinformation, Science Databaseinformation, Social Science Databaseinformation, Sociology Databaseinformation, Telecommunications Databaseinformation, Turkey Databaseinformation, U.S. Newsstreaminformation, UK & Ireland Databaseinformation

1	(title(artificial* intelligence OR machine learning OR data mining OR natural language processing) OR abstract(artificial* intelligence OR machine learning OR data mining OR natural language processing)) AND (title(newborn* OR new-born* OR neonat* OR neo-nat* OR infan* OR child* OR adolesc* OR paediatr* OR pediatr* OR baby* OR babies* OR toddler* OR kid OR kids OR boy* OR girl* OR juvenile* OR teen* OR youth* OR pubescen* OR preadolesc* OR prepubesc* OR preteen*) OR abstract(newborn* OR new-born* OR neonat* OR neo-nat* OR infan* OR child* OR adolesc* OR paediatr* OR pediatr* OR baby* OR babies* OR toddler* OR kid OR kids OR boy* OR girl* OR juvenile* OR teen* OR youth* OR pubescen* OR preadolesc* OR prepubesc* OR preteen*)) AND (title(surger* OR surgic* OR surgeon* OR procedure* OR operation? OR laparoscop* OR postop*) OR abstract(surger* OR surgic* OR surgeon* OR procedure* OR operation? OR laparoscop* OR postop*))	673 654

Web of Science [Clarivate Analytics] (January 24, 2023)

Indexes= Web of Science Core Collection (IC, CCR, SCI, AHCI, BHCI, BSCI, ESCI, ISTP, SSCI, ISHP), Timespan=All years

#	Search Query	Results
1	TI=((artificial* or computat* or machine* or deep or supervi* or unsupervi* or semisupervi* or shallow* or competitive) NEAR/1 (intelligen* or learn*)) OR AB=((artificial* or computat* or machine* or deep or supervi* or unsupervi* or semisupervi* or shallow* or competitive) NEAR/1 (intelligen* or learn*))	496911
2	TI=(computer* NEAR/1 media* NEAR/1 communicat*) OR AB=(computer* NEAR/1 media* NEAR/1 communicat*)	3299
3	TI=(natural-language or chat-bot? or chatbot? or convers* NEAR/0 agent?) OR AB=(natural-language or chat-bot? or chatbot? or convers* NEAR/0 agent?)	49652
4	TI=((bayes* or neural or deep or echo or generative or adversarial) NEAR/1 (network* or naive* or learning* or reservois*)) OR AB=((bayes* or neural or deep or echo or generative or adversarial) NEAR/1 (network* or naive* or learning* or reservois*))	634052
5	TI=(comput* NEAR/1 (heuristic or reasoning or soft or evolutionary)) OR AB=(comput* NEAR/1 (heuristic or reasoning or soft or evolutionary))	19588
6	TI=((data or text) NEAR/1 mining)OR AB=((data or text) NEAR/1 mining)	83909
7	TI=(fuzzy NEAR/1 (logic or cognit* or inference* or classific* or rule* or system* or control*)) OR AB=(fuzzy NEAR/1 (logic or cognit* or inference* or classific* or rule* or system* or control*))	111996
8	TI=(knowledge* NEAR/1 (acquisition* or representation*)) OR AB=(knowledge* NEAR/1 (acquisition* or representation*))	25755
9	TI=(natural language processing* or autoencoder* or metaheuristic* or support vector* or expert system* or markov model* or computer vision system*) OR AB=(natural language processing* or autoencoder* or metaheuristic* or support vector* or expert system* or markov model* or computer vision system*)	452552

10	TI=(random* NEAR/2 forest*) OR AB=(random* NEAR/2 forest*)	53732
11	TI=((case-based or approximate* or automated) NEAR/1 reasoning*) OR AB=((case-based or approximate* or automated) NEAR/1 reasoning*)	9502
12	TI=((genetic or bio-inspired or learning or clustering) NEAR/1 algorithm*) OR AB=((genetic or bio-inspired or learning or clustering) NEAR/1 algorithm*)	290258
13	TI=((sentiment NEAR/1 (analys* or classification*)) or opinion mining) OR AB=((sentiment NEAR/1 (analys* or classification*)) or opinion mining)	17069
14	TI=((pattern* or document) NEAR/1 classif*) OR AB=((pattern* or document) NEAR/1 classif*)	16490
15	TI=(learning NEAR/1 (transfer* or hierarchical)) OR AB=(learning NEAR/1 (transfer* or hierarchical))	24461
16	TI=((sentiment NEAR/1 (analys* or classif*)) or opinion mining) OR AB=((sentiment NEAR/1 (analys* or classif*)) or opinion mining)	17206
17	TI=((latent or structural or equation?) NEAR/1 (class or variable* or probabilistic) NEAR/1 (analys* or model*)) OR AB=((latent or structural or equation?) NEAR/1 (class or variable* or probabilistic) NEAR/1 (analys* or model*))	18916
18	TI=(multifactor* NEAR/1 dimension* NEAR/1 reduction*) OR AB=(multifactor* NEAR/1 dimension* NEAR/1 reduction*)	1219
19	#1 OR #2 OR #3 OR #4 OR #5 OR #6 OR #7 OR #8 OR #9 OR #10 OR #11 OR #12 OR #13 OR #14 OR #15 OR #16 OR #17 OR #18	1694598
20	TI=(newborn* or new-born* or neonat* or neo-nat* or infan* or child* or adolesc* or paediatr* or pediatr* or baby* or babies* or toddler* or kid or kids or boy* or girl* or juvenile* or teen* or youth* or pubescen* or preadolesc* or prepubesc* or preteen*) OR AB=(newborn* or new-born* or neonat* or neo-nat* or infan* or child* or adolesc* or paediatr* or pediatr* or baby* or babies* or toddler* or kid or kids or boy* or girl* or juvenile* or teen* or youth* or pubescen* or preadolesc* or prepubesc* or preteen*) OR SO=(pediatr* or paediatr*)	3604159
21	#19 AND #20	32939
22	TI=(surger* or surgic* or surgeon* or operati* or reoperat* or bypass* or by-pass* or resect* or re-sect* or transplant* or procedure* or debridement* or laparoscop* or laparotom* or postop*) OR AB=(surger* or surgic* or surgeon* or operati* or reoperat* or transplant* or laparoscop* or laparotom* or postop*)	5361924
23	TI=(adenoidectom* or laryngectom* or laryngoplast* or laryngoscop* or pharygectom* or tonsillectom* or tympanoplast* or tracheostom* or tracheotom* or orchidopex* or orchiopex* or orchiectom* or orchidectom* or herniorrhaph* or hernioplast* or herniaplast* or herni* NEAR/0 plast* or herniotom* or circumcis* or gastrostom or ileostom* or colostom* or enterostom* or portoenterostom or "roux-en-y" or kasai or pyloromyotom* or piloromyotom* or pyloromiotom* or piloromiotom* or diverticulectom* or diverticulotom* or cholecystectom* or cholangiopancreatograph* or cholangio-pancreatograph* or choledoduodenostom* or choledo-duodenostom or appendicectom* or appendectom* or splenectom* or pneumonectom* or amputation* or amputate* or craniotom* or craniostom* or hydrocelectom* or thoracostom* or fasciotom*) OR AB=(adenoidectom* or laryngectom* or laryngoplast* or laryngoscop* or pharygectom* or tonsillectom* or tympanoplast* or tracheostom* or tracheotom* or orchidopex* or orchiopex* or orchiectom* or orchidectom* or herniorrhaph* or hernioplast* or herniaplast* or herni* NEAR/0 plast* or herniotom* or circumcis* or gastrostom or ileostom* or colostom* or enterostom* or portoenterostom or "roux-en-y" or kasai or pyloromyotom* or piloromyotom* or pyloromiotom* or piloromiotom* or diverticulectom* or diverticulotom* or cholecystectom* or cholangiopancreatograph* or cholangio-pancreatograph* or choledoduodenostom* or choledo-duodenostom or	234853

	appendicectom* or appendectom* or splenectom* or pneumonectom* or amputation* or amputate* or craniotom* or craniostom* or hydrocelectom* or thoracostom* or fasciotom*)	
24	TI=((opthalmolog* or eye* or vision or ocular or retina* or retinopath*) NEAR/5 (operat* or procedur* or surger* or surgical*)) OR AB=((opthalmolog* or eye* or vision or ocular or retina* or retinopath*) NEAR/5 (operat* or procedur* or surger* or surgical*))	41177
25	TI=((perforation* or incision* or laceration*) NEAR/3 (repair* or drain* or closure*)) OR AB=((perforation* or incision* or laceration*) NEAR/3 (repair* or drain* or closure*))	10883
26	TI=((tooth or teeth or dental or abcess) NEAR/2 (extract* or drain*)) OR AB=((tooth or teeth or dental or abcess) NEAR/2 (extract* or drain*))	14900
27	TI=((abdomen or abdominal or intestin* or bowel* or gastrointestin*) NEAR/3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)) OR AB=((abdomen or abdominal or intestin* or bowel* or gastrointestin*) NEAR/3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*))	81035
28	TI=(escharotom* or ((skin or derm*) NEAR/2 (graft* or transplant*))) OR AB=(escharotom* or ((skin or derm*) NEAR/2 (graft* or transplant*)))	20164
29	TI= ((cancer or neoplas* or tumor* or tumour* or carcinom* or sarcoma*) NEAR/3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or biopsy or biopsie* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*))OR AB=((cancer or neoplas* or tumor* or tumour* or carcinom* or sarcoma*) NEAR/3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or biopsy or biopsie* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*))	286040
30	TI= (fundoplicat* or ((nissen* or toupet or dor) NEAR/3 (operat* or procedur* or surger* or surgical*))) OR AB=(fundoplicat* or ((nissen* or toupet or dor) NEAR/3 (operat* or procedur* or surger* or surgical*)))	7017
31	TI= ((hernia* or extraperitoneal or preperitoneal or peritoneal or TEP or TAPP or umbilic* or inguinal or omphalocele* or exomphalos) NEAR/3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)) OR AB=((hernia* or extraperitoneal or preperitoneal or peritoneal or TEP or TAPP or umbilic* or inguinal or omphalocele* or exomphalos) NEAR/3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*))	34907
32	TI= ((liver or hepatic or lung or lungs or pulmon* or kidney) NEAR/3 (transplant* or graft*)) OR AB=((liver or hepatic or lung or lungs or pulmon* or kidney) NEAR/3 (transplant* or graft*))	207843
33	TI=(thoracoscop* or thoracotom* or pleurectom* or pleuroscop* or pleuracotom* or pleurotom* or (pleura* NEAR/3 (endoscop* or incision*))) OR AB=(thoracoscop* or thoracotom* or pleurectom* or pleuroscop* or pleuracotom* or pleurotom* or (pleura* NEAR/3 (endoscop* or incision*)))	33197
34	TI=((lung or lungs or pulmon* or wedge or trauma* or postrauma* or posttrauma* or neurotrauma* or fracture*) NEAR/3 (ablat* or excis* or laparoscop* or laparotom* or	116058

	operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*)) OR AB=((lung or lungs or pulmon* or wedge or trauma* or postrauma* or posttrauma* or neurotrauma* or fracture*) NEAR/3 (ablat* or excis* or laparoscop* or laparotom* or operativ* or surger* or surgical* or reconstruct* or repair* or resect* or intraoperative* or perioperative* or perisurg* or postoperative* or postsurg* or preoperative* or presurg*))	
35	TI=((esophag* or oesophag* or endoesophag* or intraesophag* or tracheoesophag*) NEAR/3 (atres* or atretic* or atroph*)) OR AB=((esophag* or oesophag* or endoesophag* or intraesophag* or tracheoesophag*) NEAR/3 (atres* or atretic* or atroph*))	4181
36	TI=((anal or anus or anorect* or rectal) NEAR/3 (artificial* or malformat* or mal-format* or anomal* or abnormal* or ectopic or stenosis or atres* or atroph* or imperforat* or inperforat* or praet* or pret* or fistula*)) OR AB=((anal or anus or anorect* or rectal) NEAR/3 (artificial* or malformat* or mal-format* or anomal* or abnormal* or ectopic or stenosis or atres* or atroph* or imperforat* or inperforat* or praet* or pret* or fistula*))	9684
37	TI=(hirschsprung* or ((megacolon or colon* or rectosigmoid or intestin*) NEAR/3 (congenital* or aganglion*))) OR AB=(hirschsprung* or ((megacolon or colon* or rectosigmoid or intestin*) NEAR/3 (congenital* or aganglion*)))	6757
38	TI=(agene* NEAR/2 (hemidiaphragm* or diaphragm* or ((unilat* or hern*) NEAR/1 diaphragm*))) OR AB=(agene* NEAR/2 (hemidiaphragm* or diaphragm* or ((unilat* or hern*) NEAR/1 diaphragm*)))	124
39	TI=((bochdalek* or morgagni*) NEAR/2 (hernia* or defect*)) OR AB=((bochdalek* or morgagni*) NEAR/2 (hernia* or defect*))	1099
40	TI=((congenital* or neonat* or neo-nat* or newborn* or new-born* or birth* or maternal* or fetal or fetus* or fetu or feto or foet* or prenatal* or pre-natal* or antenatal* or ante-natal* or trimester* or pregnan* or uter* or preterm* or pre-term* or premature* or pre-mature* or preemie*) NEAR/5 (posterolateral* or substernal*) NEAR/2 hernia*) OR AB=((congenital* or neonat* or neo-nat* or newborn* or new-born* or birth* or maternal* or fetal or fetus* or fetu or feto or foet* or prenatal* or pre-natal* or antenatal* or ante-natal* or trimester* or pregnan* or uter* or preterm* or pre-term* or premature* or pre-mature* or preemie*) NEAR/5 (posterolateral* or substernal*) NEAR/2 hernia*)	64
41	TI=((congenital* or neonat* or neo-nat* or newborn* or new-born* or birth* or maternal* or fetal or fetus* or fetu or feto or foet* or prenatal* or pre-natal* or antenatal* or ante-natal* or trimester* or pregnan* or uter* or preterm* or pre-term* or premature* or pre-mature* or preemie*) NEAR/2 diaphragm* NEAR/2 (hernia* or defect*)) OR AB=((congenital* or neonat* or neo-nat* or newborn* or new-born* or birth* or maternal* or fetal or fetus* or fetu or feto or foet* or prenatal* or pre-natal* or antenatal* or ante-natal* or trimester* or pregnan* or uter* or preterm* or pre-term* or premature* or pre-mature* or preemie*) NEAR/2 diaphragm* NEAR/2 (hernia* or defect*))	5848
42	TI=(congenital* and hernia* and diaphragm*) OR AB=(congenital* and hernia* and diaphragm*)	6020
43	TI=((pectus or chest) NEAR/1 (funnel or sunken or excavatum or carinatum)) OR AB=((pectus or chest) NEAR/1 (funnel or sunken or excavatum or carinatum))	2756
44	#43 OR #42 OR #41 OR #40 OR #39 OR #38 OR #37 OR #36 OR #35 OR #34 OR #33 OR #32 OR #31 OR #29 OR #30 OR #28 OR #27 OR #26 OR #25 OR #24 OR #23 OR #22	5613555
45	#44 AND #21	2947
46	PMID=(0* OR 1* OR 2* OR 3* OR 4* OR 5* OR 6* OR 7* OR 8* OR 9*)	26935187
47	#45 NOT #46	803

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