Archives of Academic Emergency Medicine. 2024; 12(1): e22

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REVIEW ARTICLE

Artificial Intelligence in Optimizing the Functioning of Emergency Departments; a Systematic Review of Current Solutions

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Received: November 2023; Accepted: December 2023; Published online: 27 January 2024

Abstract: **Introduction:** The burgeoning burden on emergency departments is a global challenge that we have been confronting for many years. Emerging artificial intelligence (AI)-based solutions may constitute a critical component in the optimization of these units. This systematic review was conducted to thoroughly examine and summarize the currently available AI solutions, assess potential benefits from their implementation, and identify anticipated directions of further development in this fascinating and rapidly evolving field. **Methods:** This systematic review utilized data compiled from three key scientific databases: PubMed (2045 publications), Scopus (877 publications), and Web of Science (2495 publications). After meticulous removal of duplicates, we conducted a detailed analysis of 2052 articles, including 147 full-text papers. From these, we selected 51 of the most pertinent and representative publications for the review. **Results:** Overall the present research indicates that due to high accuracy and sensitivity of machine learning (ML) models it's reasonable to use AI in support of doctors as it can show them the potential diagnosis, which could save time and resources. However, AI-generated diagnoses should be verified by a doctor as AI is not infallible. **Conclusion:** Currently available AI algorithms are capable of analysing complex medical data with unprecedented precision and speed. Despite AI's vast potential, it is still a nascent technology that is often perceived as complicated and challenging to implement. We propose that a pivotal point in effectively harnessing this technology is the close collaboration between medical professionals and AI experts. Future research should focus on further refining AI algorithms, performing comprehensive validation, and introducing suitable legal regulations and standard procedures, thereby fully leveraging the potential of AI to enhance the quality and efficiency of healthcare delivery.

Keywords: Artificial intelligence; Emergency service, hospital; Emergency medicine; Machine learning

Cite this article as: Aleksandra S, Robert K, Klaudia K, et al. Artificial Intelligence in Optimizing the Functioning of Emergency Departments; a Systematic Review of Current Solutions. Arch Acad Emerg Med. 2024; 12(1): e22. https://doi.org/10.22037/aaem.v12i1.2110.

1. Introduction

The overburdening of emergency departments is an alarming global issue that has been steadily escalating for decades. The crisis in these medical units' functioning arises from multifaceted reasons. Primarily, waiting times in emergency departments (EDs) are extended due to frequent non-emergency patient presentations, recurrent visits for similar complaints, as well as a lack of sufficient beds and medical staff (1-3). These constraints result in a rise in mortality rates, complications, medical errors, and also the phenomena of patients genuinely needing care abandoning further treatment. Additionally, patient satisfaction deteriorates, and the occurrence of burnout among physicians becomes evident (2, 4). In facing these challenges, the search for new solutions becomes crucial, and those based on artificial intelligence (AI) are among the most promising. Machine learning and deep learning techniques distinguish themselves among other computer tools. They not only perform tasks or generate data based on pre-programmed assumptions but are capable of independently "learning" by formulating and testing autonomously generated hypotheses based on the analysis of large data sets (5).

Companies such as AssistAI and Google Health are competing in creating AI-based tools that can aid decision-making by medical emergency teams prior to hospital arrival, in patient triage processes within the emergency departments, diagnostics, and decisions concerning hospitalization or discharge (6). Badal, in his review using breast disease diagnostics as an example, outlined goals that AI-equipped devices should meet to provide real benefits for doctors and patients (2). Among the listed objectives, the key ones appear to be: ensuring universal access, minimizing cases of unnecessary diagnostic expansion and treatment initiation, adapting to local conditions, and facilitating decision-making processes. AI-based tools have already proven their effectiveness in various areas, including image interpretation, triage, and clinical decision-making (3). Many tech manufacturers aim to reduce the time needed for medical documentation by developing natural language processing devices that create documentation based on real-time recording of patient-doctor in-

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teractions (7). Vearrier notes that collaboration between doctors and new devices is key, with the latter remaining under constant medical supervision. It's also important to contextualize results within the clinical scenario and build patient trust in new technologies through physicians (8). In this article, we will focus on summarizing existing solutions and potential benefits derived from AI technology application, and identify potential directions for further development of this technology in the context of emergency departments.

2. Methods

2.1. Study design and setting

The research process involving the analysis of available publications on the application of AI in emergency departments was conducted in accordance with the international PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines.

2.2. PICO frame work

The basis for the selection criteria was the structure of the PICO model (patients, interventions, comparison group, outcomes). The results of works in which the authors classified their actions as models based on artificial intelligence were considered, and the target group were emergency department patients. Figure 2 shows the details of PICO framework of study.

2.3. Search strategy

PubMed, Scopus, Web of Science databases were searched to identify relevant studies published from January 2020 to May 2023. Additionally, we manually searched the reference lists within the located publications to identify potential sources that might have been overlooked. In each of these databases, an advanced search was carried out by combining appropriate words and/or expressions, making use of "AND" and "OR" connectors. Our analysis was based on the search string 'Artificial Intelligence OR Machine Intelligence OR Machine Learning' AND 'emergency medicine OR emergency department OR emergency ward OR emergency unit'.

2.4. Study selection

The main sources of information used in this review were three well-known databases: PubMed (2386 publications), Scopus (338 publications), and Web of Science (3098 publications). After removing duplicates, 3052 articles were evaluated (screened). Then, to further narrow down the research field, a detailed evaluation of 186 full-text publications was carried out, from which 59 were finally included in the review. This analysis included studies published from January 2020 to May 2023. This limitation was necessary due to the rapid development of AI technology in medicine, where studies conducted in earlier years might be based on solutions and models that are currently outdated and have been significantly improved since. Abstracts, reviews, comments, and editorial articles were excluded from the analysis, and it was limited only to primary articles. Only studies in English language were included in this study (Figure 1).

2.5. Eligibility criteria

After reviewing the abstracts, we decided to exclude publications regarding further hospital care, specialist solutions used in departments dedicated to patients requiring hospital admission, forecasting disease progression in patients qualified for hospitalization, as well as analyses predicting recurrence or disease progression. These actions aimed to narrow down the research area and focus on key aspects of AI use in emergency departments.

2.6. Publication bias

In the field of machine learning, it's common to assume that AI is more precise, more accurate and faster than human; therefore, it's common for researches not to publish results of studies if models developed by them aren't performing better than human. Therefore, publication bias in field of machine learning is at high risk due to an unrealistic expectation that AI is consistently more precise, more accurate, and faster than humans.

3. Results

3.1. Characteristics of the included studies

A total of 5822 articles were identified through electronic database searches and additional sources. After removing duplicates and screening titles and abstracts, 186 articles were selected for full-text review. Following the full-text review, 59 articles met the inclusion criteria and were included in the systematic review.

The included studies comprised a variety of study designs, including 29 retrospective studies, 7 randomized controlled trials, 4 cohort studies, and 4 prospective studies. The sample sizes ranged from 362 to 43000 participants. The studies were conducted in various geographical locations, with a majority originating from United States and Taiwan (Table 1).

Most of the studies are based on numerical real-world data, which allows to present measurable result of studies. In most cases data aggregates in above thousands of participants, which result in reasonable sample sizes of datasets that indicate data diversity, making machine learning models used in studies learn on diversified data, which reduces the risk of overfitting the model (Table 2).

3.2. Sensitivity analysis

A sensitivity analysis was conducted to evaluate the robustness of the findings. This analysis involved the exclusion of studies with a high risk of bias and the re-evaluation of the pooled effect sizes and overall conclusions. Most of the included studies contained sensitivities higher than 75%, which may indicate good quality of machine learning algorithms used in studies included in this systematic review.

Sensitivity on that level combined with high accuracy allows to make an assumption that AI could be used in emergency medicine to support doctors in making decisions, which should be verified by the doctors first as AI is not infallible since none of the algorithms had accuracy amounting to 100% (Figure 3).

4. Discussion

The Food and Drug Administration (FDA) has approved 521 AI-based medical devices since 1995, indicating the dynamic development of technology in this area (9). Of this number, as many as 391 devices are used in radiology, highlighting the key role of AI in the field of image interpretation. Additionally, 57 and 14 AI-utilizing devices have been approved in cardiology and neurology respectively, showing that the potential of artificial intelligence technology is recognized and utilized in other areas of medicine as well. In the context of emergency departments, based on the analysed publications, we have identified several key stages and tasks where the use of artificial intelligence seems most beneficial. These include the pre-hospital stage, triage process, cardiovascular diagnostics, imaging diagnostics, and neurological diagnostics.

At the pre-hospital stage, AI can support emergency medical teams in making decisions about the direction of treatment and patient transport. By analysing patient data, such as health status, medical history, and current symptoms, AI systems can help rescue teams assess the patient's condition and choose the most appropriate course of action. In the area of triage, artificial intelligence can help in quickly and effectively directing patients to appropriate diagnostic or therapeutic paths. By analysing patient data and comparing it with disease patterns, AI can support medical staff in making decisions about treatment priorities.

Cardiovascular, imaging, and neurological diagnostics are further areas where AI exhibits great potential. In the case of cardiovascular diagnostics, artificial intelligence can analyse complex data patterns, such as electrocardiograms (ECG) recordings, to identify life-threatening conditions like a heart attack. Imaging diagnostics, on the other hand, can benefit from AI for precise interpretation of complex computed tomography (CT) or magnetic resonance imaging (MRI) images. Similarly, in neurological diagnostics, AI can assist in identifying subtle brain oedema, bleeding, or other significant pathologies. The review also considered publications on the application of ChatGPT for medical diagnostics. This is a technology that is gaining popularity among the general public, which is increasingly looking for answers to health-related questions on the Internet. Systems like ChatGPT, based on advanced language models, can generate reliable responses to medical questions, drawing on available medical knowledge (10). This application of AI has the potential to improve access to health information and support patients in self-care processes.

4.1. Prehospital stage and triage

The prehospital stage and triage are pivotal elements in the functioning of any Emergency Department (ED), which is tasked with properly organizing its team's work and ensuring effective communication with patients concerning anticipated waiting times. A substantial body of literature focuses on identifying factors contributing to ED overcrowding and attempts to minimize patients' return visits for identical ailments (11). It is crucial to note that the majority of the currently utilized models unfortunately do not account for unforeseen situations, which are inherent in the functioning of EDs (12-14). Modern algorithms that utilize AI might offer a solution to this issue. Research indicates that these algorithms can calculate expected waiting times for admission to the ED with greater precision, taking into account current workload, emergency states, and the condition of patients in the ED (12-14).

Triage, the medical procedure of segregating patients based on basic life parameters, is the second key element in the ED's operation. Machine Learning (ML) models used in the ED can effectively assist the triage process, improving its accuracy and efficiency. The KATE, AI-powered triage decision support solution, predicted accurate ESI (Emergency Severity Index) acuity assignments 75.7% of the time compared with nurses (59.8%)(15). Artificial intelligence also has found use in predicting the need for intensive hospital care, which is particularly helpful in categorizing trauma patients even before their arrival at the ED (4). Weng's study demonstrated the feasibility of calculating an anticipated "burden" on the facility based on data collected during a patient's first hour in the ED (16, 17). Another intriguing ML model is Yong Yu's proposal, which created a tool for triage capable of more accurately predicting potential diagnostic outcomes in the ED than existing triage systems - KTAS and SOFA (18). In cases of severe sepsis or the risk of developing septic shock, early identification of such patients can significantly streamline the process of further diagnostics and treatment (19). Cotte et al. compared the results of triage performed by an ED nurse based on the Manchester triage system with the results of triage conducted by patients independently using the ADA app (20). The analysis revealed considerable differences in patient categorization, suggesting the potential to reduce ED workload by utilizing this kind of application at the home stage (20).

A 24-month study based on regular telephone contact between a caregiver and a patient suggests that this approach might contribute to a decrease in later ED visits and shorten patient stay (21). Remote triage systems can be helpful and expedite diagnostics, yet there remains a risk of reducing the accuracy of such triage due to a limited amount of data analysed by AI (4).

Multifaceted studies point to the potential of AI in various aspects of medical diagnostics, from identifying urgent ophthalmological conditions (22), through non-invasive diagnostics of anaemia (23), to the effective identification of

lower respiratory tract infections, which reduced the number of chest X-rays performed (24). Mueller's research findings indicate the efficacy of machine learning algorithms in predicting the development of delirium within 72 hours of hospital admission, which might facilitate the earlier implementation of appropriate treatment and prevent confusion (1).
The use of laboratory test results in AI models for the diagnosis of Kawasaki Disease (KD) enabled the isolation of KD cases among febrile children in the ED (25). An application was also created that, using basic clinical and laboratory parameters, assists physicians in deciding on discharge or hospitalization of patients with SARS-CoV-2 pneumonia (26). For example, an attempt to create a screening tool detecting opioid misuse, though small, demonstrates the possibility of applying algorithms in various medical aspects (27). Lastly, it is noteworthy that the algorithm used by D'Amato confirmed the prognostic role of eosinophil blood count as a risk factor for exacerbation of bronchial asthma and the need for hospitalization (28). All of this, point to the incredibly broad and versatile possibilities of employing AI in the future of medicine.

4.2. Enhancements in cardiovascular diagnosis

The application of AI in cardiovascular diagnostics, especially in the context of using various machine learning models, represents a significant step towards innovative and efficient strategies for diagnosing and treating diverse cardiovascular pathologies. The main benefits of AI application include reducing the time required for diagnosis, improving diagnostic accuracy, and personalizing therapeutic strategies (29, 30) Cardiovascular pathology diagnosis often poses challenges, particularly due to the broad spectrum of possible causes leading to similar symptoms such as chest pain. Numerous diseases, both of musculoskeletal and cardiovascular nature, such as acute coronary syndromes, aortic dissection, and pulmonary embolism, can produce such symptoms, increasing the urgency to quickly identify life-threatening cases (31).
From a clinical practice perspective, the significance of AI in cardiovascular diagnostics is well illustrated by a study conducted by Chen et al. The authors demonstrated that a portable mini-device for identifying ST-segment elevation myocardial infarction (STEMI) based on AI had an efficacy comparable to cardiology specialists. This AI-enabled device facilitated the shortening of the pre-hospital phase and the triage process (32) Liu et al. observed similar benefits of AI in cardiovascular diagnostics. They proposed a model based on a 12-lead ECG analysis, which was more effective in identifying STEMI than doctors. Moreover, the device was capable of recognizing STEMI equivalents, such as Wellens' syndrome, bundle branch block, or posterior wall infarction. The model's application by emergency medical teams could reduce the time needed to transmit ECGs to the reference centre, thus speeding up the diagnostic process (33) A model developed by Wu, also based on a 12-lead ECG, not only allows STEMI identification but also indicates with high probability the vessel that could be occluded (34).
One of the key studies in this area was conducted by Emakhu, which enabled the identification of significant variables and the designation of patients with non-ST segment elevation myocardial infarction (NSTEMI) and unstable angina (35). Another multicentre model used in a study showed high effectiveness in ECG interpretation during STEMI and NSTEMI (36). This model utilized an algorithm that assisted doctors in early detection of acute pericarditis and differentiating it from STEMI (37). One of the most promising achievements in this area was Zhang's scientific work, where he developed a model trained with artificial intelligence. This model was more effective in estimating mortality risk in patients after STEMI and NSTEMI than previously used Thrombolysis in Myocardial Infarction (TIMI) and Global Registry of Acute Coronary Events (GRACE) scales (31). This significant achievement illustrates how far artificial intelligence technologies can contribute to increasing accuracy in forecasting patient outcomes. Studies also showed that models based on deep learning techniques, combining ECG records and basic laboratory tests, are able to predict survival rates with high accuracy (38).
A significant challenge in cardiovascular diagnostics is the identification of atrial fibrillation, a condition often diagnosed in emergency departments. Schwab et al.'s study demonstrated the effectiveness of the Lucia application, which identifies atrial fibrillation, estimates the risk of ischemic stroke and bleeding in the CHA2DS2-VASc and HAS-BLED scales, and assesses the necessity of anticoagulant use, based on AI (39). Raghunath's team, analysing a dataset of 430,000 ECGs, developed a model capable of predicting the risk of atrial fibrillation in patients without a prior history of arrhythmias. Identifying patients at increased risk of ischemic stroke due to thromboembolism is a key element of preventive cardiology (40).
AI also found a place in the diagnosis of pulmonary embolism. Silva et al. created a deep learning model identifying pulmonary embolism (PE) based on a 12-lead ECG, which achieved 100% specificity in diagnosing PE (41). An innovative approach to the use of artificial intelligence in cardiovascular diagnostics was presented by a group of scientists from China led by Shen Lin. They constructed a model that recognizes coronary artery disease based on facial images. Despite certain limitations, the algorithm had 80% sensitivity and 54% specificity. However, this study encountered several constraints. They used a solely Chinese population, which limits the generalization of results to other ethnic groups. Additionally, they interchangeably used contrast-enhanced CT and coronary angiography, which could influence the results. In its current form, the algorithm is not optimized for clinical practice, but it shows significant potential for ambulatory diagnosis of coronary disease (42).
Non-invasive coronary disease diagnosis based on ECG is also the subject of research. However, due to the non-specific

changes occurring in this disease, current models show limited effectiveness(43). In 2021, Blomberg conducted a study that showed no significant improvement in the recognition of circulatory arrest by medical dispatchers when using AI-based tools (44). A study conducted two years later yielded false-negative results at the level of 15.5% (45). Medical innovation also encompasses the CardioCube application, which allows for conducting medical interviews with a voice assistant. Patients answer a set of predefined questions, and the system generates a detailed report. Another application from CardioCube, FCNcare, enables patients with heart failure and diabetes to input information about their current health status.

The application sends a report to nurses, who, based on the collected data, can assess the necessity of a medical visit (46).

The above examples illustrate how artificial intelligence, despite certain limitations, can contribute to modernizing cardiovascular diagnostics, reducing diagnostic time and cost, and increasing its precision. It is important to continue research on optimizing existing algorithms and creating new ones to enable more precise, rapid, and effective diagnosis of cardiovascular pathologies.

4.3. Imaging diagnostics

Forecasts regarding the impact of artificial intelligence on radiology vary - ranging from the opinion that AI will eliminate radiologists from the labor market to the belief that it will have no significant influence (47). However, there is considerable evidence to suggest that artificial intelligence can significantly expedite the process of analysing medical images, thereby facilitating early detection of abnormalities and assisting doctors in making further care decisions (48). Algorithms can scan radiological images to identify anomalies, tumours, fractures, or other significant changes, enabling faster diagnosis and implementation of appropriate treatment, which can significantly improve patient outcomes in life-threatening conditions (4). Studies have shown that the model proposed by Shahbandegan was effective in identifying patients requiring computed tomography based on data available after performing triage (49). Tools have also been developed to interpret X-ray images of patients with SARS-CoV-2 infection with an accuracy comparable to specialists.

Moreover, these tools were able to assess parameters indicating further infection progress, enabling earlier initiation of appropriate treatment or patient transportation to another centre (50).

In recent years, portable devices for imaging studies have been developed, which allow diagnostics to be performed on-site during the pre-hospital phase. Such solutions help to reduce congestion in emergency departments. Additionally, AI-based algorithms have been proposed to assist clinicians in deciding whether to perform imaging tests. The work by Hwang's team and others shows that the use of AI-based tools for interpreting chest X-ray images did not result in higher sensitivity and reduction of false-positive results in patients presenting to the emergency department with acute respiratory symptoms (51).

However, the issue of responsibility for generating false-positive or false-negative results remains unresolved. Therefore, despite advances in the field of artificial intelligence, it is unlikely to replace the work of radiologists soon, as the final diagnosis should be decided by the physician (52). An example of this approach might be a tool developed by Cheng, which marks areas on an X-ray image identified by AI as a fracture, but the final diagnostic decision should be left to the radiologist (53). Grant suggests that AI-based devices should primarily be used to confirm diagnoses, not to rule them out. In such a model, there is less risk of missing a key diagnosis, and artificial intelligence can still accelerate the description of tests and assist doctors (5).

In summary, artificial intelligence has considerable potential in the field of imaging diagnostics. It can speed up the analysis of medical images, support doctors in making diagnostic decisions, and allow for earlier detection of abnormalities. However, there are still many aspects to consider, such as responsibility for diagnostic results and cooperation with doctors. Further research and technological development are necessary to fully harness the potential of artificial intelligence in the field of imaging diagnostics.

4.4. Neurological diagnostics

Emergencies such as head injuries, intracranial haemorrhages, and ischemic strokes present high mortality rates and potentially irreversible neurological effects. Therefore, rapid identification of these cases through neuroimaging is crucial to enable proper treatment. The effectiveness of reperfusion therapy applied in the case of ischemic strokes depends on the time elapsed since the onset of symptoms (54).

Artificial intelligence (AI)-based tools can automatically identify different urgent neurological conditions, contributing to shortened diagnostic time and the choice of the most appropriate therapy (29, 48, 55, 56). In a study conducted by Chen, a model was developed that allowed the recognition of strokes at the pre-hospital stage, even before obtaining imaging and laboratory results, with greater accuracy than the scales used to date. This tool was also expanded to identify stroke-mimicking conditions such as brain tumours, somatization disorders, Wernicke's encephalopathy, epileptic seizures, migraines, and hypertensive encephalopathy (29).

There is also a model based on 15 selected laboratory and clinical parameters that streamline the diagnosis of ischemic stroke (57).

Research conducted by Yang points to a connection between blood morphology, particularly the number of leukocytes, and the likelihood of primary or secondary headache occurence. Using this model, in conjunction with the patient interview and physical examination, can reduce the amount of unnecessary imaging (58). The model proposed by Kaothanthong also showed high efficiency and accuracy

in detecting ischemic stroke based on computed tomography (55). In his review of currently available technologies improving the identification of ischemic stroke symptoms, Bat-Orgil Bat-Erdene mentions the recognition of altered body posture, gait, speech, and face by devices such as smartphones, smart speakers, watches and fitness bands, voice assistants, smart clothing, beds, computers, and laptops (54).
In summary, AI-based tools have significant potential in the field of neurological diagnostics. They can expedite the identification of urgent neurological conditions, enabling prompt therapeutic decision-making. Developed models and algorithms demonstrate promising results in recognizing ischemic strokes and various neurological states. The introduction of AI-based technologies may contribute to enhancing the quality of neurological care and therapeutic outcomes.

4.5. Integration of chatbots in medical practice

Since November 2022, ChatGPT, developed by OpenAI, has gained popularity and proven its usefulness in various fields. This chatbot uses a large language model to generate responses to user input (59). Although ChatGPT was not specifically trained on medical data, attempts are ongoing to utilize this tool in medicine. A study conducted by Cadamuro involved inputting hypothetical patient laboratory tests and asking the chatbot to interpret these results. A definite advantage of this approach was the chatbot's correct recognition of all parameters and their comparison to reference values, as well as recommending contacting a doctor in each case. However, the limitations of this analysis included a failure to distinguish between values slightly deviating from the norm and critical values, and a lack of comprehensive interpretation of results (60). Models like MedAssistAI, BioGPT, and Med-PaLM, which are trained to interpret medical data, are also being developed. Van Bulck and colleagues compared the accuracy of diagnoses made by ChatGPT with opinions of medical specialists. The experts indicated that the responses generated by ChatGPT could be considered credible and valuable for patients, but could sometimes also be dangerous. Over 40% of specialists believed that ChatGPT's responses were more valuable than those generated by Google (61). In early 2023, Google and DeepMind presented Med-PaLM, a chatbot whose purpose is to generate answers to questions concerning medical and health issues, based on data from medical publications and current guidelines. A study conducted by Nadarzynski et al. demonstrated that the drawbacks of using artificial intelligence-based chatbots include the risk of inaccuracy, safety concerns, and lack of empathy. However, respondents identified advantages such as anonymity and increased availability of such devices (62).
In summary, chatbots such as ChatGPT have the potential for application in medicine. Conducted studies demonstrate that chatbots can be a valuable source of information for patients, but they require further development and refinement. It's important that the responses generated by chatbots are credible and comprehensive, and that they cooperate with doctors in the process of diagnosing and treating conditions. To date, most of the literature regarding artificial intelligence in emergency medicine has primarily focused on retrospective reviews. To enable the real-time application of artificial intelligence algorithms, electronic medical documentation and reporting systems will require modification.
Collaboration with the Ministry of Health, National Health Fund, and medical societies can contribute to improving trust, privacy protection, and enhancing patient and physician acceptance of new technologies. By analysing patient data, artificial intelligence algorithms will be able to tailor pharmacological therapies and invasive procedures to an individual patient's needs and predispositions.
A key factor is collaboration between medical experts and artificial intelligence specialists to effectively utilize this technology in transforming health care and reducing the load on emergency departments. Future research should focus on further developing AI algorithms, their validation, and the introduction of appropriate regulations to fully exploit the potential of artificial intelligence in enhancing health care.

5. Limitations

The unique nature of emergency departments, which handle patients requiring interventions from various medical fields, is a significant factor to consider when analysing the application of AI in this context. In this review, we focused on publications directly categorized as pertaining to artificial intelligence in emergency medicine or emergency departments based on their titles and abstracts. However, there is a possibility that our search strategy may have missed models or studies describing technologies that could be applicable in emergency departments but were described in the context of other medical fields, such as cardiology or radiology. It's also important to note that our analysis mainly focused on English-language publications, which may introduce certain limitations. Publications in other languages could contain significant information regarding the application of artificial intelligence in emergency medicine that we did not incorporate in our review. Additionally, during our review, we excluded articles that only provided an abstract and not the full text. This decision may impose some limitations, as a thorough analysis and understanding of a particular study might require access to the full text of the publication. It's also crucial to acknowledge that numerous research studies and projects could describe cutting-edge artificial intelligence-based technologies but were not included in our review. Some of these publications might be published in scientific journals not directly related to emergency medicine, leading to the omission of some significant advancements and solutions in the field of artificial intelligence.
Overall, the analysis of the application of artificial intelligence in emergency medicine has its limitations. One must bear in mind the specificity of emergency departments and the diversity of medical fields, as well as potential limitations

associated with the exclusion of certain publications and language barriers. To fully harness the potential of artificial intelligence in emergency medicine, further research is necessary, considering diverse sources and state-of-the-art AI-based technologies.

6. Conclusions

Artificial intelligence in emergency departments has numerous applications and proven effectiveness. Despite its enormous potential, artificial intelligence remains a relatively novel and unfamiliar domain, which can sometimes prove challenging to understand. This introduces a host of ethical dilemmas and limitations that demand resolution. Reviewing the articles shows that, despite the development of numerous artificial intelligence-based models, few are genuinely applied in emergency medicine practice. Furthermore, few publications addressed the perspectives of patients and physicians concerning the use of artificial intelligence in this field.

7. Declarations

7.1. Acknowledgments

None.

7.2. Conflict of interest

The authors declare no conflict of interest.

7.3. Funding

This research received no external funding.

7.4. Authors' contribution

Aleksandra Szymczyk: writing - original draft, writing - review & editing, investigation, data curation, methodology; Robert Krion: writing - review & editing, resources, conceptualization; Klaudia Krzyzaniak: project administration, mentoring, data validation; Dawid Lubian: data analysis, data validation, data curation; Mariusz Sieminski: mentoring, supervision. All authors have read and agreed to the published version of the manuscript.

7.5. Using artificial intelligence chatbots

None.

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Table 1: Summary of available publications

Author	Year	Type of study	Country	Outcome	Participants	Field
Annis	2022/09	Cohort study	USA	To develop a risk factor-based machine learning model to identify opioid use disorder quickly	345 728	Poisoning
Badal	2023/04	Review	USA	To formulate guiding principles for the responsible development of artificial intelligence tools for healthcare	Not applicable	Not applicable
Bat-Orgil Bat-Erdene	2021/07	Review	Mongolia	To show the advances in acute stroke symptom automatic detection and Emergency Medical Systems alerting by mobile health technologies	Not applicable	Stroke
Blomberg	2023/01	Randomized clinical trial	Denmark	To investigate emergency call characteristics where the machine-learning model failed to recognize out-of-hospital cardiac arrest	169 049	Cardiac arrest
Blomberg	2021/01	Randomized clinical trial	Denmark	To examine how a machine learning model was trained to identify out-of-hospital cardiac arrest	169 049	Cardiac arrest
Cadamuro	2023/04	Assessment	Austria, Italy, Croatia, Spain	To find out if ChatGPT was able to evaluate laboratory results	10	Laboratory test analysis
Casano	2023/03	Cohort study	Italy	To manage safe discharge or hospitalization of unvaccinated COVID-19 patients	779	COVID-19
Cellina	2022/12	Review	Italy	Overview of AI applications in emergency radiology	Not applicable	Not applicable
Chamberlin	2022/07	Retrospective study	USA	To develop an algorithm for the diagnosis and prognosis of COVID-19 pneumonia from chest X-rays	2 456	COVID-19
Chang	2022/12	Cohort study	Taiwan	To establish a machine learning model for prediction of low-severity patients with short length of stay in ED	44 839	Triage
Chang	2022/09	Review	Korea	To show artificial intelligence-based clinical decision support points during emergency department phases	Not applicable	Not applicable
Chen	2023/05	Retrospective study	China	To develop a multimodal system, EE-Explorer, to triage eye emergencies and assist in primary diagnosis using metadata and ocular images	2 405	Triage
Chen	2023/01	Retrospective study	Taiwan	To develop a stroke prediction algorithm based on data widely available at the time of patients' hospital presentations	143 203	Stroke
Chen	2022/10	Randomised controlled trial	Taiwan	To implement an all-day online artificial intelligence-assisted detection of ST-elevation myocardial infarction (STEMI) using prehospital 12-lead electrocardiograms	362	Myocardial infarction
Cheng	2020/11	Retrospective study	Taiwan	To enhance physicians' hip fracture diagnostic performance	3 605	Fracture
Cotte	2022/03	Prospective study	Germany	To evaluate the safety of urgency advice given by the app	378	Triage
Crampton	2020/01	Case study	Canada	To develop autoscribe using artificial intelligence-based natural language processing tools to automate tasks and to output high-quality EMR data	Not applicable	Triage
D'Amato	2022/10	Prospective study	Italy	To identify the main predictors of severe asthma exacerbations requiring hospital admission	260	Asthma
Dave	2023/05	Review	Ukraine	To overview of chatGPT applications, advantages, limitations, future prospects, and ethical considerations	Not applicable	Chatbots
Ellertsson	2023/05	Retrospective study	Iceland	To reduce the number of chest x-rays	1 500	Respiratory disorders
Elston	2022/09	Randomised controlled trial	United Kingdom	The effectiveness of a targeted telephone-based case management service that aimed to reduce ED attendance amongst frequent attenders	808	Primary care
Emakhu	2022/10	Retrospective study	USA	To identify patients with acute coronary syndrome early through further refinement and validation	31 228	Acute coronary syndrome
Grant	2020/06	Review	Canada	To indicate the barriers to widespread implementation in the context of the ED from technical, regulatory, and clinical flow perspectives and discusses potential solutions to these challenges	Not applicable	Not applicable

Table 1: Summary of available publications (continue)

Author	Year	Type of study	Country	Outcome	Participants	Field
Gustafsson	2022/11	Randomised controlled trial	Sweden	To predict myocardial infarction in real-world emergency department patients	214 250	Myocardial infarction
Hunter	2023/03	Review	Canada	To outline the utility of artificial intelligence along the entire continuum of trauma care	Not applicable	Data collection
Hwang	2023/03	Randomized clinical trial	Korea	To compare the accuracy of chest X-ray interpretation assisted by AI-CAD to that of conventional interpretation in patients who presented to the ED	1 761	Respiratory disorders
Ivanov	2020/12	Retrospective study	USA	To determine whether historical EHR data can be used with clinical natural language processing and machine learning algorithms (KATE)	166 175	Triage
Jadczyk	2019/09	Prospective study	USA	To collect, index and document medical data using a voice interface	22	Data collection
Jalal	2021/02	Review	Canada	To evolve the role of artificial intelligence in assisting the imaging pathway in an emergency and trauma radiology department	Not applicable	Imaging
Kaothanthong	2022/12	Retrospective study	Thailand	To detect the brain infarct area on the non-contrast computed tomography (CT)	804	Stroke
Karatzia	2022/10	Review	United Kingdom	To sum up applications of artificial intelligence use in cardiology	Not applicable	Cardiology
Kuo	2020/07	Retrospective study	Hong-Kong	To apply machine learning algorithms for real-time and personalized waiting time prediction in emergency departments	12 440	Waiting time prediction
Lin	2020/08	Randomized clinical trial	China	To develop a tool for detecting coronary artery disease based on facial photos	5 796	Coronary artery disease
Liu	2022/07	Retrospective study	Taiwan	To develop a tool to detect acute pericarditis	66 633	Pericarditis
Liu	2021/10	Retrospective study	Taiwan	To develop a diagnostic support tool based on a 12-lead electrocardiogram	450	Myocardial infarction
Mueller	2023/05	Retrospective study	USA	To identify a clinically valuable risk estimation model for prevalent delirium in patients being transferred from the ED to inpatient units	28 531	Triage
Nadarzynski	2019/08	Mixed methods approach	United Kingdom	To explore participants' willingness to engage with AI-led health chatbots	215	Chatbots
Neri	2020/06	Review	Italy	To answer who is responsible for the benefits and harms of using artificial intelligence in radiology	Not applicable	Imaging
Pak	2021/01	Retrospective study	Australia	To find evidence that the proposed estimators generate more accurate ED waiting time predictions than the rolling average	122 716	Waiting time prediction
Park	2023/05	Retrospective study	Korea	The utility of an existing artificial intelligence-based quantitative electrocardiography (QCG) analyser in stable-angina and developing a new ECG biomarker more suitable for stable angina	723	Coronary artery disease
Raghunath	2021/03	Retrospective study	USA	To demonstrate the high potential to identify patients who later have an atrial fibrillation-related stroke	430 000	Atrial fibrillation
Safaripour	2022/06	Retrospective study	Canada	To compare the performance of logistic regression and four other machine learning classification models for predicting frequent ED use	24 616	Not applicable
Schwab	2021/08	Retrospective	USA	To determine the rate of accurate AF identification and appropriate anticoagulation recommendations in ED patients ultimately diagnosed with atrial fibrillation (AF)	70 000	Atrial fibrillation
Shahbandegan	2022/12	Retrospective	Canada	To predict computer tomography exams in the ED	81 118	Imaging
Silva	2023/04	Retrospective	Portugal	To develop a deep learning-based AI model for pulmonary embolism diagnosis using a 12-lead ECG	1 014	Pulmonary embolism
Sun	2023/02	Retrospective	Canada	To develop ECG-based machine learning models to predict risk of mortality among patients presenting to an emergency department	240 077	Mortality risk prediction

Table 1: Summary of available publications (continue)

Author	Year	Type of study	Country	Outcome	Participants	Field
Tahayori	2020/10	Retrospective	Australia	To predict disposition of patients based on triage notes in the ED	249 532	Triage
Tsai	2023/04	Retrospective	Taiwan	To develop a prediction model to differentiate children with Kawasaki disease from other febrile children	74 641	Kawasaki disease
Van Bulck	2023/04	Review	Belgium	To show the trustworthiness, value, and danger of information provided by ChatGPT on virtual prompts by patients	Not applicable	Chatbots
Vearrier	2022/04	Review	USA	To indicate benefits, risks, and recommendations	Not applicable	Not applicable
Wang	2021/06	Retrospective	USA	To demonstrate the potential of using electronic health record data to predict patient-related workload automatically in the emergency department	5 532	Not applicable
Wardi	2021/04	Retrospective	USA	To develop a tool for the prediction of delayed septic shock in a cohort of patients treated in the ED	9 354	Septic shock
Weisberg	2020/08	Review	USA	To show the impact of artificial intelligence on radiology	Not applicable	Imaging
Wu	2022/03	Retrospective	China	To develop ECG-based systems to detect STEMI and predict culprit vessel occlusion	883	Myocardial infarction
Yang	2023/03	Retrospective	Switzerland	To use routine blood test results as a triage tool to perform neuroimaging on patients presenting with severe headache	121 241	Headache
Yu	2020/01	Retrospective	Korea	To develop nursing assessment-based emergency department triage to predict adverse clinical outcome	54 501	Triage
Zhang	2022/11	Prospective study	China	To develop an algorithm to predict anaemia using video	316	Anaemia
Zhang	2020/09	Retrospective	Taiwan	To improve predicting cardiac events in patients with chest pain in the emergency department	85 254	Chest pain
Zheng	2022/05	Retrospective	China	To develop and validate ML-based models for the diagnosis of ischaemic stroke using the results of common blood tests	10 476	Stroke

ED: emergency department; EMR: electronic medical record; HER: electronic health record; ECG: electrocardiogram; AI: artificial intelligence; ML: machine learning; STEMI: ST-segment elevation myocardial infarction.

Table 2: Screening performance characteristics of tools which were used in the included studies

Author	Year	Accuracy	AUC	Sensitivity	Specificity
Annis	2022/09	0.96	0.71	0.45	0.97
Badal	2023/04	null	null	null	Null
Bat-Orgil Bat-Erdene	2021/07	null	null	null	Null
Blomberg	2023/01	null	null	0.85	0.97
Blomberg	2021/01	0.93	null	0.85	0.97
Cadamuro	2023/04	null	null	null	Null
Casano	2023/03	0.91	null	null	Null
Cellina	2022/12	null	null	null	Null
Chamberlin	2022/07	0.89	null	null	Null
Chang	2022/12	0.76	null	null	Null
Chang	2022/09	null	null	null	Null
Chen	2023/05	null	0.98	null	Null
Chen	2023/01	0.834	0.83	0.970	0.647
Chen	2022/10	0.99	0.99	0.90	0.99
Cheng	2020/11	0.96	null	0.97	0.96
Cotte	2022/03	null	null	null	Null
Crampton	2020/01	null	null	null	Null
D'Amato	2022/10	null	0.97	null	Null
Dave	2023/05	null	null	null	Null
Ellertsson	2023/05	null	null	null	Null
Elston	2022/09	null	null	null	Null
Emakhu	2022/10	0.86	0.93	0.86	0.93
Grant	2020/06	null	null	null	Null
Gustafsson	2022/11	0.75	null	null	Null
Hunter	2023/03	null	null	null	Null
Hwang	2023/03	null	null	0.67	Null
Ivanov	2020/12	0.98	0.85	0.99	0.99
Jadczyk	2019/09	null	null	null	Null
Jalal	2021/02	null	null	null	Null
Kaothanthong	2022/12	0.91	null	0.77	Null
Karatzia	2022/10	null	null	null	Null
Kuo	2020/07	null	null	null	Null
Lin	2020/08	null	0.73	0.80	0.54
Liu	2022/07	null	0.98	0.98	0.97
Liu	2021/10	0.99	0.94	0.89	0.99
Mueller	2023/05	0.8	0,839	null	Null
Nadarzynski	2019/08	null	null	null	Null
Neri	2020/06	null	null	null	Null
Pak	2021/01	null	null	null	Null
Park	2023/05	0.76	0.80	0.76	0.76
Raghunath	2021/03	null	0.83	0.69	0.81
Safaripour	2022/06	null	0.96	0.95	0.98
Schwab	2021/08	0.98	null	null	Null
Shahbandegan	2022/12	0.76	0.87	0.87	0.71
Silva	2023/04	null	0.75	0.50	0.100
Sun	2023/02	null	0.83	null	Null
Tahayori	2020/10	0.83	0.88	0.72	0.86
Tsai	2023/04	null	0.98	0.93	0.97
Van Bulck	2023/04	null	null	null	Null
Vearrier	2022/04	null	null	null	Null
Wang	2021/06	0.80	null	null	Null
Wardi	2021/04	null	0.83	0.85	0.64
Weisberg	2020/08	null	null	null	Null
Wu	2022/03	0.93	0.96	0.88	0.90
Yang	2023/03	0.61	0.85	null	Null
Yu	2020/01	null	0.87	null	Null
Zhang	2022/11	0.82	null	0.93	0.69
Zhang	2020/09	0.91	0.91	0.93	0.89
Zheng	2022/05	null	0.92	null	null

AUC: area under the receiver operating characteristic (ROC) curve.

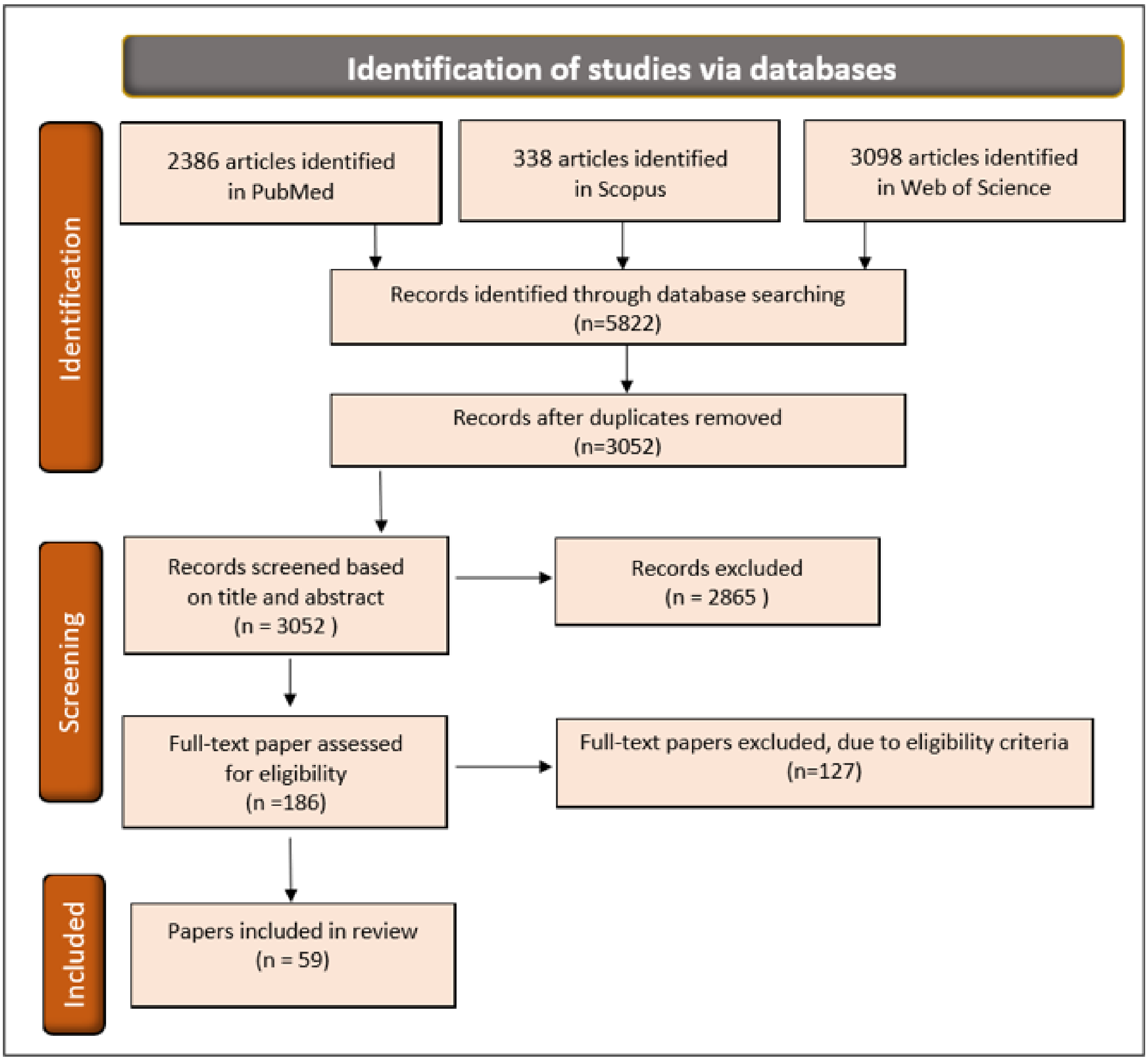

Figure 1: Method of article selection.

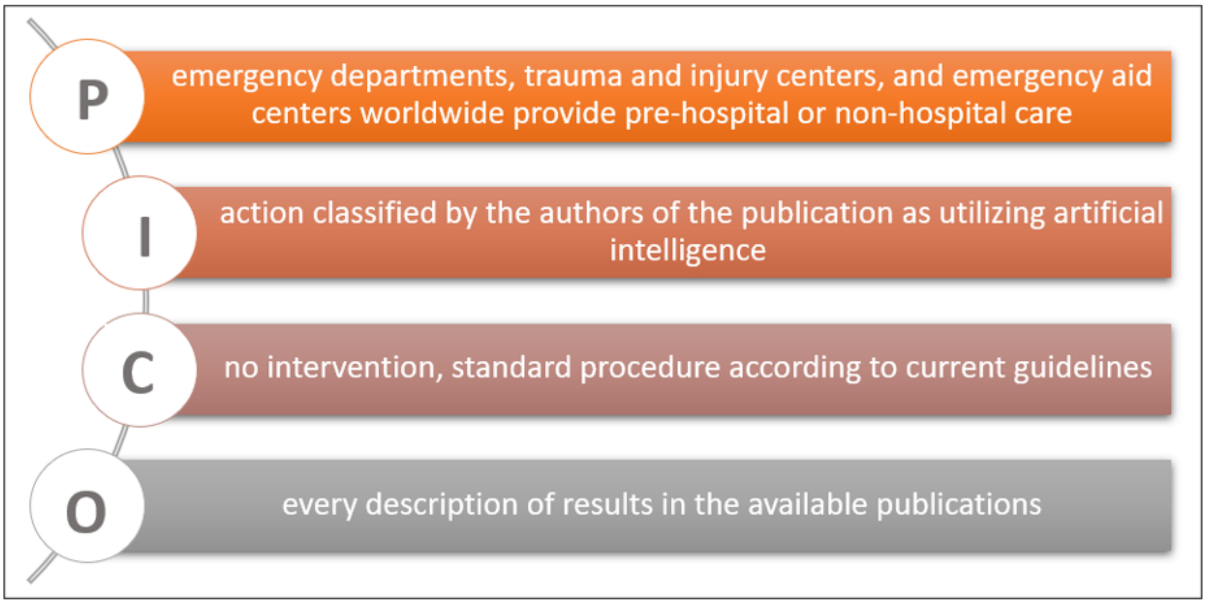

Figure 2: PICO framework of the study.

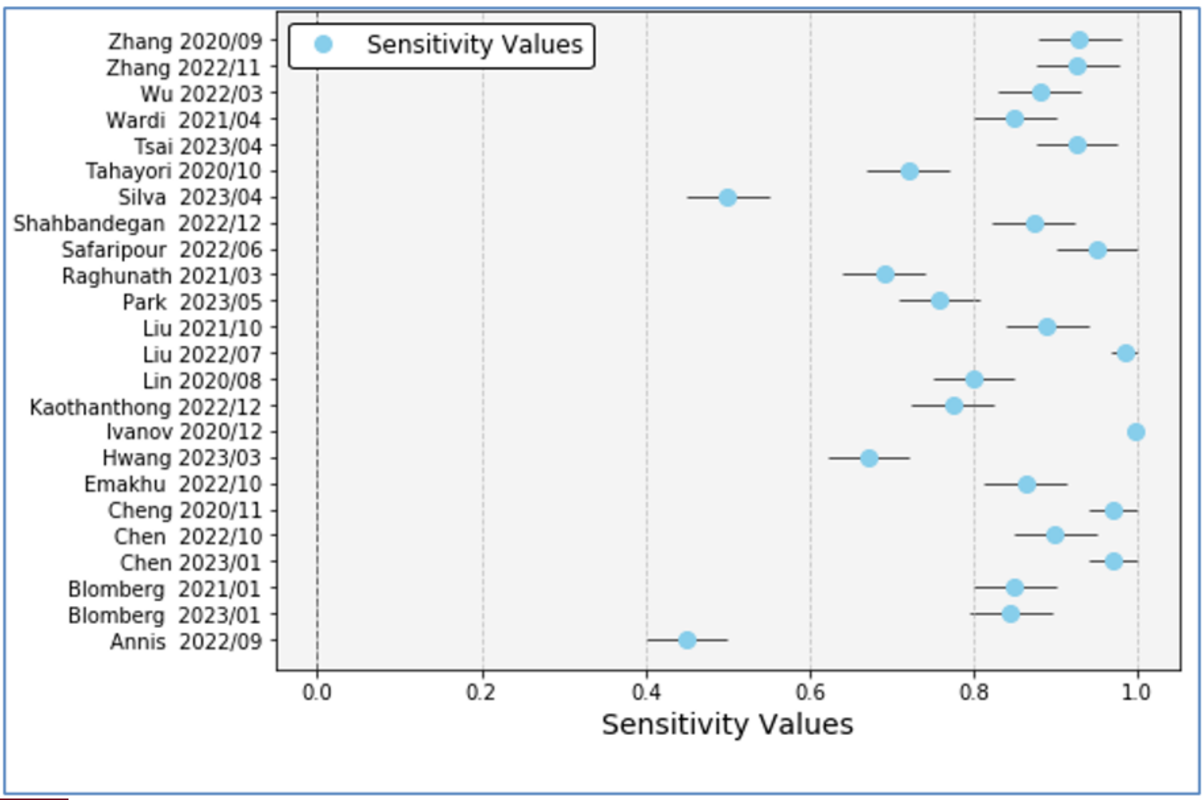

Figure 3: Forest plot for sensitivity of included studies.