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A Review of How Artificial Intelligence Could Influence the Emergency Department Workflow

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Abstract
Emergency departments play a critical role in healthcare systems, serving the initial point that patients and hospitals contact. Emergency physicians deal with emergent and life-threatening conditions in an unpredictable environment. With the growing prominence of artificial intelligence in the medical environment, understanding its potential impact on the quality of care delivered by physicians and staff is crucial to improving patient care and increasing patient satisfaction. While existing literature has explored artificial intelligence's influence on emergency department workflow from a specific point of view, this study briefly examines how artificial intelligence could transform care delivery in emergency departments from triage to patient disposition.

Keywords: Artificial Intelligence (AI), Emergency Department (ED), Emergency Room, Triage, Image Analysis, ECG Interpretation, Risk Prediction, Metrics

1. Introduction

Artificial intelligence (AI) refers to a technology that enables computers to play human cognitive functions (Kachman et al., 2024). AI uses previous data and knowledge to enhance the efficacy and accuracy of human ability and performs tasks that require human intelligence or intervention (Nagahisarchoghaei et al., 2023). AI could empower services used every day and has the potential to transform healthcare and the medical field (Jiang et al., 2017). In the healthcare setting, AI can speed up data analysis, helping practitioners identify conditions that would otherwise be overlooked and enhancing medical decision-making (Jiang et al., 2017). By leveraging AI in hospital settings, the system would become faster, smarter, and more efficient in providing patient care and could be future-transforming (Alowais et al., 2023). Embracing innovative AI approaches in emergency medicine could transform the care delivered to patients, improve patient outcomes and satisfaction, and reduce costs (Tareen et al., 2023). In the setting of ED, the utilization of generative AI has been studied in different aspects: patient triage, interpretation of medical images, managing patient flow, risk prediction, and metrics to optimize resource utilization (Kachman et al., 2024, Jiang et al. 2017, Tareen et al., 2023). Many variables could influence the efficacy of services provided in the ED. Lack of staff is one important issue. Another major element every ED deals with is overcrowding, which increases the risk of errors and gives rise to insufficient treatment, delayed diagnosis, and longer patient wait times. The lack of resources is also an essential factor influencing the quality of delivered care (Tareen et al., 2023). These variables may also affect medical team members' capacity to perform critical and life-saving procedures, so it seems to be crucial that every ED applies innovative technologies to improve patient care and augment the care providers' effectiveness. AI-powered technology has the potential to provide feasible, quicker, and more precise care (Tareen et al., 2023, Kirubarajan et al., 2020). In this review, we first introduce types of AI mainly used in the healthcare field and medicine based on their applied technology. Then, demonstrate how AI could be useful and assist the healthcare provider in the emergency field and explore the capacity of AI to empower ED care. While most previous works have assessed the utilization of AI in a specific domain, in this study, authors, aim to take a more detailed but brief look at the capability of AI to reform emergency care delivery.

2. Types of AI

AI is a collection of technologies. Some of them have higher significance to the healthcare field that will be explained here:
The most popular and primary AI technologies used in the healthcare area were rule-based expert systems (composed of sets of 'if-then' rules). Sets of rules in each field were produced by human experts and knowledge engineers. The initial aim of these technologies was to tackle complex challenges and provide a specific solution (Alowais et al., 2023). Though they are simple to comprehend, they might become unstable if there are many rules, and in the sphere of healthcare, machine learning algorithms are gradually replacing them (Shaw et al., 2019).

Machine learning (ML) is a statistical method for fitting models to data. It is characterized as supervised learning because it needs a training dataset for which the final variable, such as disease onset, is known (Nagahisarchoghaei et al., 2023). The most popular use of classic ML in the healthcare industry is the precision medicine field, which aims to determine which therapeutic regimen is likely to be effective for a specific condition based on a variety of patient characteristics and treatments (Shaw et al., 2019). Additionally, neural networks (a more sophisticated type of ML) approach problems in terms of input and connect the input to output and are commonly employed in classification tasks such as predicting a person's tendency to obtain a specific disease.

Another more advanced AI technology is called deep learning (DL), which employs multi-layer neural networks with multiple layers of variables. It is helpful and effective in predicting outcomes. Otherwise, Image analysis, illness diagnosis, and acute disease detection are common uses of DL in the healthcare scope (Alowais et al., 2023).

Natural language processing (NLP) technology can recognize speech, analyze texts, translate, and perform other language-related objectives. NLP has several uses in the medical sector, such as question answering, summarizing texts, classifying structured data, and mapping it to organized fields. Thus, it could enhance the integrity of clinical data (Jiang et al., 2017).

Other important technologies used in the healthcare area are physical robots which are trained by a predetermined task, and in recent times, they have become more cooperative with humans. Surgical robots have the potential to enhance a surgeon's visual perception, facilitate precise and minimally invasive incisions, and perform other tasks (Alowais et al., 2023).

Computer vision, a newly advanced technology, uses ML and neural networks to derive information from images, videos, and every visual input. It is applicable in healthcare systems for the purpose of medical image analysis and surveillance (Nagahisarchoghaei et al., 2023). Figure 1 summarizes the different types of AI used in the healthcare system.

Recently, the application of AI in medicine has become increasingly popular. EDs can significantly benefit from AI, as it is potentially practical across various aspects of care delivery in the ED (Kachman et al., 2024).

In Figure 2, we summarized the points that AI could influence emergency design.

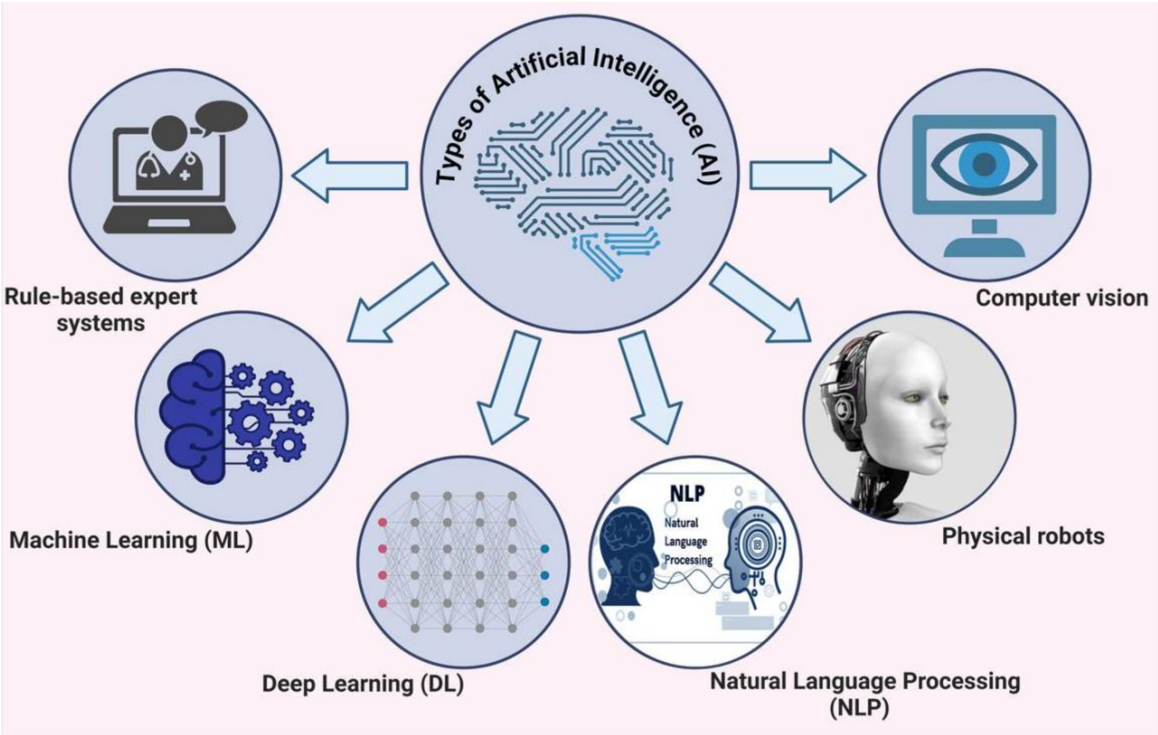

Figure 1: Different types of artificial intelligence used in healthcare system

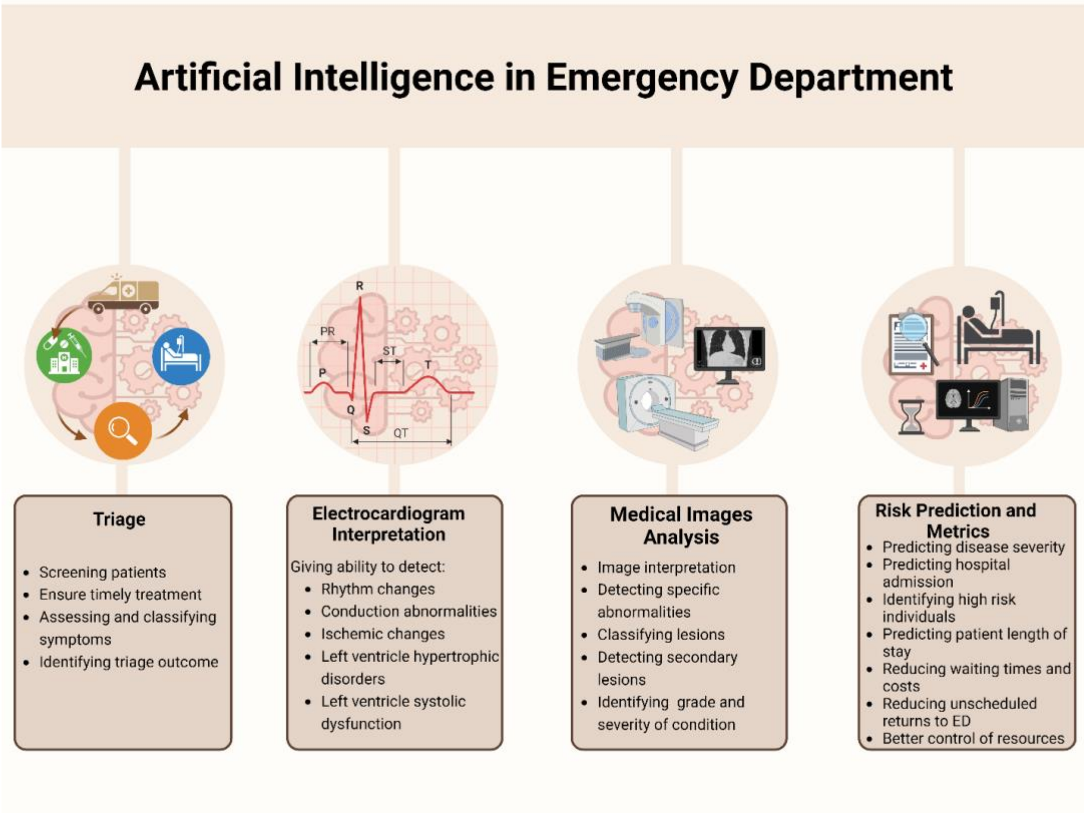

Figure 1: Spots where artificial intelligence can influence emergency departments. ED: emergency department

3. Triage

Upon arrival at the ED, patients are categorized based on their vital signs and the severity of their conditions. Various systems are in place for this categorization named triage. However, all triage systems share a common goal: to streamline time utilization while giving priority to resources. Under-triage can lead to delayed treatment and escalate morbidity and mortality, while over-triage could exacerbate overcrowding in the ED and increase resource consumption (Cameron et al., 2015). AI-based applications have shown their ability in retrospective studies to help physicians and nurses in the triage bay and provide precise support for medical triage decisions (Niederdockl et al., 2021). In most AI-based tools, the ED triage outcome is classified into two disposition classes: hospital admission or not and critical condition or not (Delshad et al., 2021). It seems that applying NLP techniques, such as recurrent and convolutional neural networks, could be probed in the future for better triage performance (Pasli et al., 2024). However, research has shown that ML improves triage capacity by screening patients efficiently and reducing errors. Advanced AI models that are based on big data would find critically ill patients for timely and best available care (Gao et al., 2022). AI-based triage tools that use ML and NLP technologies accurately assess symptoms and classify patients to identify those needing urgent treatment, thus helping care providers prioritize high-risk individuals (Zhang et al., 2021). A recent meta-analysis showed that AI technologies for patient triage demonstrate acceptable levels of accuracy and facilitate prompt and precise decision-making (Kaboudi et al., 2024).

4. Electrocardiogram (ECG) interpretation

AI has given clinicians a special diagnostic ability to interpret ECGs to detect arrhythmia, QT prolongation, ST segment and T-wave changes, and other abnormalities; the potential to translate the ECG into a unique modality that is integrated into practice workflow (Attia et al., 2021. Martinez et al., 2023). Studies have demonstrated that some algorithms can accurately identify heart rhythms and provide thorough ECG analyses; these models perform very well for various rhythm disturbances, conduction abnormalities, ischemic changes, and waveform morphology; providing a promising capability of the algorithm to predict beyond rhythm abnormalities (Kashou et al., 2020). Choi et al. (2022) demonstrated superior performance in detecting ST-elevation myocardial infarction compared to clinicians. Additionally, Attia et al. (2021) demonstrated that applying AI to the standard ECG could potentially enhance its ability to identify medical conditions that were previously undetectable using a standard ECG or to do so with exceptional accuracy. Such improvements include precise identification of heart rhythm, detection of atrial fibrillation during normal heart rhythm, identification of valvular heart disease, channelopathies, and diagnosis of hypertrophic cardiomyopathy. Therefore, a simple, non-invasive method would empower physicians with challenging differential diagnoses. Adedinsewo et al. (2020) explored that AI could enable ECG to detect patients presenting with dyspnea who have left ventricular systolic dysfunction (LVSD). Utilizing a convolutional neural network has given ECG algorithms to identify LVSD with ejection fraction< 35%, making the ECG an inexpensive, painless, rapid, and effective choice in detecting LVSD when analysed with AI. This has the potential to enhance the confidence of healthcare practitioners when evaluating differential diagnoses in the ED. Some deep neural network (DNN) algorithms for 12-lead ECG interpretation showed a high accuracy rate in the ED (Smith et al., 2019).

5. Medical Images Analysis

Imaging is widely used in EDs and plays a crucial role in diagnosing abnormalities and therapeutic plan decisions. Regarding image analyses, DL algorithms have achieved high accuracy in detecting abnormalities, classifying conditions, and providing predictions (Li et al., 2023). Multiple algorithms have been created with high-performance levels and acceptable sensitivity and specificity, making AI a promising option for future use in medical diagnosis (Yoon et al., 2021). AI tools in radiology practice have become increasingly prevalent and provide valuable assistance in the ED radiology practice (Dundamadappa et al., 2021). The most used imaging modalities in the EDs will be discussed next.

Bone X-ray: Specific fractures could be complicated for junior physicians to diagnose; the misdiagnosed fractures affect patient management and may cause serious complications. Several research studies have used DL models to analyze and classify fractures, and DL has become a cutting-edge technique for improving medical image analysis. Combined with convolutional neural networks, it can significantly reduce classification errors (Rayan et al., 2019. Reichert et al., 2021). Additionally, some fractures are subtle or challenging to diagnose; such as subtle spinal compression fractures (Oppenheimer et al., 2021), distal radius fractures (Oka et al., 2021), scaphoid fractures (Kraus et al., 2023), and ankle fractures (Kim et al., 2021); and AI models could be reasonable assistance in the diagnosis. The results of the Dupuis et al. (2022) algorithm had an accuracy of 90–93% in children's fractures, especially those above four. Additionally, Rosa et al. (2023), demonstrated that AI had a high negative predictive value in detecting pelvic fractures. Assistance of AI in trauma radiology has led to a significant decrease in false-negative findings and an increase in sensitivity by around 20%. Additionally, there has been a 0.6% increase in specificity. The time taken to interpret fractures per study has also decreased by 10–16 seconds on average, based on the Reichert et al. (2021) study.

Chest Radiographs (CXR): Interpreting CXR is difficult and demands both experience and expertise, and emergency physicians may not perform as well as experienced radiologists (Al Aseri et al., 2009). In a specific establishment, Hwang et al. (2023) evaluated the effectiveness of DL algorithms in interpreting CXR in EDs. Their results indicated that the algorithms were highly capable of classifying CXR with significant abnormalities. Although some models did not enhance the accuracy of diagnosing acute thoracic conditions in patients who arrived at the ED with acute respiratory symptoms compared to diagnosis by a radiology trainee, overall, it makes the CXR more valuable in detecting specific conditions (Nana et al., 2019). The coronavirus disease 2019 (COVID-19) pandemic led to the development of AI algorithms for detecting pneumonia in CXR, achieving accuracies of 83.5% to 98% (Laino et al., 2021). Liong-Rung et al. (2021) released an AI-based model that performed well in identifying pulmonary edema in elderly patients who presented with dyspnea. It provided critical information that could assist physicians in narrowing the differential diagnoses of the patients manifesting with dyspnea in the ED. In addition, Su et al. (2021) DL model could detect subphrenic air on CXR in cases suspected of hollow organ perforation and pneumoperitoneum.

Abdominal X-Ray: Abdominal X-ray is still used as an adjunct or optional test in the EDs. Small bowel obstruction is a serious surgical situation that can lead to tissue death and perforation. AI-based models accurately detected small bowel obstruction in abdominal radiographs (Cheng et al., 2018. Km et al., 2021). Their model had a sensitivity of 83% and a specificity of 68% in detecting bowel obstruction. Park et al. (2023) developed a DL model that detected pneumoperitoneum in both supine and upright positions, which can help evaluate patients for whom taking an upright X-ray is impossible. In a study on ileocolic intussusception in young children, Kim et al. (2019) found that the AI algorithm demonstrated higher sensitivity than the radiologists, while there was no difference in specificity.

Chest Computed Tomography (CT): CT of the chest is a cross-sectional examination of the lungs, heart, airways, mediastinum, bones, and soft tissue. Work on CT scans includes numerous models that commonly evaluate one class of abnormalities at a time, such as pneumothorax, emphysema, interstitial lung disease, and pneumonia (Kim et al., 2019. Laino et al., 2021. Liong-Sung et al., 2021. Su et al., 2021). Draelos et al. (2020) created a DL model to classify multiple abnormalities; they trained the model to recognize nine labels: nodule, opacity, atelectasis, pleural effusion, consolidation, mass, pericardial effusion, cardiomegaly, and pneumothorax with excellent performance. Laino et al. 's research (2021) demonstrated the benefits of AI in different domains in the case of COVID-19 infection, including identification, screening, and risk stratification of cases. Additionally, the Rueckel et al. model (2021) streamed data for multiple trauma patients, which reduced missed secondary thoracic findings. Computed tomography pulmonary angiogram (CTPA) is the preferred diagnostic method for detecting pulmonary embolism (PE). AI algorithms have been created to identify PE on CTPA images. Ma et al. two-step DL system (2022) effectively recognized severe and life-threatening PE cases, particularly those that were central and acute. It also helped in ruling out PE and had the potential to demonstrate different subtypes of existing PE. Kligerman et al. (2018) and Soffer et al. (2021) review demonstrated that AI-based technology has 88% sensitivity and 86% specificity for diagnosing PE on CTPA images.

Abdominopelvic CT: Singh et al. (2020) created a DL algorithm with reconstruction capabilities that demonstrated better performance in terms of image quality and detection of clinically important abnormalities in chest and abdominopelvic CT scans compared to iterative reconstruction methods. Katzman et al. algorithms (2023) offered similar image quality and diagnostic confidence when assessing abdominal and pelvic CT scans for female pelvic conditions. Prod'homme et al. (2024) demonstrated that DL models effectively detected urolithiasis, providing better image quality than iterative reconstruction and requiring less radiation. The Vanderbecq et al. model (2024) showed great potential in detecting obstruction, which evaluated bowel obstruction by CT.

Brain CT Scan: Prevedello et al. model (2017) utilized AI to detect important findings on head CT scans automatically, and scans were initially interpreted and categorized as either having potential positive (e.g., hemorrhage, stroke, hydrocephalus) or negative findings. Recently, Li et al. (2024) developed a deep learning model that effectively diagnoses intracerebral hemorrhage (ICH) in brain CT scans. Their results demonstrated both effectiveness and robustness in ICH detection. However, according to Kundisch's research (2021), AI often fails to detect some cases of ICH located in the subarachnoid space and under the calvaria. Buchlak et al. (2024) showed the ability of a comprehensive AI-based model to assist radiologists in detecting a variety of abnormalities on non-contrast CT images.

Ultrasound Imaging: Research specifically addressing the combined application of point-of-care ultrasound (POCUS) and AI is limited. However, AI has demonstrated its effectiveness in evaluating the inferior vena cava during POCUS assessments (Blaivas et al., 2020). Motazedian et al. (2023) found that AI-assisted POCUS has more than 92% sensitivity and specificity in detecting abnormal left ventricle ejection fraction. The accuracy of lung ultrasound was investigated by Lehmann et al. (2022) and was acceptable, and Abdel-basset et al. (2022) demonstrated the efficacy of lung US for diagnosing COVID-19 pneumonia. According to Nhat et al. (2023), applying AI assistance to lung ultrasound significantly enhanced the performance of beginners. Kim et al. (2024) reviewed the accuracy of AI in POCUS and demonstrated that the use of AI is practical and feasible overall.

6. Risk Prediction and Metrics

Arrivals to the ED show some variations and usually peak at predictable times; there are usually some mismatches with workflows in other parts of the hospital. Otherwise, crowded EDs are a global issue that could lead to delays in providing medical care and worsen patient outcomes. It is essential to assess and prioritize patients promptly. Hu et al. (2023) developed a model to predict ED volume that could be used to enhance patient care. Patel and colleagues' model (2022) used triage notes and electronic health records (EHR) to foresee hospital admissions from the ED. Establishing this predictive model, they incorporated ED-specific data like patient demographics, vital signs, ESI triage level, triage notes, and laboratory information. Their work demonstrated the effectiveness of ML in anticipating hospital admissions originating from the ED. Raita et al. (2019) employed ML models to forecast patient outcomes and contrasted their accuracy with the Emergency Severity Index (ESI) system. The model displayed better accuracy in predicting critical care and hospitalization results and additionally exhibited a greater sensitivity for critical care outcomes, leading to higher specificity for hospitalization results. Lee et al. (2022) developed an AI model to determine the need for urgent hospitalization for patients, that utilized a small set of factors to predict which patients would require hospitalization, enabling timely care or quick discharge. However, the model's predictive ability varied across different patient groups, such as nontraumatic adults, pediatrics, trauma, and environmental emergencies. In addition, hospital admission prediction in the Cusido et al. model (2022), which used an extensive database of emergency registered patients, demonstrated excellent predictive performance. During COVID-19, the Arnaud et al. model (2022) effectively categorized the patients who had presented in the ED with COVID-19 infection. It showed the capability of AI models for better resources management during pandemics by predicting whether patients are likely to be discharged or admitted. ML-driven models have demonstrated great potential in predicting the severity of diseases. Sepsis is the leading cause of death in hospitals globally, and early prediction of the mortality rate can assist physicians in providing timely care. Park et al. (2024) developed a model for predicting mortality in sepsis patients, demonstrating excellent predictive performance. ML-based prediction models have also shown their potential in trauma patients. Tu et al. (2022) ML-based algorithm predicted the outcome and mortality of TBI patients. The model provided early and quick mortality prediction, which could guide physicians in better patient management.

While waiting times influence patient satisfaction in EDs, Pak et al. (2021) streamed a model that could predict waiting times in patients with minor medical concerns. Such information and taking actions to reduce waiting times impact the experience and anxiety levels of patients and may also lead to fewer patients leaving without

receiving medical attention. Bin et al. study (2022), during the COVID-19 pandemic, used AI technology to reduce the time required for medical care registration, health screening, and waiting for care. It improved the waiting time by about 12 minutes.
Regarding trauma patients' length of stay in the ED, Stonko et al. (2023) developed a model that could predict the length of stay with great specificity. It used only the data that were available at the patient admission. Another aspect of the quality of care is unexpected ED returns, and ML models could assist in identifying high-risk patients to minimize errors and save time and costs (Lee et al. 2024). Providing a comprehensive overview of patient volume, symptom severity, and patient outcomes and reducing wasted time is a significant step forward in successful ED management, and AI can be very helpful in this regard.

6. Challenges and Limitations

Despite AI's promising role in improving care delivered in the EDs, some ethical concerns should be addressed. First, AI may exhibit bias in the decision-making process, sometimes providing inaccurate results, which could lead to incorrect patient management (Li et al., 2023). In addition, there is a lack of transparency regarding how AI arrives at conclusions, which makes it difficult to trust (Li et al., 2023. Chenais et al., 2023). Data privacy during the analysis process is a concern that should be addressed (Li et al., 2023). Most studies of AI Applications in the medical field and ED are retrospective data set analyses that need validation in clinical trials (Kirubarajan et al., 2020). Regarding diagnostic image interpretation, there are concerns as model performance may vary when it comes to specific subtypes (Seyam et al., 2022). For predictive purposes, the range of algorithms used is limited and needs to be addressed in future works (Kinoshita et al., 2022). Issues regarding the accuracy and practicality of some predictive models should be marked to use these models with greater confidence (Lee et al., 2024). Finally, it's crucial to consider how AI will integrate and be adopted into existing systems, as well as the potential challenges healthcare providers may face when using AI-based tools (Challen et al., 2019).

7. Conclusion

AI is expected to be used in more medical applications, such as ED care. It would support doctors and staff as they provide care in the ED. AI can predict ED arrivals so managers can modulate their resources according to demands. AI tools can assist in triage and guide patients to the appropriate setting using AI-driven symptom-checking systems. AI aids in interpreting medical images and reduces time spent on medical image interpretation. Some subtle and second findings could be discovered by AI, reducing the risk of missed diagnosis and missed management. AI algorithms can be helpful in resource-limited EDs and in settings that do not have around-the-clock radiology coverage. Healthcare professionals can benefit from the integration of AI in various aspects of clinical decision-making. AI can assist in predicting patient outcomes, identifying clinical deterioration, assessing the likelihood of hospital admissions, estimating the duration of a patient's length of stay in the ED, and predicting ED return. The information from resource allocation allows managers to convert hospital wards into dedicated units based on the predicted bed demand. Overall, AI assistance has the potential to improve the quality of care and enhance patient safety and satisfaction significantly.

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