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REVIEW ARTICLE

Current Applications, Challenges, and Future Directions of Artificial Intelligence in Emergency Medicine: A Narrative Review

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Abstract: Artificial intelligence (AI) systems have witnessed notable advancements, revolutionizing various fields of research and medicine. Specifically, advancements of AI and the rapid growth of machine learning hold immense potential to significantly impact emergency medicine. This narrative review aimed to summarize AI applications in prehospital emergency care, emergency radiology, triage and patient classification, emergency diagnosis and interventions, pediatric emergency care, trauma care, outcome prediction, as well as the legal and ethical challenges and limitations of AI use in emergency medicine.

A comprehensive literature search was conducted in Web of Science, Scopus, and Medline using a wide range of artificial intelligence and machine learning-related keywords combined with terms related to emergency medicine to identify relevant published studies. The findings show that AI-powered tools can assist clinicians in emergency departments in improving the management of prehospital emergency care, emergency radiology, triage, emergency department workflow, complex diagnoses, treatment, clinical decision-making, pediatric emergency care, trauma care, and the prediction of admissions, discharges, complications, and outcomes. However, the majority of these applications have been reported in retrospective studies, whereas randomized controlled trials (RCTs) are essential to determine the true value of AI in emergency settings. These applications can serve as effective tools in emergency departments when they are continuously supplied with high-quality real-time data and are adopted through collaboration between skilled data scientists and clinicians. Implementing these AI-assisted tools in emergency departments requires adequate infrastructure and machine learning operation systems.

Since emergency medicine involves various clinical decision-making scenarios based on classifications, flowcharts, and well-structured approaches, future well-designed prospective studies are necessary to achieve the goal of replacing conventional methods with new AI and machine learning techniques.

Keywords: Artificial Intelligence; Data Science; Deep Learning; Emergency Medicine; Machine Learning; Prediction Algorithms; Technology

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1. Introduction

Artificial intelligence (AI) technologies have witnessed considerable advancements, revolutionizing various fields of research and medicine. Specifically, advancements of AI and the rapid growth of machine learning hold immense potential to significantly impact emergency medicine (1-6). Optimizing resource utilization, improving medical diagnosis, enhancing therapeutic interventions and patient outcomes, and supporting clinical decision-making are some of the key advantages of AI applications in emergency medicine. The emergence of big data in the field of emergency medicine also emphasizes the necessity of using AI applications and computational methods in machine learning to effectively leverage these vast datasets for improving healthcare delivery (7). Since emergency medicine involves various clinical decision-making scenarios related to classifications, flowcharts, and well-structured approaches, these conventional methods can be replaced with new AI and machine learning techniques (8, 9). Autonomous data processing, analysis, and prediction development based on associations between variables in large databases are some applications of AI in emergency medicine. Moreover, most conventional models are relatively simple, whereas AI models can identify complex data patterns and reduce the risk of missing information (10). Personalized and precision medicine can be more effectively achieved using AI methods, as they can provide more accurate diagnoses and finely categorized patient groups through big data processing. Triage optimization, risk stratification, patient categorization, prediction of patient outcomes, real-time monitoring of patient status, automated documentation of patient data, and interpretation of medical data and images using deep learning algorithms are emerging potentials of AI in emergency medicine (11-15). Overcrowding due to limited resources, high patient volumes, and the lengthy decision-making process can lead to medical errors, physician fatigue, and cognitive biases. AI applications, by improving the triage system and enhancing clinical decision-making, can help mitigate human limitations and reduce overcrowding in emergency departments (15). However, the development and application of AI tools in this field require a substantial amount of machine-readable data, as well as the collaboration, expertise, and willingness of emergency medicine specialists and physicians as end users to integrate this data. These requirements may slow down the adoption of AI methods in various areas of emergency medicine (8). The lack of evidence and the limited body of peer-reviewed studies on the impact of AI applications on patient safety, along with ethical challenges and the difficulties emergency medicine specialists face in understanding AI tools and interventions due to the interdisciplinary nature of AI methods, have hindered the development and implementation of AI in emergency medicine (16). This comprehensive narrative review aims to explore the current landscape

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of artificial intelligence applications in emergency medicine, including its use in prehospital care, emergency radiology, triage systems, diagnosis and interventions, pediatric and trauma care, and outcome prediction, while also critically examining the associated ethical and legal challenges. By synthesizing existing evidence, we aim to highlight current capabilities, identify gaps in knowledge, and inform future research and clinical integration.

2. Methods

A comprehensive search using “artificial intelligen*”, “machine learn*”, “deep learn*”, “convolutional neural network*”, “supervised learning”, “semi-supervised learning”, “unsupervised learning”, “reinforcement learning”, “transfer learning”, “random forest”, “support vector machine”, “autonomous robots”, “image processing”, “Language Model”, “principal component analysis”, “decision tree”, “k-nearest neighbor”, and “random-forest” in combination with “emergency medicine” and similar keywords were performed to retrieve pertinent published papers. The search was carried out in electronic databases such as Web of Science, Scopus, and Medline.

3. AI in Prehospital Emergency Care

Prompt clinical decision-making using dynamic and limited patient data is a pivotal aspect of prehospital emergency care. Various guidelines, such as those provided by the American College of Surgeons, are available for the field triage of patients in prehospital settings (17). Despite significant advancements in prehospital patient management, traumatic injury remains a major cause of death worldwide and the leading cause of death in the United States, highlighting the critical role of prehospital emergency care (18). However, evidence regarding the application of AI and machine learning in managing acute injuries in prehospital settings remains scarce. Furthermore, collaboration between various fields, including emergency medicine departments, disaster management centers, transportation control, and critical care, is essential for effective prehospital emergency care. AI technologies may, in part, facilitate and enhance these collaborative efforts (19).

Rapid and safe transportation of critical patients to emergency departments can enhance the chances of providing timely and appropriate medical interventions, ultimately improving patient outcomes (20, 21). On the other hand, delays in emergency patient transport are associated with increased complications, morbidity, and mortality (22, 23). In addition to ensuring the secure transport of patients, transferring critical data such as symptoms, clinical manifestations, level of consciousness, vital signs, prehospital interventions, and results of other clinical evaluations to emergency specialists can accelerate clinical decision-making and allow for better preparation to address patients’ specific medical needs (24, 25).

A novel platform was designed by Kim et al. (26) titled CONnected Network for EMS Comprehensive Technical-Support using Artificial Intelligence (CONNECT-AI), aimed at optimizing patient transport and facilitating the transfer of prehospital data to medical emergency centers. This platform collects real-time patient data, receives information on the capacities of medical centers, and suggests the most efficient patient transport to an appropriate facility. Clinical trials using the platform demonstrated a significant reduction in mortality rates; however, further studies are needed to evaluate its efficacy in different regions.

Using AI large language models for prehospital patient management can provide access to clinical information and evidence-based guidelines (27). These applications for emergency conditions require prior immersive training simulations with large datasets. Nevertheless, as with other AI applications, clinicians should always be aware of AI "hallucinations," which can generate incorrect or inaccurate responses (28).

4. AI Applications in Emergency Radiology

Acute management of patients in emergency departments commonly requires rapid evaluations, emergency diagnostic imaging, and accurate interpretation. Along with advancements in emergency imaging technologies, more accurate diagnoses based on these imaging reports in urgent situations are increasingly demanded. These expectations from emergency radiologists place a larger burden on them, increasing the need for AI methods to assist radiologists. Many fields of healthcare are being transformed by AI technologies, and emergency radiology also has the potential to be significantly improved by AI (29, 30). Providing a well-structured imaging report, supervised or automatic identification of anomalies, interpretation of radiologic images, reconstruction of images, the imaging process, patient positioning, and selecting the most appropriate imaging modality for each case are some aspects where AI can be used in emergency departments (31).

Deep learning is a field of AI that enables many applications in emergency radiology. Neural networks and learning capabilities similar to human cognition form the core of deep learning. Large datasets of labeled data are required to develop deep learning algorithms (32, 33). The need for cooperation from emergency radiology specialists, along with the requirement for large sets of well-labeled data, has resulted in a paucity of studies investigating deep learning methods in emergency radiology. Copious examples of deep learning applications assisting emergency radiologists and physicians have been reported in the literature, but further studies are needed to establish these applications as a promising tool for accurate diagnosis (32, 34).

AI and deep learning applications are mostly used for the interpretation of radiologic images and diagnosis in emergency radiology. The increased use of AI for diagnosis and interpretation is driven by the complexity of some diagnoses, the need for rapid reporting, and the growing volume of imaging that emergency radiologists encounter (35). The process of developing deep learning models has led to the creation of algorithms, each of which is typically designed for detecting a specific pathology. As discussed in previous sections, developing AI models requires large datasets, and chest radiography, being one of the most commonly ordered imaging modalities, is a well-suited candidate for deep learning model development (35).

In a study comparing the diagnostic performance of radiology residents with an AI algorithm for interpreting chest radiographs, results showed that the AI model could even outperform the residents in some cases (36). Notably, the study reported no significant difference between the AI model and radiology residents in terms of sensitivity for interpreting chest radiographs. However, the specificity of the AI algorithm was superior to that of the radiology residents.

AI algorithms can also be used for other imaging modalities. It is well known that computed tomography (CT) evaluation provides more data to achieve a more accurate diagnosis compared to abdominal radiography. In a study by Winkel et al. (37), important findings from abdominal CT scans were extracted using AI-based software. Fat stranding, free fluid, and free gas were the main findings that this software could identify from CT scans. Finally, the results of this study revealed that the software had a specificity of 97% and a sensitivity of 93% for diagnosing patients with the chief complaint of abdominal pain.

5. AI for Emergency Triage

It has been reported that each year, approximately 131 million visits are made to hospital emergency departments, resulting in around 19 million hospital admissions (38). The number of these visits has been increasing due to a decrease in the number of downstream beds, patient revisits, and a rise in non-emergent visits. The burden of this overload can impact complications, length of hospitalization, morbidity, and mortality, as well as cause stress for healthcare providers (39). Various solutions emphasizing the improvement of patient workflow, such as increasing physician practice hours, adding healthcare providers and more beds in emergency departments, preventing visits for cases that do not require clinical intervention, and enabling earlier physician evaluation, have been proposed to reduce the negative outcomes of patient overload in emergency departments (40). However, these solutions have not adequately reduced patient volume, and since they do not focus on appropriate triage, they have failed to improve patient outcomes (39).

Rapid analysis of large volumes of patient data for accurate clinical decision-making and improvement of triage through the quick assessment of signs, symptoms, physical evaluation results, medical history, and risk factors are novel advancements that can be achieved using AI-powered triage tools (40, 41). Improved patient outcomes and the triage process were reported in several studies investigating AI-powered tools to standardize triage flow and assist triage staff. For example, an AI tool named ML-based remote triage was used to receive and transfer patient information to hospitals through telemedicine servers and categorize patients in the triage process of the emergency department (42). In another study by Gao et al. (43), an extreme gradient boosting machine learning model was used as a triage model. They found a specificity of 78.9% and a sensitivity of 83.6%, with an accuracy of 80.2% for this machine learning-based triage model, which could improve the allocation of medical resources, enhance treatment efficiency, and reduce the workload of healthcare providers.

Overall, the digitalization of emergency departments using next-generation computers can enable the implementation of algorithm-based triage and the integration of AI in emergency care (44).

6. AI in Emergency Department Management

There are considerable challenges in estimating future medical service requirements in emergency departments due to wide variations in patient admission status, required diagnostic evaluations and medical interventions, and the duration of diagnostic tests and treatments. AI and machine learning models have the capacity to manage emergency departments and serve as hospital leaders in improving patient workflow from arrival to discharge. Using AI-powered tools for emergency department management can also be cost-effective, as they help better match resources to patient needs, improve outcomes, and reduce costs (45).

Patient overload resulting from disasters and surge events can be predicted by AI models, allowing for better staffing planning and preparation for future medical requirements. Machine learning models also have the potential to predict wait times in emergency departments and suggest the best choices for patients based on their condition and travel distance (27). However, not all AI models may gain the trust of healthcare managers and clinicians. In the field of emergency medicine, radiology and triage are likely to be the fastest areas for the adoption and integration of AI tools (45). Nevertheless, the goal of real-time bed availability can be achieved by an AI-powered digital hospital, which continuously collects and processes data on admitted and discharged patients to estimate bed availability rates for each emergency department (46). A digital emergency department utilizes both traditional factors as well as epidemiological and environmental data to ensure appropriate patient referrals, reduce wait times, decrease unnecessary hospitalizations, and facilitate the transfer of patients to downstream service beds (47, 48). Furthermore, emergency departments within a region or state can establish a network to better manage patient admissions by improving real-time visibility of bed availability and the capacity to provide specialized care. This AI-powered emergency department management can lead to more efficient resource allocation and dynamic adaptation to emergency situations (39).

7. AI for Diagnostic Support in Emergency Settings

A major challenge in emergency departments is diagnostic errors, which can increase morbidity, mortality, patient safety risks, and healthcare costs. Among healthcare settings, the emergency department is one of the most demanding sections for accurate diagnosis. A formidable challenge for emergency clinicians is making numerous decisions in the chaotic environment of the emergency department and under intense time constraints while treating a diverse range of patients (49-51). They must monitor the condition of critical patients while also managing circadian rhythm disruptions, which further complicate accurate diagnosis (52, 53). The high workload, fatigue, and cognitive biases collectively contribute to the risk of diagnostic errors in emergency departments. Previous solutions, such as decision training, education, decision support systems, and debiasing strategies, have shown varying degrees of success (54, 55).

Cognitive biases and diagnostic errors can be reduced using AI-assisted clinical decision-making systems that are information-based. These AI-powered tools are highly dependent on data, so their efficacy is influenced by the accuracy, format, and timing of input data. They require continuous adaptation and reevaluation to prevent unintended biases and ensure fairness (56-59). A more comprehensive list of differential diagnoses based on a patient's data can be automatically generated by AI-powered clinical decision-making tools and large language models. Availability and anchoring biases can be minimized by suggesting a broader range of differential diagnoses and highlighting alternative possibilities (60, 61).

The applications of AI-powered clinical decision-making tools are not limited to extending the list of differential diagnoses; they can also provide assessment, evaluation, and uncertainty estimation for emergency clinicians. Better judgment of differential diagnoses based on their probability scores can be achieved through the accurate calibration of AI tools before implementation (62). Studies have shown that large language models, even without complex training, can be well-calibrated after a simple initial training phase to suggest appropriate recommendations for clinicians (63, 64). Moreover, explainable AI, which provides understandable explanations for its suggested decisions, can serve as a more trusted tool for clinical decision-making and diagnosis in emergency departments (65, 66).

8. AI-Assisted Emergency Treatments

Various interventions, such as robotic and laparoscopic surgeries, are currently performed using controlled robotic systems. The ultimate goal of robotic surgery is to achieve fully autonomous interventions using AI-powered instruments. While most of these procedures are currently performed under human supervision, future advancements may enable AI-driven surgical robots to operate independently (67-69). Studies have suggested that robotic systems could potentially reduce errors, shorten intervention times, and enhance performance and consistency compared to human surgeons (70). Assisting in and managing complex surgeries by reconstructing CT images using AI techniques is another important aspect of AI's role in medical interventions (71).

AI tools can be used to predict outcomes and complications following medical interventions. A machine learning AI tool named POTTER was used by Bertsimas et al. (72) to predict surgical site infections, morbidity, mortality, and other post-operative complications. This AI model outperformed linear regression, as it was better suited to capturing the nonlinear patterns in data for complication prediction. Since the model demonstrated moderate to high accuracy for most complications, the authors suggested that it could be used as a decision-support tool alongside surgeons to identify potential post-operative complications for patients.

Another AI-powered predictor was developed by Bihorac et al. (73) to classify patients as low-risk or high-risk for post-intervention complications based on patient characteristics, complication rates, and prior surgical cases from a dataset of 51,457 emergency and major elective surgeries. Similar to the previous study, this AI model could predict complications and provide both relative and absolute risk scores. Despite numerous studies on the use of AI for preoperative diagnosis and the prediction of postoperative outcomes, the number of randomized controlled trials (RCTs) evaluating their practical efficacy in medical interventions remains limited (74). Moreover, the majority of studies on the application of AI in emergency medicine are retrospective, whereas RCTs are essential to determine the true value of AI. However, implementing AI models in emergency surgeries faces several barriers. These challenges arise from the time-consuming processes of randomization and obtaining consent, identifying eligible cases, and the overall urgent nature of interventions in emergency departments (75).

9. AI in Pediatric Emergency Medicine

A large proportion of AI applications in the field of pediatric emergency medicine are related to clinical decision-making, the prediction of overcrowding, the prognosis of critical cases, revisits, and early warning systems for pediatric patients (8, 76-79). Currently, clinical settings provide only limited improvements in outcomes from these applications, and their real-world use is hindered by significant challenges (80). Pediatric care is negatively affected by overcrowding, which is one of the most critical issues in emergency departments. This overcrowding results from the admission of a wide variety of cases, including high-risk patients (81, 82).

Telephone triage, fast-track processes, and telemedicine are some strategies used to overcome overcrowding in pediatric emergency departments. The National ED Overcrowding

Scale (NEDOCS), Emergency Department Work Index (EDWIN), Skåne Emergency Department Assessment of Patient Load (SEAL), and International Crowding Measure in Emergency Departments (ICMED) are tools designed to predict and manage overcrowding in emergency departments, each with varying levels of effectiveness. However, the main weakness of these tools is that they primarily predict overcrowding after it has already occurred (83-86).

Neural Basis Expansion Analysis (N-BEATS), Neural High-Order Time Series (N-HiTS), Time-Series Dense Encoder and Reversible Instance Normalization (TiDE RIN), and Temporal Convolutional Network (TCN) are recognized as advanced deep learning algorithms (79). Decomposing time-series data, modeling multi-scale patterns, using temporal interactions, and modeling long sequences are strengths of these models, respectively. However, these models require continuous data input to remain adaptable and accurate across different conditions. This highlights their potential for ongoing development and real-time prediction of time-series events in pediatric emergency departments (79).

Distress and pain in pediatric patients undergoing needle-related interventions are common concerns in pediatric emergency departments. Failure to manage distress during these procedures can lead to adverse outcomes such as delays in care, needle phobia, intervention failure, and healthcare avoidance (87-89). Socially assistive robotics (SAR), a novel technology designed to assist humans through interactive communication, has the potential to create a more immersive and comforting environment in pediatric emergency departments, thereby reducing distress and pain associated with medical interventions (90, 91).

10. AI in Trauma Care

Various emergency scenarios can be rapidly predicted using AI technologies that incorporate multiple factors. Several investigations have been conducted to assess the efficacy of AI models in predicting outcomes for patients with fractures, osteoarthritis, and other orthopedic conditions (92, 93). Trauma is a leading cause of morbidity and mortality, responsible for over 5 million deaths annually worldwide (94). However, evidence on the use of AI in the field of trauma remains limited, and only a few studies have explored the application of AI in clinical decision-making for severe trauma and polytrauma cases (95).

A systematic review was conducted to evaluate the application of AI models in guiding treatment decisions for severe trauma and polytrauma (95). Eight eligible studies were included in this review, six of which demonstrated good performance in supporting clinical decision-making. Overall, the promising performance of AI models in predicting outcomes and assisting decisions for polytrauma patients highlights their potential. Their study can serve as a foundation for future research aimed at expanding the applications of AI-powered tools in the management of trauma patients.

Improving outcomes for trauma patients through AI technologies can have a significant impact on global public health, as trauma is a leading cause of death in individuals under 40 years of age and contributes to a substantial loss of active life years worldwide (96). Moreover, the vast amount of trauma-related data and electronic health records can be leveraged to train and validate AI models for the effective management of trauma patients (97).

It has been proposed that AI technologies can also be implemented before an injury occurs to predict the time of occurrence using factors such as weather conditions, vehicle features, time of day, and date. However, the adaptability and accuracy of these AI models have not yet been established due to the complexity of the models and the challenges of using real-time data for the influencing factors (98, 99).

11. AI for Prognosis and Predictive Analytics in Emergencies

Negative outcomes can be predicted and also prevented by appropriate interventions in emergency departments. A well-known example of these events is neurological sequelae following cardiac arrest and trauma (100-102). These predictive strategies are effective during the resuscitation process and affect the interventions and approaches of emergency health care providers (103). The prediction of patient admissions to the intensive care unit (ICU) or emergency department, as well as discharge predictions, can also be performed using AI models (104).

The prediction of urgent care needs for critical patients can be performed based on patients' input data and its analysis by AI models. For example, LightGBM uses imaging data, blood pressure, and shock index to predict the need for critical interventions (105). Other predictive applications of AI-powered tools were discussed in previous sections.

12. Ethical and Legal Challenges of AI in Emergency Medicine

Challenges in using AI in emergency departments include human and technological limitations in implementing AI systems, scarcity of effective tools, lack of supporting evidence from RCTs, complex stakeholder relationships, and inadequate infrastructure. A large proportion of proposed AI tools have been evaluated locally and have not demonstrated widespread adoption or consistent clinical outcomes (66). Insufficient infrastructure and the lack of machine learning operational systems in many emergency departments hinder the implementation of AI tools for triage, diagnosis, imaging, decision-making, trauma management, treatment, and overall emergency department operations. Few emergency departments have sufficient resources to provide high-quality labeled data, access real-time data, or recruit skilled data scientists to develop and maintain AI models. Additionally, cultural barriers in some institutions may limit the integration of AI tools into the emergency department workflow (106).

Exaggerated trust or distrust in AI tools in emergency departments is another barrier to their implementation and development. Complete trust and dependence on AI tools may lead to overlooking clues for other differential diagnoses and anchoring bias toward the diagnoses suggested by the AI. Conversely, distrust in AI-powered tools due to concerns about large language model hallucinations can hinder their adoption and performance improvement(66, 107, 108). Negative experiences reported by other clinicians regarding the use of AI tools can also impact the implementation of new AI technologies within an institution (109).

Incomplete utilization of pathological, physiological, radiological, and anatomical data by AI tools is another barrier to replacing physicians with AI technologies (110). Moreover, significant inconsistency in input data leads to variability in the outputs generated by AI tools. These limitations can undermine the trust of both clinicians and patients in AI systems. In pediatric departments, this lack of trust may be particularly pronounced among parents, stemming from concerns about accuracy, quality, convenience, social justice, the human element of care, shared clinical decision-making, and privacy (111). Specifically, the relationship between clinicians and parents can be seriously affected by the opaque nature of AI decision-making processes (112).

13. Conclusions

Our review showed that AI-powered tools can assist clinicians in emergency departments in improving the management of prehospital emergency care, emergency radiology, triage, emergency department workflow, complex diagnoses, treatment, clinical decision-making, pediatric emergency care, trauma care, and the prediction of admissions, discharges, complications, and outcomes. However, the majority of these applications have been reported in retrospective studies, whereas randomized controlled trials (RCTs) are essential to determine the true value of AI in emergency settings. These applications can serve as effective tools in emergency departments when they are continuously supplied with high-quality real-time data and are adopted through collaboration between skilled data scientists and clinicians. Exaggerated trust or distrust in AI tools in emergency departments should be considered a critical barrier to their implementation and development. Implementing these AI-assisted tools in emergency departments requires adequate infrastructure and machine learning operation systems. Since emergency medicine involves various clinical decision-making scenarios based on classifications, flowcharts, and well-structured approaches, future well-designed prospective studies are necessary to achieve the goal of replacing conventional methods with new AI and machine learning techniques.

To achieve the acceptable integration of AI in emergency medicine, future investigations should focus on standardizing methodologies across studies. This includes the consistent and harmonized use of validated datasets, appropriate performance metrics, and transparent reporting standards to facilitate reproducibility and generalizability. Multicenter studies using real-world clinical data are urgently required to ensure model generalizability across diverse populations and conditions. Furthermore, standardized study designs such as prospective and external validations, and impact evaluations are essential for translating AI tools into clinical practice. Collaborative frameworks between physicians, data scientists, and policymakers should also be established to develop recommendations that ensure ethical, equitable, and safe usage of AI systems in emergency medicine.

14. Declarations

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None.

14.2. Authors' Contributions

All authors contributed to study design, data collection, and writing the draft of the study. All authors read and approved final version of manuscript.

14.3. Funding/Support

None.

14.4. Conflict of interest

None.

14.5. Data Availability

Not applicable.

14.6. Using Artificial Intelligence Chatbots

We utilized AI-powered tools to check grammar and enhance the academic quality of the text, which was primarily written by the authors.

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