AI-Driven Emergency Patient Flow Optimization is Both an Unmissable Opportunity and a Risk of Systematizing Health Disparities

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Abstract

There is a burgeoning interest in harnessing artificial intelligence (AI) to enhance patient flow within emergency departments (EDs). However, this advancement is accompanied by a significant risk: by relying on historical healthcare data, these AI tools may perpetuate existing systemic biases associated with gender, age, ethnicity, and socioeconomic status. This paper surveys studies identifying biases in ED data, offering context for concern about these biases. These insights are valuable for researchers developing AI to optimize ED workflows while accounting for ethical considerations.

Introduction

Improving patient flow in emergency departments (EDs) is crucial for reducing crowding and enhancing care quality. Factors influencing patient flow include department layout, staffing levels, waiting times, investigation turnaround times, disposition decision delays, exit block, limited inpatient bed availability, and fluctuations in patient demand (Ortiz-Barrios and Alfaro-Saiz 2020). There is a growing interest in utilizing artificial intelligence (AI) to enhance ED operations (Mueller et al. 2022; Taylor et al. 2022; Piliuk and Tomforde 2023; Emami and Javanmardi 2023; Maninchedda et al. 2023). However, integrating AI raises ethical and legal concerns (van der Stigchel et al. 2023). Another crucial consideration is the potential impact of biases in data and AI methodologies on perpetuating sociodemographic disparities in patient care. Biases in ED decision-making remain indeed problematic (Morisod et al. 2021).

We introduce AI-driven patient flow optimization with examples of recent advancements. Because AI models may inherit biases from their training data, potentially exacerbating health disparities, we survey studies on biases in ED across stages of the process and discuss potential consequences.

AI-Driven Patient Flow Optimization in ED

AI-driven methods, alongside computer modeling and simulation tools, have been applied across various aspects of prehospital settings, emergency medical dispatch, and patient flow management (Arnaud et al. 2022; Alenany and Ait El Cadi 2020; El-Bouri et al. 2021; Wang et al. 2021; Terning, Brun, and El-Thalji 2022; Shokouh, Mohammadi, and Yaghoubi 2022; Boonstra and Laven 2022; Rismanchian et al. 2023). Promising results in forecasting next-day ED patient arrivals have been observed (Tuominen et al. 2022).

In mental health, AI ranges from administrative task automation to real-time data analytics supporting clinical decisions (Dawoodbhoy et al. 2021). In radiology departments, a multi-model approach to forecasting emergency patient flow demonstrates the efficacy of diverse models (Zhang et al. 2020b). Additionally, AI's broader role in healthcare, like predicting ED patient inflow, aids in early admissions and resource optimization (Zhou et al. 2023; Kishore et al. 2023). Integration of genetic algorithms with deep neural networks emphasizes advanced feature selection and model accuracy in forecasting (Harrou et al. 2020).

AI-driven tools also assist in emergency triage, prioritizing patients based on medical urgency to ensure timely and effective care allocation (Vantu, Vasilescu, and Baicoianu 2023; Defilippo et al. 2023; Mutegeki et al. 2023; Sax et al. 2023; Yu et al. 2022; Gao et al. 2022; Kipourgos et al. 2022; Sanchez-Salmeron et al. 2022; Cho et al. 2022).

Sociodemographic Disparities in ED

We conducted a non-systematic search in Medline/PubMed, targeting titles or abstracts. We employed broad terms like 'bias*' and 'emergenc*' (or related terms such as '*equit*', '*equal*', 'discrimin*', or 'disparit*'), as well as specific terms like 'ethnic*', 'triage' or their synonyms. Snowballing was employed by reviewing papers' reference lists.

Disparities in Access to Outpatient Care. Territorial disparities in accessing outpatient care, including infrastructure, medical personnel distribution, and concentration of unfavorable socioeconomic conditions in specific areas, present a multifaceted challenge. Limited objective evidence exists due to the issue's complexity. Studies explore relationships between racial, socioeconomic, or geographical factors —which are often intertwined— and difficulty accessing emergency services (Verma et al. 2023; Wu et al. 2023). Research highlights socially differentiated pathways to emergency care access, perpetuating health inequalities (Morel 2019). Inequity indicators in outpatient care access link to socioeconomic factors such as insurance status and social deprivation (Morisod et al. 2021).

Disparities in Emergency Triage. Emergency triage rapidly categorizes patients based on their condition severity upon arrival at the ED. A triage nurse assesses vital signs, medical history, and reason for the visit, assigning a triage acuity score. External factors like ED location influence triage decisions (Gorick 2022; Suamchaiyaphum, Jones, and Markaki 2023). Sociodemographic factors, including ethnicity, sex/gender, age, and insurance coverage, also impact mistriage (Zhang et al. 2020a; Peitzman et al. 2023; Essa et al. 2023; Martin et al. 2023; Fekonja et al. 2023), disproportionately affecting certain groups (Banco et al. 2022). While age and ethnicity influence prioritization, findings on sex/gender (Arslanian-Engoren 2000; Onal et al. 2022) are less conclusive, with other factors interacting. Further analysis is available in (Avalos et al. 2024).

Disparities in Quality of Emergency Care. Even within the same triage level, where 'first come, first served' is the supposed principle, unexpected behaviors are observed, with over 10% of consultations not following arrival order, prioritizing older individuals and deprioritizing racialized individuals (Lin et al. 2022). A study found that ethnicity and insurance status were associated with being passed over by another patient with the same or lower triage score, with no such link found with sex (Sangal et al. 2023). Similarly, significant disparities in patient flow acceleration/deceleration based on racial, gender, age, and insurance status were revealed (Sharperson et al. 2023). Patients from more disadvantaged areas experienced slightly longer waits during the ED care pathway (Turner et al. 2022). Additionally, they noted that disadvantaged individuals received less complex ED care and were less likely to be admitted for inpatient care. It was also observed that black patients were less likely to undergo tests in the ED (Zhang et al. 2020a). Furthermore, disparities in racial/ethnic and language-based pain management in pediatric EDs were identified (Hartford et al. 2022).

Disparities in post-ED follow-up. Although some studies suggest that women may face disadvantages at various stages of care, these results do not consistently reach statistical significance (Onal et al. 2022; Mnatzaganian et al. 2020). (Preciado et al. 2021) demonstrate that women experience fewer hospitalizations and undergo fewer tests than men. In this context, disparities in the care of both genders inadvertently benefit women by preventing unnecessary hospitalizations or cardiac tests. In the specific case of mental health emergencies, (Han et al. 2023) suggest the possibility of underestimating the genuineness of suicide attempts in young females. On the other hand, (Zhang et al. 2020a) found that black patients were less likely to be admitted to the hospital and had a higher death rate in the ED and hospital. Some of these findings contrasted with those for Hispanic and Asian patients, who generally received equivalent or greater ED resources compared to white patients.

Discussion

AI models may inherit biases from their training data, potentially exacerbating health disparities. Particularly, large language models may exhibit biases aligned with stereotypes due to under-representation in training data (Kotek, Dockum, and Sun 2023; Buslon et al. 2023). Through a literature survey, we identified biases affecting different stages of a patient's journey in the ED, potentially influencing AI-driven patient flow optimization, that could be synthethized as follows:

- Biases during initial assessment, like triage decisions affected by sociodemographic factors, may create disparities in patient prioritization. AI algorithms trained on biased data may perpetuate these patterns, worsening existing outcome disparities.
- Moreover, biases in diagnostic and treatment decisions within the ED can impact patient flow. If AI algorithms do not account for these human errors, they may fail to accurately predict the demand for diagnostic resources or treatment pathways, leading to inefficiencies in patient flow management.
- Biases in disposition decisions, such as admitting patients to inpatient care, can also have a significant impact. Patients from disadvantaged backgrounds may be less likely to be admitted due to biases in clinical assessments or resource allocation. Failure to address these biases in AI algorithms may result in inaccurate predictions of the need for inpatient resources, leading to inefficiencies in bed management and discharge planning.

The awareness that biases can infiltrate AI systems through training data, and identifying sensitive points in the patient journey through the ED, is a crucial first step. That said, much work remains to ensure that AI systems can effectively assist ED professionals, all while upholding ethical standards. Governance overseeing the integration of AI-driven solutions for patient flow optimization in EDs must remain vigilant about potential vulnerable points.

Solutions for mitigating biases have emerged (Adam et al. 2022; Thakur et al. 2023), yet using fairness metrics isn't a cure-all. The prevailing computer science approach formalizes fairness as a mathematical constraint, imposed on AI decisions to minimize predictive accuracy loss. However, it relies on oversimplified/unrealistic assumptions, assuming that fairness can be mathematically formalized and considering only a single axis of discrimination. Additionally, measuring fairness necessitates access to sensitive data, resulting in incomplete assessment of discrimination effects (Buyl and De Bie 2024).

Educational computerized approaches involve preventing bias in medical decision-making, for example, through the use of serious games (Sader et al. 2021). Another approach involves a paradigm shift, precisely utilizing AI models to objectively detect human biases. This would entail using an AI system to detect outcome differences between patients based on sociodemographic characteristics that cannot otherwise be medically explained (Avalos et al. 2024).

Acknowledgments

This work was conducted under the BPH Inserm's TARPON project, in collaboration with Bordeaux University Hospital.

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