Reducing Administrative Burden in Emergency Departments Using Artificial Intelligence : A Workflow-Based Analysis

Danusha SANCHEZ (a), Frederic PARIS (b), Said LARIBI (c), Allison GILBERT (d, e)

(a) Polish Society of Medical Simulation, Slupca, Poland.

(b) Emergency department, Tenon Hospital, Paris, France, 75020 Paris

(c) School of Medicine, University of Tours, CHU Tours, Tours, France.

(d) University Hospital Center of Liège, Avenue de l'hôpital, 1, Liège, Belgium.

(e) University of Mons, Avenue du Champs de Mars, 8, Mons, Belgium.

Correspondence:

Danusha Sanchez

Towarowa 41/114 Poznań, Poland 61-897

deeoptimal@gmail.com

Conflict of Interest:

The authors report no conflict of interest.

Funding:

None declared.

Artificial intelligence (AI) is increasingly applied in medicine to support clinical decision-making and automate routine processes that contribute to the workload of clinicians [1]. Emergency departments (EDs) face growing operational pressures, with administrative burden identified as a key factor in clinical burnout and reduced care efficiency [2,3]. Time-consuming, repetitive tasks divert from patient care and cause delays across the care pathway [3]. AI offers a strategy to streamline ED operations using Asplin's input-throughput-output model: input (registration and triage), throughput (care delivery), and output (discharge and transfer) [2,4,5]. This viewpoint examines how AI may improve efficiency and reduce administrative burden across each phase of emergency care using a revised version of Asplin et al.'s model to demonstrate AI integration in ED workflow (Figure 1).

During the input phase, various optimizations could be made through AI use. Indeed, delays in registration and triage contribute to ED overcrowding, prolonged wait times, and decreased patient safety [6,7]. AI tools have been introduced to address these inefficiencies by automating intake and supporting early clinical decisions. Considering the patient registration, natural language processing (NLP) systems can extract structured data from free-text, generate real-time intake reports, and produce handoff summaries to streamline front-end workflows and reduce redundancy [3,8,9]. Regarding the triage itself, this process is cognitively demanding and prone to bias and fatigue-related errors. In this context, AI can reduce burden by improving patient prioritization accuracy and reducing manual effort [7]. Machine learning (ML) models offer greater precision in acuity scoring, with lower undertriage rates and more efficient resource allocation [7,10]. A recent systematic review revealed that boosting algorithms such as XGBoost and LightGBM consistently outperformed the Emergency Severity Index (ESI) in predicting acuity and disposition [7]. NLP tools such as KATE have demonstrated higher triage accuracy than clinicians in high-volume settings [7]. AI streamlines intake and triage, allowing clinicians to focus on patient care [10]. Other experiments show AI can mimic clinical gestalt at triage to identify patient disposition using computer vision applications [11]. Despite these advances, AI in high-acuity settings poses safety and security concerns, including the risk of "hallucinations" [8].

Broader implementation raises concerns of data privacy, regulatory compliance, and preservation of clinician-patient relationships [8,10]. Most tools lack prospective validation in ED environments, underscoring the need for future research and careful ethical integration [10].

Considering the throughput phase, an efficient organization is essential for reducing crowding and ensuring continuous clinical flow. One AI's opportunity is to optimize the clinical assessment process in different tasks. Speech recognition tools such as Voice-Generated Enhanced Electronic Notes (VGEENS) use NLP to convert voice input into structured documentation in real time [3]. Integrated into electronic health records (EHRs) or ambient devices, these tools reduce the documentation workload and enable immediate data availability for clinician support [3]. However, research on ambient virtual scribes is limited, and has focused mainly on non-ED settings, making generalizability uncertain [3]. Moreover, early predictions of admission, imaging needs, or length of stay – while collected during intake – primarily support downstream throughput functions. AI models using patient data from the first hour of arrival help in forecasting patient flow and guiding resource allocation [7]. Real-time alerts can flag high-risk patients, improve prioritization, reduce clerical workload, and facilitate timely clinical escalation [8]. Documentation support remains the highest AI priority for ED clinicians, followed by predictive tools and vital sign analysis [2]. AI may also optimize administrative functions, such as staff scheduling and patient flow management [6,9]. These tools may reduce wait times and resource use, but current models lack ED-specific validation [6,9]. Generative AI introduces new possibilities for supporting patient-provider communication. Chatbots, for example, could help address patient questions and share updates during the ED length of stay [10].

As regards the output phase, AI technologies offer several solutions to streamline documentation tasks and reduce the administrative burden associated with discharge and transfer processes. One prominent application involves automating medical coding processes by predicting billing code levels for ED encounters via data extracted from clinical notes and triage documentation. These systems have shown promise in reducing manual documentation time, increasing reimbursement accuracy, and potentially lowering administrative costs [12]. However, variability in documentation practices and coder behavior across institutions may introduce bias, affecting model consistency and downstream billing accuracy [12]. Moreover, most of these models are trained on retrospective, single-center datasets, limiting their generalizability to broader clinical environments [12]. Regarding patients disposition and education, Large language models (LLMs) have been deployed to generate discharge summaries or information by synthesizing clinical data into draft narratives. Although they improve consistency, such systems require verification, which may increase workload [13]. These systems can improve the efficiency and consistency of discharge documentation, their outputs often require close clinical review due to the risk of generating inaccurate or incomplete information, which is commonly known as "hallucinations" [13]. LLMs remain unbenchmarked against clinician summaries, and verification may offset time savings, particularly in high-acuity or legally sensitive contexts [13]. Training bias and dataset inconsistency may compromise discharge documentation safety [10,13]. A systematic review by Hunter-Zinck et al. concluded that machine learning algorithms used in the ED output phase are associated with reductions in patient length of stay, although this benefit may come at the cost of increased operational expenditure [7]. This underscores the need to balance efficiency gains with downstream cost implications when evaluating AI implementation.

To conclude, AI has the potential to reduce administrative burden and improve efficiency across the ED workflows—from triage to documentation and resource optimization. However, most tools lack validation specific to the emergency department and have been tested primarily in other inpatient units or outpatient settings, often relying on retrospective data or simulation rather than real-life use in the ED. Robust research is needed to assess safety, reliability, and ethical aspects related to high- acuity environments to ensure effective and trustworthy AI implementation in emergency care. Finally, AI adoption among ED professionals will also represent a major challenge for the concrete implementation in clinical practice.

References

1. Haug CJ, Drazen JM. Artificial Intelligence and Machine Learning in Clinical Medicine. *N Engl J Med* 2023; 388(13):1201–8.

2. Eastwood KW, May R, Andreou P, Abidi S, Abidi SSR, Loubani OM. Needs and expectations for artificial intelligence in emergency medicine according to Canadian physicians. *BMC Health Serv Res* 2023; 23(1):798.

3. Dymek C, Kim B, Melton GB, Payne TH, Singh H, Hsiao CJ. Building the evidence-base to reduce electronic health record–related clinician burden. *J Am Med Inform Assoc* 2021; 28(5):1057–61.

4. Asplin BR, Magid DJ, Rhodes KV, Solberg LI, Lurie N, Camargo CA. A conceptual model of emergency department crowding. *Ann Emerg Med* 2003; 42(2):173–80.

5. Gandhi TK, Classen D, Sinsky CA, Rhew DC, Vande Garde N, Roberts A, et al. How can artificial intelligence decrease cognitive and work burden for front line practitioners? JAMIA Open. 2023;6(3):ooad079.

6. Sartini M, Carbone A, Demartini A, Giribone L, Oliva M, Spagnolo AM, et al. Overcrowding in Emergency Department: Causes, Consequences, and Solutions-A Narrative Review. *Healthc Basel Switz* 2022; 10(9):1625.

7. Almulihi QA, Alquraini AA, Almulihi FAA, Alzahid AA, Al Qahtani SSAJ, Almulhim M, et al. Applications of Artificial Intelligence and Machine Learning in Emergency Medicine Triage - A Systematic Review. *Med Arch* 2024; 78(3):198–206.

8. Kachman MM, Brennan I, Oskvarek JJ, Waseem T, Pines JM. How artificial intelligence could transform emergency care. *Am J Emerg Med* 2024; 81:40–6.

9. Berikol GB, Kanbakan A, Ilhan B, Doğanay F. Mapping artificial intelligence models in emergency medicine: A scoping review on artificial intelligence performance in emergency care and education. *Turk J Emerg Med* 2025; 25(2):67–91.

10. Chenais G, Lagarde E, Gil-Jardiné C. Artificial Intelligence in Emergency Medicine: Viewpoint of Current Applications and Foreseeable Opportunities and Challenges. J *Med Internet Res* 2023; 25:e 40031.

11. Ip W, Xenochristou M, Sui E, Ruan E, Ribeira R, Dash D, et al. Hospitalization prediction from the emergency department using computer vision AI with short patient video clips. *Npj Digit Med* 2024; 7(1):1–8.

12. Morey J, Winters R, Jones D. Artificial Intelligence to Predict Billing Code Levels of Emergency Department Encounters. *Ann Emerg Med* 2025; 85(1):63–73.

13. Williams CYK, Bains J, Tang T, Patel K, Lucas AN, Chen F, et al. Evaluating Large Language Models for Drafting Emergency Department Discharge Summaries. *medRxiv [Preprint]* 2024;

Appendix

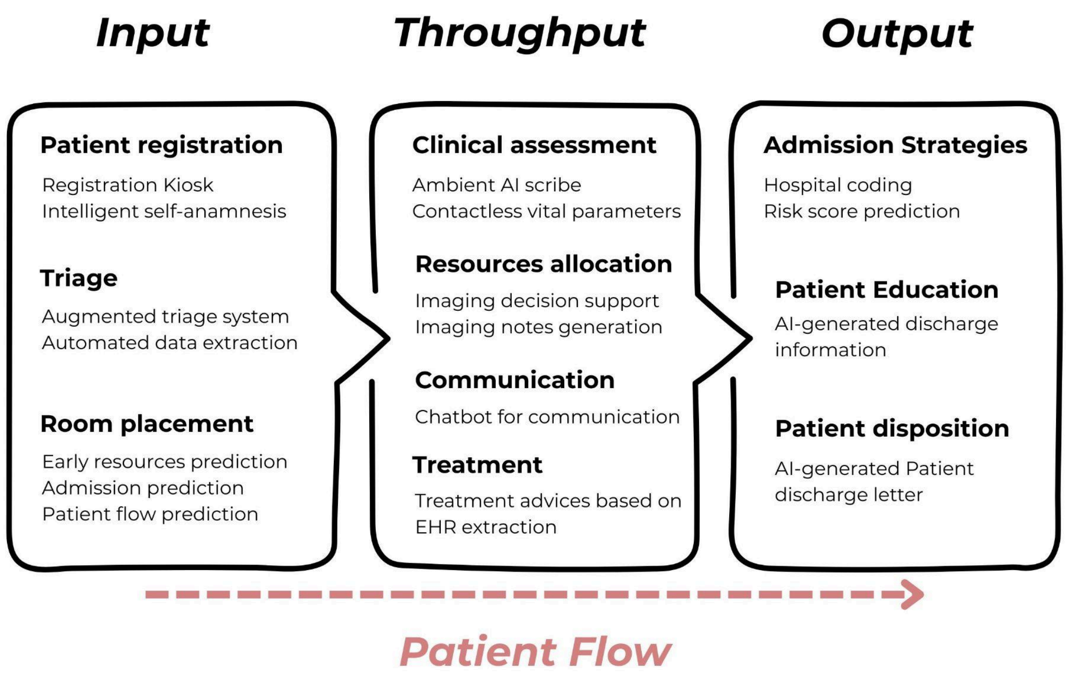

Figure 1. *Integration of AI into the patient workflow using a revised version of the Asplin et al's input-throughput-output model.*