

PERSPECTIVE ARTICLE

Use of natural language processing in the emergency department: A clinical overview on the state of the art

Carly Hudson^{1,2,3*}, **Adrian Goldsworthy^{2,4,5,6}**, **Thuy Linh Phan^{2,7}**, **Anu Joy²**, **Oystein Tronstad^{4,8}**, and **Marcus Randall²**

¹Faculty of Health Sciences and Medicine, Bond University, Gold Coast, Queensland, Australia

²Bond Business School, Bond University, Gold Coast, Queensland, Australia

³Faculty of Medicine and Health, University of New England, Armidale, New South Wales, Australia

⁴Critical Care Research Group, The Prince Charles Hospital, Brisbane, Queensland, Australia

⁵Harry Butler Institute, Murdoch University, Perth, Western Australia, Australia

⁶Institute for Molecular Bioscience, University of Queensland, Brisbane, Queensland, Australia

⁷University of Queensland Business School, University of Queensland, Brisbane, Queensland, Australia

⁸Department of Physiotherapy, The Prince Charles Hospital, Brisbane, Queensland, Australia

Abstract

Machine learning (ML) and artificial intelligence are increasingly ubiquitous in healthcare data analytics. To date, however, ML has been largely restricted to the analysis of structured data. While natural language processing (NLP) is gaining prominence in healthcare, substantial challenges remain in the generation and analysis of unstructured data. Emergency departments, which are increasingly under-resourced and overburdened, may benefit from the implementation of ML techniques that incorporate NLP to support clinical decision-making and improve patient care. Historically, regional and cultural variations have posed significant challenges to the widespread application of ML algorithms beyond their original training datasets. The rapidly increasing use of NLP within clinical note-taking applications provides avenues to assist in standardizing unstructured data and extracting meaningful insights to improve generalization and clinical translation.

Keywords: Natural language processing; Emergency department; Healthcare data; Unstructured data; Triage text

*Corresponding author:

Carly Hudson
(chudson@bond.edu.au)

Citation: Hudson C, Goldsworthy A, Phan TL, Joy A, Tronstad O, Randall M. Use of natural language processing in the emergency department: A clinical overview on the state of the art. *Artif Intell Health*. 2026;3(2):025450097. doi: 10.36922/AIH025450097

Received: November 5, 2025

Revised: January 4, 2026

Accepted: January 21, 2026

Published online: February 5, 2026

Copyright: © 2026 Author(s). This is an Open-Access article distributed under the terms of the Creative Commons Attribution License, permitting distribution, and reproduction in any medium, provided the original work is properly cited.

Publisher's Note: AccScience Publishing remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

1. Introduction

There is growing interest in the use of machine learning (ML) approaches within hospital emergency departments (EDs). Rising demands on EDs, driven by increasing patient volumes and the growing complexity of healthcare needs,^{1,2} present significant challenges that necessitate improved efficiency without compromising the quality of healthcare provision.³ In Australia, public hospital EDs recorded 9.1 million presentations in 2024–25, an increase from 7.6 million in 2015–2016, and only 67% of patients were seen within the recommended time for their triage category.⁴ Natural language processing (NLP) offers

a promising solution by enabling the extraction of relevant and meaningful information from the growing volume of free-text data generated by healthcare professionals.^{5,6} This capability may assist time-critical tasks such as triage, where timely and accurate decision-making is essential. However, optimizing NLP for ED use requires managing complex interactions among data generated by healthcare providers, administrators, and, increasingly, other artificial intelligence (AI) tools, including generative AI (GenAI) and ML algorithms that analyze structured data. This perspective explores the opportunities and challenges associated with integrating NLP into ED workflows and outlines the multifaceted considerations required for successful implementation, with the aim of improving clinician understanding and promoting collaboration and innovation in NLP development and implementation.

2. Positioning of NLP within the ED's complex data environment

Healthcare professionals generate substantial quantities of data in the form of patient notes and clinical reports, which are time-consuming to record and difficult to interpret, creating opportunities for the development of more efficient and effective methods for generating and interpreting clinical data. Data generated in EDs may include triage notes that capture early clinical impressions, ongoing nursing observations, radiology and laboratory reports, decision-making notes, and discharge summaries. However, due to the fast-paced and collaborative nature of ED care, data collected are often recorded by multiple practitioners and may include shorthand, abbreviations, and stylistic variations.^{7,8} Walker *et al.*⁹ found that the introduction of medical scribes increased the number of consultations by doctors by 25.6%; however, access to scribes is limited by both cost and labor availability. Furthermore, the use of scribes increases reliance on clear and accurate communication of clinical data. Breakdowns in this communication within the busy, fast-paced ED environment—such as compromised knowledge transfer during handovers and inconsistencies in medical recordkeeping¹⁰—have repeatedly been linked to clinical errors and adverse patient outcomes.¹¹ GenAI software, which harnesses large language models, such as Microsoft Dragon Copilot,¹² Abridge AI,¹³ or Suki Assistant,¹⁴ may assist in overcoming these challenges by standardizing free-text documentation, thereby enabling further analysis and processing using NLP. The rise of GenAI has also led to applications specifically designed to reduce the medico-legal documentation burden for healthcare professionals, providing an opportunity to extend these benefits to nursing and allied health staff. In practice, NLP tools can mitigate ED documentation and decision-making challenges in a number of ways. For example, triage classification systems

can use presenting complaints and triage narrative text to generate a predicted acuity score or risk flag that supports nurses' triage decision-making and reduces variability in urgency assignment.^{15–20} Disposition and resource prediction models can combine concepts extracted from free text with structured variables (e.g., initial vital signs) to estimate admission likelihood, the need for imaging, or short-term deterioration risk, thereby supporting earlier downstream coordination of beds, imaging, and escalation pathways in crowded ED environments.^{18,21–30}

3. Review of the use of NLP within the ED for clinical decision-making

NLP has been explored in EDs to support clinical decision-making, particularly in triage. Stewart *et al.*'s¹⁹ recent review of NLP use in EDs identified six studies that used a combination of structured and unstructured data to assign triage scores to presenting patients.^{8,15–18,20} Of these, three studies examined model performance and reported that NLP models outperformed triage nurses.^{15,16,18} While these results are promising, reported performance metrics should be interpreted cautiously. Most ED NLP models have been developed retrospectively using single-site datasets, which may encode local documentation style, triage practices, and resource-driven decision patterns. This can inflate apparent performance and limit generalizability to other ED settings without external validation.^{19,25} Models may also learn proxies for clinical decisions (e.g., local admission thresholds or ordering practices within a specific setting) rather than true underlying severity, and performance can vary across patient subgroups if training data are imbalanced or reflect existing care inequities.^{19,22}

Beyond triage, NLP has been used to predict whether patients require admission for further treatment or can be discharged.^{18,21,26,27,30} For instance, Tahayori *et al.*²⁷ showed that their model, benchmarked against emergency physician decisions, achieved higher overall accuracy but demonstrated higher specificity than sensitivity. NLP models have also been applied to identify patients at risk of critical illness, including those likely to require ICU admission or experience death within 24 h of discharge.^{22,23,25} Joseph *et al.*²⁵ found that supplementing structured data with free-text data significantly improved performance relative to the original model, surpassing conventional abnormal vital-sign alerts.

In addition to triage and disposition prediction, NLP has been used to assist clinical coding by identifying reasons for presentation to the ED.^{31,32} By extracting and interpreting clinical concepts from free-text notes, NLP models can retrospectively classify presenting complaints more accurately than structured coding systems alone, which

often rely on incomplete or inconsistent data entry. NLP has also been used to retrospectively predict the need for diagnostic imaging by analyzing presenting symptoms and clinician documentation to determine whether advanced imaging, such as computed tomography or magnetic resonance imaging, is likely to be ordered.^{28,29} In real-world ED settings, this approach may enable earlier referrals and reduce time to imaging for high-acuity cases. For example, studies have demonstrated that models incorporating both structured data (e.g., vital signs) and unstructured data (e.g., narrative descriptions of injury mechanisms) yield higher predictive performance for imaging requirements.^{28,29} In retrospective analyses, NLP models have shown utility in identifying infections such as sepsis earlier in the clinical course, where early intervention is critical.²⁴

Within Stewart *et al.*'s¹⁹ review, all but one³² of the included studies developed models retrospectively, raising concerns about their implementability and applicability of these models when deployed prospectively in real-world ED environments, which are often unpredictable and chaotic. As a result, these models may perform suboptimally when faced with real-time demands, inconsistent data entry, or atypical cases. Study designs and datasets also vary in ways that affect interpretability and generalizability across ED contexts. Many models are developed retrospectively within single health systems and therefore reflect local documentation styles, abbreviations, and operational practices, limiting transferability to other sites.^{15,19,23-27,32} Studies further differ in the extent to which they combine unstructured text with structured variables (e.g., demographics, vital signs, timestamps), making direct comparisons regarding the contribution of free text versus structured data challenging.^{7,19,21-27,30-32} Likewise, model outcomes also vary widely and may be influenced by local policy and resourcing, reinforcing the importance of external validation and prospective evaluation prior to widespread clinical deployment.^{15,19,21-27,30-32}

Successful integration of NLP models into ED workflows also presents challenges related to user interface design, clinician trust, data privacy, and regulatory approval. Moving forward, prospective validation and real-time testing of NLP systems are critical to ensure their robustness, reliability, and clinical utility. Embedding these tools seamlessly into existing electronic health record systems, with minimal disruption to clinician workflows, will be essential for sustainable adoption in the high-pressure ED environment.

4. Methods used for NLP in the ED

Achieving seamless integration into ED workflows requires careful consideration of the NLP techniques used,

as the effectiveness of these systems depends not only on preprocessing and data quality,³³ but also on the specific clinical tasks they are built to support.³⁴ For example, classification models can triage patients by urgency or risk level,³⁵ while named entity recognition allows the extraction of critical information such as symptoms, comorbidities, and medications.³⁶ Early approaches to these tasks relied heavily on rule-based or statistical methods, drawing on features such as n-grams and classifiers, including support vector machines or logistic regression.³⁷ While these approaches laid important groundwork for clinical text analysis, they were limited in their ability to capture the variability, ambiguity, and contextual complexity inherent in ED documentation. More recently, deep learning models, such as ClinicalBERT³⁸ have demonstrated higher accuracy than statistical methods because they can automatically identify patterns and meaning in clinical text rather than depending on predefined rules determined by researchers or domain experts.³⁹ In contrast to earlier rule-based methods, which required extensive manual design and struggled with variability, deep learning models adapt more flexibly to the complexity of ED documentation. Deep learning approaches are supported by systematic reviews, which show strong performance in clinical text classification and information extraction tasks, particularly when pretrained language models are adapted to healthcare text.^{37,39} In ED contexts specifically, deep learning models incorporating clinical narrative text have been used for critical outcome prediction and triage risk stratification, demonstrating the practical relevance of deep learning-based NLP in acute care workflows.^{7,25}

Although unstructured, free-text data captures rich contextual detail, many high-value ED indicators are temporal. Vital signs (e.g., heart rate, blood pressure, respiratory rate) and other continuously or repeatedly measured parameters are best represented as time series, where trends, variability, instability, and cyclical patterns may carry more clinical signal than single time-point measurements.²⁴ Future ED decision-support systems are therefore likely to benefit from hybrid modelling approaches that integrate NLP-derived representations (e.g., data derived from free-text clinical notes) with standard time-series methods.⁴⁰ These time-series features can be combined with NLP outputs, enabling models to account for both narrative context and physiological changes when predicting acuity, deterioration risk, or disposition.^{41,42}

As NLP methods continue to evolve to account for these complexities, there has also been increasing interest in extending analysis beyond text to other modalities (Figure 1).^{43,44} For instance, AI tools are emerging to analyse multimodal data such as imaging, video, and

audio recordings.^{43,44} These tools may be linked with GenAI systems to enhance the accessibility of information available to healthcare professionals and inform NLP-driven insights.⁴³ To achieve optimal outcomes, such outputs will likely need to be integrated into broader AI models that also incorporate ML algorithms trained on structured data (e.g., patient demographics, vital signs, and temporal markers such as arrival date and time), which are routinely collected and provide critical patient information but are often underutilized.^{44,45} Ultimately, the integration of sophisticated, multilayered AI systems, used alongside existing clinical decision support systems and expert clinical judgement, has the potential to improve the efficiency and effectiveness of healthcare delivery.

5. Barriers and facilitators for implementation

While the use of GenAI in ED documentation and decision support is increasing, its implementation to date has been fragmented. This transitional period presents challenges for researchers, AI specialists, and clinicians seeking to develop NLP tools for use in the ED context. Table 1 outlines several barriers and facilitators to the implementation of NLP models in the ED, based on the clinical expertise of two authors (Adrian Goldsworthy and Oystein Tronstad).

These factors were mapped to the capability, opportunity, motivation, and behavior (COM-B) model and theoretical domains framework (TDF), two widely used behavioral science frameworks for understanding and supporting implementation of change in healthcare settings.^{46,47} Barriers and facilitators were first generated and refined through iterative discussion, with duplicates removed and items worded to reflect workflow and implementation issues. Each item was then mapped to COM-B and corresponding TDF domains using published definitions and guidance, with the final mapping reviewed to ensure conceptual fit and internal consistency across domains.^{46,48}

Beyond behavioral determinants, successful adoption in EDs depends on designing NLP tools that fit chaotic workflows and demonstrating benefit under live conditions. Early implementation should prioritise prospective, real-time evaluation in the intended clinical environment. User-driven design and usability testing are also critical to minimise disruption (e.g., reducing clicks, aligning with ED task flow, and ensuring outputs appear at the point of decision-making), as workflow-integration studies in ED clinical decision support highlight that even effective tools may fail if they increase cognitive load or interrupt clinical flow.⁴⁹ Actionable strategies to build clinician trust and safe use include co-design with ED clinicians, iterative usability testing, clear presentation of

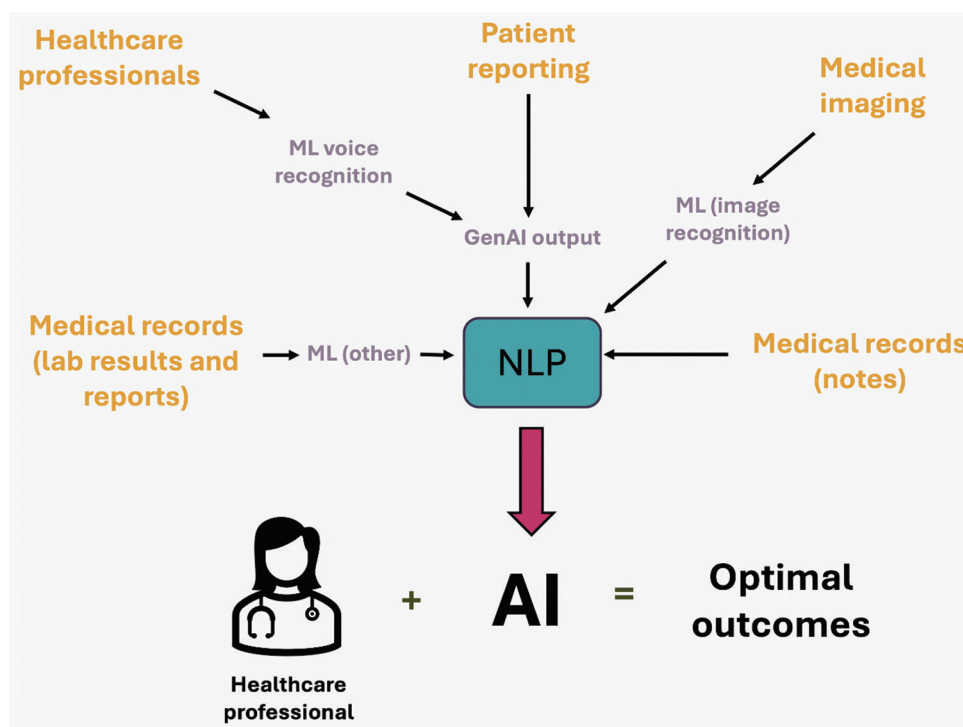


Figure 1. Illustration of how NLP and GenAI can interface with structured and multimodal data streams in the ED to support real-time decision-making. Image created by the authors.

Abbreviations: AI: Artificial intelligence; GenAI: Generative artificial intelligence; ML: Machine learning; NLP: Natural language processing.

Table 1. Barriers and facilitators to implementation of NLP models in the ED based on authors' clinical expertise

COM-B domain	TDF domain	Barriers	Facilitators
Capability	Knowledge	<ul style="list-style-type: none"> • Lack of knowledge about how NLP models are developed and provide predictions 	<ul style="list-style-type: none"> • Delivery of robust, multi-phased educational programs
	Skills	<ul style="list-style-type: none"> • Lack of expertise in using AI/NLP tools (e.g., entering data, interpreting outputs) • Generational differences in technological abilities 	<ul style="list-style-type: none"> • Practical, hands-on, mandatory workshops to use AI/NLP tools in a face-to-face format • Training platform with dummy data for clinicians to practice with until they feel confident
	Memory, attention, and decision processes	<ul style="list-style-type: none"> • Competing demands during ED shifts • Managing conflicting treatment options from clinician's judgement and NLP output 	<ul style="list-style-type: none"> • NLP tools which are fast to run, simple to use, and integrate well into the existing ED workflow
	Behavioral regulation	<ul style="list-style-type: none"> • Poor interface design preventing ease of use 	<ul style="list-style-type: none"> • Interfaces co-designed end users to ensure suitability for purpose
Motivation	Beliefs about capabilities	<ul style="list-style-type: none"> • Lack of confidence in using AI/NLP • Lack of confidence in AI/NLP's abilities 	<ul style="list-style-type: none"> • Practical, hands-on workshops to demonstrate proficiency and build confidence in capabilities
	Social/professional role identity	<ul style="list-style-type: none"> • Perceived loss of professional identity 	<ul style="list-style-type: none"> • Clear delineation of NLP as a support tool, not as a replacement for clinicians
	Beliefs about consequences	<ul style="list-style-type: none"> • Concerns for legal or ethical implications 	<ul style="list-style-type: none"> • Rigorous quality control and evaluation • Clear guidelines outlining ethical and legal responsibilities
	Emotions	<ul style="list-style-type: none"> • Fear of unknown/change which may have unintended consequences during the initial implementation phase • Frustration with new systems 	<ul style="list-style-type: none"> • User engagement in design of AI/NLP interface • Ongoing quality improvement processes to address user feedback
	Goals	<ul style="list-style-type: none"> • Competing goals 	<ul style="list-style-type: none"> • Alignment of NLP model outcomes with clinical needs
	Intentions	<ul style="list-style-type: none"> • Lack of interest/perceived irrelevance of AI/NLP 	<ul style="list-style-type: none"> • Having additional NLP outputs explaining the reasoning behind clinical-related decisions or other outputs
	Reinforcement	<ul style="list-style-type: none"> • Lack of time to engage in training due to competing priorities • Financial cost and time burden for providing incentives 	<ul style="list-style-type: none"> • Formal recognition for continuing professional development • Incentives to become AI trained (e.g., pin badges)
	Optimism/pessimism	<ul style="list-style-type: none"> • Personal and peer burnout 	<ul style="list-style-type: none"> • Peer leader to champion integration of AI/NLP within department
Opportunity	Environmental context and resources	<ul style="list-style-type: none"> • Lack of technological infrastructure 	<ul style="list-style-type: none"> • Investment in infrastructure • Future-proofing hospitals
	Social influences	<ul style="list-style-type: none"> • Negative societal attitudes and beliefs towards AI tools • Lack of buy-in from key stakeholders 	<ul style="list-style-type: none"> • Positive societal attitudes and beliefs towards AI tools

Abbreviations: AI: Artificial intelligence; COM-B: Capability, opportunity, motivation, and behavior; ED: Emergency department; NLP: Natural language processing; TDF: Theoretical domains framework.

model scope and limitations, interpretable outputs that align with clinical reasoning, continuous performance monitoring post-implementation, and explicit ethical governance covering privacy, accountability, and transparency.

While some EDs may be nearing readiness for AI implementation, many healthcare systems and/or hospitals, even in high-income countries such as Australia, continue to rely on paper-based medical records and lack the physical and technological infrastructure, workforce capacity, and AI literacy needed to support the deployment of multiple AI systems.

The implementation of AI and NLP in clinical settings must also account for ethical and legal considerations, particularly given the use of sensitive patient data, often accessed under a waiver of consent and without the patient's knowledge. This necessitates robust protocols for data storage, access, and governance to ensure privacy and security, requiring unprecedented cooperation between healthcare sectors and departments, as well as coordination across state and national government levels.

Although AI and NLP models have the potential to mitigate bias by reducing the influence of subjective

human decision-making, this benefit is contingent on the quality and representativeness of the training data. If underlying datasets are biased by gender, race, or other sociodemographic factors, the models are likely to perpetuate or even exacerbate existing inequities in care. The adoption and acceptability of integrating NLP models into healthcare will largely be guided by societal attitudes toward these innovations. Alongside healthcare providers' trust, public confidence in these technologies depends not only on demonstrated accuracy and utility, but also on transparency, ethical use of data, and perceived fairness.

6. Conclusion

Looking ahead, as the use of AI in healthcare continues to expand rapidly, the future of NLP in emergency care lies in the development of adaptive, generalizable, user-friendly, and ethically grounded systems that function reliably across diverse clinical environments. As AI capabilities continue to evolve, the infrastructure, workforce capacity, and governance mechanisms (e.g., patient consent, data sharing frameworks) must also evolve to support their safe and effective integration. NLP models should be trained on large-scale, representative datasets that integrate existing structured and unstructured data sources and should undergo prospective validation within real-time ED workflows to ensure they reflect the complexity and diversity of real-world practice. Crucially, future systems should not replace clinical judgement but should enhance it by supporting healthcare professionals with timely insights that improve efficiency, reduce diagnostic error, and promote equitable patient care. Integration with generative AI, multimodal data sources, and structured data fields will further strengthen NLP's potential to transform triage, diagnosis, and disposition planning. NLP has the potential to become an integral component of evolving healthcare systems, enabling them to adapt, improve, and respond to patient needs. While challenges remain and will take time to overcome, when integrated into routine clinical practice, NLP is unlikely to replace clinical judgement; instead, it can sharpen and improve clinical decision-making and support clinicians in delivering faster, smarter, and fairer emergency care.

Acknowledgments

None.

Funding

This research was funded by the Queensland Mental Health Commission.

Conflict of interest

The authors declare that they have no competing interests.

Author contributions

Conceptualization: Carly Hudson, Marcus Randall

Visualization: Carly Hudson, Adrian Goldsworthy

Writing – original draft: Carly Hudson, Marcus Randall,

Anu Joy, Thuy Linh Phan, Adrian Goldsworthy

Writing – review & editing: All authors

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

Data is available upon reasonable request to the corresponding author.

References

1. Payne K, Risi D, O'Hare A, Binks S, Curtis K. Factors that contribute to patient length of stay in the emergency department: A time in motion observational study. *Australas Emerg Care*. 2023;26(4):321-325.
doi: 10.1016/j.auec.2023.04.002
2. National Center for Health Statistics. *Emergency Department Visits*. Available from: <https://www.cdc.gov/nchs/fastats/emergency-department.htm> [Last accessed on 2025 Dec 04].
3. Mostafa R, El-Atawi K. Strategies to measure and improve emergency department performance: A review. *Cureus*. 2024;16(1):e52879.
doi: 10.7759/cureus.52879
4. Australian Institute of Health and Welfare. *Emergency Department Care*. Available from: <https://www.aihw.gov.au/hospitals/topics/emergency-departments> [Last accessed on 2026 Jan 02].
5. Hirschberg J, Manning CD. Advances in natural language processing. *Science*. 2015;349(6245):261-266.
doi: 10.1126/science.aaa8685
6. Zhou B, Yang G, Shi Z, Ma S. Natural Language Processing for Smart Healthcare. *IEEE Rev Biomed Eng*. 2024;17:4-18.
doi: 10.1109/rbme.2022.3210270
7. Chen MC, Huang TY, Chen TY, Boonyarat P, Chang YC. Clinical narrative-aware deep neural network for emergency department critical outcome prediction. *J Biomed Inform*. 2023;138:104284.
doi: 10.1016/j.jbi.2023.104284
8. Choi SW, Ko T, Hong KJ, Kim KH. Machine learning-based prediction of Korean triage and acuity scale level in emergency department patients. *Healthc Inform Res*.

- 2019;25(4):305-312.
doi: 10.4258/hir.2019.25.4.305
9. Walker K, Ben-Meir M, Dunlop W, *et al.* Impact of scribes on emergency medicine doctors' productivity and patient throughput: Multicentre randomised trial. *BMJ*. 2019;364:l121.
doi: 10.1136/bmj.l121
10. Pun JK, Matthiessen CM, Murray KA, Slade D. Factors affecting communication in emergency departments: Doctors and nurses' perceptions of communication in a trilingual ED in Hong Kong. *Int J Emerg Med*. 2015;8(1):48.
doi: 10.1186/s12245-015-0095-y.
11. Manias E, Geddes F, Watson B, Jones D, Della P. Communication failures during clinical handovers lead to a poor patient outcome: Lessons from a case report. *SAGE Open Med Case Rep*. 2015;3:2050313X15584859.
doi: 10.1177/2050313X15584859
12. Microsoft. *Microsoft Dragon Copilot*. Available from: <https://www.microsoft.com/en-us/health-solutions/clinical-workflow/dragon-copilot> [Last accessed on 2025 Jun 13].
13. Abridge AI. *Abridge*. Available from: <https://www.abridge.com> [Last accessed on 2025 Jun 27].
14. Suki AI. *Suki Assistant*. Available from: <https://www.suki.ai/suki-assistant> [Last accessed on 2025 Jun 29].
15. Gligorijevic D, Stojanovic J, Satz W, *et al.* Deep Attention Model for Triage of Emergency Department Patients. In: *Proceedings of the 2018 SIAM International Conference on Data Mining. Society for Industrial and Applied Mathematics*; 2018:297-305.
doi: 10.1137/1.9781611975321.34
16. Ivanov O, Wolf L, Brecher D, *et al.* Improving ED emergency severity index acuity assignment using machine learning and clinical natural language processing. *J Emerg Nurs*. 2021;47(2):265-278.e7.
doi: 10.1016/j.jen.2020.11.001
17. Kim D, Oh J, Im H, Yoon M, Park J, Lee J. Automatic classification of the Korean triage acuity scale in simulated emergency rooms using speech recognition and natural language processing: A proof of concept study. *J Korean Med Sci*. 2021;36(27):e175.
doi: 10.3346/jkms.2021.36.e175
18. Sterling NW, Brann F, Patzer RE, *et al.* Prediction of emergency department resource requirements during triage: An application of current natural language processing techniques. *J Am Coll Emerg Phys Open*. 2020;1(6):1676-1683.
doi: 10.1002/emp2.12253
19. Stewart J, Lu J, Goudie A, *et al.* Applications of natural language processing at emergency department triage: A narrative review. *PLoS One*. 2023;18(12):e0279953.
doi: 10.1371/journal.pone.0279953
20. Wang G, Liu X, Xie K, Chen N, Chen T. DeepTriager: A Neural Attention Model for Emergency Triage with Electronic Health Records. In: *2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*. IEEE; 2019:978-982.
doi: 10.1109/bibm47256.2019.8983093
21. Arnaud E, Elbattah M, Gignon M, Dequen G. Deep Learning to Predict Hospitalization at Triage: Integration of Structured Data and Unstructured Text. In: *2020 IEEE International Conference on Big Data (Big Data)*. IEEE; 2020:4836-4841.
doi: 10.1109/bigdata50022.2020.9378073
22. Fernandes M, Mendes R, Vieira SM, *et al.* Risk of mortality and cardiopulmonary arrest in critical patients presenting to the emergency department using machine learning and natural language processing. *PLoS One*. 2020;15(4):e0230876.
doi: 10.1371/journal.pone.0230876
23. Fernandes M, Mendes R, Vieira SM, *et al.* Predicting Intensive Care Unit admission among patients presenting to the emergency department using machine learning and natural language processing. *PLoS One*. 2020;15(3):e0229331.
doi: 10.1371/journal.pone.0229331
24. Horng S, Sontag DA, Halpern Y, Jernite Y, Shapiro NI, Nathanson LA. Creating an automated trigger for sepsis clinical decision support at emergency department triage using machine learning. *PLoS One*. 2017;12(4):e0174708.
doi: 10.1371/journal.pone.0174708
25. Joseph JW, Leventhal EL, Grossestreuer AV, *et al.* Deep-learning approaches to identify critically ill patients at emergency department triage using limited information. *JACEP Open*. 2020;1(5):773-781.
doi: 10.1002/emp2.12218
26. Roquette BP, Nagano H, Marujo EC, Maiorano AC. Prediction of admission in pediatric emergency department with deep neural networks and triage textual data. *Neural Netw*. 2020;126:170-177.
doi: 10.1016/j.neunet.2020.03.012
27. Tahayori B, Chini-Foroush N, Akhlaghi H. Advanced natural language processing technique to predict patient disposition based on emergency triage notes. *Emerg Med Australas*. 2021;33(3):480-484.
doi: 10.1111/1742-6723.13656
28. Zhang X, Belloio MF, Medrano-Gracia P, Werys K, Yang S, Mahajan P. Use of natural language processing to improve predictive models for imaging utilization in children presenting to the emergency department. *BMC Med Inform Decis Mak*. 2019;19:287.
doi: 10.1186/s12911-019-1006-6

29. Zhang X, Kim J, Patzer RE, Pitts SR, Chokshi FH, Schrager JD. Advanced diagnostic imaging utilization during emergency department visits in the United States: A predictive modeling study for emergency department triage. *PLoS One*. 2019;14(4):e0214905.
doi: 10.1371/journal.pone.0214905
30. Zhang X, Kim J, Patzer RE, Pitts SR, Patzer A, Schrager JD. Prediction of emergency department hospital admission based on natural language processing and neural networks. *Methods Inform Med*. 2017;56(05):377-389.
doi: 10.3414/ME17-01-0024
31. Chang D, Hong WS, Taylor RA. Generating contextual embeddings for emergency department chief complaints. *JAMIA Open*. 2020;3(2):160-166.
doi: 10.1093/jamiaopen/ooaa022
32. Greenbaum NR, Jernite Y, Halpern Y, *et al*. Improving documentation of presenting problems in the emergency department using a domain-specific ontology and machine learning-driven user interfaces. *Int J Med Inform*. 2019;132:103981.
doi: 10.1016/j.ijmedinf.2019.103981
33. Gupta N, Mujumdar S, Patel H, *et al*. Data Quality for Machine Learning Tasks. In: *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*. ACM; 2021:4040-4041.
doi: 10.1145/3447548.3470817
34. Gao Y, Dligach D, Christensen L, *et al*. A scoping review of publicly available language tasks in clinical natural language processing. *J Am Med Inform Assoc*. 2022;29(10):1797-1806.
doi: 10.1093/jamia/ocac127
35. Clapp MA, Kim E, James KE, Perlis RH, Kaimal AJ, McCoy TH Jr. Natural language processing of admission notes to predict severe maternal morbidity during the delivery encounter. *Am J Obstet Gynecol*. 2022;227(3):511.e1-e8.
doi: 10.1016/j.ajog.2022.04.008
36. Durango MC, Torres-Silva EA, Orozco-Duque A. Named entity recognition in electronic health records: A methodological review. *Healthc Inform Res*. 2023;29(4):286-300.
doi: 10.4258/hir.2023.29.4.286
37. Sim JA, Huang X, Horan MR, *et al*. Natural language processing with machine learning methods to analyze unstructured patient-reported outcomes derived from electronic health records: A systematic review. *Artif Intell Med*. 2023;146:102701.
doi: 10.1016/j.artmed.2023.102701
38. Huang K, Altosaar J, Ranganath R. ClinicalBERT: Modeling Clinical Notes and Predicting Hospital Readmission. *arXiv*. Preprint posted online 2019.
doi: 10.48550/arXiv.1904.05342
39. Wang Y, Wang Y, Peng Z, Zhang F, Zhou L, Yang F. Medical text classification based on the discriminative pre-training model and prompt-tuning. *Digit Health*. 2023;9:20552076231193213.
doi: 10.1177/20552076231193213
40. Lyu W, Dong X, Wong R, *et al*. A multimodal transformer: Fusing clinical notes with structured ehr data for interpretable in-hospital mortality prediction. *AMIA Annu Symp Proc*. 2023;2022:719-728.
41. Hayat N, Geras KJ, Shamout FE. *MedFuse: Multi-Modal Fusion with Clinical Time-Series Data and Chest X-Ray Images*. In: *Proceedings of Machine Learning Research*; 2022:479-503.
42. Wang Y, Yin C, Zhang P. Multimodal risk prediction with physiological signals, medical images and clinical notes. *Heliyon*. 2024;10(5):e26772.
doi: 10.1016/j.heliyon.2024.e26772
43. AlSaad R, Abd-Alrazaq A, Boughorbel S, *et al*. Multimodal large language models in health care: Applications, challenges, and future outlook. *J Med Internet Res*. 2024;26:e59505.
doi: 10.2196/59505
44. Judge CS, Krewer F, O'Donnell MJ, *et al*. Multimodal artificial intelligence in medicine. *Kidney360*. 2024;5:1771-1779.
doi: 10.34067/KID.0000000000000556
45. Chiu CC, Wu CM, Chien TN, Kao LJ, Li C, Chu CM. Integrating structured and unstructured EHR data for predicting mortality by machine learning and latent Dirichlet allocation method. *Int J Environ Res Public Health*. 2023;20(5):4340.
doi: 10.3390/ijerph20054340
46. Atkins L, Francis J, Islam R, *et al*. A guide to using the Theoretical Domains Framework of behaviour change to investigate implementation problems. *Implement Sci*. 2017;12:77.
doi: 10.1186/s13012-017-0605-9
47. Ahn C. Exploring ChatGPT for information of cardiopulmonary resuscitation. *Resuscitation*. 2023;185:109729.
doi: 10.1016/j.resuscitation.2023.109729
48. Michie S, Van Stralen MM, West R. The behaviour change wheel: A new method for characterising and designing behaviour change interventions. *Implement Sci*. 2011;6:42.
doi: 10.1186/1748-5908-6-42.
49. Salwei ME, Carayon P, Hoonakker PL, *et al*. Workflow integration analysis of a human factors-based clinical decision support in the emergency department. *Appl Ergon*. 2021;97:103498.
doi: 10.1016/j.apergo.2021.103498