Intensive Care Med (2025) 51:590–592 https://doi.org/10.1007/s00134-024-07775-z

EDITORIAL

How AI can help in error detection and prevention in the ICU?

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The intensive care unit (ICU) is a dynamic, high-stakes environment where cutting-edge technology meets the most human aspects of patient care. Life-saving interventions may need to be performed at any time of the day, with high precision and often under immense pressure. Such an environment is inherently prone to human errors, which are often preventable [1]. In this context, technological advances—such as artificial intelligence (AI)—have the potential to transform critical care. Utilised thoughtfully and responsibly, AI could become an invaluable ally in enhancing patient safety, supporting staff, and significantly reducing the risk of errors.

Errors are often not solely the result of an individual's failure but rather caused by a culmination of systemic weaknesses, where multiple layers of defence fail. This is commonly referred to as the Swiss cheese model [2]. Medication errors are responsible for half of all errors in the ICU and cause preventable harm to 17% of patienst [1]. Tools such as computerised provider order entry systems, decision support software, barcode medication administration, and smart infusion pumps have already been implemented as additional safety layers [3–5]. Implementing AI algorithms into these tools could help detect preventable errors even earlier and ultimately increase patient safety by integrating more data and adapting to patients. For instance, recent work has shown the possibility to detect medication errors by utilizing AI enabled wearable cameras [6]. Further use cases of error detection and prevention through AI include predictive modelling to identify at-risk patients, clinical decision support systems, and automation of routine tasks [7].

Vital sign monitoring is a crucial tool to pinpoint deteriorating patients in the ICU and initiate adequate care rapidly. However, the implementation of novel technologies and the associated growing information load has led to another increasingly prevalent issue: monitoring and alarm fatigue [8]. The overwhelming number of alarms, failure to respond to them and the general overload of patient monitoring data are increasingly leading to missed critical events [9]. This problem could be exacerbated with the introduction of new AI alerting technologies.

AI could significantly enhance patient safety in the ICU by reducing false alarms, ensuring that alarms requiring immediate attention are prioritised. AI-driven smart alarms can transform clinical workflows by focusing attention on true emergencies, improving response times, and reducing the risk of alarm fatigue. These systems prioritize alarms based on severity, enabling clinicians to address the most critical situations first, while minimizing non-urgent alarms that disrupt workflow. Adaptive AI algorithms are static by design and cannot learn from past events, making them unsuitable for refining alarm accuracy over time. However, the effectiveness of this AI-driven approach hinges on the quality, quantity, and diversity of data collected, underscoring the need for a comprehensive data ecosystem to realize its full potential.

To advance both AI research and clinical care in the ICU, a robust data ecosystem must be at the core of digital transformation (Fig. 1). Building this ecosystem requires seamless collaboration between industry, researchers, and healthcare providers [10]. At its foundation is high-quality data, without which AI-driven progress is impossible. Some of the most reliable data can be obtained from automated systems like patient monitors, infusion pumps, and ventilators. It is therefore essential to move towards the deployment of strategies for reliable automatic data collection. However, collecting data is just the first step. Efficient storage, particularly using scalable cloud solutions that facilitate federated learning, is critical given the enormous volume of data [11]. To unlock its full potential for a wide range of AI applications, this data must be pre-processed and integrated with other sources. Moreover, creating openly accessible datasets, following the lead of initiatives like the Medical Information Mart for Intensive Care (MIMIC) [12], is crucial to support AI research and development. Publicly available datasets not only drive innovation but also enable the development of new methods to improve data collection and quality and help to ensure that AI algorithms can advance across various healthcare systems [13].

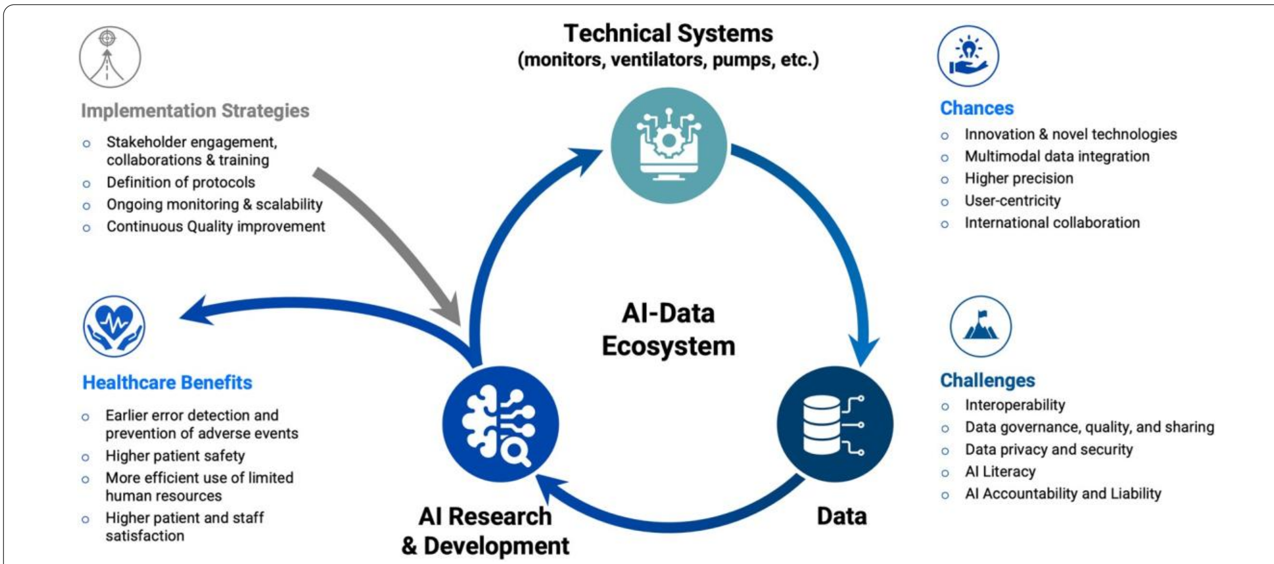

Fig. 1 The AI-Data Ecosystem: Challenges, chances, healthcare benefits and implementation strategies

AI can enhance error detection and prevention in the ICU. However, its success hinges on creating a robust data ecosystem, which requires collaboration between industry, research, and healthcare providers. To foster innovation in the intensive care setting, it is our responsibility as data-driven ICU professionals to ensure reliable data collection at the bedside, efficient storage, and the use of open-access or federated datasets. However, technology goes hand in hand with education and implementation strategies. Though considerable advances in the domain of explainable AI have been made, ICU professionals need a basic understanding of data science for making responsible use of AI technology in daily practise. Together, these efforts can lead to safer, more effective ICU environments and improved patient outcomes.

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Funding

Open Access funding enabled and organized by Projekt DEAL.

Declaration Conflict of interest

The authors declare that they do not have any conflict of interest.

Publisher's Note

Received: 30 September 2024 Accepted: 23 December 2024

Published: 22 January 2025

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