Narrative Review

Role of artificial intelligence in haemodynamic monitoring

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ABSTRACT

This narrative review explores the evolving role of artificial intelligence (AI) in haemodynamic monitoring, emphasising its potential to revolutionise patient care. The historical reliance on invasive procedures for haemodynamic assessments is contrasted with the emerging non-invasive AI-driven approaches that address limitations and risks associated with traditional methods. Developing the hypotension prediction index and introducing CircEWS™ and CircEWS-lite ™ showcase AI's effectiveness in predicting and managing circulatory failure. The crucial aspects include the balance between AI and healthcare professionals, ethical considerations, and the need for regulatory frameworks. The use of AI in haemodynamic monitoring will keep growing with ongoing research, better technology, and teamwork. As we navigate these advancements, it is crucial to balance AI's power and healthcare professionals' essential role. Clinicians must continue to use their clinical acumen to ensure that patient outliers or system problems do not compromise the treatment of the condition and patient safety.

Keywords: Artificial intelligence, early warning signs, haemodynamic monitoring, hypotension prediction index, machine learning

INTRODUCTION

Haemodynamic monitoring is crucial to patient care in various medical settings, especially in operating rooms, critical care units, and during specific interventional procedures. It involves continuous assessment and measurement of cardiovascular parameters to understand blood circulation dynamics and ensure optimal organ perfusion. It aids in decision-making as well as evaluation of the effectiveness of treatment strategies.

Historically, haemodynamic monitoring relied on invasive procedures, such as inserting a pulmonary artery catheter to measure cardiac output, mixed venous oxygenation, and pulmonary artery pressures. This invasive approach provided direct and accurate measurements but came with associated risks, including infections, bleeding, and vascular complications. Furthermore, these methods often require specialised training. They posed challenges regarding patient comfort and acceptance, leading to the emergence of non-invasive cardiac output monitoring, which overcame several limitations and risks associated with invasive methods. However, like any medical technology, it has limitations and disadvantages, including lesser accuracy and precision, dependency on operator skills, and limited ability to select patient populations.[1]

Artificial intelligence (AI) has the potential to revolutionise haemodynamic monitoring by addressing the limitations associated with traditional approaches, offering real-time insights, and contributing to improved patient outcomes. AI is pivotal in enhancing

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the accuracy and reliability of non-invasive cardiac output monitoring. Machine learning algorithms can process complex data from various non-invasive sensors, improving the precision of cardiac output estimates and providing valuable insights for clinical decision-making.[1,2]

This narrative review aims to explore and analyse the evolving role of AI in haemodynamic monitoring, shedding light on the advancements, challenges, and potential implications for clinical practice.

METHODS

We conducted a comprehensive literature review to explore the role of AI in haemodynamic monitoring. The search was conducted across various electronic databases, including PubMed, IEEE Xplore, Google Scholar, and relevant medical and technology journals. Articles published in the English language from 2001 to 2023 were included. Primary research articles, systematic reviews, and meta-analyses were considered to ensure the inclusion of rigorous studies performed in humans. Articles were included if they directly addressed the application of AI in haemodynamic monitoring.

The search strategies employed a combination of Medical Subject Headings (MeSH) terms and keywords related to AI, haemodynamic monitoring, and cardiovascular health. The primary search terms included 'artificial intelligence', 'machine learning', 'haemodynamic monitoring', and variations of these terms. Boolean operators (AND, OR) were used to refine the search and ensure relevance.

RATIONALE FOR THE USE OF ARTIFICIAL INTELLIGENCE IN HAEMODYNAMIC MONITORING

Physicians need help in accurately predicting the occurrence of circulatory shock and determining the optimal treatment strategies for individual patients due to limitations in existing diagnostic and prognostic techniques.[3] Understanding circulatory shock's physiological mechanisms is imperative for guiding appropriate therapeutic interventions. Typically, the administration of vasoactive medications and fluid resuscitation becomes necessary, along with addressing concurrent issues such as inflammation, multiple organ failure, hypotension, and haemodynamic instability. The symptoms of different causes of shock are similar, making early decisions challenging. The current management of hypotension tends to be reactive, relying on observing declining blood pressure trends. However, this approach often leads to delays in interventions. Studies have shown a direct correlation between the duration of mean arterial pressure (MAP) below 65 mm Hg and increased mortality in non-cardiac patient populations.[4,5] It is reasonable to consider that minimising the severity and duration of hypotension could improve patient outcomes.

Therefore, it is crucial to develop quick, reliable, and easy-to-understand methods for planning treatments to reduce mortality and avoid irreversible consequences linked to shock, which AI can facilitate.

APPLICATIONS IN HAEMODYNAMIC MONITORING

Artificial intelligence for prediction of hypotension

Hatib *et al.* developed a system to predict hypotension by using a logistic regression model. This system, called the hypotension prediction index (HPI), is integrated into the Haemo Sphere Advanced Monitoring Platform ™ (Edwards Lifesciences, California, USA). The HPI can accurately forecast hypotension several minutes before a drop in blood pressure occurs. The Acumen HPI algorithm™ is a mathematical model developed by learning from almost 59,000 past hypotensive events and over 144,000 non-hypotensive events.[6] Through performance analysis and sequential feature selection, 2.6 million features are reduced to the 23 most predictive features to build the HPI model. Features from the current patient's Acumen IQ arterial waveform features are fed into the model to determine the HPI parameter value. The model compares the current patient's Acumen IQ arterial waveform features to those from development dataset patients.

The HPI model generates a numerical value between 1 and 100 to indicate the likelihood of hypotension. Beyond MAP, the model considers various parameters such as stroke volume, cardiac output, stroke volume variation, systemic vascular resistance, dP/dt (an indicator of cardiac contractility), and Eadyn (a measure of dynamic elastance). These inputs help guide decisions using fluids, inotropes, or vasopressors to enhance haemodynamic stability and prevent anticipated hypotensive events. The main objective of the method is to detect minute multivariate fluctuations that occur before hypotensive events but are invisible to the naked eye or basic signal processing. It uses sophisticated machine learning to map these subtle changes and forecast the probability of approaching hypotension.

The EU HYPROTECT Registry monitored 749 patients undergoing major non-cardiac surgery by using the Acumen™ Hypotension Prediction Index software.[7] The analysis of 702 patients revealed a notably low median time-weighted average MAP of <65 mmHg (0.03 mmHg). A significant proportion (41%) experienced no extended hypotensive episodes, while 59% had at least one episode, with a median of 1 episode lasting ≥1 minute. Patients spent a median of 2 minutes, constituting merely 1% of the total surgical time below a MAP of 65 mmHg. These findings indicate that employing HPI software monitoring might decrease both the severity and duration of intra-operative hypotension in non-cardiac surgery patients.

Artificial intelligence to overcome alarm fatigue

In hospitals, healthcare workers use alarms to monitor patients' vital signs and identify those in danger of worsening. However, these alarms can generate false alarms, leading to alarm fatigue. This can be dangerous for patients. Alarm fatigue is when healthcare workers become desensitised to safety alerts and ignore or fail to respond appropriately to such warnings.[8-10] This was ranked seventh on the Emergency Care Research Institute list of the top ten technological hazards.[11,12] AI can help reduce alarm fatigue by providing real-time monitoring, often incorporating alert systems triggered by predefined thresholds. When specific haemodynamic parameters deviate from the normal range, the system generates alerts, notifying healthcare providers promptly. This proactive notification system is crucial for time-sensitive interventions in critical care scenarios.

Artificial intelligence for other early warning systems

Smith and Wood found that 51% of patients had one or more abnormal vital signs in the form of tachycardia, hypotension, hypo or hyperthermia, tachypnoea, altered mental status, or decreased urine output in the 24 hours before their cardiac arrest.[13] These warning signs in the form of derangement of physiologic variables often go unnoticed. AI provides real-time monitoring in haemodynamic assessment involving the continuous analysis of physiological data, such as blood pressure, heart rate, and cardiac output. ML algorithms process this data instantaneously, providing a dynamic and up-to-the-moment understanding of a patient's cardiovascular status that can augment the physician's decision-making abilities and improve patient outcomes.[14]

SL Hyland *et al*.[15] introduced CircEWS and CircEWS-lite, two early-warning systems specifically engineered to alert clinicians to anticipated circulatory failure events within 8 hours. Developing and validating these systems involved utilising patient data sourced from the High Time Resolution ICU dataset. A continuous risk score, updating every 5 minutes, was generated to forecast the likelihood of a patient developing circulatory failure within the subsequent 8 hours. Notably, the model achieved a 90% prediction accuracy for circulatory failure events in the test set, with 82% identified more than 2 hours in advance. The authors implemented an alarm system featuring a silencing policy, where subsequent alarms are suppressed for 30 minutes once an initial alarm is triggered. The system resets if a patient experiences circulatory failure and subsequently recovers.

Artificial intelligence for cardiac surgery and shock

Various AI models have been created for post-cardiac surgery and septic shock. Denai M *et al*.[16] have described fuzzy decision support systems (DDS) for managing post-surgical cardiac intensive care patients. Paetz H *et al*.[17] and Paetz J *et al*.,[18] the former, in conjunction with an artificial neural network (ANN), have tackled the problem of rule generation for patients suffering from septic shock. Later, Ross *et al.* developed an ANN model of inflammation and septic shock in conjunction with a system of ordinary differential equations.[19] ML methods have also been used with varying success for the more specific problem of predicting mortality caused by sepsis. A diagnostic system for septic shock based on ANNs (radial basis functions (RBFs) and supervised growing neural gas) was presented.[20]

These models and studies present various methods that use AI and predictive techniques to predict haemodynamic instability, treat conditions such as septic shock and post-cardiac surgery care, and forecast circulatory failure. These methods offer promising ways to improve patient care in critical situations.

Using pre-operative and intra-operative data, a real-time prediction model for large transfusion during surgery showed high accuracy (AUROC of 0.972 in internal validation and 0.943 in external validation).[21] This model shows the promise of AI-supported clinical decision-making in surgical settings by enabling early identification of high-risk patients and maybe enabling timely interventions.

Artificial intelligence-assisted ultrasonography

The role of AI in various ultrasonographic procedures has been reported. Shaikh *et al*.[22] examined how well-inexperienced users could quantify cardiac output (CO) during point-of-care ultrasonography (POCUS) using manual methods versus an automation-assisted method supported by AI. The automated method supplied real-time feedback for appropriate aortic outflow velocity measurement. Results demonstrated that although there was a correlation between human and automated measures, the automated approach had better repeatability, lower variability, and more constrained measurement ranges. Although both groups overestimated readings compared to experts, the automated method showed higher accuracy when measuring CO. Accordingly, AI-assisted ultrasonography may improve accuracy and decrease unpredictability in critical care environments, which may facilitate the evaluation of haemodynamic responses to therapies.

Closed loop systems

Closed-loop systems that integrate monitoring with therapy have been developed. Combining monitoring of various systems with therapy to correct values in a closed-loop system would be the most efficient and intelligent use of a monitoring system. A closed-loop control system is where the actual behaviour is sensed and fed back to the controller. This is compared to the system's set, reference, or desired state to adjust it to its desired state. These include closed-loop control of blood glucose levels,[23] use of the electroencephalogram to administer propofol to maintain a predetermined level of sedation in intensive care unit patients,[24] a fluid-administration system based on dynamic predictors of fluid responsiveness,[25] and to manage blood pressure.[26]

Thus, monitoring and therapy will be seamless with advanced technology. Frequent monitoring, frequent titration, and adherence to the protocol can lead to reduced error, increased safety, reduced nursing and staff workload, and reduced mortality and hospital stay. However, clinicians must identify the parameters of interest, develop and validate clinically valuable sensors, develop clinically validated management algorithms, validate the entire closed-loop system, and demonstrate the utility of these closed-loop systems in clinical trials.

CHALLENGES AND LIMITATIONS

The quality of data used to train ML models is paramount. Challenges arise from the potential biases and inaccuracies in the training data, which can impact the performance of algorithms, particularly in diverse patient populations. Some ML models, incredibly complex neural networks, may need more interpretability. Understanding how these models arrive at specific conclusions can take time, raising concerns about transparency and trust in decision-making. Incorporating AI-driven haemodynamic monitoring systems into existing healthcare structures presents a multi-faceted challenge. Compatibility issues, interoperability, and the need for seamless data exchange between different systems pose challenges to implementation. Furthermore, establishing effective collaboration between healthcare professionals and AI systems remains challenging. Encouraging physicians to leverage AI to their advantage is challenging due to the misconception that AI aims to replace them. In reality, it serves as a complementary tool, offering those with AI knowledge a distinct edge without seeking to replace their expertise.

AI in healthcare raises ethical concerns, including patient privacy, consent, and the responsible handling of sensitive medical data. Clear guidelines and regulations are necessary to address these ethical considerations. Haemodynamic parameters are dynamic and can change rapidly in response to various factors. AI models may face challenges adapting to these dynamic changes and providing real-time accurate predictions. AI models developed for haemodynamic monitoring need rigorous validation across diverse patient populations and healthcare settings to ensure their reliability and generalisability.

THE FUTURE OF ARTIFICIAL INTELLIGENCE IN HAEMODYNAMIC MONITORING

The future of AI in haemodynamic monitoring is poised for exciting developments that aim to enhance patient care and clinical decision-making. One key direction is the move towards personalised monitoring, where AI algorithms can be tailored to individual patient characteristics, optimising precision in assessing haemodynamic status. Real-time adaptive models are anticipated, allowing AI systems to dynamically respond to changes in a patient's condition, facilitating more timely interventions.

Integrating AI with wearable devices is another forward-looking trend, offering continuous and unobtrusive monitoring of haemodynamic parameters. This could prove valuable in various healthcare settings, providing patients and healthcare professionals with insightful data. Blockchain technology may be incorporated to address data security and privacy concerns, ensuring a secure and decentralised system for managing patient information.

The future also holds promise for more transparent AI models with improved interpretability. This is crucial for building trust among healthcare professionals, particularly as AI becomes more integral to clinical decision-making. Advanced signal processing techniques, including incorporating cutting-edge imaging modalities and sensor technologies, are expected to improve the accuracy and reliability of haemodynamic measurements.

AI applications in haemodynamic monitoring may evolve to predict instability and anticipate complications or adverse events. This predictive analytics approach enables proactive interventions, potentially improving patient safety. Continuous learning models that adapt and improve over time based on real-world patient data represent another exciting frontier.

Technological advancements such as edge computing, which processes data locally near the patient, could reduce latency, particularly in critical care scenarios where real-time decision-making is critical. As AI in haemodynamic monitoring progresses, the development of regulatory frameworks will become essential to ensure these technologies' safe, effective, and ethical use in healthcare.

The present-day noise in Intensive care units (ICU), primarily attributed to existing alarm systems, could potentially transform into a quieter environment; in the foreseeable future, ICUs might transition into 'silent zones', facilitated by the integration of wearable and remote monitoring devices, fostering an environment focused on patient comfort and tranquillity.

Despite these challenges, the future of AI in haemodynamic monitoring holds tremendous promise. Ongoing innovations, including real-time adaptive models, personalised monitoring approaches, and the incorporation of wearable devices, suggest a trajectory toward more efficient and patient-centric care. The potential for AI to predict complications and adverse events further underscores its role as a valuable tool in clinical decision-making.

As we navigate these advancements, it is crucial to balance AI's power and healthcare professionals' essential role. The collaboration between man and machine, where AI complements rather than replaces clinical judgment, is pivotal for successful integration. Ethical considerations surrounding data privacy and security also necessitate careful attention, emphasising the importance of clear regulations and standards.

AI in haemodynamic monitoring will likely witness continual growth in the coming years, fuelled by ongoing research, technological innovations, and collaborative efforts across the healthcare and technology sectors. Ultimately, the successful integration of AI can usher in a new era of proactive and personalised healthcare, where the intersection of AI and clinical expertise optimally serves the well-being of patients.

ROLE OF THE CLINICIAN

What will the clinician's role be in this highly automated, computer- and data-driven environment? Arguably, this could dehumanise medical care even further. On the other hand, automation of several processes will save considerable time for the doctor. This time could be devoted to talking and listening to patients and their families, examining patients, and focusing on the humane aspects of care. Another benefit will be the reduction or elimination of physician error. However, the system's strength depends on the reliability of the databases and algorithms built into the software. Finally, not all processes can be automated. Clinicians must continue to use their clinical acumen to ensure that patient outliers or system problems do not compromise the treatment of the condition and patient safety.

CONCLUSIONS

Integrating AI into haemodynamic monitoring represents a transformative frontier in healthcare, offering a spectrum of benefits and presenting unique challenges. The current landscape showcases the potential for AI to revolutionise the precision and personalisation of haemodynamic assessments, providing timely insights for clinicians and optimising patient outcomes. With the advent and refinement of AI, future monitors will not be a mere collective display of numbers and waveforms. Monitoring systems will integrate current and trends of physiological data and data from the electronic medical records (EMR) and use bioinformatics to identify disease patterns, predict events, determine appropriate therapy, and help prognosticate. Intelligent monitoring will help clinicians with decision support, eradicate unnecessary alarms, and allow the clinician to focus on the patient. Closed-loop systems will integrate monitoring with therapy in an automated manner, leading to better adherence to protocol, elimination of human error, excellent patient safety, and better outcomes. However, challenges such as data quality, model interpretability, and seamless integration into existing healthcare infrastructures must be diligently addressed to unlock the full potential of AI in this domain. As we navigate these advancements, it is crucial to balance AI's power and healthcare professionals' essential role. Clinicians must continue to use their clinical acumen to ensure that patient outliers or system problems do not compromise the treatment of the condition and patient safety.

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Conflicts of interest

There are no conflicts of interest.

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REFERENCES

1. Scheeren TWL, Ramsay MAE. New developments in hemodynamic monitoring. J Cardiothorac Vasc Anesth 2019;33:S67–72.
2. Mamdani M, Slutsky AS. Artificial intelligence in intensive care medicine. Intensive Care Med 2021;47:147–9.
3. Schinkel M, Paranjape K, Nannan Panday RS, Skyttberg N, Nanayakkara PWB. Clinical applications of artificial intelligence in sepsis: A narrative review. Comput Biol Med 2019;115:103488.
4. Vincent JL, Nielsen ND, Shapiro NI, Gerbasi ME, Grossman A, Doroff R, *et al*. Mean arterial pressure and mortality in patients with distributive shock: A retrospective analysis of the MIMIC-III database. Ann Intensive Care 2018;8:107.
5. Maheshwari K, Nathanson BH, Munson SH, Khangulov V, Stevens M, Badani H, *et al*. The relationship between ICU hypotension and in-hospital mortality and morbidity in septic patients. Intensive Care Med 2018;44:857–67.
6. Hatib F, Jian Z, Buddi S, Lee C, Settels J, Sibert K, *et al*. Machine- learning algorithm to predict hypotension based on high-fidelity arterial pressure waveform analysis. Anesthesiology 2018;129:663-74.
7. Kouz K, Monge García MI, Cerutti E, Lisanti I, Draisci G, Frassanito L, *et al*. Intraoperative hypotension when using hypotension prediction index software during major noncardiac surgery: A European multicentre prospective observational registry (EU HYPROTECT). BJA Open 2023;6:100140.
8. Ruppel H, De Vaux L, Cooper D, Kunz S, Duller B, Funk M. Testing physiological monitoring alarm customization software to reduce alarm rates and improve nurses' experience of alarms in a medical intensive care unit. PLoS One 2018;13:e0205901.
9. Simpson KR, Lyndon A. False alarms and overmonitoring: Major factors in alarm fatigue among labor nurses. J Nurs Care Qual 2019;34:66-72.
10. Borowski M, Görges M, Fried R, Such O, Wrede C, Imhoff M. Medical device alarms. Biomed Tech (Berl) 2011;56:73-83.
11. Top 10 health technology hazards for 2019. ECRI Institute. 2019. Available from: https://www.ecri.org.
12. Graham KC, Cvach M. Monitor alarm fatigue: Standardizing use of physiological monitors and decreasing nuisance alarms. Am J Crit Care 2010;19:28-34.
13. Smith AF, Wood J. Can some in-hospital cardio-respiratory arrests be prevented? A prospective survey. Resuscitation 1998;37:133-7.
14. Clermont G. Artificial neural networks as prediction tools in the critically ill. Crit Care 2005;9:153-4.
15. Hyland SL, Faltys M, Hüser M, Lyu X, Gumbsch T, Esteban C, *et al*. TM. Early prediction of circulatory failure in the intensive care unit using machine learning. Nat Med 2020;26:364-73.
16. Denai M, Mahfouf M, Ross J. A Fuzzy decision support system for therapy administration in cardiovascular intensive care patients. 2007 IEEE International Fuzzy Systems Conference. London, UK; 2007. p. 1-6.
17. Paetz H. Metric rule generation with septic shock patient data. Proceedings 2001 IEEE International Conference on Data Mining. San Jose, CA, USA; 2001. p. 637-8.
18. Paetz J. Intersection based generalization rules for the analysis of symbolic septic shock patient data. 2002 IEEE International Conference on Data Mining, 2002. Proceedings. Maebashi City, Japan; 2002. p. 673-6.
19. Ross JJ, Mason DG, Paterson IG, Linkens DA, Edwards ND. Development of a knowledge-basedsimulator for haemodynamic support of septic shock. In: IEEE Colloquium on Simulation in Medicine (Ref. No. 1998/256). 1998; 3/1-3/4.
20. Brause R, Hamker F, Paetz J. 2002. Septic shock diagnosis by neural networks and rule based systems. In: Schmitt M, Teodorescu HN, Jain A, Jain A, Jain S, Jain LC, editors. Computational Intelligence Processing in Medical Diagnosis. Studies in Fuzziness and Soft Computing, vol 96. Physica, Heidelberg; 2002. p. 323–56.
21. Denn S, Schneck E, Jablawi F, Bender M, Schmidt G, Habicher M, *et al*. The use of artificial intelligence and machine learning monitoring to safely administer a fluid-restrictive goal-directed treatment protocol to minimize the risk of transfusion during major spine surgery of a Jehovah's Witness: A case report. J Med Case Rep 2022;16:412.
22. Shaikh F, Kenny JE, Awan O, Markovic D, Friedman O, He T, *et al*. Measuring the accuracy of cardiac output using POCUS: The introduction of artificial intelligence into routine care. Ultrasound J 2022;14:47.
23. Chee F, Fernando T, van Heerden PV. Closed-loop control of blood glucose levels in critically ill patients. Anaesth Intensive Care 2002;30:295-307.
24. Albrecht S, Frenkel C, Ihmsen H, Schüttler J. A rational approach to the control of sedation in intensive care unit

patients based on closed-loop control. Eur J Anaesthesiol 1999;16:678-87.

25. Rinehart J, Alexander B, Le Manach Y, Hofer C, Tavernier B, Kain ZN, *et al*. Evaluation of a novel closed-loop fluid-administration system based on dynamic predictors of fluid responsiveness: An in silico simulation study. Crit Care 2011;15:R278.
26. Mason DG, Packer JS, Cade JF, McDonald RD. Closed-loop management of blood pressure in critically ill patients. Australas Phys Eng Sci Med 1985;8:164-7.