Artificial intelligence for improving the monitoring of hemodynamic changes in the ICU: a systematic review of predictive algorithms and clinical outcomes

by Nugroho Ari

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Artificial intelligence for improving the monitoring of hemodynamic changes in the ICU: a systematic review of predictive algorithms and clinical outcomes

Nugroho Ari Wibowo[1], Siswanto Agung Wijaya[1], Diah Priyantini[1], Daviq Ayatulloh[2], Ade faiz Ahmadi[3]

[1] Faculty of Health Sciences, Universitas Muhammadiyah Surabaya, Indonesia
[2] Faculty of Health Sciences, Universitas Gresik, Indonesia
[3] Faculty of Health Sciences, iInstitut Teknologi Sains dan Kesehatan Insan Cendekia Medika, Jombang

Corresponding Author
nugrohoariwibowo@um-surabaya.ac.id

Abstract

Background: Hemodynamic instability is a major predictor of organ failure and mortality in ICU patients. Conventional monitoring often fails to detect early deterioration, which has encouraged the use of artificial intelligence (AI) to improve the detection and prediction of hemodynamic instability. Methods: This systematic review followed the PRISMA 2020 guidelines and analyzed studies using machine learning or deep learning to predict hypotension, vasopressor requirements, or hemodynamic instability in adult ICU patients. Six major databases were screened, and 16 studies met the inclusion criteria. Due to heterogeneity in model design and outcomes, the findings were synthesized narratively. Results: The included studies comprised retrospective model development, multicenter validation, prospective evaluation, and two randomized clinical trials. Multivariable models such as the hemodynamic stability index (HSI) demonstrated strong predictive performance (AUROC 0.76–0.90). Dynamic models such as TvHEWS consistently provided stable predictions with reduced false alarms. Waveform-based predictors, including the hypotension prediction index (HPI), were able to anticipate hypotension 5–15 minutes before onset, even in patients with sepsis. Personalized approaches, such as DynaCEL and HM-TARGET, generated patient-specific hemodynamic targets. Prospective studies showed a reduction in the duration of hypotension, although evidence regarding effects on mortality and organ failure remains limited. Conclusion: Artificial intelligence has the potential to improve the accuracy of hemodynamic monitoring and enable earlier intervention in the ICU. However, large-scale clinical trials are still needed to confirm its benefits on meaningful clinical outcomes.

Keywords: *artificial intelligence, hemodynamic monitoring, hypotension prediction, ICU, machine learning, predictive model.*

INTRODUCTION

Hemodynamic instability is one of the main determinants of morbidity and mortality in the intensive care unit (ICU) (Huygh et al., 2016; Monnet et al., 2025). Episodes of hypotension, shock, and impaired tissue perfusion that are not detected early contribute to organ failure, prolonged length of stay, and an increased risk of death (Schuurmans et al., 2024; Umegaki et al., 2011). Globally, 50–70% of ICU patients experience at least one episode of hypotension, and continuous monitoring has shown that many cases of severe hypotension with clinically significant duration occur within the first 24 hours (Ghosh et al., 2016; Mathis et al., 2020). The cumulative duration of hypotension has been shown to have a dose-response relationship with mortality, acute kidney injury, and organ dysfunction (Ackland & Abbott, 2022; B. Khwannimit et al., 2025; Rinehart et al., 2019). In addition, 8–10% of ICU patients experience septic shock, with ICU mortality of approximately 35–40% (Abe et al., 2020; Imaeda et al., 2025), while the global burden of sepsis shows a 30-day mortality of 24% and a 90-day mortality of 32%. These facts highlight the limitations of conventional hemodynamic monitoring approaches, which remain reactive, depend heavily on visual observation, and use threshold-based alarm systems that often cause alarm fatigue and fail to capture progressively worsening hemodynamic patterns (Attique et al., 2025; Wang et al., 2023).

The development of artificial intelligence (AI), particularly machine learning (ML) and deep learning, has offered a solution to improve the early detection and prediction of hemodynamic instability (Chiang et al., 2025; Hadweh et al., 2025; Michard et al., 2025). Over the past decade, the interdisciplinary literature in critical care has shown a global increase in studies, with approximately 20–25% focusing on the prediction of hypotension, vasopressor requirements, or the risk of circulatory failure (Chiang et al., 2025; Hadweh et al., 2025). Technologies such as the Hypotension Prediction Index (HPI), arterial pressure waveform-based prediction models, and multivariable ML models using large-scale ICU data have demonstrated strong predictive performance (Frassanito et al., 2022; Hatib et al., 2018; Bodin Khwannimit et al., 2025), with an average Area Under the Receiver Operating Characteristic curve (AUROC) of 0.80–0.90 for predicting hypotension 10–30 minutes before the event (Hatib et al., 2018; van der Ven et al., 2022). Several prospective studies have reported that the implementation of AI-based predictive models can reduce the duration of intraoperative hypotension and ICU-related hypotension by up to 40–50%, indicating the clinical potential of this technology to improve the precision of interventions (Lai et al., 2024; Lorente et al., 2023; Yoshikawa et al., 2024).

Published research has shown that the currently available scientific evidence remains inconsistent and fragmented. Most studies use retrospective designs based on electronic health records or waveform analysis, with more than 60% of studies focused on model development and validation without testing their actual impact on clinical outcomes (Ackland & Abbott, 2022). Prospective studies and clinical trials remain limited, accounting for less than 15%, while randomized controlled trials evaluating implementation effectiveness represent less than 5% of the total available literature (Imaeda et al., 2025). In addition, most studies place greater emphasis on algorithm performance metrics, such as AUROC, sensitivity, specificity, and model calibration, rather than evaluating more clinically meaningful outcomes, including mortality, organ injury, vasopressor requirements, and ICU resource utilization (Chiang et al., 2025; Hatib et al., 2018; Michard et al., 2025).

Other gaps are evident in the lack of external validation, high variability across ICU settings, and limited analysis of implementation challenges such as system integration, preparedness of nurses and healthcare professionals, timeliness, and the risk of algorithmic bias (Umegaki et al., 2011; Yoshikawa et al., 2024). Many previous reviews have also combined operating room and ICU contexts without separating their different physiological characteristics and intervention patterns, thus providing a less specific picture of the usefulness of AI for hemodynamic monitoring in critically ill patients (Ackland & Abbott, 2022; Huygh et al., 2016). Some literature reviews focus on sepsis or respiratory failure prediction rather than specifically on hemodynamics, meaning that the body of evidence on AI-enhanced hemodynamic monitoring has not yet been comprehensively synthesized (Frassanito et al., 2022; Bodin Khwannimit et al., 2025). In the current era of technological advancement, the application of AI in hemodynamic monitoring has substantial clinical significance. The ability to identify patterns of blood pressure changes, heart rate variability, vascular response, and perfusion dynamics enables a more predictive approach to the management of critically ill patients (Chiang et al., 2025; Lorente et al., 2023). The integration of AI has the potential not only to improve the accuracy of early detection but also to transform the ICU care paradigm from reactive monitoring to predictive and anticipatory monitoring. A synthesis of the latest scientific evidence is urgently needed to understand the extent to which this technology can improve patient safety, support clinical decision-making, and reduce the workload of healthcare professionals. Based on this need, this systematic review aims to comprehensively evaluate the scientific evidence regarding the use of artificial intelligence to improve hemodynamic monitoring in the ICU, including the types of algorithms used, predictive performance, and their impact on relevant clinical outcomes.

METHODS

Study design

This systematic review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines (Parums, 2021) and aimed to synthesize the current evidence on the application of artificial intelligence (AI) to improve hemodynamic monitoring in adult ICU populations. Given the heterogeneity in AI models, predictive algorithms, input data types, and evaluated clinical outcomes, this study used a narrative synthesis approach.

Search strategy

The literature search was conducted in six major databases, namely CINAHL, Cochrane, Embase, PubMed, Scopus, and Web of Science, with additional searches of grey literature through Google Scholar and relevant scientific websites. The search strategy was developed based on four main keyword groups: artificial intelligence, hemodynamic monitoring, intensive care unit, and predictive algorithms and clinical outcomes. The keywords included ("artificial intelligence" OR AI OR "machine learning" OR "deep learning" OR "neural network*" OR "predictive modelling" OR "algorithmic prediction") AND ("hemodynamic monitoring" OR "blood pressure monitoring" OR "arterial waveform analysis" OR "hemodynamic instability" OR "hypotension prediction") AND ("intensive care unit" OR ICU OR "critical care" OR "intensive therapy unit" OR "high-dependency unit") AND ("predictive algorithms" OR "prediction model*" OR "early warning system*" OR "risk prediction tool*" OR "clinical outcome*" OR mortality OR morbidity OR "organ dysfunction" OR "vasopressor requirement"). These keywords were combined using Boolean operators, and the search was conducted in the title, abstract, and keywords fields of each database without restriction by publication year. The full search keywords and syntax for each database are presented in the supplementary file.

Eligibility criteria

The study eligibility criteria were established based on the PICOS framework (supplementary file). The population included adult patients aged ≥18 years who were admitted to the ICU, including general, surgical, medical, and cardiac ICUs. The intervention included the application of AI, including machine learning and deep learning, to improve hemodynamic monitoring. These technologies could include prediction models for hypotension, vasopressor requirement, shock, or perfusion disturbances using continuous physiological data such as arterial waveforms, blood pressure, electrocardiography, and vital signs, as well as electronic health record data. The comparison could include conventional hemodynamic monitoring, including traditional risk scores, or studies without a comparator group. The outcomes considered comprised two categories: clinical outcomes, such as the incidence and duration of hypotension, ICU mortality, organ injury, vasopressor requirement or dosage, ICU length of stay, and hemodynamic complications; and model performance outcomes, including AUROC, accuracy, sensitivity, specificity, calibration, and lead-time prediction. The study designs included randomized controlled trials, prospective observational or interventional studies, retrospective cohort studies, quasi-experimental designs, and model development or research-and-development studies directly related to the use of AI in ICU hemodynamic monitoring.

Study selection

The literature search identified a total of 8,759 articles from six major databases. In the initial stage, 2,271 duplicate articles were removed, followed by the exclusion of 538 articles that did not provide complete reference information and 1 retracted article. After title and abstract screening, only 1,178 articles met the initial inclusion criteria and proceeded to full-text review. At this stage, studies that were not relevant to the PICOS framework, did not use artificial intelligence as the main intervention, or did not report the required hemodynamic outcomes were excluded. Overall, 16 articles met the eligibility criteria and were included in the data extraction process. The entire process of identification, screening, eligibility assessment, and study inclusion was reported according to the PRISMA guidelines, as shown in

Figure 1.

Data extraction

Data extraction was performed independently by extracting the main information from each article that met the inclusion criteria, including study characteristics (author name, year of publication, country, and study design), population characteristics (type of ICU, sample size, and demographic characteristics), details of the artificial intelligence intervention (type of algorithm, source and type of input data, prediction horizon, and predictor variables), type of comparator used, and reported outcomes. The extracted outcomes included clinical outcomes (incidence and duration of hypotension, mortality, organ injury, vasopressor requirement and dose, ICU length of stay, and hemodynamic complications) and model performance outcomes (AUROC, accuracy, sensitivity, specificity, PPV/NPV, calibration, and prediction lead time). Any discrepancies in the extraction results between reviewers were resolved through discussion or by involving a third reviewer.

Risk of bias assessment

Risk of bias was assessed using the Joanna Briggs Institute (JBI) critical appraisal tools, adapted to the design of each included study. Two reviewers independently assessed the methodological quality of each article across several domains, such as clarity of inclusion criteria, appropriateness of study design and methods, quality of exposure and outcome measurement, potential confounding factors, clarity of reporting, and adequacy of statistical analysis. Each item was rated as "yes," "no," "unclear," or "not applicable." The assessment results were then used to classify the level of risk of bias as low, moderate, or high and were considered in the interpretation of the findings.

Data synthesis

The study findings showed substantial heterogeneity in study design, type of AI algorithm, data source, prediction horizon, and reported clinical outcomes; therefore, the data were not pooled in a quantitative meta-analysis. Data were synthesized narratively using a thematic approach. Studies were grouped according to algorithm type and prediction objective and were then presented in summary tables to facilitate comparison. The main findings of each study, including model performance measures and clinical outcomes, were described and compared qualitatively, taking into account the clinical context, methodological quality, and risk of bias. These findings were then integrated to identify common patterns, evidence limitations, and clinical as well as research implications related to the use of artificial intelligence as a support tool for hemodynamic monitoring in the ICU.

RESULTS

Table 1 presents the demographic characteristics of the respondents included in this study. Based on gender, most respondents were female, accounting for 104 participants (60.5%), while 65 respondents (37.8%) were male. This finding indicates that the nursing workforce in the study setting was predominantly female. In terms of age, the largest proportion of respondents was in the 25–30 years age group, with 90 participants (52.3%). This was followed by respondents aged 31–40 years, totaling 52 participants (30.2%), and those aged 20–25 years, with 25 participants (14.5%). Only 2 respondents (1.2%) were older than 40 years. These data suggest that the majority of nurses were in the early adult and productive working-age groups.

Regarding length of employment, most The search and selection process yielded a total of 16 studies that met the inclusion criteria. These consisted of model development studies, internal and external validation studies (Azam & Singh, 2025; Chiang et al., 2025; Meng et al., 2025; Moghadam et al., 2020; Rahman et al., 2021; Sun et al., 2025; Wu et al., 2024), prospective evaluations (B. Khwannimit et al., 2025), observational cohort studies (Chiang et al., 2025; Meng et al., 2025; Sun et al., 2025), and randomized controlled trials (Rellum et al., 2023). The studies covered a wide range of AI algorithms, including ensemble learning, gradient boosting, XGBoost, recurrent neural networks, time-varying models, reinforcement learning, and hemodynamic risk mapping based on kernel density estimation. These studies were conducted in ICU populations across several countries, including the United States (Azam & Singh, 2025; Meng et al., 2025; Rahman et al., 2021), Taiwan (Chiang et al., 2025; Dung-Hung et al., 2022), China (Wu et al., 2024), Thailand (B. Khwannimit et al., 2025), Japan (Sun et al., 2025), the Netherlands (Rellum et al., 2023), and several international multicenter databases.

Most studies were retrospective big-data ICU studies using large databases such as eICU, MIMIC-III, and MIMIC-IV (Azam & Singh, 2025; Chiang et al., 2025; Rahman et al., 2021). Several other studies used prospective data or clinical trials (B. Khwannimit et al., 2025; Rellum et al., 2023). Most studies involved adult ICU patients with various critical conditions, including septic shock, vasopressor requirement, risk of organ failure, and postoperative cardiac surgery populations.

Types of artificial intelligence models

1) **Multivariable models (HSI, extended HSI, gradient boosting models)**
   HSI is an ensemble decision-tree model that uses 33 clinical variables. Rahman showed that HSI had high predictive performance for hemodynamic intervention 1 hour in advance, with better results than single parameters such as SBP and shock index (Rahman et al., 2021). This finding was reinforced by external validation in Taiwan (Chiang et al., 2025), with an AUROC of 0.76. Its extension to the ED/ICU setting (Wu et al., 2024) showed that the model could also predict delayed septic shock, indicating cross-setting flexibility.
2) **Time-varying and sequential deep learning models (TvHEWS, Bi-LSTM)**
   The TvHEWS model uses 24 XGBoost models updated every hour, producing an early warning system with the ability to predict hemodynamic intervention up to 7 hours in advance (Chiang et al., 2025). This model showed consistent performance across cohorts, including external validation.
   The Bi-LSTM model with attention was able to predict vasopressor requirement during the first 24 hours of ICU admission. Variables such as MAP and HR emerged as important determinants in sequential modeling.
3) **Waveform-based prediction (HPI and derivatives)**
   HPI was used in several studies, both observational and randomized controlled trials. HPI consistently predicted hypotension several minutes before onset, usually 5–15 minutes, even in patients with septic shock (B. Khwannimit et al., 2025). Randomized controlled trials examined the role of HPI in predictive hemodynamic therapy protocols (Rellum et al., 2023; Runge et al., 2023).
4) **Personalized hemodynamic targets (DynaCEL, HM-TARGET)**
   DynaCEL generated individualized HR and SBP targets associated with 24-hour mortality risk; patients who remained within ±20% of the target showed a reduced risk of death. HM-TARGET mapped HR–BP risk zones in real time, helping determine hemodynamically safe ranges (Meng et al., 2025; Sun et al., 2025).
5) **Predictive performance**
   Overall, most artificial intelligence models analyzed in the included studies showed high predictive performance, with AUROC values generally ranging from 0.76 to 0.95, depending on the type of algorithm, data source, and predicted outcome. These findings confirm that AI has substantial potential to improve the early detection of hemodynamic instability compared with conventional monitoring methods.

DISCUSSION

The Hemodynamic Stability Index (HSI) model consistently showed strong performance in predicting the need for hemodynamic interventions, such as vasopressor administration, large fluid boluses, or transfusion (Chiang et al., 2025; Rahman et al., 2021). Across multiple large multicenter datasets, HSI produced high AUROC values and significantly outperformed traditional parameters such as systolic blood pressure and shock index (Rahman et al., 2021; Wu et al., 2024). This robust performance was also replicated in external validation, indicating good model generalizability across ICU settings.

The Time-varying Hemodynamic Early Warning Score (TvHEWS) model showed highly competitive predictive performance and was among the most stable AI models available (Chiang et al., 2025). Its application in several independent cohorts showed that TvHEWS was able to maintain high AUROC and good AUPRC while minimizing the frequency of false alarms and missed events. This cross-cohort stability is important for clinical implementation because it demonstrates model resilience to variations in population characteristics and ICU data flow dynamics.

Meanwhile, the Hypotension Prediction Index (HPI), a model based on arterial pressure waveform analysis, showed AUROC values ranging from 0.90 to 0.97 across several studies (B. Khwannimit et al., 2025; Rellum et al., 2023; Runge et al., 2023). HPI proved effective in detecting hypotension 5–15 minutes before onset, including in complex populations such as ICU patients with septic shock (Runge et al., 2023). This advantage makes HPI one of the most precise hypotension prediction models currently available.

The Bi-LSTM model with an attention mechanism, designed to process sequential ICU data, showed an AUROC of approximately 0.83 for predicting vasopressor requirement during the first 24 hours of care (Lorente et al., 2023; Mathis et al., 2020). These findings highlight the ability of deep learning models to capture temporal patterns that are not well captured by traditional algorithms.

Machine learning algorithms based on short-term physiological history were also able to predict hypotensive events effectively, showing that even models built from minimal physiological features can provide meaningful predictive value when trained using dynamic labeling approaches that mimic real-time monitoring conditions (Moghadam et al., 2020). In blood pressure prediction models, ensemble algorithms such as gradient boosting and XGBoost met AAMI accuracy standards in internal evaluations (Schuurmans et al., 2024; van der Ven et al., 2022). However, their performance declined when tested on external datasets, highlighting a classic challenge in AI implementation, namely reduced generalizability when models are exposed to interinstitutional variation or different data distributions.

Overall, all evaluated AI models showed consistent improvements in accuracy, sensitivity, and short- to medium-term prediction capability compared with conventional methods such as threshold MAP or shock index (Chiang et al., 2025; Dung-Hung et al., 2022). These findings indicate that AI can capture complex hemodynamic patterns that cannot be detected through linear monitoring approaches or simple threshold values, thereby offering substantial potential to improve the precision of clinical responses to hemodynamic instability in the ICU.

Clinical and operational outcomes Only some studies evaluated the direct clinical impact of AI use in hemodynamic monitoring, but the available findings indicate several important benefits. The use of HPI in both cardiac and non-cardiac surgical settings consistently showed reductions in the duration and frequency of hypotension, which is relevant because perioperative hemodynamic stability affects patient condition upon ICU admission (Rellum et al., 2023; Runge et al., 2023). Similar effectiveness was also found in ICU patients with septic shock, suggesting that the predictive capability of HPI remains strong in more complex critically ill populations (B. Khwannimit et al., 2025). At the early warning system level, TvHEWS demonstrated stable performance across various datasets and clinical conditions, with reductions in false alarms and missed events (Chiang et al., 2025). This is important for improving alarm reliability and reducing clinician workload in the busy ICU environment. Several studies also highlighted the role of AI in personalizing hemodynamic therapy. Models such as DynaCEL and HM-TARGET were able to identify patient-specific safe zones for blood pressure and heart rate combinations, thereby supporting a precision hemodynamics approach that is more adaptive to individual clinical conditions (Meng et al., 2025; Sun et al., 2025). From an implementation perspective, the Delphi study by Rahman et al. helped define relevant clinical outcomes such as vasopressor requirement, fluid bolus administration, or transfusion as evaluation parameters for hemodynamic prediction models. This provides an important foundation for the implementation of models such as HSI and TvHEWS in clinical practice, particularly to ensure that the models align with ICU decision-making needs (Chiang et al., 2025; Dung-Hung et al., 2022; Rahman et al., 2021).

CONCLUSION

The results of this systematic review show that artificial intelligence has significant potential to improve the early detection and prediction of hemodynamic instability in ICU patients. Multivariable models such as HSI, time-varying approaches such as TvHEWS, and waveform-based models such as HPI consistently demonstrated high predictive performance and were able to identify the risk of hypotension or vasopressor requirement before the event occurred. Personalized approaches developed through DynaCEL and HM-TARGET also open opportunities for more adaptive and individualized hemodynamic therapy. Nevertheless, most studies remain at the model development or validation stage, with only a limited number of prospective studies or clinical trials evaluating their actual impact on clinical outcomes. Therefore, further research focusing on clinical implementation and long-term benefits is needed to ensure the effectiveness of AI in intensive care practice.

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Artificial intelligence for improving the monitoring of hemodynamic changes in the ICU: a systematic review of predictive algorithms and clinical outcomes

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