

Review Article

Natural Language Processing and Machine Learning Solutions for Patient Wait Time-Related Safety Risks in High-Risk Clinical Care

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ABSTRACT

Patient delays in emergency departments, intensive care units, trauma centres, and other high-risk clinical settings can increase the risk of patient deterioration, medication errors, missed warning signs, adverse events, and even mortality. At the same time, Natural Language Processing (NLP) and Machine Learning (ML) are increasingly being used to analyse clinical and operational data, identify risks, and support healthcare decision-making. However, it remains unclear how effectively these technologies can be applied specifically to patient wait time-related safety risks during clinical delays. This study adopts a critical literature review approach to examine applications of natural language processing and machine learning in addressing patient wait-time-related safety risks in high-risk clinical care environments. Relevant literature published between 2014 and 2026 was searched across PubMed, Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar using database-adapted search strategies combining terms related to artificial intelligence, clinical delays, patient waiting times, patient safety, and high-risk care. A total of 1,545 records were identified, of which 487 duplicates were removed. Following screening and full-text assessment, 20 core studies and 33 contextual studies were included in the final synthesis. The findings show that NLP and ML can extract useful information from electronic health records, clinical notes, patient safety reports, and other unstructured and structured healthcare data. ML models, particularly ensemble and deep learning approaches, demonstrated potential for identifying high-risk patients, predicting adverse outcomes, and supporting clinical decision-making. NLP was particularly useful for uncovering safety signals and adverse events that may remain hidden in free-text clinical documentation. The literature also shows that patient waiting times are influenced by multiple factors, including patient characteristics, staffing, workload, bed availability, clinical complexity, and downstream capacity constraints. However, concerns about explainability, bias, data quality, cybersecurity, workflow integration, and human oversight remain. This review concludes that NLP and ML have promising potential to support earlier identification of patients whose safety may be threatened by prolonged clinical delays. Therefore, this review recommends that healthcare organisations, hospitals, emergency departments, and healthcare administrators may use NLP and ML to support patient flow monitoring, early identification of deterioration risks, resource allocation, bed management, and prioritisation of high-risk patients to improve both efficiency and quality of care while reducing preventable harm.

Keywords: NLP; ML; Patient Safety Risks; Patient Wait Times; Clinical Delays; High-Risk Clinical Care

Introduction

Healthcare systems across the world are under increasing pressure due to rising patient numbers, overcrowded emergency departments, workforce shortages, and growing demands for faster and safer care delivery (Morley et al., 2018; Shen & Lee, 2019). In high-risk clinical care environments such as emergency departments, trauma centers, intensive care units, and acute medical wards, delays in treatment can quickly become dangerous. Patients who wait too long for assessment, diagnosis, or treatment may experience worsening health conditions, avoidable complications, medication errors, or even death in severe cases (Verma et al., 2021).

Extant studies on emergency department waiting times consistently show that delays may be caused by a combination of factors, including increasing patient demand, limited staffing, inefficient patient flow, delayed specialist consultations, and shortages of hospital beds (Bobrovitz et al., 2017; Hajzargarbashi et al., 2019). Similarly, studies also show that emergency department congestion is not caused by one isolated problem but by interconnected bottlenecks across the healthcare system (Shen & Lee, 2019; Sorić et al., 2022). Although hospitals have introduced several strategies to improve patient flow, including Lean process redesign, digital queue systems, and performance targets, many healthcare systems still struggle to maintain safe and efficient care during peak periods and emergency situations (Tejedor-Panchón et al., 2014; Ehrler et al., 2022).

At the same time, the rapid growth of Artificial Intelligence (AI) has created new opportunities for improving healthcare delivery and patient safety. Technologies such as Natural Language Processing (NLP) and Machine Learning (ML) are increasingly being used to support clinical decision-making, predict patient risks, improve diagnostic accuracy, and analyze large amounts of healthcare data more efficiently (James, Willson & Fenix, 2024; Khalate, Gite, Pradhan & Lee, 2024). Unlike traditional healthcare systems that mainly rely on structured data, NLP allows healthcare organisations to extract meaningful information from unstructured data sources such as clinical notes, electronic health records (EHRs), patient safety reports, and physician documentation (Jerfy et al., 2024; Kaduba et al., 2024). The literature shows that NLP and ML technologies have the potential to improve healthcare outcomes. For example, AI-driven predictive systems have demonstrated strong performance in identifying high-risk pregnancies, adverse drug events, diagnostic errors, suicide risks, and patient deterioration in emergency care settings (Pi et al., 2025; Golder et al., 2025; Sarkar et al., 2026). Other studies show that NLP

systems may uncover hidden safety risks from free-text clinical documentation that conventional reporting systems may fail to detect (Abrisqueta-Costa et al., 2024; Vilanti et al., 2025; Tabaie et al., 2026).

Beyond clinical diagnosis and risk prediction, AI is also being used to improve operational efficiency within healthcare systems. The literature has also shown that AI-based systems have the potential to support patient flow management, hospital scheduling, resource allocation, and real-time patient monitoring (Khare et al., 2025; Kumar & Verma, 2026). In theory, these technologies may help hospitals identify overcrowding risks earlier, predict patient deterioration while waiting for care, and optimize the use of limited healthcare resources (Sirigineedi, 2025; Cao et al., 2025). Despite these promising developments, the growing use of AI in healthcare also raises important concerns. Extant studies warn that AI systems may be affected by issues such as algorithmic bias, poor transparency, weak explainability, privacy concerns, and limited external validation (Agarwal et al., 2024; Osifowokan et al., 2025). Some advanced ML models operate as “black boxes,” meaning healthcare professionals may not fully understand how predictions are generated (Haque, 2025; Ali et al., 2025; Hasan et al., 2026). This creates challenges for trust, accountability, and clinical decision-making, especially in high-risk situations where incorrect predictions may directly affect patient safety. Soberano and Condes (2025) further demonstrate that AI systems may also be vulnerable to adversarial attacks capable of reducing model reliability and clinical accuracy.

Another important issue is that much of the current research treats patient wait times and AI-driven patient safety systems as separate areas of investigation. Many studies focus on improving operational efficiency without fully examining how delays affect patient safety outcomes, while AI-focused studies often emphasize predictive accuracy without considering how prolonged waiting times may increase clinical risks (Vezyridis & Timmons, 2014; Abaneme et al., 2025; Lam et al., 2026). In addition, many existing studies rely on retrospective datasets, simulation modelling, or institution-specific data, making it difficult to determine how AI systems perform consistently in real-world healthcare settings characterized by uncertainty, staff fatigue, communication delays, and rapidly changing patient conditions (Alhuntushi et al., 2022; Chukwunonso-Ogbu et al., 2025).

The literature therefore reveals an important gap. Although NLP and ML technologies have shown strong potential in healthcare, limited research has

specifically examined how these technologies can be integrated to predict, monitor, or reduce patient safety risks associated with prolonged wait times in high-risk clinical care environments. Existing studies rarely combine patient flow management, adverse event detection, clinical deterioration monitoring, and operational decision support into one integrated AI-driven framework. This study seeks to address this gap by critically examining the existing literature on NLP, ML, patient wait times, and patient safety in high-risk clinical care. The study contributes to the literature by bringing together research areas that are often

discussed separately. Many previous studies focus either on emergency department waiting times and operational efficiency or on AI-driven clinical prediction and patient safety systems. This study helps connect these discussions by showing that prolonged patient waiting times should also be understood as an important patient safety issue. Thus, this study provides a more comprehensive assessment of how operational delays, clinical deterioration, and AI technologies interact within real healthcare environments.

Methodology

This study adopted a critical literature review design to examine the applications of Natural Language Processing (NLP) and Machine Learning (ML) in addressing patient wait time-related safety risks in high-risk clinical care environments. The review focused on evidence relating to patient waiting times, clinical deterioration, patient safety, adverse events, risk prediction, clinical decision support, and the use of NLP and ML in healthcare. A structured literature search was conducted between February 1 and May 31, 2026. Searches were performed across relevant electronic databases, including PubMed, Scopus, Web of Science, IEEE Xplore, ScienceDirect and Google Scholar. The search strategy combined keywords and Boolean operators such as “Natural Language Processing” OR NLP, “Machine Learning” OR ML, “patient wait time” OR “waiting time” OR “clinical delay”, “patient safety” OR “adverse events” OR “clinical deterioration”, and “high-risk clinical care” OR “emergency department” OR “acute care” OR “intensive care.” The search was limited primarily to studies published in English and focused on healthcare applications of NLP, ML, patient flow, clinical delays, and patient safety. The initial search produced 1,545 records. After removing 487 duplicate records, 1,058 unique records remained for title and abstract screening.

The studies were selected in stages using predefined inclusion and exclusion criteria. At the first stage, the titles and abstracts of the 1,058 unique records were reviewed. A study was considered potentially relevant when it addressed at least one of the main areas of interest, including the use of NLP or ML in healthcare, patient waiting times or clinical delays, patient safety or adverse events, prediction of clinical deterioration or high-risk patients, and AI-supported clinical decision-making or patient-flow management. After the initial screening, 808 records were excluded because they were outside the scope of the review, did not involve healthcare applications of NLP or ML, did not address patient safety or clinical delays, or were not

sufficiently related to high-risk clinical care. This left 250 articles for full-text assessment. Full texts were then reviewed against the eligibility criteria. A further 197 articles were excluded. The main reasons for exclusion were limited relevance to patient waiting times or clinical safety, a general focus on AI without a clear connection to the objectives of the review, the absence of an NLP or ML component, non-healthcare applications, inadequate methodological information, or insufficient evidence for meaningful synthesis.

Finally, a total of 53 studies were included in the critical synthesis. These studies were divided into two groups to make the interpretation clearer. The first group was the core evidence base, consisting of 20 studies that dealt more directly with patient wait-time-related safety risks, clinical delays, clinical deterioration, adverse events, patient safety, or high-risk clinical care. The second group consisted of 33 contextual studies.

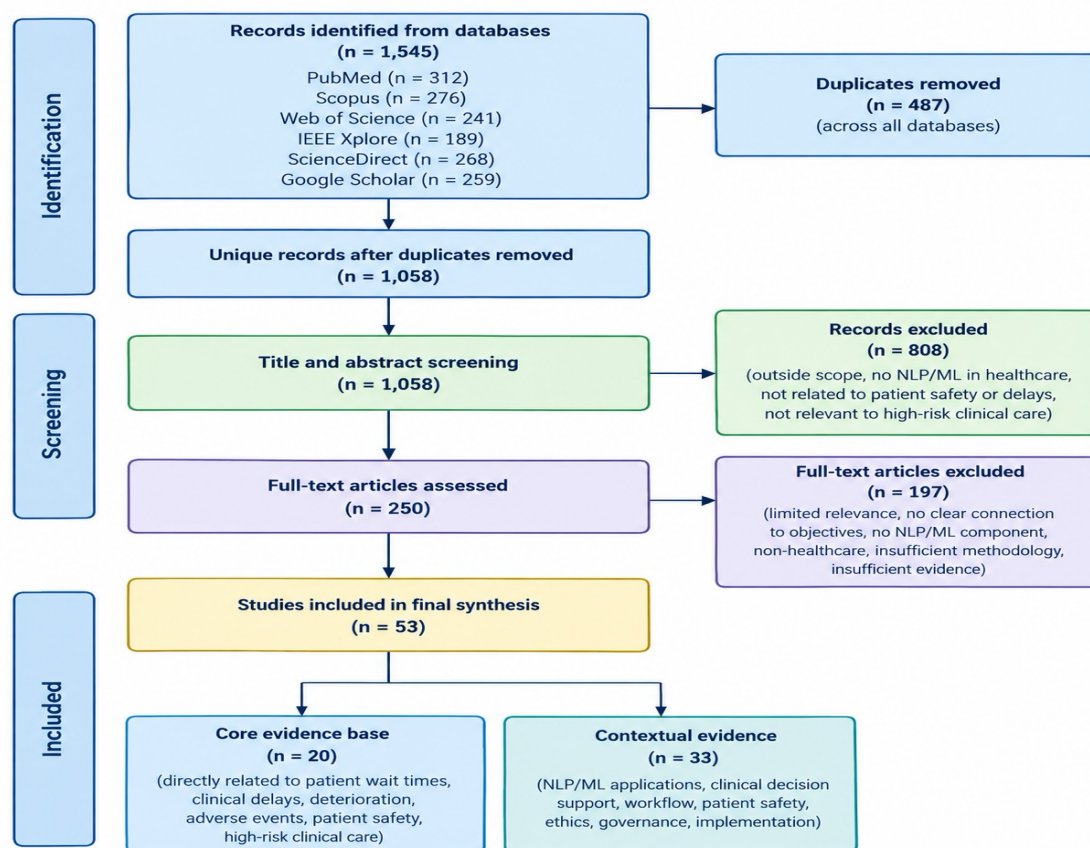


Fig. 1: PRISMA Flow Diagram for Study Selection

To improve consistency during the selection process, two reviewers independently screened the titles and abstracts and assessed potentially relevant full-text articles. Both reviewers used the same predefined inclusion and exclusion criteria when deciding whether a study should be included. Any disagreements between the two reviewers were first discussed and resolved through consensus. Where disagreement remained, a third reviewer was consulted to make the final decision. For data extraction, one reviewer extracted the relevant information using a structured extraction form, while a second reviewer checked the extracted data for completeness, accuracy, and consistency. Any disagreements identified during the checking process were discussed and resolved through consensus. This process helped ensure that study selection was not based solely on the judgement of a single reviewer. However, the study was designed as a critical literature review rather than a systematic review or meta-analysis. The purpose was therefore not to calculate a pooled effect size but to examine patterns, methodological strengths and weaknesses, contradictions, and gaps across the existing evidence.

Thus, data from each of the 20 studies comprising the core evidence base were extracted using a structured framework. The data included author and year, country or clinical setting, study design, sample or dataset, AI method, clinical application, validation

approach, key performance measures, major findings, and reported limitations. Particular attention was also given to whether studies used retrospective or prospective data, single-centre or multi-centre datasets, structured or unstructured clinical data, and internal or external validation.

The methodological quality of the 20 core studies was examined through a structured critical appraisal. No formal quality-assessment or risk-of-bias instrument was used, and no numerical quality score was assigned to the studies. This approach was considered appropriate because the studies differ considerably in their research designs, clinical settings, datasets, AI methods, and research objectives. Attention was given to study design, sample or dataset size, data quality, model development, validation methods, performance measures, transparency, external validation, and applicability to real-world clinical settings. Rather than treating predictive accuracy alone as evidence of clinical effectiveness, the review considered whether the reported models had been tested beyond the dataset or institution in which they were developed. Studies based on retrospective, single-centre, simulated, or institution-specific datasets were therefore interpreted cautiously, particularly where external validation or real-world implementation evidence was lacking.

The same critical appraisal approach was applied to both groups of studies. The 20 core studies were examined mainly in terms of their direct relevance to patient waiting times, clinical delays, deterioration, adverse events, and patient safety. The 33 contextual studies were considered in terms of the broader evidence they provided on NLP and ML applications, healthcare workflow, patient safety, governance, ethics, and implementation.

Because the included studies differed substantially in their populations, clinical settings, datasets, AI techniques, outcomes, and evaluation methods, a quantitative meta-analysis was not considered appropriate. Instead, the evidence was

synthesized thematically. The synthesis focused on five broad areas: (i) NLP and ML for clinical decision-making and risk prediction; (ii) detection of hidden patient safety risks from unstructured healthcare data; (iii) patient flow, waiting times, and operational efficiency; (iv) human, ethical, and organisational factors affecting AI-supported patient safety; and (v) implementation, validation, explainability, and governance challenges. The review then examined how these themes relate to the central problem of patient wait time-related safety risks during clinical delays in high-risk clinical care. Attention was also given to areas where the evidence converged, where findings differed, and where important evidence was still missing.

Literature Review

The reviewed studies varied considerably in design, setting, data source, AI technique and clinical application. The studies include narrative, scoping, and integrative reviews; retrospective and secondary-data studies, predictive modelling, qualitative and mixed-method research, and experimental evaluations of AI safety. Most AI/ML studies relied on electronic health records, clinical narratives, patient safety reports or other secondary datasets, while only a smaller number examined real-world implementation across multiple healthcare settings. The studies also focused on diagnosis, risk prediction, adverse-event detection, clinical documentation and healthcare operations. Relatively few studies directly examined patient waiting time as a time-dependent patient safety risk, particularly in high-risk clinical environments. This pattern supports the need for an integrated perspective linking waiting-time prediction, clinical deterioration, safety-event detection and operational decision-making.

Table 1 presents selected 20 core evidence studies from the 53 studies included in the critical

literature review. The table is not intended to provide an exhaustive list of all included studies. The studies presented were selected to illustrate the main methodological approaches, healthcare settings, AI techniques, clinical applications, and patient-safety issues identified in the literature. Selection was guided by the studies’ relevance to the review objectives, their contribution to understanding NLP/ML applications in healthcare, their methodological diversity, and their ability to demonstrate important opportunities and limitations associated with AI-supported patient safety. The table includes studies that provide direct evidence relevant to the review. As such, studies with a more direct connection to clinical risk, patient deterioration, adverse events, diagnostic errors, or high-risk care were considered alongside contextual studies addressing healthcare operations, organisational safety, AI governance, clinical communication, and implementation challenges. The remaining included studies were considered in the broader thematic synthesis but are not individually presented in the table.

Table 1: Selected Studies Illustrating the Characteristics of Reviewed Literature

Author/Year	Country/Setting	Study Design	Sample/Data	AI Method	Application	Key Findings
James, Willson & Fenix (2024)	Not clearly stated; healthcare/EHR and stroke care	Literature review	Publications from PubMed, IEEE Xplore and Scopus, January 2018-August 2024	AI, ML and NLP	EHR management, stroke diagnosis, treatment and clinical decision-making	AI/ML/NLP can improve diagnostic accuracy, prediction and treatment planning. NLP can make unstructured clinical notes more useful for decision-making. Key concerns include data integration, bias and privacy.
Khalate, Gite, Pradhan & Lee (2024)	Not clearly stated; healthcare/EMR and medical imaging	Literature review	100 papers published between 2015-2023; SCOPUS and other literature sources	NLP, ML and Deep Learning	EMR analysis, medical imaging and healthcare decision-making	NLP and ML can extract useful information from unstructured data and improve diagnosis and patient care. Major gaps include scalability, practical implementation, ethics and longitudinal data analysis.

Author/Year	Country/Setting	Study Design	Sample/Data	AI Method	Application	Key Findings
Abrisquet a-Costa et al. (2024)	Spain; seven hospitals	Real-world retrospective study	EHR data from 385,904 patients; 534 CLL patients included	NLP and ML (EHRead®)	Detection of adverse events and healthcare resource use in chronic lymphocytic leukaemia	AI-based extraction identified adverse events that may be underreported using conventional approaches, showing the value of NLP/ML for patient safety monitoring.
Jerfy, Selden & Balkrishnan (2024)	Not clearly stated; healthcare/public health	Narrative review	27 selected papers published between 2018-2023	NLP and Deep Learning	EHR screening, patient communication, public health monitoring and clinical decision support	NLP can extract useful information from large volumes of unstructured text and support risk prediction, communication and treatment decisions.
Golder et al. (2025)	Multiple healthcare settings; studies varied	Scoping review	7 studies identified from six databases	Rule-based NLP, statistical ML and Deep Learning	Adverse drug event detection and pharmacovigilance	NLP/ML improved detection of underreported adverse events and safety signals. However, differences in methods and validation make comparison and implementation difficult.
Permana & Sari (2025)	West Java, Indonesia; three regional public hospitals	Qualitative phenomenological study	15 healthcare workers	No AI; human/organisational safety factors	Occupational safety and patient safety	Patient safety is influenced by organisational culture, workplace conditions and psychological factors, showing that technology alone cannot address all safety risks.
Soberano & Condes (2025)	Medical AI applications; specific healthcare setting not stated	Experimental/systematic evaluation of adversarial risks	CNN, RNN and Transformer-based medical AI models across five trials	CNN, RNN and Transformer; adversarial ML	AI security and patient safety	AI models experienced substantial performance reductions under adversarial attacks, highlighting the need for robust and secure AI systems in clinical care.
Chukwunonso-Ogbu et al. (2025)	UK; three high-acuity hospitals within one NHS Trust	Cross-sectional mixed-method study	102 healthcare workers surveyed; 87 interviewed	No AI; human factors	Staff fatigue and patient safety	Fatigue, inadequate sleep and missed breaks were common and were associated with reported performance lapses and clinical errors.
Pi et al. (2025)	Bangladesh; hospitals, community clinics and maternal health centres	Predictive ML study	1,014 pregnant women	MLP, LR, DT, RF, XGBoost and SVM	High-risk pregnancy prediction	MLP achieved the strongest performance, with 82% overall accuracy and 91% accuracy for high-risk predictions, demonstrating the potential for early risk identification.
Liu et al. (2025)	Internet healthcare; HIPAA-related data	Comparative ML modelling study	HIPAA database containing medical, personal and treatment information	XGBoost, SVM, RF, DNN and PCA+RF	Legal risk assessment in healthcare	DNN performed strongly in legal risk assessment, while RF-based models also showed stable performance. The study highlights the importance of data quality and governance.
Vilanti et al. (2025)	Higher education institutions; healthcare education	Cross-sectional study	44 students: 24 medical and 20 midwifery students	NLP and automated text analysis	AI-supported healthcare communication training	NLP successfully identified important clinical communication topics in AI-generated patient dialogues, suggesting potential for AI-supported healthcare education.
Abaneme, Aboh, Moshood & Assumang (2025)	Healthcare information technology (HIT); setting not specifically stated	Integrative review	Literature from 2013-2025, including empirical, theoretical and technical sources	ML including Gradient Boosting, RF and SVM	Healthcare IT project risk prediction and resource allocation	ML can support prediction of project delays, cost overruns and compliance risks. Implementation remains constrained by infrastructure, transparency and ethical concerns.
Pickup et al. (2025)	UK/NHS healthcare	Critical/practice-based paper	Healthcare workforce evidence and authors'	No AI; fatigue-risk	Staff fatigue and patient safety	Staff fatigue is an important patient safety risk and requires organisation-wide fatigue-risk management rather than relying only on individual staff responsibility.

Author/Year	Country/Setting	Study Design	Sample/Data	AI Method	Application	Key Findings
			professional experience	management		
Osifowoka n, Agbadam asi, Adukpo & Mensah (2025)	United States healthcare system	Qualitative literature and policy review	Peer-reviewed literature, government publications and industry reports	AI, ML and NLP	AI governance, liability, compliance and patient safety	AI can improve diagnosis and workflow efficiency, but algorithmic bias, privacy, liability and regulatory challenges remain important barriers to safe implementation.
Hasan et al. (2026)	United States; clinical cirrhosis care	Predictive ML study	Publicly available U.S. liver cirrhosis dataset	Random Forest and SHAP	Mortality-risk prediction and explainable AI	The model showed strong predictive performance and identified clinically meaningful risk factors. SHAP improved transparency at both overall and individual-patient levels.
Sarkar et al. (2026)	United States; psychiatric emergency department, Texas	Retrospective predictive modelling study	15,987 patients using EMR and medical examiner data	NLP and XGBoost	Suicide and intentional self-harm risk prediction	XGBoost achieved an AUROC of 0.81 for 30-day prediction. Combining structured and unstructured EMR data supported identification of high-risk patients.
Lam, Barras, Abdel-Hafez & Falconer (2026)	Tertiary hospital; general medical and geriatric wards	Secondary-data ML study	279 adult patients; 40 experienced 51 medication-harm events	Eight ML models; Random Forest performed best	Medication-harm prediction	Random Forest achieved an AUROC of 0.76 and identified several clinical risk factors. The findings support early identification of patients at risk of medication harm.
Hanumant h加里 (2026)	Clinical documentation; setting not specifically stated	Critical/analytical study	Clinical text/documentation examples	Clinical NLP/LLM framework	Clinical documentation and text compression	Aggressive text compression can remove clinically important information and create safety risks. Clinical NLP therefore needs safety constraints, not efficiency alone.
Mabodi, Mbunge, Makaba & Ndlovu (2026)	Social media/X; mental health context	Predictive ML study	Social media posts collected through X API	NLP, ML, XGBoost, LIME and feature importance	Depression-risk detection	XGBoost achieved high predictive performance, while explainability techniques improved model transparency. The study highlights the value of combining NLP, ML and explainable AI.
Tabaie et al. (2026)	United States; multi-hospital healthcare system in the Mid-Atlantic region	Retrospective ML/NLP study	Patient safety event reports, January 2016-August 2021	Logistic Regression, Elastic Net, XGBoost and Deep Neural Network	Cardiovascular diagnostic-error detection	XGBoost performed best, achieving an AUROC of 0.914. NLP/ML successfully identified diagnostic-error narratives, although external validation remains necessary.

Source: Authors

The reviewed literature includes narrative, scoping and integrative reviews; retrospective and secondary-data studies; predictive modelling studies; qualitative and mixed-method studies; and experimental assessments of AI vulnerability. This diversity is important because the strength of evidence is not the same across all studies. A second important pattern is that many of the AI/ML studies are retrospective, secondary-data or institution-specific studies. For example, Abrisqueta-Costa et al. (2024)

used real-world EHR data from seven Spanish hospitals, Sarkar et al. (2026) used EMR and medical examiner data from a U.S. psychiatric emergency department, and Tabaie et al. (2026) analysed patient safety reports from a multi-hospital system. These studies provide useful evidence of predictive potential, but they do not necessarily demonstrate how the models would perform across different healthcare systems or under real-time clinical pressure.

Results: What the Literature Shows

A clear pattern is that most AI/ML studies rely on existing or retrospective data rather than real-time clinical data. Electronic health records (EHRs),

electronic medical records (EMRs), clinical notes, patient safety reports, social media data, and other secondary datasets are commonly used. For example,

Abrisqueta-Costa et al. (2024) analysed EHR data from seven hospitals in Spain, while Sarkar et al. (2026) used structured and unstructured EMR data from 15,987 patients to develop a suicide and self-harm prediction model. Similarly, Tabaie et al. (2026) used patient safety event reports from a multi-hospital healthcare system to identify cardiovascular diagnostic errors. The reviewed studies also show increasing use of more advanced ML techniques. Random Forest, XGBoost, deep neural networks, support vector machines, multilayer perceptrons, and other ensemble and deep-learning approaches were commonly applied. XGBoost performed particularly well in several studies. For example, Sarkar et al. (2026) reported an AUROC of 0.81 for predicting suicide and intentional self-harm, while Tabaie et al. (2026) reported an AUROC of 0.914 for identifying cardiovascular diagnostic-error reports. Lam et al. (2026), however, found more moderate performance, with Random Forest achieving an AUROC of 0.76 for medication-harm prediction. These differences show that model performance depends on the clinical problem, dataset, outcome being predicted, and research setting.

NLP and ML Applications

The first major finding is that NLP and ML can turn large amounts of unstructured healthcare information into useful clinical information. Studies by James, Willson and Fenix (2024), Khalate et al. (2024), and Jerfy, Selden and Balkrishnan (2024) show that clinical notes, EHRs, patient communications and other forms of unstructured text contain information that can support diagnosis, risk prediction and clinical decision-making. NLP is particularly useful because much of this information cannot be easily analysed using conventional structured databases. This potential is demonstrated more clearly in patient safety research. Golder et al. (2025) found that NLP and ML could identify adverse drug events and previously underreported safety signals from unstructured EHR data. Abrisqueta-Costa et al. (2024) similarly found that NLP/ML-based analysis could identify adverse events among patients with chronic lymphocytic leukaemia, suggesting that AI can make safety problems more visible than some conventional approaches. Tabaie et al. (2026) further demonstrated that NLP and ML could identify cardiovascular diagnostic errors from patient safety event reports. Thus, these studies suggest that NLP is particularly valuable for finding hidden safety information in clinical narratives, while ML is useful for recognising patterns and estimating future risk. The two technologies therefore have complementary roles rather than simply being alternative approaches.

Clinical Risk Prediction

A second major finding is the growing ability of ML models to identify patients who may be at

increased risk of poor outcomes. Pi et al. (2025), for example, used six ML algorithms to predict high-risk pregnancies and found that the multilayer perceptron achieved the strongest overall performance. Lam et al. (2026) used eight ML models to predict medication harm and found Random Forest to be the strongest-performing model. Sarkar et al. (2026) combined structured and unstructured EMR data with NLP and XGBoost to predict suicide and intentional self-harm risk among psychiatric emergency patients. These findings are important for high-risk clinical care because they suggest that AI could identify vulnerable patients before their condition becomes critical. However, the literature does not yet establish that high predictive performance automatically leads to better patient outcomes. Most of these studies evaluate model performance using measures such as accuracy, AUROC, precision, recall and F1-score rather than measuring whether implementation actually reduces adverse events, waiting-related deterioration, complications or mortality.

Patient Waiting Times and Clinical Delays

The literature on patient waiting times shows that delays are multifactorial and system-wide. Earlier studies identify factors such as patient age, arrival time, referral source, triage category, diagnostic complexity, work shifts, specialist consultations, bed availability and downstream hospital capacity as important contributors to waiting times (Bobrovitz et al., 2017; Hajzargarbashi et al., 2019; Shen & Lee, 2019). The evidence also shows that reducing waiting time is not simply a matter of making one department work faster. Delays can arise from bottlenecks elsewhere in the patient pathway. Shen and Lee (2019), for example, highlight delays in bed allocation and ward acceptance, while Sorić et al. (2022) show the importance of emergency medicine expertise in improving patient throughput. Simulation and process-improvement studies also report benefits from better staffing, resource allocation, capacity planning and Lean-based workflow redesign (Luo et al., 2018; Bahari & Asadi, 2020; Tejedor-Panchón et al., 2014). However, these studies generally examine waiting time as an operational problem rather than as a dynamic patient safety risk. This distinction is important. A patient who waits for two hours is not necessarily exposed to the same level of risk as another patient who waits for the same period but is clinically deteriorating. The reviewed literature therefore suggests that waiting time should not be viewed only as a measure of efficiency; it can also become a marker of increasing clinical risk when patient condition changes during the delay.

Clinical Delays and Patient Safety

The literature provides evidence that delays can become more serious when they occur among high-

risk patients. Verma et al. (2021), for example, associate prolonged emergency department stays with increased mortality among critically ill patients. This is particularly important in emergency departments, intensive care settings and other high-acuity environments where patient conditions can change rapidly. At the same time, the literature shows that patient safety is influenced by factors beyond waiting time itself. Chukwunonso-Ogbu et al. (2025) and Pickup et al. (2025) highlight the role of staff fatigue, inadequate rest and workload in patient safety. Permana and Sari (2025) similarly show that safety is shaped by organisational culture, working conditions and staff experiences. The combined evidence therefore suggests that patient safety during clinical delays is produced by the interaction of patient condition, waiting time, staffing, workload, communication, resource availability and organisational processes. This is important because an AI system that considers waiting time alone may miss other factors that determine whether a delay becomes harmful.

AI Safety and Trust

Another strong finding is that the benefits of AI are accompanied by important safety and governance concerns. The reviewed studies repeatedly identify problems relating to explainability, bias, privacy, accountability, cybersecurity and human oversight. James et al. (2024), Osifowokan et al. (2025), and Liu et al. (2025) all emphasise the importance of appropriate governance when AI is introduced into healthcare. Explainability is particularly important in high-risk care. Hasan et al. (2026) demonstrate how SHAP can be used to make ML predictions more understandable to clinicians. This is important because healthcare professionals need to know not only what a model predicts but also why the prediction was made, especially when the prediction may influence urgent clinical decisions. The literature also shows that AI itself can introduce new safety risks. Soberano and Condes (2025) found that medical AI models were vulnerable to adversarial attacks, while Hanumanthgari (2026) warns that excessive compression of clinical text can remove important information and potentially change its clinical meaning. These findings challenge the assumption that automation is automatically safer. Instead, they suggest that AI systems used in high-risk care must be designed around safety, robustness and human oversight from the beginning.

Conceptual Framework Development

The conceptual framework explains how Natural Language Processing (NLP) and Machine Learning (ML) can be used to reduce patient wait time-related safety risks in high-risk clinical care settings. The framework begins with various healthcare data

sources, including electronic health records, clinical notes, patient monitoring information, operational data, and safety reports. These data provide the foundation for AI systems. Using NLP and ML, both structured and unstructured data are analysed to extract important clinical information, identify patterns, predict waiting times, and recognize patients who may be at risk of deterioration while waiting for treatment. The insights generated by these technologies support operational decisions such as resource allocation, staff deployment, workflow management, and prioritization of high-risk patients.

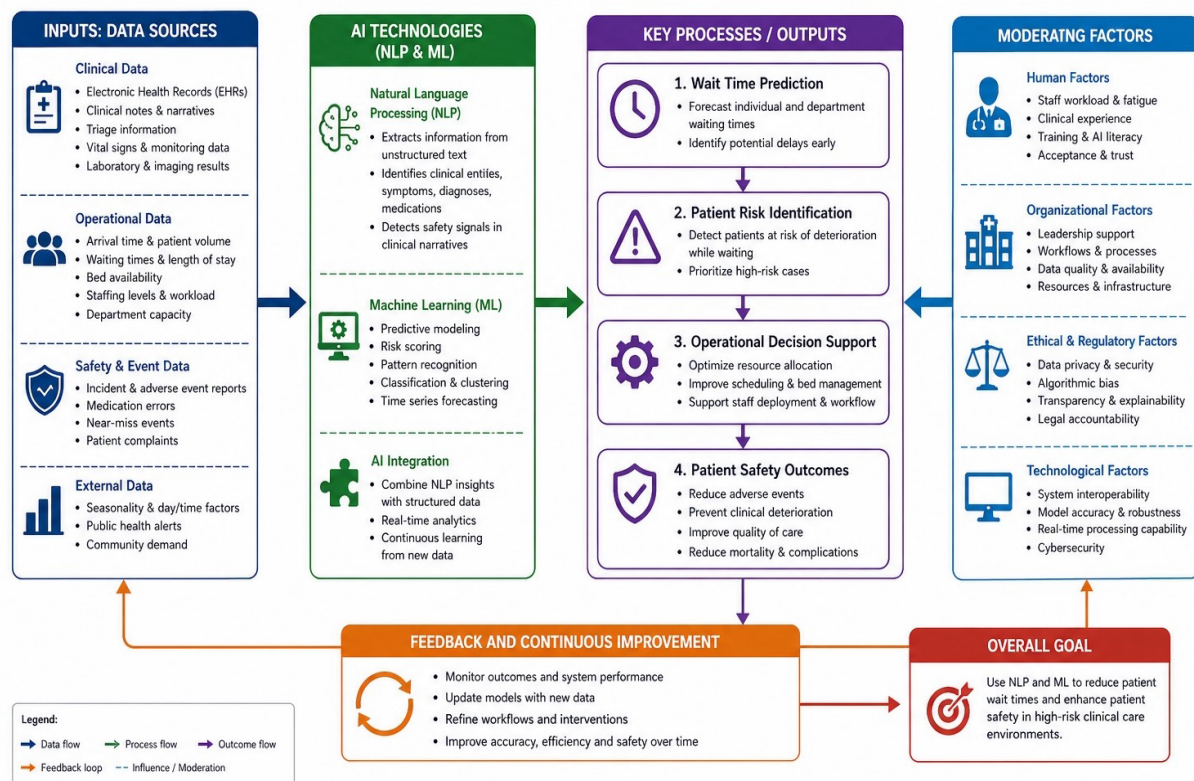


Fig. 2: Conceptual Framework

The framework shows that these processes contribute to improved patient safety outcomes through earlier intervention, reduced adverse events, prevention of clinical deterioration, and better quality of care. However, successful implementation depends on several moderating factors, including human factors, organisational support, ethical and regulatory considerations, and technological capabilities. Finally, the framework incorporates a feedback and continuous

improvement process in which outcomes are monitored and AI models are refined using new information. Thus, the framework demonstrates that effective management of wait time-related safety risks requires the combined interaction of quality data, AI technologies, supportive healthcare systems, and ongoing learning to achieve safer and more efficient patient care.

Discussion

One of the clearest findings is that healthcare organisations already hold large amounts of information that may be used to identify safety risks. This information is found not only in structured data such as vital signs, laboratory results, triage scores, and waiting times, but also in unstructured clinical notes, incident reports, patient complaints, and other narratives. NLP provides a way of extracting useful information from these text-based sources, while ML can analyse patterns across different types of data and generate risk predictions. This is particularly relevant in high-risk clinical environments because important warning signs may not always appear in a single structured variable. The findings by Golder et al. (2025) and Abrisqueta-Costa et al. (2024), for example, imply that NLP and ML can identify adverse events and safety signals from unstructured EHR information that may be underreported through conventional approaches.

Similarly, Tabaie et al. (2026) demonstrated that NLP and ML could identify narratives associated with cardiovascular diagnostic errors from patient safety event reports. These findings imply that clinical organisations could use AI to make better use of information that is already being generated during routine care. Thus, an emergency department could combine information from triage records, clinical notes, patient arrival patterns, staffing levels, bed availability, and previous safety events. An ML model could then flag patients who are likely to experience prolonged waits or whose risk may increase during the delay. NLP could add information from the patient's clinical narrative that might otherwise be missed. The purpose would not be to replace clinical judgement, but to give clinicians an earlier warning that a patient may require reassessment or prioritisation.

The findings also suggest that patient waiting time should not be viewed only as a measure of operational efficiency. Earlier studies show that waiting times are affected by several interacting factors, including patient characteristics, arrival patterns, triage level, staffing, specialist availability, bed capacity, and downstream hospital bottlenecks. This means that a patient may continue waiting even when the initial clinical assessment has been completed because another part of the healthcare system is unable to accommodate the patient. This has important implications for high-risk care. If a patient's clinical condition changes while waiting, the original triage decision may no longer accurately reflect the patient's current level of risk. Therefore, healthcare organisations should move beyond a "first assessment and wait" approach towards continuous risk monitoring during periods of delay.

NLP and ML could support this approach by continuously analysing new clinical information and identifying changes in risk. For example, a patient initially classified as relatively stable could become a higher-risk patient because of changes documented in clinical notes, vital signs, laboratory results, or reported symptoms. An AI-supported system could alert the clinical team that reassessment may be required. However, the reviewed evidence does not yet demonstrate that such integrated real-time systems consistently reduce waiting-related adverse outcomes in actual clinical settings. Most of the available evidence focuses on related applications such as risk prediction, adverse event detection, or operational optimisation. Therefore, this application should currently be regarded as a promising direction rather than an established clinical intervention.

Another important finding is that many waiting-time problems are caused by system-level constraints. The literature on waiting times shows that delays can result from inadequate staffing, limited beds, specialist consultation delays, patient surges, and poor coordination between departments. This means that even a highly accurate AI model cannot remove a shortage of beds or create additional healthcare professionals. The practical value of ML therefore lies in helping organisations use available resources more effectively. Predictive models could help forecast periods of high demand, anticipate patient flow, identify likely bottlenecks, and support decisions about staffing and bed allocation. The findings by Abaneme et al. (2025), for example, demonstrate the potential of ML for predicting project and operational risks and supporting resource allocation. Healthcare organisations should therefore avoid implementing AI as a stand-alone technological solution. Instead, AI should be integrated into existing patient-flow and clinical governance systems. Predictions should lead to

practical actions, such as redeploying staff, prioritising reassessment, escalating a deteriorating patient, or identifying alternative care pathways.

The findings also make it clear that patient safety is not determined by technology alone. Chukwunonso-Ogbu et al. (2025) found high levels of fatigue, missed breaks, and fatigue-related performance problems among healthcare staff, while Pickup et al. (2025) argue that fatigue should be treated as an organisational patient safety risk. These findings are particularly important in environments where prolonged waiting times increase workload and pressure on healthcare professionals. An AI system may identify a high-risk patient correctly, but the benefit may be lost if staff are overwhelmed, alerts are excessive, or there is no capacity to respond. Similarly, clinicians may ignore an AI alert if they do not understand how the prediction was generated or do not trust the system. Healthcare organisations should therefore treat AI implementation and workforce management as connected issues. Staff need appropriate training, clear responsibilities, sufficient time to respond to alerts, and confidence in the technology. AI should support professional judgement rather than create another layer of workload.

A major concern emerging from the reviewed studies is the need for transparency. High-performing models are not necessarily clinically useful if healthcare professionals cannot understand or appropriately interpret their predictions. Hasan et al. (2026) demonstrate the potential value of explainable ML through the use of SHAP to identify the factors contributing to mortality-risk predictions. Similarly, Mabodi et al. (2026) emphasise the importance of explainability for improving trust and reducing false positives. This matters greatly when AI is used to influence patient prioritisation. If an algorithm identifies a patient as high risk, clinicians need enough information to understand why that patient has been flagged. Otherwise, there is a danger of either blindly following the recommendation or ignoring it altogether. The practical implication is that healthcare organisations should prioritise human-AI collaboration rather than autonomous decision-making. AI should provide a risk signal, explanation, or recommendation, while appropriately trained clinicians remain responsible for interpreting the information and making the final clinical decision.

The reviewed ML studies demonstrate encouraging predictive performance. For example, Pi et al. (2025) reported strong performance in predicting high-risk pregnancy, Sarkar et al. (2026) achieved an AUROC of 0.81 for predicting suicide and intentional self-harm, while Tabaie et al. (2026) reported an AUROC of 0.914 for identifying cardiovascular

diagnostic-error reports. Lam et al. (2026) also demonstrated the potential of Random Forest models for predicting medication harm. However, these results should be interpreted carefully. Good performance in a retrospective or institution-specific dataset does not necessarily mean that a model will perform equally well in another hospital, patient population, or clinical environment. Tabaie et al. (2026), for instance, specifically identified the need for external validation before broader application. Golder et al. (2025) also identified substantial differences in methods and evaluation approaches across studies. This means that healthcare organisations should not only select AI systems simply because they report high accuracy or AUROC values, but also examine false-negative rates, clinical usefulness, robustness, and performance across different patient groups. In high-risk care, a false negative may be more dangerous than a false positive because failing to identify a deteriorating patient could delay necessary intervention.

Conclusion

This review shows that Natural Language Processing (NLP) and Machine Learning (ML) have considerable potential to support the management of patient wait time-related safety risks in high-risk clinical care. Across the reviewed studies, these technologies were able to extract useful information from unstructured clinical records, identify safety signals, predict clinical risks, and support operational decision-making. These capabilities suggest that NLP and ML could help healthcare teams identify patients who may deteriorate while waiting and respond to emerging risks more quickly. Therefore, current evidence only supports the feasibility of NLP and ML rather than providing conclusive evidence of their clinical effectiveness in reducing wait time-related harm in high-risk clinical care. Therefore, this study recommends that healthcare organisations, hospitals, emergency departments, and healthcare administrators may use NLP and ML to support patient flow monitoring, early identification of deterioration risks, resource allocation, bed management, and prioritisation of high-risk patients to improve both efficiency and quality of care while reducing preventable harm. In addition, successful implementation of AI requires strong governance frameworks, transparent and explainable models, high-quality data infrastructure, staff training, and continuous human oversight. As such, collaboration between clinicians, data scientists, healthcare managers, and regulatory bodies would be essential to ensure that AI technologies are implemented safely, ethically, and effectively.

However, AI is not risk-free. Soberano and Condes (2025) demonstrate that medical AI models may experience substantial performance deterioration when exposed to adversarial attacks. Hanumanthgari (2026) similarly highlights the danger of losing clinically important information when clinical text is excessively compressed. In real-world practice, this means that AI systems should themselves be treated as part of the clinical safety environment. Healthcare organisations need mechanisms for monitoring model performance, detecting unexpected errors, protecting systems against cybersecurity threats, and reviewing changes in model behaviour over time. This is important for NLP systems because a seemingly small change in clinical language can alter meaning. Therefore, a system that incorrectly removes a negation, medication dose, or anatomical detail could create a new safety risk rather than prevent one (Hanumanthgari, 2026).

Limitations and Future Directions

First, the search was restricted to English-language publications, which may have excluded relevant evidence published in other languages and may introduce language bias. Second, the reviewed studies were methodologically heterogeneous, including retrospective observational studies, machine-learning studies, qualitative research, simulation studies and review articles. This heterogeneity prevented meaningful quantitative pooling or meta-analysis. Third, many of the AI studies relied on retrospective and institution-specific datasets, limiting the generalisability of their findings. Fourth, differences in algorithms, outcome definitions, performance measures and validation approaches made direct comparison between studies difficult. Finally, the review did not conduct a meta-analysis because the available evidence was not sufficiently homogeneous.

Therefore, future research should prioritize the development of integrated real-time AI systems capable of combining patient wait time prediction, patient deterioration monitoring, adverse event detection, and operational decision support into a single framework. Future research should move beyond retrospective model development towards prospective, multi-centre, externally validated studies that examine how AI performs in real clinical environments. Such studies should assess not only technical measures such as accuracy, sensitivity, specificity, and AUROC, but also clinically meaningful outcomes, including waiting times, deterioration during waiting, adverse events, patient outcomes, staff

workload, and unintended consequences. Finally, more prospective studies, pilot implementations, and longitudinal evaluations are needed to understand how

NLP and ML systems perform under real clinical pressure where patient conditions, staffing levels, and operational demands constantly change.

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