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Review article

The role of digital twin technology in modern emergency care

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ABSTRACT

Background: Emergency care is operationally defined as time-critical acute care across pre-hospital services, emergency departments, and critical care units (excluding routine urgent care and elective admissions), demanding rapid decision-making under pressure. Digital twin technology, creating real-time virtual replicas through continuous data integration, represents a transformative shift in managing acute conditions, resource allocation, and outcome prediction in emergency medicine.
Aim: This review examines the current applications, benefits, challenges, and future directions of digital twin technology in emergency care and medicine, highlighting its potential to revolutionise emergency healthcare delivery.
Method: A comprehensive narrative literature review was conducted using PubMed, IEEE Xplore, Scopus, and Web of Science databases. Studies published between January 2015 and June 2025 focusing on digital twin applications in emergency departments, trauma care, critical care, and prehospital emergency services were included. Grey literature, conference proceedings, and technical reports were also reviewed to capture emerging developments.
Results: Digital twins demonstrate significant utility across multiple emergency care domains including patient monitoring, resource allocation, workflow optimisation, predictive analytics, and training simulations. Key applications include real time patient condition prediction, emergency department capacity management, trauma response coordination, and personalised treatment planning. Despite promising outcomes, implementation challenges persist, including data integration complexities, computational requirements, and regulatory considerations.
Conclusion: Digital twin technology holds substantial promise for enhancing emergency care delivery through improved decision support, resource optimisation, and predictive capabilities. Continued research, standardisation efforts, and interdisciplinary collaboration are essential for successful clinical integration and widespread adoption.

1. Introduction

Emergency medicine operates at the intersection of time critical decision making, resource constraints, and patient complexity [1]. Healthcare providers in emergency settings must rapidly assess, diagnose, and treat patients presenting with diverse acute conditions whilst managing unpredictable patient volumes and limited resources [2]. The emergency care continuum, as operationally defined in this review, encompasses three interconnected settings: pre-hospital emergency services (ambulance and paramedic care), emergency departments (initial assessment, triage, and stabilisation), and critical care units (intensive monitoring and management of life-threatening

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conditions). This continuum is characterised by time-critical decision making, unpredictable patient acuity, and the need for rapid resource mobilisation. Specifically excluded from this definition are routine urgent care facilities, elective acute admissions, scheduled procedures, and general ward-based care that do not involve immediate threats to life or limb. The challenge intensifies as emergency departments worldwide face increasing patient loads, longer waiting times, and growing pressure to deliver high quality care efficiently [2]. Traditional approaches to emergency care management, whilst effective, often rely on retrospective data analysis and experience-based intuition, which may not adequately address the dynamic and complex nature of modern emergency healthcare environments [3].

Digital transformation in healthcare has introduced innovative technologies that promise to enhance clinical decision making, streamline operations, and improve patient outcomes [4]. Among these technologies, digital twin technology stands out as particularly promising for emergency care applications [3]. Originally developed in manufacturing and aerospace industries, digital twins create virtual replicas of physical entities that mirror their real-world counterparts in real time [5]. When applied to healthcare, this technology enables clinicians to visualise, analyse, and predict patient conditions, system performance, and operational dynamics with unprecedented precision [6]. The integration of artificial intelligence, machine learning, and Internet of Medical Things devices has further enhanced the capabilities of healthcare digital twins, making them increasingly relevant for time sensitive medical specialties [7].

In emergency care contexts, digital twins offer unique advantages by providing real time situational awareness, predictive insights, and decision support capabilities [3]. They can model individual patient physiology to predict deterioration, simulate emergency department workflows to optimise resource allocation, and create virtual environments for training and preparedness [8]. Recent technological advances in sensor technologies, cloud computing, and data analytics have made it feasible to develop sophisticated digital twin systems that can process vast amounts of clinical and operational data instantaneously [9]. This convergence of technologies creates opportunities to address longstanding challenges in emergency medicine, from overcrowding and prolonged waiting times to diagnostic uncertainty and treatment variability [10].

Despite the growing interest in digital twin applications across healthcare, comprehensive reviews specifically examining their role in emergency care remain limited [9]. Existing literature often focuses on individual applications or specific technological components without providing an integrated perspective on how digital twins can transform emergency care delivery holistically [11]. Furthermore, whilst pilot studies and proof of concept implementations demonstrate potential benefits, there is insufficient synthesis of evidence regarding practical implementation challenges, clinical effectiveness, and scalability of digital twin solutions in real world emergency settings [9]. Understanding these aspects is crucial for healthcare administrators, clinicians, and technology developers seeking to leverage digital twin technology effectively [12].

This review addresses the knowledge gap by systematically examining digital twin applications in emergency care and medicine. The problem being addressed is the lack of comprehensive understanding of how digital twin technology can be effectively implemented and utilised across various emergency care settings. The rationale for this review stems from the urgent need to identify evidence-based strategies for improving emergency care delivery amidst growing healthcare demands and technological possibilities. The novelty of this work lies in its integrated approach to analysing digital twin applications across the entire emergency care continuum, from pre hospital settings to emergency departments and critical care units. The aim is to provide a thorough overview of current applications, assess their impact on emergency care outcomes, and identify future research directions. The objectives are threefold: first, to categorise and describe existing digital twin applications in emergency medicine; second, to evaluate the benefits and challenges associated with their implementation; and third, to propose recommendations for advancing digital twin adoption in emergency care settings.

2. Method

2.1. Search strategy

A comprehensive literature search was conducted across multiple electronic databases including PubMed/MEDLINE, IEEE Xplore, Scopus, Web of Science, and Google Scholar. The search covered publications from January 2015 to June 2025 to capture both foundational work and recent developments in digital twin technology applications. Search terms included combinations of "digital twin," "virtual patient," "digital replica," "emergency medicine," "emergency department," "emergency care," "trauma care," "critical care," "acute care," and "pre hospital care." Boolean operators (AND, OR) were used to refine searches and capture relevant literature comprehensively.

A representative full search string used in PubMed was: ("digital twin" OR "virtual patient" OR "digital replica*" OR "virtual model*") AND ("emergency medicine" OR "emergency department*" OR "emergency care" OR "trauma care" OR "critical care" OR "acute care" OR "pre-hospital care" OR "paramedic*" OR "intensive care"). Medical Subject Headings (MeSH) terms were not systematically employed in this search strategy, as digital twin technology represents an emerging field with limited standardised indexing in traditional medical databases. Instead, we relied on comprehensive keyword combinations to ensure broad literature capture across multiple disciplines including computer science, engineering, and healthcare.

Similar search strategies with appropriate adaptations were employed across IEEE Xplore (focusing on technical implementations), Scopus (for interdisciplinary coverage), Web of Science (for citation tracking), and Google Scholar (for grey literature and emerging publications). Reference lists of identified articles were manually screened to identify additional relevant publications not captured through database searches.

2.2. Inclusion and exclusion criteria

Studies were included if they described digital twin technologies, applications, frameworks, or implementations specifically related to emergency care settings as operationally defined in Section 1 (pre-hospital emergency services, emergency departments, and critical care units managing acute life-threatening conditions). This encompassed research articles, systematic reviews, case studies, conference proceedings, technical reports, and white papers that discussed digital twin use in emergency departments, trauma centres, critical care units, or pre hospital emergency services. Studies focusing on general healthcare digital twins without specific emergency care applications were excluded. For instance, digital twins developed for chronic disease management in outpatient settings, elective surgical planning, rehabilitation monitoring, or general wellness tracking were excluded unless they explicitly addressed acute emergency presentations or time-critical decision-making scenarios. Similarly, digital twins for hospital-wide resource planning without specific emergency care focus, or those limited to non-emergency specialties such as routine primary care or elective orthopaedics, were excluded. Non-English publications, opinion pieces without substantial technical or clinical content, and duplicate publications were also excluded from the review.

2.3. Review methodology and rationale

This review employs a narrative synthesis approach rather than a systematic review methodology following PRISMA 2020 guidelines. This methodological choice was deliberate and justified by several factors: First, digital twin technology in emergency care represents an emerging and rapidly evolving field with significant heterogeneity in definitions, implementations, architectures, and outcome measures across studies. The literature spans multiple disciplines (computer science, engineering, clinical medicine, and healthcare management) with diverse publication types including technical reports, proof-of-concept demonstrations, pilot implementations, and theoretical frameworks. Second, the primary aim of this review is to provide a comprehensive conceptual overview of digital twin applications across the emergency care continuum, rather than to synthesise quantitative evidence for specific clinical outcomes. Third, many relevant publications are found in grey literature, conference proceedings, and technical reports that would be systematically excluded in rigid systematic review protocols, yet provide valuable insights into emerging developments and implementation experiences.

Given these considerations, a narrative approach enables broader literature capture and more flexible synthesis of diverse evidence types, which is appropriate for mapping an emerging technology landscape and identifying research gaps. However, we acknowledge this approach as a limitation, which is discussed comprehensively in Section 9.

2.4. Data extraction and analysis

Selected publications were reviewed systematically, and relevant information was extracted including study objectives, digital twin architecture, application domains, technologies employed, outcomes reported, and implementation challenges. Data were categorised thematically based on application areas within emergency care, including patient level digital twins, operational digital twins, and hybrid systems. A narrative synthesis approach was employed to analyse and present findings, given the heterogeneous nature of the literature and diverse methodologies employed across studies. Quality assessment focused on evaluating the technical rigour (adequacy of technical description, validation methods, and reproducibility), clinical relevance (applicability to real-world emergency care settings and potential clinical impact), and evidence strength (study design, sample size, and robustness of reported outcomes) presented in each publication. However, we did not employ a standardised critical appraisal tool such as ROBIS or Newcastle-Ottawa Scale, as the diverse nature of included publications (ranging from technical specifications to pilot implementations) precluded uniform quality assessment using a single framework. This represents a limitation of our approach and is acknowledged in Section 9.

3. Digital twin technology: Conceptual framework

3.1. Definition and core components

Digital twin technology represents a virtual representation of physical entities that continuously receives data from its physical counterpart, enabling real time monitoring, analysis, and prediction [13]. In healthcare contexts, digital twins integrate patient specific data from multiple sources including electronic health records, medical imaging, laboratory results, vital sign monitors, and wearable sensors [14]. The core components of a healthcare digital twin system include data acquisition layers, communication infrastructure, data processing and analytics engines, visualisation interfaces, and feedback mechanisms [15]. Advanced digital twins incorporate machine learning algorithms that enable them to learn from historical data, predict future states, and suggest optimal interventions based on simulated scenarios [16]. As illustrated in Fig. 1, healthcare digital twin systems integrate data from multiple sources including electronic health records, medical imaging, laboratory results, vital sign monitors, and wearable sensors through cloud-based infrastructure powered by machine learning algorithms, enabling real-time monitoring and predictive clinical insights.

3.2. Types of digital twins in emergency care

Digital twins in emergency medicine can be categorised into three primary types based on their scope and application [3]. Patient specific digital twins create virtual models of individual patients, incorporating physiological parameters, medical history, genomic data, and real time monitoring information to predict disease progression and treatment responses [17]. Operational digital twins model emergency department workflows, resource utilisation, patient flow patterns, and capacity dynamics to optimise operational efficiency [18]. System level digital twins integrate multiple components including equipment, staff, patients, and infrastructure to provide comprehensive situational awareness and support strategic decision making [19]. Hybrid digital twins combine elements from multiple categories to address complex challenges requiring both clinical and operational perspectives [20].

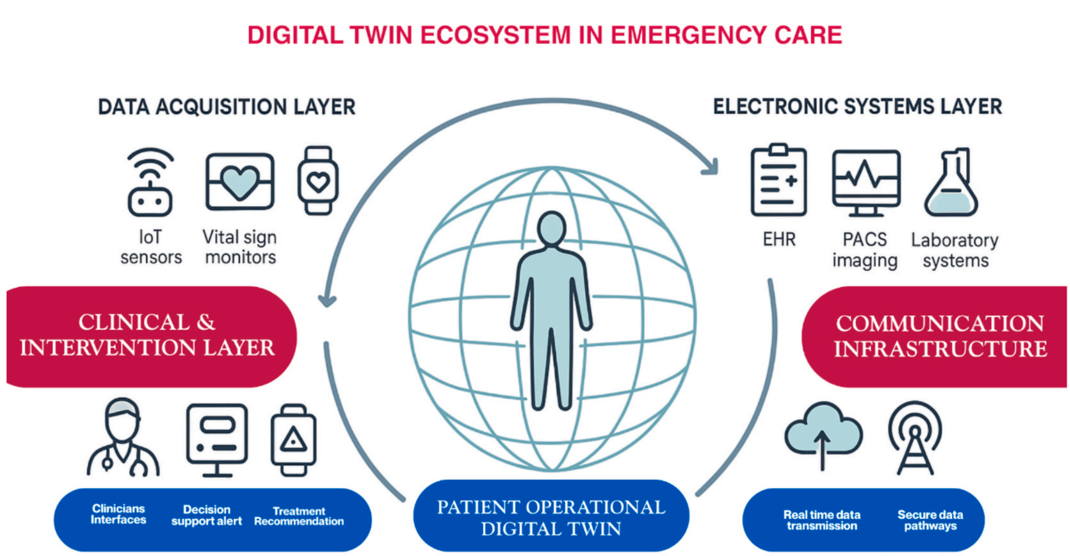

Fig. 1. Integrated Digital Twin Ecosystem for Emergency Care. The architecture illustrates core components of a healthcare digital twin system, including real-time data acquisition from Internet of Medical Things (IoMT) devices, integration with electronic health records and imaging systems, cloud-based computational infrastructure, artificial intelligence and machine learning analytics engines, and clinical decision support feedback mechanisms.

3.3. Technological enablers

Several technological advances have made healthcare digital twins increasingly sophisticated and clinically viable [20]. Internet of Medical Things devices provide continuous, high resolution physiological data that feeds digital twin models [21]. Cloud computing platforms offer the computational power and storage capacity necessary for processing complex simulations and managing large datasets [22]. Artificial intelligence and machine learning algorithms enable predictive analytics, pattern recognition, and automated decision support [23]. Digital communication networks ensure real time data transmission between physical and virtual entities. Advances in computer graphics and virtual reality create immersive visualisation environments that enhance understanding and interaction with digital twin models [24]. Together, these technologies create an ecosystem that supports the development and deployment of clinically meaningful digital twin applications [17].

4. Applications of digital twins in emergency care

Table 1 synthesises the diverse applications of digital twin technology across emergency care domains, illustrating the breadth of implementation possibilities. The table demonstrates that whilst different application areas require distinct technological infrastructures, they share common benefits centred on improved decision making, enhanced efficiency, and optimised resource utilization [3]. Digital twin applications span the entire emergency care continuum, as shown in Fig. 2, from pre-hospital patient assessment and real-time data transmission through emergency department operations, clinical decision-making, critical care monitoring, and community-based preventative interventions, demonstrating the technology's potential to provide integrated support across multiple care settings and phases.

Table 1
Key Applications of Digital Twin Technology in Emergency Care Settings.

Application Domain	Specific Use Cases	Primary Benefits	Technology Requirements
Patient Monitoring [25]	Vital sign integration, deterioration prediction, sepsis detection	Early warning, personalised alerts, reduced monitoring burden	IoT sensors, AI algorithms, real time data processing
Clinical Decision Support [26]	Treatment planning, outcome prediction, intervention simulation	Evidence based decisions, reduced variability, improved outcomes	Machine learning, clinical databases, simulation engines
Emergency Department Operations [3]	Patient flow optimisation, resource allocation, capacity management	Reduced waiting times, improved throughput, efficient resource use	Operational data systems, predictive analytics, visualisation tools
Training and Education [27]	Clinical simulation, procedural training, crisis management	Safe learning environment, competency development, preparedness	Virtual reality, scenario engines, performance analytics
Trauma Coordination [19]	Pre hospital integration, team coordination, resource preparation	Enhanced preparedness, seamless handoffs, reduced response time	Mobile data transmission, integrated displays, communication platforms
Quality Improvement [6]	Outcome analysis, process evaluation, benchmarking	Continuous improvement, evidence generation, performance monitoring	Analytics platforms, data warehousing, reporting systems

4.1. Patient monitoring and clinical decision support

Digital twins excel in providing real time patient monitoring and predictive analytics for emergency patients [6]. By continuously integrating vital signs, laboratory values, imaging findings, and clinical observations, patient specific digital twins can detect subtle changes in patient condition before they become clinically apparent [28]. Studies have demonstrated that digital twin models can predict patient deterioration, sepsis onset, cardiac events, and respiratory failure with greater accuracy than traditional clinical scoring systems [29]. For trauma patients, digital twins can simulate physiological responses to injuries and predict outcomes based on different treatment strategies, enabling clinicians to select optimal interventions rapidly [29]. The technology supports personalized medicine approaches by accounting for individual patient characteristics, comorbidities, and genetic factors when generating predictions and recommendations [3].

4.2. Emergency department operations and resource management

Operational digital twins address critical challenges in emergency department management by modelling patient flow, resource allocation, and capacity dynamics [17]. These systems can predict patient arrival patterns, estimate waiting times, and suggest optimal resource distribution to minimise bottlenecks and improve patient throughput [30]. Digital twins have been employed to simulate triage processes, treatment area assignments, and discharge planning, identifying inefficiencies and testing improvement strategies before implementation [3]. Several emergency departments have reported reduced waiting times, decreased crowding, and improved staff satisfaction following digital twin-based process optimization. [31]. The technology also supports dynamic capacity management by predicting surge events and recommending proactive measures such as staff reallocation, additional bed preparation, or diversion protocols [32].

4.3. Training and simulation

Digital twin technology creates realistic training environments for emergency medicine education and preparedness planning [33,34]. Virtual emergency departments populated with digital twin patients allow healthcare providers to practice clinical skills, crisis management, and team coordination without risking patient safety [35]. These simulations can replicate rare or high-risk scenarios that trainees might encounter infrequently in clinical practice, such as mass casualty incidents, pediatric emergencies, or complex trauma cases. Digital twins enable personalised training experiences that adapt to learner performance, providing targeted feedback and progressively challenging scenarios [36]. For disaster preparedness, digital twins of entire emergency care systems can simulate various disaster scenarios, test response protocols, and identify vulnerabilities before actual events occur [37].

4.4. Trauma care coordination

Trauma care requires seamless coordination across multiple teams and specialties within compressed timeframes. Digital twins facilitate this coordination by providing shared situational awareness and enabling simultaneous planning across surgical, anaesthesia, radiology, and critical care teams. Pre hospital providers can transmit real time patient data to create initial digital twin models before patient arrival, allowing emergency department teams to prepare resources and plan interventions proactively [38]. During trauma resuscitation, digital twins display integrated information from multiple monitoring devices, imaging systems, and laboratory interfaces, reducing cognitive load on trauma team members [19]. Some systems incorporate augmented reality displays that overlay digital twin information onto the physical patient, enhancing spatial awareness and procedural guidance [39].

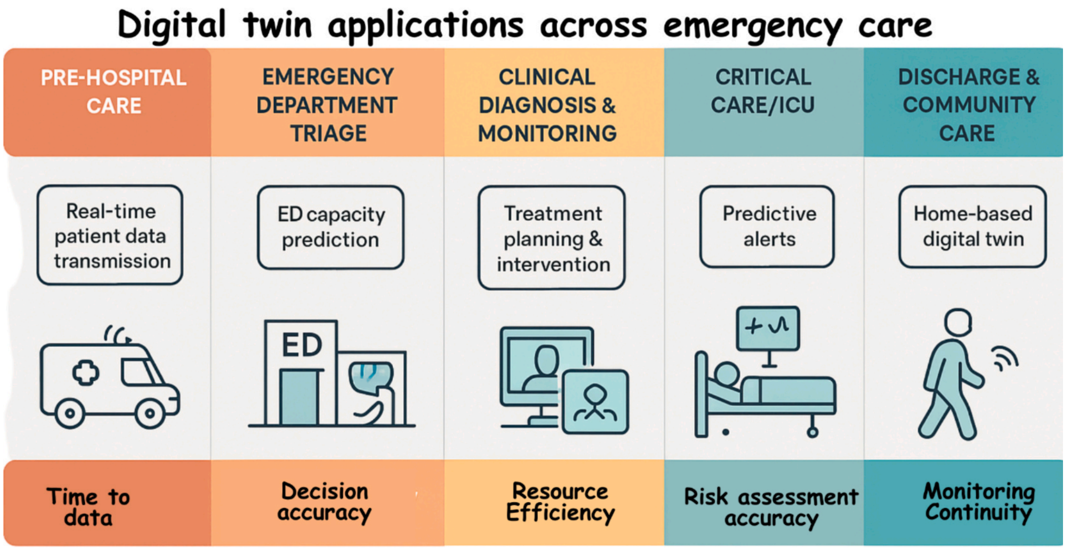

Fig. 2. Digital Twin Applications Across the Emergency Care Continuum. The figure maps digital twin deployment across six critical phases of emergency medicine: pre-hospital care coordination with real-time data transmission, emergency department triage and resource allocation optimization, clinical diagnosis and deterioration prediction, treatment planning with scenario simulation, critical care monitoring with predictive analytics, and post-discharge community-based monitoring for prevention.

4.5. *Predictive analytics for patient outcomes*

Beyond immediate clinical management, digital twins support prognostic assessments that inform treatment intensity decisions and family discussions [40]. By simulating disease trajectories under different treatment scenarios, digital twins provide evidence-based outcome predictions that complement clinical judgment. This capability proves particularly valuable in emergency settings where limited prior information about patients necessitates rapid prognostic assessments. Research indicates that digital twin-based predictions can identify patients at high risk for complications, prolonged intensive care unit stays, or mortality with sufficient accuracy to guide resource allocation and advance care planning discussions [41,42]. The technology also facilitates quality improvement by enabling retrospective analysis of patient outcomes against predicted trajectories, identifying opportunities for care optimization [17].

5. Benefits and advantages

5.1. *Enhanced clinical decision making*

Digital twins provide clinicians with comprehensive, real-time information synthesised from multiple data sources, supporting more informed clinical decisions [43]. Unlike traditional monitoring systems that display isolated parameters, digital twins integrate diverse data streams into coherent patient models that highlight relationships and trends [44]. This integration reduces cognitive burden on emergency physicians who must process vast amounts of information rapidly whilst managing multiple patients simultaneously [45]. Predictive capabilities enable anticipatory rather than reactive care, allowing teams to intervene before clinical deterioration occurs [46]. Evidence suggests that digital twin assisted decision making can reduce diagnostic errors, decrease time to definitive treatment, and improve adherence to evidence-based protocols [43,47].

5.2. *Operational efficiency*

By modelling emergency department workflows and resource utilisation patterns, digital twins identify inefficiencies and optimise processes systematically [48]. Healthcare systems implementing operational digital twins report measurable improvements in key performance indicators including door to provider time, length of stay, left without being seen rates, and ambulance diversion hours. The technology enables data driven decision making regarding staffing patterns, bed allocation strategies, and resource investments [49]. Real time visibility into departmental status allows managers to respond dynamically to changing conditions, implementing contingency plans when capacity thresholds are approached. Long term, digital twins support strategic planning by simulating the impact of proposed changes such as physical layout modifications, new clinical pathways, or technology implementations before committing resources.

5.3. *Personalised patient care*

Emergency medicine traditionally relies on population-based guidelines and clinical experience to guide treatment decisions. Digital twins enable personalised approaches by accounting for individual patient characteristics, risk factors, and predicted responses to interventions [6]. This personalisation extends beyond clinical management to include communication strategies, discharge planning, and follow-up recommendations tailored to specific patient needs. For patients with chronic conditions presenting with acute exacerbations, digital twins can incorporate historical patterns and previous responses to inform current management [41]. The technology also supports shared decision making by generating patient specific outcome predictions under alternative treatment strategies, facilitating informed consent discussions even in urgent situations [48].

5.4. *Resource optimisation*

Healthcare resources remain perpetually constrained, particularly in emergency settings where demand fluctuates unpredictably. Digital twins optimise resource allocation by matching supply with anticipated demand more accurately than traditional approaches [49]. Predictive models forecast patient arrivals, acuity distributions, and resource requirements hours or days in advance, enabling proactive staffing adjustments and supply chain management [50]. Within departments, digital twins guide real time resource deployment, ensuring high acuity patients receive appropriate attention whilst maintaining flow for lower acuity presentations [31]. Equipment utilisation tracking through digital twins identifies underutilised assets and informs purchasing decisions, improving return on investment for capital equipment [51]. Staff scheduling optimised through digital twin simulations can reduce both understaffing and overstaffing situations, improving cost efficiency whilst maintaining quality standards.

5.5. Research and innovation

Digital twins generate rich datasets that accelerate clinical research and innovation in emergency medicine [48]. By capturing detailed information about patient presentations, clinical decisions, interventions, and outcomes, digital twins create virtual laboratories for testing hypotheses and evaluating innovations. Researchers can conduct in silico trials to assess potential interventions before undertaking costly clinical trials, reducing research timelines and resource requirements [52]. The technology facilitates comparative effectiveness research by simulating alternative treatment approaches under controlled conditions. Digital twins also support quality improvement research by enabling rapid iteration testing of process changes, identifying successful strategies that can be disseminated across multiple sites [53]. As datasets grow, machine learning algorithms trained on digital twin data may discover novel clinical patterns, risk factors, and therapeutic targets that advance emergency medicine knowledge.

6. Challenges and barriers to implementation

Table 2 provides a systematic categorisation of implementation barriers and corresponding mitigation strategies, revealing that successful digital twin deployment requires coordinated approaches across technical, organisational, and regulatory dimensions. The table highlights that whilst technical challenges such as data integration and interoperability present immediate obstacles, they are addressable through established solutions including standards adoption and cloud infrastructure investment.

Table 2
Implementation Challenges and Potential Mitigation Strategies for Digital Twins in Emergency Care.

Challenge Category	Specific Barriers	Impact on Implementation	Mitigation Strategies
Technical [54]	Data integration, system interoperability, computational requirements	Delayed deployment, increased costs, reduced functionality	Adopt standards (FHIR, HL7), invest in middleware, cloud infrastructure
Data Quality [11]	Missing data, errors, inconsistencies, outdated information	Reduced model accuracy, unreliable predictions	Data governance frameworks, validation protocols, quality monitoring
Clinical Validation [55]	Limited evidence, trust concerns, explainability challenges	Slow adoption, underutilisation, resistance from clinicians	Prospective trials, transparent reporting, explainable AI methods
Privacy and Security [11,56]	Data breaches, unauthorised access, regulatory compliance	Legal liability, patient harm, loss of trust	Encryption, access controls, regular security audits, compliance frameworks
Financial [11,55]	High implementation costs, uncertain ROI, ongoing expenses	Limited adoption, resource allocation conflicts	Phased implementation, cost benefit analysis, shared infrastructure
Organisational [57]	Change resistance, workflow disruption, training requirements	Implementation failures, suboptimal utilisation	Stakeholder engagement, change management, comprehensive training
Regulatory [3]	Unclear oversight, liability concerns, approval pathways	Delayed implementation, legal uncertainty	Regulatory dialogue, industry standards, clear documentation

6.1. Technical challenges

Implementing digital twin systems in emergency care environments presents substantial technical challenges [3]. Data integration across heterogeneous systems with incompatible formats, standards, and interfaces remains a primary obstacle. Emergency departments utilise numerous medical devices, information systems, and data repositories that were not designed for interoperability, requiring significant technical effort to create unified data streams [58]. Real time processing requirements demand robust computational infrastructure capable of handling high velocity data streams without latency, which can be prohibitively expensive. Model accuracy depends on data quality, yet healthcare data frequently contains errors, inconsistencies, and gaps that degrade digital twin performance [59]. Ensuring system reliability and redundancy becomes critical when clinical decisions depend on digital twin outputs, necessitating fail safe mechanisms and backup systems.

6.2. Data privacy and security

Healthcare data sensitivity necessitates stringent privacy and security measures for digital twin systems. Patient specific digital twins aggregate comprehensive personal health information that, if compromised, could cause substantial harm. Compliance with regulations such as the General Data Protection Regulation and Health Insurance Portability and Accountability Act requires technical safeguards, access controls, and audit mechanisms that add complexity and cost. The continuous data transmission required for real time digital twin updates creates multiple potential vulnerability points for cyber-attacks. As digital twins increasingly incorporate genomic data, behavioural information, and social determinants of health, privacy concerns intensify. Balancing data accessibility for clinical benefit against privacy protection remains an ongoing challenge, particularly when digital twins might be shared across institutions or used for secondary research purposes [60].

6.3. Clinical validation and trust

Widespread clinical adoption depends on rigorous validation demonstrating that digital twin predictions and recommendations are accurate, reliable, and clinically meaningful. Many current implementations lack the prospective clinical trial evidence necessary to establish effectiveness definitively [3]. Clinicians express legitimate concerns about overreliance on algorithmic decision support that might overlook nuanced clinical factors or rare presentations not represented in training data [61,62]. Black box machine learning models that cannot explain their reasoning pose additional trust challenges, particularly when recommendations conflict with clinical judgment [63]. Establishing appropriate validation frameworks for digital twin systems proves difficult given their continuous learning nature and context specific performance variations [64]. Building clinical confidence requires transparent reporting of system limitations, ongoing performance monitoring, and clear guidance about appropriate use case [65].

6.4. Cost and resource requirements

Developing and implementing comprehensive digital twin systems requires substantial financial investment in hardware, software, technical expertise, and ongoing maintenance [66]. Many healthcare systems, particularly those serving under resourced communities, may find costs prohibitive. Beyond initial implementation expenses, digital twins generate ongoing costs for data storage, computational resources, software licensing, system updates, and technical support [64]. Return on investment timelines remain uncertain, making business case development challenging for healthcare administrators. Training clinical and operational staff to utilise digital twins effectively requires time and resources that strain already busy emergency departments. The technology may exacerbate healthcare disparities if accessible only to well-funded institutions, potentially creating a two-tiered system where some patients benefit from advanced digital twin supported care whilst others do not [67].

6.5. Regulatory and legal considerations

Regulatory frameworks for digital health technologies continue evolving, creating uncertainty about digital twin oversight requirements [68]. Questions persist regarding whether specific digital twin applications constitute medical devices requiring regulatory approval, which pathways are appropriate for validation, and what evidence standards apply. Liability considerations when adverse outcomes occur following digital twin guided decisions remain unclear. Determining responsibility amongst technology developers, healthcare institutions, and individual clinicians presents legal complexities without established precedents. Intellectual property issues arise when digital twin algorithms incorporate proprietary methods or training data, potentially limiting transparency and independent evaluation [69]. As digital twins increasingly enable autonomous or semi-autonomous clinical actions, regulatory bodies face pressure to develop frameworks that ensure safety without stifling innovation.

7. Case studies and real-world implementations

7.1. Patient specific digital twin for sepsis prediction

Several academic medical centres have implemented patient specific digital twins focused on early sepsis detection in emergency departments [3]. These systems integrate vital signs, laboratory results, and clinical observations to create dynamic patient models that predict sepsis risk continuously. One implementation reported a 40 per cent improvement in early sepsis identification compared to traditional screening tools, enabling earlier antibiotic administration and reducing progression to septic shock. The digital twin system learned from historical patient data to identify subtle patterns indicative of developing sepsis before meeting conventional diagnostic criteria [70]. Clinicians received real time alerts when the digital twin detected increasing sepsis probability, prompting reassessment and consideration of empiric therapy [25]. The system demonstrated particular value for atypical presentations and immunocompromised patients where conventional sepsis criteria perform poorly.

7.2. Emergency department operational digital twin

A large urban hospital implemented an operational digital twin to address chronic emergency department overcrowding and prolonged waiting times [31]. The digital twin modelled patient arrivals, triage decisions, provider assignments, diagnostic workflows, and disposition processes to identify bottlenecks and test improvement strategies. Simulations revealed that minor adjustments to triage protocols and diagnostic resource allocation could substantially reduce length of stay for specific patient populations. After implementing digital twin recommended changes, the emergency department achieved a 25 per cent reduction in average length of stay and a 35 per cent decrease in patients leaving without being seen [71]. The system continues monitoring departmental performance in real time, alerting administrators when unusual patterns emerge and suggesting dynamic adjustments to maintain optimal flow.

7.3. Trauma response coordination platform

A regional trauma system developed an integrated digital twin platform connecting pre hospital providers, emergency departments, trauma surgeons, and ancillary services. When paramedics activated the system for major trauma cases, patient vital signs and assessments streamed continuously to create preliminary digital twin models [72]. Receiving facilities accessed these digital twins before patient arrival, enabling resource preparation including operating theatre readiness, blood product availability, and specialist team assembly [3]. The digital twin predicted injury severity and resource requirements based on mechanism of injury, vital sign trends, and examination findings [73]. Implementation resulted in a 15-minute reduction in time from emergency department arrival to operating theatre for patients requiring emergency surgery [74]. Communication errors decreased substantially, and trauma teams reported improved situational awareness and coordination.

8. Ethical, legal, and social implications (ELSI)

The implementation of digital twin technology in emergency care settings raises substantial ethical, legal, and social considerations that require systematic attention. This section consolidates these considerations into an integrated framework addressing key domains of concern.

8.1. Ethical considerations

Digital twin technologies in emergency care present unique challenges for patient autonomy and informed consent. In time-critical emergency situations, obtaining informed consent for digital twin use may be impractical or impossible. This raises questions about implicit consent, opt-out mechanisms, and the ethical framework for using patient data to create virtual representations without explicit permission. Emergency contexts often involve incapacitated patients unable to provide consent, necessitating clear ethical guidelines about when digital twin creation and use is appropriate. Healthcare institutions must develop policies balancing the potential clinical benefits of digital twins against respect for patient autonomy, particularly for patients who might object to extensive data aggregation or algorithmic decision support.

Digital twin systems trained on historical data risk perpetuating existing healthcare disparities if training datasets underrepresent certain populations. Emergency digital twins may perform less accurately for demographic groups inadequately represented in development datasets, potentially exacerbating health inequities. For instance, predictive algorithms developed primarily using data from majority populations might generate less accurate predictions for minority patients, leading to suboptimal treatment recommendations [75]. Ethical implementation requires proactive efforts to ensure diverse, representative training datasets and ongoing monitoring for performance disparities across patient populations [76]. Healthcare systems must consider whether digital twin access will be equitably distributed or restricted to well-resourced institutions, potentially creating tiered care quality.

The appropriate balance between algorithmic recommendations and human clinical judgment remains ethically complex [77]. Over-reliance on digital twin predictions might lead to “automation bias,” where clinicians defer to algorithmic recommendations even when clinical judgment suggests alternative approaches. Conversely, systematic disregard for digital twin insights might negate their potential benefits. Ethical frameworks must preserve clinician autonomy whilst encouraging appropriate consideration of data-driven insights. Emergency medicine’s high-stakes, time-pressured environment intensifies these concerns, as clinicians may feel compelled to follow algorithmic recommendations to avoid liability even when uncomfortable doing so [78].

8.2. Legal and liability considerations

When adverse outcomes occur following digital twin-guided decisions, determining legal responsibility presents substantial challenges [79]. Potential liable parties include digital twin developers (for algorithmic errors), healthcare institutions (for implementation failures), and individual clinicians (for inappropriate use or disregard of recommendations) [80]. Current legal frameworks inadequately address these scenarios, creating uncertainty that may inhibit both development and adoption [81]. Clear documentation of digital twin capabilities, limitations, and intended use cases becomes crucial for liability protection, as does transparent communication about system performance and validation status [29].

Digital twin systems may constitute medical devices requiring regulatory approval, though classification criteria remain unclear [82]. Regulatory bodies including the FDA and MHRA are developing frameworks for artificial intelligence-based medical technologies, but specific guidance for digital twin systems remains limited [83,84]. The continuous learning nature of many digital twin systems complicates regulatory oversight, as system behaviour may evolve post-approval [83]. Healthcare institutions implementing digital twins must navigate uncertain regulatory landscapes whilst ensuring patient safety and legal compliance [82]. International harmonisation of regulatory standards would facilitate technology development and transfer across jurisdictions [85].

Legal questions persist regarding ownership of data generated by digital twins, rights to access twin-derived insights, and permissible uses of aggregated twin data for research or commercial purposes [86]. Patients may claim ownership of data about their virtual representations, whilst developers and healthcare institutions assert proprietary interests in algorithms and analytical methodologies [86,87]. Clear legal frameworks defining data rights, usage permissions, and benefit-sharing arrangements are necessary to support ethical implementation whilst protecting legitimate stakeholder interests [82].

8.3. Social and professional implications

Public trust in digital twin technology depends on transparency about system capabilities, limitations, and performance [82]. Healthcare institutions must communicate clearly with patients about digital twin use, data practices, and potential risks. "Black box" algorithms that cannot explain their reasoning undermine trust and complicate informed consent processes [87]. Explainable AI methods that provide interpretable rationale for recommendations may enhance trust, though technical complexity limits accessibility for many patients and clinicians. Professional societies should develop guidelines for transparent digital twin implementation and communication [87].

Digital twin adoption will transform emergency care workforce requirements and roles [82]. Clinicians will need new competencies in interpreting algorithmic recommendations, understanding system limitations, and integrating digital twin insights into clinical reasoning [82]. Technical specialists will be needed to implement, maintain, and optimise digital twin systems [21]. Training curricula must evolve to prepare future emergency medicine professionals for digital twin-enabled practice [87]. Concerns about de-skilling or professional displacement require attention, as excessive algorithmic reliance might erode clinical competencies if humans become passive consumers of machine-generated recommendations [88].

Socioeconomic disparities in digital twin access risk exacerbating existing health inequities [82]. Well-resourced healthcare systems may implement sophisticated digital twin capabilities whilst under-resourced facilities lack necessary infrastructure, creating quality gaps in emergency care. Geographic disparities may emerge between urban academic centres and rural or community hospitals [82]. Intentional policy efforts to promote equitable access, including shared infrastructure models, public investment, and technology transfer programmes, will be necessary to prevent digital twin technology from widening healthcare gaps [85,87].

Comprehensive data aggregation required for effective digital twins raises surveillance concerns, particularly as systems integrate genomic, behavioural, and social data [82]. Patients may feel uncomfortable with extensive monitoring and data collection, even when intended for clinical benefit [87]. Healthcare institutions must implement robust data governance frameworks that protect privacy whilst enabling beneficial digital twin applications [82]. Clear limitations on data use, strong security measures, and patient control over data sharing are essential for maintaining trust and respecting privacy rights [82,85].

9. Discussion

This section provides critical interpretation of findings, addresses inconsistencies in the literature, and contextualises digital twin technology within broader emergency care challenges and healthcare transformation efforts.

9.1. Current state and maturity of digital twin technology in emergency care

The literature review reveals that digital twin technology in emergency care remains predominantly in proof-of-concept and pilot implementation phases rather than widespread clinical deployment [31]. Whilst numerous publications describe theoretical frameworks, technical architectures, and simulated scenarios, relatively few reports validated clinical effectiveness data from prospective controlled studies [56]. This maturity gap between technological possibility and clinical reality reflects several factors: the nascent state of the field, significant technical and organisational implementation barriers, and the substantial validation requirements necessary before widespread clinical adoption [56,82].

The evidence base demonstrates greater maturity in operational digital twins (addressing patient flow and resource optimisation) compared to clinical digital twins (supporting individual patient care decisions) [56]. This discrepancy likely reflects lower implementation barriers and validation requirements for operational applications, as well as more straightforward outcome measurement (waiting times, throughput metrics) compared to clinical outcomes (morbidity, mortality). Patient-specific digital twins capable of real-time predictive analytics remain largely aspirational, with most implementations focusing on narrower applications such as sepsis prediction or deterioration detection rather than comprehensive patient modelling [82].

9.2. Integration challenges and interoperability

A consistent theme across the literature is the substantial challenge of data integration and system interoperability [6]. Emergency departments employ numerous disconnected information systems, medical devices, and data repositories that were not designed for seamless data exchange [89]. Creating the unified, real-time data streams necessary for effective digital twin operation requires significant technical investment in middleware, interface engines, and data harmonisation infrastructure [6,56]. The absence of universal healthcare data standards exacerbates these challenges, though efforts around FHIR (Fast Healthcare Interoperability Resources) and HL7 standards offer promise [56].

Interestingly, the literature reveals a tension between the desire for comprehensive data integration and pragmatic implementation constraints [89]. Several successful implementations achieved meaningful benefits by focusing on specific, well-defined use cases with limited data requirements rather than attempting comprehensive digital twin ecosystems [56]. This suggests a phased implementation approach may be more realistic than "big bang" transformational deployments, though such incremental approaches risk creating fragmented systems with limited integration [6,56].

9.3. Clinical validation and evidence gaps

A critical weakness in the current evidence base is the paucity of rigorous prospective clinical validation studies demonstrating that digital twin technology improves patient outcomes [56]. Most publications describe technical implementations, simulation results, or retrospective analyses rather than randomised controlled trials or prospective cohort studies with clinical endpoints [82]. This evidence gap is understandable given the field's nascent state, yet it represents a substantial barrier to widespread clinical adoption and guideline incorporation [56].

The validation challenge is compounded by digital twins' continuous learning capabilities [56]. Traditional medical device validation assumes static system behaviour, enabling one-time approval processes [88]. However, digital twins that learn from new data and update their algorithms over time require ongoing validation frameworks that current regulatory structures inadequately address [85]. The literature lacks consensus on appropriate validation methodologies, acceptable performance thresholds, and ongoing monitoring requirements for clinical digital twin systems [56,87].

Furthermore, several publications report impressive performance metrics (prediction accuracy, sensitivity, specificity) without adequately addressing clinical utility, whether the predictions enable actionable interventions that improve outcomes [87]. High predictive accuracy is necessary but insufficient; digital twins must provide timely, actionable insights that clinicians can and will act upon to benefit patients. The gap between technical performance and clinical impact requires greater research attention.

9.4. Reconciling promising benefits with implementation challenges

The literature simultaneously describes transformative potential benefits and substantial implementation barriers, raising questions about realistic near-term adoption trajectories. Several factors may reconcile this apparent contradiction:

First, different emergency care settings face different implementation feasibility profiles. Large academic medical centres with substantial technical infrastructure, IT support, and research capabilities may successfully implement sophisticated digital twin systems that would be impractical for smaller community hospitals. Geographic and institutional variability in adoption rates should be expected, with potential implications for healthcare equity.

Second, the literature suggests a spectrum of digital twin sophistication, from relatively simple operational models requiring modest technical infrastructure to comprehensive patient-specific twins demanding extensive integration and computational resources. Early adopters may focus on simpler applications delivering meaningful benefits with manageable implementation burden, progressively advancing toward more sophisticated capabilities as infrastructure matures and experience accumulates.

Third, cost-benefit calculations depend heavily on local context including baseline performance, patient volumes, and resource constraints. Institutions facing severe overcrowding, long waiting times, or resource inefficiencies may find operational digital twins cost-effective despite substantial implementation expenses, whilst facilities with well-optimised baseline operations may struggle to justify investments. The literature inadequately addresses when and where digital twin implementation represents sound resource allocation versus technological enthusiasm.

9.5. Ethical and social implementation considerations

The review identified an important gap in the literature: insufficient attention to ethical, legal, and social implications (ELSI) of digital twin technology in emergency care. Most publications focus on technical capabilities and clinical applications whilst minimally addressing consent challenges, algorithmic bias, privacy concerns, liability questions, and equity implications. This represents a critical oversight, as these considerations significantly influence successful implementation and public acceptance.

The emergency care context intensifies several ethical concerns [87]. Time-critical decision-making limits opportunities for informed consent, whilst high-stakes outcomes amplify concerns about algorithmic errors [56]. Vulnerable populations disproportionately utilise emergency services, raising equity concerns if digital twin benefits accrue primarily to well-resourced institutions [87]. The literature would benefit from greater interdisciplinary engagement incorporating bioethics, health law, and social science perspectives alongside technical and clinical viewpoints [82].

9.6. Future trajectories and research priorities

Based on the current evidence base and identified gaps, several research priorities emerge:

First, prospective clinical validation studies with patient-centred outcomes are urgently needed. Whilst technical proof-of-concept work has demonstrated feasibility, rigorous evidence of clinical effectiveness, safety, and cost-effectiveness is necessary for widespread adoption. Such studies should employ robust methodologies including randomised controlled trials where feasible, or well-designed pragmatic trials and interrupted time series analyses when randomisation is impractical.

Second, implementation science research examining effective strategies for digital twin adoption, workflow integration, and sustained use is essential. Technical feasibility is necessary but insufficient; understanding organisational, social, and professional factors influencing implementation success will accelerate clinical translation. Comparative studies examining different implementation approaches across diverse settings would generate valuable insights.

Third, research addressing algorithmic bias, fairness, and equity in digital twin systems requires prioritisation. Development of diverse, representative datasets and validation across demographic subgroups should become standard practice. Studies explicitly examining whether digital twin technology reduces or exacerbates healthcare disparities will inform equitable implementation strategies.

Fourth, standardisation efforts around digital twin architectures, data models, interoperability specifications, and performance metrics would accelerate field development. The proliferation of proprietary, incompatible systems limits knowledge accumulation and hinders multisite research. Professional societies and standards organisations should collaborate to develop consensus frameworks.

Finally, interdisciplinary research incorporating clinical, technical, ethical, legal, and social perspectives is needed to address the complex challenges digital twin technology presents. Siloed approaches focusing exclusively on technical capabilities without attending to clinical context and societal implications will produce incomplete solutions. Successful digital twin implementation requires coordinated attention to technical excellence, clinical validity, ethical acceptability, legal compliance, and social benefit.

10. Limitations of the review

This review has several limitations that warrant acknowledgement. First and most significantly, this review employed a narrative synthesis approach rather than the systematic review methodology outlined in PRISMA 2020 guidelines. This methodological decision was deliberate, justified by the emerging and heterogeneous nature of digital twin literature spanning multiple disciplines, publication types, and implementation contexts. However, this approach introduces limitations including potential selection bias, lack of formal quality assessment using standardised tools (e.g., ROBIS, AMSTAR, Newcastle-Ottawa Scale), and absence of systematic risk of bias assessment. We did not employ formal critical appraisal instruments, instead relying on qualitative evaluation of technical rigour, clinical relevance, and evidence strength. This limits the objectivity and reproducibility of our quality assessments compared to systematic reviews employing validated appraisal tools.

Second, we did not produce a PRISMA flow diagram documenting search yields, screening decisions, and reasons for exclusions at each stage. Whilst we described our search strategy and inclusion/exclusion criteria, the absence of quantitative reporting on the number of records identified, screened, excluded, and included limits transparency and reproducibility. Similarly, we did not provide a comprehensive summary table systematically documenting characteristics of all included studies (publication year, study design, sample size, setting, digital twin type, outcomes measured, key findings). These omissions reflect the narrative rather than systematic approach but represent methodological limitations nonetheless.

Third, the rapidly evolving nature of digital twin technology means that recent developments may not yet appear in peer reviewed literature, potentially causing this review to underrepresent cutting edge innovations. The heterogeneity of digital twin definitions, architectures, and applications across studies made systematic comparison challenging, necessitating a narrative synthesis approach that may introduce subjective interpretation. Publication bias likely affects the literature, with successful implementations more likely to be reported than failed attempts or negative findings, potentially creating an overly optimistic perspective on digital twin effectiveness.

Fourth, the quality and rigour of included studies varied considerably, with much of the literature comprising proof of concept demonstrations, pilot studies, and simulation work rather than prospective clinical trials with robust outcome measures. This limits the strength of conclusions regarding clinical effectiveness and real-world impact. Few studies reported long term follow up data or assessed sustainability of digital twin implementations beyond initial deployment periods, leaving questions about durability of benefits unanswered. Cost effectiveness analyses remain scarce, making it difficult to provide definitive guidance regarding return on investment or value propositions for healthcare decision makers.

Fifth, geographic and institutional diversity in the literature review is limited, with most published work originating from well-resourced academic medical centres in high income countries. This restricts the generalisability of findings to resource limited settings or community hospitals where implementation challenges may differ substantially. The review focused primarily on technical and clinical aspects of digital twins, with less emphasis on organisational, cultural, and social factors that significantly influence technology adoption and utilisation. Patient perspectives on digital twin use in their care, including concerns about privacy, preferences for human versus algorithmic decision making, and understanding of the technology, remain underexplored in the literature and consequently in this review.

Sixth, the search strategy, whilst comprehensive, may have missed relevant grey literature, internal technical reports, or proprietary implementations that organisations choose not to publish publicly. Language restrictions to English language publications may have excluded valuable work from non-English speaking countries. We did not systematically employ Medical Subject Headings (MeSH) terms or other controlled vocabularies, instead relying on broad keyword combinations. This approach was appropriate given the nascent state of digital twin indexing in medical databases, but may have resulted in missed relevant publications indexed under alternative terminology. The interdisciplinary nature of digital twin technology spans computer science, engineering, medicine, and healthcare management, potentially causing relevant work published in specialised journals outside traditional medical databases to be overlooked.

Finally, the pace of technological advancement means that some technical limitations discussed in this review may already be outdated, whilst emerging challenges not yet apparent in the literature may become significant as implementations mature. The absence of a formal protocol registered in advance (e.g., PROSPERO registration) represents a methodological limitation compared to systematic reviews, as it precludes verification that our review followed predetermined methods rather than post-hoc adjustments based on findings.

These limitations are inherent to the narrative review approach and the current state of the digital twin literature. Future systematic reviews employing PRISMA methodology, formal quality assessment tools, and comprehensive study characteristic tables will provide more rigorous evidence synthesis as the field matures and the evidence base expands. Our narrative approach was appropriate for this exploratory review of an emerging technology but should be complemented by systematic reviews as primary research evidence accumulates.

11. Conclusion

Digital twin technology represents a transformative innovation with substantial potential to enhance emergency care delivery across multiple dimensions. By creating dynamic virtual representations of patients, operational systems, and entire care ecosystems, digital twins provide unprecedented capabilities for real time monitoring, predictive analytics, decision support, and process optimisation. The applications reviewed demonstrate tangible benefits including earlier detection of clinical deterioration, improved resource allocation, reduced waiting times, enhanced coordination, and more personalised patient care. As emergency departments worldwide face mounting pressures from increasing patient volumes, aging populations, and resource constraints, digital twins offer evidence-based approaches to working more efficiently and effectively within these constraints.

However, the evidence base remains predominantly in early-stage development, with most implementations representing proof-of-concept demonstrations and pilot studies rather than rigorously validated, widely deployed clinical systems. Substantial challenges spanning technical infrastructure, clinical validation, data privacy, cost justification, organisational change, and regulatory uncertainty must be addressed before digital twin technology achieves its transformative potential in emergency care.

Despite promising applications and reported benefits, significant challenges remain before digital twin technology achieves widespread adoption in emergency care settings. Technical hurdles including data integration, interoperability, and computational requirements demand continued innovation and investment. Clinical validation through rigorous prospective studies is essential to build the evidence base and clinical confidence necessary for routine use. Privacy and security concerns require ongoing attention and robust safeguards, particularly as digital twins aggregate increasingly comprehensive patient information. Cost considerations and uncertain return on investment create barriers for resource constrained healthcare systems. Regulatory frameworks must evolve to provide clear guidance whilst fostering continued innovation. Ethical, legal, and social implications require systematic attention through interdisciplinary collaboration incorporating bioethics, health law, and social science perspectives alongside technical and clinical expertise.

Moving forward, successful integration of digital twins into emergency care will require coordinated efforts across multiple stakeholders. Technology developers must prioritise user centred design, interoperability standards, and transparent performance reporting. Healthcare institutions need to invest in necessary infrastructure, training, and change management processes that support successful implementation. Clinicians should engage actively in design, testing, and refinement of digital twin systems to ensure clinical utility and workflow integration. Researchers must conduct rigorous evaluations that generate evidence about effectiveness, implementation strategies, and long-term impacts. Policymakers and regulators should develop frameworks that ensure patient safety and data protection whilst enabling innovation to flourish.

The future of digital twins in emergency medicine appears bright, with emerging technologies promising even greater capabilities. Integration with advanced artificial intelligence, extended reality interfaces, genomic data, and community monitoring systems will create increasingly sophisticated and comprehensive digital twin ecosystems. As these technologies mature and implementation challenges are addressed, digital twins may become as fundamental to emergency care as electronic health records or computed tomography scanners are today. The transformation will not happen overnight, requiring sustained commitment, investment, and collaboration across the healthcare ecosystem. However, for a specialty defined by the imperative to make optimal decisions rapidly under uncertainty, the promise of digital twins to provide real time insights, predictive intelligence, and evidence-based decision support makes them uniquely suited to advancing emergency medicine into its next era. Continued research, development, and thoughtful implementation will determine whether this promise is fully realised in practice.

CRediT authorship contribution statement

David B. Olawade: Conceptualization, Formal analysis, Supervision, Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation. **Osazuwa Ighodaro:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation. **Emmanuel Oghenetejiri Erhieyovwe:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Nebere Elias Hankamo:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Ismail Tajudeen Hamza:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Claret Chinenyenwa Analikwu:** Writing – review & editing, Writing – original draft, Methodology, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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