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REVIEW PAPER

Leveraging digital technologies to enhance patient safety

Stephen Agius[1] · Vincent Cassar[1] · Frank Bezzina[1] · Luke Topham[2]

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Abstract

Aims This study aims to examine how digital technologies can be safely and effectively integrated into clinical practice to enhance patient safety, with a particular focus on emergency department triage.

Background Patient safety remains a persistent challenge in high-pressure environments such as emergency care. The complexity of clinical workflows, cognitive demands on healthcare professionals, and system-level constraints often contribute to patient safety risks. While digital tools such as Clinical Decision Support Systems (CDSS) offer promise, their impact depends on how well they align with real-world decision-making processes.

Methods A Cognitive Task Analysis (CTA) was conducted with triage nurses in the emergency department (ED) of Malta's main acute hospital. The study involved semi-structured interviews and direct observations to elicit the cognitive challenges, decision strategies, and contextual constraints experienced during triage. Findings were synthesised into a Cognitive Demands Table to identify sources of risk and variation in decision-making.

Results The CTA revealed key challenges affecting patient safety at triage, including cognitive overload, incomplete information, reliance on intuition, protocol deviations, communication gaps, and fatigue. These findings informed the development of a conceptual framework comprising six pillars essential for safe digital integration: governance and policy alignment, human-centred design, clinical validation, digital literacy, interoperability, and continuous monitoring.

Conclusion Digital technologies have the potential to significantly improve patient safety, but their effectiveness depends on thoughtful integration into clinical environments. This study highlights the importance of designing digital systems that are context-aware, ethically governed, and co-developed with end users. The proposed framework offers practical guidance for healthcare leaders, developers, and policymakers seeking to embed safety into the digital transformation of care.

Keywords Patient safety · Digital health technologies · Predictive analytics · Clinical decision · Healthcare automation · Data-driven decision support · Health information technology · Digital transformation in healthcare · Healthcare quality improvement

1 Introduction

Patient safety is a fundamental component of high-quality healthcare and a core concern for clinicians, administrators, and policymakers alike [1]. Defined by the World Health Organisation as "the absence of preventable harm to a patient during the process of healthcare," patient safety has evolved into a global priority as health systems confront the dual pressures of increasing complexity and rising patient expectations (WHO, 2017). Despite advances in clinical knowledge and practice, adverse events, many of which are preventable, continue to occur at alarming rates, contributing to avoidable morbidity, mortality, and escalating healthcare costs [1].

✉ Stephen Agius
stephen.agius@um.edu.mt

Vincent Cassar
vincent.cassar@um.edu.mt

Frank Bezzina
frank.bezzina@um.edu.mt

Luke Topham
L.K.Topham@ljmu.ac.uk

1 Department of Business and Enterprise Management, Faculty of Economics, Management & Accountancy, University of Malta, Tal-Qroqq, Malta

2 Liverpool John Moorse University, Liverpool, UK

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Examples of such adverse events include medication errors, delayed or missed diagnoses, failure to detect clinical deterioration, hospital-acquired infections, and communication breakdowns during handovers [2–4]. These incidents can have severe, sometimes fatal, consequences. For instance, diagnostic errors involving conditions such as stroke, sepsis, pneumonia, venous thromboembolism, and lung cancer contribute significantly to serious patient harm. A recent national estimate suggests that nearly 800,000 Americans suffer permanent disability or death each year due to misdiagnosis, with just 15 diseases accounting for over half of these serious harms. The five most harmful conditions alone are responsible for nearly 39% of all serious diagnostic error-related outcomes, underscoring the urgency of early and accurate diagnosis in high-risk clinical scenarios [5]. Similarly, medication-related harm is among the most frequent causes of patient injury, leading to unnecessary hospital admissions, prolonged stays, and additional treatment costs. The World Health Organisation estimates that unsafe medication practices result in over 1.3 million injuries and at least one death every day globally [6]. Failure to identify clinical deterioration in time, particularly in emergency and inpatient settings, can lead to preventable cardiac arrests or ICU admissions, highlighting the need for continuous patient monitoring and timely escalation of care [7].

Many of these adverse events share a common characteristic: they are often system-level failures that occur not due to a lack of clinical knowledge, but because of cognitive overload, information gaps, or breakdowns in communication and coordination. As such, addressing them requires more than clinical vigilance. It calls for systemic interventions that can support real-time decision-making, streamline processes, and enhance visibility across care pathways. Digital technologies, particularly those underpinned by real-time data, machine learning, and automation, are uniquely positioned to address these root causes by enabling earlier detection, risk stratification, and better-informed clinical action.

Digital technologies are emerging as powerful enablers in the effort to improve patient safety [8, 9]. From predictive models that anticipate clinical deterioration to electronic systems that reduce medication errors, digital tools have the potential to enhance situational awareness, support clinical decision-making, and enable more coordinated and responsive care [10].

Recent evidence underscores how machine learning (ML) is reshaping patient triage and operational forecasting in emergency care [11, 12]. ML-based triage models can outperform traditional rule-based systems such as the Emergency Severity Index (ESI) by incorporating a broader range of features including vital signs, free-text notes, and historical health records to predict key outcomes like admission, mortality, and critical care needs [12, 13]. Studies have demonstrated that ML triage systems not only improve accuracy but also reduce under-triage of high-risk patients, thereby enabling more timely clinical responses [13, 16]. These tools contribute to safer and more equitable care by identifying deterioration risks that may be missed in standard workflows, particularly in overcrowded ED environments [17, 18].

In addition to clinical triage, predictive analytics are increasingly being used to forecast ED patient arrivals, enhancing operational readiness and mitigating risks related to crowding and delayed care [13, 19, 20]. Forecasting models, leveraging time-series analysis and deep learning approaches, have been shown to accurately predict patient inflow at hourly and daily levels, allowing hospitals to better align staffing levels, bed management, and resource allocation [21, 22]. Such proactive planning is critical for patient safety, as ED crowding has been consistently associated with higher rates of medical errors, prolonged wait times, and increased inpatient mortality [24, 25]. Collectively, these applications highlight how digital tools can directly address core patient safety challenges in emergency settings, from identifying critically ill patients earlier to reducing systemic delays through intelligent resource planning.

The acceleration of digital transformation in healthcare, spurred further by the COVID-19 pandemic, has brought renewed urgency to questions of how best to integrate these technologies without compromising human oversight, trust, or equity [26, 27].

This paper explores the intersection of patient safety and digital innovation. It provides a critical overview of current technologies being deployed to reduce harm in healthcare, including predictive analytics, clinical decision support systems (CDSS), electronic health records (EHRs), telemedicine, and automation. Drawing from relevant literature and grounded in naturalistic research, this paper examines both the opportunities and limitations of leveraging digital technologies to enhance patient safety. The aim is not only to highlight technical potential, but also to propose a framework for ethical, sustainable, and human-centred integration that supports clinicians, empowers patients, and aligns with broader health system goals.

2 Background

Digital technologies have become increasingly integral to healthcare delivery, offering tools that improve precision, efficiency, and safety [28]. In the context of patient safety, these technologies function as critical support mechanisms, helping clinicians make timely, informed decisions while reducing the likelihood of human error [9, 29]. Figure 1 illustrates key categories of digital technologies that are enhancing patient safety.

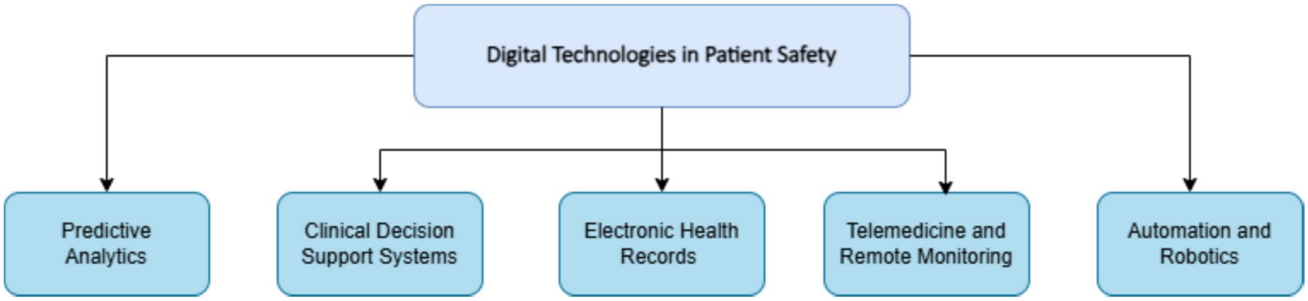

Fig. 1 Key digital technologies in patient safety

Predictive analytics leverages historical and real-time data to forecast clinical events before they occur [30, 31]. In patient safety, this translates into earlier detection of clinical deterioration, sepsis, or adverse drug events [32, 33]. Machine learning models on large datasets can uncover subtle patterns not easily visible to the human eye, supporting earlier interventions and targeted care. For instance, predictive tools can identify patients at high risk of readmission or escalation, enabling pre-emptive clinical action [34, 35]. In emergency care settings, such models are increasingly used to prioritise patients at triage, predict admission likelihood, and estimate appropriate ward placement, helping to reduce overcrowding and improve resource allocation, and contain healthcare costs [37].

CDSS are digital platforms that provide clinicians with evidence-based recommendations, alerts, and diagnostic support at the point of care [38, 39]. These systems have been widely adopted to reduce medication and diagnostic errors, flag potential drug interactions, and prompt compliance with clinical guidelines [40, 41]. Effective CDSS can significantly enhance safety by reducing cognitive burden on clinicians, especially in environments like ED and intensive care units [42]. When appropriately integrated, CDSS represent a powerful mechanism for mitigating risk and standardising care decisions in complex clinical settings.

EHRs play a foundational role in improving patient safety through better information accessibility and care coordination [43]. They allow clinicians to view a comprehensive history of a patient's medications, allergies, investigations, and previous encounters, reducing duplication and miscommunication. EHRs can also generate safety alerts and facilitate handovers between care teams [44].

Telemedicine offers a safe alternative to in-person visits, particularly for patients with mobility challenges or those at high risk of infection [45]. Its role became especially prominent during the COVID-19 pandemic, which accelerated the adoption of remote care solutions to minimise exposure and maintain continuity of care [46]. Telemedicine has proven invaluable in managing chronic conditions, mental health follow-ups, and post-discharge monitoring areas where continuity is critical for patient safety. Remote patient monitoring technologies, such as wearable sensors and home-based diagnostic tools, enable clinicians to track vital signs and symptoms in real time, helping to detect early warning signs and trigger timely interventions before complications arise. Telehealth also empowers patients to participate actively in their care, reinforcing adherence and early reporting of concerns. Automation technologies ranging from robotic-assisted surgeries to automated medication dispensing reduce variability and enhance precision in clinical procedures. Robotics in surgery can minimise tissue damage, shorten recovery times, and lower infection risks [47].

Automated systems in pharmacies and laboratories have helped reduce transcription errors, improved inventory management through better stocking levels, enhanced tracking capabilities, and streamlined high-volume workflows [48]. These applications free clinicians from repetitive tasks, allowing them to focus on complex decision-making and patient interaction.

Despite the significant promise of these technologies in advancing patient safety through improved decision-making, early detection, and streamlined workflows, their implementation introduces a range of critical challenges that must be carefully addressed. These include technical limitations, ethical risks, and user-centred design concerns that, if not addressed, may undermine safety outcomes [49, 50]. Issues such as data privacy, algorithmic bias, system usability, and clinician trust must be carefully considered to ensure that digital solutions support, rather than compromise, safe and equitable care [16, 52, 53].

The reliance of digital tools on sensitive patient information introduces data protection concerns [55]. Cybersecurity breaches can lead to identity theft, compromised treatment, and loss of public trust. Notable incidents involving ransomware in healthcare settings have underscored the need for strong encryption, multi-factor authentication, and clear incident response protocols . Ensuring data security is fundamental to the safe adoption of digital health solutions.

Algorithmic bias remains a serious concern. Many AI systems are developed using historical datasets that may reflect existing inequities in care, potentially leading to discriminatory outputs [56, 57]. Without deliberate efforts to audit for bias and ensure representative training data, these tools risk reinforcing disparities. Equity-focused design, subgroup testing, and transparent reporting are critical to ensure safe and fair deployment [58, 59].

Poorly designed digital tools may also contribute to cognitive overload and "alert fatigue" among clinicians, particularly in already high-pressure environments [60, 61]. Constant notifications, difficult navigation, and non-intuitive systems can reduce time spent with patients and increase the risk of missed or delayed decisions [62]. Designing technologies that streamline rather than disrupt clinical workflows is vital for patient safety and clinician wellbeing [63].

Trust is another essential component of safe digital integration. Clinicians are unlikely to rely on AI tools that function as "black boxes" without providing understandable justifications for their outputs [36, 64]. Explainable AI (XAI) frameworks are being developed to provide transparency into algorithmic logic and foster clinician confidence in using digital decision aids [65, 66].

Regulatory gaps persist regarding the approval, monitoring, and liability of AI-enabled systems in healthcare [67, 68]. It remains unclear in many jurisdictions who is accountable when a digital tool contributes to an adverse event. Clear, adaptable, and patient-safety-driven regulatory frameworks are essential to guide responsible innovation [69, 70].

The successful implementation of digital technologies also requires cultural adaptation. Resistance from clinicians driven by concerns over autonomy, unfamiliarity, or fear of redundancy can hinder uptake [50, 71]. Without meaningful engagement, training, and leadership support, even the most promising innovations may fail to deliver safety gains [72].

Taken together, these considerations highlight the need for context-sensitive, ethically grounded, and clinician-informed approaches to the design and implementation of digital technologies in patient care.

3 Objectives

In line with growing efforts to enhance patient safety through digital innovation, this study investigated the cognitive processes and decision-making strategies of triage nurses in emergency care settings. With patient acuity assessment, uncertainty management, and decision verification being critical to safe and timely care, particular attention was given to the cognitive demands nurses face during triage interactions. Guided by Cognitive Task Analysis (CTA), the study aimed to translate these findings into a structured Cognitive Demands Table, a foundational step toward the development of a CDSS that aligns with the real-world cognitive workflows and pressures experienced by frontline staff. This approach recognises that effective digital tools must be shaped by the realities of clinical practice to enhance patient safety and support safer, more responsive care.

4 Methods

This study adopted a qualitative, multi-method approach to examine the cognitive strategies and decision-making behaviours of triage nurses within the emergency care environment. Drawing on the principles of CTA, data collection involved 16 semi-structured interviews and six hours of structured observation at Mater Dei Hospital, Malta's primary acute general teaching hospital. A purposive sampling strategy ensured a diverse participant pool in terms of experience, education, and demographic background, facilitating a rich exploration of cognitive variation in clinical reasoning. By combining interviews to elicit explicit and tacit knowledge with real-time behavioural observations, the study aimed to capture both the subjective and observable dimensions of triage practice. The methodological integration of these data sources enabled a robust triangulation of findings, supporting the development of a Cognitive Demands Table and informing the design of decision-support technologies that align with frontline cognitive workflows to enhance consistency, reduce error, and improve patient safety.

4.1 Participants

This study involved 16 semi-structured interviews with triage nurses and six hours of structured observational fieldwork, conducted between December 2023 and February 2024. Participants in the interview component were all full-time registered nurses working in EDs, each providing direct clinical care for a minimum of 36 hours per week. There were no exclusion criteria; participants were eligible if they had at least six years of nursing experience, including 2 to 29 years in triage.

A purposive sampling method was adopted to ensure a diverse participant pool in terms of clinical experience, educational attainment, and age. This sampling strategy was designed to capture a broad range of cognitive approaches and decision-making styles relevant to emergency care. Given the known influence of clinical exposure, heuristic reasoning, and pattern recognition on triage cognition, the study aimed to maximise variation to reflect this complexity. Participants' educational qualifications included Bachelor's degrees (n = 9), Master's degrees (n = 6), and one doctoral degree (n = 1). All had completed accredited nursing programmes and received dedicated training in triage protocols. The age of participants ranged from 24 to 55 years, with the largest group falling within the 24–29 age band. The cohort consisted of 13 women and 3 men. Table 1 provides a summary of the participants included in the study.

Observational data were collected across four sessions, each lasting 90 min, resulting in a total of six hours of observation covering 55 triage cases. These sessions were conducted on separate days and scheduled across both morning and evening shifts to reflect variations in patient volume and case severity. Timing was deliberately varied to capture both high- and low-demand periods, thereby enhancing the ecological validity of the observations. Importantly, the nurses observed were not part of the interview sample, enabling triangulation between reported and observed practices and offering a richer understanding of the cognitive and procedural dynamics in triage settings.

4.2 Data collection

Guided by the principles of CTA, this study integrated both interview and observational methods to explore the cognitive mechanisms underpinning triage decision-making. The interview component aimed to elicit both explicit and tacit forms of knowledge, capturing how nurses reason through clinical uncertainty and make rapid decisions under pressure. In parallel, structured observations provided behavioural data that illuminated real-time strategies, environmental constraints, and workflow adaptations. The combination of these methods allowed for a richer, more multidimensional understanding of clinical cognition. While the participants involved in interviews and those observed were not the same, this design was intended to enhance methodological triangulation rather than serve as a direct validation mechanism. It also helped reduce participant burden and safeguarded the authenticity of individual contributions. The complementary nature of the two approaches, interviews providing insight into internal reasoning and observations capturing behaviour aligned with established CTA methodology and enhanced the interpretative depth of the findings.

All interviews were conducted by the lead researcher using a semi-structured protocol. Observations were guided by a structured template adapted from CTA literature, focusing on cognitive behaviours such as information gathering, prioritisation, communication patterns, and task-switching under pressure.

To access tacit knowledge which is defined as experiential insight that is often difficult to articulate [73, 74], interviews included open-ended and scenario-based prompts encouraging participants to describe specific triage encounters in detail. Probing questions such as "What influenced that decision?" or "Did you notice anything subtle in the patient's behaviour?" were used to surface intuitive, experience-based reasoning that may not be readily verbalised. In addition to audio recordings, field notes documented non-verbal cues such as tone, hesitations, and body language to enrich the interpretation of underlying cognitive processes.

To ensure analytical rigour, data coding was initially carried out by the lead researcher and subsequently reviewed by a second researcher with expertise in clinical practice. Coding reliability was addressed through iterative comparison and consensus discussions, with discrepancies resolved collaboratively. Thematic saturation was achieved by the 13th interview, after which no novel codes emerged, indicating sufficient depth and coverage across both data sources.

4.3 Research location and characteristics

This study was conducted amongst triage nurses at Mater Dei Hospital, Malta. Mater Dei Hospital is an acute gen eral teaching hospital offering a full range of hospital services. It is the only healthcare facility in Malta, catering for a population of over 550,000 inhabitants. The hospital caters for all medical specialities including medicine, surgery, orthopaedics, cardiac services, ophthalmology, dentistry, paediatrics, neuroscience, obstetrics and gynaecology, and oncology. Apart from inpatient services, the hospital also offers emergency services, day care services and outpatient services. Data collection took place between 10 October and 31 December 2023.

4.4 Ethical considerations and consent

Ethical approval was obtained from both the University of Malta Research Ethics Committee (FEMA −2023–00285) and the Data Protection Office at Mater Dei Hospital (34/2023). Written informed consent was obtained from all interview participants and from nurses and patients involved in the observations. To preserve the validity of observational data, nurses were informed of the observation period and

Table 1 Participants in the study

Characteristic	Summary
Sample Size	16 participants
Gender Distribution	13 female (81%), 3 male (19%)
Age Range	24 to 50 years; majority (50%) aged 24–29
Triage Experience	Range: 1 to > 20 years; median experience: 8–10 years
Qualification Level	8 Bachelor's (50%), 7 Master's (44%), 1 PhD (6%)

purpose in general terms without disclosing the specific behavioural focus.

4.5 Study design

The proposed design recommendations in this study are informed by three key sources: (1) empirical data derived from interviews and observations, (2) established insights from the naturalistic decision-making (NDM) literature, and (3) existing evidence on the development of CDSS in healthcare contexts. By integrating these elements, the study aims to demonstrate how digital tools can enhance clinical reasoning, support timely and accurate decision-making, and reduce cognitive load, ultimately contributing to improved patient safety.

CTA served as the primary framework for investigating the triage decision-making process. Data obtained through interviews and observational sessions were analysed using thematic analysis to identify salient patterns and recurrent cognitive demands. This process was guided by Braun and Clarke's six-phase methodology, which includes data familiarisation, code generation, theme development, and iterative refinement. NVivo software (Release 1.7.1) supported the coding and organisation of data, ensuring consistency and analytical rigour throughout the process.

The thematic analysis yielded 26 distinct themes across the two data sources. These themes were then synthesised into a structured Cognitive Demands Table through a hybrid method combining inductive theme generation with deductive categorisation based on CTA principles. Themes were conceptually grouped and mapped to core CTA domains, including prioritisation, uncertainty management, decision verification, communication, and error mitigation. The CDT was populated by linking each thematic cluster to specific cognitive challenges, cues, potential sources of error, and design implications for CDSS, thereby providing a coherent bridge between empirical findings and practical application.

5 Results

The CTA conducted as part of this research uncovered several recurring cognitive demands faced by triage nurses operating in the ED environment. These findings, which were based on semi-structured interviews and direct observations, are summarised in the Cognitive Demands Table (see Table 2). The Cognitive Demands Table is a structured analytical tool used to examine the mental workload associated with complex clinical tasks in this case triage decision-making. It provides a systematic way to identify where and why decision points are challenging, what errors may result, and how systems or processes can be redesigned to better support clinical staff [75, 76]. The "Cognitive Demand" column outlines the specific mental activities required, such as prioritising patients or processing incomplete information. The "Why Difficult" column explains the underlying factors that contribute to cognitive strain, including time pressure, ambiguity, or information overload. The "Potential Errors" column highlights the types of mistakes that may arise if these demands are not adequately supported such

Table 2 Cognitive Demands Table

Cognitive Demand	Why Difficult	Potential Errors	Design Ideas
Patient assessment in Triage	Balancing efficiency with accuracy in a very limited time-window	Misclassification, rushed assessments, missed critical details	Automated priority suggestion; real-time triage dashboard
Patient assessment during peak hours	High patient influx, time-sensitive nature of emergency care	Delayed recognition of urgent cases, inefficient resource use	Predictive analytics to anticipate surges; dynamic resource tracking
Data collection for assessment	Limited time for gathering critical information to inform decisions	Incomplete/inaccurate assessments, missed critical information	Voice-to-text entry; structured triage templates
Observation cues and patterns	Rapid interpretation of non-verbal cues under time pressure	Inconsistent cue interpretation, judgment errors	AI for pattern recognition and vital sign interpretation
Uncertainty, incomplete information, and communication barriers	Incomplete data, language/cultural barriers, and patient communication difficulties	Over-triage or under-triage due to unclear or missing data	Multilingual support and real-time translation tools
Deviations from triage	Judging when to depart from established protocols safely	Risk of inconsistent or unsafe decisions when deviating	Deviation logging system with safety prompts and justifications
Seeking advice during triage	Accessing input from peers under time pressure and without structured systems	Delayed or inconsistent decision verification	Built-in collaboration features and escalation workflows
Long shifts	Fatigue and emotional strain reduce attentiveness and empathy	Reduced care quality, empathy lapses, increased risk of error	Fatigue alerts, shift-aware nudges, cognitive offloading tools

as misjudgements, omissions, or delayed responses and the "Design Ideas" column proposes practical interventions, ranging from interface enhancements to workflow adjustments or decision aids, aimed at reducing cognitive load and improving performance. Collectively, the table helps bridge the gap between human cognitive challenges and actionable design improvements.

The results below present the most salient cognitive challenges impacting triage decision-making and, by extension, patient safety.

5.1 Cognitive load and time pressure

Triage nurses reported consistently high cognitive load, especially during peak hours and periods of high demand. The need to assess patients rapidly, multitask, respond to queries, and handle interruptions created a cognitively taxing environment. This contributed to mental fatigue and increased the likelihood of delays or errors in patient classification.

5.2 Incomplete and unreliable information

A frequent challenge was the need to make decisions based on incomplete or ambiguous information. This included patients who were uncommunicative, had language barriers, lacked accompanying medical records, or situations where the clinical presentation was unclear. Nurses described instances of "erring on the side of caution," often leading to over-triage in the absence of reliable data.

5.3 Reliance on observational cues and intuition

Non-verbal cues, such as skin colour, facial expressions, and breathing patterns, were critical to the nurses' rapid assessment of acuity. These cues were often interpreted through intuition or past experience, particularly when clinical signs were not yet clear. However, this reliance on pattern recognition introduced variability in assessments, especially among less experienced staff or during periods of fatigue.

5.4 Protocol adherence and deviations

While the Emergency Severity Index (ESI) protocol was generally well-understood, nurses frequently described instances where they deviated from this protocol. These deviations were often based on contextual judgment, such as a "gut feeling" about patient severity or due to workflow pressures and resource constraints.

5.5 Communication and peer verification

Triage nurses frequently consulted colleagues, senior nurses, or emergency physicians when they encountered uncertainty or atypical presentations. This informal peer verification process played a central role in building confidence in decision-making, but was inconsistently applied, depending on staff availability and time pressure.

5.6 Fatigue and shift duration

Extended shifts were associated with reduced attentiveness, decision-making clarity, and interpersonal communication. Nurses on longer shifts reported feeling 'drained,' which sometimes made it more challenging to manage complex assessments or maintain empathetic interactions with patients. A tendency toward greater variability in triage decisions was observed toward the end of shifts.

6 Discussion

The safe and effective integration of digital technologies in healthcare requires more than technical innovation, it requires a systemic, multi-stakeholder approach grounded in governance, clinical evidence, and human-centred values. The findings from this study particularly the results of the CTA highlight the cognitive complexity, variability, and safety risks inherent in emergency triage decision-making. These empirical insights informed the development of a conceptual framework comprising six interdependent pillars (Fig. 2), each designed to address the specific challenges

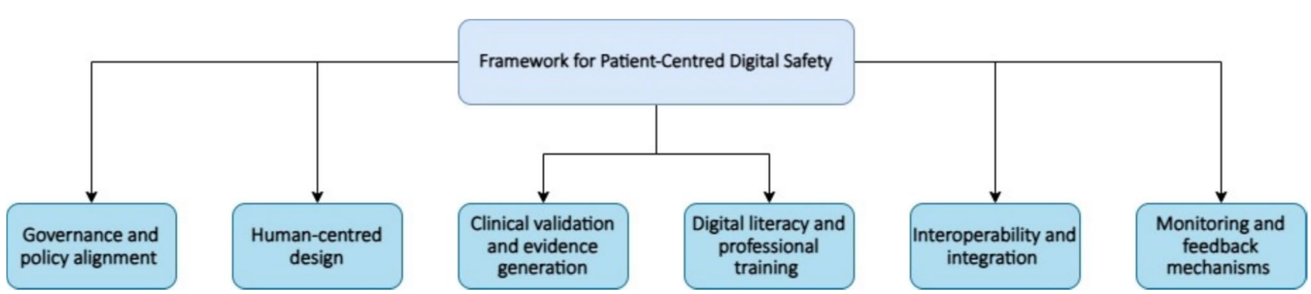

Fig. 2 Framework for Patient-centred Digital Safety

identified and to guide the responsible implementation of digital technologies in ways that prioritise patient safety.

Governance and policy alignment emerges as foundational to digital safety. Robust regulatory structures and institutional oversight are necessary to ensure that digital tools particularly those leveraging AI are ethically deployed and aligned with national healthcare priorities. As highlighted by Topol [70], the inclusion of automation in clinical decision-making introduces novel challenges of accountability and transparency, underscoring the need for explicit governance protocols.

Closely tied to governance is the principle of human-centred design, which addresses the practical realities of clinical workflows. Poor usability and system complexity have been repeatedly linked to safety risks, including alert fatigue and user disengagement[77]. Co-designing tools with end-users not only enhances usability but also improves adoption and reduces the likelihood of unintended consequences.

A critical dimension of safe digital adoption is clinical validation and evidence generation. Despite increasing enthusiasm for digital interventions, many tools still lack prospective clinical validation [78]. The framework stresses the importance of rigorous pre-deployment testing and post-implementation audits to ensure safety outcomes are demonstrable, measurable, and reproducible across contexts.

Equally, the importance of digital literacy and professional training cannot be overstated. As Laka et al. [79] argue, even well-designed systems can fail if users lack the skills to interpret and act upon their outputs. Training must extend beyond basic system use to encompass AI explainability, cybersecurity, and clinical reasoning in the presence of algorithmic suggestions.

Interoperability and integration represent another safety–critical factor. Fragmented data flows can disrupt continuity of care and create blind spots for clinicians, particularly in emergency or cross-setting scenarios. Integrating data streams from electronic health records, laboratory systems, and decision support platforms enhances clinicians'situational awareness and supports real-time, data-informed decision-making [77].

Finally, continuous monitoring and feedback mechanisms are essential to maintaining and improving digital safety. System usage must be subject to real-time surveillance, with built-in feedback loops that empower users to report issues and contribute to ongoing improvement [80]. Dashboards, audit logs, and patient-reported outcomes can together drive iterative refinement of safety systems.

The proposed framework for patient-centred digital safety offers a structured response to the cognitive and contextual challenges revealed through this study's CTA. By grounding digital transformation in governance, human factors, clinical validation, and continuous learning, the framework moves beyond abstract principles and engages directly with the realities of frontline care. It acknowledges that while digital technologies hold great promise, their safety impact depends on thoughtful integration, ethical oversight, and ongoing engagement with clinical users. As healthcare systems continue to digitalise, success will hinge not on technology alone, but on our ability to embed these tools within cultures of safety, trust, and shared responsibility.

7 Limitations

This study's findings may have limited generalisability due to the single-site setting and sample size, although efforts were made to ensure participant diversity. Observations were conducted within a specific month, limiting the ability to assess seasonal variation. The researcher's insider role offered access benefits but required strict ethical safeguards to ensure impartiality and mitigate bias. While the qualitative design followed structured methods, subjectivity in interpretation remains inherent. Awareness of being observed may have influenced nurse behaviour, and ethical considerations around informed observation were carefully managed. Future research should expand across settings, seasons, and methods to build on these findings.

8 Conclusion

Digital technologies hold transformative potential to enhance patient safety by reducing errors, improving decision-making, and enabling more responsive, coordinated care. Innovations such as predictive analytics, clinical decision support systems, remote monitoring, and automation are already reshaping the landscape of modern healthcare, offering new tools to address persistent safety challenges.

However, technology alone is not a panacea. Realising its full potential requires a balanced approach, one that harmonises innovation with oversight, and places clinicians, patients, and ethical principles at the core of system design and deployment. Successful integration of digital tools must be underpinned by robust governance frameworks, active clinical engagement, continuous evaluation, and an unwavering commitment to equity, transparency, and public trust.

The insights presented in this research paper highlights the value of context-aware, human-centred digital solutions in promoting safer care. These findings reinforce the importance of aligning digital safety initiatives with real-world clinical workflows, decision dynamics, and frontline needs.

As we look to the future, embracing a culture of digital safety one rooted in collaboration, trust, and continuous learning will be essential. Such a culture enables a healthcare system not merely where harm is reduced, but where safety is proactively embedded, sustained, and continuously improved through the responsible use of digital innovation.

Author contributions SA conceptualised and designed the study. VC and LT contributed to data collection. FB assisted in the interpretation of the results and drafted parts of the manuscript. All authors reviewed and approved the final version of the manuscript.

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Data availability The data generated and analysed during the study (interview transcripts and observation notes) are not publicly available due to privacy and ethical restrictions.

Code availability No custom code or software was developed for this study. Qualitative data analysis was performed using NVivo (Release 1.7.1), a commercially available software package.

Declarations

Ethics approval This study was conducted in accordance with the Declaration of Helsinki and received approval from the University of Malta Research Ethics Committee (Ref: FEMA-2023–00285) and the Data Protection Office at Mater Dei Hospital (Ref: 34/2023).

Consent to participate Written informed consent was obtained from all triage nurses who participated in interviews, as well as from nurses and patients involved in observational sessions.

Consent for publication All participants provided consent for the anonymised publication of study findings. No individual participant is identifiable in the article or any associated materials.

Conflict of interest No conflict of interest has been declared by the authors.

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