Original Paper

Exploring the Requirements of Clinicians for Transparent and Trustworthy Decision Support Systems in Intensive Care: Focus Group Study

Jeff Clark[1], MEng, PhD; Matthew Wragg[1], BSc, PhD; Emily Nielsen[1], BSc, MSc, PhD; Miquel Perello-Nieto[1], BSc, MSc, PhD; Nawid Keshtmand[1], BSc, MSc, PhD; Michael Ambler[2,3], MA, MBBS, PhD; Shiv Sharma[3], iBSc, MBBS; Christopher Bourdeaux[3], BCHIR, MB, MA; Amberly Brigden[1], BSc, MSc, PhD; Raul Santos-Rodriguez[1,4], BSc, PhD

[1]School of Engineering Mathematics and Technology, University of Bristol, Bristol, England, United Kingdom

[2]School of Psychology and Neuroscience, University of Bristol, Bristol, England, United Kingdom

[3]Intensive Care, Bristol NHS Foundation Trust, Bristol, England, United Kingdom

[4]ValER (Fundación de la Comunitat Valenciana de Investigación de Excelencia), València, Spain

Corresponding Author:
Jeff Clark, MEng, PhD
School of Engineering Mathematics and Technology
University of Bristol
Ada Lovelace Building, Clifton Campus
Tankard's Close
Bristol, England, BS8 1TW
United Kingdom
Phone: 44 1179289000
Email: jeff.clark@bristol.ac.uk

Abstract

Background: Understanding how digital systems can support clinical decision-making is crucial, especially with the growing deployment of increasingly complex AI models. This complexity raises concerns about trustworthiness, affecting the safe and effective adoption of such technologies. In intensive care units (ICUs), where clinicians make high-stakes, time-sensitive decisions, decision support tools must be designed to align with clinical needs and cognitive workflows. A better understanding of decision-making processes and requirements for decision support tools is vital for providing effective solutions.

Objective: This study investigates ICU clinicians' decision-making processes, their use of decision support systems (DSSs), and the design requirements for DSSs to ensure transparent and trustworthy recommendations.

Methods: We conducted 2 virtual focus groups with 7 ICU clinicians from 1 hospital in September 2024. Participants included nurses, charge nurses, and medical doctors, each with at least three years of professional experience. The focus groups explored participants' perspectives on DSSs in relation to our study objectives. Reflexive thematic analysis was applied to the focus group transcripts, and analytic decisions were made inductively using open coding. Both semantic and latent coding were used. Following independent coding, a combined codebook was developed collaboratively, from which key themes and subsequent design recommendations were identified.

Results: Three core themes emerged from the analysis: ICU Decision-Making Relies on a Wide Range of Factors (theme 1); Complexity of Patient State Is Challenging for Shared Decision-Making (theme 2); and Acceptability and Usability of DSSs (theme 3). Five design recommendations derived from clinical input provide insights to inform future DSSs for intensive care: provide variable levels of detail (recommendation 1); support integration into existing clinical systems (recommendation 2); present explanations with additional contextual information (recommendation 3); prompt independent thought (recommendation 4); and facilitate communication of patient state (recommendation 5).

Conclusions: DSSs have the potential to enhance ICU decision-making, but their adoption depends on alignment with clinicians' needs and workflows. To improve trust and usability, future systems must provide transparent recommendations, adapt to varying levels of patient complexity, and facilitate rather than replace human expertise. Our findings inform the development of transparent and trustworthy DSSs, which may improve their acceptance in ICU settings.

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KEYWORDS

clinical decision-making; intensive care; artificial intelligence; explainability; human-centered computing; participatory design

Introduction

Background

Intensive care units (ICUs) deliver care for patients in critical condition who require continuous medical supervision. The primary objective of ICU staff is to stabilize patients sufficiently to allow safe transfer to lower-acuity settings. ICU patients often remain for extended periods under the coordinated care of a multidisciplinary health care team. Although patient care is a shared focus, clinicians, including physicians, nurses, and pharmacists, have distinct roles, objectives, and workflows. Given the severity of patients' conditions, even minor physiological changes can lead to rapid and severe deterioration [1].

ICUs generate huge amounts of data through comprehensive invasive and noninvasive monitoring [2]. Decision support systems (DSSs), particularly AI-enabled DSSs, are increasingly being developed to aid ICU clinicians in the decision-making process [3-5]. Many of these systems are developed to support safety-critical decisions, yet they are not typically human-interpretable or fully stress-tested. Consequently, their clinical deployment is met with skepticism [6], and the adoption of such systems often fails [7]. As such, there is a growing need for these systems to be both transparent and trustworthy. Transparent recommendations clearly justify and explain their findings. Trustworthy recommendations are those on which clinicians can reasonably rely for decision support because they are technically robust, clinically safe, ethically sound, and legally compliant [8].

Researchers have made efforts to co-design dashboards for ICUs, aiming to improve their functionality [8]. One toolkit developed to accompany the rise of AI systems is explainable AI (XAI), which comprises techniques aimed at increasing transparency and enabling users to understand a system's decisions. Many such XAI techniques are now available [9]. Despite the growing demand for transparent explanations and trustworthy AI decisions [10,11], clinicians' requirements for DSSs remain underexplored and are an active area of research [12]. Further work is therefore required to better understand clinicians' needs in relation to current and future DSSs and how such systems can best meet these clinical requirements to achieve trustworthiness.

Prior Work

Clinical Decision Support: Applications and Design Approaches

There is growing interest in deploying DSSs in ICUs. However, most of the work is in the initial stages of development [13,14], with few applications widely deployed and used in clinical practice. One reason for the lack of adoption is the disruption that new solutions may cause to existing clinical workflows [15,16]. In this section, we provide context and review related work to better understand existing problems in ICUs, how DSSs have been applied across health care domains, recent trends in the use of AI and XAI to address health care problems, and, finally, studies on the co-design of DSSs for health care.

The ICU

The ICU differs sharply from other hospital settings, posing unique challenges for patients, families, and health care professionals. Its distinctiveness stems from the severity of critical illness and the specialized environment it requires. For patients, the ICU can feel alien because it is dominated by advanced technology and constant monitoring, and patients often have a limited ability to communicate fully. Invasive interventions and cognitive disturbances can prevent patients from expressing their needs or fears, leading to frustration and isolation [17].

Patients in the ICU often face profound uncertainty about their prognosis and the life-altering effects of critical illness, leaving them and their loved ones emotionally distressed [18]. Many loved ones must also act as surrogate decision makers, making difficult choices about life-sustaining treatments and end-of-life care [19].

Health care professionals in the ICU, though highly skilled and compassionate, work under relentless pressure. Heavy workloads and long hours contribute to burnout and fatigue [20]. The ICU itself poses systemic challenges. Limited resources, including a lack of space and privacy, affect the quality of care. The high-tech environment, with its alarms and complex equipment, adds further stress for both patients and staff [21]. Together, these factors make the ICU a uniquely demanding and emotionally charged setting within health care.

DSSs for Health Care

Classification of Decision Support Systems

DSSs can integrate clinical knowledge and patient data to facilitate decision-making at the point of care. DSSs can be categorized in multiple ways, including by timing (before, during, or after the clinical decision is made), development (knowledge-based vs non–knowledge-based), and interaction type (passive vs active) [22].

Timing

Early DSS applications were retrospective, supporting administrative functions such as guidelines and protocols, test scheduling, and patient triage. The emergence of statistical tools that can be applied proactively to patient data has since shifted the paradigm toward supporting critical medical tasks [22].

Development

Knowledge-based systems use expert-defined if-then rules [23], whereas non–knowledge-based methods learn task-relevant patterns from data, often with little expert involvement. This

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shift is closely tied to recent advances in AI, as discussed in the next subsection.

Interaction

Passive systems, which require user initiation, have largely been discontinued due to low efficacy and their dependence on engagement, often by experts [23,24]. Active systems deliver automated recommendations, including medication safety functions such as error prevention [25], drug-allergy checking, dose guidance, and drug-drug interaction monitoring [26]. However, excessive notifications can deter adoption through alert fatigue [15].

Challenges in implementing DSSs in real-world environments have led to extensive research on design requirements. Azadi and García-Peñalvo [27] synthesized findings from 43 studies and identified 12 human-computer interaction elements that influence clinical DSS usability, highlighting factors such as flexibility, visibility, explainability, user control, efficiency, effectiveness, and user satisfaction. Similarly, Castillo and Kelemen [15] identified integration into existing clinical workflows, end-user involvement in development, and adequate training as critical factors for adoption and effectiveness. Mienye et al [16] highlighted the complexity of integrating AI into clinical workflows and the need to adhere to rigorous regulatory requirements for medical device deployment. Additional details are described in the "Co-Design of DSSs for Health Care" subsection.

Trends Toward AI in DSSs

Since 2014, rapid advances in AI have increased the number of research publications on its applications to DSSs in health care [28-30]. A bibliometric analysis by Tang et al [28] of AI use in intensive care medicine highlighted an exponential increase in publications between 1986 and 2022, with approximately 73% published between 2018 and 2022. The paper found that AI was often being developed for tasks such as disease prediction, mortality estimation, prognosis, and classification. A literature review by Suresh et al [31] identified similar application areas and noted that, although the studies showed promising results, the generalizability of their findings might be limited by the localized nature of the data used in most studies.

Lack of Adoption and Ethical Concerns

Although AI solutions often match human expert performance [32], their adoption in real-world medical settings remains limited, largely due to a lack of trust and system explainability [33]. Pinsky et al [34] attributed this gap to immature situational awareness and fundamental biases that erode trust. These concerns have driven growing interest in trustworthy, explainable, and transparent AI [34,35].

Explainable AI

XAI and human-centered XAI can facilitate the acceptance of AI technologies in critical health care scenarios [36]. Several literature reviews have synthesized the most common challenges, areas of application, methodologies, and future opportunities [35,37,38].

In health care, XAI has been used in diagnostic tools and clinical DSSs, personalized medicine, medical imaging, remote diagnostics, and telemedicine [16], as well as for early disease diagnosis, discharge disposition prediction, and sepsis risk estimation [35]. Specific XAI studies in the ICU have focused on a range of prediction tasks, predominantly readmission [39,40] and mortality prediction [41,42].

Although most studies indicate that XAI has great potential to enhance health care professionals' trust in clinical settings, several factors hinder its adoption [43], including complex explanations, inconsistent results, and ambiguity [37].

Co-Design of DSSs for Health Care

Some previous studies have focused on plausible solutions using state-of-the-art technologies without involving end users in the initial design.

This approach can be useful for rapidly prototyping ideas that can be demonstrated to users at a later stage. By contrast, this study focuses on capturing clinicians' needs from the earliest stages of development.

Co-Design and Stakeholders

Human-centered XAI focuses on designing XAI systems that meet the needs, expectations, and preferences of human users [36]. However, these users span multiple stakeholder groups whose motivations differ substantially [33,35]: developers seek to verify model correctness, researchers seek to discover new sources of knowledge, clinicians seek justifications aligned with clinical plausibility and existing medical evidence [33,35], and patients seek to understand their progress [44]. While some studies ground XAI design in cognitive psychology [45], Panigutti et al [12] argued that participatory approaches are vital because effective AI decision support requires explanations that meet end users' information needs. Participatory design has been applied across health care, from dashboards for chronic diseases [46,47] to Yildirim et al's [7] multiphase study, in which clinicians, AI experts, and human-computer interaction researchers co-developed a spontaneous awakening trial– and spontaneous breathing trial–readiness prediction system through early prototyping and user feedback, highlighting the importance of making AI capabilities clear to end users.

Clinicians' Needs

Sivaraman et al [48] showed that the format of DSS outputs, including AI explanations such as feature attributions or bar charts, can influence whether ICU clinicians trust, ignore, or negotiate with suggestions in sepsis care. Tonekaboni et al [49] found that clinicians value contextual information and feature-level justifications when interpreting risk predictions in a simulated ICU setting. Corti et al [50] examined how explanations need to evolve in pulmonary care. Working with clinicians treating idiopathic pulmonary fibrosis, they showed that the use of DSSs is shaped by clinical uncertainty and the stage of the workflow, underscoring the dynamic nature of the need for explanations throughout patient care.

Patients' Needs

While much of this work centers on clinician-facing AI, Kambhamettu et al [44] shifted the focus to patient needs. They investigated how intelligent interfaces can help patients understand their medical progress notes. Through observation

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and interviews, they identified explanation needs such as deemphasizing technical jargon, highlighting key information, and providing simple, contextual summaries.

ICU-Specific Needs

Drawing on participatory design research on interventions in the ICU, several studies provide insights into contextual challenges within the ICU, highlighting its cognitively demanding nature [51,52]. Orth et al [53] considered general information requirements for intensive care decision-making, such as access to patient history and comprehensible information, and explored the implications for system requirements. Our paper builds on this work by focusing on ICU clinicians' requirements for DSSs.

Study Goals

We sought to understand ICU clinicians' requirements for DSSs by answering the following research questions (RQs):

- RQ1: How do clinicians currently use data and DSSs to formulate and explain decisions in the ICU?
- RQ2: What design requirements do clinicians have for DSSs in the ICU?

Our contributions, discussed in the "Theme 1: ICU Decision-Making Relies on a Wide Range of Factors (RQ1)" and "Theme 2: Complexity of Patient State Is Challenging for Shared Decision-Making (RQ1)" subsections, provide insights into clinical decision-making in the ICU. These include factors such as patient status (eg, trajectory and physiological data) and operational considerations (eg, bed availability and patient handovers due to work patterns) that influence decisions. The "Theme 3: Acceptability and Usability of DSSs (RQ2)" subsection highlights opportunities and challenges in using AI support systems in intensive care. Opportunities include enhancing decision-making with additional information, while challenges involve balancing detail with clarity in explanations and offering options and alerts without introducing bias. In the "Discussion" section, we propose design considerations for DSSs tailored to the highly contextual nature of intensive care. These include providing contextual explanations and concise patient information without biasing clinicians.

This study lays the groundwork for systems that better serve the needs of users in the ICU, with potential applications more broadly across health care. Such systems could improve clinicians' ability to interact with DSSs, potentially increasing their adoption and improving patient care.

Methods

Overview

To answer our RQs, we invited 7 clinicians working in different roles in the ICU at a large teaching hospital in Bristol, United Kingdom, to participate in 1 of 2 focus group sessions (Figure 1). The focus groups were conducted virtually using Microsoft Teams in September 2024. Participants were recruited using opportunistic sampling. The recruited roles included an anesthetics trainee, an intensive therapy nurse, and an outreach nurse. No consultants were recruited due to staffing issues, as acknowledged in the "Limitations and Future Work" section. To preserve anonymity, we refer to participants by their general roles: resident doctors (D) and nurses (N). Participants had at least 3 years of professional experience. Participants were provided with information about the purpose of the study before attending the focus group and were required to provide written informed consent for their feedback to be used for research purposes.

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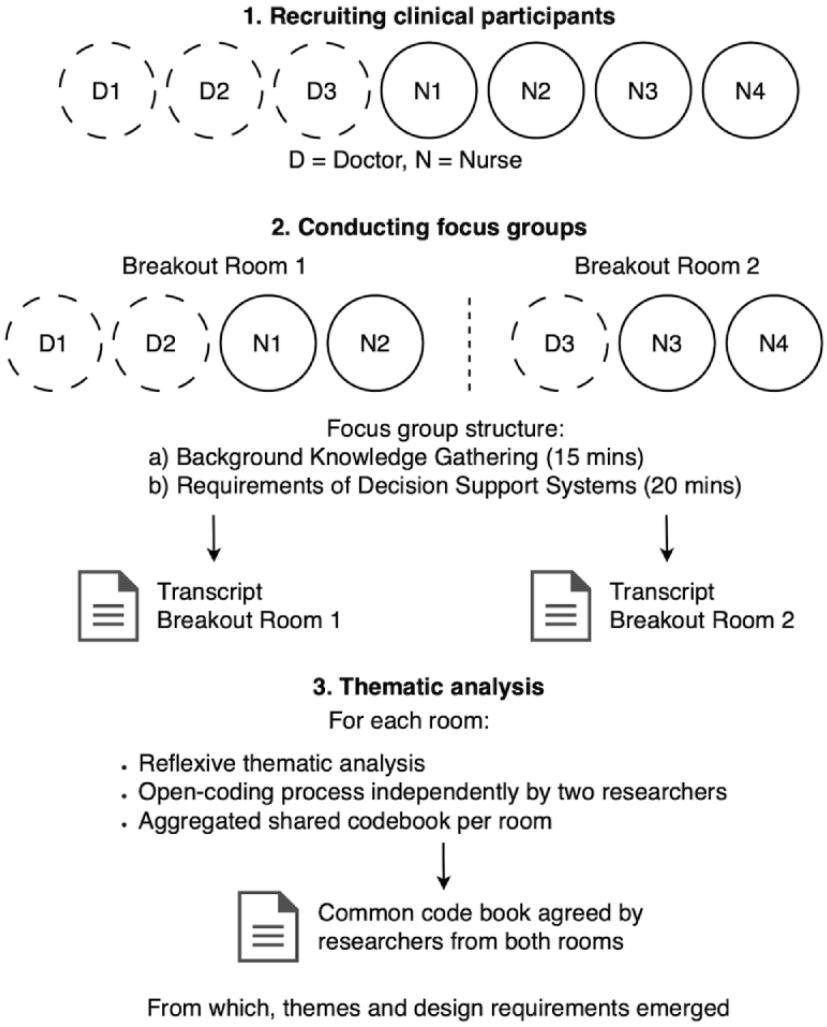
Figure 1. Methodology overview including participating doctors (D1-D3) and nurses (N1-N4), semistructured interview study design, and thematic analysis.



Ethical Considerations

Ethical approval for this project was granted by a Research Ethics Committee within the UK National Health Service (IRAS 297886). A COREQ (Consolidated Criteria for Reporting Qualitative Research) checklist was completed and is available in Multimedia Appendix 1.

Recruitment

The eligibility criterion was employment as a clinical staff member in the hospital's ICU. No previous experience with or exposure to AI-based clinical decision support tools was required for participation in the study.

Recruitment took place during the 4 weeks leading up to the focus groups. The opportunity to participate was shared via the hospital's ICU WhatsApp (Meta Platforms, Inc) group, reaching 172 eligible clinical staff members. One physician who was part of the WhatsApp group was also contacted via email and accepted the invitation to participate. In total, 7 staff members accepted the invitation and consented to participate in the study. No one explicitly declined participation. As the invitation was open to all ICU clinical staff, no potential participants were excluded from the recruitment process. Data saturation was not formally assessed.

Sampling was opportunistic; all those who responded to the invitation were invited to participate. The sample included a diverse group of ICU staff with varying levels of clinical experience and substantial experience providing bedside care in the ICU (Table 1). As recruitment was conducted alongside routine clinical activities, participation depended on staff availability on the day and at the time of the focus groups. All participants had prior experience with clinical DSSs, but none had prior experience with AI-based clinical tools.

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Table 1. Description of participants' roles, level of experience, and prior exposure to DSSs[a] and AI-based tools.

Participant	Role group	ICU[b] experience (years)	Clinical DSS experience	Clinical AI-based tools experience
1	Critical care charge nurse	5+	Yes	No
2	Critical care charge nurse	5+	Yes	No
3	Senior critical care staff nurse	5+	Yes	No
4	Senior critical care staff nurse	5+	Yes	No
5	ICU trainee (registrar)	3+	Yes	No
6	Anesthetics trainee (senior house officer)	1-2	Yes	No
7	Anesthetics trainee (senior house officer)	1-2	Yes	No

[a]DSS: decision support system.

[b]ICU: intensive care unit.

Focus Groups With Experts

Following initial introductions and a briefing, participants were split into 2 groups for the focus group sessions, which ran in parallel in separate breakout rooms on Microsoft Teams. Participants D1, D2, N1, and N2 were assigned to room 1, and D3, N3, and N4 to room 2. Repeat focus groups were not conducted; each participant attended only 1 focus group. Participants were presented with 2 synthetic patient personas on a digital whiteboard (details are available in the "Patient Personas" subsection of Multimedia Appendix 2). The personas represented patients with differing symptoms and care requirements and were created to provide examples that participants could use to contextualize the discussion. Each session was guided by 2 facilitators and lasted approximately 35 minutes. The room 1 focus group was conducted by MW and MPN, and the room 2 focus group was conducted by EN and JC. The focus groups were not pilot-tested. No one other than the participants and facilitators was present during the focus groups. Field notes were not taken during the focus groups. Audio recordings of both focus groups were made, transcribed verbatim, and fully anonymized by the authors who were present at each respective session. The sessions were semistructured around 2 sets of questions, as summarized below. The full list of questions is included in the "Focus Group Questions" subsection of Multimedia Appendix 2:

- Background knowledge gathering (15 minutes): Understanding ICU clinicians' decision-making experiences, including the information used in different contexts and how they communicate with colleagues about decisions.
- Requirements of transparent and trustworthy DSSs (20 minutes): Understanding ICU clinicians' requirements for DSSs, including what information they would like to see and how it should be presented.

Thematic Analysis

Analysis of the focus group transcripts was performed by the 4 facilitators using reflexive thematic analysis [54]. Transcripts were not returned to participants for comment or correction. Analytic decisions were made inductively, and every transcript segment related to the RQ was included for open coding. We defined this broadly, considering a text segment related to the RQ if it concerned the context of care in the ICU or factors influencing ICU decision-making. Both semantic and latent coding were used, but we primarily adopted a semantic approach. When potential latent codes emerged, they were evaluated based on the strength of the supporting evidence, considering both the presence of corroborating data elsewhere in the transcript and the extent to which the code was implicit in the text.

For each focus group session, the 2 facilitators who conducted each session independently coded the transcripts before iteratively developing and agreeing on a shared codebook. Differences between codes were reflected on and discussed to highlight the facilitators' differing perspectives and the insights each perspective offered. Where possible, codes were renamed to capture both perspectives. When codes were largely aligned, the more detailed or specific code name was used.

Following this, the 4 facilitators collectively analyzed and refined the codes from both sessions into a single, combined codebook. Once the codes were finalized, the 4 facilitators and an additional AI researcher collaboratively identified initial themes. The resulting themes were reviewed to ensure that they aligned with our RQs and provided an accurate and complete representation of the data. Participants did not provide feedback on the findings.

NVivo (Lumivero) was used to code the transcripts and combine the codebooks. The final combined codebook was exported to Microsoft Word and copied into Microsoft Visio, where the connections between codes were mapped visually to facilitate the definition and refinement of themes and subthemes.

Positionality Statement

The authors of this paper bring together a range of perspectives and backgrounds, with expertise in clinical studies and DSS development (JC, CB, and RSR), AI (JC, MPN, NK, and RSR), XAI (MPN and RSR), human-computer interaction (EN, MW, and AB), qualitative research (EN, MW, MPN, and AB), and medicine (MA, SS, and CB). All authors involved in conducting the focus groups and analysis held relevant PhDs and were employed as researchers at the University of Bristol. MA, SS, and CB are fully qualified medical doctors. EN and AB are female, and all other researchers are male. MW and MPN coded the transcript from group 1, and JC and EN coded the transcript

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from group 2. This ensured that each transcript was coded by an AI researcher (JC or MPN) and a human-computer interaction researcher (EN or MW).

Independently coding the transcripts from these different perspectives allowed for a richer analysis. In particular, human-computer interaction researchers identified greater depth in the contextual and sociotechnical challenges of the ICU, whereas AI researchers considered technical feasibility, the full pipeline of potential solutions (including stakeholders with different areas of expertise), and opportunities to build on existing work in the field. Bringing together these perspectives allowed for greater analytical depth while maintaining the relevance and accessibility of the findings for developers and researchers. In addition, another AI researcher (NK) participated in the thematic discussions to provide a fresh perspective and ensure that the themes were clearly defined, without requiring an in-depth analysis of the transcripts.

Results

Themes Identified

Through thematic analysis, we identified 3 themes pertinent to our RQs (Textbox 1). We now present each theme in detail, supported by quotations from the focus group transcripts. Some quotes have been edited to improve readability while preserving context and meaning. Edits include removing unintentionally repeated words and utterances such as "umm" and adding context to sentences where necessary using square brackets.

Textbox 1. Themes, subthemes, and key talking points identified from the focus groups.

Theme 1—ICU Decision-Making Relies on a Wide Range of Factors

- Theme 1.1—Patient Journey: Care Planning, Patient Trajectory, History, and Recent Data
- Theme 1.2—Patient Physiological Data: Organ Systems, Diagnosis-Specific Data, Variability in Baseline, and Trends
- Theme 1.3—Importance of "End-of-Bed" Information: Forming a Complete Picture of Patients (eg, Behavioral and Visual Factors)
- Theme 1.4—Operational Factors: Bed and Staff Availability, Hospital Flow, and Resource Constraints

Theme 2—Complexity of Patient State Is Challenging for Shared Decision-Making

- Theme 2.1—Collaborative Decision-Making: Checking Decisions With Colleagues, Prompting Investigation, and Family Involvement
- Theme 2.2—Patient Handover Between Clinicians: Efficiency of Handovers, and Frameworks for Information

Theme 3—Acceptability and Usability of DSSs

- Theme 3.1—Framing and Presentation of Decision Recommendations: Importance of Evidencing Recommendations, and Framing for Acceptance and Trust
- Theme 3.2—Complexity and Detail of Explanations: Layered System, Minimizing Cognitive Load, and Number of Systems
- Theme 3.3—Impact of Recommendations on Decision-Making: Bias/Obscure Judgment, Prompt New Thought, and Highlight Missed Information

Theme 1: ICU Decision-Making Relies on a Wide Range of Factors (RQ1)

Factors Influencing ICU Decision-Making

Intensive care decision-making is highly complex. Participants emphasized the importance of considering a wide range of factors that can influence patient care decisions. These include the patient's overall clinical trajectory, physiological data, observational information such as behavior, and operational factors such as bed availability and staffing.

> *You've got the human element of understanding their pathway and having that in the back of your mind, and then you've got the actual vitals to be the trigger to say potentially they're good to go.* [Nurse, N3]

Patient Journey

A patient's past, present, and anticipated clinical trajectory all inform the decision-making process. Patient history plays a vital role, as experiences can influence discharge timing. For example, N3 highlighted that, for a patient who frequently returns to the ICU, they would be "a bit more reluctant to send [them back to the ward] as soon as [their] vital numbers are correct." Potential issues, such as "a recent blood result" [N1], are also important to flag to support the reassessment of decisions.

> *That should be something that's flagged on the system so that...it kind of puts you a stop [in] place for you to think about whether that is the appropriate decision to make.* [Nurse, N1]

"Escalation planning" was discussed by several participants. N1 emphasized its importance in cases of deterioration, such as when a patient would "need more ventilation." D3 noted that "the context and causes of the deterioration" inform whether further intervention is appropriate. For care planning, participants stressed the importance of establishing "a direction of travel" [N4] for individual patients, such as moving toward full treatment or palliative care. N1 also highlighted the "trajectory of [a patient's] long-term illness" as a key factor in clinical decision-making.

Patient Physiological Data

Monitoring patients' physiological data plays a crucial role in clinical decision-making in the ICU. Determining which measurements are most important can be patient-specific, as D1 noted: "every patient comes with a different pathology and

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therefore we're going to be looking at slightly different parameters for each one." For example, N4 observed that "...a normal blood pressure is 120/80, except that for certain groups of patients, that's absolutely abnormal." When interpreting physiological data, participants emphasized the importance of examining trends rather than isolated data points. D3 explained that interpretation is "all about the trend" and that the clinical team would "never look at the one-off number." Similarly, D1 highlighted that "sometimes it's easier to see that [data] as a trend," particularly when "getting or approaching ready for discharge." Given the complexity and volume of available physiological data, D1 and D2 discussed categorizing data by organ system. D2 suggested that this approach could help clinicians track complex cases, as "pretty much every problem you can categorise as one of those [organ] systems." D2 further explained: "I often find myself going through the charts totting up organ systems and problems to explain to myself what's happening with a patient."

Observational (End-of-Bed) Information

Although physiological data are critical, participants emphasized that they are often insufficient to provide a complete picture of a patient's condition. Behavioral factors can be difficult to capture in data. D2 explained that patients experiencing delirium may require constant "...physical and verbal intervention to manage their behaviour and keep them safe". D2 also raised concerns about the suitability of current technological systems for representing this information:

> *Something that's quite hard to represent in an observation chart, and even with the very good [system] we have, I think, is requirement for sort of behavioural management.* [Doctor, D2]

Visual assessments, conducted either personally or by inviting senior staff to assess "how the patient looks clinically" [N3], were considered invaluable for decision-making. Participants explained that they "need to stand at the end of the bed, look at the patient, talk to the nurse" [D2] to make assessments. This provides information "that you can't necessarily [get] from the computer" [D3]. However, D2 also expressed concerns about the difficulty of presenting this information in technological systems:

> *...that's the bit where I kind of think it would be difficult for a technology system to represent that one. I'm sure there are ways of doing it, but I think that would be a challenge potentially from a system.* [Doctor, D2]

Operational Factors

Wider operational factors, such as resource constraints and bed availability outside the ICU, can affect discharge decisions. Participants emphasized the importance of ensuring that "it's an appropriate bed for this patient" [D2] and that the patient is transferred to "on an appropriately staffed ward" [D2], including one where specialist "teams [are] available out of hours or on the weekends" [N1]. Given the complexity and variability of patient requirements, N2 explained that "[Patient] flow is generally a real big problem for us within the hospital, so finding that appropriate ward is difficult". These challenges can result in unnecessarily prolonged ICU stays: "we see daily that patients stay with us a bit longer because there aren't beds in the appropriate facility for them" [N2].

Theme 2: Complexity of Patient State Is Challenging for Shared Decision-Making (RQ1)

Challenges to Shared Decision-Making in the ICU

The complex and diverse factors informing decisions (theme 1), combined with frequent changes in care team membership due to working patterns, present significant challenges for shared decision-making. However, collaboration remains an important part of the decision-making process, and effective communication within the care team is crucial for establishing a shared understanding of patients' conditions.

Collaborative Decision-Making

Participants valued collaborating with colleagues to "double-check" [D3] their decisions, particularly when they might have overlooked relevant patient information:

> *We all miss things in the data and our patients' pathways. There are times when you think you've made a decision and then someone points out a drug that was given or a blood test that's abnormal.* [Doctor, D2]

The vast amount of data and the need for context-specific approaches to interpreting it make collaborative decision-making more challenging, particularly when the care team is dealing with "...lots of abnormal data" [D2]. N3 also discussed how highlighting specific information for the care team could prompt clinicians to investigate particular decisions and draw colleagues' attention to potentially overlooked data. This, in turn, could "give a bit of confidence to other members of the team" [N3].

> *You could use the vitals to then say actually hold on, this patient doesn't need to be on a ventilator...And then you'd have to then almost give a rationale as to why you're going to continue to ventilate that patient when we know it's better to get them off a ventilator as soon as possible.* [Nurse, N3]

Another key aspect of collaborative decision-making is involving family members in clinical decisions. Participants described how they might "...invite the sister or senior nurse down to the ward to actually meet that patient, family and go through things" [N2]. Decisions about treatment escalation or withdrawal of support involve a "clinical decision between the family and the medical team" [N3].

Patient Handover Between Clinicians

Within the ICU, the care team changes regularly because of working patterns, and this "changing of clinicians really slows things down" [N4]. In particular, participants highlighted the time needed to become familiar with a patient as a key factor in delaying clinical decisions, as each care team will "want to get to know the patient, make sure everything is well before making [a] decision" [D3].

> *One of the biggest challenges is when you come back onto the ward after not being there for some time and*

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> *you don't know the patient, it can be quite difficult to ascertain exactly what the problem here right now is for a patient who's had a long stay.* [Doctor, D1]

Effective information transfer during handovers is therefore important, and participants noted that handovers are "structured with the aim of making [information transfer] as clear as you can" [N4]. Participants described several frameworks and systems used in the ICU to facilitate information transfer during handovers, including the "Situation, Background, Assessment, and Recommendation tool (SBAR)" [N4]. Handovers are not always verbal; the approach depends on the context. For example, the outreach team "don't get a verbal handover of these patients...[but] the ward would have" [N1]. Written communication is also common and may include "including ICU paperwork, [and] the discharge paperwork that goes with the patient" [N1].

Theme 3: Acceptability and Usability of DSSs (RQ2)

Balancing Information Detail and Cognitive Load in DSS Design

Decision-making in the ICU is highly complex, drawing on diverse information and clinical experience. Ultimately, decisions are made by the care team in collaboration with patients and their families. It is therefore crucial that DSSs reflect their needs and preferences and provide support in ways that promote acceptance and trust. Participants particularly highlighted the framing and level of detail of recommendations as key considerations in designing these systems. The high cognitive demands of the ICU require information to be presented in a way that facilitates efficient navigation and comprehension. However, clinicians must also be able to scrutinize and analyze the information to ensure accurate decision-making. This creates a tension between minimizing cognitive load and providing sufficient detail.

Framing and Presentation of Decision Recommendations

The introduction of DSSs in intensive care raised concerns among participants. D3 explained that they would be "really uncomfortable being recommended an action by the system". However, participants expressed interest in receiving evidence-based suggestions that would help them reach their own conclusions: "I'd rather be presented [with] the data that's there or things that happen and then let me make that decision" [D3]. N4 highlighted that the acceptance of DSSs would depend on how recommendations were framed. For example, participants felt that presenting recommendations as "options available to you" would encourage uptake more than presenting them as "you should do this." Clinicians were also interested in incorporating familiar ways of thinking, such as grouping information by organ system, into DSS explanations. As D2 suggested, "so, it could almost be a flag saying this patient is being held up by brain and cardiovascular."

D1 suggested that lists of supporting factors would be more useful than recommendations alone, explaining: "if if the system is consistently saying 'this patient is dischargeable, this patient can go to the ward', I'm not going to trust it in the same way than if it's it uses terminology like these factors support that this patient is suitable for discharge." D3 suggested presenting recommendations in the form of alerts:

> *If a computer just would give me an alert...I might be a little bit more prompted to say, oh, there's something wrong, maybe I didn't pick it up, but I wouldn't action it just based on that recommendation.* [Doctor, D3]

Reliance on evidence and explanations appears integral to decision-making in the ICU. Even when a suggestion from a person or a system is incorrect, clinicians draw on their own judgment to reach a conclusion. As D2 explained, "I'm going to note that and respectfully ignore it."

Complexity and Detail of Patient Information

Participants highlighted the importance of minimizing cognitive load when visualizing and analyzing patient information to support decision-making. D1 expressed a desire for "a very basic summary" and "some sort of dashboard or information that's concisely saying what are the problems here and now that the patient is recovering from." Ultimately, participants agreed that "anything that can speed up that process and help clinicians familiarise faster would be helpful to support decision-making" [N4]. In addition to summaries that minimize cognitive load, participants emphasized the need to avoid adding to the burden of using multiple systems, as "people get fatigued with all of the different softwares and systems that we use" [N1]. New systems should therefore "be integrated into things we already look at as part of the ward round." Although clinicians wanted to minimize excessive information and clicking, they also indicated that "a layered system would be useful to not overload the user all at once" [D1], with the option to access more detailed information on demand: "it'd be great to have the ability to click down and get deeper" [D2].

Impact of Recommendations on Decision-Making

DSSs should support clinicians in making informed decisions. Clinicians recognize that "in the heat of the moment when you admit a patient, things can be missed" [N3] and acknowledge that they "are not perfect...[and] forget a lot of option[s]" [D3]. To help address these omissions, clinicians find it useful "to get [system] alerts% from that system [Medway]...as an aid to triggering me to think about something" [N3]. In addition to system alerts, clinicians noted that presenting "a lot of data...[is] easier to see as a trend" can aid decision-making. However, despite recognizing the benefits of DSSs, clinicians expressed concerns that these systems could obscure their own judgment and introduce bias. For example, systems may consider only features captured electronically, thereby failing to account fully for the patient's condition. They may also constrain the range of options clinicians consider, as D3 explained: "if someone tells me...what about these three options? What if there's a fourth option...[that's] not presented, and now I'm just thinking about those three options."

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Discussion

Principal Findings

Overview of Key Findings and Design Implications

This study aimed to understand how intensive care clinicians make and communicate clinical decisions in practice and to identify requirements for transparent and trustworthy DSSs in intensive care. We conducted focus groups with ICU clinicians and analyzed the data using reflexive thematic analysis to capture how decisions are formed, shared, and supported in a high-acuity clinical environment.

Our analysis identified 3 overarching themes. First, ICU decision-making was highly contextual, drawing on a wide range of patient-specific, observational, and operational factors. Second, the complexity of patients' conditions and the distributed nature of clinical work introduced human variability that challenged shared decision-making and information transfer. Third, clinicians articulated clear requirements for DSSs, emphasizing the framing, level of detail, and integration of recommendations to support trust, usability, and independent clinical judgment (Textbox 1). In the following subsections, we discuss specific findings in the context of existing literature and present design recommendations for DSSs that align with clinicians' cognitive workflows, collaborative practices, and contextual constraints.

Contextual Nature of ICU Decision-Making

Our findings suggest that decision-making in the ICU is challenging because of its highly contextual nature, with decisions depending on factors both inside and outside the ICU. These include operational factors such as resource and staff availability. Although these factors are not directly related to the patient's condition, they are important considerations for AI-based DSSs. While physiological data are important for decision-making, what constitutes a normal value in the ICU can differ significantly depending on the clinical context. This may reflect the ICU's capacity to safely accommodate more extreme values through close monitoring. In addition, participants highlighted the importance of contextual information, such as medication use and diagnosis, when interpreting biomarkers. Interpreting a biomarker in isolation, without considering its context, may therefore lead to incorrect decisions. Such decisions cannot be fully trusted. Rather than relying on isolated data points to assess changes in a patient's clinical status, examining trends in biomarkers may provide a more accurate representation of the patient's clinical trajectory. AI-based systems should therefore account for contextual factors, including patient history, to support clinical decision-making. Furthermore, although trends in physiological data are important, participants emphasized that direct visual assessment of patients, including their behavior, remains invaluable to the decision-making process. Until AI systems can formally represent these observations as features, it is important to acknowledge that they do not fully capture the patient's clinical state.

Human-Introduced Variability

Patient care in the ICU is largely informed by individual clinicians' observations, experience, and clinical judgment. As patients are often managed by multiple care teams, variability is inevitable in both the information available to clinicians at any given time and how they interpret patients' conditions and care needs.

Participants highlighted that this variability is particularly relevant during patient handovers and collaborative decision-making, when information about a patient's condition must be communicated between clinicians. They also noted that the need for individual clinicians to observe and validate a patient's current condition firsthand can delay decision-making and subsequent action. Participants described using the SBAR tool during handovers to mitigate this problem by providing a framework for clinicians to communicate key patient information efficiently. Similarly, XAI tools that provide concise overviews and evidence-based recommendations for individual patients during interactions between clinicians could further expedite collaborative processes, such as patient handovers.

In addition to the distributed nature of patient care across multiple teams, variability in the information clinicians have about patients can arise from missed data. Participants viewed AI-generated recommendations as an opportunity to consider specific patient information and alternative options that they might otherwise overlook. However, they also expressed concern that such recommendations could introduce unintended bias by unconsciously narrowing clinicians' consideration of alternatives not presented by the system.

Design Recommendations

Design Recommendations for Transparent and Trustworthy DSSs

Based on our findings, we present recommendations for designing transparent and trustworthy DSSs in intensive care and discuss how these recommendations can support the integration and acceptance of such systems in clinical practice.

Provide Variable Levels of Detail

As several participants highlighted, minimizing cognitive load is crucial to delivering patient care in the ICU. DSSs should provide concise summaries of important patient information that clinicians can interpret quickly, while allowing them to examine more detailed outputs when needed. Previous work with occupational therapists highlighted simplified feature-importance information as an effective way to communicate important patient information [47]. Combining this approach with an additional view of the underlying data may provide a layered system suitable for intensive care that minimizes cognitive load.

Support Integration Into Existing Clinical Systems

Participants considered integration with existing systems a key factor in reducing cognitive load. Clinicians in neurointensive care have expressed similar views [33]. Designers should consider how new tools can be integrated into systems that clinicians already know and use to support acceptance and continued use in clinical practice. One example of an XAI

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technique that could support this approach is LIME (Local Interpretable Model-agnostic Explanations), which is model-agnostic, open-source, and computationally efficient because it does not require retraining the underlying model [55].

Present Explanations With Additional Contextual Information

Our findings highlight the highly contextual nature of ICU decision-making, which is influenced by both internal and external factors, including resource and staff availability. Although physiological data are important, what constitutes a normal value varies depending on the patient and the clinical situation. Contextual information, such as a patient's medications and diagnosis, plays a key role in interpreting physiological measurements, including biomarkers. Close monitoring in the ICU may allow clinicians to manage some more extreme values, while trends in a patient's historical measurements can provide valuable insights into their clinical trajectory. Additionally, DSSs may be able to retrieve information collected outside the ICU, such as a patient's history in another ward, which clinicians have identified as beneficial [46]. To be effective, DSS outputs should reflect the contextual nature of intensive care by incorporating, or being presented alongside, information about the patient's history and current condition, as well as operational factors such as bed availability and relevant physiological data. Case-based reasoning could be useful in this context because it explains a model's decisions by providing additional context through similar cases or examples from the data, helping users explore patterns and relationships [56].

Prompt Independent Thought

Participants highlighted that acceptance of DSSs depends on clinicians feeling confident that these systems will not negatively affect or bias their overall decision-making. In particular, participants preferred suggestions over directives and emphasized that explanations should be evidence-based to promote trust in these systems. This aligns with prior work by Szymanski et al [47], who found that some occupational therapists disliked the "suggestive" nature of counterfactual explanations. Participants valued AI-generated recommendations as an opportunity to consider specific patient information and alternative options they might not otherwise have considered. Designers should therefore carefully consider how decisions and their explanations are framed, including the language used, to support clinicians in reaching their own conclusions based on the available information. For example, several participants noted that seeing data they might otherwise have overlooked could prompt them to consider alternative options.

Facilitate Communication of Patient Status

Our results show that communication of patient status between clinicians can limit the efficiency of decision-making in intensive care, particularly during handovers between care teams. Patient care in the ICU is largely informed by individual clinicians' observations, experience, and clinical judgment. This introduces variability in both the information available to clinicians at any given time and how they interpret patients' conditions and care needs. Designers should aim to facilitate the clear and efficient communication of patient status, enabling clinicians to quickly build a picture of patients' care requirements, medical history, and future care plans and thereby improve handover efficiency. As participants suggested, this could be achieved by presenting patient information and decision recommendations in formats that align with existing communication practices. Examples include using SBAR and organ-system categories to present recommendations, reflecting how clinicians naturally organize their thoughts and communicate when making decisions.

This could be implemented, for example, by translating a rule-based system that uses organ system–specific rules into a natural-language explanation accessible to a range of users [12].

Limitations and Future Work

Our work highlights several opportunities for further research by identifying and examining clinicians' requirements for designing transparent and trustworthy DSSs. Clinicians emphasized the importance of minimizing cognitive load and facilitating efficient communication of patient status to ensure that these systems are effective in the ICU. Future work should evaluate how prototype systems developed using our design recommendations can support the interpretation and communication of patient data through concise, layered interfaces. It should also investigate the potentially differing needs of ICU clinicians, which may necessitate tailoring information to individual users based on factors such as job role, experience, and preferences. Additionally, participants identified the framing and language of decision explanations as crucial factors in promoting clinicians' acceptance of and trust in DSSs. Further research is needed to understand clinicians' preferences regarding the language used to present explanations and how this affects their confidence in using recommendations to inform their overall decision-making. Finally, although clinicians expressed a desire for additional contextual information alongside explanations, including visual and behavioral observations, the most effective ways to present such information remain unclear. Future research should investigate how contextual information not used by decision support models can be integrated into decision explanations and how its inclusion affects clinical decision-making.

Although consultants (attending physician–level doctors) provided input during the write-up phase, none participated directly in the focus groups because of staffing constraints, limiting insights from senior medical perspectives. The focus groups involved 7 staff members from a single ICU, limiting the extent to which meaningful conclusions can be drawn. Furthermore, the study included only 1 round of focus groups, with each session lasting approximately 35 minutes, limiting opportunities for in-depth discussion. The focus groups were conducted virtually to facilitate attendance, which may have affected participant engagement and interaction. Group dynamics may also have influenced participation and the insights shared. Similarly, the use of synthetic patient personas may have influenced participants' responses. Future work could address these limitations by engaging a broader range of clinicians, including consultants; conducting focus groups in person; and extending session durations or conducting multiple rounds to explore the themes in greater depth.

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Conclusions

We present insights from focus groups with 7 intensive care clinicians on decision-making and systems designed to support clinical decisions in critical care. Our analysis revealed 3 themes encompassing the factors that inform clinicians' decisions, considerations for shared decision-making, and requirements for transparent and trustworthy DSSs. These findings provide formative insights into clinicians' perspectives and highlight design considerations that may inform the development of DSSs for health care environments. By translating participants' experiences into actionable recommendations, this work contributes to a growing understanding of how DSSs can be better integrated into existing clinical workflows and decision-making processes. Further research is needed to evaluate the implementation, effectiveness, and clinical impact of such systems in practice.

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Generative AI Use

Generative AI, primarily ChatGPT (OpenAI), was used by some authors during the preparation of this manuscript to assist with editing the text for spelling, conciseness, and clarity. All AI-generated suggestions were reviewed by the authors before being incorporated into the manuscript. The authors take full responsibility for the final content.

Authors' Contributions

Conceptualization: JC, MW, EN, MPN, NK, MA, SS, CB, AB, RSR
Data curation: JC, MW, EN, MPN, NK, SS, RSR
Formal analysis: JC, MW, EN, MPN, NK, AB, RSR
Funding acquisition: JC, CB, AB, RSR
Investigation: JC, MW, EN, MPN
Methodology: JC, MW, EN, MPN, NK, AB, RSR
Project administration: JC, RSR
Resources: SS, MA, CB
Visualization: JC, MW, EN, MPN, NK
Writing – original draft: JC, MW, EN, MPN, NK
Writing – review & editing: JC, MW, EN, MPN, NK, MA, SS, CB, AB, RSR

Conflicts of Interest

None declared.

Multimedia Appendix 1

COREQ (Consolidated Criteria for Reporting Qualitative Research) checklist.
[PDF File (Adobe PDF File), 370 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Patient personas and focus group questions.
[TXT File , 2 KB-Multimedia Appendix 2]

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Abbreviations

COREQ: Consolidated Criteria for Reporting Qualitative Research
DSS: decision support system
ICU: intensive care unit
LIME: Local Interpretable Model-agnostic Explanations
RQ: research question
SBAR: Situation, Background, Assessment, and Recommendation tool
XAI: explainable AI

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