HandovAR: Towards AR and AI Support for ICU Nurse Handover

Mengxing Li[1,*,†], Phoebe Zhang[1,†], Jiazhou Liu[1], Agnes Haryanto[1], Kadek Ananta Satriadi[1], Trung Nguyen[1], Deval Mehta[1], Zerina Lokmic-Tomkins[1] and Tim Dwyer[1]

[1]*Monash University, Melbourne, Victoria, Australia*

Abstract

Effective nurse handover is crucial in high-pressure environments like Intensive Care Units (ICUs), where accurate communication of patient-specific information directly shapes patient care and clinical decision-making. We conducted seven interviews with ICU nurses to understand current handover practices. Preliminary findings reveal significant challenges, including high cognitive load from fragmented EMR data, the risk of technology hindering interpersonal rapport, and the loss of nuanced data during shift transitions. These issues lead to cognitive overload and information omission, particularly during fast-paced shift transitions when staff fatigue is prevalent. We explore the potential for in-situ Augmented Reality (AR) overlays and Artificial Intelligence (AI) agents to support ICU nurse handover by enabling hands-free information access, procedure guidance and documentation assistance.

Keywords

Information Exchange, Augmented Reality, Extended Reality (XR), Artificial Intelligence, Nursing Handover, ICU Department, Cognitive Load

1. Introduction

Effective nurse shift handover in Intensive Care Units (ICU) is critical to patient safety and continuity of care. Handovers are complex and cognitively demanding processes that require the exchange of critical and extensive patient information, including medical history, vital signs, medications, and treatment plans [1, 2]. Traditional approaches (e.g., verbal reports and handwritten notes) are susceptible to omissions and inefficiencies, which can negatively affect care quality [3]. Fragmented tools, including spreadsheets, paper-based records, and poorly integrated Electronic Medical Record (EMR) systems, further increase cognitive load and risk of information loss [4, 5]. Although electronic documentation systems and communication frameworks, such as ISBAR (Identify, Situation, Background, Assessment, Recommendation), have been introduced to standardise and support handovers, they present usability and integration challenges. Kowitlawakul et al. [6] and Pinevich et al. [1] report that existing digital systems often lack seamless EMR integration and impose rigid workflows that do not align well with clinical practice. As a result, nurses frequently resort to workarounds, leading to incomplete or duplicated information. Similarly, Spooner et al. [7] found that structured EMR-based handover tools, while improving standardisation, still suffer from missing content, interface complexity, and limited adaptability to dynamic ICU environments. Together, these findings highlight the limitations of current digital solutions and underscore the need for more intuitive, integrated, and context-aware technologies to better support ICU handovers.

Augmented Reality (AR) devices, such as head-mounted displays, enable hands-free interaction, real-time data access, and reduced workflow interruptions, which may improve task efficiency and situational awareness [8, 9]. In surgical training and medical education, AR has demonstrated effectiveness in

CHI'26: XR4CE workshop, April 14, 2026, Barcelona, Spain

*Corresponding author.

†These authors contributed equally.

hi.limengxing@gmail.com (M. Li); pzha0041@student.monash.edu (P. Zhang); joe.liu@monash.edu (J. Liu); agnes.haryanto@monash.edu (A. Haryanto); kadek.satriadi@monash.edu (K. A. Satriadi); trung.nguyen5@monash.edu (T. Nguyen); deval.mehta@monash.edu (D. Mehta); zerina.tomkins@monash.edu (Z. Lokmic-Tomkins); tim.dwyer@monash.edu (T. Dwyer)

improving learning outcomes, spatial understanding, and procedural accuracy [10, 11]. Despite these advances, the application of AR to ICU nurse handovers remains largely underexplored. Preliminary studies suggest that AR-based visualisations of patient data could enhance information clarity, reduce cognitive load, and minimise communication errors during handovers [12, 13].

Artificial Intelligence (AI) has increasing potential to support ICU nurse handover by assisting with documentation, generating concise summaries of patient information, and highlighting important changes in patient status. Advances in Natural Language Processing (NLP) and Large Language Models (LLMs) have shown promise in clinical note generation, information extraction, and summarisation from EMRs, helping reduce documentation burden and improve information clarity [14, 15, 16]. In complex care environments, such as the ICU department, AI systems have also been explored for synthesising large volumes of data and presenting key insights to support clinical decision-making [17, 18]. Despite advances in AI-driven clinical summarisation and decision support, little is known about how these technologies can be meaningfully integrated into the collaborative, time-sensitive workflow of ICU nurse handovers. In particular, empirical evidence is lacking on how AI-generated insights, potentially delivered through AR interfaces, could affect communication quality, cognitive load, and patient safety in real-world handover settings.

In this paper, we describe our initial investigation towards understanding opportunities and requirements for the above concepts. As described in Section 2, we have conducted interviews with experienced nurses to understand the role such technologies can play in assisting with handover. These interviews led us to propose an integrated solution to address challenges in ICU nurse handover that leverages AR and AI technologies through *in-situ spatial dashboards* and *AI-facilitated conversational agents*, as described in Section 4.

2. Method

We conducted semi-structured interviews with ICU nurses to gain a better understanding of their current handover practices, covering six main topics: handover practices, safety, workflow, communication, technology usability, and future technology-related improvements.

We began by eliciting participants' professional background (e.g., years of experience) and their typical handover processes, including the types of technologies currently used and how these are integrated into practice. We then examined perceived impacts of technology on care quality and safety. Participants were asked how existing tools support safe handovers, including maintaining accuracy and completeness of information, as well as ensuring continuity of care and patient safety. Next, we explored the influence of technology on workflow and efficiency. Participants reflected on how digital tools affect the efficiency of handover processes, which features are most beneficial, and what challenges arise. We further investigated the role of technology in communication and collaboration, focusing on how digital systems shape information exchange between nurses during handover. In addition, we probed usability and barriers by asking participants to evaluate the ease of use of current technologies and identify aspects that are time-consuming or difficult to operate. Finally, to establish a shared understanding of emerging technologies, we introduced AI and AR concepts through a short presentation consisting of eight slides. This included illustrative examples of AR devices (e.g., Even Realities G1 Glasses, Meta Ray-Ban Smart Glasses, and Magic Leap's Android XR prototype), as well as explanations of key concepts (e.g., differences between AR headsets and AR glasses). We also presented potential AI capabilities relevant to handover, such as automated transcription, and record-keeping. These materials were used to provide a common baseline for discussion rather than to constrain participants' responses. Participants were then invited to reflect on the potential use of these technologies in future handover scenarios.

The study was approved by the Human Research Ethics Committee at Monash University (ID: 48992). Each 60 min. 1:1 interview was conducted via Zoom. In total, seven ICU nurses (P1–P7) participated in the study. The participants represent a diverse cross-section of the field, with extensive clinical experience ranging from 6 to 35 years. This includes two participants with less than 10 years of experience, two with 10–20 years, and three with over 20 years. Six of the participants worked in public clinical settings, while one nurse worked in a private hospital.

3. Preliminary Results

Thematic analysis of interview transcripts led to the grouping of the six interview topics as follows.

3.1. Nurse-Computer Interaction

Participants cited the presentation of data in current EMR systems as a primary source of cognitive load. While digital records offer superior legibility and comprehensive historical data compared to handwritten notes, the UI often obscures the clinical narrative through diminished visual salience. Significant parameters are frequently presented in small font or as tabulated raw numbers (P3), which increases cognitive effort and hinders nurses' ability to detect clinically meaningful trends (P3, P6, P7). This lack of intuitive visualisation contributes to what P3 and P4 described as difficulty in tracking patient trajectories, as current systems tend to prioritise static snapshots of data over longitudinal trends. P7 identified a temporal resolution gap, whereby the hourly data archived in EMRs fails to capture second-by-second instability visible on bedside monitors. This forces nurses to continuously cross-reference disparate sources to build an accurate clinical picture. This process introduces risks of missing subtle deterioration patterns that are not immediately visible in a tabular UI.

Cognitive burden is further compounded by navigational effort, described by participants as "click fatigue". Time is lost navigating disparate tabs to consolidate a single patient's profile (P2, P3, P5). This imposes a search latency that competes with the working memory required to sustain the handover's momentum. P7 also highlighted the issue of "double-documentation", where data entered in one module may not cross-populate other relevant logs, necessitating manual search and re-entry. This structural friction shifts the focus of clinical communication to data navigation, introducing latent risks during the transition of care.

3.2. Nurse-Nurse Interaction

Participants perceive handover as fundamentally a face-to-face, one-on-one interpersonal interaction. Eye contact, verbal communication, and non-verbal cues are considered essential for clinical safety. Therefore, any technology that obstructs this rapport is perceived to compromise the quality of the handover (P1, P2, P5). This need for unobstructed presence extends to the patient. Participants noted that visual access is vital for detecting distress cues, and that digital overlays must not obscure the patient's face or clinical field of view. To preserve this connection, participants advocated for high levels of user autonomy regarding the interface. Specifically, the ability to toggle digital panels was viewed as a necessity, ensuring that the system remains a supportive tool rather than a distraction (P2, P4).

Beyond technical utility, the visual conspicuity of head-mounted displays presents a significant barrier to empathetic care. Participants responded negatively to VR headsets, citing both ergonomic impracticality and their "odd" or alienating appearances in a clinical setting (P2, P3, P6). While AR glasses were viewed more favourably for their resemblance to standard eyewear, their presence still introduces ethical friction. Participants raised concerns that the cameras and microphones embedded in AR glasses could trigger anxiety, as they could capture sensitive audio and visual data. This underscores the necessity of informed consent, as any perceived lack of discretion risks eroding the trust fundamental to critical care (P2, P4).

Furthermore, the structural rigidity of standard EMR fields complicates the capture of soft data required for holistic care. Sensitive information, such as family restrictions and patient temperament, is often relegated to handwritten notes or verbal asides because it lacks a designated digital field (P2, P4). This suggests that existing documentation systems force a trade-off between structured data and the nuanced context required for holistic care. This "off-the-record" communication increases the risk of information loss during shift transitions, as it is not formally documented within the patient's permanent digital record.

3.3. Nurses' Perceptions of AR/AI

Participants viewed future technologies not as replacements for clinical judgement, but as safety nets to mitigate human error during high-pressure transitions. P6 explicitly noted that the "stream of consciousness" nature of verbal reporting often leads to the omission of specific checks. In response to this issue, most participants responded favourably to the concept of an intelligent agent capable of listening to and flagging omissions in real-time. This aligns with positive feedback from P1, P3 and P5 regarding the potential for AI summarisation to alleviate the administrative burden of manual documentation. This concept of "revealing the unseen" extended to AR. P7 proposed that AR could provide non-invasive visualisation of wound healing beneath dressings, eliminating the need to physically disturb the patient during checks. Similarly, P6 noted that such overlays could bridge knowledge gaps for junior staff encountering complex diagnoses. However, trust in autonomous interpretation remains a primary barrier. Participants cited privacy concerns regarding voice-enabled features, particularly the potential for unintended disclosure of sensitive diagnoses to unauthorised individuals in shared clinical environments. Furthermore, P7 warned that generative models may lack the contextual nuance to interpret clinical vernacular. This highlights the necessity of domain-specific training for AI to prevent interpretation errors that could compromise patient safety.

4. Discussion

The preliminary findings suggest that challenges in current ICU nurse handover arise not from insufficient information, but from the high interaction cost associated with retrieving, navigating, and interpreting data within the EMR. Informed by these findings, we propose two design concepts (In-Situ Spatial Dashboard and AI-Assisted Conversational Agent) to be developed as technical probes for upcoming co-design workshops. These designs are intended to reduce cognitive load by streamlining information access, supporting contextual sense-making, and minimising disruptive interface switching during handover.

4.1. In-Situ Spatial Dashboard

To mitigate the cognitive load imposed by data fragmentation, we propose an in-situ spatial dashboard. Unlike EMRs, which abstract physiological data into decontextualised tables, this concept leverages AR to restore the spatial context of clinical information. By anchoring pathological trends (e.g., fluid balance and sepsis markers) directly on the patient's body, we facilitate rapid cross-system assessment by externalising these internal states. This creates an immediate semantic link between the abstract data and its physical source, thereby reducing the cognitive effort to construct a mental model of the patient's physiological status. Crucially, these overlays are on-demand, ensuring the technology supports rather than impedes interpersonal connection.

4.2. AI-Assisted Conversational Agent

To mitigate omission errors and reduce administrative burden, we propose a multimodal AI agent that functions as a proactive safety net during clinical handover. The agent validates verbal reports against the ISBAR framework, issuing real-time prompts when critical information is absent, thereby reducing the risk of incomplete information transfer. In parallel, it extracts and schedules follow-up tasks, diminishing reliance on working memory and informal notes during shift transitions. Following handover, the system converts the spoken exchange into draft clinical documentation, decreasing the cognitive effort and time required for record keeping. Voice-based queries enable hands-free access to patient data, preserving attention at the bedside. Crucially, the system employs a human-in-the-loop architecture: all AI-generated outputs require manual verification, and the interface is fully toggleable, ensuring that nurses retain final authority over the clinical record.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

References

[1] Y. Pinevich, K. J. Clark, A. M. Harrison, B. W. Pickering, V. Herasevich, Interaction time with electronic health records: a systematic review, Applied clinical informatics 12 (2021) 788–799.

[2] P. R. Ebright, L. Urden, E. Patterson, B. Chalko, Themes surrounding novice nurse near-miss and adverse-event situations, JONA: The Journal of Nursing Administration 34 (2004) 531–538.

[3] L.-P. Cheah, D. H. Amott, J. Pollard, D. A. K. Watters, Electronic medical handover: towards safer medical care, Medical Journal of Australia 183 (2005) 369–372. doi:https://doi.org/10.5694/j.1326-5377.2005.tb07086.x.

[4] M. M. Thomas, T. Kannampallil, J. Abraham, G. E. Marai, Echo: A large display interactive visualization of icu data for effective care handoffs, in: 2017 IEEE workshop on visual analytics in healthcare (VAHC), IEEE, 2017, pp. 47–54.

[5] S. S. Hoskote, C. J. R. Africano, A. B. Braun, J. C. O'Horo, R. A. S. Berrios, T. O. Loftsgard, K. M. Bryant, V. N. Iyer, N. J. Smischney, Improving the quality of handoffs in patient care between critical care providers in the intensive care unit, American Journal of Medical Quality 32 (2017) 376–383. doi:10.1177/1062860616654758.

[6] Y. Kowitlawakul, B. S. Leong, A. Lua, R. Aroos, J. J. Wong, N. Koh, N. Goh, K. C. See, J. Phua, A. Mukhopadhyay, Observation of handover process in an intensive care unit (icu): barriers and quality improvement strategy, International journal for quality in health care 27 (2015) 99–104.

[7] A. J. Spooner, L. M. Aitken, W. Chaboyer, Implementation of an evidence-based practice nursing handover tool in intensive care using the knowledge-to-action framework, Worldviews on Evidence-Based Nursing 15 (2018) 88–96.

[8] H. Wüller, M. Garthaus, H. Remmers, Augmented reality in nursing: designing a framework for a technology assessment, in: MEDINFO 2017: Precision Healthcare through Informatics, IOS Press, 2017, pp. 823–827.

[9] K. Klinker, M. Wiesche, H. Krcmar, Digital transformation in health care: Augmented reality for hands-free service innovation, Information Systems Frontiers 22 (2020) 1419–1431.

[10] S. Yoo, S. Heo, S. Song, A. Park, H. Cho, Y. Kim, W. C. Cha, K. Kim, M. H. Son, Adoption of augmented reality in educational programs for nurses in intensive care units of tertiary academic hospitals: Mixed methods study, JMIR Serious Games 12 (2024) e54188. doi:10.2196/54188.

[11] J. G. Kovoor, A. K. Gupta, M. A. Gladman, Validity and effectiveness of augmented reality in surgical education: a systematic review, Surgery 170 (2021) 88–98.

[12] X. Wang, L. Besançon, D. Rousseau, M. Sereno, M. Ammi, T. Isenberg, Towards an understanding of augmented reality extensions for existing 3d data analysis tools, in: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, 2020, pp. 1–13.

[13] C. Albrecht-Gansohr, L. Timm, S. C. Eimler, S. Geisler, An augmented reality application for wound management: Enhancing nurses' autonomy, competence and connectedness, Virtual Worlds 3 (2024) 208–229. doi:10.3390/virtualworlds3020011.

[14] C. Lee, K. A. Vogt, S. Kumar, Prospects for ai clinical summarization to reduce the burden of patient chart review, Frontiers in Digital Health 6 (2024) 1475092.

[15] J. Silberlust, P. Solanki, E. R. Stevens, N. Genes, E. Lim, K. Sun, M. Lewis, P. Testa, A. Szerencsy, Artificial intelligence-generated encounter summaries: early insights from ambulatory clinicians at a large academic health system, JAMIA Open 8 (2025) ooaf096. doi:10.1093/jamiaopen/ooaf096.

[16] B. Shickel, P. J. Tighe, A. Bihorac, P. Rashidi, Deep ehr: a survey of recent advances in deep learning techniques for electronic health record (ehr) analysis, IEEE journal of biomedical and health informatics 22 (2018) 1589–1604.

[17] N. Ardic, R. Dinc, Emerging trends in multi-modal artificial intelligence for clinical decision support: A narrative review, Health Informatics Journal 31 (2025) 14604582251366141.

[18] M. Salimparsa, K. Sedig, D. J. Lizotte, S. S. Abdullah, N. Chalabianloo, F. T. Muanda, Explainable ai for clinical decision support systems: Literature review, key gaps, and research synthesis, Informatics 12 (2025). doi:10.3390/informatics12040119.